Advanced Early Detection of Parkinson’s Disease Using Comprehensive Gait Analysis with Selective Body Part Features

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**Abstract.** The objective of this study is to use a more advanced gait analysis technique to enhance the early detection of Parkinson's disease (PD). This will assist in overcoming the limitations of traditional diagnostic methods, which are often arbitrary, time-consuming, and unavailable in underdeveloped or rural areas. The study aims to identify the motion that function as early detection of PD by concentrating on these crucial regions. To create a solid motion analysis framework, apply machine learning algorithms can precisely categorise gait patterns, and it can refine these methods for practical use are some of the main goals. improved PD classification and detection performance. The use of camera-based systems for data collection makes the study prioritises usability and accessibility. It allows for scalable and economical deployment in a variety of contexts. The comparison of two distinct feature extraction techniques, which is full-body features, which make use of all important body points, and body part-based features, which do not include the head and concentrate on the entire range of motion from shoulder to wrist and hip to ankle, it is one of the project's distinctive features. The purpose of this comparison is to determine which method performs better in classification for PD detection. By using camera-based systems for data collection, the study prioritises usability and accessibility, allowing for scalable and economical deployment in a variety of scenarios.

# Introduction

The primary symptom of Parkinson's disease (PD) is a progressive neurodegenerative disease by the impaired motor control [1]. An irregular gait, which is frequently accompanied by symptoms like bradykinesia, postural instability, and freezing of gait, is one of the first and most obvious indicators of Parkinson's disease [2],[3]. Traditional clinical evaluations for Parkinson's disease (PD) frequently include expert observation, which can be subjective and delay timely diagnosis and treatment [4]. This study focusses on evaluating gait during both straight-line walking and turning movements to better capture the complexity of human motion. In the case of straight-line walking, gait cycles are identified using the natural order of human walking, which starts with a closed-feet stance, moves through an open-feet phase during stride, and then returns to a closed-feet stance. This cyclical pattern allows for the extraction of stable, rhythmic features that reflect general locomotor function. The study seeks to improve research on how Parkinson's disease affects movement and identify the circumstances that offer the best indicators for early detection by looking at the walking behaviors. By simulating real-world situations and improving model accuracy, this approach makes the results more applicable in real-world settings.

## LITERATURE REVIEW

The research on early detection of Parkinson's disease has been completed in recent years. The research aims to improve the precision and effectiveness of machine learning models. The research has created the non-invasive and affordable methods and enhance current diagnostic approaches. Furthermore, early-stage detection has been enhanced by the integration of wearable technology, voice recognition, gait analysis, and cutting-edge imaging technologies. Despite tremendous progress, research is still being done to address the limitations of these approaches. New biomarkers and early warning indicators are also being studied to better predict the course of disease.

Yang et al. [5] proposed a spatiotemporal gait model that uses inertial measurement units to detect Parkinson's disease in its early stages during turns. By comparing the dataset of ten healthy young subjects, ten healthy elderly subjects, and ten early-stage PD patients, the authors validate this model's ability to identify early-stage PD. The model achieved 100% accuracy in walking and turning for all groups by using rule-based machine learning for the detection of gait phases (heel strike, flat foot, heel off, and toe-off events). With a slightly higher misclassification rate on the right side (98.23%) than the left (99.06%), the Turning Detection Algorithm (Rule-based classifier) achieved an accuracy of over 98% for detecting turns across all subject groups. The Double Integration Method with Zero Velocity Update (ZVU) showed an absolute mean bias of less than 2.19 cm for stride length estimation when walking straight and turning. The walking speed estimation also demonstrated a high degree of accuracy, with a bias of less than 0.02 m/s. With Pearson's correlation coefficients ranging from 0.82 to 0.99 for all spatiotemporal gait parameters, including walking speed and stride length, the model and the Vicon system demonstrated good agreement overall.

Ouhmida et al. [6] propose the early detection of PD through voice analysis to compare the effectiveness of Convolutional Neural Networks (CNN) and Artificial Neural Networks (ANN). The study include two datasets, first database included 195 voice recordings from 31 participants, the second database included 240 recordings from 80 subjects, 40 of whom had Parkinson's disease and 40 of whom were healthy. The results showed that CNN performed better than the ANN model, with accuracy rates of 82.76% and 72.22%, respectively, with 93.10% on Database I and 88.89% on Database II. The architecture of each model differed; the ANN had two hidden layers, whereas the CNN had layers for convolution, normalization, activation, softmax, and classification.

