Deep Learning Classification of Gait Disorders in Neurodegenerative Diseases Among Older Adults Using ResNet-50

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***Abstract*—Gait disorders in older adults, particularly those associated with neurodegenerative diseases such as Parkinson's Disease, Huntington's Disease, and Amyotrophic Lateral Sclerosis , present significant diagnostic challenges. Since these NDDs primarily affect older adults, it is crucial to focus on this population to improve early detection and intervention. This study aimed to classify these gait disorders in individuals aged 50 and above using vertical ground reaction force (vGRF) data. A deep learning model was developed, employing Continuous Wavelet Transform (CWT) for feature extraction, with data augmentation techniques applied to enhance dataset variability and improve model performance. ResNet-50, a deep residual network, was utilized for classification. The model achieved a validation accuracy of 95.06% overall, with class-wise accuracies of 97.14% for ALS vs CO, 92.11% for HD vs CO, and 93.48% for PD vs CO. These findings underscore the potential of combining vGRF data with advanced deep-learning techniques, specifically ResNet-50, to classify gait disorders in older adults accurately, a demographic critically affected by these diseases.**

***Keywords*—Gait disorders; neurodegenerative diseases; deep learning; vertical Ground Reaction Force (vGRF); ResNet-50**

I. Introduction

Gait, the manner of walking, is a fundamental human activity involving the intricate coordination of the brain, nerves, and muscles. Globally, gait problems have significantly increased, leading to approximately 646,000 fatal falls annually, particularly among individuals aged 50 years and above [1]. These disorders are the second most common cause of accidental deaths worldwide and contribute substantially to healthcare costs. For instance, Norton et al. [2] estimated that gait disorders account for approximately 0.85% to 1.5% of global healthcare expenses. Jia et al. [3] highlighted the rising prevalence of gait-related falls, emphasizing the need for early detection and intervention to mitigate these issues. Particularly among older adults, gait problems significantly impact mobility, quality of life, and mortality [4].

Neurodegenerative diseases (NDDs) are one of the most significant contributors to gait disorders. These diseases result from the progressive loss of neurons, leading to impaired communication between the brain and muscles. Parkinson's disease (PD), Huntington's disease (HD), and Amyotrophic Lateral Sclerosis (ALS) are among the most prevalent NDDs, each profoundly affecting gait patterns in distinct ways. For instance, Hoff et al. [5] observed that ALS patients typically exhibit slower walking speeds and longer stride durations, while Hausdorff et al. [6] reported increased gait variability in individuals with HD and PD. These conditions impair patients' motor functions, further complicating their management.

Advanced research techniques have illuminated the complex dynamics of gait in NDDs. For example, detrended fluctuation analysis has been used to identify specific gait patterns in neurodegenerative conditions [7], while multi-resolution entropy analysis has revealed disorder-specific gait dynamics [8]. Additionally, platforms like PhysioNet have been instrumental in providing benchmark datasets for studying these disorders [9]. Despite these advancements, Setiawan et al. [10] noted that accurately diagnosing specific NDDs through gait analysis remains challenging due to overlapping symptoms across conditions. Ye et al. [11] and Zhao et al. [12] emphasized the need for more robust multi-class classification techniques to distinguish PD, HD, and ALS effectively.

Existing methods have achieved varying levels of success. For instance, Baratin et al. [13] reported 85% accuracy using Discrete Wavelet Transform (DWT) with entropy and coherence features. Similarly, Zhao et al. [12] achieved 95.6% accuracy with dual-channel LSTM networks. However, many studies, such as those by Faisal et al. [14], have struggled to distinguish closely related gait disorders in mixed cohorts. Approaches employing convolutional neural networks (CNNs) have shown higher classification rates than traditional methods [15], but Fraiwan et al. [16] noted that ensemble classifiers can significantly enhance accuracy. Nevertheless, methods like these often face overfitting challenges due to limited data variability [17].

Hybrid approaches combining CNNs with Long Short-Term Memory (LSTM) networks have also shown promise. For example, Elziaat et al. [18] achieved 92.4% accuracy in predicting freezing of gait in PD patients by integrating spatial and temporal features. Deterministic learning theory with radial basis function (RBF) neural networks demonstrated 93.75% accuracy in classifying ALS, PD, and HD [19]. Amin and Singhal [20] emphasized the importance of dimensionality reduction techniques, achieving 93% accuracy for HD and 89% for PD. Furthermore, Mehra et al. [21] utilized IoT-based

sensors to achieve an accuracy of 98.8% in early PD detection. Ensemble methods like AdaBoost, which analyze features such as vertical ground reaction force (vGRF), have also proven effective, achieving 99.17 percent.

