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Analysis of Gait Patterns in Neurodegenerative Disorders Among Older Adults: A Ground Reaction Force Data Approach

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Abstract **-** Increasing awareness of walking-related issues leading to falls, particularly in older adults, has highlighted this important concern. Even though walking is a fundamental human movement, studying it is difficult because it involves intricate brain, nerve, and muscle coordination. Neurodegenerative disorders like Amyotrophic Lateral Sclerosis (ALS), Parkinson's disease (PD), and Huntington's disease (HD) are frequently associated with walking limitations, highlighting the critical need for precise diagnostic tools. This study employed a comprehensive approach, delving into the intricate examination of gait patterns in individuals with neurodegenerative disorders. We used ground reaction force (GRF) step data from the Physionet public database, which converted into the time-frequency domain using continuous wavelet transform (CWT). We applied feature extraction techniques to identify unique gait characteristics for each disorder. Our findings revealed significant differences in gait among neurodegenerative diseases, with Parkinson's disease exhibiting the highest variability, ALS showing less variability, and Huntington's disease falling in between. These results illustrate the complex nature of walking issues in neurodegenerative diseases, highlighting the necessity of specific diagnostic approaches.

Keywords**:** Neurodegenerative disorders; gait analysis; older adults; ground reaction force; time-frequency

1. Introduction

Globally, gait problems have significantly increased, resulting in about 646,000 terminal falls annually, most commonly among those aged 50 and older [1]. Gait disorders stand as the second most common cause of accidental or unintentional injury deaths worldwide, trailing only behind traffic accidents. Moreover, they play a significant role in accidental injury deaths occurring outside of transport contexts[2]. In addition, gait disorders consume between 0.85% and 1.5% of healthcare expenditures [3]. Given the high costs of medical treatments, it's crucial to identify and directly help individuals with gait problems who are at risk of falling [4]. The increase in gait problems leading to falls globally, with significant mortality rates, especially among older adults, underscores the urgency to early address this issue. While walking is inherent to human activity, analyzing it poses challenges due to the intricate coordination of the brain, nerves, and muscles. Researchers across various disciplines have extensively studied human motion to assess patient states, facilitate rehabilitation, and devise treatments [5]. Neurodegenerative disease refers to disorders arising from brain and spinal cord cell degeneration, resulting in impaired movement[6]. Progressive neurodegenerative disorders such as ALS, PD, and HD are frequently associated with the damage of gait.

This growing concern over gait disorders, mainly due to neurodegenerative diseases, directs towards a focused examination of how these conditions alter walking patterns. Evaluating gait abnormalities in neurodegenerative diseases such as ALS, HD, and PD involves analyzing spatial and temporal gait factors, with distinct characteristics identified for each condition[7]. Specifically, ALS patients have slower walking speeds and extended stride durations, unlike those with HD and PD, who demonstrate variable stride lengths and heightened gait variability [8]. These differences notably underscore the profound effects of impaired motor function, a key symptom stemming from disruptions within the brain's control network, a finding well-supported across various [9][10]. Building on this foundation, further research has delved deeper

into the nuances of gait disruptions. Advanced studies utilizing techniques like detrended fluctuation analysis and multi-resolution entropy analysis have shed light on the extent of stride-to-stride variability. These methods have been particularly revealing in ALS cases compared to HD and PD, showcasing the distinct gait dynamics within each disorder. Such detailed investigations reinforce the urgency for precise diagnostic and therapeutic approaches to address the unique gait abnormalities associated with each neurodegenerative condition[11].

Neurodegenerative Disorders (NDDs) are a subset of neurological disorders characterized by the progressive loss of neuron structure or function, often affecting adults and associated with aging. Common examples are Parkinson's, Huntington's, and ALS [12]. Currently, the most common method for diagnosing and evaluating progress in people with NDD is to use several questionnaires. The use of questionnaires is commonly acknowledged to provide particular results. As a result, in modern clinical practice, conducting an impartial evaluation of the patient's physical functioning is critical. Using this assessment, medical practitioners can develop a more rational treatment strategy and perform a more rigorous evaluation of therapeutic outcomes. Previous studies have indicated a strong interest in applying numerical gait analysis as a non-invasive technique for detecting gait disorders. With the rapid advancement of machine learning, many approaches for extracting features and classifying data have been used to create an automated and precise diagnosis classification for clinical supporters.