Biswas et al. [7] propose research for the early detection of Parkinson's disease using two distinct deep learning models developed for hand-drawn graphic analysis. The first model, a 2D Convolutional Neural Network (CNN), processed pre-processed images of spirals, meanders, and circles. It yielded accuracy rates of 61.5% for spirals, 67.8% for meanders, and 83.6% for circles. The second model, a creative LSTM network, worked with time-series data and obtained an overall accuracy of 0.78. The authors used the NewHandPD dataset for training and testing in four experiments to present their findings. The study claims that these state-of-the-art models for early PD detection could improve treatment outcomes and the lives of those affected.

# PROposed solution

## Turning Point Identification

Parkinson's disease (PD) impairs motor skills, which frequently results in changed gait patterns like stumbling steps and trouble turning. The sensitivity of deep learning models to disease-specific movements can be improved by detecting frames surrounding motion transitions, particularly when turning. In this study, turning points are local extrema in hip displacement indicate a change in walking position, it identified using the x-axis of the left hip keypoint (see Equation (1) and (2)). A 50-frame window is taken around these pivotal moments to record important gait dynamics, emphasizing hand, leg, and hip movements. By focusing on movement patterns that are clinically linked to Parkinson's disease, this technique improves PD detection by reducing noise from non-gait postures, reducing the volume of data, and highlighting physiologically significant segments as shown in Figure 1.

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|  | (2) |

## Gait Cycle Identification

For the early detection of Parkinson's disease, accurate gait analysis is crucial. We use ankle keypoints to isolate entire gait cycles in order to extract meaningful walking patterns. This ensures straight-line walking with hip-based turning point detection. We monitor the recurring leg separation during walking by measuring the Euclidean distance between the left and right ankles (refer to Equation (3)). This distance's peaks and troughs indicate full steps or strides, enabling accurate gait cycle identification that is essential for identifying abnormalities linked to Parkinson's disease.

|  |  |
| --- | --- |
|  | (3) |

|  |  |
| --- | --- |
|  |  |
| (a) | (b) |

**Figure 1.** Turning point identification graphs: (a) turning point graph with maximum value, (b) turning point graph with minimum value

Gait cycles during straight-line walking exhibit symmetrical, regular patterns that are perfect for temporal models such as LSTMs. This regularity is broken when turning, which results in non-linear motion and stride variability. We use hip displacement to identify turning points and eliminate frames following the turn to concentrate on clean walking sequences. For each subject, the longest and most stable straight-line gait cycle is chosen. This preprocessing increases the robustness of gait-based Parkinson's disease classification and improves the quality of temporal features shown in Figure 2.

A diagram of a straight line

AI-generated content may be incorrect.

**FIGURE 2.** Illustration of straight-line walking, turning points, and the gait cycle

## Body Parts Features

A particular kind of recurrent neural network (RNN) called an LSTM is made to process sequential data with long-term dependencies. By controlling the information flow through a gating mechanism, they lessen the vanishing gradient issue that standard RNNs frequently face. Over lengthy sequences, the cell state enables LSTMs to remember pertinent information while losing track of irrelevant details. Since each frame in gait data represents a timestep, LSTM models are well-suited for PD prediction. LSTMs can learn temporal patterns in stride and step lengths, cadence, and other movement characteristics suggestive of Parkinson's disease (PD) by feeding the model a random selection of 50 frames from the straight-line portion of the gait cycle shown in Figure 3. By ensuring that only steady, linear motion is examined, cutting frames after the turning point improves data quality and increases prediction accuracy.

# EXPERIMENTAL RESULTS

## Dataset

To ensure ethical compliance, the architecture for PD prediction starts with data collection from PD patients, young adults, and the elderly. To ensure straight-line walking sequences, raw videos are processed using AlphaPose to extract keypoints. Ankle keypoints are used to identify gait cycles, and hip displacement is used to detect turning points. The model is trained using the structured keypoints. Eight PD patients from University Malaya Medical Centre (UMMC) are included in a self-collected dataset of 18 participants, ages 20 to 80, from a variety of ethnic backgrounds. TUG test evaluations are used to increase clinical relevance.

