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Gait Disorder Classification Using CNN and TensorFlow Lite in Android Apps

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Abstract - Gait disorders in older adults, especially those over 50, contribute to increased fall risk and reduced quality of life, making early detection essential. This study presents a deep learning-based approach for classifying gait patterns using vertical ground reaction force (vGRF) data. Signals from individuals with Parkinson's disease (PD) and healthy controls were pre-processed using band-pass filtering and wavelet denoising, then transformed into time-frequency spectrograms via Continuous Wavelet Transform (CWT). A Convolutional Neural Network (CNN) was trained on these spectrograms, achieving 93.48% accuracy with precision, recall, and F1-scores above 92%. The trained model was deployed in a TensorFlow Lite-powered mobile application, enabling real-time gait classification to support home-based monitoring and telemedicine. These findings highlight the potential of combining deep learning with mobile technology for accessible and automated gait disorder assessment.

***Keywords*:** Gait analysis, Parkinson's disease, older adults, vGRF, CWT, CNN, TensorFlow Lite, NDD.

1. Introduction

Globally, gait—defined as the manner or pattern of walking—is a fundamental human activity that requires complex coordination between the brain, nervous system, and musculoskeletal system. Among older adults, particularly those aged 50 and above, gait disorders are a significant concern due to their strong association with mobility impairments, increased fall risk, and diminished quality of life. These disorders contribute to approximately 646,000 fatal falls annually, ranking falls as the second leading cause of accidental deaths worldwide. Additionally, gait-related issues are estimated to account for 0.85\% to 1.5\% of global healthcare costs [1],[2]. Given their high prevalence in aging populations, the development of advanced diagnostic tools and intervention strategies is urgently needed [3].

Neurodegenerative diseases (NDDs) are a major contributor to abnormal gait. Among them, Parkinson's disease (PD) is particularly debilitating, while Huntington's disease (HD) affects gait through irregular stride lengths, reduced walking speed, and unstable posture [4]. These impairments pose additional risks for older adults already vulnerable to falls. In contrast, healthy individuals (CO) typically demonstrate stable and rhythmic gait, providing a critical baseline for comparative analysis. Despite progress in gait assessment, conventional methods often lack scalability and precision for early identification of PD-specific abnormalities [5],[6].

Machine learning (ML) and deep learning (DL) have significantly advanced automated gait analysis. Previous studies have explored various data types and learning models for classifying gait disorders. For instance, spatiotemporal parameters have been shown to be valuable in identifying neurodegenerative diseases [7]. Other approaches include IMU-derived features combined with supervised learning [8], and CNN-based models applied to speech-related gait features [9]. The integration of multimodal data has also improved diagnostic potential; one study reviewed ML techniques for NDD monitoring [10], while another proposed a two-stage neural network for PD detection using smartphone sensors [11]. A recent survey emphasized the benefits of neural networks and multimodal learning for enhancing PD classification [12].

Several DL models have achieved high classification accuracy. For example, CNN-based plantar pressure analysis successfully predicted freezing of gait in PD patients [13], and an explainable deep learning model for early PD reached over 98\% accuracy through data balancing and feature selection [14]. However, most studies have prioritized PD and underexplored HD-specific gait patterns in older adults. Additionally, recent efforts have moved toward mobile and cloud-based platforms to improve accessibility. A mobile-based gait analysis platform, for example, applied mobile deep learning to assess NDDs [15], while multimodal CNNs and human pose estimation have enabled real-time monitoring in healthcare environments [16].

Despite recent advancements, much of the existing research focuses on younger populations or broad neurodegenerative conditions. PD-specific gait abnormalities in older adults remain underexplored, and age-related gait changes require tailored models. Moreover, many approaches are limited to offline analysis, reducing their real-world applicability. To address these gaps, this study presents a CNN-based framework using vGRF signals transformed into time-frequency spectrograms via CWT. Data augmentation enhances model robustness, and the trained model classifies PD and CO gait patterns. The solution is deployed in an Android app using TensorFlow Lite, enabling real-time classification for home-based monitoring and telemedicine.

2. METHODOLOGY

The methodology illustrated in Figure 1 was followed to develop a deep-learning model for Parkinson's disease gait classification. The process involved three key stages: data collection, preprocessing, and model development. Gait data from healthy individuals and Parkinson's patients were processed using noise reduction, window selection, and time-frequency transformation via CWT. Data augmentation techniques were applied to enhance variability and model robustness. A CNN was then trained for gait pattern classification, and an Android-based application is under development to enable real-time PD gait classification.

