A Four-Stage AI Framework for Gait Disturbance Detection and Remote Alerting in Parkinson's Disease

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Abstract—Parkinson's disease functions as a progressive neurological disorder which destroys a person's ability to walk and maintain balance and move about. The conventional walker device supports users with basic mechanical assistance while it fails to identify or forecast walking pattern disturbances. The research develops an AI-based smart walker system which operates through a four-part framework which combines vision- based sensing and pose-driven feature extraction and analytical gait processing and multimodal feedback. A smartphone- mounted camera captures lower-limb motion and streams video wirelessly to a laptop-based analytical engine. The system uses pose estimation technology to obtain anatomically normalized gait features which allow for identification of freezing of gait and slow gait and fall initiation. The system shows three types of responses which include rhythmic auditory cues and emergency alerts and monitoring of remote caregivers. The experimental tests show the system achieves real-time operation between 20 to 25 frames per second while maintaining accurate detection performance. The system provides an affordable and non-invasive and scalable support system which matches medical practices that use AI technologies.

Keywords—Artificial Intelligence, Smart Walker, Gait Analysis, Parkinson's Disease, Computer Vision.

I. Introduction

The progressive neurodegenerative disorder Parkinson's Disease (PD) develops through the destruction of dopamine-producing neurons in the basal ganglia which creates motor deficits and leads to permanent disabilities according to [1] [2]. The typical motor symptoms of the condition include tremors and muscular rigidity and bradykinesia and postural instability and disturbances in walking ability. Gait-related impairments present the most severe disability because they stop people from moving independently and they create major hazards for falls and injuries according to [3][4].

Freezing of gait (FOG) represents one of the most difficult gait disorders in PD because it causes patients to lose their ability to walk either forward or backward according to research from [5]. Patients often describe this sensation as their feet being "glued to the floor." FOG occurs frequently during gait initiation and turning and narrow space navigation which leads to falls and decreased quality of life according to research from [3][6]. Most people with PD use walking aids such as walkers to help them stay mobile throughout their disease progression.

Conventional walkers, however, operate as mechanical devices which support users physically but do not track their walking patterns and do not respond to incidents which include freezing episodes and falls. The existing problem requires various technological solutions which have been developed to solve this issue. Wearable sensor-based systems which use inertial measurement units can successfully identify walking pattern defects according to research from [7][9] but their use requires users to wear sensors continuously and perform sensor calibration which elderly patients find difficult to accomplish [10] [11].

Computer vision and artificial intelligence technologies have developed better vision-based gait analysis systems which enable contactless movement tracking. Pose estimation techniques extract skeletal joint landmarks from monocular video streams, which allows researchers to measure walking patterns but without the need for wearable sensors [12][13]. The current solutions show potential for development, yet they restrict their operational capabilities to through offline analysis and laboratory testing, which stops them from being used in real-time assistance systems [14]. Smart walkers and robotic mobility aids provide active assistance but are often costly and mechanically complex, which prevents their operation in residential environments [15][17].

The study develops an AI-based predictive smart walker which uses vision-based gait analysis to enhance a standard walker through its minimal hardware requirements. The system uses a smartphone-mounted camera to record lower-body movement while a laptop-based processing unit performs real-time pose estimation and gait analysis. The system analyzes clinically relevant gait features which include ankle velocity and gait asymmetry and hip displacement to identify three different conditions which include freezing of gait and slow walking and fall initiation. The system provides proactive assistance through rhythmic auditory cues which have been shown to improve gait in PD patients [18][20] together with emergency caregiver alerts. The approach offers a cost-effective solution which requires no physical contact while providing a connection between basic mobility aids and sophisticated robotic systems used for Parkinson's Disease treatment.

II. Related Work

The research dedicated to assessing Parkinson's Disease gait focuses on two primary areas which include gait impairment and freezing of gait. The existing methods for this assessment use three main types of systems which include wearable sensors vision systems for gait evaluation and intelligent mobility aids.

The research studies which use inertial measurement unit-based wearable sensor systems detect freezing of gait and postural instability through accelerometer and gyroscope analysis [7][8][10][11]. The methods provide high accuracy results, but their continuous need for sensor attachment and calibration process limits their use in everyday situations.

The development of pose estimation and deep learning technology has enabled vision-based gait analysis to function as a non-contact assessment method. Monocular camera-based approaches allow skeletal landmark extraction without wearable sensors [12][13], with temporal refinement improving stability [14]. The majority of current research studies use offline analysis methods which do not support real-time assistance during their implementations.

