Human Pose Estimation and Gait Analysis with Convolutional Neural Networks for Alzheimer's Disease Detection

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ABSTRACT

In computer vision, human pose estimation (HPE) through convolutional neural networks (CNNs) has emerged as a promising avenue with broad applicability. This study bridges a novel application of HPE, targeting the early detection of Alzheimer's disease (AD), a condition expected to affect roughly 13.4 million Americans by 2026. Traditionally, AD diagnostic methodologies like brain imaging, Electroencephalography, and blood/neuropsychological tests are not only expensive and protracted but also require specialized medical expertise. Addressing these constraints, we introduce a cost-efficient and universally accessible system to detect AD, harnessing conventional cameras and employing pose estimation, signal processing, and machine learning. Data was sourced from videos capturing a 10-meter curve walk of 73 cognitively healthy older adults (HC) and 34 AD patients. The recording apparatus was a camera offering a resolution of 1920x1080 pixels at 30 frames/second, stationed laterally to the walking path. Using OpenPose, a state-of-the-art, bottom-up multi-person HPE method based on CNNs, we derived 25 distinctive body joint coordinates from the footage. Subsequently, 48 gait parameters were extracted from these joints and subjected to statistical scrutiny. A noticeable difference was observed in 39 out of the 48 gait parameters between the HC and AD groups. Leveraging a Support Vector Machine (SVM) to classify the data, the distinctiveness of these gait markers was further affirmed. The system accomplished a commendable accuracy rate of 90.01% and an F-score of 86.20% for AD identification. In essence, our findings advocate that the amalgamation of everyday cameras, sophisticated HPE techniques, signal processing, and machine learning can pave the way for practical AD detection in non-specialized settings, including home environments.

Keywords: Human pose estimation (HPE), Alzheimer's disease (AD) detection, Convolutional neural networks (CNN), OpenPose, Gait analysis

1. INTRODUCTION

Alzheimer's disease (AD) is a progressive neurodegenerative condition characterized initially by memory issues, escalating into significant functional impairments in daily activities such as language,

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mobility, and driving, ultimately increasing the risk of death in older adults.[1–4] As the fifth-leading cause of death for Americans aged 65 and older, an estimated 6.7 million individuals within this age group currently live with AD, a figure projected to double by 2060.[4] Early detection of AD can significantly slow the disease's progression through timely medical intervention and aid in managing the challenges faced by affected individuals and their caregivers through rehabilitation programs and lifestyle adjustments.[5]

Traditional diagnostic methodologies, encompassing a variety of neuropsychological screenings such as the Montreal Cognitive Assessment (MoCA) and Mini-Mental State Examination (MMSE), alongside blood tests and brain imaging, are conducted by a multidisciplinary team of specialists.[6] However, these methods are not without limitations, including accessibility, high costs, and a significant rate of misdiagnosis, particularly in primary care settings where dementia types can be overlooked or mistaken for normal aging processes.[7]

To address these challenges, recent research has explored novel biomarkers and diagnostic tools that can offer more accessible, cost-effective, and accurate early AD detection. Gait and balance have been explored as indicators of cognitive and motor function decline associated with AD. Studies have demonstrated the potential of gait analysis, traditionally relying on electronic walkways and infrared cameras, as an unobtrusive diagnostic tool that correlates specific gait patterns with cognitive decline.[8–12] Wearable sensors and depth cameras have also been recently proposed as alternative technologies for gait tracking in both clinical and home settings, offering detailed insights into the motor functions of older adults.[13,14] Depth cameras, such as the Kinect cameras developed by Microsoft Corporation, have shown particular promise. They offer several advantages over previous technologies, including capturing more comprehensive data from multiple body joints at a lower cost and with easier setup. Moreover, these cameras address privacy concerns by utilizing only the skeletal data they generate, making them an attractive option for unobtrusive gait analysis.

