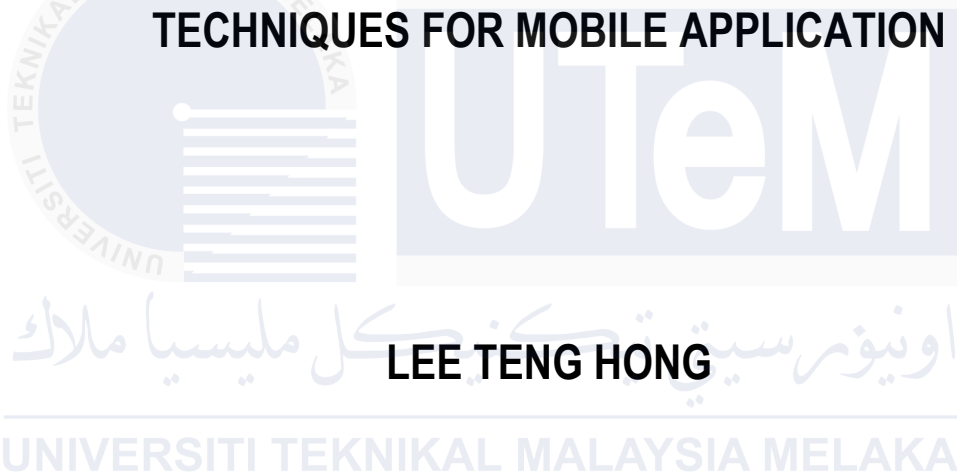




A COMPARATIVE ANALYSIS OF PARKINSON'S DISEASE CLASSIFICATION USING ARTIFICIAL INTELLIGENT TECHNIQUES FOR MOBILE APPLICATION



LEE TENG HONG

MASTER OF SCIENCE IN ELECTRICAL ENGINEERING

2025



Faculty of Electrical Technology and Engineering

**A COMPARATIVE ANALYSIS OF PARKINSON'S DISEASE
CLASSIFICATION USING ARTIFICIAL INTELLIGENT
TECHNIQUES FOR MOBILE APPLICATION**

اونيورسيتي تيكنيكل مليسيا ملاك
UNIVERSITI TEKNIKAL MALAYSIA MELAKA

Lee Teng Hong

Master of Science in Electrical Engineering

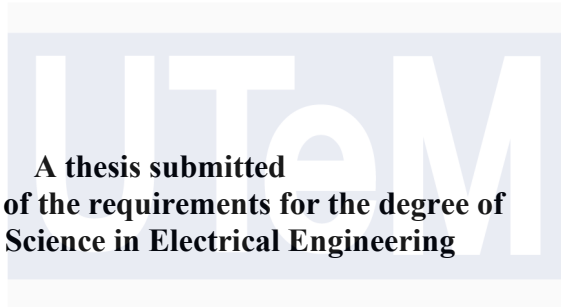
2025

**A COMPARATIVE ANALYSIS OF PARKINSON'S DISEASE CLASSIFICATION
USING ARTIFICIAL INTELLIGENT TECHNIQUES FOR MOBILE
APPLICATION**

LEE TENG HONG



**A thesis submitted
in fulfillment of the requirements for the degree of
Master of Science in Electrical Engineering**



اونيورسيتي تيكنيكل مليسيا ملاك

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

Faculty of Electrical Technology and Engineering

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

2025

DECLARATION

I declare that this thesis entitled “A Comparative Analysis of Parkinson’s Disease Classification using Artificial Intelligent Techniques” 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	Lee Teng Hong
Date	23 August 2025

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

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 Master of Science in Electrical Engineering.



Signature

Supervisor Name



Ts. Dr. Ezreen Farina binti Shair

Date 23 August 2025

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

DEDICATION

To my parents and supervisor for their endless love and support.