Smart walkers and robotic mobility aids provide active gait assistance using force sensing or haptic feedback [15] [17] but high cost and mechanical complexity restrict home deployment despite clinical effectiveness [16]. External cueing strategies, such as rhythmic auditory cues, have shown benefits in improving gait initiation and walking speed, though they are often not linked to real-time gait assessment.

The system uses vision-based gait analysis together with standard walker equipment to create three functions which include predictive detection multimodal feedback and remote monitoring capabilities. The system operates without requiring users to wear sensors or use advanced robotic devices.

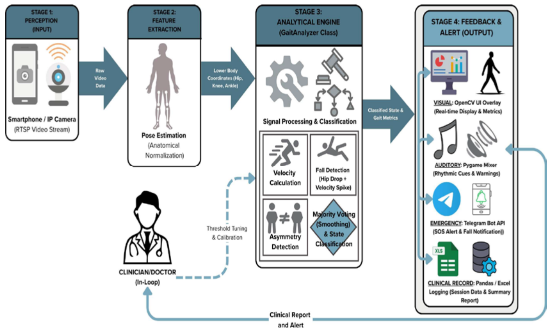

Figure 1: Overall system architecture of the proposed AI-powered predictive smart walker.

III. System Architecture

The AI-based predictive smart walker system uses a distributed and modular system design which requires only a small amount of hardware to achieve its real-time gait tracking and early warning system capabilities. As illustrated in Fig. 1, the system operates through its initial perception stage which processes video footage from smartphones and IP cameras to identify human body positions and standardize their physical features according to anatomical norms. The system processes lower-body gait data which includes hip joint and knee joint and ankle joint movement information through an analytical engine that performs signal processing and gait state identification tasks. The engine determines essential gait measurements which include walking speed and body weight distribution difference and falling risk signs through its threshold assessment process and majority decision process. The system provides dual-channel feedback through visual content which appears during the present time and through sound alerts and emergency notifications while it simultaneously saves session information for use in clinical documentation. The system requires a clinician-in-the-loop framework which facilitates dynamic threshold adjustment and system calibration to function properly within residential spaces and medical rehabilitation facilities.

The system contains four main components which include (i) a vision-based sensing module and (ii) a gait analysis and decision-making module and (iii) a feedback and alert module and (iv) a remote monitoring interface. The system demonstration shows how information moves through the system starting from motion capture until it reaches the assistive response stage.

A. Vision-Based Sensing Module

The system employs a smartphone camera as its only motion detection device to track user movement. The system uses a camera which records all lower-body movements of the user who walks with a walker. The system design needs no wearable devices because it uses non-contact gait analysis methods which researchers documented in their recent studies [12][13].

Standard Wi-Fi communication enables wireless transmission of the video stream to reach the processing unit. The smartphone camera system allows users to record high definition videos because it combines compactness and affordable pricing which enables practical usage in real environments.

B. Gait Analysis and Decision-Making Module

The system's analytical core executes its functions through a processing unit which resides on a laptop to enable real- time pose estimation and gait analysis. The pose estimation techniques extract skeletal landmarks from video frames by detecting essential anatomical joints which include the hips knees and ankles of lower limb joints [12][21].

The research team established all spatial measurements through leg length normalization which used skeletal geometry to produce estimated values. The extracted landmarks are used to compute gait features which include ankle velocity gait asymmetry hip displacement and body orientation. The selected features demonstrate clinical significance for evaluating Parkinsonian gait impairments according to research studies [4][6].

The system uses rule-based temporal analysis to create decision logic which classifies gait states into four categories: normal walking, slow gait, freezing of gait, and fall initiation. The system detects freezing of gait through its sustained low ankle velocity measurement while it uses abrupt changes in hip height and posture to detect potential fall events. The system applies temporal majority voting to decrease false detections while it maintains consistent transitions between different gait states [22][23].

C. Feedback and Alert Module

The system generates multiple real-time feedback modes which help users while improving their safety whenever it detects unusual walking patterns. The system uses established clinical pace control methods to provide patients with rhythmic sound cues which assist them during freezing of gait episodes and walking pace management [18][19].

The system automatically creates emergency alerts which it sends to caregivers during critical situations when someone falls. The alerts deliver contextual details about the event which includes the type of event and its corresponding time of occurrence. The system provides feedback through easy-to- use mechanisms which create minimal disruption to patients who need to use it throughout the day.