Recent studies have explored novel methods for improving classification accuracy. For instance, Penage et al. [22] transformed vGRF signals into recurrence plots, achieving high accuracy in multi-class classifications using CNNs. Erdas et al. [23] utilized convolutional LSTM networks combined with 3D CNNs, reaching a detection accuracy of 96.33% for NDDs, with specific accuracies of 97.68% for ALS, 94.69% for HD, and 95.05% for PD. These methods demonstrate the potential of advanced deep learning techniques but also highlight gaps in addressing the unique challenges faced by older adults [24].

Despite these advancements, most studies have focused on binary classifications or younger populations, leaving older adults—who are particularly susceptible to NDDs—understudied. To address this gap, this study employs Continuous Wavelet Transform (CWT) to transform vGRF signals into time-frequency spectrograms, enabling the extraction of both temporal and frequency-domain features. Unlike DWT, which may overlook transient signal features, CWT captures subtle gait abnormalities crucial for diagnosis. The ResNet-50 deep learning model, known for its robust feature extraction capabilities, is employed for classification. Data augmentation techniques are applied to enhance model generalizability and mitigate overfitting [25]. These advancements make the proposed method uniquely suited to addressing the challenges of accurately diagnosing neurodegenerative gait disorders in older adults.

The remainder of this article is organized as follows. Section II details the materials and methods, Section III presents the results, and Section IV discusses the findings. Finally, Section V concludes the study, summarizing key contributions and future research directions.

II. Methodology

The methodology of this study is summarised in Fig. 1. The study aimed to develop a machine-learning model for classifying gait disorders in older adults. The process involved three main steps: Data Collection, Data Preprocessing, Feature Extraction, ML Model Training and testing

A. Dataset

In this study, the "Gait in Neurodegenerative Diseases Dataset" provided by Hausdorff et al.[26] was employed. Fig. 2 illustrates the gait data collection procedure. Raw data were collected from vGRF sensors using force-sensitive resistors placed under the foot inside the shoes. During the experiment, each subject walked along a 77-meter-long hallway for five minutes at their normal pace.

The dataset includes recordings from 64 subjects, comprising 13 patients with ALS, 15 patients with PD, 20 patients with HD, and 16 CO. Since this study focuses on older adults, only data from subjects aged 50 and above were selected for analysis.

The gait parameters recorded for each subject include stance, swing, double support interval, and stride for both the left and right foot. For this study, only the right foot force data were analysed. On average, each subject contributed approximately 277 gait cycles, depending on their walking speed during the 5-minute data recording period [27].

TABLE I. Information of Gait Data Participants

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

The final dataset used in the model includes data from five healthy controls (average age: 62.6 years), seven patients with PD (average age: 66.5 years), five patients with HD (average age: 57.2 years), and four patients with ALS is (average age: 61.75 years). The breakdown of the dataset is shown in Table I. Detailed information about the participants, including their age, height, weight, and gait speed, is presented. The dataset was split for training and validation purposes, the dataset was split, with 70% of the data used for training and 30%.

B. Data Pre-processing

A five-minute gait force signal was captured and filtered using a digital band-pass filter, with the filtered signal $y(t)$ computed as the convolution of the raw signal $x(t)$ and the filter's impulse response $h(t)$, as shown in Eq. (1).

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

Wavelet denoising was then applied to further clean the signal, transforming $y(t)$ into the wavelet domain, thresholding the coefficients, and reconstructing the denoised signal $z(t)$, as expressed in Eq. (2).

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

To optimize temporal and frequency resolution, wavelet transforms were applied using window durations of 10, 30, and 60 seconds. The 10-second window was selected for the final analysis, providing the best balance for capturing relevant gait features [28].

C. Data Augmentation

To enhance model performance and prevent overfitting, various data augmentation techniques were applied to the gait signals, which were transformed into the frequency-time domain for analysis by the ResNet-50 model. Horizontal flipping, mathematically represented as $f(x, y) \rightarrow f(-x, y)$, and random rotations between -10 and 10 degrees [Eq. (1)] were used to introduce variability.

$$\begin{pmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{pmatrix} \tag{1}$$

Random translations along the x and y axes [Eq. (2)] were applied to simulate different positions.

