IJRCS
International Journal of Robotics and Control Systems
Vol. 5, No. 2, 2025, pp. 1083-1101
ISSN 2775-2658
http://pubs2.ascee.org/index.php/ijrcs
ASCEE

Classifying Gait Disorder in Neurodegenerative Disorders Among Older Adults Using Machine Learning

Kazi Ashikur Rahman [a,1], Ezreen Farina Shair [a,2,*], Abdul Rahim Abdullah [a,3], Teng Hong Lee [a,4], Nursabillilah Mohd Ali [a,5], Muhammad Iqbal Zakaria [b,6], Mohammed Azmi Al Betar [c,7]

[a] Rehabilitation and Assistive Technology Research Group, Faculty of Electrical Technology and Engineering, Universiti Teknikal Malaysia Melaka, Hang Tuah Jaya, 76100 Durian Tunggal, Melaka, Malaysia
[b] School of Electrical Engineering, College of Engineering, Universiti Teknologi MARA, 40450 Shah Alam, Selangor, Malaysia
[c] College of Engineering and Information Technology, Ajman University, P.O. Box: 346, Ajman, UAE
[1] kazia096@gmail.com; [2] ezreen@utem.edu.my; [3] abdulr@utem.edu.my; [4] leetenghong06@gmail.com;
[5] nursabillilah@utem.edu.my; [6] iqbal.z@uitm.edu.my; [7] m.albetar@ajman.ac.ae
* Corresponding Author

ARTICLE INFO

Article History
Received November 28, 2024
Revised January 23, 2025
Accepted April 25, 2025

Keywords
Neurodegenerative Disorders;
Gait Analysis;
Older Adults;
Continuous Wavelet Transform;
Machine Learning

ABSTRACT

Gait disorders are a significant concern for older adults, particularly those with neurodegenerative diseases such as Parkinson's disease, Huntington's disease, and Amyotrophic Lateral Sclerosis. Accurately classifying these conditions using gait data remains a complex challenge, especially in older populations, due to age-related changes in gait patterns, comorbidities, and increased variability in mobility, which can obscure disease-specific characteristics. This study explicitly classifies neurodegenerative diseases in older adults by analysing age-specific gait force data. Continuous Wavelet Transform (CWT) was utilised for advanced feature extraction, capturing both temporal and spectral signal characteristics. Classifiers including Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), and Multilayer Perceptron (MLP) were employed. The results demonstrated that SVM achieved an accuracy of 87.5%, outperforming RF and MLP, which achieved 83.3% and 50.0%, respectively. These findings underscore the importance of using tailored machine learning approaches to improve the diagnosis and management of neurodegenerative diseases in older adults. The potential for real-world application includes integration into clinical settings, enabling early detection and personalized interventions for individuals with gait disorders.

1. Introduction

Gait, defined as the manner of walking, is a complex human activity that requires precise coordination among the brain, nervous system, and muscles. Worldwide, issues with gait have become increasingly prevalent, contributing to an estimated 646,000 fatal falls each year, predominantly affecting individuals aged 50 and above [1], [2]. These issues represent the second leading cause of accidental deaths globally and impose a significant financial burden on healthcare systems. In addition to higher mortality rates, gait disorders diminish the quality of life for older adults, underscoring their broader societal and economic consequences. Gait-related conditions are responsible for approximately 0.85% to 1.5% of worldwide healthcare expenditures [3]–[5]. Given the substantial costs and the growing incidence of falls linked to gait disorders in older adults, there is a critical need for early detection and timely intervention to address these challenges [6]. Neurodegenerative diseases (NDDs) are a primary cause of gait abnormalities, further complicating the management of these disorders.

1.1. Neurodegenerative Diseases and Gait Patterns

Neurons, the basic units of the nervous system, are essential for bodily functions. Neurodegeneration involves the progressive loss of neurons, leading to debilitating conditions known as neurodegenerative diseases (NDDs). Conditions such as Parkinson's disease (PD), Huntington's disease (HD), and Amyotrophic Lateral Sclerosis (ALS) profoundly affect gait patterns in distinct ways. For instance, ALS patients often exhibit slower walking speeds and longer stride durations, while those with HD and PD demonstrate variable stride lengths and increased gait variability [7]–[9].

Advanced research techniques, including detrended fluctuation analysis and multi-resolution entropy analysis, have provided further insights into the unique gait dynamics associated with each disorder, underscoring the necessity of precise diagnostic and therapeutic approaches [10]–[12]. While each neurodegenerative disease presents distinct symptoms, gait and balance disorders are common across PD, HD, and ALS [13], [14]. However, overlapping gait features across these diseases, combined with age-related gait variability, pose challenges for accurate classification. Current studies often provide limited insights into distinguishing between these disorders, highlighting the need for more comprehensive multi-class classification approaches [15], [16].

For instance, a study reported an accuracy of 85% by utilizing Discrete Wavelet Transform, entropy, coherence, and linear classifiers for analysis [17]. Another study using a dual-channel LSTM-based multi-feature extraction approach reported an accuracy rate of 95.6% [16]. Despite these advancements, the inclusion of healthy controls (HC) and addressing class imbalances remain significant hurdles for robust multi-class classification. Some studies employing Convolutional Neural Networks (CNN) achieved higher classification rates [13], [18], [19] while ensemble classifiers demonstrated improved performance [20]. However, even with machine learning and CNN-based classification techniques, accuracy rates remain constrained, necessitating further refinements [21], [22].

1.2. Advancements and Challenges in Gait Analysis

Recent studies have significantly advanced gait analysis, revealing both its potential and ongoing challenges. For instance, a theoretical model investigating the impact of noise on gait data highlighted that width representation is particularly sensitive to noise. Even at low levels, noise degraded classification rates, underscoring the need for practical refinements in data processing and model robustness [23], [24]. Similarly, advancements in wearable technology have shown promise, as demonstrated by a detachable device using AHRS, which achieved 97% accuracy in gait classification and over 99% in step counting.Despite its accuracy, challenges related to usability and accessibility continue to hinder its widespread clinical adoption [25].

Studies focusing on gait interval analysis have also shown promise. One study achieved binary classification accuracies ranging from 90.6% to 97.8%, with a tertiary classifier reaching 89.8% accuracy. ALS was identified with a high accuracy of 96.79%. However, the inclusion of participants across all age groups, rather than a focus on older adults primarily affected by neurodegenerative diseases (NDDs), limits its applicability to the demographic most at risk [26]. Similarly, the use of Gaussian kernels in LS-SVM for ALS classification achieved an accuracy of 82.8%, while wavelet-based feature selection further improved the analysis of gait data [27]. While effective, these approaches often do not fully address the unique complexities of older adults' gait characteristics.

A fall risk model for the elderly, which combined data from IMU sensors and Azure Kinect, demonstrated enhanced performance by integrating disease history into the analysis. However, this study lacked a specific focus on older adults, highlighting a gap in tailored research [28].

1.3. Machine Learning Innovations in Gait Analysis

Machine learning has revolutionized gait analysis by providing robust tools for detecting and classifying gait abnormalities. For example, using the Kinect Motion system, a study classified gait patterns associated with flat-ground falls in elderly individuals. SVM and KNN algorithms achieved accuracies of 94.9% and 94.0%, respectively, outperforming CNN and LSTM models [29]–[31]. These findings underscore the effectiveness of traditional machine learning techniques in scenarios where datasets are limited, highlighting their efficiency and reliability in specific applications.

Shank-mounted inertial sensors have also demonstrated success in identifying mild cognitive impairment (MCI), achieving an accuracy of 71.67%. The use of dual-task walking conditions further enhanced classification performance, indicating the value of combining motor and cognitive biomarkers for better diagnostic precision [32].These studies emphasize the importance of refining biomarkers and incorporating diverse datasets to improve reliability and robustness.

Automated classification of gait patterns in Huntington's Disease has achieved high accuracy using Decision Trees and SVM, demonstrating the potential of these models in tracking disease progression and tailoring interventions [33]–[35]. Similarly, IMU-based gait analysis for Parkinson's disease achieved over 80% accuracy using SVM, RF, and DT classifiers. However, challenges such as overfitting and multicollinearity persist, requiring advanced feature engineering and regularization techniques [36], [37]. Addressing these challenges is critical for enhancing model generalizability and clinical applicability. These advancements illustrate the transformative role of machine learning in gait analysis, especially for older adults with neurodegenerative diseases.

