DEVELOPMENT OF EEG CLASSIFICATION MODEL FOR POST-STROKE PATIENTS OF DIFFERENT RECOVERY STAGES USING ARTIFICIAL NEURAL NETWORK

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DEDICATION

I dedicate my dissertation work to my family and many friends. A special feeling of gratitude to my loving parents, Jacky and Sandy whose words of encouragement and push for tenacity ring in my ears. My brothers Richard and Philip have never left my side and are very special.

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ABSTRACT

Stroke rehabilitation is a therapeutic process aimed at maximising the patient's physical and social potential. Although patients can recover full consciousness from stroke, most of them cannot perform activities of daily living with the affected limbs. Impairment of the limbs significantly limits the level of activity as well as social and physical interactions of a post-stroke patient. The performances of patients are then clinically assessed using standardised scales such as the Barthel Index and Functional Independence Measure to determine if aforementioned patients are able to move on to the next stage of recovery. An EEG sub-band PSD dataset is used to develop an artificial neural network predictive model to classify the post-stroke patients into their respective recovery stages. Due to the small dissimilarity in intensity of certain sub-bands, classification between intermediate and advanced stages is predicted to be more difficult. At the end of the study, an ANN predictive model is developed with a satisfactory performance of 74.1%. When comparing classification results with an actual physiotherapist, an agreement rate of 58. 22% is achieved. This research contributes to helping medical professionals in evaluating the recovery progress of a post-stroke patient, therefore easing the rehabilitation process of a patient towards full recovery.

ABSTRAK

Pemulihan strok adalah proses terapeutik yang bertujuan untuk memaksimumkan potensi fizikal dan sosial pesakit. Walaupun pesakit boleh pulih sepenuhnya daripada strok, kebanyakan mereka tidak dapat melakukan aktiviti kehidupan seharian dengan anggota yang terjejas. Kerosakan anggota badan dengan ketara mengehadkan tahap aktiviti serta interaksi sosial dan fizikal pesakit selepas strok. Prestasi pesakit kemudiannya dinilai secara klinikal menggunakan skala piawai seperti Indeks Barthel dan Ukuran Kemandirian Fungsian untuk menentukan sama ada pesakit yang disebutkan di atas dapat meneruskan ke peringkat pemulihan seterusnya. Dataset PSD sub-jalur EEG digunakan untuk membangunkan model ramalan rangkaian saraf tiruan untuk mengklasifikasikan pesakit selepas strok ke dalam peringkat pemulihan masing-masing. Disebabkan perbezaan kecil dalam keamatan sub-jalur tertentu, klasifikasi antara peringkat pertengahan dan lanjutan diramalkan menjadi lebih sukar. Pada akhir kajian, model ramalan ANN dibangunkan dengan prestasi yang memuaskan sebanyak 74.1%. Apabila membandingkan keputusan klasifikasi dengan ahli fisioterapi sebenar, kadar persetujuan 58. 22% dicapai. Penyelidikan ini menyumbang untuk membantu profesional perubatan dalam menilai kemajuan pemulihan pesakit selepas strok, oleh itu memudahkan proses pemulihan pesakit ke arah pemulihan sepenuhnya.

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LIST OF SYMBOLS AND ABBREVIATIONS

NASAM	-	National Stroke Association of Malaysia
ADL	-	Activities of daily living
EEG	-	Electroencephalography
ERP	-	Event-related potentials
qEEG	-	Quantitative electroencephalography
PSD	-	Power spectral Density
BI	-	Barthel Index
FIM	-	Functional Independence Measure
HrQoL	-	Health-related quality of life
ANN	-	Artificial Neural Network
Hz	-	Hertz
BP	-	Backpropagation
CNS	-	Central nervous system
NREM	-	Non-rapid eye movement
fMRI	-	Functional magnetic resonance imaging
TMS	-	Transcranial magnetic stimulation
MEP	-	Motor evoked potentials
BOLD	-	Blood-oxygen-level-dependent
US	-	United States
ERD	-	Event-related desynchronization
α	-	Alpha
β	-	Beta
FFT	-	Fast Fourier Transformation
STFT	-	Short time Fast Fourier Transformation
MDI	-	Maryland Disability Index
EG	-	Early group
IG	-	Intermediate group