ABSTRACT

Parkinson's disease (PD) is a progressive neurodegenerative disorder that severely affects motor functions, particularly gait and balance. The global burden of Parkinson's disease is increasing. At the same time, clinical assessments require specialized settings and are not always accessible. For gait analysis, Detrended Fluctuation Analysis (DFA) has a problem of being too sensitive to noise while the use of Short-Time Fourier Transform (STFT) and Continuous Wavelet Transform (CWT) are not compared extensively. This thesis presents a comprehensive study on classifying Parkinson's disease and its severity using both traditional biosignals such as stride interval and vertical ground reaction force (vGRF), and computer vision-based techniques derived from video analysis. DFA, STFT and CWT were applied to extract meaningful features from biosignals. These features were evaluated using machine learning classifiers, including Support Vector Machine (SVM), k-Nearest Neighbors (KNN), and Random Forest, along with deep learning models such as 1D-Convolutional Neural Networks (1D-CNN), Long Short-Term Memory (LSTM), and Gated Recurrent Units (GRU). Results showed that SVM, KNN and random forest performed well in classifying both PD and healthy individuals when paired with combination of STFT, CWT and DFA with 100% in precision, recall and F1 – score. 1D-CNN demonstrated strong robustness in handling noisy stride interval data, while LSTM and GRU excelled in vGRF classification due to their ability to capture temporal dependencies. Additionally, walking videos were analyzed using the MediaPipe Pose framework, where 33 keypoints were extracted and features computed using the Time Series Feature Extraction Library (TSFEL) library. These features were used to classify PD severity using both machine learning and deep learning models. GRU-LSTM and Random Forest achieved classification precision, recall and F1 – score above 80%. A mobile application was developed using the Flutter framework, integrating MediaPipe Pose and Google ML Kit to enable real-time gait analysis from smartphone video. The system classified subjects into healthy, mild PD, or advanced PD categories with high reliability. This work highlights the complementary strengths of signal-based and vision-based approaches for PD assessment and presents a viable framework for remote, non-invasive, and real-time monitoring of gait disorders using mobile technologies.

***ANALISIS PERBANDINGAN PENGELASAN PENYAKIT PARKINSON
MENGUNAKAN TEKNIK KECERDASAN BUATAN***

ABSTRAK

Penyakit Parkinson (PD) adalah gangguan neurodegeneratif progresif yang memberi kesan teruk terhadap fungsi motor, terutamanya gaya berjalan dan keseimbangan. Beban global penyakit Parkinson semakin meningkat. Pada masa yang sama, penilaian klinikal memerlukan persediaan khusus dan tidak selalu boleh diakses. Untuk analisis gaya berjalan, Detrended Fluctuation Analysis (DFA) mempunyai masalah terlalu sensitif terhadap bunyi bising, manakala penggunaan Short-Time Fourier Transform (STFT) dan Continuous Wavelet Transform (CWT) belum dibandingkan secara meluas. Tesis ini membentangkan kajian menyeluruh mengenai pengelasan penyakit Parkinson dan tahap keparahannya menggunakan kedua-dua biosignal tradisional seperti selang langkah dan daya tindak balas tanah menegak (vGRF), serta teknik berasaskan penglihatan komputer yang diperoleh daripada analisis video. DFA, STFT, dan CWT digunakan untuk mengekstrak ciri bermakna daripada biosignal. Ciri-ciri ini dinilai menggunakan pengelasan pembelajaran mesin, termasuk Support Vector Machine (SVM), k-Nearest Neighbors (KNN), dan Random Forest, bersama model pembelajaran mendalam seperti 1D-Convolutional Neural Networks (1D-CNN), Long Short-Term Memory (LSTM), dan Gated Recurrent Units (GRU). Keputusan menunjukkan bahawa SVM, KNN, dan Random Forest mencapai prestasi cemerlang dalam mengelaskan kedua-dua individu PD dan sihat apabila digabungkan dengan STFT, CWT, dan DFA, dengan ketepatan, recall, dan F1-score mencapai 100%. 1D-CNN menunjukkan ketahanan yang kuat dalam mengendalikan data selang langkah yang bising, manakala LSTM dan GRU unggul dalam pengelasan vGRF kerana keupayaan mereka menangkap kebergantungan temporal. Selain itu, video berjalan dianalisis menggunakan rangka kerja MediaPipe Pose, di mana 33 titik utama diekstrak dan ciri dikira menggunakan pustaka Time Series Feature Extraction Library (TSFEL). Ciri-ciri ini digunakan untuk mengelaskan tahap keparahan PD menggunakan model pembelajaran mesin dan pembelajaran mendalam. Gabungan GRU-LSTM dan Random Forest mencapai ketepatan, recall, dan F1-score melebihi 80%. Satu aplikasi mudah alih dibangunkan menggunakan rangka kerja Flutter, menggabungkan MediaPipe Pose dan Google ML Kit untuk membolehkan analisis gaya berjalan masa nyata daripada video telefon pintar. Sistem ini mengelaskan subjek kepada kategori sihat, PD ringan, atau PD tahap lanjut dengan kebolehppercayaan tinggi. Kajian ini menyerlahkan kekuatan pelengkap pendekatan berasaskan isyarat dan penglihatan untuk penilaian PD, serta membentangkan rangka kerja yang boleh dilaksanakan untuk pemantauan jarak jauh, tidak invasif, dan masa nyata bagi gangguan gaya berjalan menggunakan teknologi mudah alih.

