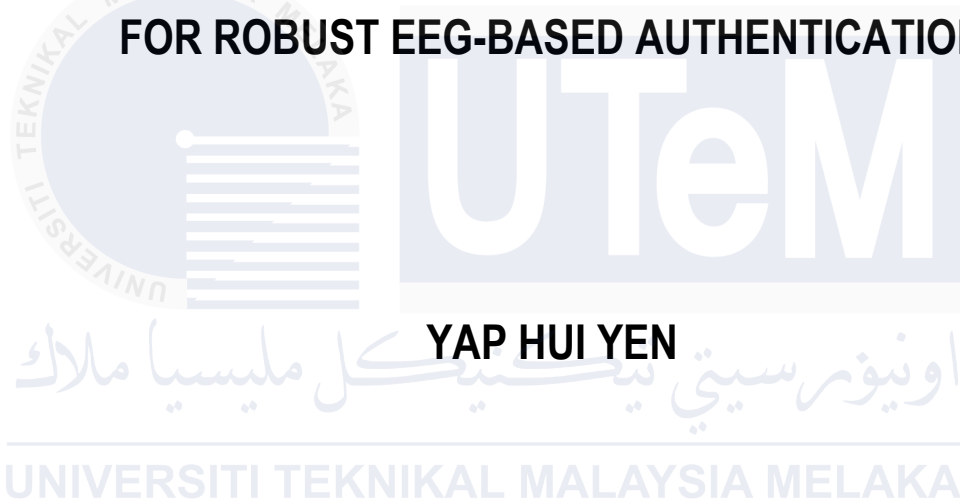




ADAPTIVE TRANSFER LEARNING AND WORD STIMULATION FOR ROBUST EEG-BASED AUTHENTICATION



YAP HUI YEN

DOCTOR OF PHILOSOPHY

2025



Faculty of Information and Communications Technology

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FOR ROBUST EEG-BASED AUTHENTICATION**

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UNIVERSITI TEKNIKAL MALAYSIA MELAKA

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EEG-BASED AUTHENTICATION**

YAP HUI YEN



UNIVERSITI TEKNIKAL MALAYSIA MELAKA

2025

DECLARATION

I declare that this thesis entitled “Adaptive Transfer Learning and Word Stimulation for Robust EEG-Based Authentication” is the result of my own research except as cited in the references. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.



Signature :

Name : YAP HUI YEN

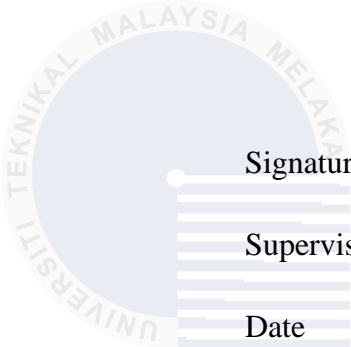
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APPROVAL

I hereby declare that I have read this thesis and in my opinion this thesis is sufficient in terms of scope and quality for the award of Doctor of Philosophy.

	Signature
	Supervisor Name	:Associate Professor Ts. Dr. Choo Yun Huoy
	Date	: 20 June 2025

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DEDICATION

To my beloved son, Zhi Rui, my supportive husband, Wee How, my beloved parents, and all my family members. Your love, encouragement, and sacrifices have been my greatest strength and inspiration throughout this journey.