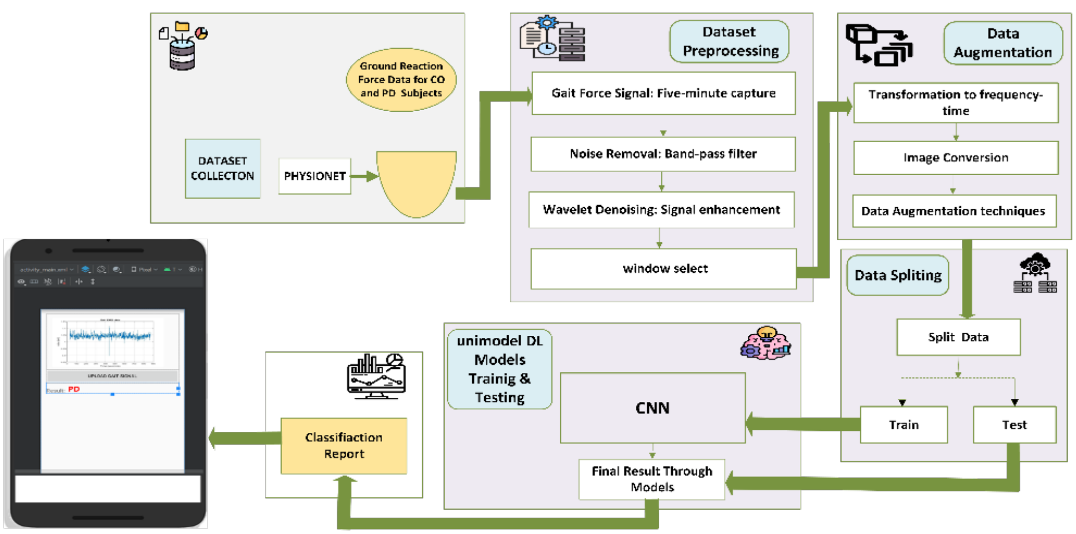

Fig. 1: Diagram of the proposed method for CO and PD gait classification.

This study used the "Gait in Neurodegenerative Diseases Dataset" by Hausdorff [7], which includes vertical ground reaction force (vGRF) signals recorded from older adults during five-minute walking trials. The signals were collected via footwear-embedded force sensors along a 77-meter hallway.

2.1. Dataset

The dataset included 64 participants with various NDDs. For this study, only those aged 50 and above were selected, focusing on 15 with PD and 16 CO. Although data from HD and ALS were available, they were excluded from a focused analysis. Each participant completed a five-minute walk, contributing an average of 277 gait cycles, using only right-foot vGRF signals for consistency. As shown in Table 1, PD participants had slightly higher gait speed than CO. These variations reflect motor differences significant for training DL models to distinguish between healthy and pathological gait.

Table 1: Information about the people in the Gait dataset.

Statistical Parameter	Mean ± STD			
	Age (Year)	Height(m)	Weight(kg)	Gait Speed(m/s)
CO	62.6 ± 8.63	1.836 ± 0.107	74.6 ± 13.02	1.294 ± 0.207
PARK	66.5 ± 9.06	1.991 ± 0.119	87.37 ± 13.684	1.3325 ± 0.270

2.2 Data Processing and Augmentation

To prepare the vGRF signals for deep learning analysis, a comprehensive data processing pipeline was applied. Initially, the raw signals were denoised using a digital band-pass filter to remove high-frequency and low-frequency noise. This operation is mathematically defined in Equation (1):

$$y(t) = h(t) \times x(t) \qquad (1)$$

Where x(t) is the original input signal, h(t) is the impulse response of the filter, and y(t) is the resulting filtered signal. To further enhance signal clarity, wavelet-based denoising was performed. The signal was decomposed, thresholded to eliminate noise components, and reconstructed using the inverse wavelet transform, as shown in Equation (2):

$$z(t) = W - 1\Big(T\big(W(y(t))\big)\Big) \qquad (2)$$

To improve generalization and minimize overfitting, data augmentation techniques were subsequently applied to the spectrogram images. These included horizontal flipping (image inversion along the vertical axis), random rotations within ±10 degrees to simulate viewpoint variations, and random translations along both the x and y axes to mimic spatial shifts. Additional transformations such as brightness and contrast adjustments replicated different lighting conditions, while scaling introduced size variability. Gaussian blur was also used to simulate changes in image focus, further diversifying the input dataset.

