IDENTIFICATION OF EEG SIGNAL PATTERNS BETWEEN ADULTS WITH DYSLEXIA AND NORMAL CONTROLS

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Declaration

I declare that this thesis is my own account of my research and contains as its main content work which has not previously been submitted for a degree at any tertiary education institutions.

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Dedication

This thesis is dedicated to the dyslexia community; hoping these research findings would be a stepping-stone towards saving millions of individuals with dyslexia from a life-long risk of illiteracy and social exclusion.

Abstract

Electroencephalography (EEG) is one of the most useful techniques used to represent behaviours of the brain and helps explore valuable insights through the measurement of brain electrical activity. Hence, it plays a vital role in detecting neurological disorders such as epilepsy. Dyslexia is a hidden learning disability with a neurological origin affecting a significant amount of the world population. Studies show unique brain structures and behaviours in individuals with dyslexia and these variations have become more evident with the use of techniques such as EEG, Functional Magnetic Resonance Imaging (fMRI), Magnetoencephalography (MEG) and Positron Emission Tomography (PET).

In this thesis, we are particularly interested in discussing the use of EEG to explore unique brain activities of adults with dyslexia. We attempt to discover unique EEG signal patterns between adults with dyslexia compared to normal controls while performing tasks that are more challenging for individuals with dyslexia. These tasks include real-word reading, nonsense-word reading, passage reading, Rapid Automatized Naming (RAN), writing, typing, browsing the web, table interpretation and typing of random numbers. Each participant was instructed to perform these specific tasks while staying seated in front of a computer screen with the EEG headset setup on his or her head. The EEG signals captured during these tasks were examined using a machine learning classification framework, which includes signal preprocessing, frequency sub-band decomposition, feature extraction, classification and verification. Cubic Support Vector Machine (CSVM) classifiers were developed for separate brain regions of each specified task in order to determine the optimal brain regions and EEG sensors that produce the most unique EEG signal patterns between the two groups.

The research revealed that adults with dyslexia generated unique EEG signal patterns compared to normal controls while performing the specific tasks. One of the vital discoveries of this research was that the nonsense-words classifiers produced higher Validation Accuracies (VA) compared to real-words classifiers, confirming difficulties in phonological decoding skills seen in individuals with dyslexia are reflected in the EEG signal patterns, which was detected in the left parieto-occipital. It was also uncovered that all three reading tasks showed the same optimal brain region, and RAN which is known to have a relationship to reading also showed optimal performance in an overlapping region, demonstrating the likelihood that the association between reading and RAN reflects in the EEG signal patterns. Finally, we were able to discover brain regions that produced exclusive EEG signal patterns between the two groups that have not been reported before for writing, typing, web browsing, table interpretation and typing of random numbers.

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Table of Contents

List of Figures

List of Tables

List of Definitions

Artefact Subspace Reconstruction: ‘relies on a sliding-window Principal Component Analysis, which statistically interpolates any high-variance signal components exceeding a threshold relative to the covariance of the calibration dataset. Each affected time point of EEG is then linearly reconstructed from the retained signal subspace based on the correlation structure observed in the calibration data’ (Mullen et al., 2013).

Dyslexia: A hidden learning disability with a neurological origin (Fletcher, Lyon, Fuchs, & Barnes, 2006), which causes difficulties in reading and spelling despite average or above average intelligence levels (Costa, Zavaleta, Cruz, et al., 2013; Perera, Shiratuddin, & Wong, 2016b) and appropriate exposure to literacy instruction.

Feature Extraction: Transforming the input data into a set of features (Shantha Selva Kumari & Prabin Jose, 2011). This helps to analyse the data in terms of a reduced but most useful set of features instead of the large original input data set.

Electroencephalogram: A record of the oscillations of brain electric potential recorded from electrodes on the human scalp’ (Nunez & Srinivasan, 2006, pp. 3).

Phonological Awareness: The ability to hear and manipulate the sounds in words (Johnston, McDonnell, & Hawken, 2008).

Phonological Decoding: Phonological decoding refers to the ability to utilize phonics knowledge when reading and is usually measured based on nonsense-word reading performance (Facoetti et al., 2010).

Rapid Automatized Naming: Rapid Automatized Naming is the ability to quickly name familiar things such as letters, digits, objects and colours (Jones, Branigan, Hatzidaki, & Obregón, 2010) and measures the speed of retrieval of language-based information from long term memory.

Support Vector Machine: Support Vector Machine is a supervised learning method, which can handle both linear and non-linear classifications. It produces a hyper-plane having the maximal margin to the support vectors. Support Vector Machine can classify even overlapping and non-separable data sets by mapping into higher dimensional spaces using the kernel functions (Garrett, Peterson, Anderson, & Thaut, 2003; Shantha Selva Kumari & Prabin Jose, 2011).

List of Abbreviations

Ap	Positive Area
ApEn	Approximate Entropy
ASR	Artefact Subspace Reconstruction
CC2	The Castles and Coltheart Test 2
CGSVM	Coarse Gaussian Support Vector Machine
CSVM	Cubic Support Vector Machine
CTOPP	Comprehensive Test of Phonological Processing
ECG	Electrocardiogram
EEG	Electroencephalogram
EMG	Electromyogram
EOB	Electrooculography
ERP	Event-Related Potential
FFT	Fast Fourier Transform
FGSVM	Fine Gaussian Support Vector Machine
FIR	Finite Impulse Response
fMRI	Functional Magnetic Resonance Imaging
FN	False Negative
FP	False Positive
GORT	Gray Oral Reading Tests
ICA	Independent Component Analysis
IIR	Infinite Impulse Response
IQ	Intelligence Quotient
KDE	Kernel Density Estimate
LSVM	Linear Support Vector Machine
MEG	Magnetoencephalography
MGSVM	Median Gaussian Support Vector Machine
MLP	Multilayer Perceptron
MOTIf	Macquarie Online Test Interface
Mp	Maximal Peak Amplitude/Time ratio

MRI	Magnetic Resonance Imaging
PCA	Principal Component Analysis
PET	Positron Emission Tomography
PSD	Power Spectral Density
QSVM	Quadratic Support Vector Machine
OWLS	Oral and Written Language Scales
QUIL	Queensland University Inventory of Literacy
RO	Research Objective
RP	Research Problem
RAN	Rapid Automatized Naming
rCBF	Regional Cerebral Blood Flow
RQ	Research Question
SFM	Spectral Flatness Measure
SPAT	Sutherland Phonological Awareness Test
SVM	Support Vector Machine
TN	True Negative
TNR	True Negative Rate
TP	True Positive
TPR	True Positive Rate
VA	Validation Accuracy
WASI	Wechsler Abbreviated Scale of Intelligence
WIAT	Wechsler Individual Achievement Test
WISC	Wechsler Intelligent Scale for Children
WJ	Woodcock Johnson
YARC	York Assessment of Reading for Comprehension

List of Publications

Journals

J1. Perera, H., Shiratuddin, M.F. & Wong, K.W. (2017). Review of EEG-based Pattern Classification Frameworks for Dyslexia, Brain Informatics. (Under review)

Conference Proceedings

C1. Perera, H., Shiratuddin, M.F. & Wong, K.W. (2016). Review of the Role of Modern Computational Technologies in the Detection of Dyslexia, 7th International Conference on Information Science and Applications – ICISA 2016, Ho Chi Minh City, Vietnam, 16 – 18 February, 2016.

C2. Perera, H., Shiratuddin, M.F. & Wong, K.W. (2016). A Review of Electroencephalogram-based Analysis and Classification Frameworks for Dyslexia, The 23rd International Conference on Neural Information Processing – ICONIP 2016, Kyoto, Japan, 16 – 21 October, 2016.

C3. Perera, H., Shiratuddin, M.F., Wong, K.W. & Fullarton, K. (2017). EEG Signal Analysis of Real-word Reading and Nonsense-word Reading between Adults with Dyslexia and without Dyslexia, 30th IEEE International Symposium on Computer-Based Medical Systems – CBMS 2017, Thessaloniki, Greece, 22 – 24 June, 2017.

C4. Perera, H., Shiratuddin, M.F., Wong, K.W. & Fullarton, K. (2017). EEG Signal Analysis of Passage Reading and Rapid Automatized Naming between Adults with Dyslexia and Normal Controls, 8th IEEE International Conference on Software Engineering and Service Science – ICSESS 2017, Beijing, China, 24 – 26 November, 2017.

C5. Perera, H., Shiratuddin, M.F., Wong, K.W. & Fullarton, K. (2017). EEG Signal Analysis of Writing and Typing between Adults with Dyslexia and Normal Controls, 7th International Conference on Information Technology and Multimedia – ICIMU 2017, Putrajaya, Malaysia, 8 – 9 November, 2017.

Summary of Contributions to the Thesis

Chapter	Contributions	Paper Number
Chapter 1 – Introduction Chapter 2 – Literature Review	Investigation on need for neurological aspect in detection of dyslexia. Review of modern computational technologies in detecting dyslexia.	C1, C2, J2
Chapter 2 – Literature Review Chapter 3 – Methodology	Review and comparison of EEG-based signal pattern recognition frames for dyslexia, which highlights the gaps to be filled in future research.	C2, J2
Chapter 3 – Methodology Chapter 4 – Discussion Chapter 5 – Conclusions	EEG-based framework and its results for identifying unique EEG signal patterns during real-word reading and nonsense-word reading between adults with dyslexia and normal controls.	C3
	EEG-based framework and its results for identifying unique EEG signal patterns during passage reading and rapid automatized naming between adults with dyslexia and normal controls.	C4
	EEG-based framework and its results for identifying unique EEG signal patterns during writing and typing between adults with dyslexia and normal controls.	C5

Chapter 1 Introduction

1.1 Background and Motivation

Dyslexia is a hidden learning disability with a neurological origin, which causes lack of proficiency in reading and spelling despite average or above average intelligence, sensory abilities and appropriate exposure to literacy instruction (Fletcher et al., 2006; Perera et al., 2016b). Common symptoms of dyslexia include poor reading skills, illegible handwriting, slow writing or copying, bad spellings, letter migration and reversals (Fletcher et al., 2006; Gvion & Friedmann, 2010; Sahari & Johari, 2012; Shalev, Mevorach, & Humphreys, 2008). Dyslexia affects a significant amount of the world population. Statistics show that approximately 20% of the child population in the United States of America (Shaywitz, 2003), approximately 4% of the students in Australia (The Dyslexia-SPELD Foundation of WA, n.d.-b) and overall approximately 15–20% of the world population (de Santana, de Oliveira, Almeida, & Baranauskas, 2012) experience dyslexia. Current assessment methods for the identification of dyslexia are based on indicators such as reading proficiency, spelling ability, writing, working memory, processing ability, a review of biographical information and the individual's educational history (The Dyslexia-SPELD Foundation of WA, n.d.-a). Standardised test such as Wechsler Individual Achievement Test (WIAT), Comprehensive Test of Phonological Processing (CTOPP), Oral and Written Language Scales (OWLS) and Woodcock Johnson (WJ) are few of the tests used to assess these abilities. The severity of dyslexia may vary from mild to severe, and therefore the symptoms of dyslexia vary from person to person.

Glancing into the internal organs and imaging without having to open the body, monitoring and analysing are few of the complexities simplified by technology. Electroencephalography, commonly known as EEG, is one such technology that helps to capture neurological behaviours. EEG is a monitoring technique used to identify unique neurological behaviours in conditions such as epilepsy (Abdulhay, V, M, V.S, & K, 2017), sleeping disorders (Hassan & Subasi, 2017) and autism (Grossi, Olivieri, & Buscema, 2017). Although EEG provides very valuable insights into the brain, discovering these are not always straightforward due to its complexity. These are often analysed using statistical techniques as well as computational techniques such as machine learning, which have been discussed in detail in following chapters.

The availability of affordable EEG devices from organisations such as Cognionics, Emotiv, OpenEEG, NeuroSky and Mindo, EEG processing toolboxes such as EEGLAB, and the availability of machine learning toolboxes makes it possible to design and develop EEG-based pattern identification and classification frameworks with less effort without having to re-invent the wheel.

As dyslexia is understood to be neurological in origin, EEG can be used to identify unique brain behaviours in individuals with dyslexia. Past research has found unique brain structures as well as distinctions in the brainwave activation patterns in individuals with dyslexia compared to normal control groups (Mohamad, Mansor, & Lee, 2013). However, there are many gaps to be filled in the literature about these unique EEG signal patterns pertaining to dyslexia, in particular the EEG patterns while performing tasks that are more challenging for individuals with dyslexia (Perera, Shiratuddin, & Wong, 2016a). Hence, in this research we aim to identify these unique EEG signal patterns in adults with dyslexia compared to normal controls. Identification of unique EEG signal patterns between individuals with dyslexia compared to normal controls can help provide a better view of dyslexia as well as help to cater more targeted assistance for dyslexia.

1.2 Aims and Objectives

This section includes the research problems (RP) identified through the literature review, and the research questions (RQ) and research objectives (RO) constructed from the gaps identified.

1.2.1 Research Problems

RP1:

Through the literature review, it was evident that dyslexia has a neurological origin (Fletcher et al., 2006) and preliminary studies show differences in brain structures and behaviours between individuals with dyslexia compared to normal controls. However, it is yet to be identified whether certain tasks, which are more challenging for individuals with dyslexia, show different brain signal patterns. These tasks are explained in the sub-problems given below.

RP2:

Individuals having dyslexia fail to attain sufficient reading skills compared to normal controls despite conventional instructions and teaching guidelines. For many individuals who are identified with dyslexia, a phonological deficit is noted (Fletcher et al., 2006) and this deficit results in poor word decoding abilities and difficulties in sound detection and isolation. This reduces the reading and spelling experience, which hinders vocabulary development.

RP3:

Recent research (Donker, Kroesbergen, Slot, Van Viersen, & De Bree, 2016; Georgiou, Parrila, Cui, & Papadopoulos, 2013; Schatschneider, Carlson, Francis, Foorman, & Fletcher, 2002) supports the notion on that Rapid Automatized Naming (RAN) is related to reading. RAN ability is often comparatively poor in individuals with dyslexia (M. Jones, Branigan, & Kelly, 2009).

RP4:

Individuals having dyslexia suffer poor writing skills. Symptoms include poor development of written expression skills, letter identity errors such as substitutions, additions and omissions, bad handwriting, slow writing and copying and poor spellings (Gvion & Friedmann, 2010).

RP5:

Typing is a modern-day task that often replaces writing, but still, affects people with dyslexia in a similar manner when it comes to spelling.

RP6:

A significant amount of everyday human tasks involves reading and writing. In reality, it is not just letters or words that an individual will have to read and understand. Browsing the web while reading and typing, interpreting tables with letters and numbers or keying in an unfamiliar number are few of the present-day challenging tasks individuals with dyslexia face.

1.2.2 Research Questions

RQ1:

Do EEG signals generated while performing specific tasks that are more challenging for individuals with dyslexia produce unique brainwave signal patterns in adults with dyslexia compared to normal controls?

Can these EEG signal patterns be detected using machine learning classification techniques?

Do these EEG signal patterns differ according to the tasks and EEG sensors spanned across each brain region?

The research questions pertaining to each task is explained in the sub-questions given below.

RQ2:

Do EEG signals generated while reading produce unique brainwave signal patterns in adults with dyslexia compared to normal controls?

Do reading real-words, nonsense-words and passages activate the same brainwave patterns?

RQ3:

Do EEG signals generated during RAN produce unique brainwave signal patterns in adults with dyslexia compared to normal controls?

RQ4:

Do EEG signals generated while writing produce unique brainwave signal patterns in adults with dyslexia compared to normal controls?

RQ5:

Do EEG signals generated while typing produce unique brainwave signal patterns in adults with dyslexia compared to normal controls?

RQ6:

Do EEG signals generated during the following everyday tasks produce unique brainwave signal patterns in adults with dyslexia compared to normal controls?

- Browsing the web
- Interpreting tables
- Keying in an unfamiliar number

1.2.3 Research Objectives

RO1:

The main aim of this research is to identify unique patterns in the EEG signals in adults with dyslexia compared to normal controls when performing tasks that are more challenging for individuals with dyslexia. These unique patterns will be identified using an EEG-based machine learning classification framework and derived through the sub-objectives explained below.

RO2:

Identify brain regions and EEG electrodes that produce unique EEG signal patterns in adults with dyslexia compared to normal controls during reading related tasks. Compare patterns during real-word, nonsense-word and passage reading.

RO3:

Identify brain regions and EEG electrodes that produce unique EEG signal patterns in adults with dyslexia compared to normal controls during RAN.

RO4:

Identify brain regions and EEG electrodes that produce unique EEG signal patterns in adults with dyslexia compared to normal controls while writing.

RO5:

Identify brain regions and EEG electrodes that produce unique EEG signal patterns in adults with dyslexia compared to normal controls while typing.

RQ6:

Identify brain regions and EEG electrodes that produce unique EEG signal patterns in adults with dyslexia compared to normal controls during the following everyday tasks.

- Browsing the web
- Interpreting tables
- Keying in an unfamiliar number

1.3 Scope

This research is primarily focused on identifying unique patterns in the EEG signals in individuals with dyslexia compared to normal controls when performing tasks that are more challenging for individuals with dyslexia.

The scope of this research is limited to right-handed adults with age of 18 years or older who are fluent in English and have a normal or corrected-to-normal vision and normal hearing. These tasks include real-word reading, nonsense-word reading, passage reading, RAN, writing, typing, browsing the web, table interpretation and typing of random numbers. The participants with dyslexia were recruited through DSF Literacy and Clinical Services and were limited to adults who had completed a recent assessment and diagnosis. The scope of this research does not include the examination of unique brainwave patterns between other specific learning disabilities such as dysgraphia or dyscalculia.

Further, this research uses machine learning as the technique to identify the unique brainwave patterns between the two groups. The machine learning classifier is selected based on the evidence on reviews and recommendations of past similar research.

1.4 Significance

With the evolution of technology, the major role that technology now plays in the identification of patterns pertaining to disorders and difficulties is paramount. Improving and evaluating the way in which patterns of results are identified and classified may help uncover answers that are not always obvious.

This research offers some important insights into the unique brainwave signal patterns generated for adults with dyslexia compared to normal controls while performing a few specific tasks that are more challenging for individuals with dyslexia. These tasks include real-word reading, nonsense-word reading, RAN, passage reading, web browsing, writing, typing, table interpretation and typing of random numbers. A literature review shows that most of the studies carried out by identifying unique brainwave patterns entail the examination of event-related potentials (ERP), which is the brain response to a stimulus. In this research, we contribute to the limited literature of the brain behaviour patterns in straight EEG while performing these tasks. These findings will help to confirm whether the greater level of difficulties seen in individuals with dyslexia while performing these tasks are reflected in the brainwave patterns and identify the specific brain regions that produce these unique brainwave signal activation patterns for each task.

EEG signals provide very valuable insights into the behaviour of the brain; however, identifying these patterns is not always quite straightforward due to its complexity. Although past studies prove that manual statistical analysis could detect these patterns, the process requires careful analysis and could take up a considerable amount of time. In this research, we also contribute towards the possibility of automating the process through machine learning classification.

This research would provide significant insights into the brainwave signal patterns between the adults with dyslexia and normal controls. Listed below are few of the noteworthy findings it may help uncover.

- If the greater level of difficulties seen during nonsense-word reading compared to real-word reading in individuals with dyslexia reflects in the EEG signal patterns. The capability to read nonsense-words is known to be one of the best ways to measure phonological decoding skills (Shaywitz, 2003), and poor phonological decoding skills is one of the common symptoms seen in individuals with dyslexia (Facoetti et al., 2010; Ziegler, Perry, & Zorzi, 2014). Therefore, the results can help confirm whether difficulties in phonological decoding skills seen in individuals with dyslexia are reflected in the EEG brainwave signal patterns.
- If all reading related tasks activate similar optimal brain regions
- If RAN, which is related to reading activate similar optimal brain regions to reading
- If everyday human tasks which include reading or interpreting words or number while writing or typing show unique brainwave activations patterns

These findings will provide a better view of dyslexia, as it would help identify distinct brain regions for each task. Hence, help psychologists provide better-targeted assistance for individuals with dyslexia. EEG signals are particularly considered as a reliable measure, as the brainwave outcome cannot be falsified. The discoveries of this research could even one day benefit the diagnosis process of dyslexia as it can complement the behavioural-based detection techniques through the introduction of the neurological symptoms. Further, the use of automated machine learning classification makes it more practical and appealing to be used in real life.

The identification of brain regions helps to narrow down the EEG sensors required to distinguish unique brainwave signal patterns specific to dyslexia. These results would perhaps enable EEG headset manufacturers to produce EEG headsets specifically to be used in the dyslexia detection process.

In summary, the outcomes of this research could help fill gaps in the limited literature on the unique brainwave patterns generated in adults with dyslexia compared to normal controls while performing specific tasks that are more challenging for individuals with dyslexia. Furthermore, the classification framework used in this research can be used as a guideline in the development of dyslexia pattern recognition software.

1.5 Outline of Thesis

This thesis is divided into 6 chapters, and the outline of the chapters is presented below.

Chapter 1 presents an introduction to the thesis that includes the background, motivation and aims of objectives of the current research. It also highlights the scope and significance.

Chapter 2 reviews relevant literature by critically evaluating prior similar work. It comprises reviews on dyslexia, the conventional dyslexia detection, role of technology played to improve dyslexia detection and EEG-based signal pattern recognition frameworks for dyslexia. Finally, summarises the gaps in the literature.

Chapter 3 describes the methodology used, which includes research strategies implemented for signal acquisition, analysis and classification. Further, it includes about pilot studies carried out in order to confirm the suitability of the adapted methods.

Chapter 4 presents the results of all the classifiers build in order to determine if there are unique EEG signal patterns between adults with dyslexia and normal controls. The results are categorised task wise, with each task containing the classifiers for each brain region along with the validation metrics.

Chapter 5 includes a critical discussion of the results on how the insights of the findings relate to the research questions, objectives and past similar research.

Chapter 6 provides a summary of the research, its contributions and recommendations for future research.

Chapter 2 Literature Review

2.1 Overview

This section outlines and reviews the literature related to the research by critically evaluating prior similar work. The review starts by discussing details of dyslexia, its symptoms, conventional dyslexia detection techniques, targeted assistance required, followed by unique brain structures and behaviours seen in individuals with dyslexia. Next, a detailed evaluation of the role of technology played in improving the dyslexia detection techniques is discussed. This includes efforts made to improve the current dyslexia detection process as well as to revolutionise the process; which explores new potential areas for dyslexia detection through symptoms that are not merely visible externally. Subsequently, a comparison of the existing EEG-based signal pattern recognition frameworks for dyslexia is conducted, where the strengths and gaps are highlighted. Further, popular pattern recognition techniques including statistical analysis and machine learning are discussed. Finally, the findings are summarised through highlighting the gaps in the literature.

2.2 Dyslexia

2.2.1 What is Dyslexia?

Dyslexia, commonly known as a word-blindness in the 1800's (Zerbin-Rüdin, 1967) is a word originated from the Greek language with the combination of the two Greek words 'dys' and 'lexia'. 'Dys' with the meaning 'difficulty' and 'lexia' with the meaning 'words' put together simply means difficulty with words (Hultquist, 2008).

A child having dyslexia can become a depressed, unmotivated or a low self-esteemed child if the condition goes undetected. Difficulty in learning to interpret letters, words or sometimes even symbols certainly causes the child to have a hard time keeping up with his or her peers in school (Mohamad et al., 2013). Although individuals having dyslexia face difficulties with reading, writing and spelling, there are many great dyslexic minds such as Albert Einstein, Leonardo da Vinci, Alexander Graham Bell, Hans Christian Andersen, Walt Disney, Henry Ford, Steve Jobs and Richard Branson (Davis, 2010). According to Davis (2010) in the book 'The gift of dyslexia: why some of the brightest people can't read and how they can learn", individuals with dyslexia are believed to be highly intuitive and insightful with the ability to alter and create perceptions. They are known to be highly aware of the environment, with more curiosity than average, thinking mainly in pictures instead of words and experiencing thought as reality with a lot of vivid imaginations (Davis, 2010).

Diagnosing dyslexia at an early stage is important to prevent a child having to go through a stressful, rough childhood and face frustrating experiences at school. Early detection helps to direct children with dyslexia to the necessary treatments required. Targeted assistance is essential for individuals with dyslexia to not only develop coping mechanisms but intervention an remediation aims to reduce the level of disadvantage that the individual experiences and to improve their underlying literacy skills. Recent studies (Sahari & Johari, 2012) states that 'dyslexia is not a disease or defect that can be cured', rather a 'condition that can be helped' with proper targeted support. Promising results have shown through children who go through intervention programs in the early stages of literacy development (Zakopoulou et al., 2011) demonstrate an improvement in reading performance as well as a reduction of anxiety (Haddadian, Alipourb, Majidi, & Maleki, 2012).

Research shows poor reading skills, bad spellings, unclear and slow writing, letter migrations and reversals as prevalent symptoms of dyslexia (Gvion & Friedmann, 2010; Sahari & Johari, 2012; Shalev et al., 2008).

> *Dyslexia is a specific learning disability that is neurological 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 the growth of vocabulary and background knowledge (Fletcher et al., 2006, pp. 104).

As stated by Fletcher et al. (2006) dyslexia is a disability with a neurological origin, causing difficulties in reading and spelling. Lack of phonological awareness; 'the ability to hear and manipulate the sounds' in words (Johnston et al., 2008) and poor phonological decoding skills (Facoetti et al., 2010; Ziegler et al., 2014) are commonly found symptoms in individuals having dyslexia. Phonological decoding refers to the ability to utilize phonics knowledge when reading and is usually measured based on nonsense-word reading performance (Facoetti et al., 2010). Further, as shown in Figure 2.1 Ziegler et al. (2008) proves that individuals having dyslexia perform worse in reading irregular and nonsense-words compared to regular words.

	Controls	Dyslexics	Δ	*t*-value
Accuracy (% correct)				
Regular	99.2 (2.8)	97.1 (5.5)	2.1	1.65
Irregular	92.5 (7.9)	68.8 (28.0)	23.7	3.99***
Nonwords	96.3 (5.8)	78.3 (17.5)	18.0	4.75***
Latency (ms)				
Regular	700 (144)	876 (235)	176	3.12**
Irregular	812 (159)	1124 (335)	312	4.11***
Nonwords	938 (188)	1186 (333)	248	3.17**

Figure 2.1: Reading performance of individuals having dyslexia (Ziegler et al., 2008)

RAN is the ability to quickly name familiar things such as letters, digits, objects and colours (Jones et al., 2010) and measures the speed of retrieval of language-based information from long term memory. Research confirms RAN is related to reading (Georgiou et al., 2013) and that it is impaired in individuals with dyslexia (Jones et al., 2010).

Dyslexia is heritable, which means a child has a possibility to inherit it from a parent who has dyslexia. It has been reported that 23-65% of children who have a parent with dyslexia are at risk of having dyslexia (Shaywitz & Shaywitz, 2005).

Dyslexia in some cases can have partly or wholly distinct genetic causes. Francks, MacPhie, and Monaco (2002) suggest looking into the genetic aspect to diagnose dyslexia instead of merely considering individual disabilities. Identification of the genetic variants would help to estimate and reduce the risk of developing severe reading problems earlier than currently possible. Studies have shown that overall reading abilities including dyslexia have significant genetic components with heritability estimated at 54-84% (Eicher & Gruen, 2013).

2.2.2 Conventional Dyslexia Detection

The conventional dyslexia detection techniques are mostly based on behavioural aspects and academic indicators, which include measures such as reading, writing and spelling abilities, IQ level, phonological awareness, working memory, processing ability, biographical information and educational history. Individuals are assessed using standardised tests to identify these capabilities and thereby detect dyslexia (The Dyslexia-SPELD Foundation of WA, n.d.-a). Given below in Table 2.1 are few of the standardised, well-recognised tests used by professionals in the industry.