AG	-	Advanced group
KDE	-	Kernel Density Estimation
UMMC	-	UM Medical Centre
RDS	-	Research Details Sheet
3S	-	Subject Survey Sheet
EMD	-	Empirical Mode Decomposition
CFT	-	Continuous Fourier Transform
DFT	-	Discrete Fourier Transform
IDFT	-	Inverse Discrete Fourier Transform
IFFT	-	Inverse Fast Fourier Transform
ERS	-	Enhanced Region-specific
ROI	-	Region of interest
SCG	-	Scaled Conjugate Gradient
IMF	-	Intrinsic Mode Functions
TP	-	True Positive
TN	-	True Negative
FP	-	False Positive
FN	-	False Negative

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CHAPTER 1

INTRODUCTION

This chapter provides an overview of the research while emphasising current issues on the assessment of recovery stages in post-stroke rehabilitation, described in Sections 1.1 and 1.2. The aim, objectives along with the scope of research are presented in Sections 1.3, 1.4 and 1.5 respectively. The outline of this thesis is then briefly explained in Section 1.6.

1.1 Research Background

Stroke is a medical condition in which poor blood flow to the brain results in cell death. As illustrated in Figure 1.1, there are two main types of stroke: ischaemic (right) and haemorrhagic (left). Ischaemic stroke occurs when a blockage or obstruction of small blood vessels occurs around the brain, whereas haemorrhagic stroke occurs when a weakened blood vessel bursts and bleeds into the surrounding brain [1]. According to the Institute for Health Metrics and Evaluation (2017), stroke represents the third leading cause of mortality in Malaysia, with more number of stroke patients being men [2]. Approximately 80% of stroke incidences are of ischaemic type, while the remaining are of haemorrhagic type. Among the ischaemic cases, 43% are due to large vessel disease, 35% from small vessel disease (lacunar stroke) and the rest cardio-embolic strokes [3].

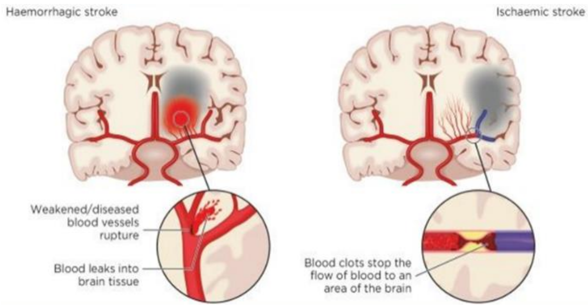

Figure 1.1: Types of Strokes: Haemorrhagic (left) and Ischaemic (right) [4]

For many years, medical teams such as the National Stroke Association of Malaysia (NASAM) have provided stroke care, except for haemorrhagic stroke, which require surgical interventions that are primarily managed by neurosurgeons [5]. Stroke patients who manage to survive this debilitating condition undergo rehabilitation treatment, so that they are able to carry out activities of daily living (ADL) with minimal dependence. Stroke rehabilitation is the process by which those with disabling stroke undergo treatment to help them return to normal life as much as possible by regaining and relearning the skills of everyday life. After a patient has undergone rehabilitative exercises for a period of time, a clinical assessment based on various standards is performed to evaluate the stage of recovery of the aforementioned patient. Based on the results, physiotherapists then make decisions on whether the patient is in the early, intermediate or advanced stage of recovery. However, due to the shortcomings of these assessments which are discussed in the problem statement, in which these assessments are often subject to the subjectivity of the physiotherapists, a supportive system classifying the stroke patients into aforementioned recovery stages using electroencephalography (EEG) is suggested.