2.3 CNN Architecture and Mathematical Formulation

The CNN model developed in this study classifies the gait patterns of older adults into PD and CO groups. To enable effective pattern recognition, vGRF signals were first converted into CWT. These spectrogram images served as input to the CNN. The overall architecture, illustrated in Figure 3, begins with the generation of gait signals, continues through signal segmentation and CWT-based conversion, and concludes with deep feature extraction and classification using convolutional and fully connected layers. The CNN accepts input images of size 224×224×3. It includes three convolutional blocks, each designed to extract hierarchical features. The first block applies a 2D convolutional layer with a 3×3 kernel and 32 filters, followed by batch normalization, ReLU activation, and a 2×2 max pooling layer with a stride of 2. The second and third blocks replicate this structure but increase the number of filters to 64 and 128, respectively.

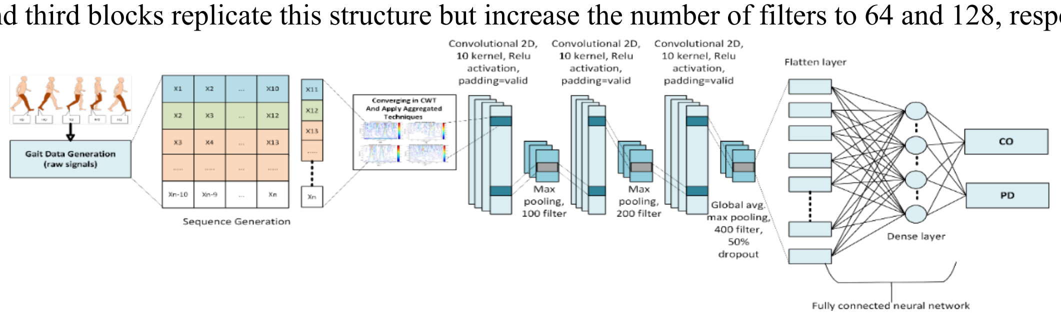

Figure 3: Architecture of the CNN Model

After convolution and pooling, the resulting feature maps are flattened and passed through a fully connected layer, followed by a SoftMax layer that produces class probabilities for CO and PD. Mathematically, the convolution operation at the layer l is represented in Equation (3):

$$O_l = f(W_l * I_l^{-1} + b_l) \quad 3$$

Here W_l and b_l represent the weights and biases of the l-th layer, I_{l-1} is the input from the previous layer, and $f(x) = \max(0,x)$ is the ReLU activation function, which introduces non-linearity into the model.

Next, pooling is applied to reduce spatial dimensions, helping the network retain essential features while reducing computation. This is defined in Equation (4):

$$P_l = pool(O_l) \quad 4$$

After feature extraction, the output is passed to the softmax function, which converts the logits z_k into a normalized probability distribution across the K classes (in this case, $K = 2$ for CO and PD). The softmax function is given in Equation (5).

$$Y_k = \frac{exp(z_k)}{\Sigma_j = 1^K exp(z_j)} \quad 5$$

This ensures that all output values are between 0 and 1 and that they sum to 1, making them interpretable as probabilities. The model is trained by minimizing the categorical cross-entropy loss, which compares the predicted class probabilities $\hat{y}_{i,k}$ with the true class labels $y_{i,k}$The loss function is defined in Equation (6).

$$L = -\Sigma_i = 1^N \Sigma_k = 1^K y_{ik} \, log(\hat{y}_{ik}) \quad 6$$

In this equation, N the number of training samples and k is the number of output classes. $y_{i,k}$ Equals one if the sample i Belong to class k and otherwise. $\hat{y}_{i,k}$ is the predicted probability for class k Minimizing this loss enables the CNN to adjust its parameters and improve classification accuracy.

2.5 Performance Evaluation

The classification performance of the model distinguishing gait patterns in PD and CO groups was assessed using several key metrics: accuracy, sensitivity, specificity, precision, recall, and F1 score. These measures were derived from the confusion matrix, which provides counts of true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN). Specificity, representing the model's ability to correctly identify negative cases, is determined by Equation (7). Sensitivity, or recall, reflects the percentage of correctly identified positive cases, calculated using Equation (8). Accuracy measures the overall effectiveness of the model across all classifications and is computed as shown in Equation (9). Precision, which indicates the proportion of correct positive predictions among all positive predictions, is calculated using Equation (10). Finally, the F1 score, a harmonic mean of precision and sensitivity, balances these metrics, as shown in Equation (11). These evaluations provide a comprehensive analysis of the model's performance in classifying PD and CO groups based on gait data.