ABSTRACT

Electroencephalogram (EEG)-based authentication has gained increasing attention as an alternative to conventional biometric systems due to its resistance to spoofing and privacy compliance. However, practical adoption remains limited, primarily due to high noise levels in consumer-grade EEG devices, high signal variation in different sessions, and the extensive training data requirements for deep learning models. Apart from ensuring biometric system performance, an EEG-based authentication system must also be user-friendly with a reasonable acquisition time to maintain user engagement. This study explores the feasibility of using consumer-grade EEG devices for authentication to address challenges such as noise and signal variability. It involves the design of a reasonably timed word-stimulation acquisition protocol to enhance signal reliability while minimizing cognitive fatigue. Additionally, due to the limited availability of training data, the performance of deep learning with transfer learning using pre-trained CNN models is investigated. The frequency spectra of the preprocessed EEG signals were extracted and used as input for pre-trained models. Experiments were conducted on a database of 30 subjects recorded over two separate sessions to evaluate the performance of the proposed method. Baseline evaluations compared pre-trained CNN models against traditional classifiers: SVM and k-NN. The results show that deep learning provides better performance within the same session. However, all methods, including pre-trained CNN models, SVM, and k-NN, experience performance degradation when tested on a different session dataset, revealing the challenge of EEG variability. In order to address this issue, an adaptive retraining strategy is proposed, which improves classification accuracy across sessions compared to direct deep learning transfer. These findings confirm the applicability of consumer-grade EEG devices for biometric authentication while addressing key challenges such as noise reduction, limited training data, and session variability. The proposed methodology contributes to the advancement of EEG-based biometric security, paving the way for practical deployment of EEG authentication systems in real-world applications.

PEMBELAJARAN PEMINDAHAN ADAPTIF DAN RANGSANGAN PERKATAAN UNTUK PENGESAHAN EEG YANG KUKUH

ABSTRAK

Autentikasi berasaskan Electroencephalogram (EEG) semakin mendapat perhatian sebagai alternatif kepada sistem biometrik konvensional kerana ketahanannya terhadap serangan penipuan (spoofing) dan pemuhan terhadap privasi. Walau bagaimanapun, penggunaannya dalam dunia sebenar masih terhad, terutamanya disebabkan oleh tahap hingar yang tinggi dalam peranti EEG gred pengguna, variasi isyarat yang ketara merentasi sesi yang berbeza, serta keperluan data latihan yang besar bagi model pembelajaran mendalam. Selain memastikan prestasi sistem biometrik, sistem autentikasi EEG juga mesti mesra pengguna dengan masa pemerolehan yang munasabah bagi mengekalkan penglibatan pengguna. Kajian ini meneroka kebolehlaksanaan penggunaan peranti EEG gred pengguna untuk tujuan autentikasi dalam menangani cabaran seperti tahap hingar yang tinggi dan variasi isyarat EEG. Ia melibatkan reka bentuk protokol pemerolehan rangsangan perkataan yang mempunyai tempoh yang munasabah bagi meningkatkan kebolehppercayaan isyarat EEG sambil mengurangkan keletihan kognitif. Selain itu, disebabkan ketersediaan data latihan yang terhad, prestasi pembelajaran mendalam dengan pembelajaran pemindahan menggunakan model CNN pralatih turut dikaji. Spektrum frekuensi isyarat EEG yang telah dipra-proses diekstrak dan digunakan sebagai input untuk model pralatih. Eksperimen telah dijalankan ke atas pangkalan data yang mengandungi 30 subjek, yang direkodkan dalam dua sesi berasingan, bagi menilai prestasi kaedah yang dicadangkan. Penilaian asas membandingkan model CNN pralatih dengan pengelas tradisional seperti SVM dan k-NN. Keputusan menunjukkan bahawa pembelajaran mendalam memberikan prestasi lebih baik dalam sesi yang sama. Walau bagaimanapun, semua kaedah, termasuk model CNN pralatih, SVM, dan k-NN, mengalami penurunan ketara dalam prestasi apabila diuji pada pangkalan data sesi yang berbeza, yang menyerlahkan cabaran variasi isyarat EEG. Bagi menangani isu ini, strategi latihan semula adaptif dicadangkan, yang meningkatkan ketepatan klasifikasi merentasi sesi berbanding pemindahan pembelajaran mendalam secara langsung. Penemuan ini mengesahkan kebolehlaksanaan penggunaan peranti EEG gred pengguna untuk tujuan autentikasi biometrik, sambil menangani cabaran utama seperti pengurangan hingar, data latihan yang terhad, dan variasi sesi. Metodologi yang dicadangkan ini menyumbang kepada kemajuan dalam keselamatan biometrik berasaskan EEG, sekali gus membuka laluan kepada penggunaan sistem autentikasi EEG dalam aplikasi dunia sebenar.