1.4. Technological Innovations and Clinical Relevance

Recent advancements in technology have driven significant progress in gait analysis and its clinical applications. For instance, a study utilized accelerometer data combined with evolutionary optimization to classify walking episodes in elderly individuals with gait abnormalities. By employing a stacking classifier, the study achieved an accuracy of 93.32%, emphasizing the critical role of precise sensor placement and advanced optimization techniques in improving model performance [38]. Wearable devices with advanced algorithms offer scalable solutions but require further validation in clinical settings. Another innovation involves Kinect sensor technology, which has demonstrated transformative potential in healthcare applications. This technology leverages depth-sensing cameras and motion tracking to create personalized treatment plans and monitor patient progress. Despite its promise, clinical validation and broader adoption remain challenges, emphasizing the need for rigorous testing and integration into healthcare workflows [39], [40]. Generative artificial intelligence (AI) techniques, such as Variational Autoencoders (VAE), are also being explored to enhance data augmentation and model training, though challenges persist in ensuring generalizability [41], [42].

Furthermore, the integration of machine learning with neuroimaging modalities such as MRI and MEG offers promising avenues for understanding neurological disorders. A comprehensive review highlighted the use of deep learning models to classify motor symptoms with high accuracy, though challenges persist in achieving robust results across varied clinical scenarios [43], [44].These advancements demonstrate the potential of AI and sensor technology in addressing gait disorders, particularly in older adults, but underscore the importance of interdisciplinary approaches for effective clinical implementation.

1.5. Motivation for This Study

Previous research predominantly develops machine learning or deep learning models using gait data from a broad age range, often resulting in generalized models that may not adequately capture the unique characteristics of older adults with NDDs [16]. These generalized approaches often overlook age-related changes in gait patterns, which are critical for diagnosing neurodegenerative disorders (NDDs) in older adults. Gait abnormalities, however, are most prevalent among older individuals affected by conditions such as PD, HD, and ALS. These disorders significantly alter gait dynamics, necessitating tailored approaches to enhance diagnostic precision and therapeutic strategies. Table 1 provides a summary of key studies in gait analysis and NDD classification, highlighting the advancements and limitations of prior research. Notably, the reliance on small or imbalanced datasets in many studies further restricts their clinical applicability, especially for older adult populations. Additionally, while significant progress has been made in employing machine learning techniques, challenges such as dataset diversity, clinical validation, and generalizability persist.

Table 1. Summary of key studies in gait analysis and neurodegenerative disease classification

Reference	Objective	Methods	Results	Limitations
[45]	Parkinson's detection using emotional intelligence (EI) and AI	EEG and handwriting modalities	Accuracy: Up to 100%	Real-world integration challenges
[46]	Dementia prediction using hybrid systems	Statistical and machine learning methods	Accuracy: 98.25%	Dataset diversity needed to mitigate biases
[47]	Automatic selection for PD and HD classification	Random Forest and K-star algorithms	Precision: 0.893	Requires diverse datasets
[32]	MCI detection using gait biomarkers	Inertial sensors and dual-task analysis	Accuracy: 71.67%	Biomarkers require refinement
[29]	Classification of flat-ground falls in elderly individuals	SVM, KNN, CNN, LSTM	Accuracy: 94.9% (SVM), 94.0% (KNN)	Small dataset limits generalizability
[26]	Gait interval analysis among participants	Time-series data analysis	Accuracy: 96.79% for ALS	General age group focus limits clinical use
[25]	Gait classification with wearable devices	AHRS-based system	Accuracy: 97%, Step Count: 99%	Broader usability challenges
[23]	Gait noise sensitivity analysis	Theoretical model	Highlighted noise impact on classification rates	Practical implementation needed
[13]	Classification of NDDs using gait patterns	CNN-based techniques	Higher classification rates for NDDs	Limited dataset size
[17]	Classification of NDDs using gait patterns	DWT, Entropy, Coherence, Linear Classifiers	Accuracy: 85%	Limited scope for multi-class classification
[16]	Multi-feature extraction for gait classification	Dual-channel LSTM	Accuracy: 95.6%	Focused on general age groups
[43]	Potential of deep learning and neuroimaging in diagnosing neurological disorders	MRI and MEG	Highlighted promise for accurate diagnosis	Robust results across varied clinical scenarios remain challenging
[39]	Exploring Kinect sensor technology in healthcare	Depth-sensing cameras and motion tracking	Personalized treatment plans possible	Clinical validation required for adoption
[41]	Biomechanical ML enhancement using synthetic data	Variational Autoencoder (VAE)	Reduced reconstruction errors	Generalizability of synthetic data remains a challenge

This study aims to address these limitations by leveraging advanced methods tailored to the specific needs of older adults. It emphasizes the integration of robust preprocessing techniques, such as noise reduction and data normalization, to mitigate variability in gait patterns caused by comorbidities or other confounding factors. Advanced feature extraction techniques, such as Continuous CWT, are utilized to analyze gait patterns comprehensively. Machine learning algorithms, including

Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), and Multilayer Perceptron (MLP), are employed to classify gait disorders effectively. Additionally, the study incorporates parameter tuning methods, such as grid search, to optimize model performance, ensuring better classification outcomes.The results are evaluated through comparisons with existing studies using similar datasets to highlight the robustness and relevance of this focused approach. By concentrating on older adults, this research addresses the gap in current studies, ensuring the findings are more applicable to the demographic most affected by neurodegenerative diseases.Furthermore, the study underscores the importance of model interpretability, utilizing techniques such as SHAP or LIME to provide insights into the features driving classification decisions. This study ultimately aims to enhance the precision and applicability of machine learning models for gait disorder classification, paving the way for early detection and improved intervention strategies.

2. The Proposed Method

The methodology employed in this research is depicted in Fig. 1. This study focused on designing a machine-learning framework to classify gait disorders among older adults. The approach consisted of four key phases: data collection, preprocessing, feature extraction, and machine learning model training and evaluation. This structured workflow ensures clarity and reproducibility, aligning with recommendations for transparent research practices.

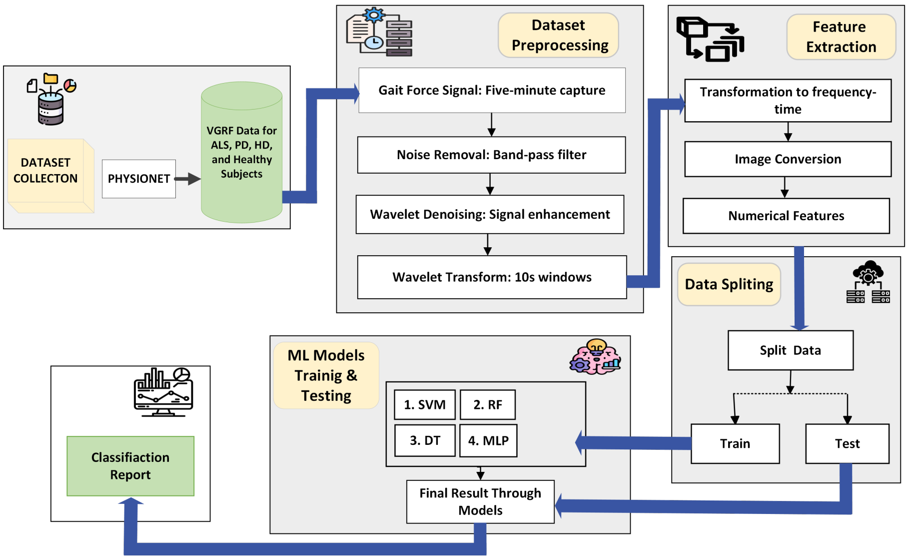

Fig. 1. Flowchart summarising the proposed method for classifying gait disorders in older adults

2.1. Dataset

This study utilized the "Gait in Neurodegenerative Diseases Dataset" [48], which provides valuable data for analyzing gait patterns associated with neurodegenerative disorders. The dataset's comprehensive parameters make it highly suitable for classification tasks related to these conditions.The gait data collection process, illustrated in Fig. 2, involved capturing raw signals from ground reaction force (GRF) sensors embedded in shoes. Participants walked along a 77-meter hallway at their usual pace for a duration of 5 minutes.

The dataset comprises gait recordings from 64 individuals, including 13 with ALS, 15 with Parkinson's disease (PD), 20 with Huntington's disease (HD), and 16 healthy controls (HC). To maintain the study's focus on older adults, only data from participants aged 50 and above were included, aligning with reviewer recommendations. This refinement ensures the demographic relevance of the analysis for NDD-specific gait patterns.