ACKNOWLEDGEMENTS

First and foremost, I would like to express my deepest gratitude to my supervisor, Ts. Dr. Ezreen Farina Shair, for her invaluable guidance, encouragement, and continuous support throughout the course of my Master's journey. Her expertise, insightful feedback, and patience have been instrumental in the successful completion of this thesis.

I would also like to sincerely thank my co-supervisor, Assoc. Prof. Ir. Ts. Dr. Abdul Rahim Abdullah, for his constructive advice, technical knowledge, and unwavering support. His suggestions and input have greatly contributed to the depth and quality of my research.

My heartfelt appreciation goes to Universiti Teknikal Malaysia Melaka (UTeM) for awarding me the Kesidang Scholarship, which provided essential financial support and allowed me to focus fully on my research.

Last but not least, I am deeply grateful to my family, friends, and colleagues for their endless encouragement, motivation, and understanding throughout this academic endeavor. This achievement would not have been possible without their support.

TABLE OF CONTENTS

DECLARATION	i
APPROVAL	
DEDICATION	
ABSTRACT	i
ABSTRAK	ii
ACKNOWLEDGEMENTS	ii
TABLE OF CONTENTS	iv
LIST OF TABLES	vii
LIST OF FIGURES	ix
LIST OF ABBREVIATIONS	xii
LIST OF SYMBOLS	xv
LIST OF APPENDICES	xvii
LIST OF PUBLICATIONS	xviii
CHAPTER	
1. INTRODUCTION	1
1.1 Research Background	1
1.2 Motivation and Problem Statement	3
1.3 Aims and Objectives	4
1.4 Scope of Research	5
1.5 Research Contributions	6
1.6 Thesis Structure	7
2. LITERATURE REVIEW	9
2.1 Overview of Parkinson's Disease Diagnosis	9
2.2 Existing Parkinson's Disease Diagnostic Methods	10
2.3 Gait Analysis for Parkinson's Disease	13
2.4 Parameters of Gait Analysis	13
2.4.1 Temporal Gait Parameters Detection using Vertical Ground Reaction Force (vGRF)	19
2.4.2 Computer Vision-Based Gait Analysis	24
2.5 Synthetic Data Generation for Medical Applications	29
2.6 Feature Extraction Techniques for Gait Analysis	32
2.6.1 Sensor-Based Feature Extraction Techniques for Stride Interval and vGRF Signal	33
2.6.2 Vision-Based Feature Extraction Technique using MediaPipe Pose Estimation Algorithm	37
2.7 Machine Learning and Deep Learning in Parkinson's Disease Detection	40
2.8 Smartphone-Based Applications for Parkinson's Disease Monitoring	45
2.9 Summary	47
3. RESEARCH METHODOLOGY	46
3.1 Overview	49