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Many thanks go to my husband, Wee How, who has been not only my soul mate but also my steadfast supporter throughout this journey. His support, patience, and understanding have been my pillar of strength. I am deeply indebted to him for his valuable advice on Matlab discussions and for sharing ideas on my research through insightful comments.

To my newborn baby, Zhi Rui, his arrival brought huge joy and encouragement into my life. His presence has made me stronger and more resilient in facing any challenges.

Lastly, I would like to extend my heartfelt thanks to my beloved family members. I am grateful to my grandmother, who has taken care of me since childhood and nurtured me with great kindness and compassion. I am deeply appreciative of my father and my aunt, who are no longer with us. I truly appreciate their commitment as financial supporter of our family since my childhood. Their dedication and sacrifices have been a source of inspiration for me. I also deeply appreciate my mother, who has always emphasized the importance of education and made it possible for me to pursue this PhD journey. To those who contributed indirectly to this research, my profound thanks for your kindness and support.

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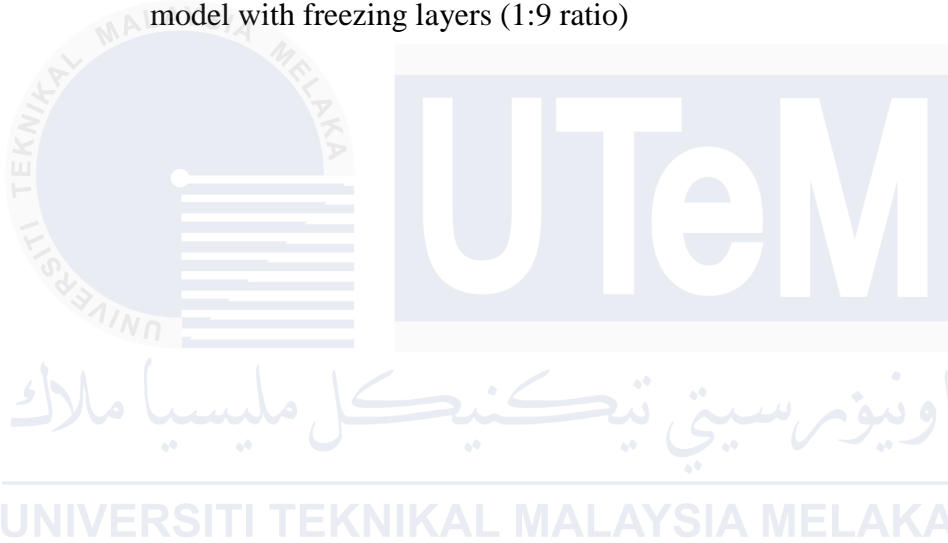
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LIST OF ABBREVIATIONS

<i>UTeM</i>	-	Universiti Teknikal Malaysia Melaka
BCI	-	Brain-Computer Interface
HCI	-	Human-to-Computer Interactions
EEG	-	Electroencephalogram
CNN	-	Convolutional Neural Network
DNA	-	Deoxyribonucleic Acid
FFT	-	Fast Fourier Transform
SVM	-	Support Vector Machine
<i>k</i> -NN	-	<i>k</i> -Nearest Neighbor
fMRI	-	functional Magnetic Resonance Imaging
fNIRS	-	functional Near-Infrared Spectroscopy
MEG	-	Magnetoencephalography
SQUID	-	Superconducting Quantum Interference Device
PET	-	Positron Emission Tomography
FAR	-	False Acceptance Rate
FRR	-	False Rejection Rate
HTER	-	Half Total Error Rate
EER	-	Equal Error Rate
EO	-	Eyes-open
EC	-	Eyes-closed
ERP	-	Event-Related Potential
VEP	-	Visual Evoked Potentials
AR	-	Autoregressive