Building on these advancements, our study introduces a cutting-edge approach to gait analysis that leverages a single regular camera combined with the OpenPose algorithm, a deep learning-based computer vision technique for human pose estimation (HPE). This novel method simplifies data collection while ensuring privacy and reducing costs, and notably, it does not require the placement of markers on the body, unlike previous methods. By extracting a wide array of macro and micro gait features directly from video data, our approach significantly expands the potential for detailed analysis without the obtrusive steps of attaching sensors or markers. Integrating descriptive statistical analysis and machine learning, we aim to identify specific gait patterns indicative of AD, thus facilitating a more objective and accurate assessment of cognitive status compared to traditional methods.

2. MATERIALS AND METHODS

2.1 Study Population

Participants underwent comprehensive checkups for assessment and diagnosis of cognitive impairments due to AD using brain imaging, blood tests, and MoCA neuropsychological test, as well as the Geriatric Depression Scale (GDS) for depression measurements. In total, 73 older adults without any cognitive impairment as the healthy control (HC) group and 34 AD patients who could perform the physical tests independently and did not have gait deficits because of surgery like knee surgery and medicine affecting their gait were chosen and completed the gait tests. These participants were either clients of Iran's Dementia and Alzheimer's Association or volunteers who responded to public recruitment efforts. Comprehensive study information was provided to all participants beforehand, ensuring informed consent was obtained. Participants were also informed of their freedom to withdraw from the study at any point. The ethical conduct of this study was reviewed and approved by the Ethics Committee of the Semnan University of Medical Sciences in Iran.

2.2 Image-Based Gait Analysis

To assess gait for AD detection, participants walked a 10-meter curved path, validated and widely used in clinical settings. Participants initially undertook a single trial as a practice session before completing three main trials for detailed analysis. Between each trial, individuals were allowed rest periods ranging from 1 to 3 minutes to ensure optimal performance during the tests. The selection of the 10-meter distance was based on previous studies that have established this measure as a standard clinical tool for functional assessment.[15]

Data capturing of the gait tests was achieved using a high-definition single camera, set to a resolution of 1920 x 1080 pixels and operating at a frame rate of 30 frames per second. The camera was securely mounted on a tripod to maintain a stable lateral view of the participants' walking path. The data acquisition setup was managed using an ASUS FX503 laptop equipped with an Intel Core i7-7700HQ CPU operating at 2.80 GHz and 8.00 GB of RAM, ensuring efficient processing and storage of the collected gait data. The equipment arrangement and methodology for recording the 10-meter curved path walking tests are depicted in Fig. 1, illustrating the setup utilized for capturing the gait data of participants.

2.3 Innovations in Image Processing for AD Detection

After collecting RGB data from participants during their curved path walks, we performed a series of processing steps to facilitate AD detection from the recorded data. This approach involved several key phases: detecting body joints within the RGB images, preprocessing the signals from these detected joints, extracting relevant features, conducting descriptive statistical analysis for feature selection, and employing machine learning models to identify AD in older adults. Fig. 2 delineates these primary phases of our algorithm.

2.3.1 Automated body joint detection

The automated detection of body joints from RGB images was achieved through the OpenPose algorithm; a real-time 2-D HPE technique characterized by its bottom-up approach. Utilizing an advanced multi-stage convolutional neural networks (CNNs), OpenPose identifies the locations of body joints and connects them, creating a skeletal structure through Part Affinity Fields.[16] This method's ability to provide real-time pose estimations offers significant advantages, especially in scenarios involving multiple individuals, setting it apart from traditional top-down estimation techniques.[16] In our research, the Python implementation of OpenPose was used for HPE to identify 25 critical body joints within the captured images, covering key anatomical landmarks such as the feet, elbows, and hands. Fig. 3 provides a visual representation of the joints identified and the skeletal framework constructed from RGB images obtained during the 10-meter curved path walking tests, highlighting the effectiveness of OpenPose in our study.