Table 2.1: Dyslexia standardised tests

Category	Test
IQ	WISC (Wechsler Intelligent Scale for Children) or WASI (Wechsler Abbreviated Scale of Intelligence) and WJ (Woodcock Johnson)
Reading	WIAT (Wechsler Individual Achievement Test) TOWRE (Test of Word Reading Efficiency) YARC (York Assessment of Reading for Comprehension) GORT (Gray Oral Reading Tests)
Writing	OWLS (Oral and Written Language Scales) WIAT (Wechsler Individual Achievement Test)
Phonological	CTOPP (Comprehensive Test of Phonological

Processing	Processing) SPAT (Sutherland Phonological Awareness Test) QUIL (Queensland University Inventory of Literacy)
Mathematics	WIAT (Wechsler Individual Achievement Test)
Memory	WISC (Wechsler Intelligent Scale for Children) or WJ - iii (Woodcock Johnson)

Listed below are few of the standardised tests in more detail.

- WISC: WISC measures IQ along with critical insights into children's cognitive functionalities. This test is tailored for children of age range 6 years and 0 months to 16 years and 11 months, which includes assessment areas of fluid reasoning, working memory and processing speed (Wechsler, 2003)

- WIAT: WIAT measures all areas important for detecting and categorizing learning disabilities as specified by the IDEA legislation. It assesses patterns of strengths and weaknesses of individuals in order to identify learning disabilities.

  WIAT-III offers a total of 16 subtests for individuals ranging from age 4 years and 0 months to 50 years and 11 months. The assessments include oral reading, math, early reading skills, listening comprehension, oral expression and written expression (Wechsler, 2009).

- OWLS: OWLS uses mainly four scales; listening comprehension, oral expression, reading comprehension, and written expression for assessing language skills accordance with IDEA requirements. It is available for age ranges 3 years and 0 months to 21 years and 11 months (Listening Comprehension and Oral Expression); 5 years and 0 months to 21 years and 11 months (Reading Comprehension and Written Expression) to identify learning disabilities and language difficulties (Carrow-Woolfolk, 2011).

- CTOPP: CTOPP is used to assess phonological processing skills as a prerequisite to reading fluency. It helps to determine the strengths and weaknesses in phonological processing capabilities of individuals of age ranges 4 years and 0 months to 24 years and 11 months (Wagner, Torgesen, Rashotte, & Pearson, 2013).

2.2.3 Targeted Assistance

Individuals with dyslexia fail to achieve sufficient reading and writing skills despite conventional teaching instructions and guidelines (Démonet, Taylor, & Chaix, 2004). They often require targeted assistance and modified teaching techniques.

The Orton-Gillingham approach is one such widely used successful multi-sensory teaching approach, which includes visual, auditory and touch combined with the learning practices (Beetham, 2011; Mohamad et al., 2013; Purkayastha, Nehete, & Purkayastha, 2012).

Targeted multi-sensory teaching game tools are one of the successful techniques introduced by research to keep children with dyslexia interested in the learning process. Educational multisensory games have shown effective results in the learning curves of people with dyslexia (Malekian & Askari, 2013).

Daud and Abas (2013) proposed a mobile application named ‘Dyslexia Baca’ to support children having dyslexia with letter recognition. The applications specifically focused on aiding difficulties with letter reversals such as ‘d and b’ and ‘w and m’ using multi-sensory teaching techniques in an enjoyable approach.

Individuals with dyslexia are often given extra time at exams to compensate for their difficulties. Although this does not help to remediate the difficulties directly, it helps to mitigate the difficulties faced to a certain extent by allowing additional time to process and review written information. The British Dyslexia Association recommends 25% extra time during exams for students with dyslexia (Allison Schwartz, n.d.; The British Dyslexia Association, n.d.).

Web accessibility could also be challenging for persons having dyslexia due to the related deficiencies. Recent research (de Santana et al., 2012; Rello, Kanvinde, & Baeza-Yates, 2012) has initiated focusing on providing custom tailored web layout guidelines for improving the web accessibility experience. The difficulties faced while browsing the web have been captured using conventional ways such as interviews and questionnaire as well as modern techniques such as eye tracking.

Such custom layout guidelines can also be useful for virtual learning environments used in higher education. A study (Habib et al., 2012) carried out regarding the struggles encountered by students with dyslexia in higher education show that the information overload in virtual learning environments is quite problematic.

2.2.4 Brain Structures and Behaviours

Recent studies (Mohamad et al., 2013) show that with the advancements in neuroimaging techniques, researchers are looking into how neurological techniques can assist to detect unique differences specific to dyslexia. The existence of the variances in the brain anatomy between individuals with dyslexia and normal individuals has been disclosed through findings.

Individuals with dyslexia often have to consciously interpret written words instead of instantaneously recognizing it. This is because the Broca's and Wernicke's areas of the brain function separately. The Wernicke's area is important for language and speech organisation and production, whereas Broca's area is important for language processing and reading. This brain behaviour certainly contributes toward causing difficulties to attain sufficient reading skills in individuals with dyslexia (Mohamad et al., 2013).

The distribution of Cerebral White Matter and the structure of the Corpus Callosum of the brain are example of different anatomy found in individuals with dyslexia. 3D Texture Analysis of MRI brain images has proven the clear differentiation of the individuals with dyslexia compared to normal individuals (El-Baz et al., 2008; Elnakib, El-Baz, Casanova, & Switala, 2010).

Analysis of the brain cortex to detect dyslexia through 3D images has been investigated by research (Nitzken et al., 2011). Specifically, the comparison of cortex gyrifications shows noteworthy differences between individuals with dyslexia and without dyslexia.

Further research (Heim & Keil, 2004; Hudson, High, & Al Otaiba, 2007) also shows a difference in brain hemisphere structures in individuals with dyslexia compared to individuals without dyslexia. In general, right-handed non-dyslexic individuals have asymmetrical brains where the left hemisphere is larger than the right hemisphere. On the contrary, individuals who have been identified as having dyslexia tend to have larger right hemispheres compared to the left hemispheres and sometimes even symmetrical hemispheres.

Soo-Yeon and van Najarian (2008) have proposed an fMRI-based method for dyslexia detection. fMRI scans depict changes in the blood flow (Soo-Yeon & van Najarian, 2008). Through this research, they were was able to identify distinguishable brain patterns in the fMRIs between the individuals with dyslexia and normal controls to word recognition stimulus. The final outcome of the research was a model that can detect unique brain activation patterns of dyslexia based on a hierarchical optimisation algorithm.

In a nutshell, research has found differences in the brain structures and behaviours of individuals with dyslexia and without dyslexia. This would give a better picture of the disability since it looks into variance in brain structure and processing skills that are present internally of the human brain.

2.3 Role of Technology in Dyslexia Detection

Technology undoubtedly helps to improve detection processes through the use of improved data capturing techniques as well as improved data analysis techniques. In the past few years, researchers have been working on how to use advanced technology to detect and improve identification techniques of dyslexia. Research carried out to improve the detection process of dyslexia are orderly categorised and discussed below. An overview of the categorization is shown in Table 2.2.

Table 2.2: Overview of the categorization of the technologies used for dyslexia detection

Improving Conventional Process	Efficient Data Analysis using Computational Intelligence Techniques	
	Improved Data Capturing	Interactive Multimedia
		Game-based Techniques
Revolutionising Process	Eye-Movements	Statistical Techniques
		Computational Intelligence and Pattern Recognition
	EEG	Statistical Frequency Analysis
		Classification Algorithms

2.3.1 Improving Conventional Process

The initiatives that have been made by recent research to automate the traditional paper-based detection approach are divided into two categories as explained below.

2.3.1.1 Efficient Data Analysis using Computational Intelligence Techniques

An early dyslexia screening system based on microcomputers was proposed by Cresswell, Monteith-Hodge, and Winfield (1997). The main intent of this research was to implement software that can learn the patterns of grammatical mistakes made by individuals with dyslexia, improving the accuracy of the screening results with time.

A computational Artificial Neural Network based model proposing to distinguish between the learning disabilities dyslexia, dysgraphia and dyscalculia was introduced by Jain, Manghirmalani, Dongardive, and Abraham (2009). The model presented is an Artificial Neural Network with a signal layer perceptron based learning disability diagnostic tool. By training the model, a level of 90% accuracy rate was obtained through this proposed research for the diagnostics.

Fuzzy logic has become a popular choice for diagnostic systems because of its many-valued nature of logic instead of the binary valued nature. A research team from Spain (Palacios, Sánchez, & Couso, 2010) have worked on a diagnosis system for dyslexia using Artificial Intelligence techniques. They attempt to automate the complex scoring task of the diagnostic process, which is usually carried out by a human expert. A Genetic Fuzzy system, which consists of a genetic cooperative–competitive algorithm with a rule-based classifier, is suggested to tackle this uncertain dataset.

Researchers Manghirmalani, Panthaky, and Jain (2011) have proposed a model to diagnose learning disabilities using a Soft Computing approach called Learning Vector Quantization. The model classifies subjects as learning disabled or non-learning disabled using Learning Vector Quantization. Further, it uses the Rule Based approach to identify and categorise the learning disability of the subjects, namely dyslexia, dysgraphia or dyscalculia.

2.3.1.2 Improved Data Capturing

2.3.1.2.1 Interactive Multimedia

An Interactive multimedia based early screening system, replacing the paper-based dyslexia screening approach was presented by Ekhsan, Ahmad, Halim, Hamid, and Mansor (2012). This alternative approach offered more reliable results compared to the manual screening process.

2.3.1.2.2 Game-based Techniques

The traditional dyslexia diagnosis test was attempted to be implemented as a set of games by a Spanish research team (Bartolome, Zorrilla, & Zapirain) in (2012). A web-based game application was introduced which evaluates word and syllable reading as well as syllabic, verbal and auditory memory capabilities to detect dyslexia. This application assesses the progress following therapy as well.

An Italian research group (Gaggi, Galiazzo, Palazzi, Facoetti, & Franceschini, 2012) proposed a similar game based dyslexia prediction system. A serious game was introduced to detect dyslexia through finding the capabilities of eye and hand coordination and visual and auditory stimuli. Once the symptoms are detected, the system treats the individuals by training the impairments in phonological skills and visual-spatial attention.

A prototype using Neural Networks for screening individuals who are at risk of dyslexia was presented by Costa, Zavaleta, Serra da Cruz, et al. (2013) The computational tool supports the identification process and predetermine intervention strategies.

Through these researches it is clear that technologies such as fuzzy logic and neural networks have contributed towards assisting the conventional dyslexia detection techniques. Most of the approaches have focused on identifying the patterns and hence perform classifications to differentiate individuals with dyslexia from the rest. Substitute approaches such as multimedia and serious gaming applications are also being trialled for its detection capabilities.

2.3.2 Revolutionising Process

This section covers research carried out to improve dyslexia detection techniques that go beyond the conventional methods. The detection techniques involve looking into symptoms that are not visible externally.

2.3.2.1 Eye-Movements

Eye movement patterns are another area currently being covered by research (Bellocchi, Muneaux, Bastien-Toniazzo, & Ducrot, 2013; De Luca, Borrelli, Judica, Spinelli, & Zoccolotti, 2002; De Luca, Di Pace, Judica, Spinelli, & Zoccolotti, 1999; Macas, Lhotska, & Novak, 2013) to detect symptoms of dyslexia. Research has been able to find unique eye movement patterns pertaining to individuals with dyslexia compared to individuals without dyslexia when performing reading related tasks. The following provides the findings of such research.

2.3.2.1.1 Statistical Techniques

Eye-movement patterns of individuals having dyslexia performing linguistic and non-linguistic tasks have been compared through research (De Luca et al., 1999). It was observed that there was no difference between the fixation and saccade eye-movement patterns in visual tasks of individuals with dyslexia compared to normal controls, but there were significant altered eye-movement patterns in individuals with dyslexia while performing reading tasks. This research proved that individuals having dyslexia suffer dysfunctions in the orthography to phonology conversion (letter to sound) and not in oculo-motor dysfunction.

De Luca et al. (2002) carried out research to identify how eye-movement patterns differ between individuals with dyslexia and normal controls while reading words and pseudo-words. The findings showed that in normal controls with the word length the saccade amplitude increased regardless of an associated change in the number of saccades, but for pseudo-words the number of saccades increased with the length. On the other hand, for individuals with dyslexia for both words and pseudo-words the saccade amplitude was small and constant, the number of saccades depended on the word length.

Eye-movement patterns of individuals having dyslexia during reading and visual search tasks have been compared through research. It was observed that there was no significant difference between the eye-movement patterns in visual tasks of persons with dyslexia compared to persons without dyslexia, but there were significant altered eye-movement patterns in persons with dyslexia while performing reading tasks. They showed more rightward fixations while reading, which suggested that they can process only a few letters simultaneously (Prado, Dubois, & Valdois, 2007).

2.3.2.1.2 Computational Intelligence and Pattern Recognition

Unsupervised classification was performed using eye-movements captured from videography systems of individuals with dyslexia was proposed by Novak et al. (2004) for automatic dyslexia analysis. The eye movements were captured from subjects during two non-verbal and one-verbal tasks. The self-organizing maps used in the method were capable of distinguishing between persons with dyslexia, without dyslexia and persons with other reading difficulties.

A first step towards building a non-verbal based diagnostic system through eye-movements was proposed by Macas et al. (2013). A simple non-verbal based feature extraction is proposed for future dyslexia detection systems.

In short, the above-elaborated research relating to the eye-movement shows that individuals with dyslexia have unique eye movement patterns when performing task relating to reading. This behaviour is not caused because of any problems with the motions of the eyes, but due to complications occurred during the conversion of orthography to phonology functions.

2.3.2.2 EEG

'EEG is a record of the oscillations of brain electric potential recorded from electrodes on the human scalp' (Nunez & Srinivasan, 2006, pp. 3) as shown in Figure 2.2.

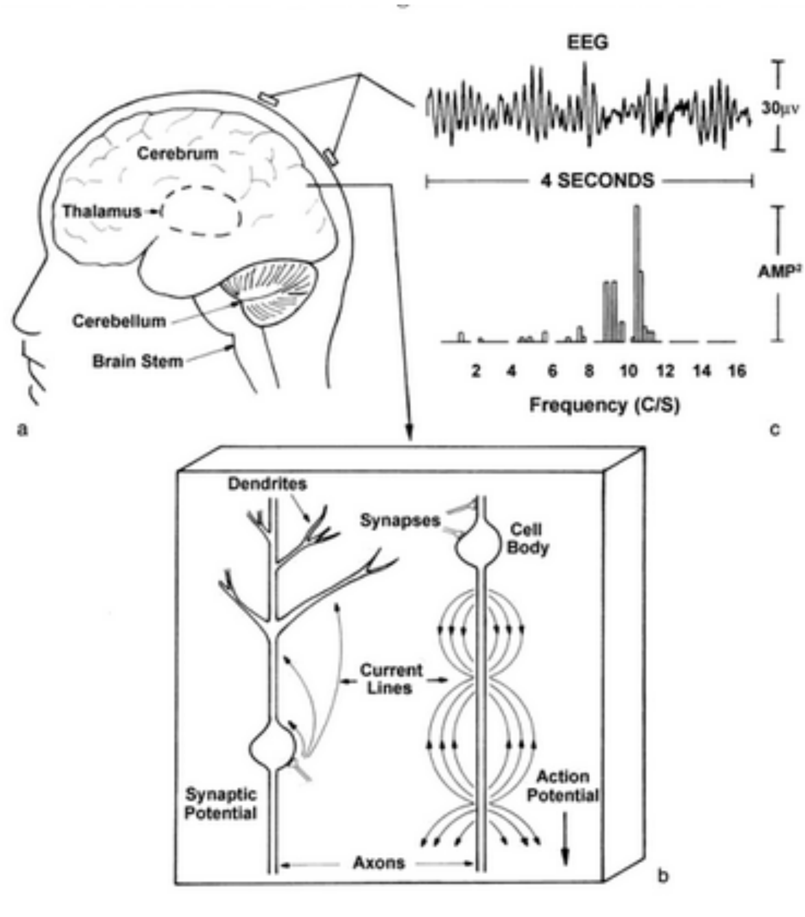


Figure 2.2: Capturing EEG (Nunez & Srinivasan, 2006, pp. 5)

As discussed in 2.2.4 individuals with dyslexia have different brain structures and behaviours compared to individuals without dyslexia. EEG is a technique that can be used to monitor and detect brain functions. The electrical activity of the brain for various stimuli can be identified via the electrodes placed on the scalp. EEG is often used for detecting conditions in the brain such as epilepsies, seizures, brain tumours and sleeping disorders (Nunes, Coelho, Lima, Papa, & de Albuquerque, 2014; Plante et al., 2013; Shantha Selva Kumari & Prabin Jose, 2011; Silipo, Deco, & Bartsch, 1999).

Researchers have also started looking into the possibility of using EEG to detect dyslexia. These are categorised and discussed below.

2.3.2.2.1 Statistical Frequency Analysis

An analysis of EEG signals to differentiate subtypes of dyslexia using neural networks was introduced by Ramadan (1998). The EEG was recorded during relaxing and reading states. Next, using neural networks the model was able to distinguish between normal and subtypes of dyslexia; dysphonetic dyslexics and dysorthographic dyslexics. The neural network was able to differentiate between the groups through the EEG from the reading state, but could not perform classifications from the data collected from the relaxed state since the relax state did not show significant changes between the groups.

Rippon and Brunswick (2000) have found unique event-related EEG patterns in people with dyslexia when performing readings compared to people without dyslexia. Significant changes were discovered during phonological processing tasks whereas the EEG responses for visual related tasks did not show any significant changes as such.

Increased Slow activity in the delta and theta bands in the frontal and right temporal areas of the brain of individuals having dyslexia have also been uncovered through EEG research (Arns, Peters, Breteler, & Verhoeven, 2007). Significant correlations were uncovered between reading-related tasks such as rapid naming of letters, deletion of phoneme, articulation, spellings and EEG coherence profiles.

Furthermore, EEG has also shown different brain activation patterns in individuals with dyslexia during phonological tasks compared to normal controls. Individuals with dyslexia show a right-lateralized pattern in brainwaves while normal controls show theta and beta activations at the brain left frontal (Spironelli, Penolazzi, & Angrilli, 2008).

A research (Fuad, Mansor, & Lee, 2013) conducting Wavelet Packet Analysis of EEG during writing has been able to discriminate between the brain activation patterns between the individuals with dyslexia and without dyslexia. The EEG signals from the channels were C3, C4, P3 and P4 were recorded during writing, letter recognition and the relaxed state. The signals were assessed through decomposing the signals into 5 level sub-bands using Wavelet Packet Analysis. The alpha sub-bands, which are usually present in the relaxed state, did not appear to have a significant difference between individuals with dyslexia and without dyslexia. However, during the writing conditions higher beta sub-bands frequencies were seen in individuals with dyslexia.

A study was carried out by Che Wan Fadzal, Mansor, Lee, Mohamad, and Amirin (2012) in order to identify the brain behaviours of individuals with dyslexia while performing writing tasks. The study comprised of the analysis of 4 EEG channels; C3, C4, P3 and P4, which included capturing the EEG while performing six tasks; relaxed state, recognition of alphabets, sounding out alphabets, writing alphabets, spelling words and writing words. Through this study, it was found that individuals with dyslexia produce higher frequency beta waves in the range of 22-28Hz compared to normal controls when performing written task utilising more energy.

2.3.2.2.2 Classification Algorithms

Approximate Entropy (ApEn), a 'statistical parameter used to quantify the regularity of a time series data of physiological signals' (Andreadis, Giannakakis, Papageorgiou, & Nikita, 2009) has also been used in past research (Andreadis et al., 2009) to detect brainwave features of individuals with dyslexia. The EEG from a group with dyslexia and control group were recorded in the relaxed state and to a single sound tone given to listen through earphones which was either a high frequency with a value of 3000Hz or a low frequency value of 500Hz followed by random numbers to be memorised. The features extracted using ApEn is then trained using

Support Vector Machines (SVM) for classifying. The framework presented promising results for differentiating dyslexia group from the control group.

A SVM based algorithm using ERP have been conducted by Frid and Breznitz (2012) to distinguish dyslexia readers from the normal readers. The brain activities of all subjects were recorded for button presses in response to a target stimulus. The features Positive Area, Maximal Peak Amplitude/Time ratio, Spectral Flatness Measure, Standard Deviation and Skewness, Power Spectral Density were extracted and trained using SVM for the classification.

A Malaysian research team (Karim, Abdul, & Kamaruddin, 2013) have presented an EEG-based Classification between the individuals with dyslexia and normal controls during the relaxed state. The feature extraction from the EEG recorded was performed using the Kernel Density Estimate (KDE) method and the classifier was implemented using Multilayer Perceptron (MLP).

In recapitulating, the research regarding brainwave activation patterns of dyslexics demonstrate the capability of EEG signals to detect dyslexia. The prior research has been able to capture differences in the EEG frequencies during task relating to reading and writing, specifically high beta wave frequencies. However, the explorations regarding to reading have not been drilled down to different types of word reading such as regular words, non-words and the writing hasn't been compared with the modern day alternative task being typing. Overall, EEG can be identified as an assuring and favourable choice to detect unique brainwave behaviour of individuals with dyslexia according to previous parallel studies and investigations.

2.4 EEG Signal Pattern Recognition Framework for Dyslexia

As discussed above, it is clear that many researchers have attempted to identify unique EEG signal patterns of individuals with dyslexia. In this section, we look into these studies more thoroughly in order to identify gaps in the literature.

2.4.1 Existing Frameworks

A study carried out by Arns et al. (2007) was able to uncover unique brain activation patterns in children with dyslexia. A total of 38 participants: 19 with dyslexia (11 males and 8 females) and 19 controls (11 males and 8 females) between the ages of 8 to 16 years took part in this study. The exclusion criteria included mental illness or genetic disorders in person or family history, neurological disorder, brain injury, addiction to drug or alcohol and serious medical conditions. The EEG data was acquired at a sampling rate of 500Hz using the internationally recognized 10-20 electrode positioning system having 28 channels namely: Fp1, Fp2, F7, F3, Fz, F4, F8, FC3, FCz, FC4, T3, C3, Cz, C4, T4, CP3, CPz, CP4, T5, P3, Pz, P4, T6, O1, Oz and O2. The experiment was performed in a sound and light attenuated room, which was controlled at a room temperature of 22 degree Celsius. The EEG data was recorded for 2 minutes while being seated with eyes open, focusing the attention on a red dot displayed on a computer screen. The group of participants with dyslexia was also given a few language tests. These tests consist of articulation, rapid naming of letters, phoneme deletion and spelling. These reading related tasks were collected to find the correlation between EEG and the neurological findings of dyslexia. However, EEG was not recorded while these tasks were performed. Instead, the above-explained tasks with eyes open were used since the EEG of resting state highly correlated with the tests. The data is Electrooculography (EOG) corrected prior to the analysis. This data is then examined using the power spectral analysis. The approach followed is that the data is first partitioned into adjacent 4-second sections, next the data is transformed to the frequency domain from the time domain using Fast Fourier Transform (FFT) and finally the average power spectra are calculated for specified frequency bands ranging within the delta, theta, alpha and beta bands. The EEG data is then analysed statistically using one-way ANOVA to find the significant differences between the dyslexic and control group. Further, a correlation matrix is acquired for correlations between the variables within the group with dyslexia. The significant measures of the EEG power and coherence data obtained from the two groups are submitted for the correlation analysis with the four language tests explained above. The study revealed that the dyslexic group had increased slow theta and delta activity in the frontal and right temporal areas of the brain. Beta was clearly increased at F7 and significant correlations were found between the EEG coherence and the dyslexia tests (Arns et al., 2007). This study performs statistical analysis using the EEG data and does not present any classification mechanisms to differentiate between the group with dyslexia and the control group. The EEG data is collected only in the resting state and not while the tests are actually being undertaken, important artefacts specific to each task are most likely to be missed out. Since the EEG was recorded only in the resting state the only main unwanted artefact being the eye blinks have been removed in the preprocessing step of the analysis. The input features using the EEG recordings include the power spectra for specified frequency bands such as alpha, beta and theta at each EEG channel.

A framework for detecting abnormalities in dyslexia using approximate entropy of EEG signals was proposed by Andreadis et al. (2009). This study consisted of a total of 57 participants: 38 with dyslexia (26 males and 12 females) and 19 Control (7 males and 12 females) between the ages of 2 to 13 years. The exclusion criterion comprises of difficulties in hearing, history of head injury, neurological diseases or attention deficit disorders. The EEG for this study was recorded using the International 10-20 system, containing 15 channels which are namely: Fp1, F3, C5, C3, Fp2, F4, C6, C4, O1, O2, P4, P3, Pz, Cz and Fz. The experiment for this study is that a single sound tone was presented to the participant via earphones, which was of a high frequency of 3000 Hz or low frequency of 500 Hz, followed by numbers that had to be memorised. The brainwave data was collected as EEG signal for 500ms before the stimulus and as ERP after the stimulus for 1000ms. The preprocessing mechanisms used in this study include two main steps. The first step was recording the EOG and rejecting values higher than 75μV and the second step was normalising the waveforms by subtracting the mean value and dividing by the standard deviation of each signal. This data is then analysed using ApEn and Cross-ApEn (comparing EEG signals from two electrodes). A SVM classifier was then implemented using the statistical significant electrodes for all subjects obtained using ApEn as input features. This classifier offered promising results. The study was then taken a step forward to enhance the classifier using the input features from Cross-ApEn. This method looks at significant pairs of electrodes instead of evaluating electrodes on its own. Although this technique delivered better discrimination abilities, no clear pattern has yet been found because there was a very high number of statistically significant pairs of electrodes. In looking at the study as a whole, it can be stated that the researchers have been able to successfully develop a classifier that can differentiate between the group with dyslexia and the control group. However, the experiment used looks into only the working memory abilities and does not involve any reading or writing related elements. Since dyslexia is a condition that causes deficiencies in reading and writing abilities important factors required for the differentiation process could be missed out. The same research team performed another analysis using the same experiment and data by using Wavelet Entropy (Giannakakis, Tsiaparas, Xenikou, Papageorgiou, & Nikita, 2008). The findings revealed that Wavelet Entropy could be used as a quantified measure to observe and analyse EEG and ERP signals to detect brain patterns specific to dyslexia.

A Malaysian research team conducted a frequency analysis of EEG signals generated between children with and without dyslexia during writing (Che Wan Fadzal, Mansor, Lee, Mohamad, & Amirin, 2012; Che Wan Fadzal, Mansor, Lee, Mohamad, Mohamad, et al., 2012). The EEG was recorded from a total of 6 right-handed children: 3 with dyslexia and 3 controls between the ages of 8 and 12 years using the standard international 10-20 system. This study uses only 4 EEG channels, namely: C3, C4, P3 and P4. The experiment involved collecting EEG in the relaxed state and while performing writing related activities, which were designed based on the conventional method of diagnosing dyslexia. During the preprocessing phase, unwanted artefacts being Electrocardiograms (ECG) and EOG were filtered out. Next, the signals containing the writing related data was extracted using a band-pass FIR filter ranging from 8Hz to 30Hz. For the frequency analysis, the signals are transformed to the frequency domain from the time domain using FFT. The study revealed that the children with dyslexia consume more energy and resulting in high-frequency beta wave relaxed states and well as during writing related activities compared to normal children. The frequency range identified for children with dyslexia is between 22-28Hz whereas for normal children it is between 14-22Hz. Overall this study does not provide any classification mechanism. It only analyses the frequencies obtained from the two groups. The study has explicitly used subjects that are right-handed, which in fact, is an important factor since the handedness has an effect on the EEG activities between the right-handed and left-handed subjects (Andrew Ng & Leong, 2014; Provins & Cunliffe, 1972). Additionally, is it not indicated whether a silent and temperature controlled room were used to carry out the experiment. The preprocessing techniques used in this study is similar to previous similar studies, however since this study involves hand movements, it is not specified how the artefacts generated from the hand movements were filtered out. Furthermore, the experiment focuses only on the writing related tasks.