The primary objective of this study is to identify gait characteristics in older adults (aged 50 and above), differentiating between control gait patterns and those affected by neurodegenerative disorders (NDD) through feature extraction. Previous studies focus on various age groups. This research specifically focuses on the older adult population. Previous research employed statistical and nonlinear computing techniques for extracting insights from gait rhythm data. This study engagements Continuous Wavelet Transform (CWT) to enhance the accuracy of feature extraction [9], [10]. This method involves converting CWT plots into images from which pertinent features are extracted. These features are utilized to construct a box model that visually compares healthy gait patterns and those altered by NDD.

2. Materials and Methods

The methodology, illustrated in Figure 1, involves four key steps: collecting gait rhythm data from older adults, pre-processing this data to filter noise, using MATLAB to transform the data into time-frequency spectrograms with wavelet transform, and then extracting statistical features such as mean, standard deviation, instantaneous RMS, and variance. These features are crucial for differentiating healthy gait patterns from those altered by gait diseases.

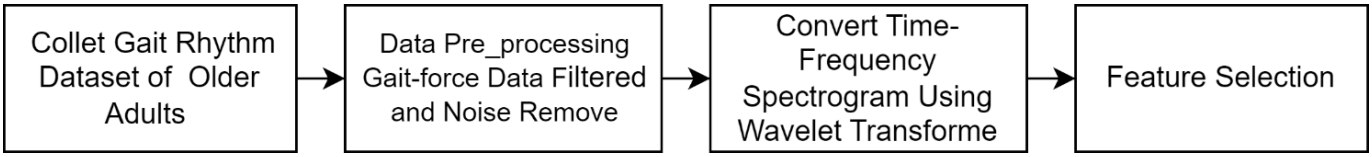

Fig. 1: Flowchart of the proposed categorization method for the gait of NDD patient

2.1. Dataset

Figure 2 shows the Gait dataset collected through the Physionet public database[11]. Shows the prevalence of neurodegenerative diseases among specific subjects. The ground reaction force (GRF) step data from the Physionet database was applied to investigate and diagnose gait disorders. The force under each subject's foot is measured using force-sensitive resistors as an integral component of the gait analysis. In this experiment, eight sensors were implanted in each subject's feet to measure the vertical ground reaction force. The data consists of locomotion patterns intentionally omitted during the physical exertion of both male and female participants. The database contains information on five healthy subjects: 7 patients with Parkinson's disease, five patients with Huntington's disease, and four patients with Amyotrophic Horizontal Sclerosis (ALS). The gait parameters for each subject, including stance, swing, double support interval, and stride of the left and right foot, are collected in the Physionet database, as illustrated in Figure 1. Regarding every subject, the clinical [11].

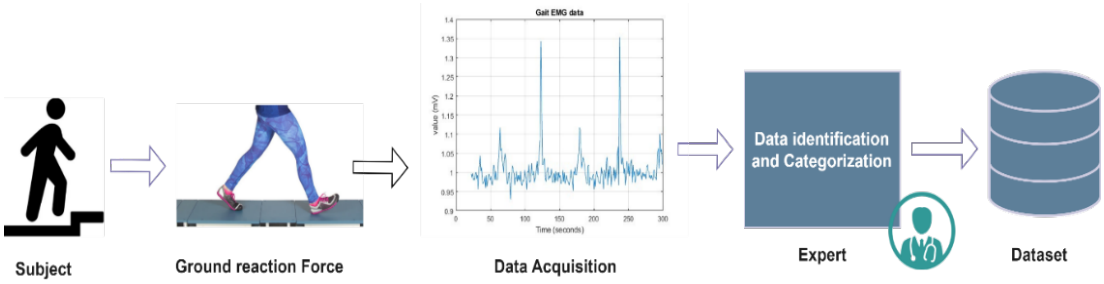

Fig. 2: Data collected using Ground reaction force sensor.

Table 1 briefly outlines key factors, statistically summarizing our subjects' clinical profiles. Our investigation targets individuals aged 50 and above. From the dataset, we specifically selected five healthy individuals, alongside five diagnosed with Huntington's disease, seven with Parkinson's disease, and four with ALS, enabling precise analysis of gait patterns and clinical data among older adults affected by a range of neurodegenerative disorders. Table 1 delineates the demographic and physiological traits of the four groups—control, Huntington's (Hunt), Parkinson's (Park), and ALS—showcasing means and standard deviations for age, height, weight, and gait speed. This comparative analysis illuminates the distinct differences between individuals across the different disease states, offering valuable insights into their unique conditions.