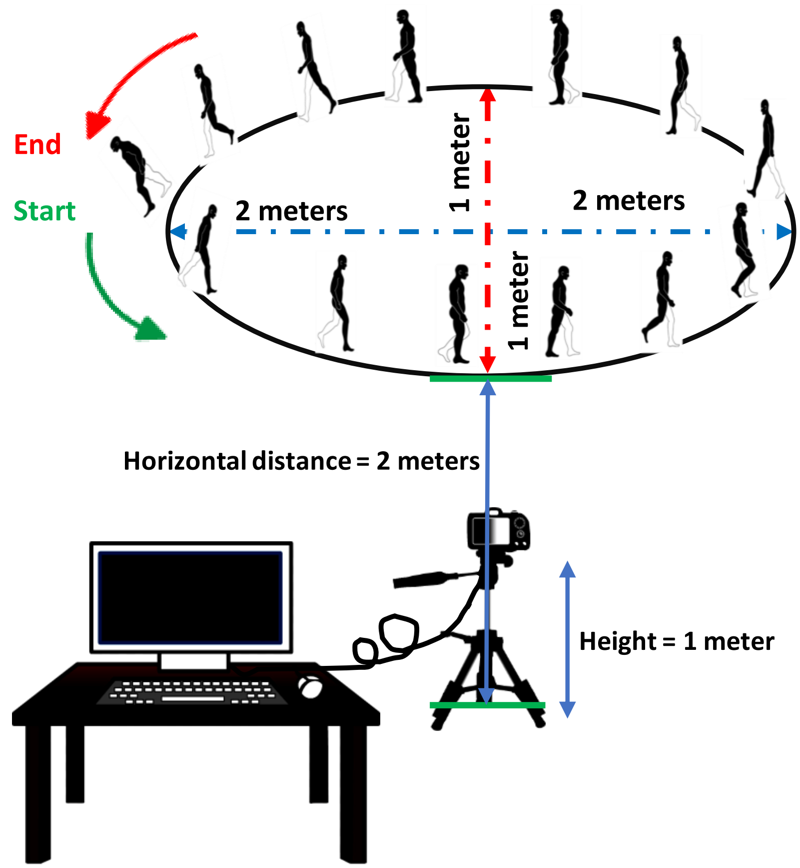

Figure 1. Setting up a 10-meter curved path walking and recording tools.

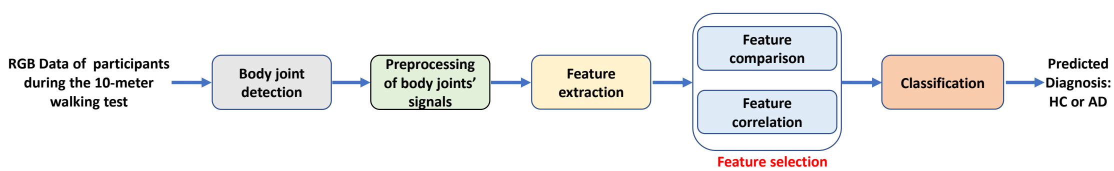

Figure 2. Flowchart illustrating the algorithmic process for AD detection, from capturing and processing RGB data during the 10-meter curved path walking test to the final classification and diagnosis as HC or AD.

2.3.2 Signal preprocessing and conversion

As participants navigated the curved path, the movement of their body joints produced signals in both horizontal (x) and vertical (y) directions over time, which are critical for extracting key gait features such as average velocity and step length. To ensure the accuracy of these signals, we

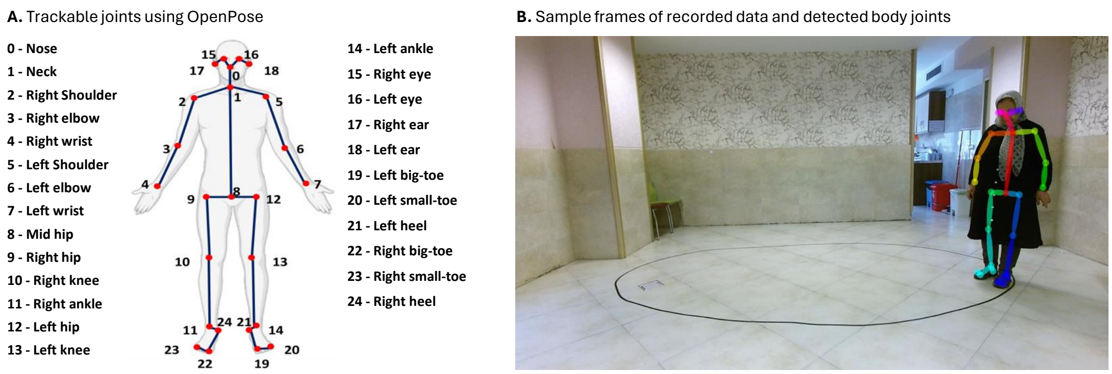

Figure 3. Body joint detection using the human pose estimation algorithm of OpenPose for curved path walking test. A) Detectable joints of the body via OpenPose; B) Sample of recorded RGB data and detected body joints for a participant during the gait test.