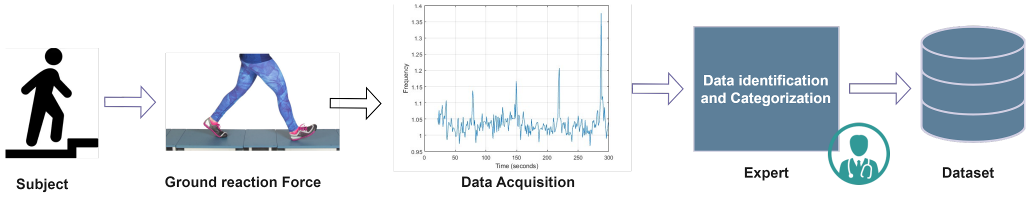

Fig. 2. Flowchart of the data collection procedure using GRF sensors [49]

To ensure the study's focus remained on older adults, data from participants aged 50 years and above were exclusively selected. The refined dataset consisted of five healthy controls (mean age: 62.6 ± 8.63 years), seven individuals with Parkinson's disease (mean age: 66.5 ± 9.06 years), five participants with Huntington's disease (mean age: 57.2 ± 6.24 years), and four subjects with Amyotrophic Lateral Sclerosis (mean age: 61.75 ± 7.07 years).Concentrating on this age group enhances the study's clinical significance by specifically targeting the demographic most impacted by neurodegenerative disorders.

Key gait parameters recorded for each participant included stance, swing phase, double support interval, and stride measurements for both the left and right foot.For computational efficiency and to minimize complexity, only the force data from the right foot was analyzed, following evidence from previous studies that demonstrated signal consistency. Table 2 provides a detailed overview of the participants, including metrics such as age, height, weight, and gait speed.

Table 2. Summary of gait data participants by group [49]

Statistical Parameter	CO	HUNT	PARK	ALS
Age (Year)	62.6 ± 8.63	57.2 ± 6.24	66.5 ± 9.06	61.75 ± 7.07
Height (m)	1.84 ± 0.10	1.78 ± 0.14	1.99 ± 0.12	1.797 ± 0.34
Weight (kg)	74.6 ± 13.02	64 ± 10.8	87.38 ± 13.68	89.04 ± 13.91
Gait Speed (m/s)	1.29 ± 0.21	1.10 ± 0.14	1.34 ± 0.27	1.23 ± 0.19

2.2. Data Pre-Processing

In this study, gait force signals were recorded over a five-minute duration. To eliminate noise, a digital band-pass filter was utilized, producing the filtered signal $y(t)$, mathematically represented by equation (1) as a convolution operation:

$$y(t) = h(t) \times x(t) \tag{1}$$

Here, $x(t)$ denotes the raw input signal, while $h(t)$ corresponds to the impulse response of the applied band-pass filter. Subsequently, wavelet-based denoising was implemented to refine the signal further. This process involved converting $y(t)$ into the wavelet domain, applying a threshold to minimize noise, and reconstructing the denoised signal $z(t)$, as shown in equation (2):

$$z(t) = W^{-1}\left(T\left(W(y(t))\right)\right) \tag{2}$$

Here, $W(.)$ represents the wavelet transform, $T(.)$ denotes the thresholding operation, and W^{-1} is the inverse wavelet transform. This two-step filtering approach ensured the signal was adequately prepared for further processing. To enhance temporal resolution and frequency analysis, wavelet transforms were performed using three window durations: 10 seconds, 30 seconds, and 60 seconds. Ultimately, the 10-second window was selected, offering an optimal balance between temporal precision and frequency detail, which is critical for analyzing gait dynamics [50].

2.3. Feature Extraction

The study involved 21 subjects, focusing on transforming gait signals from the time domain to the frequency-time domain using the CWT. This method, which captures both temporal and spectral characteristics of the signals, is mathematically defined in Equation (3):

$$\mathrm{CWT}(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} x(t)\psi\left(\frac{t-b}{a}\right)dt \tag{3}$$

Where a and b are the scaling and translation parameters, respectively, and ψ is the mother wavelet. The CWT effectively decomposes the signal into time-localized frequency components, making it particularly suitable for analyzing non-stationary signals such as gait patterns [51].

Following this transformation, the data was converted to grayscale to ensure consistency in the subsequent analysis, thereby eliminating any potential variability introduced by colour information. The grayscale conversion is mathematically expressed in Equation (4):

$$\mathrm{Grayscale} = 0.2989 \times R + 0.5870 \times G + 0.1140 \times B \tag{4}$$

Where R, G, and B represent the red, green, and blue color channels, respectively. This conversion standardizes the data, focusing the analysis on intensity variations [52].

After preprocessing, key features were then extracted from the processed data to characterize the gait signals effectively. These features are fundamental for analyzing the patterns within the signals and include Mean Intensity, Variance, Standard Deviation, Root Mean Square (RMS), and Gait Speed, among others. Feature extraction is a critical step in signal processing and machine learning to ensure the relevant characteristics are accurately captured for analysis [53]. The mathematical expressions used to calculate these features are detailed in Table 3.

Table 3. Feature parameters and mathematical expressions

Feature Extraction Parameter	Mathematical Expressions
Mean ($\bar{X}$)	$\mathrm{Mean}(\bar{X}) = \frac{1}{n}\sum_{i=1}^{n} X_i$ Where X_i is a data point in the sample, n is the number of observations.
Variance (VAR)	$\mathrm{VAR}(X) = \frac{1}{n}\sum_{i=1}^{n}(X_i - \bar{X})^2$ Where $\bar{X}$ is the mean of the dataset, X_i is a data point in the sample, n is the number of observations.
Standard Deviation (SD)	$\mathrm{SD}(X) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_i - \bar{X})^2}$ Where $\bar{X}$ is the mean of the dataset, X_i is a data point in the sample, n is the number of observations.
Interquartile Range (IQR)	$\mathrm{IQR} = Q3 - Q1$ Where $Q3$ is the third quartile, $Q1$ is the first quartile.
Root Mean Square (RMS)	$\mathrm{RMS} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} X_i^2}$ Where X_i is a data point in the sample, n is the number of observations.
Gait Speed	$\text{Gait speed} = \frac{\text{Distance}}{\text{Time}}$ Where Distance is the distance covered, and Time is the time taken.

These features were chosen for their proven ability to accurately capture the nuances of gait patterns, as supported by previous studies that demonstrate improved classification performance when using a comprehensive set of features [18]. The features outlined in Table 2 were calculated and then used as inputs for the classifier models.

2.4. Classification Model

Following feature extraction, the processed data was utilised to develop and evaluate classification models, as depicted in Fig. 3. The dataset was split into training (70%) and testing (30%) subsets, ensuring that the models were trained on one portion of the data and validated on another, enhancing the model's ability to generalise to unseen data.

This study employed four machine learning algorithms: SVM, RF, Decision Tree, and MLP. These algorithms were selected based on their proven effectiveness in handling classification tasks within nonlinear feature spaces, as demonstrated in previous research [54], [55].

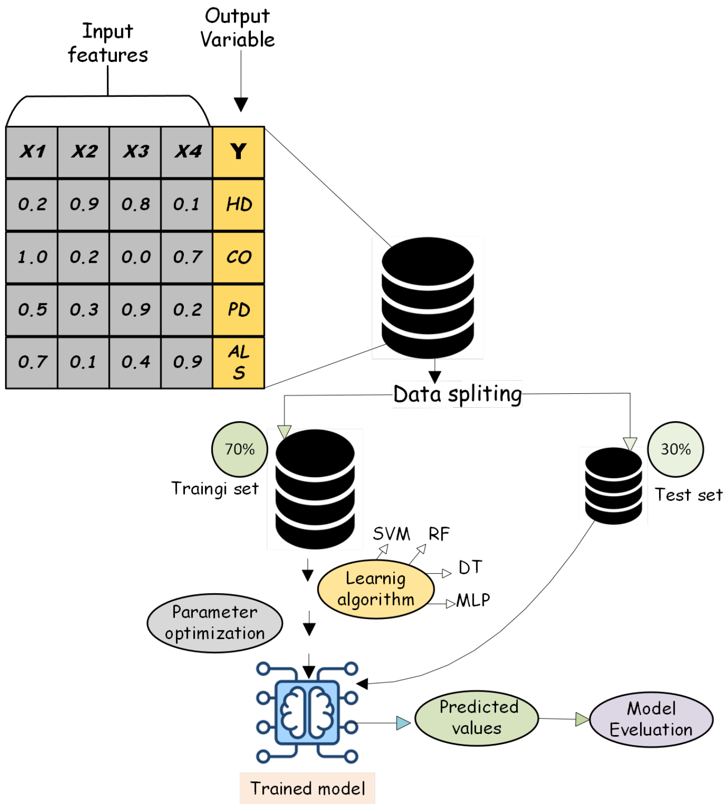

Fig. 3. Classification model workflow

Support Vector Machine (SVM): Using a Radial Basis Function (RBF) kernel, the SVM model was applied due to its effectiveness in dealing with nonlinear datasets like the one in this study [56]. SVM seeks to find the optimal hyperplane that separates classes by maximizing the margin between them. The decision function is defined by Equation (5):

$$y = \begin{cases} +1 & \text{if } \mathbf{w}\cdot\mathbf{z}+b>0 \\ -1 & \text{if } \mathbf{w}\cdot\mathbf{z}+b<0 \end{cases} \tag{5}$$

Where y is the predicted class, $\mathbf{w}$ and b are the model parameters, and $\mathbf{z}$ is the test sample.