Table 1: Basic 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
HUNT	57.2 ± 6.24	1.778 ± 0.137	64 ± 10.8	1.104 ± 0.142
PARK	66.5 ± 9.06	1.991 ± 0.119	87.375 ± 13.684	1.3325 ± 0.27025
ALS	61.75 ± 7.071	1.797 ± 0.035355	89.0375 ± 13.913	1.2275 ± 0.099925

2.2 Feature extraction

For feature extraction, the study selected 21 subjects, transforming gait signals from their original time domain into frequency-time domain. This transformation was achieved using MATLAB's contour function; this step primed the data for deeper analysis. Following this transformation, the data was rendered into image form, allowing for the extraction of critical statistical measures, which are mean, variance, standard deviation, and instantaneous root mean square (RMS) of the gait signals—which are essential for identifying and characterizing the gait patterns under study.

Mean: - often denoted by $\bar{x}$ (pronounced "x-bar"), is a measure of central tendency in a dataset. It represents the average value of the data points. Mathematically, the mean of a dataset X with n data points x_1, x_2, ..., x_n is calculated as:

$$\text{Mean } (\bar{x}) = \frac{1}{n}\sum_{i=1}^{n} x_i \qquad (1)$$

Eqn (1) $\bar{x}$ is the mean of the dataset. Xi represents each data point and denotes summation over all data points. In the context of the given data, each row represents a sample or observation, and the "Mean" column contains the mean values calculated from specific measurements or features associated with each observation.

Variance (VAR): - A measure of the spread or dispersion of data points. In statistics, it quantifies how much the values in a dataset differ from the mean (average) value. Mathematically, the variance of a dataset X with n data points x_1, x_2, ..., x_n is calculated as:

$$\mathrm{VAR}(X) = \frac{1}{n}\sum_{i=1}^{n} (x_i - \bar{x})^2 \quad (2)$$

Eqn (2) $\bar{x}$ is the mean of the dataset. Xi represents each data point. Σ denotes the summation of all data points. In the context of the given data, each row represents a sample or observation, and the "VAR" column contains the variance values calculated from specific measurements or features associated with each observation.

Standard deviation (Stdev): - Often denoted by σ (sigma) or s, is a measure of the dispersion or spread of data points around the mean. It quantifies the extent to which the values in a dataset deviate from the mean value. Mathematically, the standard deviation of a dataset X with n data points x_1, x_2, ..., x_n is calculated as:

$$\mathrm{Stdev}(X) = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (x_i - \bar{x})^2} \quad (3)$$

Eqn. (3) σ is the standard deviation of the dataset. $\bar{x}$ is the mean of the dataset. x_i represents each data point. Σ denotes the summation of all data points. Sqrt denotes the square root. In the context of the given data, each row represents a sample or observation, and the "Stdev" column contains the standard deviation values calculated from specific measurements or features associated with each observation.

Instantaneous RMS: - Also known as Root Mean Square, is a measure commonly used in signal processing and engineering to quantify the amplitude or power of a time-varying signal. It measures the average magnitude of the signal over a short duration, often referred to as an "instant" in time. Mathematically, Instantaneous RMS of a signal x(t) sampled at discrete time points t_1, t_2, ..., t_n is calculated as:

$$\text{Instantaneous RMS} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (x_i)^2} \quad (4)$$

Eqn (4) sqrt denotes square root. X_i represent the amplitude of the signal at time point i. Σ denotes summation over all time points, the total number of samples. In the context of the given data, each row represents a sample or observation, and the "Instantaneous RMS" column contains the RMS values calculated from specific measurements or features associated with each observation.

3. Result:

Figure 3 presents original gait data plots illustrating the frequency of ALS, Huntington's, and Parkinson's diseases over time compared to healthy groups. The graphs show that people with ALS have changeable step frequency, people with Huntington's disease have erratic gait patterns, and people with Parkinson's disease have alternating episodes of stability and high frequency, which shows how their unique gait is affected. The control group's plot has a more stable frequency, which shows a steady walking rhythm.