Electroencephalography (EEG) is a type of electrophysiological detection technique designed to record and measure brain electrical activity. Electrodes are placed on the scalp, and recent advancements in technology have made it possible to be non-invasive. EEG measures voltage fluctuations in the brain neurons arising from ionic current. Clinically, EEG refers to the analysis of the spontaneous electrical activity of the brain over a period of time, as measured from several electrodes mounted on the scalp [6]. In general, the diagnostic applications of EEG emphasise on either event-related potentials (ERPs) [7] or the spectral content [8]. ERP analysis captures the synchronous neuronal activity in the EEG signal that is phase-locked to the onset of a discrete event. Spectral analysis quantifies the relative contribution of a particular frequency to the EEG signal. Various excitatory and inhibitory feedback loops interact to entrain the activity of neuronal populations at a particular frequency. Such synchrony between disparate brain regions is thought to promote the binding of information across widespread neural networks.

In particular, it is well established that quantitative EEG (qEEG) indices based on the relationship between the power of slow and fast activities as estimated by EEG power spectrum analysis, are reliable markers to characterize the brain status [9]. qEEG can also be employed to improve patient management during ischemic stroke [10] and to predict clinical efficacy of rehabilitation even in the chronic stage [11].

Therefore, this research proposes an implementation of an artificial neural network trained to classify post-stroke patients into three recovery categories: early, intermediate and advanced of the inpatient rehabilitation stage. The network is trained with data collected from EEG signals of the brain with a non-invasive method, which is through wearing a head gear: the Emotiv Insight. The EEG signals are processed quantitatively, obtaining the power spectral density (PSD) of four frequency sub-bands: delta (0.5 – 4 Hz), theta (4 – 7 Hz), alpha (8 – 12 Hz) and beta (12 – 30 Hz). The designed classification network is aimed at providing a second opinion to physiotherapists during assessment of a patient's recovery stage. The overall performance of the developed network is evaluated using qualitative and quantitative approaches to assess its practicality and reliability.

1.2 Problem Statement

Stroke rehabilitation is a therapeutic process aimed at maximizing the physical, psychological and social potential of a patient. Patients can regain full consciousness after a stroke, but most patients are unable to perform activities of daily living (ADL) on their affected limbs. Extremity dysfunction severely limits the level of activity, social and physical interactions of stroke victims and requires rehabilitation. Functional recovery of the limbs can be observed, in whole or in part, after long-term rehabilitation exercises.

Clinically, the various sequelae in the limbs with an impact on ADL have been assessed using the available standardised scales [12]. Based on the results of these scales, the best chance of recovery is between the second and fifth months after a stroke. In general, there are five stages of post-stroke care settings: medical treatment in hospitals, in-patient rehabilitation, at-home health care, out-patient rehabilitation and self-care after discharge. When symptoms of stroke are identified on an individual, he/she should be taken to a hospital immediately for treatment. The duration of stay in the hospital is varied based on the severity of stroke. After treatment, the next step would be to continue rehabilitation. An in-patient rehabilitation facility such as the National Stroke Association of Malaysia (NASAM) is a facility for patients to participate in a minimum of three hours of therapy a day, provided by an organised team of specially trained professionals. During rehabilitation, physiotherapists assist patients in practising and performing simple tasks intensively. The level of tasks differs based on the progress of recovery for each individual patient, mainly into three categories: early, intermediate and advanced. The performances of patients are then clinically assessed using the available standardised scales such as the Barthel Index (BI) [13] and the Functional Independence Measure (FIM) [14] to determine if aforementioned patients are able to move on to the next stage of recovery. However, these scales have a limited capacity for detecting less-sensitive changes that are still required for measuring stroke patient outcomes. More importantly, these assessments are often subject to the subjectivity of the physiotherapists. Therefore, a supportive tool of classifying post-stroke patients into recovery stages using quantitative EEG is proposed in this thesis.