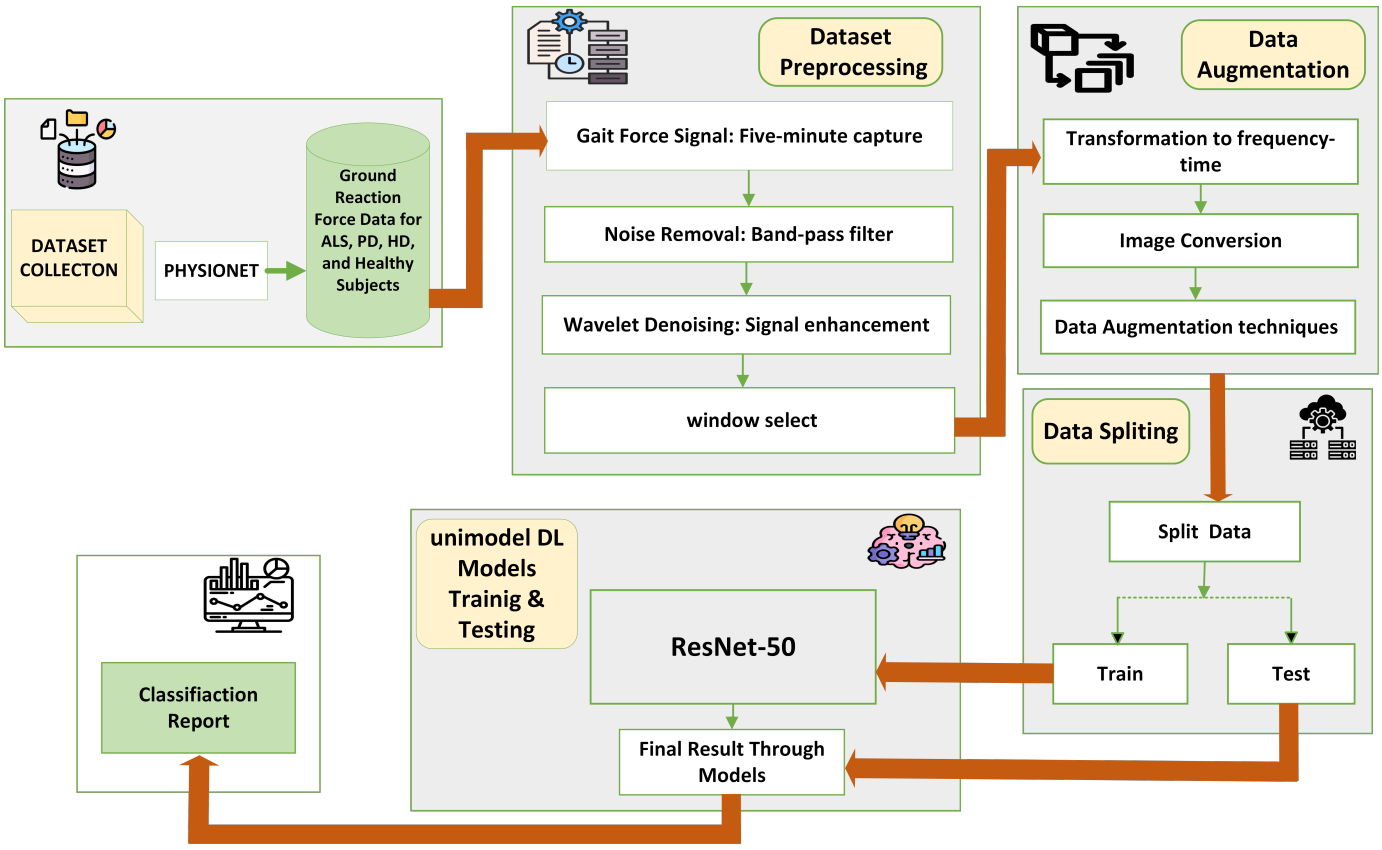

Fig. 1. Diagram of the proposed method.

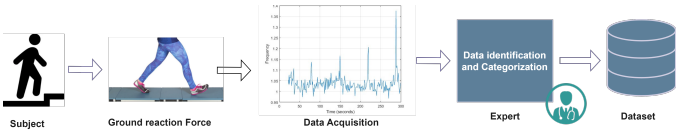

Fig. 2. Data collecting procedure.

$$(x, y) \rightarrow (x + \Delta x, y + \Delta y) \tag{2}$$

Brightness and contrast adjustments [Eq. (3)], scaling [Eq. (4)], and Gaussian blur [Eq. (5)] were also implemented to increase dataset diversity.

$$I' = \alpha I + \beta \tag{3}$$

$$(x, y) \rightarrow (sx, sy) \tag{4}$$

$$G(x, y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right) \tag{5}$$

Each transformation introduced new variations in the dataset, improving model robustness by simulating different object sizes, perspectives, and noise levels, which helped the model generalize better in classification tasks.