Frid and Breznitz (2012) proposed an SVM-based algorithm for differentiating between dyslexic readers and regular readers using ERP. The study was carried out with a total of 50 participants: 20 with dyslexia and 30 controls of the ages between 24 to 40 years. The signals were recorded at a sampling rate of 2048Hz using the standard 10-20 system with 64 channels. The experiment used in the study is that the subject is required to press a button in response to a target stimulus, which is a tone. The conditions consist of 50 stimuli of target tones at frequencies of 1000Hz and 50 non-target tones of 2000Hz. The data collected is first preprocessed using a band pass filter at 0.1-100Hz, and then a notch filter at 50Hz is used to remove noise caused by electric power lines and finally unwanted artefacts such as eye and muscle movements are filtered out. The next step is the feature selection where the features with the most relevance and the ability to discriminate are chosen. The five features selected are Positive Area (Ap), Maximal Peak Amplitude/Time ratio (Mp), Spectral Flatness Measure (SFM), Standard Deviation and Skewness, Power Spectral Density (PSD). Although the classification was first attempted using a single classifier for all features, it was not successful. Therefore, the approach follows was to use ensemble SVM. The classification results were compared for the combinations: the best single feature, an ensemble of three SVM and only the left or right hemispheres. To recapitulate, the study uses a simple experiment task, which relates to working memory and reasoning abilities but does not engage any stimulus with regard to reading or writing which are important factors in detecting unique patterns to dyslexia. This may have bypassed on activating vital areas of the brain specific to dyslexia. The study does not indicate whether they were any inclusion and exclusion criteria taken into account when recruiting the participants, which could increase the likelihood of having outliers within the groups selected.

A classification model to distinguish children with dyslexia from the normal children during rest state was suggested by (Karim et al., 2013). A total of 6 participants: 3 with dyslexia and 3 controls within the ages of 4 to 7 years took part in this study. The EEG is collected using the International 10-20 electrode placement system using 8 channels with a sampling rate of 250Hz. The experiment is carried out in a room with controlled temperature and lighting while the participants are in the resting state with both eyes closed and eyes open. During the preprocessing phase, noise and irrelevant artefacts have been removed. Since the data collection is done in the resting state, the frequency band relating to this state is alpha, and this has been extracted using band-pass filtering. The next phase being the Feature Extraction is performed using Kernel Density Estimation (KDE), which is an artificial neural network technique organised in several different layers (Karim et al., 2013). Finally, the classifier is trained using Multilayer Perceptron (MLP). This mechanism was able to obtain an accuracy rate of 90% to classifying between individuals with dyslexia and control during both eyes open and eyes closed conditions. To wrap-up, the study uses EEG data from only the resting state disregarding the essential reading and writing related brainwave data. No inclusion or exclusion criteria for participants used is indicated.

A Wavelet packet analysis of EEG signals between children with dyslexia and without dyslexia during writing was proposed by (Fuad et al., 2013). A total of 8 subjects: 4 with dyslexia and 4 controls between the ages of 7 to 12 years took part in this study. The EEG was recorded in the temperature controlled room at 24 degrees Celsius using the international 10-20 system with 4 channels, namely: C3, C4, P3 and P4 having a sample rate of 256Hz. The signals were captured in the relaxed state, writing state and during letter recognition and each task was repeated 6 times. This is then examined using wavelet packet analysis for alpha and beta frequency bands. The outcome of the study discovered that there were no significant differences in the alpha band frequencies during the relaxed state and writing state in children with dyslexia, however, for normal children the alpha band frequency was higher during relaxed state compared to writing state. During writing beta frequency was higher in children with dyslexia compared to normal controls. This study looks into the brain behaviours during the resting and writing states, but does not look into the reading state. No information is provided about preprocessing the signal to remove unwanted artefacts such as eye blinks. Finally, the study performs only an analysis and does not perform any classifications.

2.4.2 Highlights and Gaps in Exiting Frameworks

In this section, we discuss important findings and gaps found in the above-described EEG signal pattern recognition frameworks implemented to identify patterns unique to individuals with dyslexia.

- Age Range

According to previous similar studies, EEG-based pattern identification frameworks for dyslexia studies have been carried out on children as well as adults, which means that the research can be used on either group.

However, it is important to make sure that the subjects within the age range selected have parallel reading and writing abilities.

- Environment

The data collection location and its environment is a very important factor to be looked at when recording EEG. Below given is a summary of typical environment extracted from the review and more suggestions. These factors are important to make sure no interference is caused to the signals, the subjects are comfortable and are not distracted.

- Sound and light attenuated room
- Temperature controlled room – if subjects are perspiring, it could cause problems to the recordings.
- Any extra equipment in the room should be electrically quiet – this can be checked via a probe test for electromagnetic signals ("Preparing the Experiment Room," 2015)

- EEG Recording System and Channels

The recommended electrode placement system is the International 10-20 system. This method describes the location electrodes on the scalp. The '"10" and "20" refer to the fact that the actual distances between adjacent electrodes are either 10% or 20% of the total front-back or right-left distance of the skull' (Khazi, Kumar, & Vidya, 2012).

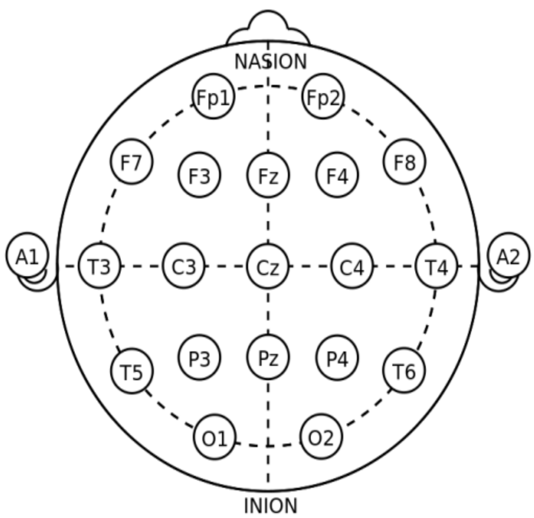


Table 2.3: Arrangement of the International 10-20 electrode system (Khazi et al., 2012)

- Inclusion and Exclusion criteria of the subjects

The inclusion and exclusion criteria summarised from the reviews are given below.

Exclusions:

- Mental illness
- Genetic disorders in person or family history
- Neurological disorders
- Brain injuries
- Drug or alcohol addiction
- Serious medical condition
- Difficulties in hearing/ vision – this would not apply if the subject has corrected vision/hearing
- Attention deficit disorders

Inclusions:

- Handedness – The participants recruited need to be either left handed or right handed and not have a mix of the both. This is because there is a difference in EEG activities between the right-handed and left-handed subjects (Andrew Ng & Leong, 2014; Provins & Cunliffe, 1972).

- Experiment

The research presented thus far provide evidence that most of the EEG-based studies relating to dyslexia have been carried out by measuring the brain response to a stimulus. Since individuals with dyslexia experience high level of difficulties compared to normal controls while performing reading and writing tasks, it is useful to know if the EEG signals generated during these tasks reflect these differences. In this research we address this gap in RQ1 and aim to identify these unique EEG signal patterns in individuals with dyslexia compared to normal controls as explained in RO1. Summarised below are a few tasks identified as more challenging for individuals with dyslexia.

- Reading - Previous research has established that poor reading skills seen in individuals with dyslexia is caused by a deficit in phonological decoding abilities (Fletcher et al., 2006) and in fact lower levels of performance is seen in reading nonsense-words compared to real-words (Ziegler et al., 2008). These findings highlight the need to investigate if these behavioural differences show as neurological differences through brainwave signal patterns. This is addressed in RQ2 and RO2.
- RAN - The association between RAN and reading fluency has been confirmed in prior research (Georgiou et al., 2013) and is identified as a poor skill in individuals with dyslexia (Jones et al., 2010). Therefore, this opens the need to examine if the EEG signals generated during RAN in individuals with dyslexia have differences compared to normal controls, as it has not been revealed in past research. This is addressed in RQ3 and RO3.
- Writing and typing - Difficulties in writing skills is yet another deficiency caused by dyslexia (Gvion & Friedmann, 2010). Preliminary studies have shown unique EEG signals pertaining to dyslexia, however, it has been investigated in only few EEG channels (Fuad et al., 2013). Therefore, relatively only a little is known about these EEG signal patterns. Examination using more EEG channels as well as exploring the effects during typing which is the modern-day task for writing is a gap to be filled in the literature. This is addressed in RQ4 and RQ5, and RO4 and RO5.
- Everyday human tasks - Realistic day-to-day activities include a combination of reading and writing tasks together with additional tasks such as interpreting tables and numbers. Past studies provide no information as to how EEG signal patterns behave during such complex tasks in individuals with dyslexia. Hence, this is yet another area to be explored. This is addressed in RQ6 and RO6.

- Preprocessing

Preprocessing is one of the most important steps in the analysis process of the signals. This step makes sure unwanted artefacts are removed from the signal. When recording EEG signals one of the most commonly seen irrelevant artefacts are the eye-movements and eye blinks and the common practices used for removing these from EEG signals are Independent Component Analysis (ICA) and Principal Component Analysis (PCA) (Shi-Yun, Kai-Quan, Chong Jin, Wilder-Smith, & Xiao-Ping, 2009; Turnip & Junaidi, 2014). Comparison studies between these two techniques show ICA produces better results compared to PCA (Bugli & Lambert, 2007; Turnip & Junaidi, 2014).

In addition to EOG, which is produced from eye-movements, EEG recordings can contain contamination signals such as electromyogram (EMG) and ECG. Typically, body movements are kept to a minimum during EEG-based experiments. This is because movements cause unwanted artefacts in the EEG signal making the analyses and classifications difficult. In fact, sometimes trials with unwanted artefacts are manually rejected from studies (Sabisch, Hahne, Glass, von Suchodoletz, & Friederici, 2006). However, new methods have now been introduced making it possible to collect data during real-life activities instead of only collecting data during resting state or simple activities such as button clicks. Artefact Subspace Reconstruction (ASR) is one such method which can be used to filter out body movement and muscle burst artefacts from the EEG signals (Bulea, Prasad, Kilicarslan, & Contreras-Vidal, 2014; Mullen et al., 2013). ASR 'relies on a sliding-window Principal Component Analysis, which statistically interpolates any high-variance signal components exceeding a threshold relative to the covariance of the calibration dataset. Each affected time point of EEG is then linearly reconstructed from the retained signal subspace based on the correlation structure observed in the calibration data' (Mullen et al., 2013).

ASR requires a 1-minute EEG recording in the relaxed state, which is known as the calibration data set. This technique performs PCA on a sliding-window, removes high-variance up to three standard deviations above the mean and finally reconstructs using the remaining signal. This automated artefact removal technique is quite easy to use as it is available as a plugin in EEGLAB. An example of filtration of movements from an EEG using ASR is shown in Figure 2.3.

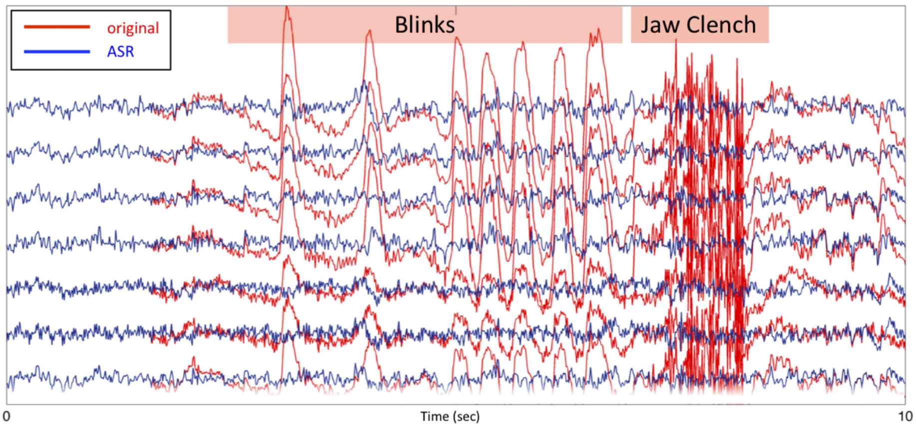


Figure 2.3:Example of filtering out movements from EEG using ASR (Mullen et al., 2013)

Another important aspect to be filtered prior to the analysis is the noise caused by electric power lines. This is often seen at 60Hz or 50Hz and this can be filtered out using a notch filter.

- Analysis

There are mainly two types of analysis that could be used, which are namely Frequency/Fourier Analysis and Wavelet Analysis.

- Frequency Analysis

One of the commonly used analyses in EEG-based pattern recognition frameworks for dyslexia is the frequency analysis. The raw EEG signal recorded is in the time domain. This waveform is a combination of a number of sinusoidal waves although it is not directly visible. FFT is one of the methods that can be used for the decomposition of the waveform into a sum of sinusoids of different frequencies. Therefore, by performing the Fourier transform, it helps detect spikes in the frequency domain which could not have been visible before.

- Wavelet Analysis

On the other hand, wavelet analysis is a method that decomposes a signal onto a set of basic functions called wavelets (Akin, 2002) and allows analysis on the frequency domain as well as and time domain.

The type of analysis should be selected based on the expected outcome. Although wavelet gives extra information, this might not be important if the intension of the research is only to identify the voltages are present at each frequency and not the time the particular voltage was present. The decision for the analysis method should purely base on the objective of the experiment and the expected outcome.

2.4.3 Pattern Recognition Techniques

The research discussed thus far show mainly 2 techniques used to identify if there is a significant difference in the brainwave patterns between the individuals with dyslexia and the normal controls.

2.4.3.1 Statistical Analysis

Statistics 'is a field of knowledge that enables an investigator to derive and evaluate conclusions about a population from sample data' (Koch & Droege, 2006). These techniques are used to determine whether there are any statistically significant differences in the EEG signals between the two groups, and thereby use conclusions about the dataset to reach a broader conclusion. T-test, Analysis of Variance (ANOVA) and regression analysis are few of the commonly used statistical methods (Koch & Droege, 2006).

2.4.3.2 Machine Learning

Machine learning helps to solve complex computations and 'creates new knowledge by finding previously unknown patterns in data', by '"learning" patterns in data, with little or no intervention by an expert' (Mitri & Wilburn, 2006). Given below are few of the popular machine learning approaches used in EEG classifications, along with the pros and cons of each method.

2.4.3.2.1 Linear Discriminant Analysis

Linear Discriminant analysis classifies data by first creating 'models of the probability density functions for data generated from each class. Then, a new data point is classified by determining the probability density function whose value is larger than the others' (Eslahi & Dabanloo, 2013). The algorithm 'assumes that each of the class probability density functions can be modelled as a normal density, and that the normal density functions for all classes have the same covariance' (Eslahi & Dabanloo, 2013).

Linear Component Analysis is known to be a simple classifier that requires very small computations. However this algorithm is not suitable for complex non-linear EEG classifications since it does not produce good results for such scenarios (Lotte, Congedo, Lécuyer, Lamarche, & Arnaldi, 2007).

2.4.3.2.2 Neural Networks

Neural Networks is 'an assembly of several artificial neurons which enables to produce nonlinear decision boundaries' (Lotte et al., 2007).

Neural networks perform better for EEG classifications compared to Linear Discriminant Analysis since it can be used to implement boundaries for non-linear classifications. But to acquire the desired level of accuracy, it is important to choose a suitable number of hidden units, which can become problematic. Having a larger number of hidden units than required results in memorising the training set which causes poor generalization (Garrett et al., 2003).

2.4.3.2.3 Support Vector Machines

SVM is a supervised learning method, which can handle both linear and non-linear classifications. It produces a hyper-plane having the maximal margin to the support vectors. SVM can classify even overlapping and non-separable data sets by mapping into higher dimensional spaces using the kernel functions (Garrett et al., 2003; Shantha Selva Kumari & Prabin Jose, 2011).

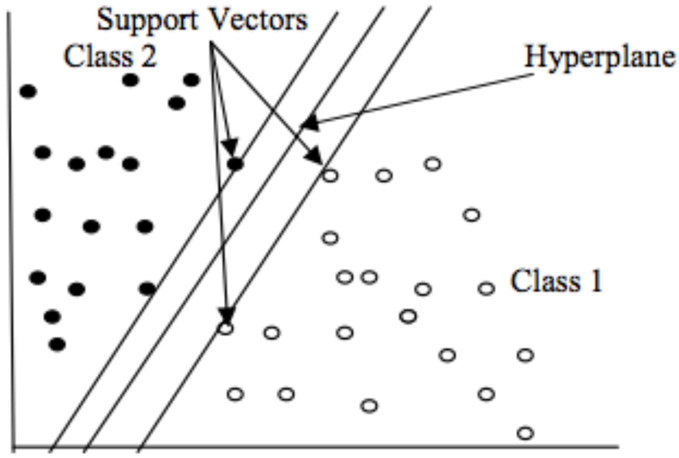


Figure 2.4: Overview of Support Vector Machines (Shantha Selva Kumari & Prabin Jose, 2011)

Furthermore, SVM has good generalisation characteristics; it is insensitive to overtraining and curse of dimensionality but could lose the speed of execution achieving these benefits (Lotte et al., 2007). Curse of dimensionality is 'if the number of training data is small compared to the size of the feature vectors, the classifier will most probably give poor results' (Lotte et al., 2007). An overview of SVM is shown in Figure 2.4.

2.4.3.2.4 Popular Machine Learning Technique for EEG classification

Through the comparison of the popular choices of the classification algorithms for EEG signals, it can be concluded that SVM is a better choice.

SVM has been used in past research for many EEG signal classifications. Successful results have been obtained in classifying mental-tasks (Hosni, Gadallah, Bahgat, & AbdelWahab, 2007), seizure detection (Shantha Selva Kumari & Prabin Jose, 2011), discrimination between individuals with dyslexia and normal controls (Andreadis et al., 2009; Frid & Breznitz, 2012), epilepsy diagnosis (Nunes et al., 2014) and vigilance analysis (Lei, Jie, Yaoru, Huaping, & Chungang, 2010).

Furthermore, research by (Ahmad et al., 2015; Garrett et al., 2003; Lotte et al., 2007) has recommended SVM as a more appropriate choice for EEG signal classifications.

2.5 Summary

Through the literature review, it is understood that dyslexia is a disability with a neurological origin, affecting a significant amount of the population, which causes difficulties in reading, writing and spelling despite normal or above average intelligence levels. It is a heritable condition, but not a disease or defect that can be cured, rather a state that can he helped with proper targeted support such as multi-sensory learning techniques.

Research has proven differences in the brainwave activation patterns and brain structures of individuals with and without dyslexia. Technology plays a great role in improving the detection techniques of dyslexia. The traditional dyslexia detection techniques have been attempted to be improved by technologies such as fuzzy logic, soft computing approaches, neural networks and alternative approaches such as presenting the diagnosis as series of serious of games. Technology has also helped the detection techniques go beyond the conventional methods. Eye-movements, brain imaging (MRI, fMRI) and brainwave activation patterns (EEG) are few of the upcoming trends.

In particular, EEG has become a popular technique used to identify unique brain activation behaviours. In all research reviewed thus far, it was evident that most of the research carried out in order to identify unique EEG signal patterns between individuals with dyslexia compared to normal controls were based on ERP analysis. However, such studies remain narrow in focus dealing only with the reactions to a certain stimulus. Since dyslexia is a condition, which causes difficulties in reading and writing, analysing the EEG signal during the actual reading and writing tasks could give light to insights of the brain behaviours unknown thus far. Although literature does contain a few of these studies, relatively little is known. Therefore, this highlights the need to examine the unique EEG signal patterns between individuals with dyslexia compared to normal controls when performing tasks that are more challenging for individuals with dyslexia. This includes real-word reading, nonsense-word reading, passage reading, RAN, writing, typing and everyday human tasks that includes a combination of reading or interpreting and writing or typing together.

Further in terms of the computational analysis, past studies advocate SVM as a suitable choice of algorithm for the classification of EEG signals. The ability to tackle linear, non-linear, overlapping or non-separable datasets are undoubtedly beneficial properties of SVM. Moreover the insensitivity to overtraining and the curse-of-dimensionality make SVM preferential over the other EEG classification options.

In summary, it can be concluded that through the gaps identified by this review, more important insights about the brainwave signal patterns between individuals with dyslexia and normal controls can be revealed.

Chapter 3 Methodology

3.1 Overview

This chapter describes the research methodology used to achieve the objectives of this research. The chapter begins with a detailed outline of the research strategies deployed for the investigation. It then gradually moves on to a comprehensive explanation of the sample size, EEG acquisition and measurement instruments, procedure for data collection and the techniques adapted for data analysis and classification. The classification section also includes details about the pilot study adapted to determine the classification algorithm used for this research. Next, it explains the verification process of the classifiers developed, followed by a summary of the chapter.

3.2 Research Design

This research attempts to discover differences in the EEG signals generated between adults with dyslexia compared to normal controls while performing specific tasks. These include reading, writing and typing tasks that are comparatively more challenging for people with dyslexia. The research design and execution stages followed in this research are shown in Figure 3.1.

The first stage of the research, which is the preparation stage, includes reviewing of literature, formulation of the research problems, questions, aims and objectives, designing the data collection experiments with a psychologist specialising in dyslexia assessment and diagnosis, designing the data analysis and classification model, developing a website to host the experiment tasks, obtaining the human research ethics approval and recruiting participants. Prior to performing the actual research, stages two to four were executed in order to confirm the suitability of the data collection environment and to verify the reliability of the data collection instruments used. The first pilot study was carried out with one participant. This research helped to determine the EEG headset setup time, accuracy and the reliability of the tasks hosted on the website, especially the time taken for each task. Few of the tasks required minor amendments in order to fit the total timeframe. These changes were made under the supervision of the psychologist and the human ethics application was revised with these changes. Once the human ethics application changes were approved, the second pilot study was carried out with one participant for confirmation. Next, the actual experiment was carried out with all the participants and the data was analysed and classified using the model built. Finally, during the last stage, the classifier results were produced.

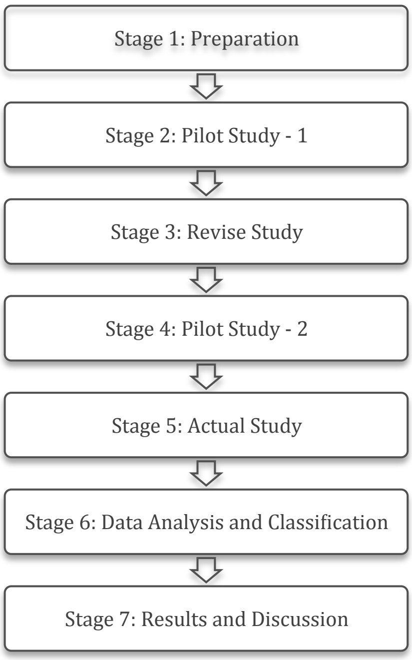


Figure 3.1: Research design and execution stages

3.3 Research Framework

Shown below in Figure 3.2 is an overview of the research framework consisting of 6 main steps namely signal acquisition, preprocessing, frequency sub-band decomposition, feature extraction, classification and verification. The following sections explain each step in detail.

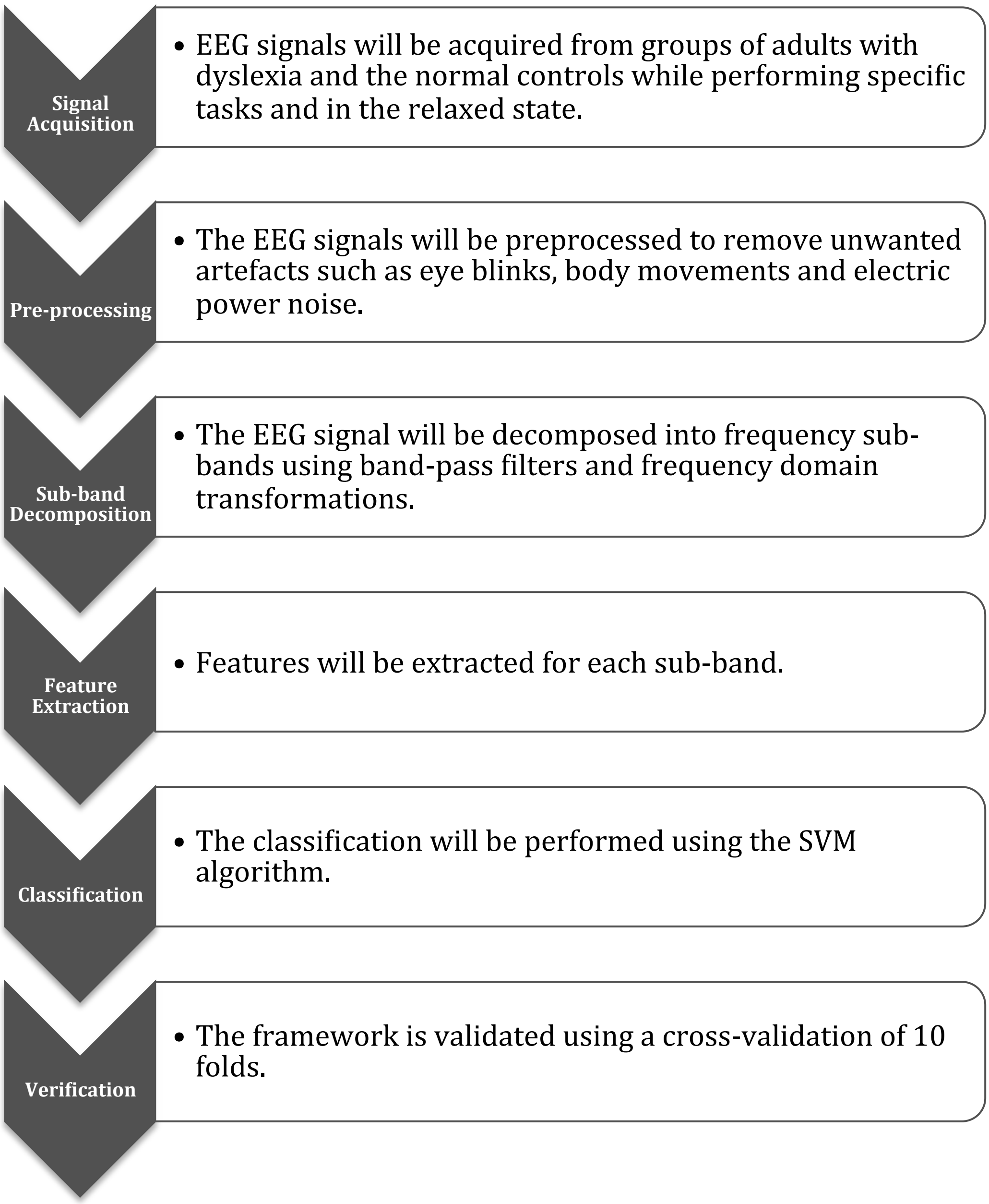


Figure 3.2: Overview of the research framework

3.4 Signal Acquisition

This section describes the design and execution of the data collection. The data collection for this research was approved by the Murdoch University Human Research Ethics Committee (approval 2014/204). All participants signed a consent letter confirming voluntary participation.

3.4.1 Determination of Sample Size

The determination of the sample size in research is a very important decision to be made. In medical related research, the number of subjects used for a research is mostly limited because of uniqueness, ethical considerations, time and cost. Therefore, it is important to identify the optimal sample size to avoid the sample being too small resulting in not being able to recognise important effects and the sample being too large resulting in a waste of resources.

The number of participants for this research was determined using the Altman's Nomogram sample size calculation as shown in Figure 3.3. According to this calculation for a power of 0.80 (p-value significance of 0.05) and a standardised difference value between 0.8 and 1.0 (Cohen's d effect size), the total number of participants could vary between 30 to 50 participants. Therefore, the number of subjects per group would vary between 15 and 25.

This research was carried out on a total of 32 participants: 17 participants with dyslexia (10 females and 7 males) and 15 participants without dyslexia (7 females and 8 males).