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| (a) | (b) | (c) |

**FIGURE 3.** Different body part features, (a) complete gait features, (b) hand features, (c) leg features

## Evaluation of Gait Cycle Detection

In accurate gait analysis using specific body part features, the experimental results offer a thorough assessment of the various models used for PD prediction. To improve data reliability, the study used LSTM models trained on gait cycle data, paying particular attention to straight-line motion extracted after the turning point. The application of these deep learning models to two consecutive gait cycles and random selections of 50 frames highlighted the significance of temporal dependencies in differentiating PD from non-PD subjects. High-quality, noise-reduced input data is crucial for PD detection, as the experimental results showed that preprocessing to isolate the straight-line gait cycle greatly increased the predictive accuracy across all models.

Regular leg movement and step frequency are represented by steady peaks and valleys in the smooth, rhythmic, and periodic patterns of non-PD people's gait cycles as shown in Figure 4. A solid foundation for a typical gait is provided by this steady walking rhythm. On the other hand, the irregular, erratic patterns with inconsistent peaks and valleys in the gait cycles of people with Parkinson's disease (PD) reflect symptoms such as poor coordination, shorter strides, and shuffling gait. These anomalies, which include irregular step intervals and freezing of gait, demonstrate how motion keypoint analysis can be used to diagnose motor impairments associated with Parkinson's disease.

## Analysis on Straight Line Walking Behavior

In this experiment, accuracy is used as the sole evaluation metric mentioned in Table 1. Accuracy measures the proportion of correctly classified samples out of the total predictions made by the LSTM model. It is a straightforward and widely used metric for binary classification problems like PD vs. non-Parkinson's (NP).

**TABLE 1.** Table gait cycle comparison of LSTM model

|  |  |  |  |
| --- | --- | --- | --- |
| **Gait Cycle** | **Complete Gait Sequences (Accuracy)** | **1 Gait Cycle** | **2 Gait Cycle** |
| **Full Body Key points** | 0.75 | 0.75 | 0.60 |
| **Body Part Features** |  |  |  |
| Full Body Without Head  Hand Features  Leg Features | 1.00  1.00  1.00 | 0.25  0.25  0.50 | 0.25  0.25  0.67 |

This study used gait analysis to assess various body key points for PD detection. Though they included redundant or less informative areas like the head, full body key points, which include data from head to toe, offered moderate accuracy (0.75). Poor accuracy (0.25) was obtained when the head was removed from the body part features subset, indicating that it may contain subtle but significant cues. A lack of temporal depth and outside influences may have contributed to the hand features subset's poor performance (0.25), which focused on arm and hand movements. In contrast, leg features, which focus on the hips, knees, and ankles, proved most informative, achieving 100% accuracy in identifying PD. Even with fewer gait cycles, leg features maintained high performance (0.67), highlighting that lower-limb movement is the most critical for reliable PD detection. This study suggests that focusing on leg movement improves accuracy, especially in noisy or variable environments.

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| A graph with blue and green lines  AI-generated content may be incorrect. | A graph with blue and red lines  AI-generated content may be incorrect. |
| A graph of a graph  AI-generated content may be incorrect. | A graph with blue and green lines  AI-generated content may be incorrect. |
| (a) | (b) |

**Figure 4.** Comparison of gait cycle graph. (a) PD patients, (b) non-PD patients

## Analysis on Gait Behavior During Turning

The gait pattern becomes more intricate during turning movements shown in Table 2, which may indicate mild motor impairments linked to Parkinson's disease. The effectiveness of various key point features during turning sequences was assessed in this analysis. Despite the variability brought about by directional changes, holistic motion data still retains important information, as evidenced by the full body key points' moderate accuracy of 0.75. It's interesting to note that hand features alone had the highest accuracy (1.00), indicating that asymmetrical or diminished arm swings, which are typical in PD, become more noticeable and effective detection indicators during turns. However, features like hip value alone, leg key points, and full body without head performed worse (0.50 accuracy), suggesting that these areas might not have enough discriminative power on their own. Regarding its important function in turning dynamics, the hip is the central axis of body rotation, it was included as a specific feature. The hip value, which represents balance control and rotational movement, is still an essential part of modeling turning behavior even though it did not by itself improve classification results. This implies that even though the hip is biomechanically crucial, turning-related gait abnormalities in Parkinson's disease may require combining it with other body parts, particularly upper limb dynamics.