Equations:

$$\text{Specificity} = \frac{\sum_i^n TN_i}{\sum_i^n (TN_i + FP_i)} \quad 7$$

$$\text{Sensitivity} = \frac{\sum_i^n TP_i}{\sum_i^n (TP_i + FN_i)} \quad 8$$

$$\text{Accuracy} = \frac{\sum_i^n (TP_i + TN_i)}{\sum_i^n (TP_i + TN_i + FP_i + FN_i))} \quad 9$$

$$\text{Precision} = = \frac{\sum TP}{\sum TP + FN} \quad 10$$

$$\text{F1 Score} = \frac{2 \times (Precision \times Sensitivity)}{(Precision + Sensitivity)} \quad 11$$

3. Result:

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

3.1 Statistical Analysis

Figure 4 shows clear differences in gait signal patterns between the CO and PD groups across both time and frequency domains. The CO signals are marked by consistent amplitude and regular stride intervals, indicating stable and rhythmic gait. In contrast, the PD signals show reduced amplitude and irregular timing, which are common signs of bradykinesia and freezing of gait. When viewed in the frequency domain, the CWT spectrograms for CO display well-organized, compact energy bands, while those for PD are more scattered and fragmented, reflecting tremors and inconsistent stride rhythms. These findings are consistent with results from [17], where spectrograms and box models were used to distinguish between different gait patterns.

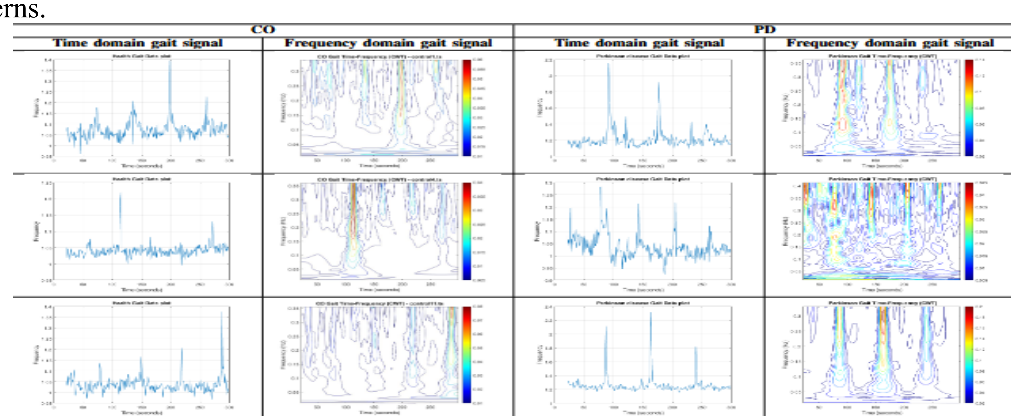

Fig. 4: comparison of time and frequency domain gait signals for CO and PD

3.2 CNN Model Training Progress

Figure 5 illustrates the progression of the CNN model during training, achieving a final validation accuracy of 93.48% after 90 iterations over 30 epochs. The initial learning rate was set to $\eta = 0.001$, ensuring a stable convergence of the optimization process. The training objective was to minimize the categorical cross-entropy loss function, as defined in Equation Y, where $N = 90$ represents the total number of training iterations and $K = 2$ denotes the binary classification of the two classes: CO and PD. Here, y_{ik} indicates the true label, while $\hat{y}_{ik}$ corresponds to the predicted probability for class k.

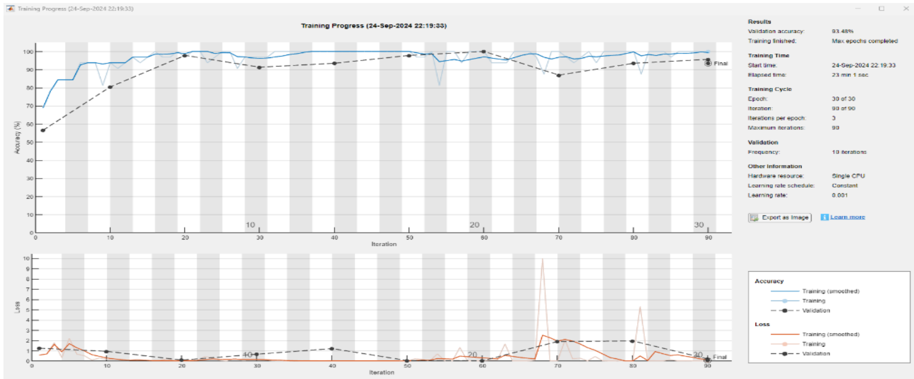

Fig. 5: Data collected using a Ground reaction force sensor.