3.2	Research Design	50
3.2.1	Comparative Analysis of Machine Learning and Deep Learning in the Classification of Stride Interval of Young and Old People	51
3.2.2	Comparative Analysis of Machine Learning and Deep Learning in the Detection and Classification of Parkinson's Disease with Varied Severity Levels Based on vGRF signal	53
3.2.3	Comparative Analysis of Machine Learning and Deep Learning in the Detection and Classification of Parkinson's Disease with Varied Severity Levels Utilizing Computer Vision Technique Based on MediaPipe Pose	56
3.2.4	Design of Mobile Application to Detect and Classify Parkinson's Disease with Varied Severity Levels Based on Google ML Kit Pose Detection and MediaPipe Pose	59
3.3	Dataset	63
3.3.1	Subject's Demographic Details	63
3.3.2	Experimental procedures	64
3.4	Synthetic Data Generation	65
3.5	Signal Feature Extraction	68
3.5.1	Short-Time Fourier Transform (STFT)	69
3.5.2	Continuous Wavelet Transform (CWT)	69
3.5.3	Detrended Fluctuation Analysis (DFA)	70
3.6	Signal Classification Models	71
3.6.1	Machine Learning Classification Models	71
3.6.2	Deep Learning Classification Models	78
3.7	Model Performance Evaluation	85
3.7.1	Evaluation Metrics	86
3.8	Development of the Smartphone-Based Application	87
3.8.1	Platform and Development Tools	87
3.8.2	Application Testing and Validation	90
3.9	Summary	90
4.	RESULTS AND DISCUSSION	88
4.1	Overview	92
4.2	Effectiveness of Synthetic Data Generation	93
4.2.1	Comparison of Maximum STFT RMS, Maximum CWT RMS and DFA of the Original Data, and Synthetic Data Produced by CTGAN, Noise Jittering and ACTGAN Gretel from Healthy Old Sample	93
4.2.2	Comparison of STFT Time-Frequency Plot and Instantaneous STFT RMS of the Original Healthy Old Sample, Synthetic Data	

Generated by using CTGAN, Noise Jittering and ACTGAN Gretel	96
4.2.3 Comparison of CWT Time-Frequency Plot and Instantaneous CWT RMS of the Original Healthy Old Sample, Synthetic Data Generated by using CTGAN, Noise Jittering and ACTGAN Gretel	100
4.3 Impact of Feature Extraction Techniques	104
4.4 Comparative Analysis of Machine Learning and Deep Learning Models	114
4.4.1 Classification of Stride Interval of Healthy Old People and Healthy Young People	115
4.4.2 Classification of Parkinson's Disease and the Severity Level using vGRF Signal	121
4.4.2 Classification of Parkinson's Disease with Varied Severity Levels Utilizing Computer Vision Technique Based on MediaPipe Pose	126
4.5 Real – Time Implementation	127
4.5.1 System Interface	128
4.5.2 System Performance and Validation	130
4.5.3 System Limitations	131
4.6 Summary	133
5. CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH	129
5.1 Conclusions	134
5.2 Recommendations for Future Research	135
REFERENCES	137
APPENDICES	161

