GAIT FORCE-BASED MULTIMODAL FUSION ARCHITECTURES WITH DEEP NEURAL NETWORKS FOR GAIT DISORDERS IN OLDER ADULTS

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Master Of Science In Electrical Engineering

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DECLARATION

I declare that this thesis entitle "Gait Force-Based Multimodal Fusion Architectures With Deep Neural Networks for Gait Disorders in Older Adults, " 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 : ....

Student Name : **RAHMAN KAZI ASHIKUR**

Date : 27/05/2025

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 : 27/05/2025

DEDICATION

To my family, my master's supervisor, and my friends for their invaluable support and generous prayers.

ABSTRACT

Gait analysis is an important way to help diagnose neurodegenerative diseases early, especially in older adults. Small changes in the way people walk can show the start of diseases like Parkinson's Disease (PD), Huntington's Disease (HD), and Amyotrophic Lateral Sclerosis (ALS). This study looks at the time and frequency patterns of gait signals using Continuous Wavelet Transform (CWT). This method helps better understand the vertical Ground Reaction Force (vGRF) signals and find small problems in walking. Even though this is useful, it is still hard to tell these diseases apart because their walking features can be similar, and aging also changes how people walk. The study used data from 64 people: 13 with ALS, 15 with PD, 20 with HD, and 16 healthy controls. Since the focus is on older adults, only data from those aged 50 and above were used. The main goal was to build a strong model that uses time-frequency features from vGRF signals along with clinical information to improve early detection and work well for different people. The work was done in three steps. First, common machine learning methods, Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), and Multilayer Perceptron (MLP) were trained using handpicked features from the vGRF data. SVM gave the best accuracy of 83.3%. These methods worked well but depended on features chosen by hand, which limits how well work on new data. Next, deep learning methods were used by changing the vGRF signals into time-frequency images using CWT. Convolutional Neural Networks (CNN) and ResNet-50 models learned features automatically from these images. They reached accuracy rates of 95.18% and 95.06%, respectively. But these models only used signal data and did not include clinical details like age, gender, and disease severity, which can affect walking. Finally, a combined deep learning model was made that used both the spectrogram images and clinical data together. This model could learn walking patterns and personal differences at the same time. It had the highest accuracy of 98.46%, with good sensitivity, specificity, precision, and F1-score. This shows it can reliably tell apart different neurodegenerative gait disorders.

SENI BINA PENGGABUNGAN MULTIMODAL BERASASKAN KEKUATAN GAIT DENGAN RANGKAIAN NEURAL DALAM UNTUK GANGGUAN GAIT DALAM KALANGAN WARGA EMAS

ABSTRAK

Analisis gaya berjalan adalah cara penting untuk membantu mendiagnosis penyakit neurodegeneratif lebih awal, terutamanya pada orang dewasa yang lebih tua. Perubahan kecil dalam cara orang berjalan boleh menunjukkan permulaan penyakit seperti Penyakit Parkinson (PD), Penyakit Huntington (HD), dan Amyotrophic Lateral Sclerosis (ALS). Kajian ini melihat corak masa dan kekerapan isyarat gaya berjalan menggunakan Continuous Wavelet Transform (CWT). Kaedah ini membantu lebih memahami isyarat Ground Reaction Force (vGRF) menegak dan mencari masalah kecil dalam berjalan. Walaupun ini berguna, masih sukar untuk membezakan penyakit ini kerana ciri berjalan mereka mungkin serupa, dan penuaan juga mengubah cara orang berjalan. Kajian itu menggunakan data daripada 64 orang: 13 dengan ALS, 15 dengan PD, 20 dengan HD, dan 16 kawalan sihat. Memandangkan tumpuan diberikan kepada orang dewasa yang lebih tua, hanya data daripada mereka yang berumur 50 tahun ke atas digunakan. Matlamat utama adalah untuk membina model kukuh yang menggunakan ciri kekerapan masa daripada isyarat vGRF bersama-sama dengan maklumat klinikal untuk meningkatkan pengesanan awal dan berfungsi dengan baik untuk orang yang berbeza. Kerja itu dilakukan dalam tiga langkah. Pertama, kaedah pembelajaran mesin biasa, Mesin Vektor Sokongan (SVM), Hutan Rawak (RF), Pokok Keputusan (DT) dan Multilayer Perceptron (MLP) telah dilatih menggunakan ciri pilihan daripada data vGRF. SVM memberikan ketepatan terbaik sebanyak 83.3%. Kaedah ini berfungsi dengan baik tetapi bergantung pada ciri yang dipilih secara manual, yang mengehadkan keberkesanan data baharu. Seterusnya, kaedah pembelajaran mendalam digunakan dengan menukar isyarat vGRF kepada imej frekuensi masa menggunakan CWT. Model Rangkaian Neural Convolutional (CNN) dan ResNet-50 mempelajari ciri secara automatik daripada imej ini. Mereka mencapai kadar ketepatan 95.18% dan 95.06%, masing-masing. Tetapi model ini hanya menggunakan data isyarat dan tidak menyertakan butiran klinikal seperti umur, jantina dan keterukan penyakit, yang boleh menjejaskan berjalan.Akhirnya, model pembelajaran mendalam gabungan telah dibuat yang menggunakan kedua-dua imej spektrogram dan data klinikal bersama-sama. Model ini boleh mempelajari corak berjalan dan perbezaan peribadi pada masa yang sama. Ia mempunyai ketepatan tertinggi 98.46%, dengan kepekaan, kekhususan, ketepatan dan skor F1 yang baik. Ini menunjukkan ia boleh membezakan dengan pasti gangguan gaya berjalan neurodegeneratif yang berbeza.