D. Classification Model: ResNet-50

The proposed ResNet-50 model was employed to classify gait disorders using gait data transformed into the frequency-time domain via Continuous Wavelet Transform (CWT). The model architecture and data preprocessing steps are depicted in Fig. 3. The architecture consists of several key components aimed at extracting hierarchical features and classifying the four target gait disorder classes: CO, HD, PD, and ALS.

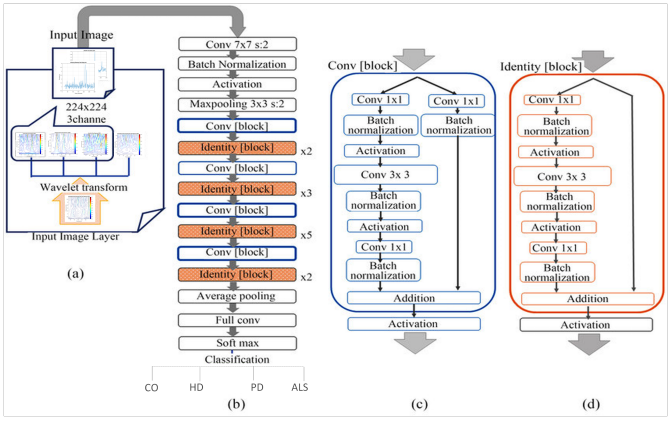

Fig. 3. Overview of the ResNet-50 architecture.

1) Model Architecture Overview: The architecture begins with the input image, processed through several convolutional

layers [Fig. (3b)], each followed by batch normalization and ReLU activation to capture local patterns. The convolutional layers are organized into residual blocks, as shown in Fig. 3(c) and 3(d), where identity and convolutional shortcuts allow the network to retain information and mitigate the vanishing gradient problem, enabling the training of deeper networks.

The convolutional operation for any layer l is mathematically expressed as:

$$O_l = f(W_l * I_{l-1} + b_l) \tag{6}$$

where O_l is the output feature map, W_l is the convolutional filter applied to the input I_{l-1}, and $f(x) = \max(0, x)$ is the ReLU activation function. After each convolutional block, pooling layers reduce the spatial dimensions of the feature maps to prevent overfitting and reduce computational load, as described by:

$$P_l = \text{pool}(O_l) \tag{7}$$

As the network deepens, feature complexity increases through the five stages of the network, eventually resulting in global average pooling, which reduces the spatial dimensions of each feature map to a single value:

$$y_k = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} O_{i,j}^k \tag{8}$$

Finally, the pooled features are passed through a fully connected layer, followed by the softmax activation function to produce a probability distribution across the gait disorder classes. The softmax is expressed as:

$$P(y = k|x) = \frac{\exp(z_k)}{\sum_{j=1}^{K} \exp(z_j)} \tag{9}$$

2) Training and Optimization: The model was trained using the Adam optimizer, with an initial learning rate of 0.001 and a mini-batch size of 32. Training was conducted over 30 epochs, with 70% of the dataset used for training and 30% for validation. The network minimized the categorical cross-entropy loss function:

$$L = -\sum_{k=1}^{K} y_k \log(P(y = k|x)) \tag{10}$$

The architecture was fine-tuned by replacing the fully connected and classification layers of the pre-trained ResNet-50 model to adapt it for the specific task of gait disorder classification. The training showed consistent improvement in accuracy, with a final validation accuracy of 95.06%.

This architecture, shown in Fig. 3, highlights the model's ability to learn intricate gait features effectively, addressing the reviewer's request for details on the number of layers, optimization method, and training parameters.

E. Performance Evaluation

To evaluate the effectiveness of the Gait Neurodegenerative Disorders classification model, key performance metrics including accuracy, sensitivity, specificity, precision, recall, and F1 score were calculated. These metrics were derived from the confusion matrix, which tracks the true positives (TPs), false positives (FPs), false negatives (FNs), and true negatives (TNs) for each class. Specificity, defined as the proportion of true negatives out of the total actual negatives, is calculated using Eq. (9). Sensitivity, also known as recall, measures the proportion of true positives out of the total actual positives and is given by Eq. (10). Accuracy, indicating the overall correctness of the model, is computed as per Eq. (11). Precision, reflecting the proportion of true positive predictions among the total predicted positives, is calculated in Eq. (12).Lastly, the F1 score, which balances precision and recall, is provided by Eq. (13). Together, these metrics offer a comprehensive assessment of the model's performance in classifying neurodegenerative disorders based on gait data.