## Discussion

The experiment tested multiple configurations of body key points to evaluate their individual and combined contributions. Results revealed that, Full Body Key Points provided a moderately accurate prediction (75%) but were affected by possible noise from less relevant regions like the head. Head Exclusion surprisingly resulted in a drop in accuracy (25%), suggesting that even minor head movements might encode subtle indicators or help maintain balance in the overall feature space. Hand Features alone were insufficient during straight-line walking (25% accuracy), possibly due to limited arm motion or occlusion. In Leg Features, which directly represent walking patterns, proved most reliable, achieving 100% accuracy with full gait sequences. Even with shorter gait cycles, the leg key points retained high predictive power.

These results demonstrate that the most discriminative biomarker for gait-based Parkinson's disease detection is lower limb movement. Isolating the most pertinent segments, such as leg movements, simplifies computation and improves model accuracy, even though holistic motion offers context. It's interesting to note that the analysis of turning phases showed a change in the significance of key features. Hand features alone produced perfect accuracy (1.00) during directional changes. This implies that abnormalities of the upper limbs, like asymmetric or reduced arm swing, become more apparent when turning, which makes them essential for identifying Parkinson's disease in more dynamic situations. On the other hand, hip and leg characteristics alone were less trustworthy. Although the hip keypoint is biomechanically significant for rotation and balance, it lacked independent discriminative power, suggesting that its utility is more in enhancing other features than in independent analysis.

**TABLE 2.** Turning point comparison for LSTM model

|  |  |
| --- | --- |
| **Column Header Goes Here** | **Complete Gait Sequences** |
| **Full Body Key points** | 0.75 |
| **Body Part Features** |  |
| Full Body Without Head  Hand Features  Leg Features  Hip Value | 0.50  1.00  0.50  0.50 |

# CONCLUSION

This study offers a useful technique for early Parkinson's disease detection that makes use of body part features and selective gait analysis. The method improves the precision and resilience of motion-based diagnostic models by integrating pose estimation, turning point detection, and gait cycle segmentation. The results indicate that PD affects both hand and lower limb features, which are crucial for straight-line walking and turns, respectively. LSTM-based classification employing region-specific models performs better than full-body models, lowering noise and enhancing predictive performance. This study offers a scalable, reasonably priced method for detecting Parkinson's disease early on that can be used for remote diagnoses and telemedicine.

# References

1. J. Li, et al., “A deep learning hybrid model for Parkinson’s disease diagnosis based on electroencephalogram signals,” Proceedings of the 2023 17th International Conference on Complex Medical Engineering (CME), IEEE, pp. 55–58 (2023).
2. Y.F. Ti, T. Connie, and M.K.O. Goh, “GenReGait: Gender Recognition using Gait Features,” Journal of Informatics and Web Engineering **2**(2), 129–140 (2023).
3. V.W.S. Tan, W.X. Ooi, Y.F. Chan, C. Tee, and M.K.O. Goh, “Vision-Based Gait Analysis for Neurodegenerative Disorders Detection,” Journal of Informatics and Web Engineering **3**(1), 136–154 (2024)
4. W. Wang, et al., “Early detection of Parkinson’s disease using deep learning and machine learning,” IEEE Access **8**, 147635–147646 (2020).
5. Y. Yang, et al., “Validation of a spatiotemporal gait model using inertial measurement units for early-stage Parkinson’s disease detection during turns,” IEEE Transactions on Biomedical Engineering **69**(12), 3591–3600 (2022).
6. A. Ouhmida, et al., “Voice-based deep learning medical diagnosis system for Parkinson’s disease prediction,” Proceedings of the 2021 International Congress of Advanced Technology and Engineering (ICOTEN), IEEE, pp. 1–5 (2021).
7. S. Biswas, et al., “Early detection of Parkinson’s disease from hand drawings using CNN and LSTM,” Proceedings of the 2022 4th International Conference on Artificial Intelligence and Speech Technology (AIST), IEEE, pp. 1–4 (2022).