3.3 Confusion Matrix for the CNN Model

Figure 6 illustrates The confusion matrix for the validation data, as shown in Figure X, provides an overview of the model's performance in distinguishing between the CO and PD groups.CO: Out of 19 samples, 17 were correctly classified as CO, achieving an accuracy of 89.5%. However, two samples were misclassified as PD, accounting for a misclassification rate of 10.5%.

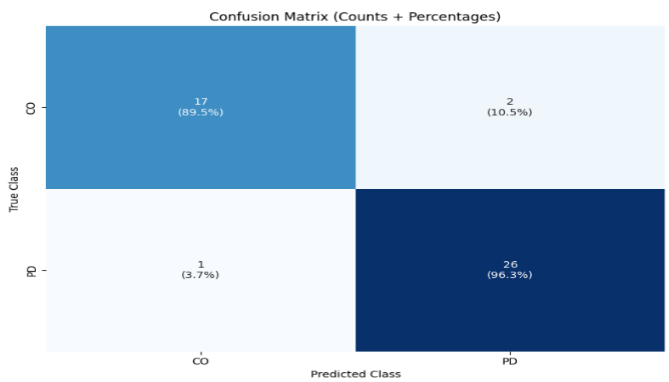

Fig. 6: Validation Confusion Matrix for the CNN Model

PD: Out of 27 samples, 26 were correctly classified as PD, achieving an accuracy of 96.3%. Only 1 sample was misclassified as CO, corresponding to a misclassification rate of 3.7%.These results demonstrate the model's robustness in distinguishing between CO and PD groups. The high classification accuracy and low misclassification rates highlight the reliability of the CNN model in analyzing gait patterns associated with neurodegenerative disorders.

3.3 Classification Results

Table 2 presents the performance metrics of the CNN model in classifying gait patterns between healthy controls (CO) and Parkinson's disease (PD) participants. The model achieved a strong overall validation accuracy of 93.48%, indicating its effectiveness in binary classification. Precision for PD was higher (96.30%) compared to CO (89.47%), suggesting the model was slightly more confident and correct when predicting PD cases. In contrast, the sensitivity (recall) for CO was 94.44%, slightly exceeding PD at 92.86%, showing the model's strength in correctly identifying true positives in both classes.

Table 2: performance metrics for the CNN model

Metric	CO	PD
Validation Accuracy (%)	93.48	93.48
Precision (%)	89.47	96.30
Sensitivity (%)	94.44	92.86
Specificity (%)	92.86	94.44
F1 Score (%)	91.89	94.56

Specificity values were closely matched across both groups, with 92.86% for CO and 94.44% for PD, demonstrating the model's capability to reject negative cases correctly. The F1 Score, which balances precision and recall, further reflects the robustness of the model — 91.89% for CO and 94.56% for PD. These consistent results across all metrics confirm that the CNN model, combined with CWT-based spectrogram features, effectively differentiates gait patterns associated with PD and healthy aging.

3.4 Discussion

This study confirms the effectiveness of CNN in classifying gait patterns between PD and CO using vGRF and CWT spectrograms, achieving 93.48% accuracy. Unlike traditional ML approaches [7] and IMU-based models [9], which rely on handcrafted or sensor-fusion features, the CNN automatically extracts meaningful patterns, improving reliability. A TensorFlow Lite-based mobile app is under development for real-time deployment. Future work should incorporate multi-modal data and broader validation for enhanced clinical relevance.

4. Conclusion

This study proposed a deep learning approach to classify gait patterns in older adults using vGRF signals. With CWT-based spectrograms and a CNN model, the system effectively distinguished between PD and CO groups. The model showed high accuracy and reliability in capturing key gait differences. To support practical use, the trained model was also deployed in a mobile app for real-time gait monitoring. These results highlight the potential of combining vGRF and DL for early detection and remote assessment of gait disorders in aging individuals.

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