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

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

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

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

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

III. Result

In this study, MATLAB 2022b was used for data preprocessing, augmenting data, and training the Deep learning model for classification.

A. Statistical Analysis

Fig. 4 illustrates the time-domain frequency plots for the gait data of Control (CO) subjects and patients with Huntington's disease (HD), Parkinson's disease (PD), and Amyotrophic Lateral Sclerosis (ALS). The CO group (A) displays stable and consistent gait frequencies, while HD (B) shows erratic patterns, indicative of severe gait disturbances. PD (C) presents a mix of stable and fluctuating frequencies, whereas ALS (D) shows moderate variability in step frequency.

Fig. 5 provides the time-frequency spectrograms generated using Continuous Wavelet Transform (CWT) for each group. ALS (D) shows stable walking patterns with tightly packed contours, while HD (B) reflects irregular and erratic gait frequencies. PD (C) exhibits mixed contours, and the control group (A) maintains consistent patterns.

These findings are consistent with [29], offering further insight into the distinct gait characteristics of each condition.

Fig. 6 presents box plots that compare key gait features across ALS, PD, HD, and control groups. The mean gait

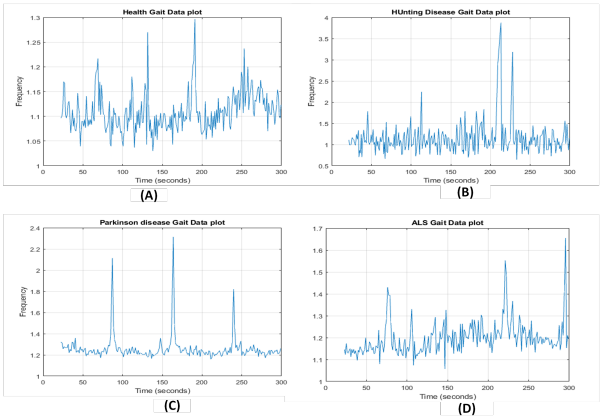

Fig. 4. Gait Time-Domain Patterns: (A) Control, (B) Huntington Disease, (C) Parkinson Disease, (D) ALS.

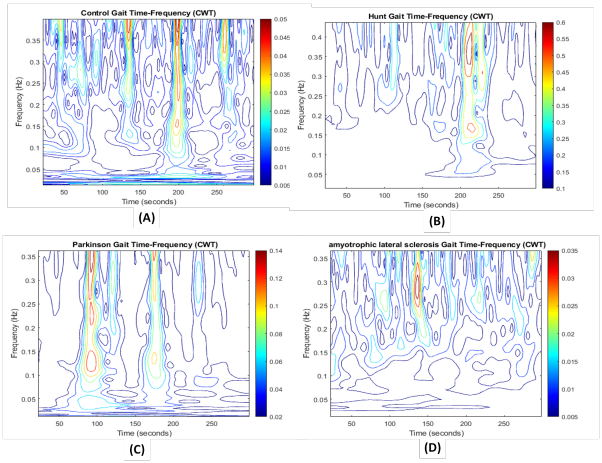

Fig. 5. Gait Time-Frequency Patterns (CWT): (A) Control, (B) Huntington Disease, (C) Parkinson Disease, (D) ALS.

values show that ALS patients have a lower median, reflecting their slower gait. The interquartile range (IQR) is wider for HD, indicating more variable gait patterns, characteristic of Huntington's disease.

The standard deviation and variance for PD suggest moderate variability, indicating motor fluctuations, while RMS and instantaneous RMS reveal greater dispersion in the neurodegenerative groups compared to controls, highlighting reduced gait control.

The gait speed box plot shows a significant decrease in ALS patients, emphasizing their slower walking patterns. These features will be key inputs for training deep learning models to accurately classify gait disorders, facilitating early detection and intervention. By integrating these insights with machine learning techniques, we can effectively monitor and classify gait abnormalities associated with neurodegenerative diseases.

B. ResNet-50 Model Training Progress

Fig. 7 shows the training and validation accuracy, as well as the training and validation loss, across iterations. The accuracy plot indicates steady improvement, with validation accuracy peaking around 95% and training accuracy reaching near 100%, demonstrating the model's effective learning of the data patterns.