applied a six-order Butterworth Filter with a cut-off frequency of 3 Hz, using MATLAB 2019,[17] to remove any extraneous noise. We converted these dimensions into real-world measurements after the initial detection of body joint positions by OpenPose and their representation in pixel-based measurements. This conversion to real dimensions was performed using the methodology outlined by Stenum *et al.* (2021)[18] and facilitated subsequent analysis of the data.

2.3.3 Extraction and selection of gait features

From the signals derived from detected body joints during gait assessments, we extracted a total of 48 gait features. These were categorized into 6 macro features (like walking duration, average velocity, and step and stride counts), 24 micro temporal features (such as stance and swing durations), 12 micro spatial features (including step length and its variability), and 6 micro spatiotemporal features (for example, step and stride velocity). Macro features calculation involved methods such as dividing the total displacement of the ankle joint by the test duration for average velocity. For micro features, identifying gait cycles and their phases was essential, accomplished by analyzing distance signals from ankles and using their peaks to segment gait into stance, swing, single support, and double support phases. Statistical analysis of these features then provided metrics of mean, median, and variability, the latter expressed as the standard deviation's percentage of the mean.

A systematic feature selection process was implemented to refine the feature set for AD detection, beginning with a descriptive statistical analysis to consider potential confounding demographic and clinical factors. Tests such as Shapiro-Wilk, unpaired t-tests or Mann-Whitney U tests, and Chi-square tests were applied to ensure that comparisons between the AD and HC groups accounted for variable distribution and category differences. Significant gait features that were distinguished between the groups were then adjusted for confounders like age, weight, and education level using Analysis of Covariance (ANCOVA), and these adjusted features were then compared to pinpoint those with statistically significant differences. This selection was further refined through correlation analysis, where among correlated features ($r > 0.9$), the one with the most significance (lowest p-value) was chosen as the prime indicator for distinguishing between AD and HC groups, streamlining the analysis to the most discriminative features.

2.3.4 Machine learning-based AD classification

For the classification of AD from our study's gait analysis data, we utilized a Support Vector Machine (SVM) classifier. SVM was selected due to its proven effectiveness in accurately categorizing distinct groups, an advantage especially relevant for analyses with limited data sizes. Its principal strength lies in transforming data into a higher dimension where linear separation is possible, facilitating the distinction between participants diagnosed with AD and those categorized as HC.

We ensured the reliability and generalizability of our classification model by adopting a 5-fold cross-validation strategy. This method divides the dataset into five parts, using four for training and the remaining one for testing, iteratively. For each training phase, we further segmented the data, allocating 80% for model training and 20% for validation. This approach helped fine-tune the model's performance, optimizing it for higher accuracy in subsequent testing phases. Key to the success of the SVM classifier is the careful selection of kernels and hyperparameters, tasks we accomplished using grid search techniques. This systematic search allowed us to identify the optimal settings for our SVM model, ensuring the best possible performance in classifying AD and HC participants based on their gait features. To uphold the integrity of our testing process and avoid the potential bias of feature selection leakage, the selected gait features for each classification task were determined solely from the training data. This precaution ensured that the validation and testing of our model were conducted on entirely unseen data, thus providing a more accurate and trustworthy assessment of its capability to classify AD from gait features.