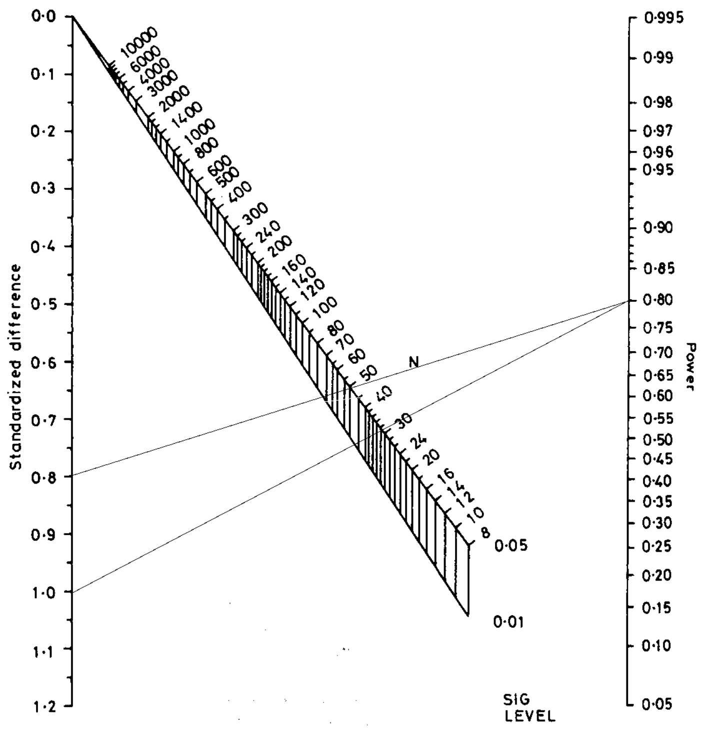


Figure 3.3: Altman's Nomogram sample size calculation (Bland, 2011)

3.4.2 Subject Inclusion and Exclusion Criteria

All subjects were adults 18 years and above, right-handed, fluent in English, have a normal or corrected-to-normal vision and normal hearing. It was a prerequisite that the participants with dyslexia to be diagnosed by a psychologist as having a specific learning disorder or disability in reading and spelling, also known as dyslexia, whereas the control group had to be free from motor and neurological conditions such as dyslexia, ADHD and autism. The participants with dyslexia were recruited with the help of DSF Literacy and Clinical Services in Western Australia (The Dyslexia-SPELD Foundation WA Inc.) using the past patient database. This research was limited to right-handed participants since research has shown that handedness could cause a difference in EEG recordings between right-handed and left-handed people (Goez & Zelnik, 2008; Tonnessen, Lokken, Hoien, & Lundberg, 1993).

3.4.3 Environment

The signal acquisition was carried out in a quiet, temperature-controlled room, maintaining the temperature between 20-24°C. Further, all equipment that was not used in the data collection process was kept electronically silent to minimise interference with the EEG recordings.

3.4.4 EEG Acquisition and Measurement Instruments

3.4.4.1 EEG Headset

The EEG headset used for this research is the Cognionics 32-channel dry EEG headset. The channels used are AF7, Fp1, Fpz, Fp2, AF8, AF3, AF4, F5, F3, Fz, F4, F6, C5, C3, C1, Cz, C2, C4, C6, Cp5, Cpz, Cp6, P3, Pz, P4, P7, PO3, PO4, P8, O1, Oz and O2. The EEG was recorded at a sampling rate of 300Hz using the internationally recognised 10-20 placement system as shown in Figure 3.4. The EEG channel map on the left shows an output from EEGLAB with only the channels used in this research, the EEG channel map on the right shows a better view of the EEG channels retrieved from the EEG headset manufacturer (Cognionics Inc, n.d.), where the channels used on this specific EEG headset are indicated in grey.

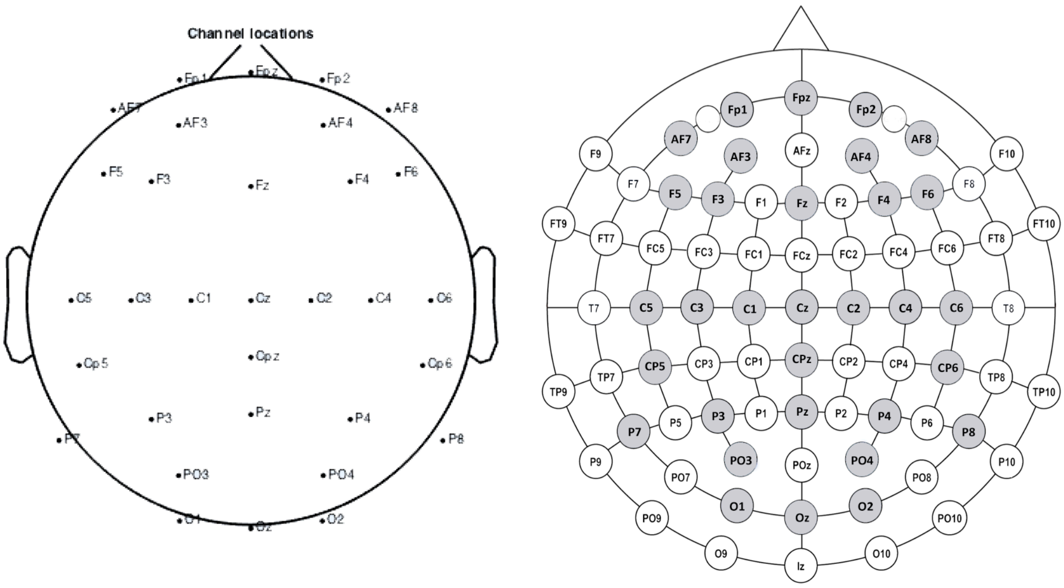


Figure 3.4: EEG channel maps

The Cognionics EEG headset is equipped with two types of sensors; namely the flex sensors and dry pad sensors. The flex sensors are to be used on the area with the hair and the dry pad sensors are to be used on areas touching hairless-skin such as the forehead.

3.4.4.2 Tasks

The participants were given tasks related to reading and writing, which were designed similar to the standardised psychometric tests used in the dyslexia diagnosis process. The datasets required for the activities were created under the supervision of a psychologist specialised in dyslexia assessments. Some of these datasets were obtained from well-recognised books and tests, which have been explained in detail below. Some of the datasets were condensed in order to fit the time frame and nature of the task.

3.4.4.2.1 Relaxed state

Participants were instructed to stay seated in the relaxed position with their eyes closed, avoiding body movements including jaw clenches for 60 seconds at a stretch.

3.4.4.2.2 Real-word Reading

The participants were instructed to read aloud each word as it flashed on the screen every 10 seconds, which were presented on a computer screen.

The words for this task were taken from the 'Phonics Handbook' by Tom Nicholson (Nicholson, 2006, pp. 84). Although the original dataset consisted of 110 words, only 25 words were used for this task.

3.4.4.2.3 Nonsense-word Reading

The instructions for the participants for this task were the same as reading real-words. The only difference was having a different dataset.

The words for this task were obtained from the Macquarie Online Test Interface (MOTIf) 'The Castles and Coltheart Test 2' (CC2) developed at Macquarie University (Macquarie Online Test Interface (MOTIf), n.d.). This test includes a total of 40 nonsense words, and 25 words were selected for this task.

3.4.4.2.4 Passage Reading

The passage for this task was taken from the 'Phonics Handbook' (Nicholson, 2006, pp. 53). The passage consisted of 93 words.

3.4.4.2.5 Rapid Automatized Naming

The activity selected for this task is the rapid naming of colours. The participants were instructed to name aloud colours from a colour card presented on the computer screen as quickly as possible. The colours used for this test were red, blue, green, yellow and black. Prior to the actual test, each participant was presented with a sample colour card on screen as shown in Figure 3.5, and told to identify these colours accurately to make sure the participant was not colour blind. During the actual rapid colour-naming task, a colour card with a total of 50 instances of the unique colours indicated in the sample colour card was presented to the participant to name aloud (Horne, 2012), see Appendix A.

Figure 3.5: Sample colour card

3.4.4.2.6 Writing

The participants were given a topic to write a simple short paragraph. They were provided with paper and a pen, the topic given was 'My family'.

3.4.4.2.7 Typing

This task is similar to the writing task, where the participants were given a topic to type a simple short paragraph using a standard QWERTY keyboard. The topic given was 'How I spent my weekend'.

3.4.4.2.8 Web Browsing

The participants were given a simple web-browsing task to perform using a keyboard and mouse. The task selected was online shopping. The participants were given a set of instructions to ensure consistency (see

Appendix B). Participants were given the instructions prior to the EEG recording to read and understand.

The instructions included;

- Navigating to a pre-defined online clothing store
- Selecting a top of his/her size and adding it to the cart
- Selecting a bottom of his/her size and adding it to the cart

3.4.4.2.9 Interpreting Table

A simple table containing information of tourists visiting Australia was presented on screen. The participant was required to interpret this table and answer a simple question by selecting a radio button out of the multiple options provided (see Appendix C).

3.4.4.2.10 Typing Random Number

The participants were given a randomly generated 10-digit number to key into a textbox.

3.4.4.3 Mapping tasks to the research problems, questions and objectives

Table 3.1 depicts how each data collection tasks are related to the research problems, questions and objectives explained in Chapter 1.

Table 3.1: Relationship between data collection tasks and research problems, questions and objectives

Tasks	RP	RQ	RO
Real-word Reading	RP1, RP2	RQ1, RQ2	RO1, RO2
Nonsense-word Reading	RP1, RP2	RQ1, RQ2	RO1, RO2
Passage Reading	RP1, RP2	RQ1, RQ2	RO1, RO2
RAN	RP1, RP3	RQ1, RQ3	RQ1, RQ3
Writing	RP1, RP4	RQ1, RQ4	RQ1, RQ4
Typing	RP1, RP5	RQ1, RQ5	RQ1, RQ5
Web browsing	RP1, RP6	RQ1, RQ6	RQ1, RQ6
Interpreting Table	RP1, RP6	RQ1, RQ6	RQ1, RQ6
Typing Random Number	RP1, RP6	RQ1, RQ6	RQ1, RQ6

3.4.4.4 Software

There were two software programs used during the data collection sessions. The first software used was a custom-built website to host all the tests and test instructions in electronic form. This password protected website was developed using PHP, HTML, JavaScript and MySQL. A text-to-speech plugin named 'ReadSpeaker' was incorporated on to the website to enable the participants to listen to the test instructions. This was a feature added specially to help the participants having dyslexia. The second software used was the Cognionics data acquisition software, which records the EEG.

3.4.5 Procedure

As shown in Figure 3.6, each participant was instructed to perform the tasks explained in section 3.4.4.2 while staying seated in front of a computer screen with the EEG headset setup on his or her head. The EEG device was wirelessly paired to another computer which had the EEG data acquisition software installed. The live impedance check provided in the software was used to ensure all electrodes were in contact. The EEG signal data was acquired while the participants performed each task as well as in the relaxed state. All instructions to be followed by the participant were presented on screen and played via the text-to-speech software prior to each test (see Appendix D). The average time taken for each participant to complete all the tasks was approximately one hour. As a fatigue management strategy, all participants were offered the freedom to take any much of breaks with refreshments in-between tasks.

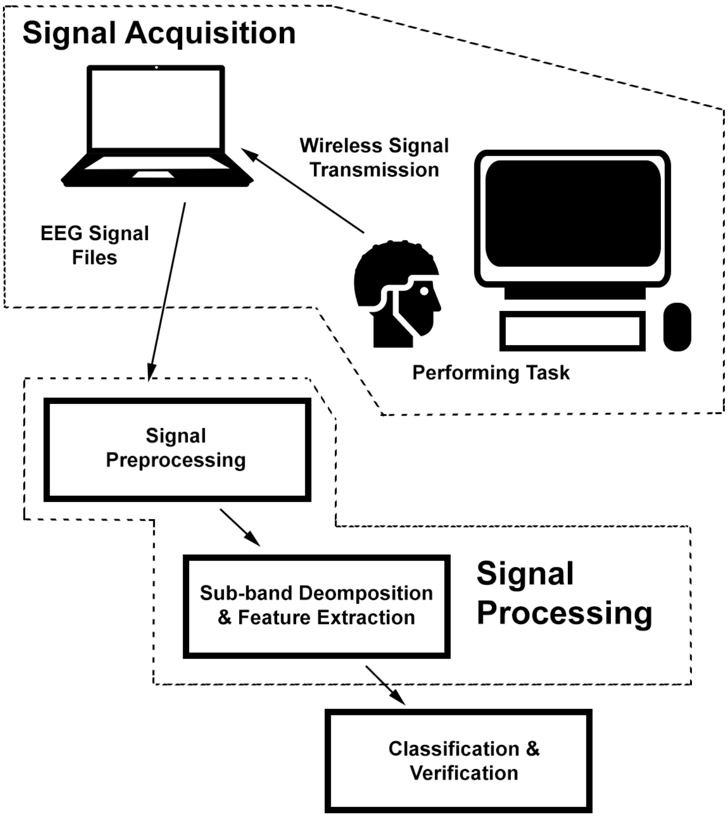


Figure 3.6: Overview of the procedure

3.5 Signal Processing

Once the EEG signals are acquired, the next step is to prepare the predictors to train the classifier. This includes removing unwanted artefacts, decomposing signal into frequency sub-bands and extracting features. This process needs to be performed on each participant for every task. Figure 3.7 shows an outline of this process through a pseudocode. The signal processing was performed using MATLAB R2015a and EEGLAB v13.4.5b.

Although the actual number of EEG channels is 32, the raw EEG signal output file shows 37 channels, which consists of 5 additional parameters, which are occupied by the 3-axis accelerometer, packet counter and trigger. In analysing the EEG signals only the 32 channels were taken into account.

```
foreach  participant {

            foreach  task {

                        preprocess EEG signal using ASR

                        remove electric power noise from EEG signal

                        foreach EEGChannel {

                                    decompose signal into sub-bands (delta, theta, alpha, beta, gamma)
                                      using band-pass filters

                                    foreach sub-band {

                                                transform signal into the frequency domain using FFT

                                                calculate features: mean, median, mode, standard deviation,
                                                   maximum, minimum, skewness and kurtosis

                                    }

                        }

            }

}
```

Figure 3.7: Signal processing pseudocode

3.5.1 Signal Preprocessing

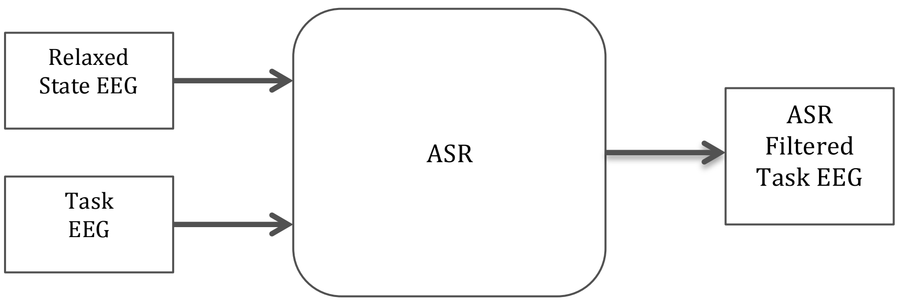


Figure 3.8: Overview of preprocessing EEG signal

Preprocessing signals is one of the most important steps in the signal analysis process. This includes removing unwanted artefacts from the signal. In this case, the unwanted signals seen on the EEG signals were eye movements, eye blinks, body movement and muscle burst artefacts. These artefacts were reduced using ASR, which has been explained in detail in section 2.4.2. The data was cleaned using the EEGLAB ASR plugin. An overview of this process is shown in Figure 3.8. A 60-second long relaxed state EEG recording was used as the calibration dataset for each participant. The input for the ASR filter requires the DC-offsets removed. This was achieved by using a simple 0.5Hz high-pass butter filter. Further, the filter settling artefacts were eliminated by removing few of the initial samples. Once the data was ready, the ASR algorithm was applied to the data. The graphical representations of the signals are depicted in Figure 3.8, Figure 3.9, Figure 3.10 and Figure 3.11.

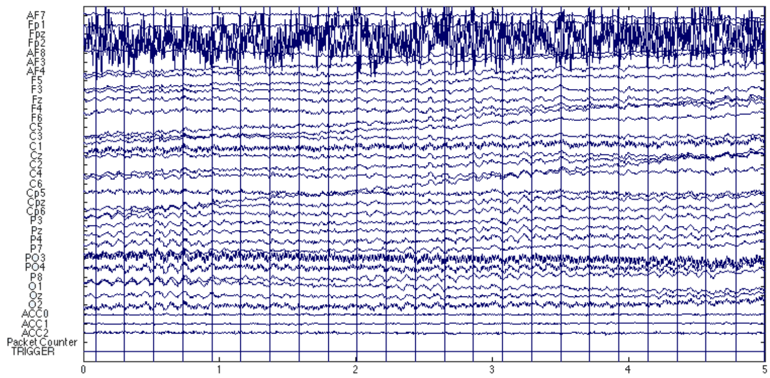


Figure 3.9: Raw relaxed state EEG recording (calibration data)

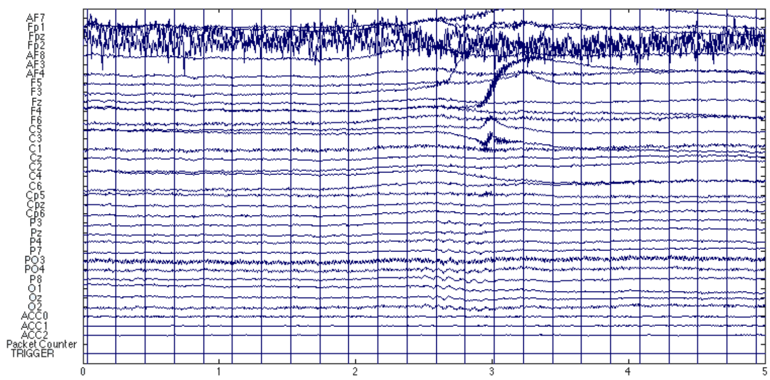


Figure 3.10: Raw experiment EEG recording (while performing a task)

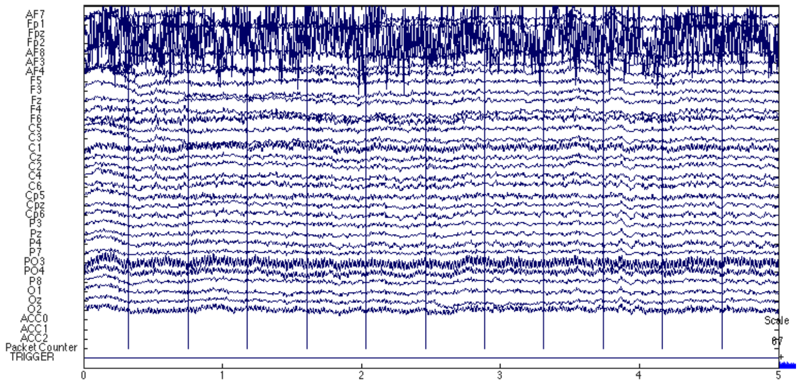


Figure 3.11:ASR filtered EEG recording

Once the data was cleaned using ASR, there was yet another unwanted artefact in the signal which needed to be filtered. This was the noise caused by electric power lines at 50Hz. As shown in Figure 3.12, this was filtered out using a band-stop IIR Butterworth digital filter by removing at least half the power of the frequency between 49Hz to 51Hz.

Figure 3.12: Overview of filtering 50Hz electric power noise

Figure 3.13 displays a single EEG channel with the electric power noise and Figure 3.14 shows the filtered channel.

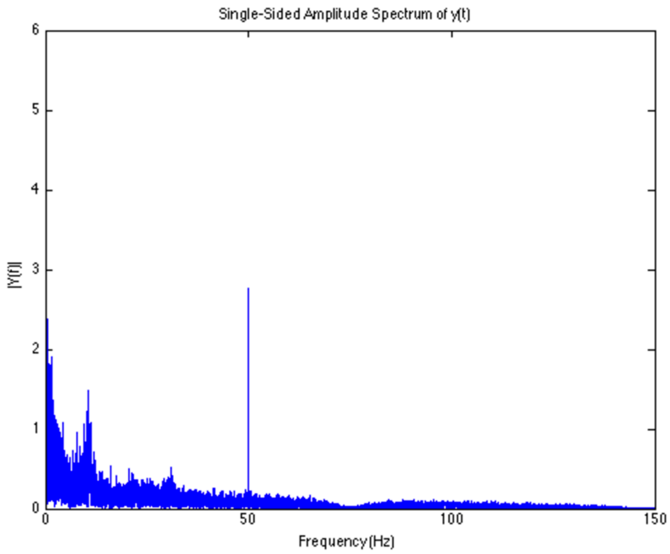


Figure 3.13: Example of a 50Hz electric power noise in a single channel

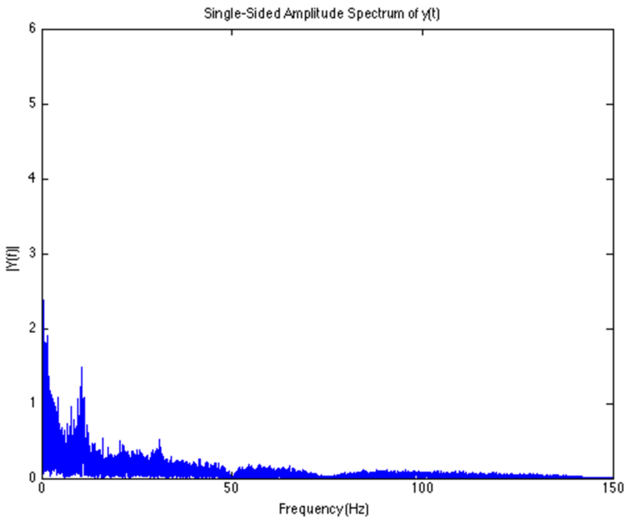


Figure 3.14: Example of a 50Hz electric power noise in a single channel filtered

3.5.2 Frequency Sub-band Decomposition

The original EEG recording is in the time domain. Although it is not directly visible, this waveform is essentially made of a sum of sinusoidal waves. Therefore, to perform a frequency analysis the data needs to be transformed into the frequency domain.

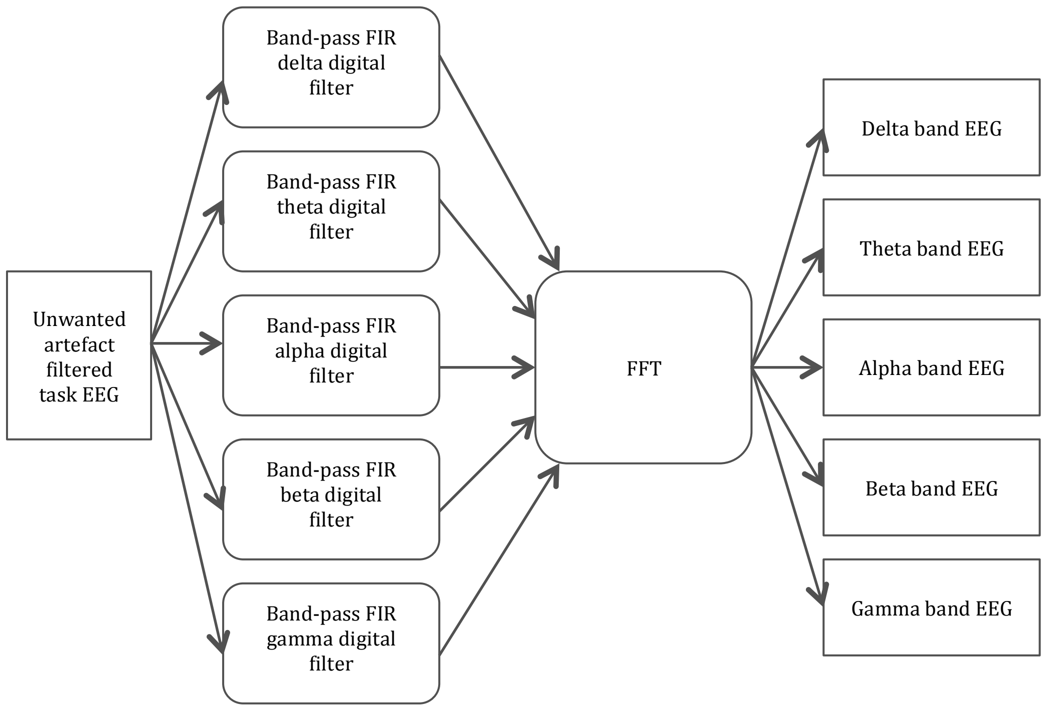


Figure 3.15: Overview of EEG sub-band decomposition and frequency domain transformation

In this research, the EEG signals are analysed by decomposing the EEG signals into pre-defined sub-bands. The sub-bands are namely delta, theta, alpha, beta and gamma. The sub-band decomposition was performed using band-pass FIR digital filters. The filter orders for each frequency range as shown in Table 2.1 was determined using EEGLAB eegfiltnew function (Callan, Durantin, & Terzibas, 2015). Figure 3.16 depicts a graph of frequency sub-bands for a single channel.

Table 3.2: Frequency sub-bands and filter orders

Sub-band	**Frequency Range**	**Filter Order**
Delta	1 – 3.9	992
Theta	4 – 7.9	496
Alpha	8 – 13.9	496
Beta	14 – 29.9	284
Gamma	30 – 64	134

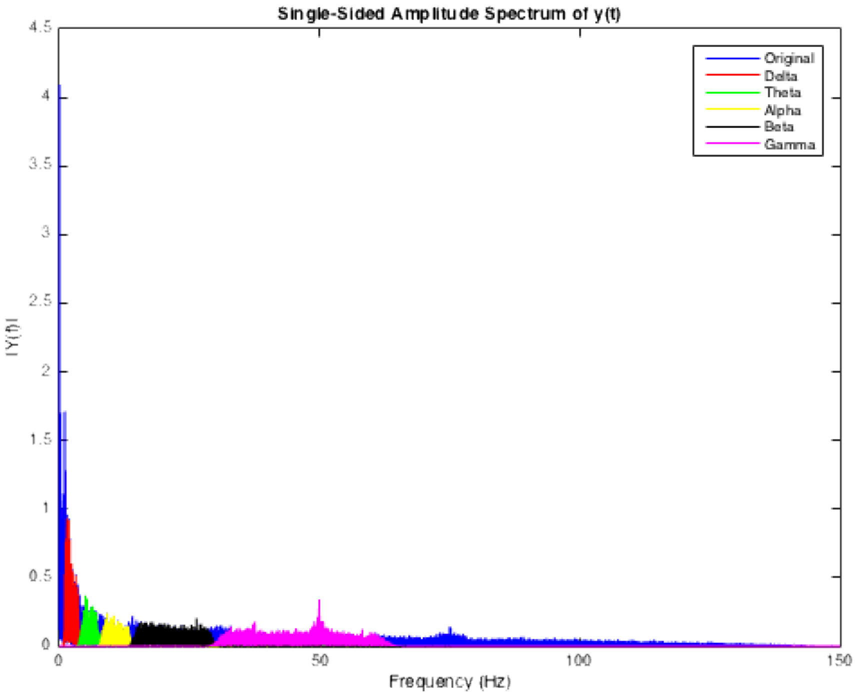


Figure 3.16: Example of Frequency Sub-bands for a Single Channel

Once the data was sent through the above-described filters and divided into the frequency sub-bands, the frequency domain transformation was performed using MATLAB's fft function. This function returns the Discrete Fourier Transform (DFT) computed using a FFT algorithm.

3.5.3 Feature Extraction

Feature extraction is transforming the input data into a set of features (Shantha Selva Kumari & Prabin Jose, 2011). This helps to analyse the data in terms of a reduced but most useful set of features instead of the large original input data set.

As shown in the pseudocode in Figure 3.7, the features mean, median, mode, standard deviation, maximum, minimum, skewness and kurtosis are calculated (Siuly, Li, & Zhang, 2017) for each participant, for each task, at each frequency sub-band (delta, theta, alpha, beta and gamma) in a channel. The minimum, median and maximum represents a three-number summary about the characteristics of the dataset. The mean and standard deviation are important measures to quantify the dispersion of the dataset. Although the mean is a popular measure of central tendency, the median gives a better measurement of the central tendency if the dataset is skewed. Skewness represents the symmetry of a dataset and the kurtosis represents whether the dataset is heavily or lightly tailed in regard to the normal distribution. Thus, all of these features collectively represent important characteristics of the EEG signal datasets.