Table 1 Heuristic Thresholds and Operational Logic

Parameter	**Value**	**Logic / Clinical Basis**
T_{Normal}	> 0.035	Healthy gait cycles.
T_{slow}	$0.012 - 0.035$	Bradykinesia indicator.
T_{FOG}	≤ 0.012	FOG detection.
T_{asym}	> 0.35	Limb variance $> 35\%$.
T_{fall}	> 0.05	Hip drop $> 5\%$.
Update Int.	$1.0s$	Voting window (Eq. 8).

D. Remote Monitoring Interface

The system provides a remote monitoring interface which displays both live video streams with annotations and all detected gait states to help clinicians evaluate patients and enable caregivers to participate in their work. Caregivers can use this system to monitor walking patterns in real time. They can also access recorded instances of gait movement which happened throughout the day. The use of remote monitoring systems demonstrates improved patient protection while enabling healthcare providers to implement continuous medical treatment which follows current AI-based healthcare system development [24][25].

The proposed system design shows three main features which make it cost-effective and non-disruptive and expandable to larger systems. The system design enables vision- based intelligent capabilities to function within regular walkers because it does not need advanced robot components or user body-worn sensors.

IV. METHODOLOGY

The system uses a vision-based analytical framework to identify gait abnormalities which occur in patients with Parkinson's Disease through real-time detection. The methodology includes four components which are pose estimation and gait feature extraction and event detection logic and temporal decision smoothing. The system functions as a continuous operation which delivers quick response times while maintaining its ability to handle various user and environmental conditions.

A. Pose Estimation and Skeletal Modeling

The system tracks human body movement through video streams by detecting and recording specific body parts that create human skeleton joints. A monocular pose estimation framework is used to identify key anatomical joints of the lower limbs, including the hip, knee, and ankle joints [12] [21]. The selected joints show direct connections to both gait dynamics and balance control functions.

Let the 2D coordinates of a joint at time frame t be represented as:

$$J_t = (x_t, y_t) \tag{1}$$

The researchers measure all distances by using estimated leg length which provides equal scale measurements for all users regardless of their distance from the camera. The formula for leg length L calculates the distance from hip to knee and the distance from knee to ankle which together create the total leg length measurement.

$$L = ||J_{hip} - J_{knee}|| + ||J_{knee} - J_{ankle}|| \tag{2}$$

Normalization improves robustness and enables comparison of gait features across different subjects [4].

B. Gait Feature Extraction

The extraction process of clinically essential gait characteristics begins with the use of normalized skeletal landmarks. Ankle velocity calculation uses frame-to-frame measurements of ankle joint movement through time.

$$Vt = \frac{|| J\ \text{ankle}(t) - J\ ankle\ (t-1)||}{\Delta t} \quad (3)$$

The Presence of decreased ankle speed throughout an extended time period serves as a reliable indicator of freezing of gait which occurs in Parkinson's Disease according to the research of Nutt and Mazilu. The assessment of gait asymmetry involves measuring the speed of both left and right limbs throughout multiple walking cycles.

$$A_t = |V_{left}(t) - V_{right}(t)| \quad (4)$$

The condition known as asymmetrical body movement increases its effects on people who suffer from bradykinesia and motor coordination deficits according to the research study.

The monitoring of hip displacement detects postural instability and indicates the start of possible falls. The system monitors vertical hip position changes throughout time and considers sudden downward movement together with speed increases as indicators of a fall [26].

C. Event Detection Logic

The system uses rule-based temporal logic to identify events through analysis of medically recorded walking patterns. A freezing of gait (FOG) event is detected when normalized ankle velocity remains below a predefined threshold T_{FOG} for a minimum duration D_{FOG}:

$$V_t < T_{FOG} \quad \forall\ t \in [t_0, t_0 + D_{FOG}] \quad (5)$$

The identification of slow walking occurs when ankle speed drops below the established minimum value while gait asymmetry shows increased levels. The following equation describes this condition:

$$V_t < T_{slow} \ \wedge\ A_t > T_{asym} \quad (6)$$

The process of fall detection begins when two conditions are met which include sudden hip movement and change in body position. The following equation describes this condition:

$$\Delta H_t > T_{fall} \ \wedge\ V_{hip}(t) > T_{vel} \quad (7)$$

The existing real-time vision system operates through threshold rules which researchers developed from previous studies on wearable devices and visual systems for gait assessment [22][23][27].