3. RESULTS

Table 1 shows study participants' demographic and clinical information. A comparison of this information using descriptive statistical analysis showed significant differences between AD and HC participants in terms of age, weight, and years of education, with no significant differences in gender, height, and GDS variables between the two study groups. Also, the comparison of the cognitive assessment using neuropsychological test scores of MMSE and MoCA revealed that older adults with AD had significantly lower cognitive scores than HC participants (See Table 1)

Table 1. Demographic and clinical information of study participants

Characteristic	**HC (N=73)**	**AD (N=34)**	***p*-value**
Age (years)	64.67 ± 5.73	76.06 ± 7.24	< 0.001*
Female, N (%)	38 (53)	19 (56)	0.715
Height (cm)	168.09 ± 6.25	165.17 ± 6.45	0.057
Weight (kg)	69.32 ± 9.44	66.09 ± 8.69	0.038*
Education (years)	13.43 ± 2.38	10.88 ± 4.11	0.001*
MMSE	28.96 ± 0.91	22.56 ± 3.86	<0.001*
MoCA	28.03 ± 0.05	20.76 ± 2.49	<0.001*
GDS	2.04 ± 1.24	3.29 ± 1.85	0.389

Mean ± Standard deviation was shown. N = Number of participants; HC = Healthy Cognitive Control Group; AD = Alzheimer's Disease; $MMSE$ = Mini-Mental State Examination (maximum score, 30); $MoCA$ = Montreal Cognitive Assessment (maximum score, 30); GDS = Geriatric Depression Scale (maximum score, 15), * shows the significant difference for the level of $p < 0.05$.

3.1 OpenPose's Performance in Body Joint Detection for Gait Analysis

Our evaluation of OpenPose's capability in body joint detection during curved path walking sessions revealed it to be highly effective in recognizing and tracking essential body joints throughout the motion sequences. These reliable and accurate body joint detection results via OpenPose confirmed the superiority of CNNs for HPE in comparison to traditional computer vision, which involved designing handcrafted features and models to detect and locate body joints.[19] OpenPose accurately pinpointed critical bodily segments, including the legs, arms, and torso. This accuracy provides valuable insights into the dynamics of human locomotion and extracts a comprehensive collection of gait features for AD detection. Despite its overall promising performance, our detailed examination across various frames highlighted that OpenPose's effectiveness varied depending on specific conditions. Challenges in detecting and tracking body joints and segments were encountered in certain scenarios.

Fig. 4 illustrates OpenPose's performance across different situations within our dataset. In a majority of the frames, OpenPose effectively identified and tracked body joints and segments without any occlusion by external objects or self-occlusion, except for minor cases where partial occlusion of segments, such as the knees, occurred (as depicted in Fig. 4.A). However, instances of full occlusion due to overlapping body parts significantly impacted OpenPose's ability to detect and track certain joints, particularly in the upper body—wrist, elbow, and shoulder joints—and the segments connecting these joints faced detection issues in frames where one side was entirely obscured (illustrated in Fig. 4.B). This variability in detection underscores the importance of acknowledging OpenPose's limitations under specific conditions, particularly when analyzing gait data for movement assessment depending on the application in hand.