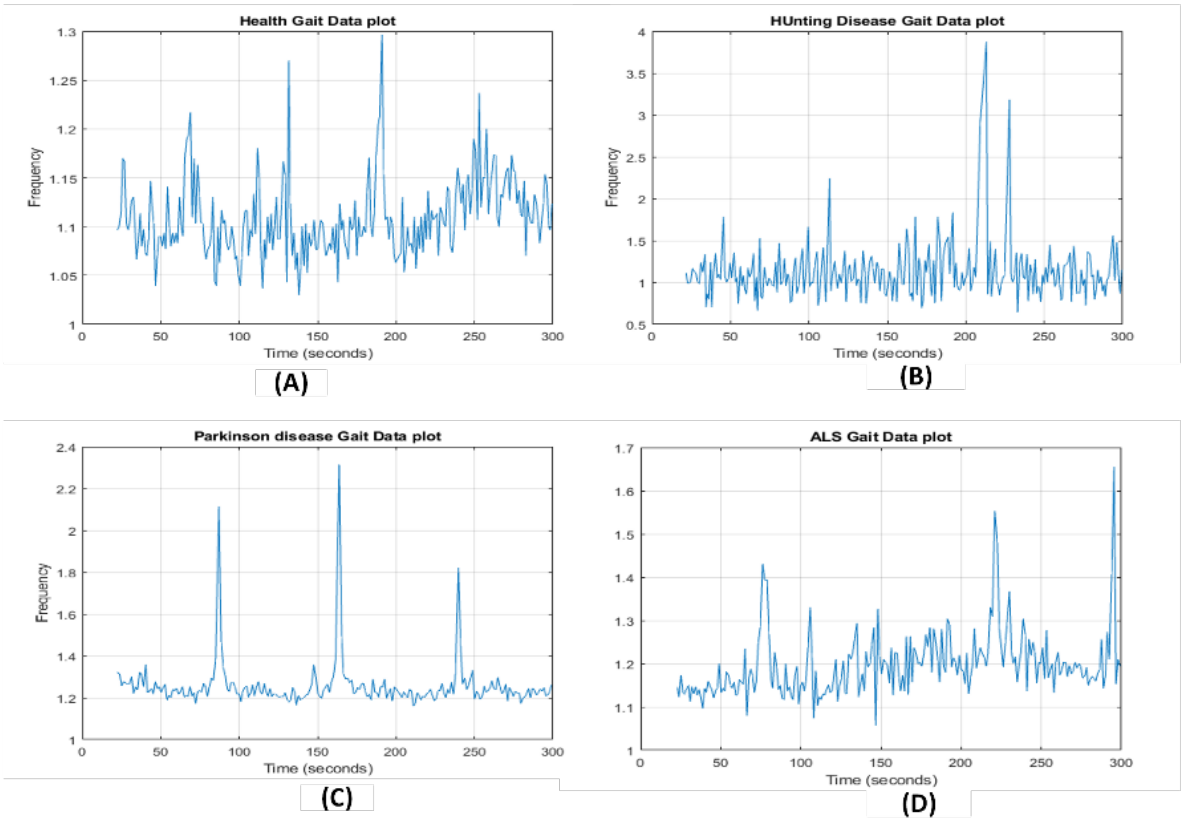

Fig 3: Time-Domain Gait Patterns in Neurodegenerative Disorders vs. Healthy Controls

Figure 4 shows time-frequency domain plots, which can be used to look at the complex patterns of gait frequencies in people with neurodegenerative diseases compared to a healthy control group. These graphs use contour lines to show how the strength of gait frequencies changes over time. This shows the rhythm and any irregularities in the way each group walks. The contour lines in the ALS group are closer together, suggesting a more stable walking pattern. In Huntington's group, on the other hand, the contour lines are spread out more, which indicates a less stable walking pattern. The outlines of the Parkinson's disease plot are both closely packed and spread out, which shows how the patient's patients' walking frequency changes over time. On the other hand, the healthy control group has a more even contour distribution, which means they walk at a steady pace. These plots give detailed visual information that lets specific features linked to walking patterns be extracted. It is possible to isolate and measure unique gait traits because frequency changes over time are apparent. This can be very important for determining how different neurodegenerative conditions affect moving.