For each participant, for each task, for all 32 channels, for 5 frequency bands and for 8 features the input predictors for the classifier were calculated. This adds up to a total of 1280 predictors per participant. Table 3.3 shows an example of 5 predictors calculated, i.e. the delta mean from channel 1 to 5 for 32 participants.

Table 3.3: Classifier predictors – delta mean for 5 channels for 32 participants

	1 delta_mean_c1	2 delta_mean_c2	3 delta_mean_c3	4 delta_mean_c4	5 delta_mean_c5
1	0.0048	0.0068	0.0057	0.0060	0.0047
2	0.0058	0.0067	0.0062	0.0066	0.0056
3	0.0041	0.0070	0.0060	0.0053	0.0057
4	0.0118	0.0076	0.0090	0.0081	0.0114
5	0.0082	0.0097	0.0084	0.0088	0.0070
6	0.0066	0.0079	0.0078	0.0085	0.0072
7	0.0051	0.0051	0.0050	0.0057	0.0046
8	0.0084	0.0054	0.0051	0.0053	0.0044
9	0.0053	0.0064	0.0061	0.0069	0.0056
10	0.0057	0.0076	0.0075	0.0076	0.0057
11	0.0071	0.0097	0.0082	0.0083	0.0090
12	0.0098	0.0128	0.0108	0.0085	0.0102
13	0.0093	0.0098	0.0116	0.0091	0.0094
14	0.0039	0.0044	0.0050	0.0046	0.0035
15	0.0039	0.0056	0.0054	0.0053	0.0049
16	0.0051	0.0062	0.0063	0.0063	0.0054
17	0.0060	0.0059	0.0074	0.0067	0.0073
18	0.0073	0.0081	0.0061	0.0069	0.0072
19	0.0093	0.0158	0.0142	0.0160	0.0106
20	0.0039	0.0051	0.0063	0.0050	0.0038
21	0.0064	0.0055	0.0053	0.0054	0.0053
22	0.0071	0.0097	0.0083	0.0091	0.0082
23	0.0039	0.0046	0.0050	0.0049	0.0051
24	0.0044	0.0040	0.0041	0.0043	0.0036
25	0.0050	0.0069	0.0062	0.0066	0.0051
26	0.0044	0.0051	0.0051	0.0051	0.0045
27	0.0049	0.0060	0.0060	0.0066	0.0053
28	0.0077	0.0097	0.0087	0.0094	0.0079
29	0.0040	0.0056	0.0055	0.0056	0.0046
30	0.0049	0.0059	0.0058	0.0057	0.0049
31	0.0105	0.0076	0.0069	0.0095	0.0088
32	0.0046	0.0060	0.0067	0.0064	0.0057
33					

3.6 Classification

Once the predictors are calculated, the next step is to build the classifiers for all the tasks.

3.6.1 Feature Grouping

In this research, in addition to building classifiers with all the EEG channels as a whole, classifiers were also built for different parts of the brain. This helps to identify sections of the brain that have more prominent brainwave activation patterns that can differentiate a specific group from the other with higher validation accuracies.

EEG channels are given unique names based on its position. Given below are the brain lobes considered for the classifiers used and how it was determined.

1. Brain Left Hemisphere - Channel names with 'odd numbers' at the end
2. Brain Right Hemisphere - Channel names with 'even numbers' at the end
3. Brain Center - Channel names with 'z' at the end
4. Frontal Lobe - Channel names starting with 'F'
    - 4.1. Frontal Pole - Channel names starting with 'FP'
    - 4.2. Anterior Frontal - Channel names starting with 'AF'
5. Central Lobe - Channel names starting with 'C'
    - 5.1. Centro Parietal - Channel names starting with 'Cp'
6. Parietal Lobe - Channel names starting with 'P'
    - 6.1. Parieto Occipital - Channel names starting with 'PO'
7. Occipital Lobe - Channel names starting with 'O'

The 32 channels were divided into the following groups as shown in Table 3.4. The EEG channel maps for each of the brain areas are depicted from Figure 3.17 to Figure 3.30. The EEG channels pertaining to each group are marked in green and the other EEG channels used in this research are marked in grey.

Table 3.4: EEG channel grouping according the brain sections

Brain Area		EEG Channels
Brain Left Hemisphere		Fp1, AF7, AF3, F5, F3, C5, C3, C1, Cp5, P3, P7, PO3, O1
Brain Right hemisphere		Fp2, AF8, AF4, F4, F6, C2, C4, C6, Cp6, P4, P8, PO4, O2
Brain Center		Fpz, Fz, Cz, Cpz, Pz, Oz
Frontal Lobe	Frontal Pole	Fp1, Fpz, Fp2
	Anterior-Frontal	AF7, AF3, AF4, AF8
	Frontal	F5, F3, Fz, F4, F6
Central Lobe	Central	C5, C3, C1, Cz, C2, C4, C6
	Centro-Parietal	Cp5, Cpz, Cp6
Parietal Lobe	Parietal	P7, P3, Pz, P4, P8
	Parieto-Occipital	PO3, PO4
Occipital Lobe		O1, Oz, O3