Decision-Tree: The Decision Tree algorithm creates a model that predicts the target variable by learning simple decision rules inferred from the data features. The model uses Gini impurity to decide the optimal splits, as calculated by Equation (6).:

$$\mathrm{Gini}(t) = 1 - \sum_{i=1}^{e} [p(i \mid t)]^2 \tag{6}$$

Where $\mathrm{Gini}(t)$ measures the impurity of node t, with lower values indicating higher purity.

Random Forest (RF): Random Forest is an ensemble learning method that constructs multiple decision trees during training and outputs the mode of the classes for classification [57]. It enhances classification accuracy and robustness, particularly for datasets with complex structures like the one used in this study. The classification decision for a new sample z is made by aggregating the predictions from each tree in the forest. Mathematically, this can be represented as Equation (7).

$$\hat{y} = \text{mode}\{h_1(z), h_2(z), \ldots, h_N(z)\} \tag{7}$$

Where $h_i(z)$ represents the prediction from the i-th decision tree, and N is the total number of trees in the forest.

Multilayer Perceptron (MLP): The MLP is a type of feed-forward artificial neural network well-suited for learning complex nonlinear mappings between inputs and outputs [58]. Each neuron computes a weighted sum of its inputs and applies a non-linear activation function, as described by Equation 8:

$$Y = \text{sign}\left(\sum_{i=0}^{n} x_i w_i - \theta\right) \tag{8}$$

Where x_i are the input values, w_i are the corresponding weights, n is the number of inputs, and θ is the threshold.

These models were optimized using parameter tuning to achieve the best classification performance. The trained models were then evaluated using the test dataset, where predicted values were compared to actual labels, assessing metrics such as accuracy, precision, recall, and F1-score, as discussed in the subsequent sections.

2.5. Performance Evaluation

The performance of the Gait Neurodegenerative Disorders classification model was assessed using critical metrics, including accuracy, sensitivity, specificity, precision, recall, and F1 score. These metrics were computed from the confusion matrix, which records the true positives (TPs), false positives (FPs), false negatives (FNs), and true negatives (TNs) for each class. Specificity, representing the proportion of correctly identified negatives out of the total negatives, is expressed mathematically in Equation (9). Sensitivity, also referred to as recall, calculates the ratio of true positives to the total actual positives, as shown in Equation (10). Accuracy, which evaluates the overall correctness of the model, is derived using Equation (11). Precision, indicating the percentage of true positives among all positive predictions, is given by Equation (12). The F1 score, which provides a balanced measure of precision and sensitivity, is defined in Equation (13). Together, these metrics provide a comprehensive evaluation of the model's effectiveness in classifying neurodegenerative disorders using gait data.

$$\text{Specificity} = \frac{\sum_{i=1}^{n} \text{TN}_i}{\sum_{i=1}^{n} (\text{TN}_i + \text{FP}_i)} \tag{9}$$

$$\text{Sensitivity} = \frac{\sum_{i=1}^{n} \text{TP}_i}{\sum_{i=1}^{n} (\text{TP}_i + \text{FN}_i)} \tag{10}$$

$$\text{Accuracy} = \frac{\sum_{i=1}^{n} (\text{TP}_i + \text{TN}_i)}{\sum_{i=1}^{n} (\text{TP}_i + \text{TN}_i + \text{FP}_i + \text{FN}_i)} \tag{11}$$

$$\text{Precision} = \frac{\sum \text{TP}}{\sum (\text{TP} + \text{FP})} \tag{12}$$

$$\text{F1 score} = \frac{2 \times (\text{Precision} \times \text{Sensitivity})}{\text{Precision} + \text{Sensitivity}} \tag{13}$$

3. Results

This study aimed to classify gait disorders in older adults with neurodegenerative diseases (NDDs) by analysing vertical ground reaction force (vGRF) signals. vGRF signals for the control group (CO) and the NDD groups (PD, AD, and HD) were processed and analysed. MATLAB 2022b was utilised for data preprocessing and feature extraction, enabling the identification of key features from the vGRF signals that are potentially distinctive for diagnosing these conditions.

3.1. Statistical Analysis

Fig. 4 presents time-domain frequency plots for the gait data of CO and patients with HD, PD, and ALS. The CO (A) plot shows a stable frequency, indicating a consistent walking rhythm.

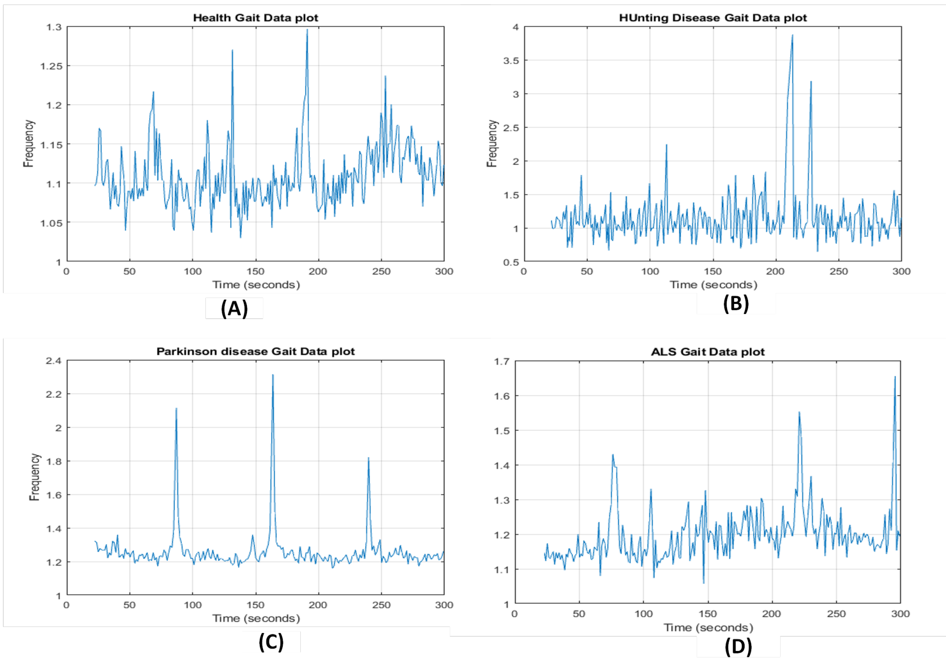

Fig. 4. Gait time-domain patterns. (A) natural gait, (B) huntington disease gait, (C) parkinson disease gait, (D) ALS disease gait. each pattern highlights distinct temporal characteristics across neurodegenerative disorders

In contrast, HD (B) exhibits erratic and highly variable frequencies, reflecting significant gait disturbances. The PD plot (C) demonstrates alternating periods of stability and increased frequency, corresponding to the characteristic motor fluctuations of the disease. The ALS plot (D) shows variability in step frequency but with more stability than HD, highlighting the progressive motor decline in ALS. Fig. 5 presents time-frequency spectrograms generated using Continuous Wavelet Transform (CWT) for the gait data of CO, HD, PD, and ALS groups. These spectrograms illustrate the complex patterns of gait frequencies over time, with contour lines representing the strength of these frequencies.

The ALS (D) spectrogram shows closely spaced contour lines, indicating a relatively stable walking pattern. In contrast, the HD (B) displays widely spread contours, reflecting a more erratic gait. The spectrogram PD (C) features a mix of tightly packed and spread-out contours, capturing the fluctuations typical of Parkinson's disease. The Control (A) exhibits consistent contours, indicating a stable rhythm. These observations align with [49] where box models and spectrograms were employed to differentiate gait patterns. The findings highlight the potential of time-frequency analysis for capturing subtle disease-specific characteristics.