LIST OF TABLES

TABLE	TITLE	PAGE
2.1	Hoehn and Yahr (HY) Scale (Varlıbaş et al., 2025)	10
2.2	Comparative Analysis of Diagnostic Tools (Sethi and Baggan, 2025)	12
2.3	Summary of Classification Work on vGRF Signal	21
2.4	The Comparison of Different Human Pose Estimation Algorithms (Tang, 2025)	25
2.5	Summary of Gait Related Work using MediaPipe Pose	27
2.6	Table of Comparison of CTGAN, ACTGAN and Noise Jittering	30
2.7	Comparison of STFT, CWT and DFA	35
2.8	Summary of the Work on Features of Stride Interval	36
2.9	The List of Features Derived by the TSFEL under Statistical Domain, Temporal Domain, Spectral Domain and Fractal Domain	38
2.10	Comparison of 1D – CNN, GRU and LSTM	43
2.11	Summary of Gait-Related Work on Smartphone Mobile Application	46
3.1	The Demographics of the Groups of Experiment for the Analysis 1	63
3.2	The Demographics of the Groups of the Experiment for the Analysis 2	64
3.3	The Demographics of the Groups of the Experiment for the Analysis 3	64
3.4	The Parameters in Random Search Method for SVM	76
3.5	The Parameters in Random Search Method for random Forest	76
3.6	The Parameters in Grid Search Cross – Validation in KNN	77

4.1	The Comparison of Maximum STFT RMS, Maximum CWT RMS and DFA of the Original Data, and Synthetic Data Produced by CTGAN, Noise Jittering and ACTGAN Gretel from Healthy Old Sample	94
4.2	Comparison of STFT Time -Frequency Plot and Instantaneous STFT RMS of the Original Healthy Old Sample, Synthetic Data Generated by using CTGAN, Noise Jittering and ACTGAN Gretel	98
4.3	Comparison of CWT Time – Frequency Plot and Instantaneous CWT RMS of the Original Healthy Old Sample, Synthetic Data Generated by using CTGAN, Noise Jittering and ACTGAN Gretel	102
4.4	The Time-Frequency Plot of STFT (Hanning Window), Derived Instantaneous RMS of STFT and Recorded Processing Time with Varied Window Length of Old Subject	108
4.5	The Actual Maximum Time Derived from STFT of Varied Window Length from Old Subject	109
4.6	The Time – Frequency Plot of CWT, Derived Instantaneous of CWT and Recorded Processing Time with Varied Scale from Old Subject 1	111
4.7	The Actual Maximum Time Derived from CWT of Varied Window Length from Old Subject	113
4.8	The Summary of the Weighted Average Score of Different Machine Learning Algorithm in Classification of Stride Interval	116

LIST OF FIGURES

FIGURE	TITLE	PAGE
Figure 2.1	Temporal Parameters for Gait Analysis (Trojaniello et al., 2014)	14
Figure 2.2	Kinematic Parameters for Gait Analysis (Na et al., 2024)	15
Figure 2.3	Electromyography (EMG) Signal of the Muscle (Cappellini et al., 2006)	16
Figure 2.4	Study of Balance for Gait Analysis (Middleton and Fritz, 2013; Tisserand et al., 2016)	17
Figure 2.5	The Position of the Location Sensors underneath Subject's Feet (Abdulhay et al., 2018)	19
Figure 2.6	The Time-Domain Representation of the vGRF Signal (Abdulhay et al., 2018)	20
Figure 2.7	The Extraction of the 33 Keypoints using the MediaPipe Pose	26
Figure 3.1	The Major Analysis of the Overall Research Methodology	50
Figure 3.2	The Flow Chart of the Comparative Analysis of ML and DL in the Classification of Stride Interval of Young and Old People	53
Figure 3.3	The Flow Chart of the Comparative Analysis of ML and DL in the Detection and Classification of Parkinson's Disease with Varied Severity Levels Based on vGRF Signal	55
Figure 3.4	The Flow Chart of the Comparative Analysis of ML and DL in the Detection and Classification of Parkinson's Disease with Varied Severity Levels Utilizing Computer Vision Technique Based on MediaPipe Pose	58
Figure 3.5	The Flow Chart of the Design of Mobile Application to Detect and Classify Parkinson's Disease with Varied Severity Levels Based on Google ML Kit Pose Detection and MediaPipe Pose using DL	60
Figure 3.6	The Perpendicular Direction of People Walking to the Direction of the Smartphone Camera	61
Figure 3.7	The Flow Chart of the Design of Mobile Application to Detect and Classify Parkinson's Disease with Varied Severity Levels	