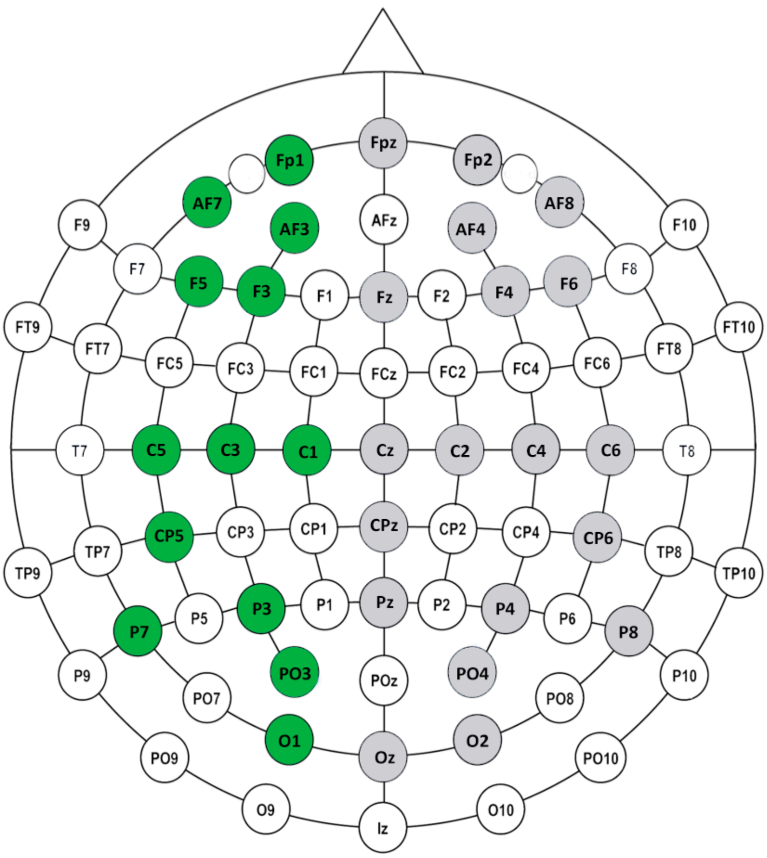


Figure 3.17: EEG channel map for brain left hemisphere

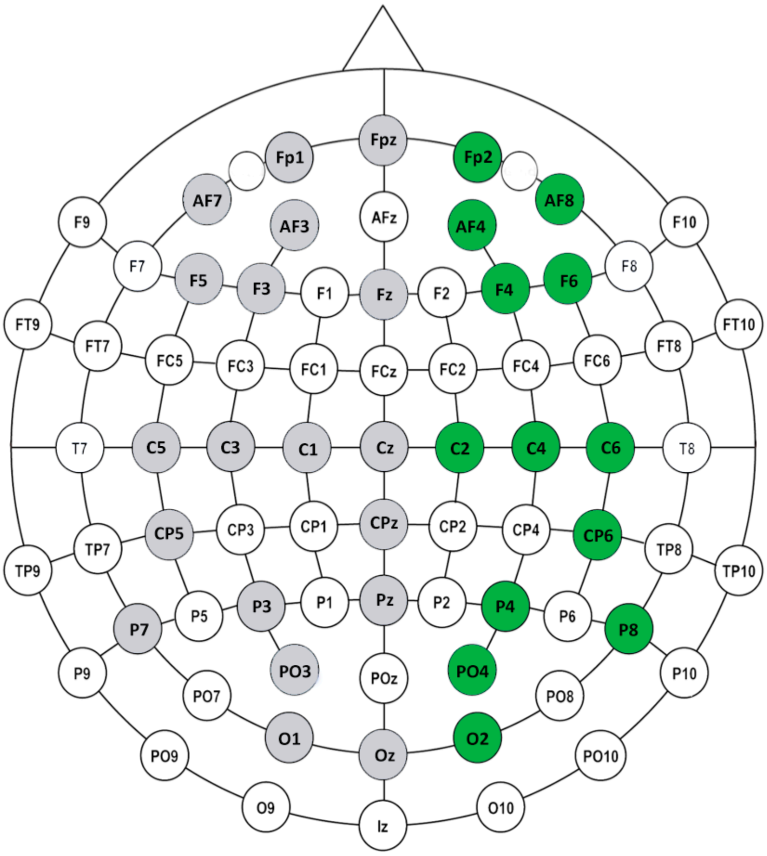


Figure 3.18: EEG channel map for brain right hemisphere

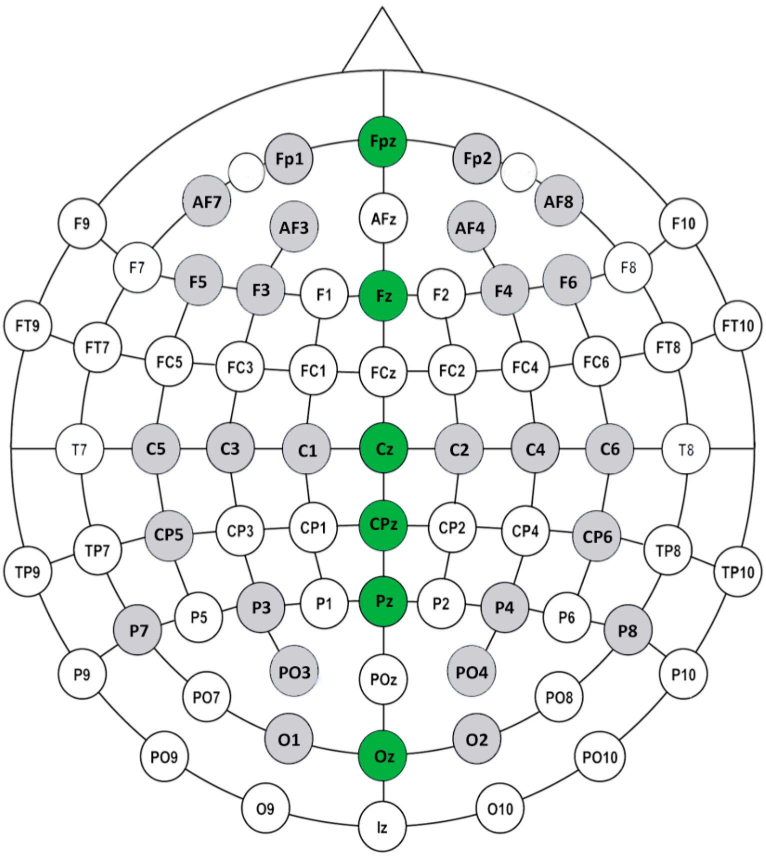


Figure 3.19: EEG channel map for brain center

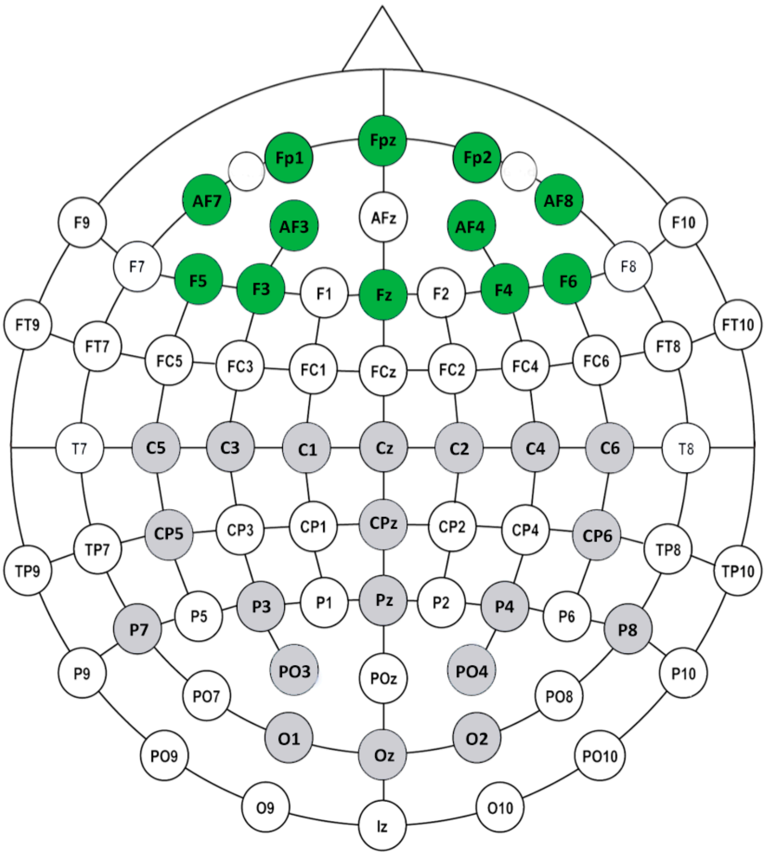


Figure 3.20: EEG channel map for frontal lobe

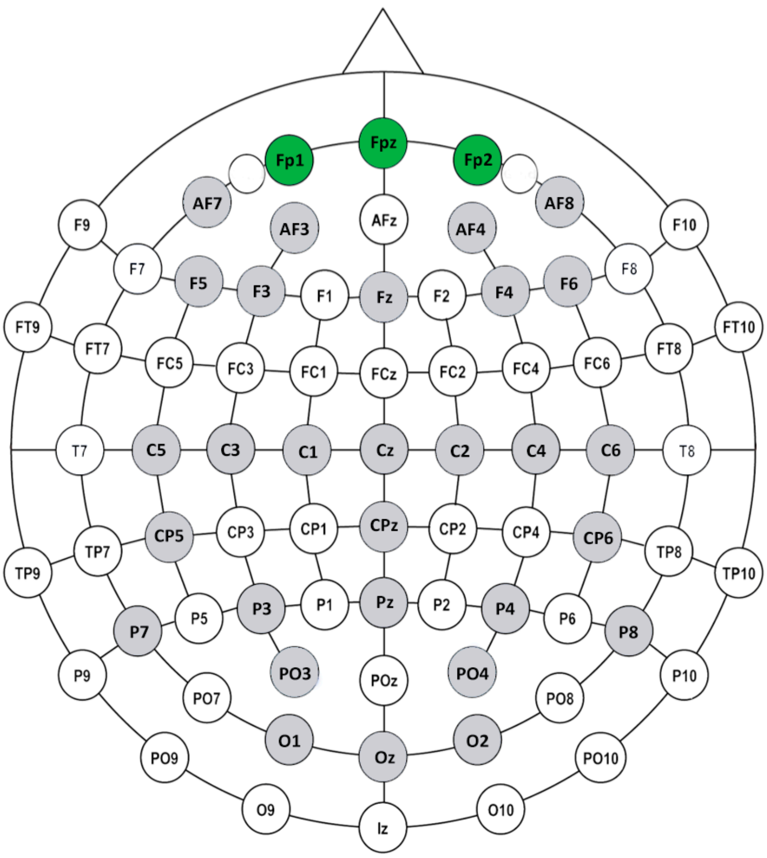


Figure 3.21: EEG channel map for frontal pole

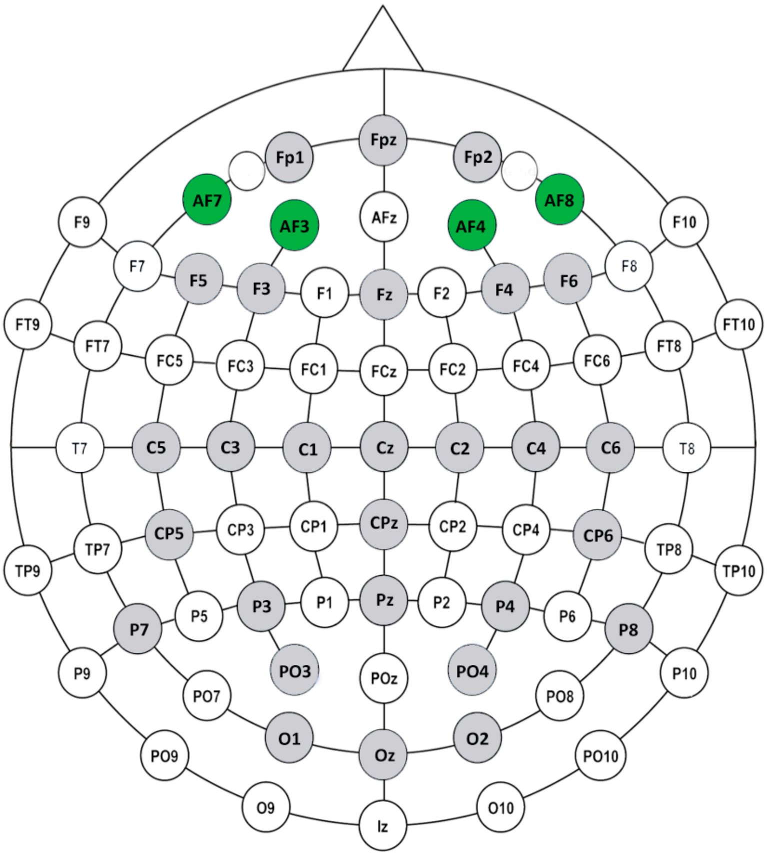


Figure 3.22: EEG channel map for anterior-frontal

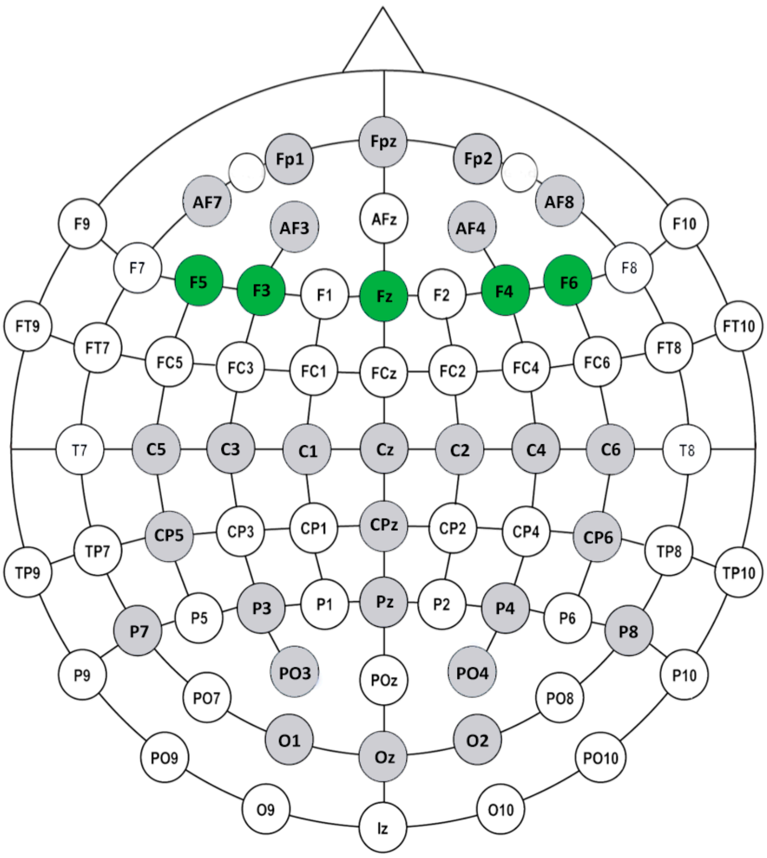


Figure 3.23: EEG channel map for frontal

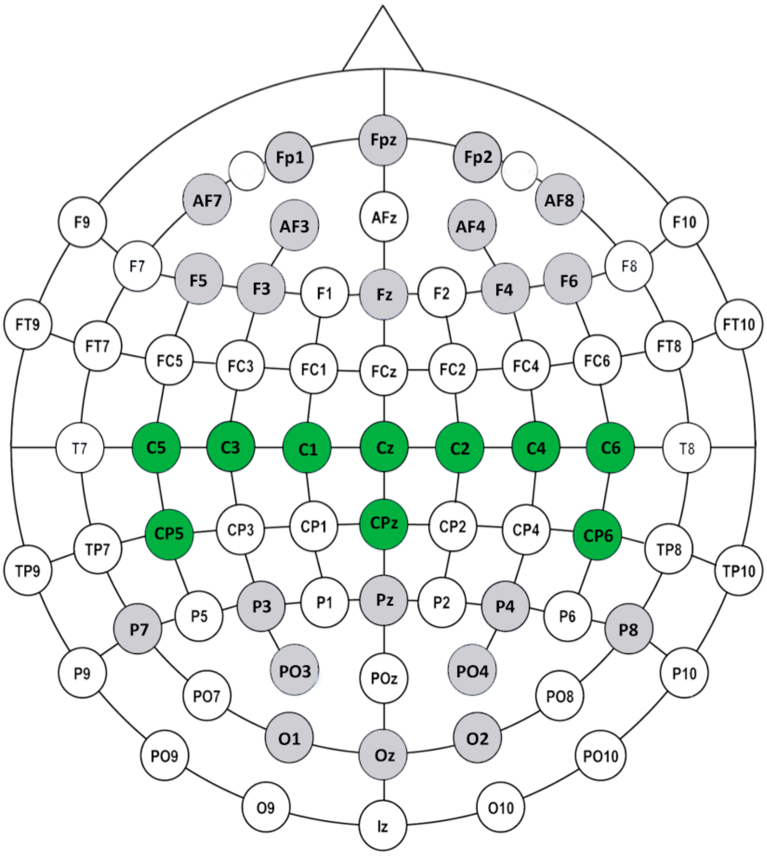


Figure 3.24: EEG channel map for central lobe

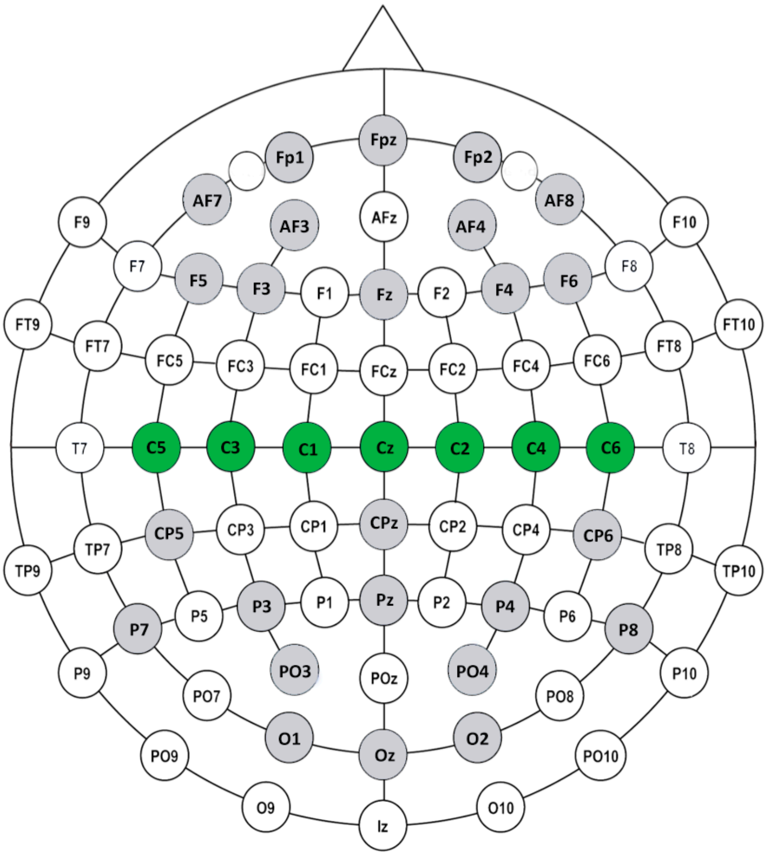


Figure 3.25: EEG channel map for central

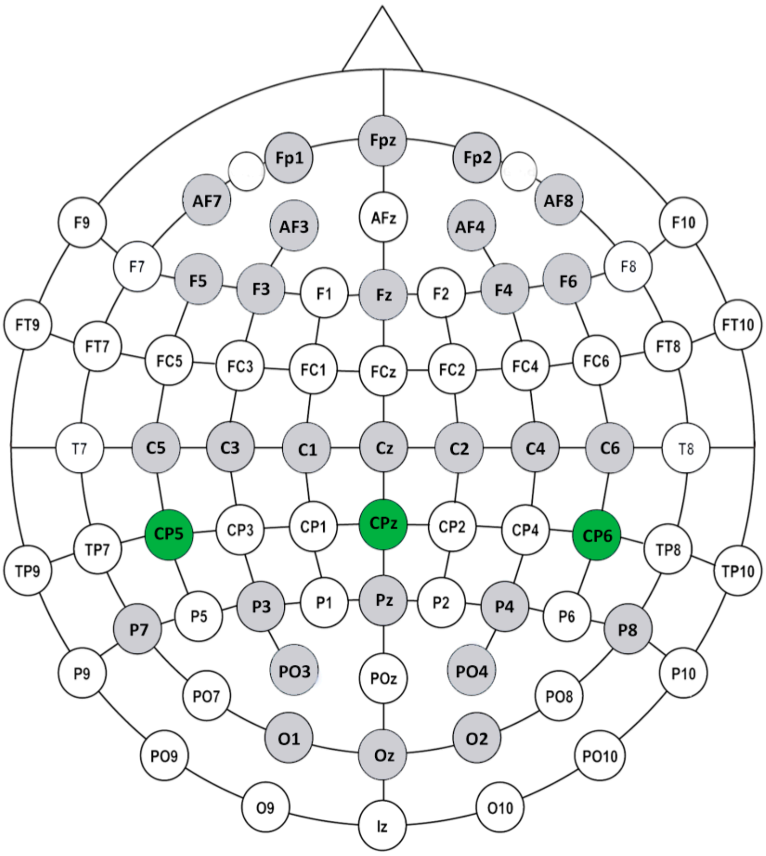


Figure 3.26: EEG channel map for centro-parietal

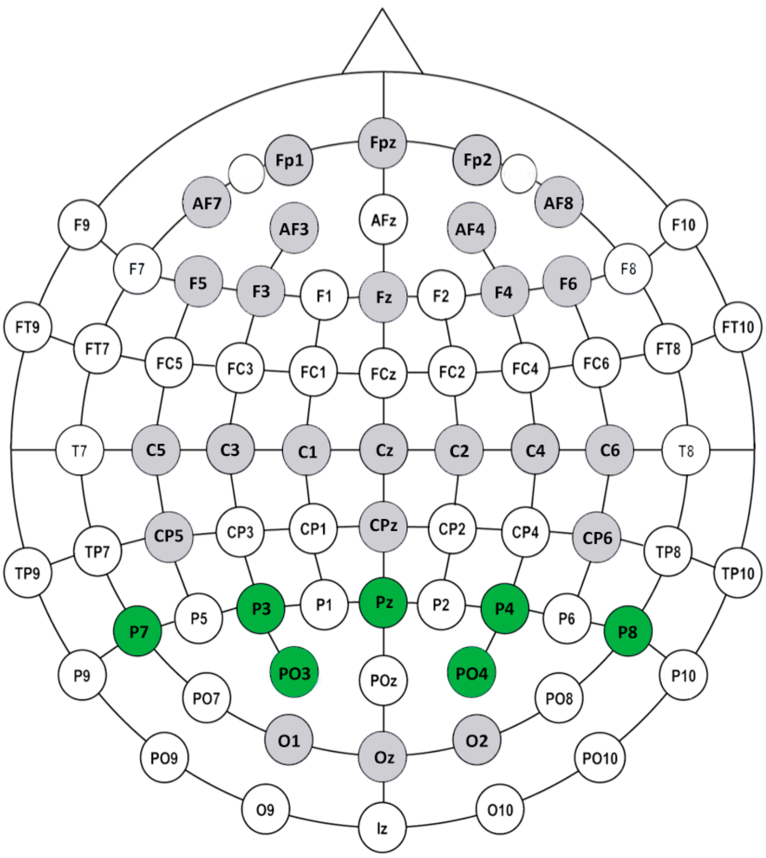


Figure 3.27: EEG channel map for parietal lobe

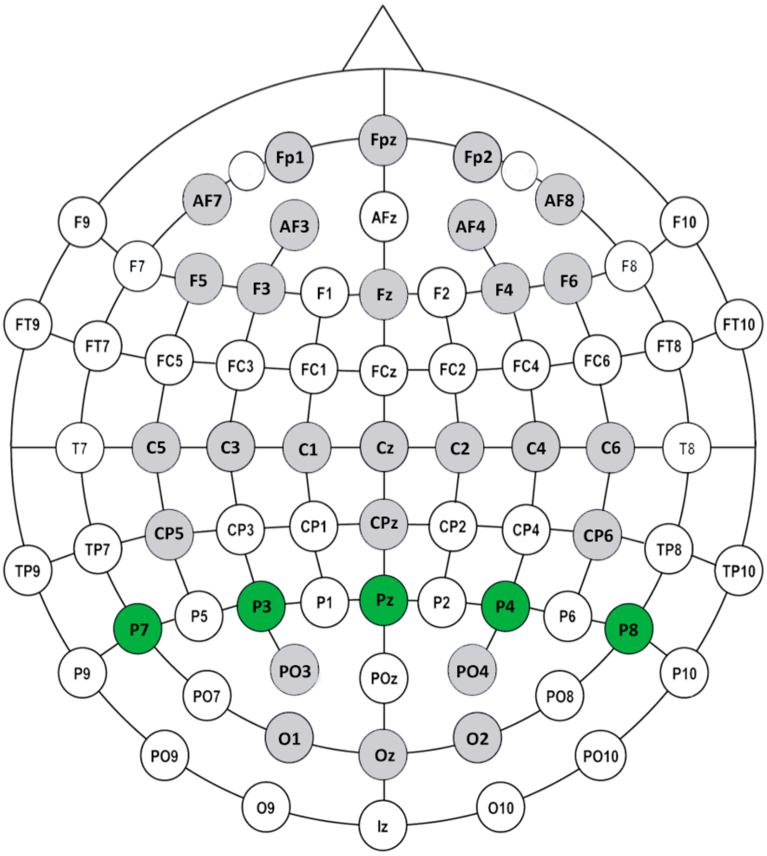


Figure 3.28: EEG channel map for parietal

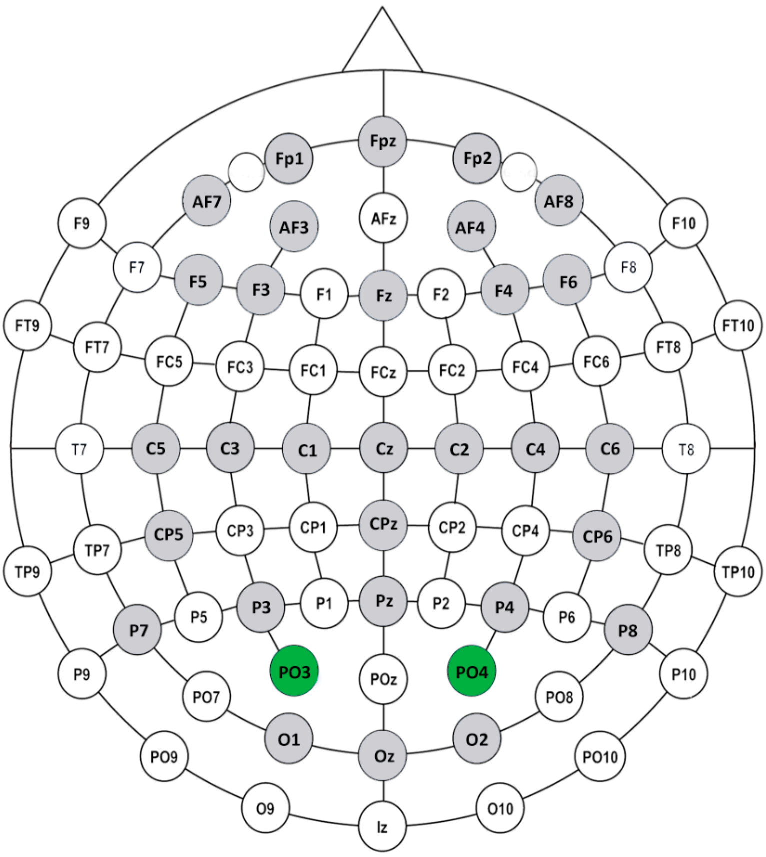


Figure 3.29: EEG channel map for parieto-occipital

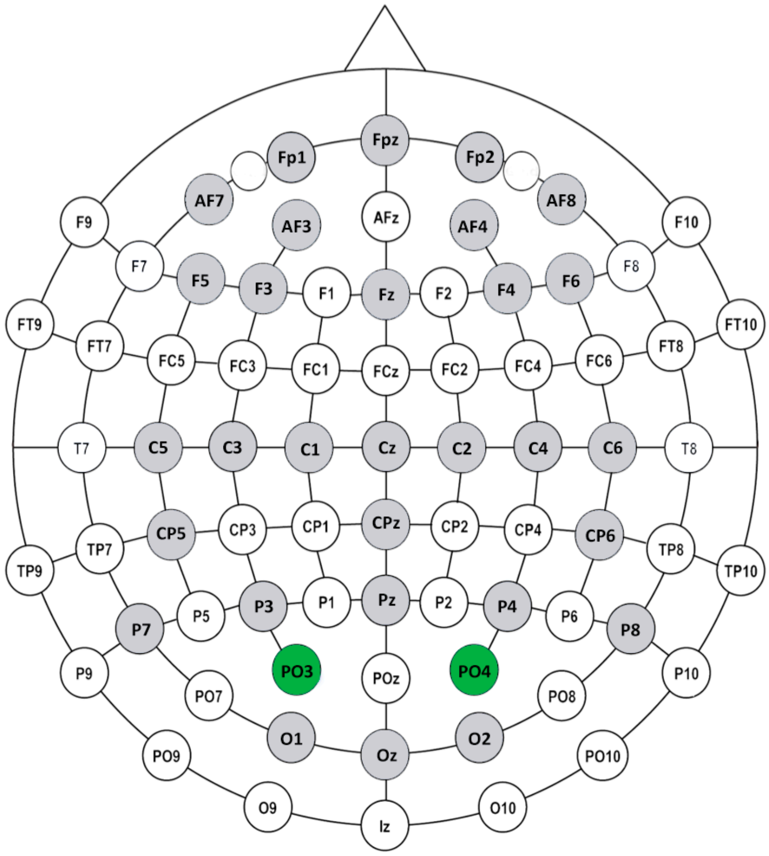


Figure 3.30: EEG channel map for occipital lobe

3.6.2 Classifier

According to previous studies (Garrett et al., 2003; Lotte et al., 2007; Perera et al., 2016a), one of the most suitable classifiers to be used for EEG classifications is SVM. This has been discussed in detail in section 2.4.3.2. The purpose of the classifier is to identify the validation accuracy between the group with dyslexia and control group.

However, there are many types of SVM classifiers. In order to determine which classifier to be used in our research, we conducted a preliminary analysis using 6 types of SVM classifiers, namely, Linear Support Vector Machine (LSVM), Quadratic Support Vector Machine (QSVM), Cubic Support Vector Machine (CSVM), Fine Gaussian Support Vector Machine (FGSVM), Median Gaussian Support Vector Machine (MGSVM) and Coarse Gaussian Support Vector Machine (CGSVM). Further, we selected 3 unique tasks out of the 9 tasks that were considerably different from each other, namely, nonsense-word reading, writing and typing. The results of the outcome of this pilot analysis is described in section 4.2

The classifier was setup by importing the calculated predictors and including the 'type' (dyslexic or non-dyslexic) as the response. The classifier was validated using cross-validation of 10 folds. Since the dataset used for this research is not large, to make efficient use of all the data, cross-validation was selected over holdout-validation.

The SVM classifies group with dyslexia and control group by identifying the best hyperplane that separates the data points of the group with dyslexia from those of the control group. In this case, the best hyperplane would mean the hyperplane with the biggest margin between the group with dyslexia and the control group. Overview of this classification is depicted in Figure 3.31.

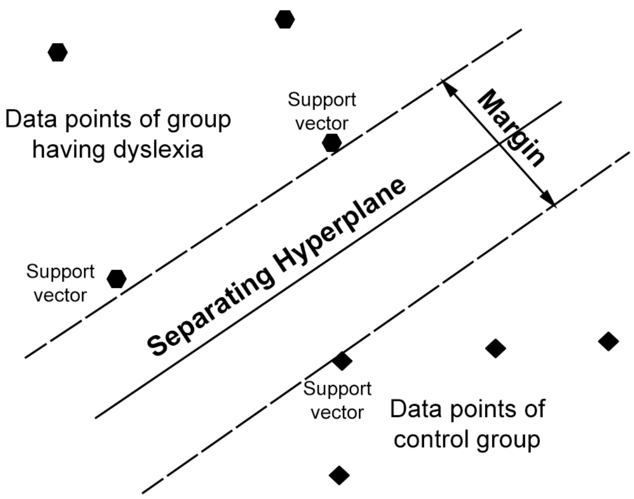


Figure 3.31: Overview of SVM classification

3.6.3 Verification

3.6.3.1 Confusion matrix

The outcome of the classifiers was measured based on the Validation Accuracy (VA), Sensitivity/True Positive Rate (TPR) and Specificity/True Negative Rate (TNR). These values were calculated using the resulting confusion matrix of the classifier shown in Figure 3.32. The calculations are shown in equations (1), (2), and (3).

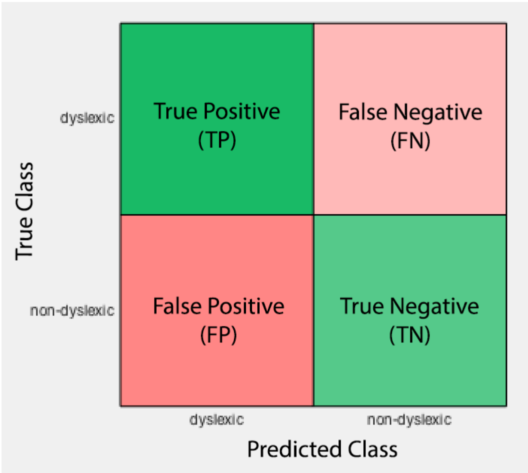


Figure 3.32: Confusion matrix

$$TPR = \frac{TP}{(TP + FN)} \times 100 \tag{1}$$

$$TNR = \frac{TN}{(TN + FP)} \times 100 \tag{2}$$

$$VA = \frac{TP + TN}{(TP + FP + FN + TN)} \times 100 \tag{3}$$

3.7 Summary

This chapter provided an elaboration of the methodology used in this research in order to determine the unique EEG signal patterns between adults with dyslexia and normal controls. This research uses a SVM based classification framework on a total of 32 participants, which includes EEG signal acquisition, signal preprocessing, frequency sub-band decomposition, frequency domain transformation, feature extraction, classification and verification. Classifiers are developed for different brain regions within each task. The next chapter discusses the results of these classifiers.

Chapter 4 Results

4.1 Overview

The main aim of this research is to identify unique brainwave signal patterns in adults with dyslexia compared to normal controls when performing tasks that are more challenging for individuals with dyslexia. This chapter reports the results obtained from the classifiers for each task.

This chapter first describes the results from the pilot analysis carried out to determine the most suitable classifier to be used to classify the data collected and concludes with the classifier selected. Next, we move on to elaborate the results of each task explained in Chapter 3. Each section allocated to describe a task shows multiple results from classifiers pertaining to different regions of the brain. The classifier performance is measured using VA, sensitivity and specificity. All these results are demonstrated orderly in tables followed by the confusion matrix and the validation predictions of the best performing classifier for the specific task's brain region. The following grey scale colour coding as shown in Table 4.1 was adapted to represent the validation predictions.

Table 4.1: Grey Scale colour coding for validation predictions

	Colour Coding	Representation
1	Dyslexic	TP
2	Non-dyslexic	FN
3	Non-dyslexic	TN
4	Dyslexic	FP

Lastly, a summary of the results is presented exhibiting the similarities and differences between the task results and how the optimal classifier results together contribute towards the final conclusions.

4.2 SVM Classifier Selection

As discussed in detail in the literature review (Garrett et al., 2003; Lotte et al., 2007; Perera et al., 2016a) SVM is recognised as one of the most suitable classifiers specifically for EEG classifications, and as explained in the methodology there are many types of SVM classifiers. In order to determine which classifier to be used in our research, we conducted a preliminary analysis using the SVM classifiers LSVM, QSVM, CSVM, FGSVM, MGSVM and CGSVM on the tasks nonsense-word reading, writing and typing. Table 4.2 shows the VA obtained from each classifier. Through this pilot analysis, CSVM was identified as the best performed SVM classifier. Therefore, comprehensive analysis for each task was performed using the CSVM.

Table 4.2: Comparison of VA between different SVM classifiers

Task	LSVM	QSVM	CSVM	FGSVM	MGSVM	CGSVM
Nonsense-word reading	59.4	65.5	**71.9**	43.8	59.4	53.1
Writing	50.0	53.1	**56.2**	46.9	46.9	53.1
Typing	50.0	59.4	**68.8**	53.1	65.6	53.1

4.3 Real-word Reading Task Results

Table 4.3 shows the results from 11 classifiers developed for the real-word reading task. The classifier 'All', which consists of all the channels and features calculated did not indicate significant differences between the 2 groups by achieving only a 56.25% VA.

Next, we created the classifiers for the left and right hemisphere brain regions. Although these 2 classifiers also did not exhibit distinct brainwave characteristics, it was observed that the VA of the brain right hemisphere area was higher compared to the brain right hemisphere area. The frontal, central and occipital lobes provided similar results. However, the parietal lobe classifier stood out among the others by obtaining a VA accuracy of 68.75%.

Thereafter, we drilled down into the sections around the parietal lobe by developing classifiers for the parieto-occipital, parieto-occipital left region and parieto-occipital right regions. A significant outcome was attained by the left region of the parieto-occipital through a 71.88% VA, 70.59% sensitivity and 73.33% specificity.

Table 4.3: Real-word reading classifier results

Brain Area	VA%	Sensitivity%	Specificity%
All	56.25	64.71	46.67
Left Hemisphere	53.13	58.82	46.67
Right Hemisphere	62.50	70.59	53.33
Frontal Lobe	37.50	47.06	26.67
Central Lobe	62.50	76.47	46.67
Parietal Lobe	68.75	64.71	73.33
Occipital Lobe	46.88	58.82	33.33
Parieto-Occipital	68.75	70.59	66.67
Parieto-Occipital Left	**71.88**	**70.59**	**73.33**
Parieto-Occipital Right	65.63	70.59	60.00
Anterior-Frontal	43.75	58.82	26.67

Table 4.4: Confusion matrix of the best performance classifier for real-word reading

TP 12	**FN** 5
FP 4	**TN** 11

Table 4.4 and Table 4.5 presents the confusion matrix and validation predictions respectively, for the best performing classifier which in this case is the parieto-occipital left.

Table 4.5: Validation predictions of the best performance classifier for real-word reading

Participant ID	Prediction Results
1	Dyslexic
2	Dyslexic
3	Non-dyslexic
4	Dyslexic
5	Dyslexic
6	Dyslexic
7	Dyslexic
8	Dyslexic
9	Dyslexic
10	Dyslexic
11	Dyslexic
12	Non-dyslexic
13	Non-dyslexic
14	Dyslexic
15	Dyslexic
16	Non-dyslexic
17	Non-dyslexic
18	Non-dyslexic
19	Non-dyslexic
20	Non-dyslexic
21	Non-dyslexic
22	Non-dyslexic
23	Non-dyslexic
24	Non-dyslexic
25	Dyslexic
26	Dyslexic

27	Non-dyslexic
28	Dyslexic
29	Non-dyslexic
30	Non-dyslexic
31	Non-dyslexic
32	Dyslexic

4.4 Nonsense-word Reading Task Results

Similar to the real-word reading task, the scores from the 11 classifiers created for the nonsense-word reading task is set out in Table 4.6. The classifier with all the EEG electrodes showed a significant VA of 78.13% as opposed to the corresponding real-word reading classifier.

Subsequently, the EEG signal outcome of the left and right hemispheres were analysed separately using classifiers. Although these results presented less significance compared to all the sensors as a whole, interestingly, the right hemisphere classifier VA was higher than the left hemisphere classifier VA similar to the equivalent real-word reading classifiers.

Next, classifiers were built for the frontal, central, parietal and occipital lobes, where the parietal and occipital lobes produced distinctive VA of 81.25% and 75.0% respectively. In consequence, we inspected the region between the lobes, which is the parieto-occipital and was able to achieve a higher VA of 84.38%.

Then we examined the left and right parieto-occipital individually, through which we were able to reach a superior VA as high as 87.50% for the left parieto-occipital.

The confusion matrix and the validation predictions for the best classifier in the nonsense-word reading task are shown in Table 4.7 and Table 4.8 respectively.

Table 4.6: Nonsense-word reading classifier results

Brain Area	VA%	Sensitivity%	Specificity%
All	78.13	82.35	73.33
Left Hemisphere	65.63	76.47	53.33
Right Hemisphere	68.75	70.59	66.67
Frontal Lobe	50.00	64.71	33.33
Central Lobe	68.75	76.47	60.00
Parietal Lobe	81.25	82.35	80.00
Occipital Lobe	75.00	82.35	66.67
Parieto-Occipital	84.38	88.24	80.00
Parieto-Occipital Left	**87.50**	**88.24**	**86.67**
Parieto-Occipital Right	81.25	82.35	80.00
Anterior-Frontal	68.75	76.47	60.00

Table 4.7: Confusion matrix of the best performance classifier for nonsense-word reading

TP 15	**FN** 2
FP 2	**TN** 13

Table 4.8: Validation predictions of the best performance classifier for nonsense-word reading

Participant ID	Prediction Results
1	Dyslexic
2	Dyslexic
3	Dyslexic
4	Dyslexic
5	Dyslexic

6	Dyslexic
7	Dyslexic
8	Dyslexic
9	Dyslexic
10	Dyslexic
11	Dyslexic
12	Non-dyslexic
13	Dyslexic
14	Dyslexic
15	Dyslexic
16	Non-dyslexic
17	Dyslexic
18	Dyslexic
19	Non-dyslexic
20	Non-dyslexic
21	Non-dyslexic
22	Non-dyslexic
23	Non-dyslexic
24	Non-dyslexic
25	Non-dyslexic
26	Non-dyslexic
27	Non-dyslexic
28	Dyslexic
29	Non-dyslexic
30	Non-dyslexic
31	Non-dyslexic
32	Non-dyslexic

4.5 Passage Reading Task Results

The classifier results from the final reading task being the passage reading task is depicted in Table 4.9. The classifier results produced from the left hemisphere, right hemisphere, frontal lobe, central lobe, occipital lobe as well as all the EEG channels as a whole did not show significant differences in the brainwave signal patterns between the two groups.

However, the parietal lobe showed slightly positive results. Since the two previous reading tasks revealed substantial VA levels in the parieto-occipital region, we attempted to examine this region using a classifier. As expected, a significant VA of 71.88% was obtained.

Table 4.9: Passage reading classifier results

Brain Area	VA%	Sensitivity%	Specificity%
All	53.13	52.94	53.33
Left Hemisphere	59.38	64.71	53.33
Right Hemisphere	59.38	64.71	53.33
Frontal Lobe	59.38	58.82	60.00
Central Lobe	53.13	70.59	33.33
Parietal Lobe	62.50	64.71	60.00
Occipital Lobe	56.25	52.94	60.00
Parieto-Occipital	71.88	76.47	66.67
Parieto-Occipital Left	**75.00**	**88.24**	**60.00**
Parieto-Occipital Right	62.50	58.82	66.67
Anterior Frontal	68.75	70.59	66.67

Table 4.10: Confusion matrix of the best performance classifier for passage reading

TP 12	**FN** 5
FP 5	**TN** 10

Next, the left and right of the parieto-occipital region were analysed, and the left parieto-occipital region showed the highest VA of 75.00% for this task, which yet again was in parallel with the two previous reading tasks.

The best performance confusion matrix and prediction validations are showing through Table 4.10 and Table 4.11.

Table 4.11: Validation predictions of the best performance classifier for passage reading

Participant ID	Prediction Results
1	Dyslexic
2	Dyslexic
3	Dyslexic
4	Dyslexic
5	Dyslexic
6	Dyslexic
7	Dyslexic
8	Dyslexic
9	Dyslexic
10	Non-dyslexic
11	Dyslexic
12	Dyslexic
13	Dyslexic
14	Non-dyslexic
15	Dyslexic
16	Dyslexic
17	Dyslexic
18	Dyslexic
19	Non-dyslexic
20	Dyslexic
21	Non-dyslexic
22	Non-dyslexic
23	Non-dyslexic

24	Non-dyslexic
25	Dyslexic
26	Dyslexic
27	Dyslexic
28	Non-dyslexic
29	Non-dyslexic
30	Non-dyslexic
31	Non-dyslexic
32	Dyslexic

4.6 RAN Task Results

The results from all the classifiers created for the RAN task are summarised in Table 4.12. In can be seen from the table that the first seven classifiers fail to obtain sufficient VA in order to be able to distinguish the group with dyslexia compared to the normal control group.

Although at this point we assumed that may be the RAN task does not show adequate differences in the brainwave patterns, surprisingly, the parieto-occipital showed a VA of 75.00%.

Overall, the results of RAN were not as promising in comparison to the real-word reading task and the nonsense-word reading task. However, the region with the high VA was consistent with those tasks. The lowest VA was shown in the brain left hemisphere classifier.

Table 4.13 depicts the confusion matrix relevant to the highest performance classifier with the RAN task, and Table 4.14 depicts the validation predictions relevant to the highest performance classifier with the RAN task.

Table 4.12: RAN classifier results

Brain Area	VA%	Sensitivity%	Specificity%
All	40.63	41.18	40.00
Left Hemisphere	34.38	41.18	26.67
Right Hemisphere	40.63	41.18	40.00
Frontal Lobe	43.75	41.18	46.67
Central Lobe	53.13	58.82	46.67
Parietal Lobe	56.25	70.59	40.00
Occipital Lobe	56.25	52.94	60.00
Parieto-Occipital	**75.00**	**82.35**	**66.67**
Parieto-Occipital Left	59.38	70.59	46.67
Parieto-Occipital Right	68.75	70.59	66.67
Anterior Frontal	40.63	35.29	46.67

Table 4.13: Confusion matrix of the best performance classifier for RAN

TP 14	**FN** 3
FP 5	**TN** 10

Table 4.14: Validation predictions of the best performance classifier for RAN

Participant ID	Prediction Results
1	Dyslexic
2	Non-dyslexic
3	Dyslexic
4	Dyslexic
5	Dyslexic

6	Dyslexic
7	Dyslexic
8	Dyslexic
9	Dyslexic
10	Dyslexic
11	Dyslexic
12	Non-dyslexic
13	Dyslexic
14	Dyslexic
15	Non-dyslexic
16	Dyslexic
17	Dyslexic
18	Non-dyslexic
19	Dyslexic
20	Dyslexic
21	Non-dyslexic
22	Non-dyslexic
23	Non-dyslexic
24	Dyslexic
25	Non-dyslexic
26	Non-dyslexic
27	Non-dyslexic
28	Non-dyslexic
29	Non-dyslexic
30	Non-dyslexic
31	Dyslexic
32	Dyslexic

4.7 Writing Task Results

Table 4.15 provides the summary statistics for all the classifier results relating to the writing task. The outcomes of this task were quite different compared to the other tasks discussed above. Although up to now the parieto-occipital region portrayed significant results, for this task the parieto-occipital region classifier did not produce significant results.

However, the anterior frontal attained a VA of 71.88%, a sensitivity of 76.47% and specificity of 66.67%.

Table 4.16 and Table 4.17 display the confusion matrix and validation predictions for the anterior frontal.

Table 4.15: Writing classifier results

Brain Area	VA%	Sensitivity%	Specificity%
All	59.38	64.71	53.33
Left Hemisphere	65.63	70.59	60.00
Right Hemisphere	50.00	64.71	33.33
Frontal Lobe	56.25	64.71	46.67
Central Lobe	59.38	64.71	53.33
Parietal Lobe	59.38	64.71	53.33
Occipital Lobe	62.50	64.71	60.00
Parieto-Occipital	46.88	58.82	33.33
Parieto-Occipital Left	46.88	52.94	40.00
Parieto-Occipital Right	59.38	58.82	60.00
Anterior Frontal	**71.88**	**76.47**	**66.67**

Table 4.16: Confusion matrix of the best performance classifier for writing

TP 13	**FN** 4
FP 5	**TN** 10

Table 4.17: Validation predictions of the best performance classifier for writing

Participant ID	Prediction Results
1	Non-dyslexic
2	Non-dyslexic
3	Dyslexic
4	Dyslexic
5	Dyslexic
6	Dyslexic
7	Dyslexic
8	Dyslexic
9	Dyslexic
10	Dyslexic
11	Dyslexic
12	Non-dyslexic
13	Dyslexic
14	Dyslexic
15	Dyslexic
16	Non-dyslexic
17	Dyslexic
18	Non-dyslexic
19	Non-dyslexic

20	Dyslexic
21	Non-dyslexic
22	Dyslexic
23	Non-dyslexic
24	Non-dyslexic
25	Dyslexic
26	Non-dyslexic
27	Non-dyslexic
28	Dyslexic
29	Non-dyslexic
30	Non-dyslexic
31	Non-dyslexic
32	Dyslexic

4.8 Typing Task results

Table 4.18 illustrates the behaviour of seventeen classifiers built to analyse the typing task. The classifier with all the EEG sensors collectively produced a VA of 78.13%.

We next examined the left hemisphere, right hemisphere, frontal lobe, central lobe, parietal lobe and the occipital lobe. Except for the parietal lobe, others showed a substantial difference between the sensitivity and specificity rates, which is not preferable. The classifiers from parietal and parieto-occipital performed fairly well. However, it was not the best performing region similar to most the tasks.

The frontal classifier showed the top VA of 78.13% and the confusion matrix and validation predictions particular to the classifier are shown in Table 4.19 and Table 4.20 respectively.