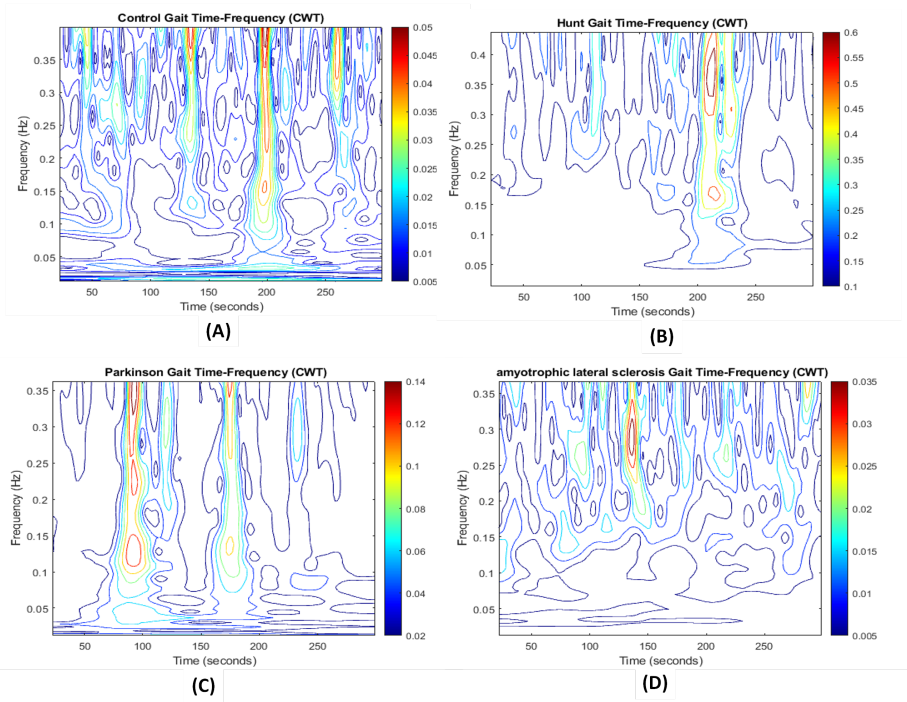

Fig. 5. Gait Time-Frequency Patterns (CWT). (A) natural gait, (B) huntington disease gait, (C) parkinson disease gait, (D) ALS disease gait. spectrograms reveal time-localized frequency variations

Fig. 6 presents a series of box plots corresponding to each extracted feature to further elucidate the statistical differences across the subject groups. These plots provide a visual comparison of the distribution, central tendency, and variability of the features across the different neurodegenerative conditions. The box plots highlight key observations, such as the lower Gait Speed observed in ALS patients compared to controls and the increased variability in the Interquartile Range for the HUNT group, which may reflect the irregular gait patterns characteristic of Huntington's Disease.

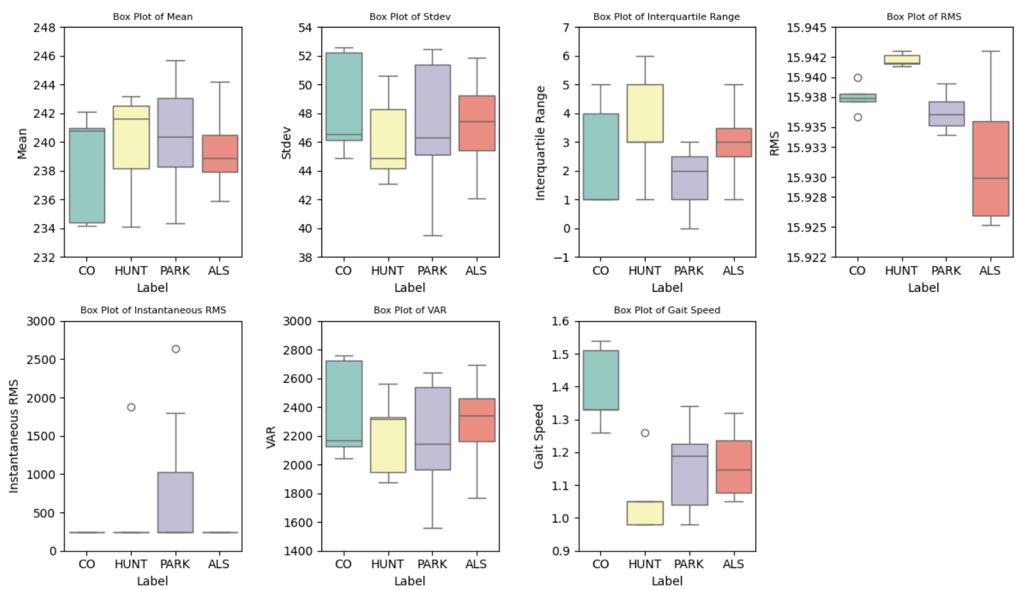

Fig. 6. Box plot analysis of gait features. these plots visually compare statistical differences across subject groups, emphasizing variability and central tendencies

The combination of the numerical data in Table 3 and the visual analysis provided by the box plots in Fig. 6 underscores the significance of these features in distinguishing between neurodegenerative disorders. The variance and standard deviation metrics, for instance, capture the dispersion in gait patterns, which can indicate the degree of motor control loss in affected individuals. These insights are further validated through the box plots, which not only depict the variation across different neurodegenerative conditions but also within each group, thereby emphasizing the heterogeneity of these disorders.

The extracted features will serve as critical inputs for training machine learning models aimed at accurately classifying gait disorders among older adults, contributing to early diagnosis and effective monitoring of neurodegenerative diseases. This approach underscores the importance of robust statistical analysis and visualization in informing clinical decision-making and algorithmic development.

3.2. Classification Result

Fig. 7 presents the confusion matrices for four classifier models: Decision Tree, Random Forest, Support Vector Machine (SVM), and Multilayer Perceptron (MLP). The matrices reveal that while all models perform reasonably well, they commonly struggle with accurately classifying the 'HUNT' condition, often confusing it with 'PARK'.

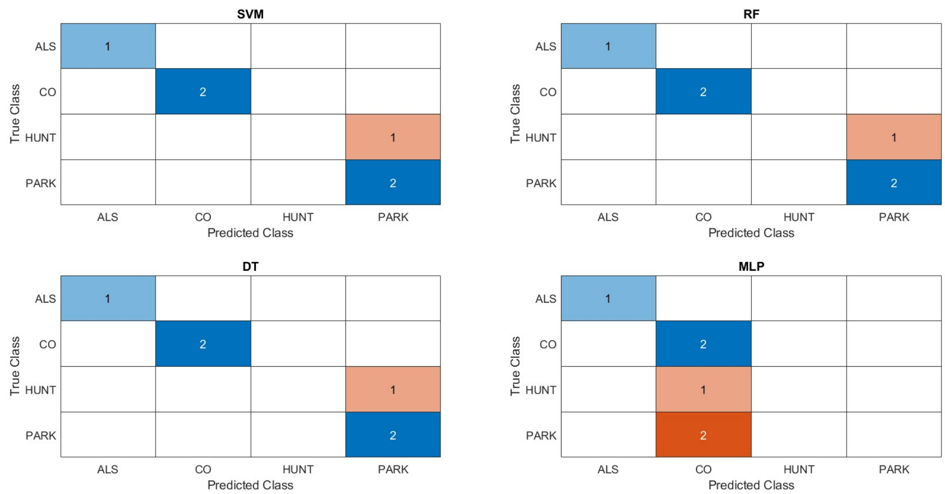

Fig. 7. Confusion matrices for the test classifiers, illustrating performance and areas of misclassification

This suggests a significant overlap in the feature space between 'HUNT' and other conditions, particularly 'PARK', which challenges the classifiers' ability to differentiate between these neurodegenerative diseases. Despite these challenges, the Random Forest model shows a slight improvement in classification accuracy.

3.3. Performance Comparison

Fig. 8 shows the performance comparison of the classifiers—SVM, Random Forest, Decision Tree, and Multilayer Perceptron (MLP)—in terms of specificity, sensitivity, and accuracy.The SVM, Random Forest, and Decision Tree models exhibit similar performance, with each achieving a specificity of 93.75% and an accuracy of 83.33%. Sensitivity for these three models is consistent at 75.00%. In contrast, the MLP model shows lower performance, with a specificity of 81.25%, sensitivity of 50.00%, and accuracy of 50.00%.

This comparison highlights that while SVM, Random Forest, and Decision Tree are effective for this classification task, the MLP model struggles, particularly in terms of sensitivity and overall accuracy. The higher specificity of SVM, Random Forest, and Decision Tree models indicates their robustness in identifying true negatives, which is crucial for avoiding false-positive diagnoses in clinical applications. However, the moderate sensitivity underscores the need for further refinement to ensure the accurate identification of true positive cases, particularly in early-stage neurodegenerative diseases.