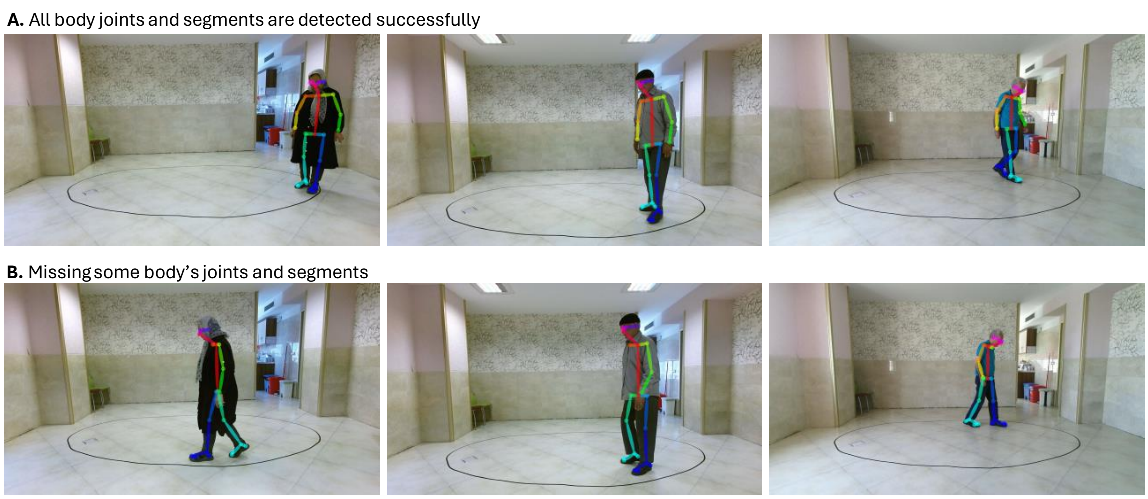

Figure 4. A) OpenPose performance with clear visibility, accurately tracking body joints and segments during unobstructed walking sequences; B) Challenges in OpenPose detection due to full occlusion of body parts, illustrating missed joints and segments in obscured walking frames.

3.2 Significant and Selected Features for AD Detection

Following the adjustment of gait features for age, weight, and education levels, the descriptive statistical analysis described in Sec. 2.3.3 identified significant gait markers between HC and AD.

Our statistical examination revealed that out of 48 gait features analyzed from the 10-meter curved walking test, 39 exhibited significant differences between the AD and HC groups. These included various features: 6 macro, 16 micro temporal, 12 micro spatial, and 5 spatio-temporal gait features (See Fig. 5.A). Subsequent correlation analysis among these significant features pinpointed a subset with high correlation (r > 0.9), leading to a refined selection based on their diagnostic power as shown in Fig 5.B. Notably, mean step time emerged as a key indicator due to its profound significance in distinguishing between AD and HC subjects (with the lowest p-value = $1.21 * 10^{-22}$), reducing the number of significant gait features to 18 unique markers. These markers comprise a comprehensive profile of gait dynamics, including macro, micro temporal, micro spatial, and micro spatiotemporal features, which collectively enhance the accuracy of AD detection.

Moreover, our study highlights a weaker gait performance in older adults with AD than HC during the 10-meter curved path walking test. AD participants exhibited notably lower average velocity and cadence, requiring more time to complete the assessment. Specifically, the average velocity and cadence for the AD group were 35.29 ± 19.42 cm/s and 75.90 ± 19.33 steps/minute, respectively, versus 51.15 ± 16.67 cm/s and 88.76 ± 12.36 steps/minute for the HCs, with a statistically significant difference (p-value < 0.001, see Fig. 5.C).

This trend extends to micro-gait features. AD individuals demonstrated longer durations in various subphases of gait cycles and reduced step and stride lengths and velocities, significantly impacting their mobility and balance. Notably, the duration for stance and single support phases was significantly higher in the AD group, with durations of 0.78 ± 0.39 s and 0.55 ± 0.23 s, respectively, compared to 0.40 ± 0.19 s and 0.37 ± 0.15 s in HCs (p-value < 0.001; See Fig. 5.C). Additionally, mean step and stride lengths in AD participants were significantly shorter, at 23.89 ± 5.55 cm and 47.98 ± 11.20 cm, respectively, compared to 30.68 ± 4.81 cm and 61.79 ± 9.30 cm in HCs. A similar reduction was observed in step and stride velocity, with micro spatiotemporal features decreased to 34.31 ± 11.92 cm/s and 32.82 ± 12.02 cm for AD in comparison to 50.99 ± 10.91 cm/s and 49.90 ± 9.86 cm/s for ADs (see Fig. 5.C). These findings highlight the profound impact of AD on gait dynamics, with marked differences in velocity, cadence, and gait cycle subphases serving as potential indicators of AD progression.

3.3 Classification of Participants into AD and HC Groups

We employed the Support Vector Machine (SVM) algorithm to classify participants into AD or HC groups based on the selected gait features. The classification process included training, validation, and testing phases, with the outcomes presented in Table 2, where various evaluation metrics such as accuracy, sensitivity, precision, and F-score were used to assess performance. The SVM achieved an impressive accuracy rate of 90.01%, along with a sensitivity of 87.00%, precision of 85.63%, and an F-score of 86.20% on the test dataset.