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LIST OF ABBREVIATIONS

ALS	–	Amyotrophic Lateral Sclerosis
CNN	–	Convolutional Neural Network
CO	–	Normal gait (Control)
CWT	–	Continuous Wavelet Transform
DL	–	Deep Learning
DT	–	Decision Tree
FMCW	–	Frequency-Modulated Continuous Wave
GRF	–	Ground Reaction Force
HD	–	Huntington’s Disease
IMU	–	Inertial Measurement Unit
IQR	–	Interquartile Range
kNN	–	k-Nearest Neighbors
LSTM	–	Long Short-Term Memory
MDL	–	Machine Learning
ML	–	Machine Learning
MLP	–	Multilayer Perceptron
MRI	–	Magnetic Resonance Imaging
NDD	–	Neurodegenerative Diseases
PD	–	Parkinson’s Disease
PET	–	Positron Emission Tomography
RF	–	Random Forest
ResNet	–	Residual Network

ReLU	–	Rectified Linear Unit
SD	–	Standard Deviation
SVM	–	Support Vector Machine
vGRF	–	vertical Ground Reaction Force
RMS	–	Root Mean Square
RNN	–	Recurrent Neural Network
CT	–	Computed Tomography

LIST OF SYMBOLS

a	–	The number of angels per unit area
N	–	The number of angels per needle point
A	–	The area of the needle point
$\mathscr{L}$	–	The Laplacian matrix

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A. Journal

1. **K. A. Rahman**, E. F. Shair, A. R. Abdullah, T. H. Lee, and N. H. Nazmi., 2024. Deep Learning Classification of Gait Disorders in Neurodegenerative Diseases Among Older Adults Using ResNet-50. *International Journal of Advanced Computer Science and Applications*, vol. 15, no. 11, 2024. **(WOS(Q3)) & (Scopus(Q3)) (Published)**

2. **K. A. Rahman**, E. F. Shair, A. R. Abdullah, T. H. Lee, and N. H. Nazmi., 2025. Classifying Gait Disorder in Neurodegenerative Disorders Among Older Adults Using Machine Learning. *International Journal of Robotics and Control Systems*, Vol 5, No 2 (2025). **(Scopus(Q3)) (Published)**

3. **K. A. Rahman**, E. F. Shair, A. R. Abdullah, T. H. Lee, and N. H. Nazmi., 2024. Classification of Parkinsonian Gait in Older Adults via CWT and Convolutional Neural Networks. *IAES International Journal of Artificial Intelligence (IJ-AI)*, **(Scopus(Q2) (Accepted)**

4. T. Lee, E. F. Shair, A. R. Abdullah, **K. A. Rahman**, N. Ali, N. Saharuddin, and N. Nazmi., 2025. 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, 2025, DOI: 10.31763/ijrcs.v5i1.1588. **(Scopus)(Q3) (Published)**

5. 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 (IJISAE)*, vol. 12, no. 4, pp. 1007–1015.**(Scopus)(Q3) (Published)**