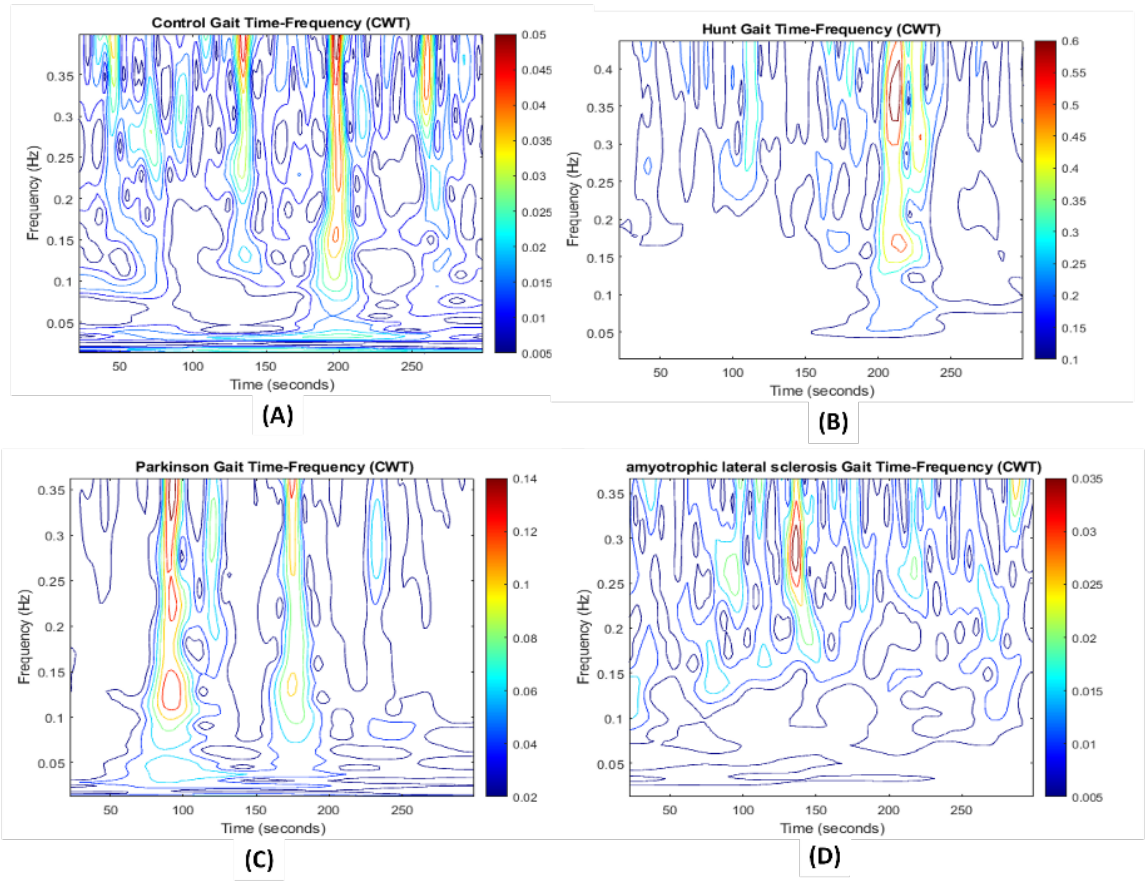

Fig. 4: Gait time-frequency Gait Patterns in Neurodegenerative Disorders vs. Healthy Controls.

Figure 5 shows box plots of how the walking styles of people with Parkinson's, ALS, Huntington's, and a healthy control group are different. The analysis of the box plots showed that the groups' walking parameters were intensely different. Parkinson's patients' walking speeds were all over the place, with a median of 242 and an interquartile range of 238 to 246, which shows how the disease affects people's movement skills differently. In contrast, the ALS group had a slightly faster median walking pace of around 244. Given the relationship of ALS with motor function impairment, the narrower range of speeds within this group suggested that it has a more significant impact on walking speeds. It was seen that healthy people walked more steadily, with a narrow interquartile range showing regular walking patterns that aren't generally changed by neurodegenerative diseases. Within the Parkinson's group, instantaneous RMS values showed the most significant changes in walking speed, showing that their gait was significantly more variable. Not surprisingly, the healthy group had the lowest marks, which showed they walked steadily.