D. Temporal Smoothing and State Classification

The system uses temporal majority voting across consecutive frames to block false positives which result from short-term noise or occlusion. A gait state is confirmed only if the same classification persists for a predefined number of frames N:

$$State = \text{mode}(S_{t-N}, \ldots, S_t) \quad (8)$$

The method from this research enhances detection stability while providing smooth transitions between different gait states [14]. Emergency states such as falls receive top priority which causes them to automatically take precedence over all other classifications.

E. Feedback Triggering Mechanism

The system maps detected gait events to specific feedback actions which need to be executed. The system uses rhythmic auditory cues which help users start walking and maintain their walking speed whenever freezing of gait and slow walking events occur. The external cueing strategies which doctors use in clinical settings show that they help patients with Parkinsons Disease to walk better [18]–[20]. The system generates emergency alerts for caregivers whenever a fall event occurs and accompanies the alerts with precise timestamps which help caregivers respond promptly.

The proposed methodology combines clinical gait features with efficient vision-based analysis methods to deliver real-time predictive assistance through minimal hardware requirements.

V. Experimental Results and Discussion

The research team tested their recommended AI-driven intelligent walking assistance solution in an artificial environment which simulated typical walking paths used by Parkinson's Disease patients. The assessment of the system concentrated on measuring its actual performance capabilities together with its ability to identify events and its speed of operation.

A. Experimental Setup

The researchers conducted their experiments inside a controlled space which maintained consistent lighting and provided a level walking area. The walker used a smartphone camera system to record his lower body movements while a laptop processing unit conducted real-time pose estimation and gait analysis. The smartphone and laptop shared data through a standard Wi-Fi connection which established their wireless communication link.

The test scenarios involved testing different walking speeds together with simulating freezing of gait episodes and testing various walking patterns and testing turning movements and fall-related postures. The researchers selected these scenarios because they represented actual walking difficulties experienced by people with Parkinson's Disease. The walking sessions continued for multiple minutes which enabled the system to record various walking patterns and different gait

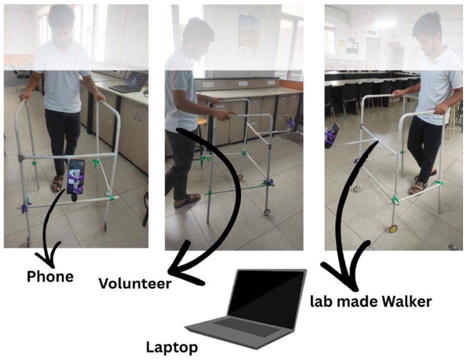

Figure 2: Hardware Implementation of the system.

transition moments. The setup for the experiment includes a piping walker that uses an integrated smartphone provision, designed to serve as a low-cost and universally accessible solution.

B. Performance Metrics

System performance was evaluated through three metrics which included frame processing rate and detection accuracy and response latency. The system maintained its ability to track human movements in real time by processing between 20 and 25 frames each second. The system evaluated detection accuracy by matching detected events with ground truth data which was obtained through visual inspection of video recordings.

Freezing of gait detection achieved an accuracy range of approximately 87% to 92% across test scenarios. The system achieved detection accuracy of slow gait between 85% and 90% while it reached fall initiation detection accuracy of 95% during simulated conditions. These results match the performance metrics which earlier studies reported in their research about wearable systems and vision-based gait analysis systems [7][23][26].

The complete system delay which includes motion capture and feedback creation process took between 200 and 400 milliseconds to complete. The system delay, which operates at this level, enables users to receive immediate help during freezing episodes and fall events, thus proving that real-time support is operational.

C. Qualitative Observations

People who have freezing of gait show persistent ankle velocity decreases which become their most reliable freezing of gait indicator especially during gait initiation and turning. The combination of gait asymmetry with the ability to dif- ferentiate between slow walking and freezing events showed better results than using hip displacement for fall detection during sudden posture changes which resulted in some false positives when people transitioned to sitting.

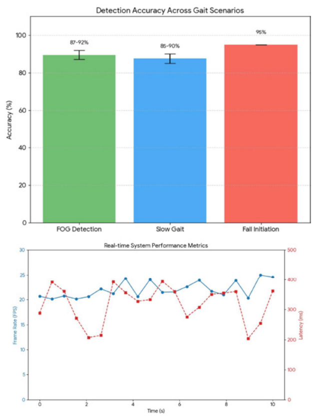

Figure 3 : Performance metrics of the proposed system.