Table 4.18: Typing classifier results

Brain Area	VA%	Sensitivity%	Specificity%
All	78.13	88.24	66.67
Left Hemisphere	71.88	94.12	46.67
Right Hemisphere	62.50	76.47	46.67
Frontal Lobe	68.75	88.24	46.67
Central Lobe	68.75	82.35	53.33
Parietal Lobe	65.63	76.47	53.33
Occipital Lobe	56.25	82.35	26.67
Parieto-Occipital	62.50	70.59	53.33
Parieto-Occipital Left	68.75	76.47	60.00
Parieto-Occipital Right	68.75	76.47	60.00
Anterior Frontal	65.63	88.24	40.00
Central	68.75	76.47	60.00
Centro Parietal	59.38	76.47	40.00
Frontal Pole	68.75	94.12	40.00
Frontal	**78.13**	**88.24**	**66.67**
Frontal Left	68.75	82.35	53.33
Frontal Right	68.75	82.35	53.33

Table 4.19: Confusion matrix of the best performance classifier for typing

TP 15	**FN** 2
FP 5	**TN** 10

Table 4.20: Validation predictions of the best performance classifier for typing

Participant ID	Prediction Results
1	Dyslexic
2	Dyslexic
3	Dyslexic
4	Dyslexic
5	Dyslexic
6	Dyslexic
7	Dyslexic
8	Dyslexic
9	Dyslexic
10	Dyslexic
11	Dyslexic
12	Dyslexic
13	Dyslexic
14	Non-dyslexic
15	Dyslexic
16	Non-dyslexic
17	Dyslexic
18	Non-dyslexic
19	Non-dyslexic
20	Non-dyslexic
21	Dyslexic
22	Non-dyslexic
23	Dyslexic
24	Non-dyslexic
25	Dyslexic
26	Non-dyslexic
27	Non-dyslexic
28	Dyslexic
29	Dyslexic
30	Non-dyslexic

31	Non-dyslexic
32	Non-dyslexic

4.9 Web Browsing Task Results

The results from web browsing; one of the everyday tasks incorporated in our experiment is shown in Table 4.21. The table shows that the brain regions shown from the first seven rows do not display significant results and a closer inspection shows that right hemisphere, frontal lobe, central lobe, and the occipital lobe when considered individually do not appear to have balanced sensitivities and specificities.

However, the left parieto-occipital classifier obtained a VA of 68.75% with fairly balanced values for sensitivity and specificity of 70.59% and 66.67% respectively.

The confusion matrix and prediction validations for the left parieto-occipital are shown in Table 4.22 and Table 4.23.

Table 4.21: Web browsing classifier results

Brain Area	VA%	Sensitivity%	Specificity%
All	46.88	41.18	53.33
Left Hemisphere	62.50	52.94	73.33
Right Hemisphere	53.13	29.41	80.00
Frontal Lobe	56.25	70.59	40.00
Central Lobe	59.38	41.18	80.00
Parietal Lobe	56.25	47.06	66.67
Occipital Lobe	56.25	29.41	86.67
Parieto-Occipital	68.75	64.71	73.33
Parieto-Occipital Left	**68.75**	**70.59**	**66.67**
Parieto-Occipital Right	62.50	41.18	86.67
Anterior Frontal	50.00	52.94	46.67

Table 4.22: Confusion matrix of the best performance classifier for web browsing

TP 12	**FN** 5
FP 5	**TN** 10

Table 4.23: Validation predictions of the best performance classifier for web browsing

Participant ID	Prediction Results
1	Dyslexic
2	Dyslexic
3	Dyslexic
4	Dyslexic
5	Dyslexic
6	Dyslexic
7	Dyslexic
8	Non-dyslexic
9	Dyslexic
10	Dyslexic
11	Non-dyslexic
12	Non-dyslexic
13	Dyslexic
14	Non-dyslexic
15	Dyslexic
16	Non-dyslexic
17	Dyslexic
18	Non-dyslexic

19	Dyslexic
20	Dyslexic
21	Non-dyslexic
22	Dyslexic
23	Non-dyslexic
24	Non-dyslexic
25	Non-dyslexic
26	Non-dyslexic
27	Non-dyslexic
28	Dyslexic
29	Non-dyslexic
30	Dyslexic
31	Non-dyslexic
32	Non-dyslexic

4.10 Table Interpretation Task Results

The results obtained from the table interpretation tasks are set out in Table 4.24. Although the classifier with all the EEG sensors as a whole did not show a promising number to confirm significant differences between the two groups, the parietal lobe, parieto-occipital, right of the parieto-occipital and the centro parietal showed comparatively promising results.

Even though the parieto-occipital and the centro parietal obtained the same VA of 71.88%, the sensitivity and specificity ratios were more balanced in the parieto-occipital; affirming to be the better classifier. The resulting confusion matrix is shown in Table 4.25 and the resulting validation predictions are shown in Table 4.26.

Table 4.24: Table interpretation classifier results

Brain Area	VA%	Sensitivity%	Specificity%
All	50.00	64.71	33.33
Left Hemisphere	65.63	76.47	53.33
Right Hemisphere	53.13	64.71	40.00
Frontal Lobe	53.13	76.47	26.67
Central Lobe	59.38	70.59	46.67
Parietal Lobe	68.75	70.59	66.67
Occipital Lobe	53.13	58.82	46.67
Parieto-Occipital	**71.88**	**70.59**	**73.33**
Parieto-Occipital Left	53.13	64.71	40.00
Parieto-Occipital Right	68.75	64.71	73.33
Anterior Frontal	62.50	70.59	53.33
Central	62.50	76.47	46.67
Centro Parietal	71.88	82.35	60.00
Frontal Pole	43.75	52.94	33.33
Frontal	53.13	70.59	33.33
Frontal Left	65.63	82.35	46.67
Frontal Right	56.25	58.82	53.33

Table 4.25: Confusion matrix of the best performance classifier for table interpretation

TP 12	**FN** 5
FP 4	**TN** 11

Table 4.26: Validation predictions of the best performance classifier for table interpretation

Participant ID	Prediction Results
1	Dyslexic
2	Dyslexic
3	Dyslexic
4	Dyslexic
5	Dyslexic
6	Dyslexic
7	Dyslexic
8	Dyslexic
9	Dyslexic
10	Non-dyslexic
11	Non-dyslexic
12	Non-dyslexic
13	Dyslexic
14	Dyslexic
15	Dyslexic
16	Non-dyslexic
17	Non-dyslexic
18	Non-dyslexic
19	Dyslexic
20	Non-dyslexic
21	Non-dyslexic
22	Non-dyslexic
23	Non-dyslexic
24	Non-dyslexic
25	Non-dyslexic
26	Dyslexic
27	Dyslexic
28	Non-dyslexic
29	Non-dyslexic
30	Non-dyslexic

31	Non-dyslexic
32	Dyslexic

4.11 Typing Random Number Task Results

The results from the final task, typing random number is presented in Table 4.27. As can be seen from the table, except for the brain regions around the parieto-occipital, the other classifiers portrayed disappointing results.

However, it is apparent from this table that the one region that is significant is following the same pattern as most of the tasks. In this task, the parieto-occipital right was able to acquire a VA of 68.75%, a sensitivity of 76.47% and specificity of 60.00% derived from the classifier resulting confusion matrix shown in Table 4.28. The validation predictions relating to this task is presented in Table 4.29.

Table 4.27: Typing random number classifier results

Brain Area	VA%	Sensitivity%	Specificity%
All	43.75	52.94	33.33
Left Hemisphere	43.75	58.82	26.67
Right Hemisphere	53.13	64.71	40.00
Frontal Lobe	46.88	64.71	26.67
Central Lobe	53.13	58.82	46.67
Parietal Lobe	56.25	64.71	46.67
Occipital Lobe	65.63	70.59	60.00
Parieto-Occipital	65.63	64.71	66.67
Parieto-Occipital Left	59.38	52.94	66.67
Parieto-Occipital Right	**68.75**	**76.47**	**60.00**
Anterior Frontal	53.13	64.71	40.00
Central	59.38	58.82	60.00
Centro Parietal	53.13	52.94	53.33
Frontal Pole	65.63	70.59	60.00

Frontal	56.25	64.71	46.67
Frontal Left	50.00	64.71	33.33
Frontal Right	62.50	70.59	53.33

Table 4.28: Confusion matrix of the best performance classifier for typing random number

TP 13	**FN** 4
FP 6	**TN** 9

Table 4.29: Validation predictions of the best performance classifier for typing random number

Participant ID	Prediction Results
1	Dyslexic
2	Non-dyslexic
3	Dyslexic
4	Dyslexic
5	Dyslexic
6	Dyslexic
7	Dyslexic
8	Dyslexic
9	Dyslexic
10	Non-dyslexic
11	Dyslexic
12	Dyslexic
13	Dyslexic

14	Non-dyslexic
15	Non-dyslexic
16	Dyslexic
17	Dyslexic
18	Dyslexic
19	Dyslexic
20	Non-dyslexic
21	Dyslexic
22	Non-dyslexic
23	Non-dyslexic
24	Non-dyslexic
25	Non-dyslexic
26	Dyslexic
27	Non-dyslexic
28	Non-dyslexic
29	Non-dyslexic
30	Dyslexic
31	Non-dyslexic
32	Dyslexic

4.12 Summary

The results of this chapter indicate that adults with dyslexia have unique brainwave signal patterns compared to normal controls while performing the nine tasks selected in this research. It was evident that classifying brain regions separately instead of classifying all the regions together as a whole could increase the classification accuracy levels. The results revealed that the optimal brain regions suitable for classification were dependent on the task. The summary of the findings is presented in Table 4.30, and according to our discoveries, the best task suitable for classification was nonsense-word reading with a VA of 87.50% and the least suitable tasks were web browsing and typing random number having only a VA of 68.75%. Further, it was also apparent that left of the parieto-occipital stood out as the region that attained the highest VA levels.

Table 4.30: Summary of optimal brain regions suitable for classification for each task

Task	Optimal Brain Region for Classification	VA
Real-word reading (RW)	Parieto-occipital left	71.88
Nonsense-word reading (NW)	Parieto-occipital left	87.50
RAN	Parieto-occipital	75.00
Passage reading (PR)	Parieto-occipital left	75.00
Web browsing (WB)	Parieto-occipital left	68.75
Writing (W)	Anterior Frontal	71.88
Typing (T)	Frontal	78.13
Table interpretation (TI)	Parieto-occipital	71.88
Tying random number (TRN)	Parieto-occipital right	68.75

Table 4.31 shown below summarises the prediction validations obtained from the optimal brain region classifier for each task. The first column shows the participant ID (PID), where PID 1 to 17 corresponds to the group with dyslexia and PID 18 to 32 corresponds to the control group. Columns 2 to 10 show the predictions for the 9 tasks, and where the prediction is correct is it represented as 1 and if the prediction is wrong it is represented as 0. Column 11 presents the total of the correct predictions for each participant and column 12 shows the accuracy percentage for each participant. Taken together, this table helps understand the association of the results towards finally concluding whether a person can be identified as having a significant amount of brainwave signal patterns relating to dyslexia or not and vice versa.

Table 4.31: Summary of prediction validations obtained from the optimal brain region classifiers for each task

PID	RW	NW	RAN	PR	WB	W	T	TI	TRN	Total	%
1	1	1	1	1	1	0	1	1	1	8	88.89
2	1	1	0	1	1	0	1	1	0	6	66.67
3	0	1	1	1	1	1	1	1	1	8	88.89
4	1	1	1	1	1	1	1	1	1	9	100.00
5	1	1	1	1	1	1	1	1	1	9	100.00
6	1	1	1	1	1	1	1	1	1	9	100.00
7	1	1	1	1	1	1	1	1	1	9	100.00
8	1	1	1	1	0	1	1	1	1	8	88.89
9	1	1	1	1	1	1	1	1	1	9	100.00
10	1	1	1	0	1	1	1	0	0	6	66.67
11	1	1	1	1	0	1	1	0	1	7	77.78
12	0	0	0	1	0	0	1	0	1	3	33.33
13	0	1	1	1	1	1	1	1	1	8	88.89
14	1	1	1	0	0	1	0	1	0	5	55.56
15	1	1	0	1	1	1	1	1	0	7	77.78
16	0	0	1	1	0	0	0	0	1	3	33.33
17	0	1	1	1	1	1	1	0	1	7	77.78
18	1	0	1	0	1	1	1	1	0	6	66.67
19	1	1	0	1	0	1	1	0	0	5	55.56
20	1	1	0	0	0	0	1	1	1	5	55.56
21	1	1	1	1	1	1	0	1	0	7	77.78
22	1	1	1	1	0	0	1	1	1	7	77.78
23	1	1	1	1	1	1	0	1	1	8	88.89
24	1	1	0	1	1	1	1	1	1	8	88.89
25	0	1	1	0	1	0	0	1	1	5	55.56
26	0	1	1	0	1	1	1	0	0	5	55.56
27	1	1	1	0	1	1	1	0	1	7	77.78
28	0	0	1	1	0	0	0	1	1	4	44.44
29	1	1	1	1	1	1	0	1	1	8	88.89

30	1	1	1	1	0	1	1	1	0	7	77.78
31	1	1	0	1	1	1	1	1	1	8	88.89
32	0	1	0	0	1	0	1	0	0	3	33.33
	23	28	24	24	22	23	25	23	22		

The interpretation of the prediction accuracy total and accuracy percentage is given in Table 4.32. In the group with dyslexia, we found 9 participants falling into the very good criteria out of which 5 had 100% accurate predictions. Further, there were 5 in the criteria marked as good and 1 marked as moderate. There were only 2 participants in the poor category and no participants in the very poor category. Interestingly, the 2 participants in the poor category had also been diagnosed as having ADHD. This finding possibly indicates that individuals with dyslexia having overlapping symptoms of ADHD have different brainwave signal patterns. However, further analyses with more participants with such symptoms are required to confirm this assumption, which would be a part of future work. On the other hand, the normal control group indicated 4 in very good, 5 in good and 4 in moderate category respectively. There were only 2 participants in the poor category. Fortunately, the normal control group too had no participants marked as very poor categorization.

Table 4.32: Prediction total interpretation

Accuracy as a Total	Accuracy as a Percentage	Interpretation
0 - 2	0 - 22.22	Very poor
3 - 4	33.33 - 44.44	Poor
5	55.56	Moderate
6 - 7	66.67 - 77.78	Good
8 - 9	88.89 - 100	Very good

The results of this chapter are elaborated in detail in Chapter 5 with reference to the literature review and the research questions and objectives.

Chapter 5 Discussion

5.1 Overview

The present research was designed to determine unique patterns in the EEG signals in adults with dyslexia compared to normal controls when performing tasks that are more challenging for individuals with dyslexia using machine learning classification. In this chapter, we discuss how the insights of our findings relate to the research questions and objectives. Table 5.1 given below shows an overview of the relationships.

Table 5.1: Mapping tasks, RP, RQ, RO and results

Tasks	RP	RQ	RO	Results Tables
Real-word Reading	RP1, RP2	RQ1, RQ2	RO1, RO2	Table 4.3, Table 4.4, Table 4.5
Nonsense-word Reading	RP1, RP2	RQ1, RQ2	RO1, RO2	Table 4.6, Table 4.7, Table 4.8
Passage Reading	RP1, RP2	RQ1, RQ2	RO1, RO2	Table 4.9, Table 4.10, Table 4.11
RAN	RP1, RP3	RQ1, RQ3	RQ1, RQ3	Table 4.12, Table 4.13, Table 4.14
Writing	RP1, RP4	RQ1, RQ4	RQ1, RQ4	Table 4.15, Table 4.16, Table 4.17
Typing	RP1, RP5	RQ1, RQ5	RQ1, RQ5	Table 4.18, Table 4.19, Table 4.20
Web browsing	RP1, RP6	RQ1, RQ6	RQ1, RQ6	Table 4.21, Table 4.22, Table 4.23
Interpreting Table	RP1, RP6	RQ1, RQ6	RQ1, RQ6	Table 4.24, Table 4.25, Table 4.26
Typing Random Number	RP1, RP6	RQ1, RQ6	RQ1, RQ6	Table 4.27, Table 4.28, Table 4.29

The discussion is structured in a manner where we first discuss each sub research question at a time, namely, RQ2, RQ3, RQ4, RQ5 and RPQ6 and finally discuss how the main research question RQ1 is answered through all the results of the sub-questions.

5.2 Discussion of RQ2 and RO2

RQ2: Do EEG signals generated while reading produce unique brainwave signal patterns in adults with dyslexia compared to normal controls? Do reading real-words, nonsense-words and passages activate the same brainwave patterns?

RO2: Identify brain regions and EEG electrodes that produce unique EEG signal patterns in adults with dyslexia compared to normal controls during reading related tasks. Compare patterns during real-word, nonsense-word and passage reading.

This research included 3 experiments focused directly on reading tasks, which were real-word reading, nonsense-word reading and passage reading. These tasks have been described in sections 3.4.4.2.2, 3.4.4.2.3 and 3.4.4.2.4 respectively. As per the results shown in Table 4.3, Table 4.6 and Table 4.9 all these tasks implied that there is a difference in the brainwave patterns while reading.

As discussed in the literature review past studies have proven that people with dyslexia have a greater level of difficulty in reading nonsense-words compared to real-words. Interestingly, our findings showed that for both the real-word reading and nonsense-word reading tasks, the most significant brain region was the left parieto-occipital. Further, the nonsense-word reading classifier presented a higher VA of 87.50% where as the real-word reading classifier VA was 71.88%. It can therefore be assumed that the greater level of difficulty seen in individuals with dyslexia when reading nonsense-words reflected in the brainwave signals through significant differences, enabling the classifier to distinguish between the two groups with higher VA. Deficiency of phonological decoding skills is a commonly seen symptom in individuals with dyslexia, and the capability to read nonsense-words is known to be one of the best ways to measure phonological decoding skills (Facoetti et al., 2010; Shaywitz, 2003; Ziegler et al., 2014). Studies have shown that the temporo-parieto-occipital brain regions show differences between the readers with dyslexia and non-impaired readers, and more specifically in the left temporo-parieto during phonological processing through brain imaging (Peyrin et al., 2012; Shaywitz & Shaywitz, 2005). Although this region is not available in the EEG channels used for this research, as can be seen in Figure 5.1, the temporo-parieto is very close to the parieto-occipital, which lies between the parietal and the occipital lobes. Therefore, it can be implied that the results of this EEG classification obtained from this research coincides with the past research conducted using fMRI and confirming difficulties in phonological decoding skills seen in individuals with dyslexia are reflected in the brainwave patterns.

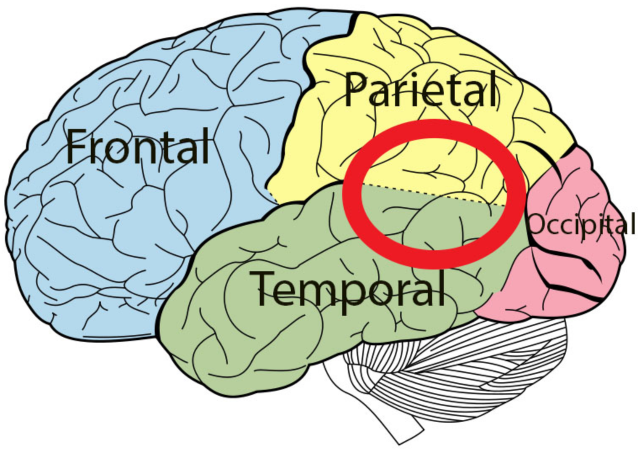


Figure 5.1: Temporo-parieto (Carter, n.d.)

The passage-reading task also achieved the highest VA of 75.00% from the left parieto-occipital classifier. Therefore this supports that all reading tasks activate somewhat the same regions of the brain.

The EEG channel that produced the most significant unique brainwave activation patterns for the real-word reading, nonsense-word reading and passage reading was on PO3, which lies in the left parieto -occipital. Figure 5.2 depicts the position of PO3.

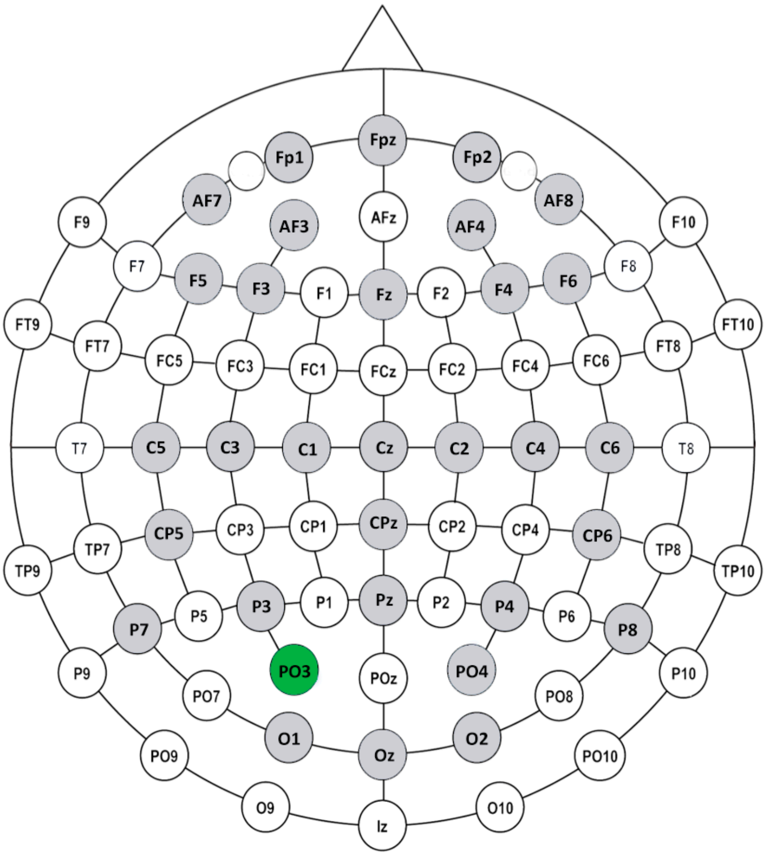


Figure 5.2: Optimal EEG channel PO3 for real-word reading, nonsense-word reading and passage reading tasks

5.3 Discussion of RQ3 and RO3

RQ3: Do EEG signals generated during RAN produce unique brainwave signal patterns in adults with dyslexia compared to normal controls?

RO3: Identify brain regions and EEG electrodes that produce unique EEG signal patterns in adults with dyslexia compared to normal controls during RAN.

RAN helps measure how quick familiar things for example letters, digits, objects or colours can be named. As explained in section 3.4.4.2.5 in the methodology, our experiment relating the RAN included the naming of colours as quickly as possible. The results for the RAN classifiers as shown in Table 4.12 prove that RAN produces unique brainwave signal patterns in adults with dyslexia compared to normal controls.

The highest VA of 75.00% for RAN was shown in the parieto-occipital classifier, thereby exhibiting PO3 and PO4 EEG channels to being the most significant EEG channels capable of distinguishing the group with dyslexia from the control group. Figure 5.3 depicts the positions of PO3 and PO4. Past studies show activations in the parietal lobe using rCBF (regional cerebral blood flow) (Wiig et al., 2002) and activations in the left superior parietal gyri using fMRI (J. Cummine, Chouinard, Szepesvari, & Georgiou, 2015; Jacqueline Cummine, Szepesvari, Chouinard, Hanif, & Georgiou, 2014) during RAN by adults. Further, differences in the parieto-occipital regions have also been found in ERP studies between individuals with dyslexia and control groups (Araújo, Faísca, Reis, Marques, & Petersson, 2016).

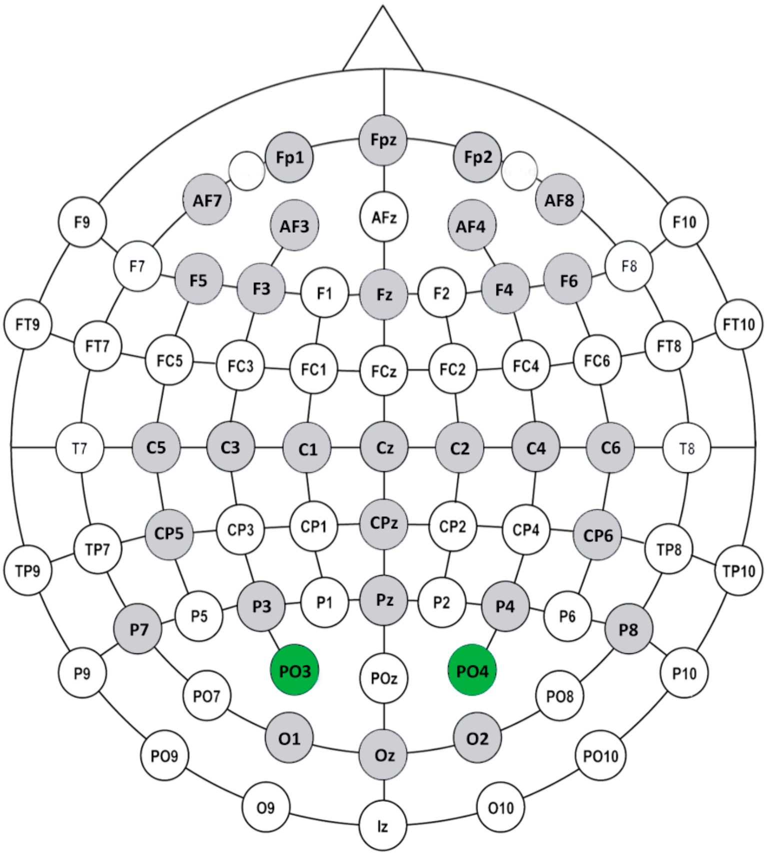


Figure 5.3: Optimal EEG channels PO3 and PO4 for RAN task

According to the literature, research confirms that RAN is related to reading (Georgiou et al., 2013) and that it is impaired in individuals with dyslexia (Jones et al., 2010). Interestingly, the parieto-occipital brain region was identified as the most prominent region for RAN and all reading related tasks, which were real-word reading, nonsense-word reading and passage reading the left parieto-occipital were identified as the most prominent.

5.4 Discussion of RQ4 and RO4

RQ4: Do EEG signals generated while writing produce unique brainwave signal patterns in adults with dyslexia compared to normal controls?

RO4: Identify brain regions and EEG electrodes that produce unique EEG signal patterns in adults with dyslexia compared to normal controls while writing.

Poor writing skills are one of the commonly seen difficulties in individuals with dyslexia. The results depicted in Table 4.15 verify that adults with dyslexia produce unique brainwave signal patterns during the writing task as explained in section 3.4.4.2.6 compared to normal controls.

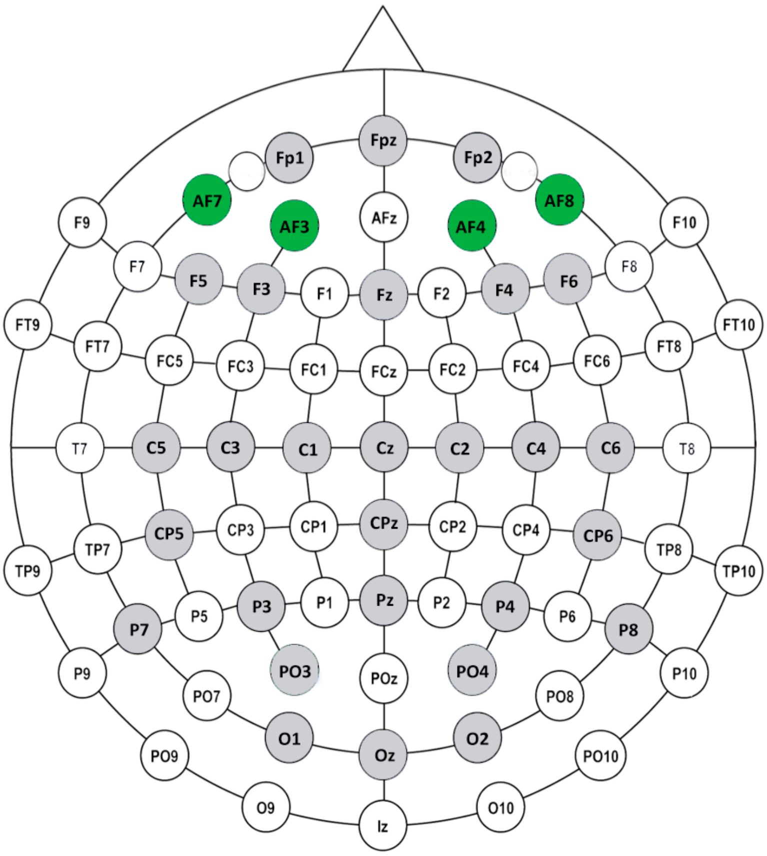


Figure 5.4: Optimal EEG channels AF7, AF3, AF4 and AF8 for writing task

The peak VA of 71.88% was produced from the anterior frontal classifier, which included the EEG electrodes AF7, AF3, AF4 and AF8. However, this outcome has not previously been reported in previous similar studies, and a possible explanation for this might be that because those studies had not used the EEG electrodes AF7, AF3, AF4 and AF8. The channels used in these similar studies were C3, C4, P3 and P4 (Che Wan Fadzal, Mansor, & Khuan, 2011; Fuad et al., 2013; Zabidi, Mansor, Lee, & Che Wan Fadzal, 2012). Therefore, these results contribute towards to the pool of knowledge as a new finding. Figure 5.4 depicts the positions of AF7, AF3, AF4 and AF8.