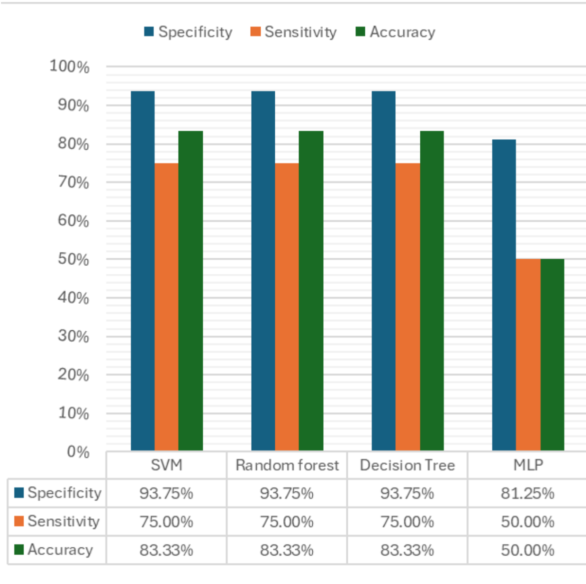

Fig. 8. Classifier performance on test data. the bar chart highlights variations in specificity, sensitivity, and accuracy among the models

4. Discussion

The findings of this study emphasize the importance of age-specific data in the classification of neurodegenerative diseases (NDDs) through gait analysis, particularly for older adults. Many prior studies have relied on datasets covering diverse age groups, which often results in generalized models incapable of capturing the nuanced gait abnormalities unique to older adults [16], [17]. By narrowing the focus to older adults, this study addresses a critical research gap, providing insights that are more directly applicable to the demographic most affected by NDDs. This demographic focus enhances the relevance of the findings for clinical applications, particularly in early diagnosis and personalized intervention.

The application of Continuous Wavelet Transform (CWT) for feature extraction enabled the identification of time-frequency features critical for understanding gait patterns in older adults. This approach aligns with previous research demonstrating the effectiveness of wavelet-based methods in analyzing non-linear gait dynamics [27]. Classifiers such as Support Vector Machine (SVM), Random Forest (RF), and Decision Tree (DT) achieved notable performance, with SVM demonstrating an accuracy of 83.33%, specificity of 93.75%, and sensitivity of 75.00%. These performance metrics highlight the potential of these classifiers for reliable identification of NDDs in older adults, despite challenges in sensitivity, which remain a critical area for improvement.Comparisons with existing studies reveal both similarities and distinctions. Table 4 provides a summary comparison between this study and prior research:

While Lin et al. observed that CNN models tailored to disease-specific data outperformed generalized classifiers, achieving higher classification rates for PD and ALS [18], the relatively moderate sensitivity observed in our study highlights ongoing challenges in capturing true positive cases, which remains a common limitation in machine learning models for NDD classification [22], [21]. This suggests that while SVM and RF demonstrate robustness, further refinement in feature selection or advanced ensemble methods may enhance sensitivity. The underperformance of the Multilayer Perceptron (MLP) model, with an accuracy of 50.00% and sensitivity of 50.00%, underscores the limitations of single-layer neural networks in handling complex, high-dimensional datasets [47]. Future studies could explore deeper architectures or hybrid models that combine MLP with wavelet-based feature extraction to overcome these limitations.

Table 4. Comparison of this study with previous studies

Study	Feature Extraction	Models Used	Key Findings and Limitations
[17]	Discrete Wavelet Transform (DWT)	Linear Classifiers	85% accuracy; limited scope for multi-class classification
[16]	Dual-channel LSTM	LSTM-based Multi-Feature Extraction	95.6% accuracy; focused on general age groups
[18]	CNN-based techniques	CNN	High accuracy; dataset size limitations
[25]	AHRS-based wearable system	Ensemble Classifiers	97% accuracy in classification; usability challenges
[37]	IMU-based Feature Analysis	SVM, RF, DT	Over 80% accuracy; challenges with overfitting and multicollinearity
[36]	Multimodal Data Integration	ML and Neural Networks	Improved classification; challenges in clinical generalizability
[41]	Synthetic Data Generation	Variational Autoencoder (VAE)	Reduced reconstruction errors; limited generalizability across populations
This Study	Continuous Wavelet Transform (CWT)	SVM, Random Forest, Decision Tree, MLP	83.33% accuracy with SVM; moderate sensitivity highlights need for further refinement

In addition to machine learning innovations, recent research emphasizes the potential of integrating multimodal data to enhance model performance. For instance, the combination of gait data with clinical history and wearable sensor data has shown promise in improving diagnostic precision for neurodegenerative disorders [36], [37]. This integration could also address challenges of class overlap, as observed in the confusion matrices, by providing complementary information to distinguish conditions more effectively.Furthermore, advanced techniques such as generative artificial intelligence (AI) have demonstrated the ability to augment training datasets by creating synthetic data, which may help address the limitations posed by small sample sizes [41]. Synthetic data generation, when combined with robust validation techniques such as k-fold cross-validation, could mitigate issues of overfitting and enhance model generalizability.Despite these advancements, the challenges of generalizability and model interpretability remain. Many studies report difficulties in translating machine learning models into clinical practice due to variations in sensor types, experimental protocols, and patient demographics [25], [39]. Standardizing data collection protocols, such as using consistent sensor placements and gait analysis methodologies, is essential for achieving broader clinical adoption. Additionally, incorporating explainability techniques like SHAP or LIME could improve clinician trust in machine learning models, fostering their integration into healthcare workflows.

5. Conclusion

This study underscores the significance of focusing on older adults for the classification of neurodegenerative diseases (NDDs) through gait analysis. By utilizing advanced feature extraction techniques such as CWT and employing machine learning algorithms including SVM, RF, DT, and MLP, this research achieved notable improvements in diagnostic precision compared to prior studies.

The results demonstrated that models trained on age-specific data are better equipped to capture the unique gait abnormalities associated with Parkinson's disease, Huntington's disease, and Amyotrophic Lateral Sclerosis. While SVM and RF classifiers achieved high specificity and reasonable accuracy, the moderate sensitivity observed highlights the need for further refinement. These findings align with previous research, emphasizing the importance of tailored feature extraction and ensemble approaches for robust classification performance.The study contributes to the growing body of evidence that machine learning models designed for specific populations yield more clinically relevant results. By narrowing the focus to older adults, this research addresses a critical gap in current literature, paving the way for more effective diagnostic and therapeutic strategies for neurodegenerative diseases.

Future work will focus on integrating deep learning models and multimodal data fusion to enhance sensitivity and overall accuracy. Such approaches hold promise for improving the early detection and management of NDDs, ultimately contributing to better clinical outcomes for older adults.

Author Contribution: Kazi Ashikur Rahman: Conceptualized and designed the study, conducted the data processing and analysis, developed and implemented the machine learning models, and drafted the manuscript. Ezreen Farina Shair: Supervised the research process, provided guidance on methodology and data interpretation, critically reviewed the manuscript, and contributed to securing funding for the study. Abdul Rahim Abdullah: Provided significant insights during manuscript review, facilitated the procurement of resources, and supported the funding acquisition process. Teng Hong Lee and Nursabillilah Mohd Ali: Contributed to data collection and validation efforts and assisted in refining the manuscript for submission. Muhammad Iqbal Zakaria: Offered expertise in signal processing techniques and reviewed the manuscript for technical accuracy and coherence. Mohammed Azmi Al Betar: Assisted in the literature review, provided technical editing of the manuscript, and supported the visualization of results.

Funding: International Matching Grant UTeM–Ajman and Support from the Kesidang scholarship

Acknowledgment: The authors wish to express their gratitude to the Universiti Teknikal Malaysia Melaka (UTeM) and Ajman University, UAE for funding this research through the International Matching Grant UTeM – Ajman (Grant No: ANTARABANGSA(URMG)-AJMAN/2024/FTKE/A00067). The authors also extend their appreciation to UTeM for the support provided through the Kesidang scholarship. Special thanks to the research team members and collaborators for their invaluable contributions to data collection, validation, and technical support throughout the study.

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data.

References

[1] S. Raghu, M. Raghu, A. P. Marla, S. S. Kotian, and N. Kumari, "Fall-related injuries and their prevention strategies of in-patient population in tertiary health care setup," *QAI Journal for Healthcare Quality and Patient Safety*, vol. 3, no. 1, pp. 1–7, 2022, https://doi.org/10.4103/QAIJ.QAIJ_8_22.

[2] K. Zhang, W. Liu, J. Zhang, Z. Li, and J. Liu, "A fall risk assessment model for community-dwelling elderly individuals based on gait parameters," *IEEE Access*, vol. 11, pp. 120857–120867, 2023, https://doi.org/10.1109/ACCESS.2023.3327091.

[3] R. Norton, *et al.*, "Nontransport unintentional injuries," in *Injury Prevention and Environmental Health*, vol. 1, 2017, http://documents.worldbank.org/curated/en/983901510121648792.