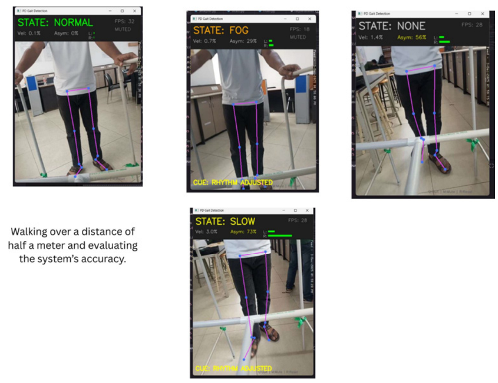

Figure 4: Testing scenarios and system response.

The use of rhythmic auditory cues during simulated freezing episodes led to better gait continuity which supports pre- vious clinical research that shows external cueing improves walking abilities of Parkinson's Disease patients according to sources [18]-[20]. The system used non-intrusive feedback mechanisms which enabled users to walk naturally without any interruptions to their movement.

D. Discussion

The experimental results demonstrate that reliable gait monitoring and predictive assistance can be achieved through a vision-based system which requires only basic hardware components. The proposed system achieves detection accuracy that competes with wearable sensor-based systems because it does not require users to wear continuous sensors [8][11]. The proposed solution for home use eliminates the need for expensive robotic walkers because it does not use complex mechanical systems [15][16].

The environmental factors of lighting conditions and camera placement determined the performance results. The accuracy

 https://doi.org/10.1051/itmconf/20268701015

of pose estimation suffered because of two factors which included decreased light conditions and partially blocked view. The limitations of vision-based systems require the development of strong preprocessing methods together with dynamic thresholding techniques.

The experimental evaluation demonstrates that vision-based gait analysis together with predictive event detection and real-time feedback can function effectively with standard walker equipment. The results demonstrate that the proposed system functions as an effective practical assistive solution which can be used for Parkinson's Disease treatment.

VI. Limitations and Future Work

The proposed AI-based predictive smart walker demonstrates effective performance in detecting Parkinsonian gait abnormalities using vision-based analysis. However, as the current system relies on a monocular camera for pose estimation, its performance can be influenced by environmental factors such as lighting variations, camera positioning, and partial occlusions. Changes in illumination and background contrast may affect pose estimation accuracy and lead to delayed or missed detections, a limitation commonly observed in vision-based systems [14]. Additionally, the use of a rule-based gait classification approach with fixed thresholds enables real-time operation with low computational complexity but may limit adaptability to highly individualized gait patterns observed in advanced stages of Parkinson's Disease [4][6]. Experimental evaluation under controlled indoor conditions with simulated freezing and fall events allowed systematic validation, though real-world variability such as uneven surfaces and outdoor environments was not fully explored [26].

Future work will focus on enhancing system robustness and adaptability through several targeted improvements. Machine learning-based classification models will be investigated to enable personalized and adaptive gait assessment, improving generalizability across patients. The integration of multimodal sensing by combining vision-based features with lightweight wearable sensors is expected to improve performance under challenging environmental conditions. Furthermore, future system extensions will incorporate automatic braking and haptic feedback mechanisms to provide physical assistance during instability. Long-term clinical studies involving Parkinson's Disease patients will be conducted to evaluate system usability, reliability, and clinical impact in real-world settings, further strengthening the system's applicability for assistive mobility.

VII. Conclusion

The researchers developed an AI system that predicts walking patterns through a smart walker which creates upcoming walking support for Parkinson's Disease patients who need a small and discreet walking aid. The system uses a smartphone camera for vision-based sensing which works with its real-time processing capabilities to track walking movements without requiring any wearable devices or advanced robotic equipment. The system uses pose estimation together with clinical gait measurements which include ankle speed and walking imbalance and hip movement to identify three different movement patterns which include freezing of gait and slow walking and falling down. The system uses rule-based temporal logic together with majority voting methods to achieve accurate classification of gait states while using rhythmic auditory signals and emergency caregiver notifications to enhance user mobility and protection. The experimental results showed the system could perform in real time through precise detection which required minimal time and produced results that matched existing wearable and robotic systems while being more affordable and simpler to use. The method connects two different types of mobility support systems by providing a Parkinson's Disease treatment solution which requires additional clinical testing to prove its effectiveness.

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