The loss plot reveals a consistent decrease in both training and validation losses over time, with the training loss stabilizing at a low value. Although the validation loss shows some fluctuations, the overall trend suggests that the model generalizes well to unseen data.

C. Confusion Matrix for the ResNet-50 Model

Fig. 8 illustrates the confusion matrix for the ResNet-50 model, demonstrating its performance in classifying the four gait disorder classes. The model exhibits high classification accuracy, particularly for the CO and PARK classes, with minimal misclassification across classes. The ALS and HUNT classes show strong sensitivity and specificity, indicating effective distinction among the different gait disorders.

D. Classification Results

The performance of the ResNet-50 model in classifying gait disorders was evaluated using key metrics such as Validation Accuracy, Precision, Sensitivity, Specificity, and F1 Score, as shown in Table II. The model achieved a high validation accuracy of 95.06% for distinguishing between neurodegenerative diseases and healthy controls, indicating strong overall performance across all classifications.

TABLE II. VALIDATION PERFORMANCE METRICS FOR THE RESNET-50 MODEL

Evaluation Parameter	ALS vs CO	HD vs CO	PD vs CO	NDD vs CO
Validation Accuracy	97.14%	92.11%	93.48%	95.06%
Precision	96.88%	94.50%	92.88%	94.04%
Sensitivity	89.50%	98.90%	93.65%	91.68%
Specificity	96.30%	98.40%	92.90%	98.85%
F1 Score	97.11%	98.70%	93.22%	92.94%

Precision scores were also robust, with ALS vs CO achieving 96.88%, HD vs CO at 94.50%, PD vs CO at 92.88%, and NDD vs CO at 94.04%, reflecting the model's capacity to correctly identify relevant instances. Sensitivity varied across the conditions, with HD vs CO attaining the highest sensitivity at 98.90%, followed by PD vs CO at 93.65%, NDD vs CO at 91.68%, and ALS vs CO at 89.50%.

Specificity, a measure of the model's ability to correctly identify negative cases, was consistently high across all classifications: ALS vs CO at 96.30%, HD vs CO at 98.40%, PD vs CO at 92.90%, and NDD vs CO at 98.85%. These values demonstrate the model's strong ability to distinguish between diseased and control cases effectively.

The F1 Score, which balances precision and sensitivity, also confirmed the model's robust classification performance. ALS vs CO achieved an F1 Score of 97.11%, HD vs CO at 98.70%, PD vs CO at 93.22%, and NDD vs CO at 92.94%, highlighting the model's consistency in both detecting true positives and avoiding false positives.