5.5 Discussion of RQ5 and RO5

RQ5: Do EEG signals generated while typing produce unique brainwave signal patterns in adults with dyslexia compared to normal controls?

RO5: Identify brain regions and EEG electrodes that produce unique EEG signal patterns in adults with dyslexia compared to normal controls while typing.

Typing can be considered as the modern day replacement to writing and is yet another task found more challenging by individuals with dyslexia. The typing task given for all the participants is explained in section 3.4.4.2.7. A total of 17 classifiers were developed for this task and the results are represented in Table 4.18. As explained in detail in the results section 4.8, although most of the classifiers showed fairly high VA, the results sensitivities were rather higher than the specificities.

However, the frontal classifier was able to obtain the highest VA of 78.13% with a fairly balanced specificity and sensitivity. Interestingly, this was close to the most significant region identified for writing, which was the anterior-frontal. The most significant EEG channels responsible for producing unique brainwave signals in individuals with dyslexia compared to normal controls were F5, F3, Fz, F4 and F6. Figure 5.5 depicts the position of these four channels. All these findings show that EEG signals generated while typing produce unique brainwave signal patterns in adults with dyslexia compared to normal controls. Further, as explained in the literature review, comparison of EEG signals patterns between persons with and without dyslexia during typing was a gap to be filled; therefore, we did not find any research results that could be directly compared against our results.

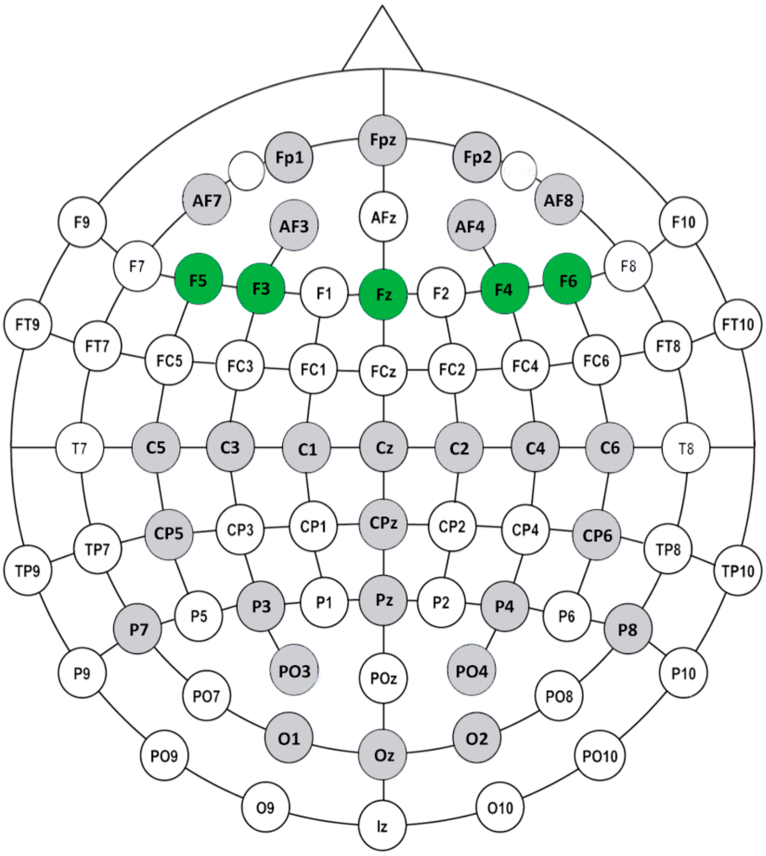


Figure 5.5: Optimal EEG channels F5, F3, Fz, F4 and F6 for typing task

5.6 Discussion of RQ6 and RO6

RQ6: Do EEG signals generated during the following everyday tasks produce unique brainwave signal patterns in adults with dyslexia compared to normal controls?

Browsing the web

Interpreting tables

Keying in an unfamiliar number

RO6: Identify brain regions and EEG electrodes that produce unique EEG signal patterns in adults with dyslexia compared to normal controls during the following everyday tasks.

Browsing the web

Interpreting tables

Keying in an unfamiliar number

Realistic everyday tasks performed by humans do not consist of reading or writing tasks in isolation and it is in fact a combination of these tasks together. In this section we selected 3 of such everyday tasks in order to compare the brainwave activity between individuals with dyslexia compared to normal controls. The tasks web browsing, interpreting tables and keying in an unfamiliar number are elaborated in sections 3.4.4.2.8, 3.4.4.2.9 and 3.4.4.2.10 respectively.

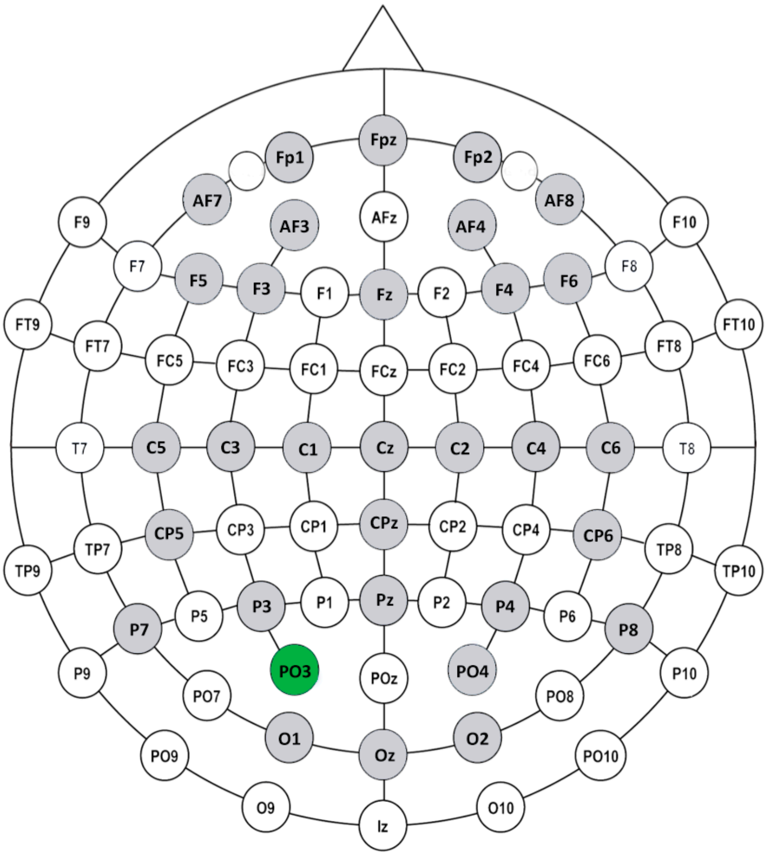


Figure 5.6: Optimal EEG channel PO3 for web browsing task

The results from the web browsing task as presented in Table 4.21 and showed the maximum VA of 68.75% at the left parieto-occipital classifier. Further, this result has not been previously reported as there were no similar studies to perform a comparison. Overall the classifier results from the web browsing task helped determined that adults with dyslexia produce unique brainwave patterns compared to normal controls during browsing the web and the prominent EEG channel was PO3. The position of this channel is depicted in Figure 5.6.

The next task being the table interpretation is yet another everyday task selected which has not been covered in previous research for brainwave activity comparison between adults with dyslexia and a control group. This task too showed differences in the brainwave signal patterns in adults with dyslexia compared to normal controls and the best VA was produced by the parieto-occipital classifier as shown in the results Table 4.24. The EEG electrodes responsible for most unique brainwave signals were PO3 and PO4, and the positions of these channels are depicted in Figure 5.7.

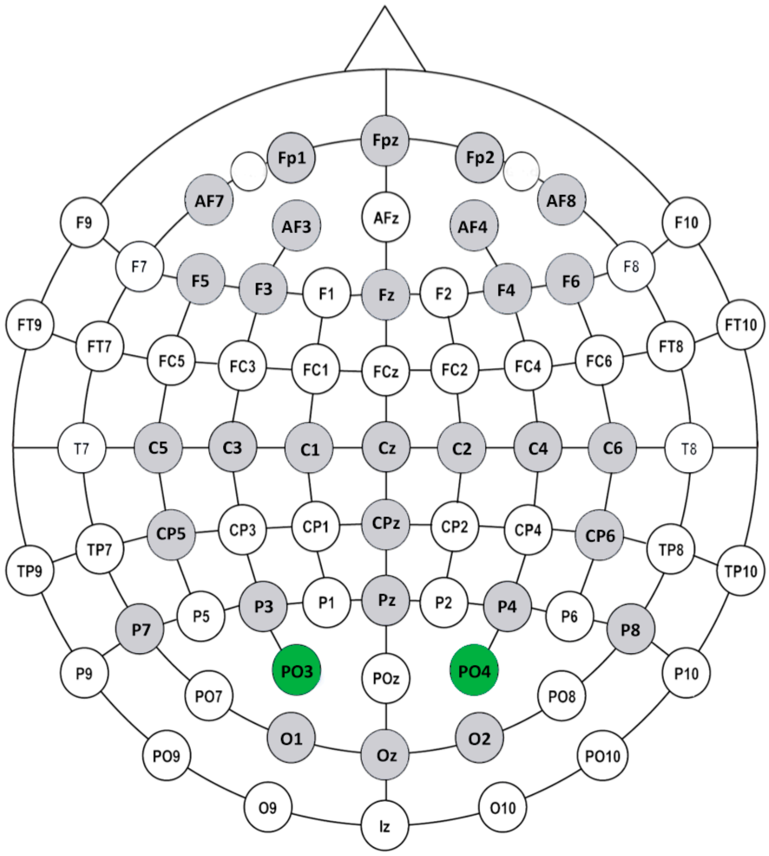


Figure 5.7: Optimal EEG channels PO3 and PO4 for table interpretation task

Keying in an unfamiliar number was the final task of this research. This task too contributed towards confirming that adults with dyslexia show exclusive brainwave signal patterns compared to normal controls as illustrated in the results Table 4.27. These exclusive brainwave patterns were more apparent in EEG electrode PO4 that falls into the right of the parieto-occipital. The position of sensor PO4 depicted in Figure 5.8. This classifier pertaining to this region achieved the highest VA of 68.75%.

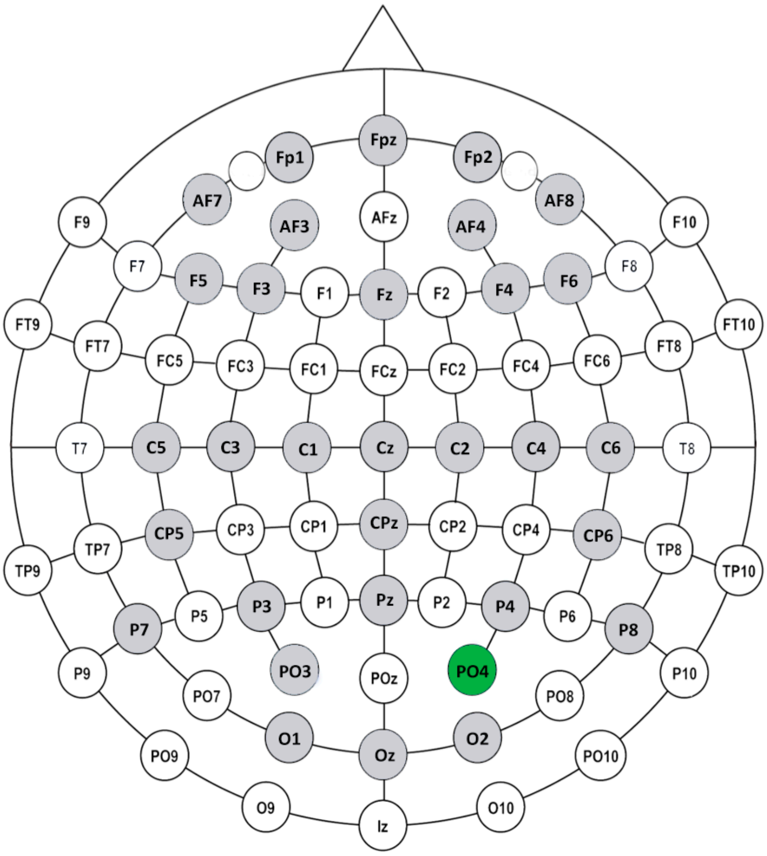


Figure 5.8: Optimal EEG channel PO4 for typing random number task

Overall, all the everyday tasks selected in this research showed unique EEG signal patterns in adults with dyslexia compared to normal controls.

5.7 Discussion of RQ1 and RO1

RQ1: Do EEG signals generated while performing specific tasks that are more challenging for individuals with dyslexia produce unique brainwave signal patterns in adults with dyslexia compared to normal controls?
Can these EEG signal patterns be detected using machine learning classification?

Do these EEG signal patterns differ according to the tasks and EEG sensors spanned across each brain region?

RO1: The main aim of this research is to identify unique patterns in the EEG signals in adults with dyslexia compared to normal controls when performing tasks that are more challenging for individuals with dyslexia. These unique patterns will be identified using an EEG-based machine learning classification framework and derived through the sub-objectives.

The main goal of this research was to determine if performing specific tasks that are more challenging for individuals with dyslexia produce unique brainwave signal patterns in adults with dyslexia compared to normal controls, and through the sub research questions and research objectives discussed above, it was evident that these tasks activated unique brainwave signal patterns. The next question answered through our findings was as to whether machine learning classifiers could identify these patterns. In our research, we adapted the machine learning classifier CSVM, and were able to successfully obtain positive results, and thereby proving machine learning classification can differentiate between EEG signal patterns from adults with dyslexia and the control group. Finally, the research revealed that the optimal brain regions and the EEG sensors differed according to the task as summarised in Table 4.30. The left of the parieto-occipital was the most significant for real-word reading, nonsense-word reading, passage reading and web browsing with the optimal EEG sensor being PO3. The parieto-occipital revealed to be the best brain region with channels PO3 and PO4 for RAN and table interpretation, and the right of the parieto-occipital region for typing random numbers with channel PO4. The anterior frontal with EEG electrodes AF7, AF3, AF4, AF8 and the frontal with F5, F3, FZ, F4, and F6 exhibited to be the paramount regions for writing and typing respectively.

5.8 Summary

This chapter presented the discussion of the results of all tasks conducted in this research. All findings were elaborated by, linking the research questions and comparing against past similar studies. RQ2, which relates to results from real-word reading, nonsense-word reading and passage reading showed similar result patterns although it was detected using other techniques such as fMRI. RQ3, which relates to RAN also coincided with past research. The writing task, which is related to RQ4 showed different brain regions compared to prior similar results and lastly RQ5 and RQ6 which includes typing, web browsing, table interpretation and typing of random numbers presented novel findings to the pool of knowledge as it was not previously been reported. Finally, RQ1 summarized all the discussions and concluded that EEG signal patterns show unique differences in adults with dyslexia compared to normal controls.

Chapter 6 Conclusions

6.1 Research Summary and Contributions

The main objective of the current research was to determine if there were differences in EEG signal patterns generated between adults with dyslexia compared to normal controls while performing tasks that were more challenging for individuals with dyslexia. This was evaluated through sub objectives where machine learning classifiers were developed for separate brain regions of each specified task. The tasks include real-word reading, nonsense-word reading, passage reading, RAN, writing, typing, web browsing, table interpretation and typing of random numbers. Ultimately, the optimal brain regions and EEG electrodes responsible for generating the most unique patterns between the two groups were identified and reported in this thesis.

This research has shown that the selected tasks exhibited unique brainwave signal patterns in adults with dyslexia compared to normal controls. Further, it was also determined that the brain regions that generate unique brainwave signal patterns are dependent on the task. We identified 5 brain regions that were optimal among the 9 tasks evaluated as illustrated in Table 6.1.

Table 6.1: Summary of optimal brain regions and EEG sensors of each task

Optimal Brain Region	EEG Sensors	Tasks
Parieto-occipital left	PO3	Real-word reading Nonsense-word reading Passage Reading Web browsing
Parieto-occipital	PO3, PO4	Table interpretation RAN
Parieto-occipital right	PO4	Tying random number

Frontal	F5, F3, Fz, F4, F6	Typing
Anterior frontal	AF7, AF3, AF4, AF8	Writing

The optimal EEG sensors have been marked in green in the channel map shown below in Figure 6.1. The other EEG sensors used in this research are marked in grey.

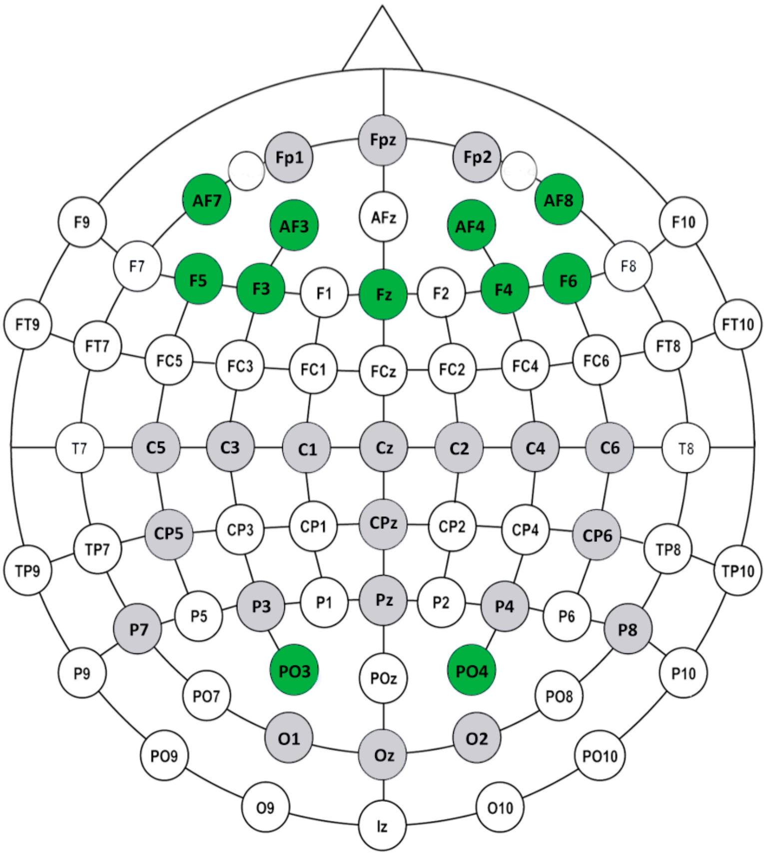


Figure 6.1: Optimal EEG sensors channel map

One of the most major findings of this research was that the nonsense-words classifiers produced higher VA compared to real-words classifiers, confirming difficulties in phonological decoding skills seen in individuals with dyslexia are reflected in the brainwave patterns.

The research also revealed some fascinating insights into the brainwave signal patterns. We found that all 3 reading related tasks which were real-word reading, nonsense-word reading and passage reading displayed the same optimal brain region left parieto-occipital and EEG sensor PO3.

Further, RAN, which is related to reading also demonstrated a wider region of the parieto-occipital with sensors PO3 and PO4 to be the optimal region producing unique brainwave signal patterns in adults with dyslexia compared to normal controls. Hence, indicating the possibility that the relationship between reading and RAN reflects in the brainwave patterns. All these insights coincided with previous studies that were conducted using other techniques, and thereby these findings complement those of earlier studies.

On the other hand, the research results also uncovered novel findings for typing, web browsing, table interpretation and typing of random numbers. These were tasks that had not been analysed in past similar studies. Finally, although similar writing tasks had been investigated in past studies, the current research was conducted with additional EEG sensors and discovered a new optimal brain region anterior frontal, which has not been reported in past studies.

This research contributes vital insights to the pool of knowledge about the unique brainwave patterns of adults with dyslexia, which could serve as a base for future studies, and could even one day help complement the conventional dyslexia diagnosis process by giving a better view of the disability through the introduction of neurological aspects.

6.2 Recommendations for Future Research

The current research presented important knowledge relating to the unique brainwave signal patterns of individuals with dyslexia that can serve as the base for more extensive future work. This section highlights such questions raised in need of further investigation.

The scope of this research was limited to adults 18 years and above who were right-handed. Further studies can be carried out in order to compare signal patterns of individuals below the age of 18 years and left-handed individuals. Further, comparisons of the brainwave patterns could also be made between males and females. Gender comparisons were not possible in the current research, as the participants used in the research did not have equal number of males and females between the two groups.

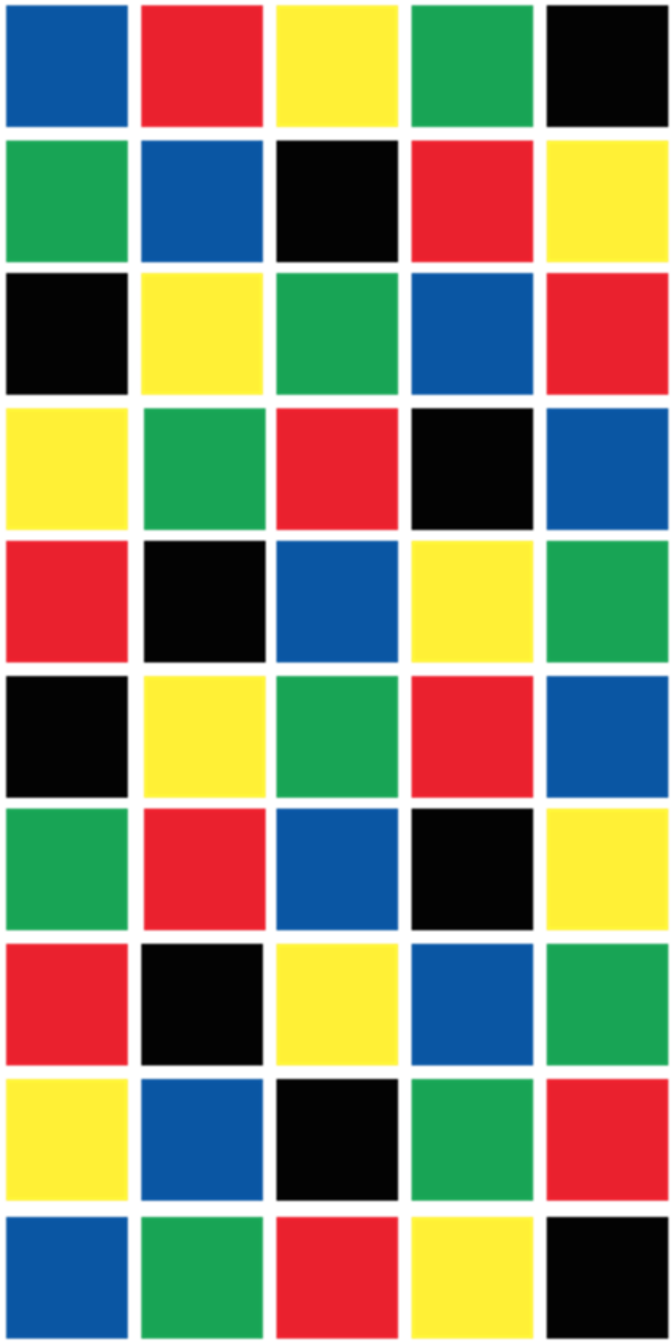
This research was conducted on adults who have been diagnosed as having dyslexia. This research can be extended in order to examine the differences between other specific learning disabilities such as dysgraphia and dyscalculia.

The outcomes of this research can be explored further for more perspectives by making variations in parameters such as input features, channels, frequency sub-bands, kernels and other classifiers such as Fuzzy SVM. This could perhaps lead to improvement of accuracies similar to how the current research obtained higher accuracies by making variations in the brain regions.

Finally, the function of each brain region needs to be mapped with the results and identify the neurological reason behind each finding.

Appendices

Appendix A Rapid Automatized Naming Task



Appendix B Web Browsing Task

Web Browsing Task - Male

- Type, "target australia" on the search bar and hit enter
- Navigate to the Target home page - http://www.target.com.au/ by selecting the search result "Target Australia: Target Online Shopping"
- Type "men's tops" on the search bar and hit enter
- Scroll down and search for a top that you like
- Select your size
- Add to basket
- Type "men's pants" on the search bar and hit enter
- Scroll down and search for a pant that you like
- Select your size
- Add to basket

Web Browsing Task - Female

- Type, "target australia" on the search bar and hit enter
- Navigate to the Target home page - http://www.target.com.au/ by selecting the search result "Target Australia: Target Online Shopping"
- Type "women's tops" on the search bar and hit enter
- Scroll down and search for a top that you like
- Select your size
- Add to basket
- Type "women's pants" on the search bar and hit enter
- Scroll down and search for a pant that you like
- Select your size
- Add to basket

Appendix C Table Interpretation Task

Interpreting Table Task

Question
Most number of visitors to Australia comes from ________________________

Tourists to Australia

Country of origin of visitors	Number of visitors	Average length of stay (nights)
Italy	51 737	42
China	308 452	48
United States of America	456 084	24
United Kingdom	734 244	34
Canada	109 843	42
New Zealand	1 075 797	14

Answers
- ◯ Italy
- ◯ China
- ◯ United States of America
- ◯ United Kingdom
- ◯ Canada
- ◯ New Zealand

Appendix D Data Collection Instructions Presented on the Computer Screen Prior to Each Test

Instructions to follow throughout all the tests

- Stay relaxed and avoid body movements as much as possible (unless otherwise specified)

- Why avoid movements? Have a look at the EEG while blinking your eyes, clenching your jaw and moving your legs/hands

- Movements are kept to a minimum to avoid unwanted artefacts in the brainwaves being recorded

- Each EEG recording will start once you have reached the relaxed state - the researcher will explain this further by showing you the EEG

- Once you have completed the instructions of each test which appear on the computer screen, remain in the relaxed state till the researcher informs you that the recording is complete

- No communication will take place during each test

- You can have as much as breaks you want in-between tests

Relaxed Position Instructions

- You are required to stay seated in the relaxed position for 1 minute at a stretch

- During this time close your eyes, avoid body movements including jaw clenches

- No communication will take place during the test

Real-word Reading Instructions

- Read aloud all the words
- Each word will flash on the screen every 10 seconds
- If you find it difficult to read a word, skip that particular word and move on to the next
- Once you have read a word, stay relaxed till the next word appears
- No communication will take place during the test

Nonsense-word Reading Instructions

- Read aloud all the nonsense-words
- Each word will flash on the screen every 10 seconds
- If you find it difficult to read a word, skip that particular word and move on to the next
- Once you have read a word, stay relaxed till the next word appears
- No communication will take place during the test

Passage Reading Instructions

- You will be given a paragraph to read

- No communication will take place during the test

Rapid Automatized Naming Instructions

- You are required to name aloud the colours in the colour card as quickly as possible

- No communication will take place during the test

- Below given is an example

Writing Instructions

- You will be given a topic to write about
- You are required to write a simple short paragraph
- You will be given a paper and a pen
- No communication will take place during the test

Typing Instructions

- No communication will take place during the test

- A text box will be presented on the computer screen to perform the test

- You are required to type a simple short paragraph about the topic given

Interpreting Table Instructions

- You will be given a simple table to interpret and answer 2 questions

- No communication will take place during the test

- Procedure
  - System displays the question
  - Participant reads the question
  - System displays the table and answers (with radio buttons)
  - Participant interprets the table
  - Participant clicks the radio button for the correct answer

- Try the example

1. Question

The least favourite sport is ______________________________

2. Table

Sport	People
Swimming	108
Tennis	45
Soccer	186
Gymnastics	54

3. Answers

○ Tennis
○ Gymnastics

Typing Random Number Instructions

- You will be given a randomly generated number to key in to a text box
- No communication will take place during the test
- Procedure
    - System displays the random number and the text box on screen
    - Participant clicks on the text box and types the number
    - Participant hits the "enter/return" key once its completed
- Try the example

Random Number: 6551

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