4. DISCUSSION

In advancing AD detection, our research emphasizes the application of imaging techniques, specifically through gait analysis on a 10-meter curved path, integrated with machine learning for precise diagnostics. Our methodology diverges from conventional strategies requiring complex and intrusive

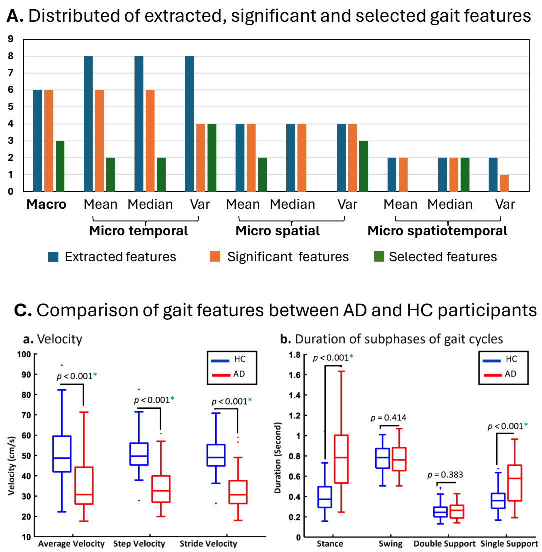

Figure 5. Comparative analysis of gait performance between AD and HC, showcasing A) the distribution of extracted, significant, and selected gait features; B) a correlation heatmap for identifying unique selected gait features; and C) a comparison of macro and micro gait features between the two groups.

Table 2. Classification results utilizing gait features with SVM to differentiate between AD and HC.

Dataset	**Evaluation metrics (%)**				
	Acc	Sen	Pre	Spec	F- score
Training	99.55	99.10	100.00	100.00	99.54
Validation	92.09	88.37	97.22	98.82	92.91
Test	90.01	87.00	85.63	93.02	86.20

Acc = Accuracy; *Sen* = Sensitivity; *Pre* = Precision; *Spec* = Specificity.

setups, such as wearable sensors, infrared cameras with reflective markers, or extensive electronic walkways. Instead, we employ a simplified yet effective system utilizing a single camera and the human pose estimation OpenPose algorithm for accurate pose estimation. This approach not only achieves cost-efficiency and ensures privacy protection but also capitalizes on the diagnostic potential of curved path walking. Previous research has indicated that this walking pattern may uncover more nuanced insights into AD than traditional straight-line gait analysis[12,20,21] due to its closer resemblance to everyday walking behaviors. By focusing on such naturalistic movement patterns, our method stands to improve the applicability and accuracy of AD detection across a diverse elderly population, accommodating various education levels and promoting wider adoption in both clinical and research settings.

4.1 Main Findings

Our exploration into gait analysis via a 10-meter curved path, employing a single camera alongside OpenPose for body joint detection in older adults, has illustrated that tracking body movements during gait assessments can be conducted with notable accuracy. Despite encountering some challenges with full occlusion, particularly in the upper body parts obscured by other segments (See Fig. 4), the overall precision in capturing body joint movements was sufficient for effective gait feature extraction for AD detection. This outcome is in harmony with existing literature that underscores the reliability of such data for gait analysis purposes.[18, 22]

Further analysis revealed clear performance differences between older adults diagnosed with AD and HCs. Specifically, AD individuals exhibited reduced velocities and increased durations in several gait cycle subphases during the curved path walking test as depicted in Fig. 5. These findings corroborate existing clinical research that points to compromised gait performance in complex walking tasks among AD patients, thus confirming the utility of our approach in identifying key gait alterations associated with AD.[11, 23, 24]

Moreover, the study extended to assess the effectiveness of machine learning by applying SVM to the extracted gait features. This analysis objectively classified participants into AD or HC categories based on their gait characteristics. The results, bolstered by a 5-fold validation process, demonstrated the SVM's robust ability to differentiate between AD and HC groups, achieving an accuracy and F-score of 90.01% and 86.20%, respectively, supporting the potential of integrating imaging and machine learning for enhancing the precision of AD detection in clinical settings (See Tab. 2).