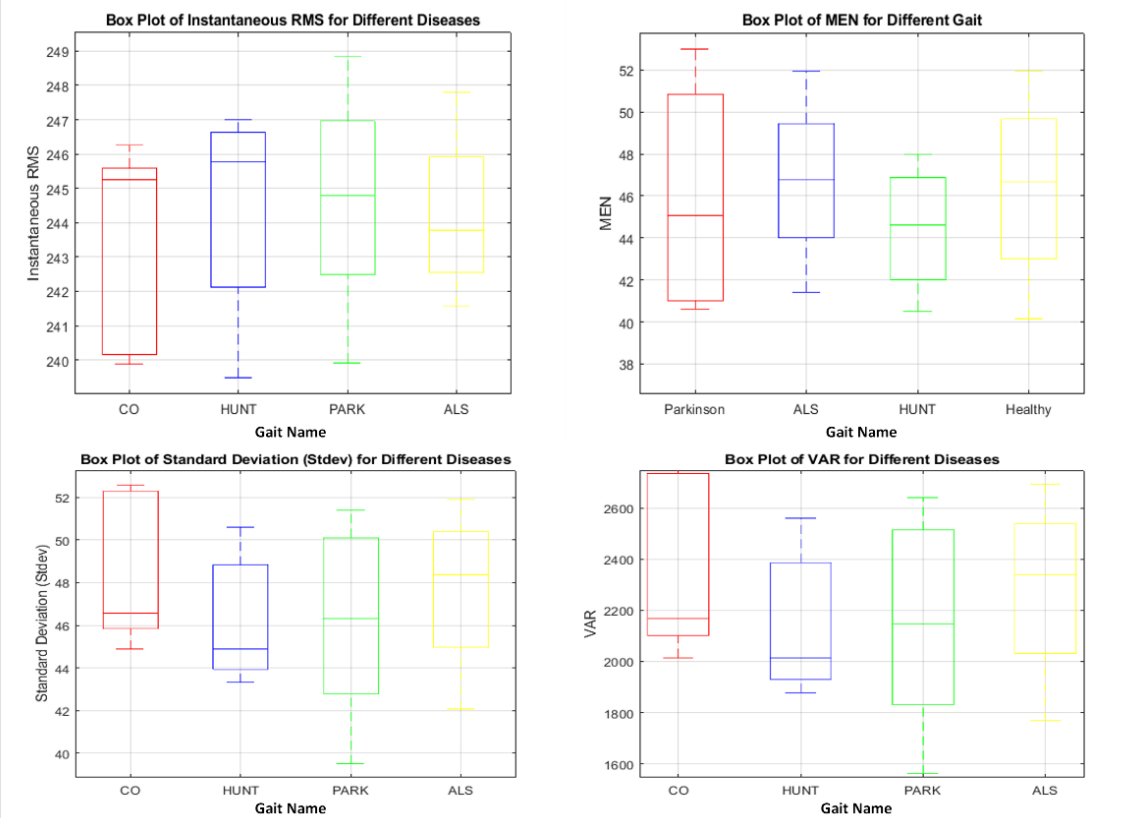

Fig. 5: Box plot of different Gait characteristics of this study.

The comprehensive examination of gait metrics utilizing the box model demonstrates notable heterogeneity among neurodegenerative disorders. For example, Parkinson's illness demonstrates significant variability in mean values, standard deviation (Stdev), Instantaneous RMS, and Variance (VAR), suggesting a broad spectrum of gait characteristics within this condition. In contrast, amyotrophic lateral sclerosis (ALS) exhibits reduced variability across these dimensions, indicating a higher degree of consistency in gait patterns than in Parkinson's disease [8] [13]. Huntington's disease is situated between amyotrophic lateral sclerosis (ALS) and Parkinson's disease, with a modest degree of variability [7]. The findings align with prior research highlighting the significance of motor function impairment as a primary characteristic of NDD [8], [14]. In general, amyotrophic lateral sclerosis (ALS) displays the highest level of consistency in gait patterns across different assessments. In contrast, Parkinson's disease shows the highest degree of variability, highlighting separate patterns of variability within each gait condition [15]. Those different walking patterns between the groups will be helpful knowledge for machine learning in the future. Figure 4 shows some differences and trends that could help scientists make better models for predicting and diagnosing neurodegenerative diseases.

5. Conclusion

Finally, this study studied gait patterns in older people with neurodegenerative illnesses such as Parkinson's disease, Huntington's disease, and Amyotrophic Lateral Sclerosis (ALS). The Study identified unique gait characteristics linked with each disorder using ground reaction force (GRF) data from the Physionet public database and advanced feature extraction function. This study's findings revealed substantial differences in gait measures across many neurodegenerative diseases. Parkinson's illness had the most variability, ALS had less, and Huntington's disease was somewhat in the middle. This variation highlights the complicated nature of gait abnormalities in neurodegenerative diseases, emphasizing the need for specialized diagnostic techniques.

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