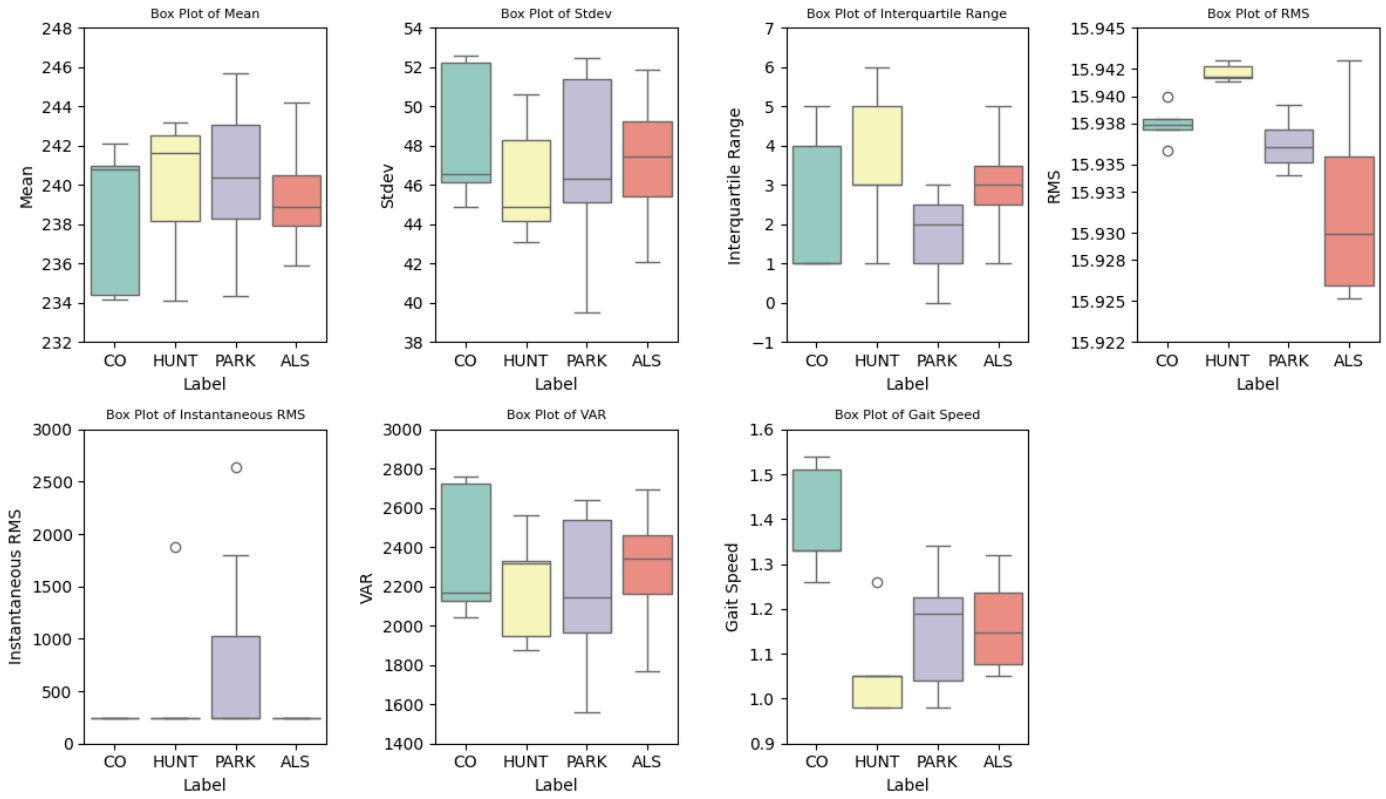

Fig. 6. Box plot analysis of gait features.

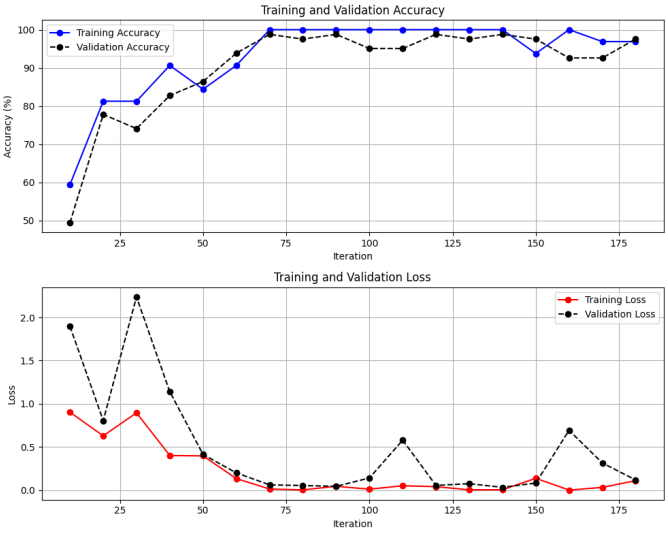

Fig. 7. Training and validation accuracy and loss over iterations.

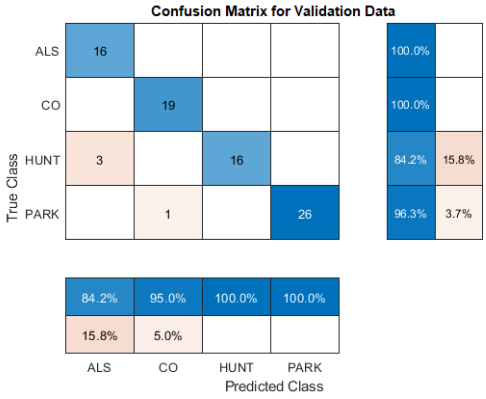

Fig. 8. Validation confusion matrix for the ResNet-50 model.

IV. Discussion and Comparison

This study specifically focused on classifying gait disorders in older adults, a demographic that is critically understudied despite being highly susceptible to neurodegenerative diseases (NDDs) such as Parkinson's Disease (PD), Huntington's Disease (HD), and Amyotrophic Lateral Sclerosis (ALS). Utilizing vertical Ground Reaction Force (vGRF) data and advanced deep learning techniques (ResNet-50), this research provides a more targeted approach, focusing on individuals aged 50 and above, whereas previous studies often included a broader age range or did not account for the unique characteristics of older adults.