4.2 Comparison with Previous Studies

The exploration of sensor technology and machine learning for detecting cognitive decline through gait analysis in AD or other types of dementia is an emerging field with relatively few studies. Previous investigations, such as the one by Ghoraani *et al.* (2021), utilized an electronic walkway to analyze single and dual-task straight walking patterns for classifying HC against individuals with mild cognitive impairment or AD, achieving an accuracy and F-score of 88.00% and 90.00%, respectively.[12] Zhang *et al.* (2021) leveraged Kinect v.2 camera to capture body joint positions. They applied convolutional neural networks for differentiating HCs from older adults with dementia, reaching a sensitivity of 74.10% in detecting dementia.[20] Furthermore, Jeon *et al.* (2023) employed wearable sensors during straight walking tasks to identify MCI in older adults, securing a 73.0% accuracy with an ensemble algorithm.[21] Contrastingly, our study extends this work by utilizing a straightforward yet effective approach—employing a single regular camera in conjunction with OpenPose for gait analysis coupled with machine learning techniques—to distinguish between 34 older adults diagnosed with AD and 73 HCs. Our method demonstrated a higher accuracy, sensitivity, and F-score, at 90.01%, 87%, and 86.20%, respectively. Such outcomes highlight the feasibility and effectiveness of using minimalistic imaging setups combined with advanced computational techniques for gait analysis in the context of cognitive decline detection. By streamlining the technology involved, our approach simplifies the logistical and financial barriers typically associated with more complex sensor-based systems and opens the door for broader, more accessible applications in clinical and potentially home-based settings. The promising results of our study, particularly in terms of accuracy and sensitivity, highlight the potential of this method to serve as a reliable tool in the early detection and monitoring of AD and other cognitive impairments. This could significantly enhance the current strategies for managing these conditions, offering an unobtrusive, efficient, and cost-effective alternative to traditional diagnostic methods.

4.3 Clinical Implications, Study Limitations, and Future Directions

Our developed screening tool for AD demonstrates significant advantages, including its non-invasiveness, ease of setup, cost-effectiveness, and minimal intrusiveness, compared to traditional diagnostic methods and earlier technological approaches. By employing just a regular camera, such as those found in smartphones, to record curved-path walking, our method sidesteps the need for large spaces or complex cognitive tasks that might challenge older adults, especially those with limited educational backgrounds. The method's capability to extensively extract and analyze gait features, identifying those uniquely indicative of AD, simplifies and enhances the accuracy and speed of clinical diagnoses.

Despite these strengths, our study acknowledges certain limitations. Primarily, the reliance on a single-task model—curved path walking—for AD detection may not fully encapsulate the complex nature of gait changes associated with the disease. Expanding the analysis to include multiple tasks could uncover deeper, more subtle gait abnormalities. Moreover, validating our findings across a broader participant base would strengthen the generalizability and reliability of our diagnostic approach. Future studies aim to include a wider population, focusing on individuals with mild cognitive impairment and more participants. We plan to incorporate various cognitive dual tasks and additional functional gait and balance assessments, like the Timed Up and Go (TUG) test, to provide a more comprehensive evaluation. This expansion would not only reinforce the reliability of our method but also provide a more comprehensive understanding of its applicability across diverse populations and stages of cognitive decline.

5. CONCLUSION

This paper has effectively showcased the potential of image analysis, particularly HPE employing CNNs, in proactively identifying AD. Utilizing standard camera technology in conjunction with the OpenPose algorithm, we have formulated an economical and accessible modality for AD diagnosis, analyzing gait dynamics during a 10-meter curved walking examination. Demonstrating substantial efficacy, our methodology differentiates HC from those with AD with an accuracy of 90.0% and an F-score of 86.20%. The innovative use of a singular conventional camera and OpenPose's intricate image analysis capabilities facilitated the derivation of 25 unique body joint coordinates. We extracted 48 gait features by analyzing these, uncovering marked differences in 39 gait features between the HC and AD cohorts. These outcomes support the utility of gait analysis as a potent biomarker in AD diagnostics. This research underlines the feasibility of leveraging accessible imaging technology, HPE techniques, signal processing, and machine learning to devise a practicable solution for AD detection. This approach broadens the scope for further studies on home-based and remote monitoring of individuals potentially affected by AD.

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