1.3 Motivation of Study

Staff-patient interaction at all post-stroke treatment levels is vital to the success at each stage of the dedicated recovery programmes. Clancy et al. [15] examined staff–patient communication in inpatient stroke environments for people with post-stroke aphasia and those who support them. As a way to improve staff-patient experiences in addressing the psychosocial needs of stroke survivors and their caregivers, ongoing staff training, the provision of an aphasia-friendly and a communicatively stimulating ward environments have been proposed. Gillespie et al. [16] confirmed, however, that stroke practitioners were commonly engaged in the routine use of non-pharmacological post-stroke emotionalism (PSE) interventions that were not clinically tested, and the efficacy of these methods is still unknown. Dohl et al. [17] recently released an updated but quick and effective questionnaire, i.e. metrics on health-related quality of life (HrQoL) as a way to recognize patients in need of post-stroke health care, as well as identifying groups for potential interventions. But, the later attempts that Parker et al. [18] had reviewed on the need for appropriate visual and auditory input for digital simulation to assist staff-patient communication seem to have been overlooked in the whole current digital technological advances.

An increased severity of the stroke contributes to increased demand for caregivers' services. Unfortunately, having compensated for the extent of the stroke, the involvement of an active caregiver did not encourage further treatment for the stroke survivors [19]. Most caregivers are unsure in their decisions, especially in the absence of specialist doctors. Thence, there is a possibility that the decided uncertain progression of the severity level was based on heuristic measure, which subjectively relied on staff-patient co-operation, caregiver experience and patient trust. Thus, as Parker et al. [18] has recognized, computational visualization for stroke rehabilitation needs to be developed and used to enhance staff-patient engagement and reduced heuristic assessment, thereby providing caregivers with the best combinations of knowledge in the absence of a specialist doctor. Therefore, in fact, a quick screening that can envision the degree of post-stroke progression is a critical innovation for solving these problems.

Hence, up to this certain application, this research is motivated to assist the caregiver with a rapid interpretation of EEG signal using different perspectives of visualization. Apart from decomposing the complex variant of the analogue EEG brainwave signal, which requires higher technical knowledge to decipher the pattern, this study alternatives are to transform the signal into a form of image, thus facilitating the patient or caregiver's comprehension of the pattern, thereby enhanced the staff-patient co-operation. A multi-layer feedforward artificial neural network (ANN) is developed to classify the EEG signals of post-stroke patients into categories based on the stages of post-stroke therapy. The ANN model is used in this study because neural networks are designed such that they are able to classify or group raw input to comprehend sensory data through machine perception.

1.4 Aim and Objectives

This study aims to develop a supportive artificial neural network (ANN) system that classifies post-stroke patients into recovery stages of early, intermediate and advanced using electroencephalography (EEG) signals. In order to achieve this aim, the following objectives have been set:

i. To acquire EEG signal data samples of post-stroke patients from different recovery stages – early, intermediate and advanced; and
ii. To visualise EEG patterns of post-stroke patients from different recovery stages – early, intermediate and advanced in terms of energy distribution; and
iii. To develop EEG signals classification using ANN predictive model; and
iv. To evaluate the performance of the developed ANN predictive model using quantitative analysis.

1.5 Scope of Research

1. In this study, the frequency domain feature of the EEG signals is utilised for post-stroke classification. The signals are processed to obtain the power spectral density (PSD) of the delta (0.5 – 4 Hz), theta (4 – 7 Hz), alpha (8 – 12 Hz) and beta (12 – 30 Hz) sub-bands. Specific band power activities are considered to be linked to brain functions and in case of stroke, are associated to different degrees of neuronal survival in the ischaemic regions and therefore can assume a prognostic value [10][20][21][22]. EEG power is markedly affected in stroke patients with a significant increase in delta power (0.5 – 4 Hz) accompanied by a decrease in alpha (8–12 Hz) and beta (14–30 Hz) power producing a diffuse slow-wave EEG pattern [23]. The theta band (4 – 7 Hz), although not common in rehabilitation studies, is reported to be associated with the ischaemic penumbra, the area surrounding an ischaemic event [24].
2. The stroke assessment scales focused on this thesis are the Barthel Index (BI) and the Functional Independence Measure (FIM). The BI was one of the earlier standardised functional assessments. The FIM was developed to be a more comprehensive tool [25]. Research has shown a relationship between the two instruments because a BI score can be derived from FIM score [26]. The scores

