



اونیورسیتی تکنیک ملیسیا ملاک

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

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

اونیورسیتی تکنیک ملیسیا ملاک

LEE TENG HONG

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

MASTER OF SCIENCE IN ELECTRICAL ENGINEERING

2025



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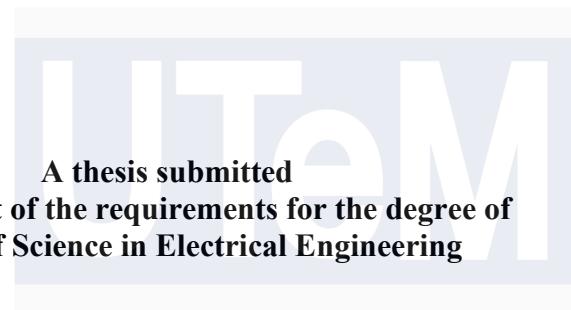
Lee Teng Hong

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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

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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 Master of Science in Electrical Engineering.



Signature :
Supervisor Name :
Date :
Ts. Dr. Ezreen Farina binti Shair

23 August 2025

جامعة ملaka التقنية

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
MENGGUNAKAN 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 kebolehpercayaan 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.

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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	- Convolved 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 Recurrent 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	-	Recurrent 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



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A1	Publication	156



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