	Based on Google ML Kit Pose Detection and MediaPipe Pose using ML	62
Figure 3.8	The Block Diagram of the Mobile Application	89
Figure 4.1	The Comparison of DFA, Maximum STFT RMS and Maximum CWT RMS of Healthy Young People and Healthy Old People for Analysis 1	105
Figure 4.2	The Feature Importance of DFA, Maximum CWT RMS and Maximum CWT RMS in the Classification of Healthy Young People and Healthy Old People	106
Figure 4.3	The Box Plot of Maximum RMS in STFT versus Old Group and Young Group with Window Length of 64 and Window Length of 128 110	
Figure 4.4	The Box Plot of Maximum RMS in CWT versus Old and Young Group on a scale of (a) 128 and (b) 2048	114
Figure 4.5	The Extraction of Parameters by 1D – CNN for the Classification of Stride Interval of Healthy Old People and Healthy Young People	118
Figure 4.6	The Extraction of Parameters by LSTM for the Classification of Stride Interval of Healthy Old People and Healthy Young People	118
Figure 4.7	The Extraction of Parameters by GRU for the Classification of Stride Interval of Healthy Old People and Healthy Young People	119
Figure 4.8	The Comparison of Processing Time of 1D – CNN, GRU and LSTM for the Classification of Stride Interval of Healthy Old People and Healthy Young People	120
Figure 4.9	The Compilation of Precision, Recall & F1 – Score using Deep Learning in Classification of Stride Interval of Healthy Old People and Healthy Young People	121
Figure 4.10	The Compilation of Precision, Recall & F1 – Score using Machine Learning Technique and Deep Learning in Classification of Patients with Parkinson’s Disease and Healthy People	123
Figure 4.11	The Compilation of Precision, Recall & F1 – Score using Machine Learning Technique and Deep Learning in	

	Classification of Patients with Parkinson’s Disease of Varied Severity	124
Figure 4.12	The Compilation of Precision, Recall & F1 – Score using Different Deep Learning & Machine Learning Techniques for Component 3 of Research Methodology	127
Figure 4.13	The User Interface of the Designed Mobile Application	129
Figure 4.14	The Integration of MongoDB and Kubeflow into Flask API	132



LIST OF ABBREVIATIONS

ACTGAN	-	Anyway Conditional Tabular Generative Adversarial Network
AB	-	Adaboost classifier
AI	-	Artificial Intelligence
ALS	-	Amyotrophic Lateral Sclerosis
AR	-	Augmented Reality
API	-	Application Program Interface
AST - DGNN	-	Adaptive Spatio-Temporal Directed Graph Neural Network
COM	-	Centre of Mass
CNN	-	Convolutud Neural Network
CSF	-	Cerebrospinal Fluid
CTGAN	-	Conditional Tabular Generative Adversarial Network
CWT	-	Continuous Wavelet Transform
CV	-	Coefficient of Variation
DFA	-	Detrended Fluctuation Analysis
DTI	-	Diffusion Tensor Imaging
ECDF	-	Empirical Cumulative Distribution Function
FFT	-	Fast Fourier Transform
GAN	-	Generative Adversarial Network
GFAP	-	Glial Fibrillary Acidic Protein
GLRA	-	Generalized Linear Regression Analysis
GRU	-	Gated Reccurent Unit