obtained from BI and FIM and utilised by physiotherapists to decide whether a patient is able to move on to the next stage of post-stroke therapy. The developed classification network is designed to support the assessment process of inpatient rehabilitation. While the network is capable of classifying post-stroke patients into the appropriate stages of therapy based on EEG, it is, by no means, an effort to replace physiotherapists during performance tests, but rather a supporting opinion so as to ensure the reliability of the assessment outcomes.

3. The EEG signals are collected using the 5-channel Emotiv Insight head wear. It is a non-invasive portable device, collecting data from the AF3, AF4, T7, T8, Pz locations. All recordings are saved in the EMOTIV Pro software, and are later transferred to MATLAB for pre-processing.
4. The neural network classification model is designed using "nntraintool" toolbox of the MATLAB 2019b software. The developed neural network is of the multi-layer feedforward architecture with backpropagation (BP) supervised training.

1.6 Thesis Outline

This thesis is organised into five chapter, discussing the theoretical aspect as well as the development process of the project. These chapters are arranged in sequence orders as follows:

Chapter 1: Introduction. This chapter presents the introduction of the research, the problem that needs to be solved, the aim and objectives, and also the scope of research.

Chapter 2: Literature Review. This chapter reviews the studies and researches accomplished by other scholars who are related to this project. The methods to assess post-stroke recovery of patients are presented in this chapter.

Chapter 3: Methodology. This chapter describes the approaches used throughout the development of this research, covering the methods of designing an EEG data collecting experiment procedure, the pre-processing of the collected data, as well as the procedure to build a classification model using the artificial neural network.

Chapter 4: Results and Discussion. This chapter presents the findings, observation and data analysis of this research in form of tables, graphical methods and data points. These results are further discussed and commented accordingly.

Chapter 5: Conclusion. This final chapter concludes the findings of this research. The hypotheses are answered accordingly. Future improvement and recommendations are presented as well, to be utilised as a contribution for others to hopefully gain benefits from this study.

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APPENDIX E

LIST OF PUBLICATIONS AND AWARDS

Publications:

1. PW QiHan, J Alipal, AAM Suberi and N Fuad, “A New Perspective on Visualising EEG Signal of Post-Stroke Patients”, *International Conference on Technology, Engineering and Sciences (ICTES) 2020,* **doi:10.1088/1757-899X/917/1/012047**

APPENDIX F

VITA

The author was born on February 22, 1993, in Sara wak, Malaysia. He went to Sekolah Menengah Kebangsaan Sacred Heart, Sibu, Sarawak, Malaysia for his secondary school, where he completed and sat in the Penilaian Menengah Rendah (PMR), Sijil Pelajaran Malaysia (SPM) and Sijil Tinggi Persekolahan Malaysia (STPM). Later on, he pursued his four-year Bachelor's Degree in Electronic Engineering in 2013, majoring in Mechatronics. In mid-year 2016, he underwent internship at to Bosch Rexroth Malaysia. During his 10 weeks internship program, he had gained experience and exposure in the electronic engineering field. The author conducted his bachelor's degree final year project entitled "Brain Exercise to Improve Attention using EEG" under the supervision of PM Dr Babul Salam, and later continued his study in Master research with the title of Development of EEG Classification Model for Post-Stroke Patients of Different Recovery Stages Using Artificial Neural Network in 2017.