6. S. Zoha, N. A. B. Moketar, A. H. Mazbah, and **K. A. Rahman**, K. A. Fariza., 2025. Leveraging YOLOv5 and Gradient Occlusion (XAI) for Interpretable Gallbladder Stone Detection in Ultrasound Imaging. *International Journal of Advanced Computer Science and Applications*, May 2025 Edition (Volume 16 No. 5). **(WOS(Q3)) & (Scopus(Q3)) (Accepted)**

7. **K. A. Rahman**, Nur Hasanah Ali, and Ahmad Sobri Muda., 2025 . A Review on Collateral Circulation Classification for Ischemic Stroke. *Results in Engineering*, Submitted for Review, Elsevier Journal. **(Scopus(Q1) & WoS (Q1) Indexed (Under Review)**

8. **K. A. Rahman**, E. F. Shair, A. R. Abdullah, T. H. Lee, and N. H. Nazmi., 2025. Gait Force-Based Multimodal Deep Neural Network for Classifying Neurological Gait Disorders in Older Adults. *Online and Biomedical Engineering*, Planned Submission, **(WoS(Q2) & Scopus(Q2) – Under Review)**

9. **K. A. Rahman**, E. F. Shair, A. R. Abdullah, T. H. Lee, and N. H. Nazmi., 2025. Performance Comparison of Traditional Machine Learning, Unimodal Deep Learning, and Multimodal Deep Learning Models for Gait Disorder Analysis in Older Adults with Neuromotor Diseases. *Online and Biomedical Engineering*, **(WoS(Q2) & Scopus(Q2) – Under Review)**

B. Conference proceedings

1. **K. A. Rahman**, E. F. Shair, A. R. Abdullah, T. H. Lee, and N. H. Nazmi., 2024. Analysis of Gait Patterns in Neurodegenerative Disorders Among Older Adults: A Ground Reaction Force Data Approach. *Proceedings of the 10th World Congress on Electrical Engineering and Computer Systems and Sciences (EECSS'24), Barcelona, Spain, August 19 - 21, 2024,* Paper No. ICBES 131. **(Scopus) (Published)**

2. **K. A. Rahman**, E. F. Shair, A. R. Abdullah, T. H. Lee, and N. H. Nazmi., 2025. Gait Disorder Classification in Neurodegenerative Disorders Using vGRF Data. *2024 27th International Conference on Computer and Information Technology (ICCIT), 20-22 December 2024, Cox's Bazar, Bangladesh* **(Scopus) (Published)**

3. **K. A. Rahman**, E. F. Shair, A. R. Abdullah, T. H. Lee, and N. H. Nazmi,M. S. Zoha., 2024. Classifying Gait Disorder in Neurodegenerative Disorders Among Older Adults Using Deep Learning. *8th IEEE-EMBS Conference on Biomedical Engineering and Sciences (IECBES2024) in Penang, Malaysia, December 11-13, 2024.* **(Scopus) (Published)**

4. **K. A. Rahman**, E. F. Shair, A. R. Abdullah, T. H. Lee, and N. H. Nazmi., 2025. Gait Disorder Classification Using CNN and TensorFlow Lite in Android Apps. *Proceedings of the 11th World Congress on Electrical Engineering and Computer Systems and Sciences (EECSS'25), Paris, France, August 2025,* Paper No. ICBES 152. **(Scopus) (Published)**

5. T. H. Lee, E. F. Shair, A. R. Abdullah, **K. A. Rahman**, and N. H. Nazmi., 2024. Combined

Utilization of STFT, CWT, & DFA in Classification of Young & Old Gait Using Machine Learning Techniques. *8th IEEE-EMBS Conference on Biomedical Engineering and Sciences (IECBES2024) in Penang, Malaysia, December 11-13, 2024.* **(Scopus) (Published)**

6. T. H. Lee, E. F. Shair, A. R. Abdullah, **K. A. Rahman**, and N. H. Nazmi., 2025. Comparison of Short Fast Fourier Transform and Continuous Wavelet Transform in Study of Stride Interval. *Proceedings of the 10th World Congress on Electrical Engineering and Computer Systems and Sciences (EECSS'24), Barcelona, Spain, August 19 - 21, 2024,* Paper No. ICBES 123. **(Scopus) (Published)**

C. Module Book

1. A. R. Abdullah, E. F. Shair, Shaarmila A/P Kandaya, **K. A. Rahman**., 2025. *"Machine Learning for All: Step by Step in MATLAB"*. published by Universiti Teknikal Malaysia Melaka(UTeM) **(Published)**.