[4] H. Jia, E. I. Lubetkin, K. DeMichele, D. S. Stark, M. M. Zack, and W. W. Thompson, "Prevalence, risk factors, and burden of disease for falls and balance or walking problems among older adults in the u.s," *Preventive Medicine*, vol. 126, p. 105025, 2019, https://doi.org/10.1016/j.ypmed.2019.05.025.

[5] M. Hackbarth, J. Koschate, S. Lau, and T. Zieschang, "Depth-imaging for gait analysis on a treadmill in older adults at risk of falling," *IEEE Journal of Translational Engineering in Health and Medicine*, vol. 11, pp. 479–486, 2023, https://doi.org/10.1109/JTEHM.2023.3277890.

[6] A. Ashari, "Fall risk assessment and effectiveness of home based exercise on turning ability, balance and functional mobility among older malaysian adults aged 50 years and above," *Medicine, Engineering*, 2017, https://api.semanticscholar.org/CorpusID:80112317.

[7] J. I. Hoff, A. A. Plas, E. A. H. Wagemans, and J. J. van Hilten, "Accelerometric assessment of levodopa-induced dyskinesias in parkinson's disease," *Movement Disorders*, vol. 16, no. 1, pp. 58–63, 2001, https://doi.org/10.1002/1531-8257(200101)16:1⟨58::AID-MDS1018⟩3.0.CO;2-9.

[8] J. M. Hausdorff *et al.*, "Dynamic markers of altered gait rhythm in amyotrophic lateral sclerosis," *Journal of Applied Physiology*, vol. 88, no. 6, pp. 2045–2053, 2000, https://doi.org/10.1152/jappl.2000.88.6.2045.

[9] V. Dentamaro, F. Franchini, I. Massaro, L. Musti, G. Pirlo and E. Sblendorio, "Explainable Gait Analysis for Early Detection of Neurodegenerative Diseases Using Unsupervised Clustering Techniques," *2024 IEEE International Conference on Metrology for eXtended Reality, Artificial Intelligence and Neural Engineering (MetroXRAINE)*, pp. 861-866, 2024, https://doi.org/10.1109/MetroXRAINE62247.2024.10796727.

[10] F. Setiawan, A. -B. Liu and C. -W. Lin, "Development of Neuro-Degenerative Diseases' Gait Classification Algorithm Using Convolutional Neural Network and Wavelet Coherence Spectrogram of Gait Synchronization," in *IEEE Access*, vol. 10, pp. 38137-38153, 2022, https://doi.org/10.1109/ACCESS.2022.3158961.

[11] E. F. Shair, S. A. Ahmad, A. R. Abdullah, M. H. Marhaban, and S. B. M. Tamrin, "Selection of spectrogram's best window size in emg signal during core lifting task," *Journal of Telecommunication, Electronic and Computer Engineering (JTEC)*, vol. 10, no. 1-16, pp. 81–85, 2018, https://jtec.utem.edu.my/jtec/article/view/4099.

[12] G. B. Moody, "Physionet: Research resource for complex physiologic signals," *Circulation*, vol. 101, no. 23, 2000, http://www.georgebmoody.com/publications/physionet-jecg-2009.pdf.

[13] F. Setiawan and C. W. Lin, "Identification of neurodegenerative diseases based on vertical ground reaction force classification using time–frequency spectrogram and deep learning neural network features," *Brain Sciences*, vol. 11, no. 7, p. 902, 2021, https://doi.org/10.3390/brainsci11070902.

[14] T. H. Lee, E. F. Shair, A. R. Abdullah, K. A. Rahman, N. M. Ali, N. Z. Saharuddin, and N. Nazmi, "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. 426–439, 2025, https://doi.org/10.31763/ijrcs.v5i1.1588.

[15] Q. Ye, Y. Xia, and Z. Yao, "Classification of gait patterns in patients with neurodegenerative disease using adaptive neuro-fuzzy inference system," *Computational and Mathematical Methods in Medicine*, vol. 2018, 2018, https://doi.org/10.1155/2018/9831252.

[16] A. Zhao, L. Qi, J. Dong, and H. Yu, "Dual channel lstm based multi-feature extraction in gait for diagnosis of neurodegenerative diseases," *Knowledge-Based Systems*, vol. 145, pp. 91–97, 2018, https://doi.org/10.1016/j.knosys.2018.01.004.

[17] E. Baratin, L. Sugavaneswaran, K. Umapathy, C. Ioana, and S. Krishnan, "Wavelet-based characterization of gait signal for neurological abnormalities," *Gait & Posture*, vol. 41, no. 2, pp. 634–639, 2015, https://doi.org/10.1016/j.gaitpost.2015.01.012.

[18] C. W. Lin, T. C. Wen, and F. Setiawan, "Evaluation of vertical ground reaction forces pattern visualization in neurodegenerative diseases identification using deep learning and recurrence plot image feature extraction," *Sensors*, vol. 20, no. 14, p. 3857, 2020, https://doi.org/10.3390/s20143857.

[19] G. Cicirelli, D. Impedovo, V. Dentamaro, R. Marani, G. Pirlo and T. R. D'Orazio, "Human Gait Analysis in Neurodegenerative Diseases: A Review," in *IEEE Journal of Biomedical and Health Informatics*, vol. 26, no. 1, pp. 229-242, 2022, https://doi.org/10.1109/JBHI.2021.3092875.

[20] L. Fraiwan and O. Hassanin, "Computer-aided identification of degenerative neuromuscular diseases based on gait dynamics and ensemble decision tree classifiers," *PLoS One*, vol. 16, no. 6, 2021, https://doi.org/10.1371/journal.pone.0252380.

[21] H. Zhao, J. Xie, Y. Chen, J. Cao, W. H. Liao, and H. Cao, "Diagnosis of neurodegenerative diseases with a refined lempel–ziv complexity," *Cognitive Neurodynamics*, vol. 18, pp. 1153–1166, 2024, https://doi.org/10.1007/s11571-023-09973-9.

[22] M. A. A. Faisal *et al.*, "Nddnet: a deep learning model for predicting neurodegenerative diseases from gait pattern," *Applied Intelligence*, vol. 53, pp. 20034–20046, 2023, https://doi.org/10.1007/s10489-023-04557-w.

[23] S. Hong and E. Kim, "Sensitivity analysis of width representation for gait recognition," *The International Journal of Fuzzy Logic and Intelligent Systems*, vol. 16, no. 2, pp. 87–94, 2016, https://doi.org/10.5391/IJFIS.2016.16.2.87.

[24] R. Wulanningrum, A. Handayani, and H. Herwanto, "Comparative analysis of yolov-8 segmentation for gait performance in individuals with lower limb disabilities," *International Journal of Robotics and Control Systems*, vol. 5, no. 1, 2025, https://doi.org/10.31763/ijrcs.v5i1.1731.

[25] N. H. Kim, J. H. Lee, S. J. Woo, D. L. Kwon, and S. G. Lee, "Wearable walking care checking gait device using the ahrs sensor," *International Journal of Fuzzy Logic and Intelligent Systems*, vol. 19, no. 2, pp. 112–118, 2019, https://doi.org/10.5391/IJFIS.2019.19.2.112.

[26] A. D. Gitler, P. Dhillon, and J. Shorter, "Neurodegenerative disease: Models, mechanisms, and a new hope," *Disease Models & Mechanisms*, vol. 10, no. 5, pp. 499–502, 2017, https://doi.org/10.1242/dmm.030205.

[27] S. P. Moustakidis, J. B. Theocharis, and G. Giakas, "Feature selection based on a fuzzy complementary criterion: Application to gait recognition using ground reaction forces," *Computer Methods in Biomechanics and Biomedical Engineering*, vol. 15, no. 6, pp. 627–644, 2012, https://doi.org/10.1080/10255842.2011.554408.

[28] K. Zhang, W. Liu, J. Zhang, Z. Li and J. Liu, "A Fall Risk Assessment Model for Community-Dwelling Elderly Individuals Based on Gait Parameters," in *IEEE Access*, vol. 11, pp. 120857-120867, 2023, https://doi.org/10.1109/ACCESS.2023.3327091.

[29] B. Chen *et al.*, "Computer vision and machine learning-based gait pattern recognition for flat fall prediction," *Sensors*, vol. 22, no. 20, p. 7960, 2022, https://doi.org/10.3390/s22207960.

[30] L. Z. Chee, H. H. Hwong and S. Sivakumar, "Diabetes Detection Using Gait Analysis and Machine Learning," *2023 International Conference on Digital Applications, Transformation & Economy (ICDATE)*, pp. 1-7, 2023, https://doi.org/10.1109/ICDATE58146.2023.10248507.