Table III compares the classification accuracy of various models across studies. Our model, using ResNet-50 and vGRF data, achieved a high validation accuracy of 95.06% for distinguishing between different neurodegenerative conditions. This performance is competitive with previous efforts that utilized a variety of techniques and features. For example, Hong et al. [30] used a combination of stride, swing, and stance intervals

TABLE III. CLASSIFICATION ACCURACY OF DIFFERENT MODELS

Study	Signal	Methodology	ALS vs CO	PD vs CO	HD vs CO	NDD vs CO
[30]	Str. Int, Sw. Int, Sta. Int, DS. Int	Statistical Features (Min, Max, Avg, Std)	96.79%	89.33%	90.28%	90.63%
[19]	Sw. Int, Sta. Int	Deterministic Learning, RBF Neural Networks	93.1%	100%	100%	93.75%
[20]	Str. Int, Sw. Int, Sta. Int, DS. Int	Statistical Features (Mean, Std, Variance, Skewness, Kurtosis)	85%	89%	93%	85%
[31]	VGRF	Statistical Features (RMS, Variance, Kurtosis)	-	-	-	99.17%
[10]	VGRF	Time-Frequency Spectrogram	100%	97.42%	100%	98.44%
[24]	VGRF, Str. Int, Sw. Int, Sta. Int	Classical Nonlinear Features	95.72%	91.68%	91.71%	92.87%
[23]	VGRF	Recurrence Plot	100%	100%	97.56%	98.93%
[22]	VGRF	Raw VGRF	92%	81%	79%	78%
This Study	**VGRF**	**Time-Frequency Spectrogram,ResNet-50**	**97.14%**	**92.11%**	**93.48%**	**95.06%**

along with statistical features, achieving 96.79% accuracy for ALS vs CO, which is comparable to our study's 97.14%. However, their study did not focus specifically on older adults, making the results of our study particularly significant for this vulnerable population.

Other studies such as Zeng et al. [19] employed deterministic learning theory and RBF neural networks, achieving 93.1% for ALS vs CO. While this is a strong result, our study surpassed it by integrating Time-Frequency Spectrograms with ResNet-50, reflecting the effectiveness of deep learning models in capturing complex gait patterns, particularly in an older demographic. Furthermore, Zeng's study targeted a broader population, while our focus on older adults emphasizes the applicability of our model to clinical settings where early detection is critical.Similarly, the approach by Amin et al. [20] used stride and swing intervals with statistical features such as mean, standard deviation, and kurtosis, achieving lower accuracy rates (85% for ALS vs CO). This indicates that traditional machine learning techniques, even when combined with well-known gait metrics, may not be as effective as deep learning-based models in identifying subtle gait differences in older adults.

In contrast, Fraiwan et al. [31] achieved an impressive accuracy of 99.17% using ensemble decision tree classifiers with vGRF data. While their accuracy is slightly higher than ours, their study focused on a general population, whereas our model's 95.06% accuracy for older adults demonstrates strong performance in a more challenging demographic. The use of ensemble methods can be further explored in future studies for enhanced model performance in older populations.Setiawan et al. [10] reported a similar performance using vGRF data and time-frequency spectrograms, achieving 97.42% for PD vs CO and 100% for HD vs CO. Our model's results for these two conditions (93.48% and 92.11%, respectively) are slightly lower, which could be attributed to the increased complexity of gait patterns in older adults, especially those aged 50 and above. However, the overall performance of our model across all NDDs remains strong and consistent.

Moreover, studies such as Zhao et al. [24] and Lin et al. [23] utilized recurrence plot features and classical nonlinear analysis methods to classify gait disorders. They achieved high accuracies for individual tasks (100% for ALS and HD), but their methodologies did not specifically target the older population. Our study not only achieved comparable performance but also focused on older adults, where gait variability and complexity are more pronounced.

V. CONCLUSION

This study utilized Continuous Wavelet Transform (CWT) for feature extraction and ResNet-50 for classification, yielding a competitive validation accuracy of 95.06%, which aligns with or exceeds results from previous studies. The model achieved class-wise accuracies of 97.14% for ALS vs CO, 92.11% for HD vs CO, and 93.48% for PD vs CO. A key distinction of our work is the focus on older adults aged 50 and above, which, combined with data augmentation techniques, enhances model generalization. This differentiates our study from prior research that typically focused on younger populations or broader age ranges. The integration of vGRF data with advanced deep learning techniques provides a robust framework for accurately classifying gait disorders, particularly in the context of early diagnosis for older adults. Future studies could expand upon these findings by incorporating additional data modalities, such as medical history or multimodal sensor inputs, to further improve diagnostic accuracy and enable comprehensive monitoring of neurodegenerative disease progression in older adults.

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