HG	-	Higuchi's Fractal Dimension
HY	-	Hoehn and Yahr
IMF	-	Intrinsic Mode Functions
IMU	-	Inertial Measurement Unit
KNN	-	K – Nearest Neighbor
LightGBM	-	Light Gradient Boosting Machine
LSTM	-	Long Short – Term Memory
MCC	-	Matthews Correlation Coefficient
MFCC	-	Mel – Frequency Cepstral Coefficients
MMOTE	-	Mahalanobis – Metric - based Oversampling Technique
MRI	-	Magnetic Resonance Imaging
MSE	-	Multiscale Entropy
NEWFM	-	Network with Weighted Fuzzy Membership
PET	-	Positron Emission Tomography
Q-BTDNN	-	Q-back Propagated Time Delay Neural Network
RAS	-	Rhythmic Auditory Stimulation
RBF	-	Radial Basis Function
RMS	-	Root Mean Square
RNN	-	Reccurent Neural Network
SVDEn	-	Singular Value Decomposition Entropy
SPECT	-	Single-Photon Emission Computed Tomography
STFT	-	Short – Time Fourier Transform
SVM	-	Support Vector Machine
TSFEL	-	Time Series Feature Extraction Library

UTeM	-	Universiti Teknikal Malaysia Melaka
vGRF	-	Vertical Ground Reaction Force
YOLO	-	You Only Look Once



LIST OF SYMBOLS

$c_{i,j}$	-	Value in CTGAN in continuous column
u_k, θ_k	-	Resp in CTGAN
n_k	-	Mean
ϕ_k	-	Standard Deviation
\mathbb{P}	-	Probability
k	-	Specific Component in CTGAN
$x(n)$	-	Input Signal
W_n	-	Window Function
N	-	FFT Number
S_n	-	Time Interval Shift
x_n	-	Discrete Time Signal
δ_t	-	Uniform Time Intervals
ψ	-	Shifted Mother Wavelet
e	-	Prediction Error
p_j	-	The Proportion of Class j in a Given Node n
f_t	-	Forget Gate
c_{t-1}	-	Amount of Information of Previous State
i_t	-	Input Gate
o_t	-	Output Gate
x_t	-	Data Entered into LSTM Memory Cell
h_t	-	Output for each LSTM Cell
W, V	-	Weight Matrix

b	- Biases
σ	- Sigmoid Activation Function
z_t	- Update Gate Vector of GRU
r_t	- Reset Gate Vector of GRU
b_z, b_r	- Bias Vectors of GRU
W_z, W_r	- Weight Matrix for the Input x_t
U_z, U_r	- Weight Matrix for the Hidden State



اونيورسيتي تيكنيكل مليسيا ملاك

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

LIST OF APPENDICES

APPENDIX	TITLE	PAGE
A1	Publication	156



اونيورسيتي تېكنيكل مليسيا ملاك

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

LIST OF PUBLICATIONS

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

Journals

T. H. Lee, E. F. Shair, A. R. Abdullah, K. A. Rahman, N. M. Ali, N. Z. Saharuddin, and N. Nazmi, 2024. Comparative Analysis of 1D-CNN, GRU, and LSTM for Classifying Step Duration in Elderly and Adolescents Using Computer Vision. *International Journal of Robotics and Control Systems*, vol. 5, no. 1, pp. 138–148, 2025. (Scopus) - Published

T. H. Lee, E. F. Shair, A. R. Abdullah, K. A. Rahman, and N. Nazmi, 2024. Machine Learning-Based Gait Analysis for Distinguishing Older and Younger Walking Patterns in Neurodegenerative Diseases. *International Journal of Intelligent Systems and Applications in Engineering*, vol. 12, no. 4, pp. 1007–1015, 2024. (Scopus) - Published

K. A. Rahman, E. F. Shair, A. R. Abdullah, **T. H. Lee**, N. Nazmi, 2025. Deep Learning Classification of Gait Disorders in Neurodegenerative Diseases Among Older Adults Using ResNet-50, *International Journal of Advanced Computer Science & Applications*, vol. 15, no. 11, pp. 1193-1200, 2024. (WoS) – Published

K. A. Rahman, E. F. Shair, A. R. Abdullah, **T. H. Lee**, N. M. Ali, M. I. Zakaria, 2025. Classifying Gait Disorder in Neurodegenerative Disorders Among Older Adults Using Machine Learning. *International Journal of Robotics and Control Systems*. (Scopus) – Published