FT	-	Fourier Transform
WT	-	Wavelet Transform
PSD	-	Power Spectral Density
WPD	-	Wavelet Packet Decomposition
STFT	-	Short-Time Fourier Transform
PCA	-	Principal Component Analysis
MLP	-	Multiple Layer Perceptron
IHAR	-	Inter-Hemispheric Amplitude Ratio
LDA	-	Linear Discriminant Analysis
SSVEP	-	Steady-State Visual Evoked Potentials
LSTM	-	Long Short-Term Memory
RNN	-	Recurrent Neural Networks
CMS	-	Common Mode Sense
DRL	-	Drive Right Leg
ISI	-	Inter-Stimulus Interval
FIR	-	Finite Impulse Response
AAR	-	Automatic Artifact Removal
DFT	-	Discrete Fourier Transform
RBF	-	Radial Basis Function
<i>Euc_Dist</i>	-	Euclidean Distance
<i>Man_Dist</i>	-	Manhattan Distance
<i>Cos_Dist</i>	-	Cosine Distance
<i>ChiQ_Dist</i>	-	Chi-Squared Distance
ReLU	-	Rectified Linear Unit
TP	-	True Positive
FP	-	False Positive

TN	-	True Negative
FN	-	False Negative
ILSVRC	-	ImageNet Large Scale Visual Recognition
RAM	-	Random Access Memory
GPU	-	Graphics Processing Unit



LIST OF PUBLICATIONS

The followings are the list of publications related to the work on this thesis:

H. Y. Yap, Y. H. Choo, and W. H. Khoh, 2017. Overview of Acquisition Protocol in EEG based Recognition System. *Brain Informatics. BI 2017. Lecture Notes in Computer Science*, vol. 10654, Springer (SCOPUS indexed, Q3)

H. Y. Yap, Y. H. Choo, I. M. Y. Zeratul, and W. H. Khoh, 2021. Person Authentication based on Eye-Closed and Visual Stimulation using EEG Signals. *Brain Informatics*, vol. 8 (21) (SCOPUS indexed, Q1)

H. Y. Yap, Y. H. Choo, I. M. Y. Zeratul, and W. H. Khoh, 2023. An Evaluation of Transfer Learning Models in EEG-based Authentication. *Brain Informatics*, vol. 10 (1) (SCOPUS indexed, Q1)

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CHAPTER 1

INTRODUCTION

1.1 Overview

In recent years, the growing interest in brain-computer interface (BCI) has increased the importance of understanding brain functions. BCI refers to a communication pathway between an external device and the human brain without involving any physical movements. These days, BCI research has been extended further to cover non-medical uses. An authentication study is an example of a BCI employing brain signals as a biometric identifier. Authentication is essential in our daily lives. It is performed in almost all human-to-computer interactions (HCI) to verify a user's identity through passwords, PIN codes, fingerprints, card readers, retina scanners, etc. Advanced biometric authentication has been developed with the growth of technology. Physiological biometrics uses a person's physical characteristics, such as face, fingerprint, palm print, retina, and iris, to identify an individual. This type of biometrics can hardly be replaced once it has been compromised.

On the other hand, behavioral biometrics analyze the digital patterns in performing a specific task in the authentication. Compared with the former biometrics, it is hard to mimic and is revocable and replaceable when compromised (Khoh *et al.*, 2019). While these traditional categorizations of biometrics, cognitive characteristics have given rise as the third category in recent years (Traore *et al.*, 2018). It assesses a person's emotional and cognitive state (biosignals) for identification and verification. It could serve as a replacement for conventional physiological and behavioral biometrics.