[31] G. T, B. Sathivel, I. M, S. K. C, P. Kumar S and S. B, "Sensor-Based Gait Analysis and Machine Learning for Predictive Fall Risk Assessment in Adults," *2024 Tenth International Conference on Bio Signals, Images, and Instrumentation (ICBSII)*, pp. 1-7, 2024, https://doi.org/10.1109/ICBSII61384.2024.10564092.

[32] A. Shahzad, A. Dadlani, H. Lee and K. Kim, "Automated Prescreening of Mild Cognitive Impairment Using Shank-Mounted Inertial Sensors Based Gait Biomarkers," in *IEEE Access*, vol. 10, pp. 15835-15844, 2022, https://doi.org/10.1109/ACCESS.2022.3149100.

[33] A. Mannini *et al.*, "A Machine Learning Framework for Gait Classification Using Inertial Sensors: Application to Elderly, Post-Stroke and Huntington's Disease Patients," *Sensor*, vol. 16, no. 1, p. 134, 2016, https://doi.org/10.3390/s16010134.

[34] D. Slijepcevic, M. Zeppelzauer, F. Unglaube, A. Kranzl, C. Breiteneder and B. Horsak, "Explainable Machine Learning in Human Gait Analysis: A Study on Children With Cerebral Palsy," in *IEEE Access*, vol. 11, pp. 65906-65923, 2023, https://doi.org/10.1109/ACCESS.2023.3289986.

[35] S. Jemimah Peace C, V. Ebenezer, B. Edwin, A. R, S. D and R. Thanka, "Pose Estimation Approach for Gait Analysis using Machine Learning," *2023 Second International Conference on Electronics and Renewable Systems (ICEARS)*, pp. 1071-1075, 2023, https://doi.org/10.1109/ICEARS56392.2023.10085311.

[36] D. Bibbo, C. De Marchis, M. Schmid, and S. Ranaldi, "Machine learning to detect, stage and classify diseases and their symptoms based on inertial sensor data: a mapping review," *Physiological Measurement*, vol. 44, no. 12, 2023, https://doi.org/10.1088/1361-6579/ad133b.

[37] D. Trabassi, M. Serrao, T. Varrecchia, A. Ranavolo, G. Coppola, R. De Icco, C. Tassorelli, and S. F. Castiglia, "Machine learning approach to support the detection of parkinson's disease in imu-based gait analysis," *Sensors*, vol. 22, no. 10, p. 3700, 2022, https://doi.org/10.3390/s22103700.

[38] A. Peimankar, T. S. Winther, A. Ebrahimi, and U. K. Wiil, "A machine learning approach for walking classification in elderly people with gait disorders," *Sensors*, vol. 23, no. 2, p. 679, 2023, https://doi.org/10.3390/s23020679.

[39] S. Das, P. Bhowmick, and Kitmo, *Revolutionizing healthcare treatment with sensor technology*, IGI Global, 2024, https://books.google.co.id/books?id=8YoREQAAQBAJ&hl=id&source=gbs_navlinks_s.

[40] T. Lee, E. Shair, A. Abdullah, K. Rahman, and N. Nazmi, "Comparison of short fast fourier transform and continuous wavelet transform in study of stride interval," *Proceedings of the 10 th World Congress on Electrical Engineering and Computer Systems and Sciences (EECSS'24)*, 2024, https://doi.org/10.11159/icbes24.123.

[41] C. Dindorf *et al*., "Enhancing biomechanical machine learning with limited data: generating realistic synthetic posture data using generative artificial intelligence," *Frontiers in Bioengineering and Biotechnology*, vol. 12, 2024, https://doi.org/10.3389/fbioe.2024.1350135.

[42] A. S. Chandrabhatla, I. J. Pomeraniec, and A. Ksendzovsky, "Co-evolution of machine learning and digital technologies to improve monitoring of parkinson's disease motor symptoms," *npj Digital Medicine*, vol. 5, no. 32, 2022, https://doi.org/10.1038/s41746-022-00568-y.

[43] A. A. Lima, M. F. Mridha, S. C. Das, M. M. Kabir, M. R. Islam, and Y. Watanobe, "A comprehensive survey on the detection, classification, and challenges of neurological disorders," *Biology*, vol. 11, no. 3, p. 469, 2022, https://doi.org/10.3390/biology11030469.

[44] K. Rahman, E. Shair, A. Abdullah, T. Lee, and N. Nazm, "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, https://www.researchgate.net/publication/386424698_Deep_Learning_Classification_of_Gait_Disorders_in_Neurodegenerative_Diseases_Among_Older_Adults_Using_ResNet-50.

[45] S. Zadoo, Y. Singh, and P. K. Singh, "Automated parkinson's disease detection: A review of techniques, datasets, modalities, and open challenges," *International Journal on Smart Sensing and Intelligent Systems*, vol. 17, no. 1, pp. 1–37, 2024, https://doi.org/10.2478/ijssis-2024-0008.

[46] A. Javeed, P. Anderberg, A. N. Ghazi, A. Noor, S. Elmståhl, and J. S. Berglund, "Breaking barriers: a statistical and machine learning-based hybrid system for predicting dementia," *Frontiers in Bioengineering and Biotechnology*, vol. 11, 2023, https://doi.org/10.3389/fbioe.2023.1336255.

[47] E. Sánchez-DelaCruz, C.-I. Loeza-Mejía, C. Primero-Huerta, and M. Fuentes-Ramos, "Automatic selection model to identify neurodegenerative diseases," *Digital Health*, vol. 10, 2024, https://doi.org/10.1177/20552076241284376.

[48] J. Hausdorff, "Gait in neurodegenerative disease database," *PhysioNet*, vol. 101, no. 23, pp. e215–e220, 2024, https://doi.org/10.13026/C27G6C.

[49] K. A. Rahman, E. F. Shair, A. R. Abdullah, T. H. Lee, N. Nazmi, and N. Fahad, "Analysis of gait patterns in neurodegenerative disorders among older adults: A ground reaction force data approach," in *Proceedings of the 10th World Congress on Electrical Engineering and Computer Systems and Sciences (EECSS'24)*, 2024, https://doi.org/10.11159/icbes24.131.

[50] E. F. Shair, S. A. Ahmad, A. R. Abdullah, M. H. Marhaban, and S. B. M. Tamrin, "Determining best window size for an improved gabor transform in emg signal analysis," *Telkomnika (Telecommunication Computing Electronics and Control)*, vol. 16, no. 4, pp. 1650–1658, 2018, http://doi.org/10.12928/telkomnika.v16i4.9049.

[51] H. Goelz *et al*., "Wavelet Analysis of Transient Biomedical Signals and its Application to Detection of Epileptiform Activity in the EEG," *Clinical EEG and Neuroscience*, vol. 31, no. 4, 2000, https://doi.org/10.1177/155005940003100406.

[52] E. Vocaturo, E. Zumpano and P. Veltri, "Image pre-processing in computer vision systems for melanoma detection," *2018 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, pp. 2117-2124, 2018, https://doi.org/10.1109/BIBM.2018.8621507.

[53] A. Phinyomark *et al*., "Analysis of Big Data in Gait Biomechanics: Current Trends and Future Directions," *Journal of Medical and Biological Engineering*, vol. 38, pp. 244–260, 2018, https://doi.org/10.1007/s40846-017-0297-2.

[54] V. N. Vapnik, *The Nature of Statistical Learning Theory*, Springer New York, 2010, https://doi.org/10.1007/978-1-4757-3264-1.

[55] S. C. Kothari and H. Oh, "Neural Networks for Pattern Recognition," *Advances in Computers*, vol. 37, pp. 119–166, 1993, https://doi.org/10.1016/S0065-2458(08)60404-0.

[56] L. Wang, *Support Vector Machines: Theory and Applications*, Springer Science & Business Media, 2005, https://books.google.co.id/books?id=uTzMPJjVjsMC&hl=id&source=gbs_navlinks_s.

[57] V. Y. Kulkarni and D. P. K. Sinha, "Random Forest Classifiers :A Survey and Future Research Directions," *International Journal of Advanced Computing*, vol. 36, no. 1, pp. 1144–1153, 2013, https://adiwijaya.staff.telkomuniversity.ac.id/files/2014/02/Random-Forest-Classifiers_A-Survey-and-Future.pdf.

[58] I. D. Mienye and Y. Sun, "A Survey of Ensemble Learning: Concepts, Algorithms, Applications, and Prospects," in *IEEE Access*, vol. 10, pp. 99129-99149, 2022, https://doi.org/10.1109/ACCESS.2022.3207287.