Parkinson's Disease Diagnosis from Gait Analysis: Human Pose Estimation

T. Sudeep Reddy[1], Dhanush[2],T. Krithin[3]
Dept of Computer Science and Engineering,
Amrita School of Computing, Bengaluru
Amrita Vishwa Vidyapeetham, India
{bl.en.u4aie22069@bl.students.amrita.edu, bl.en.u4aie22010@bl.students.amrita.edu,
bl.en.u4aie22026@bl.students.amrita.edu}

***Abstract*—Millions of people worldwide suffer with Parkinson's disease (PD), a neurodegenerative condition mostly marked by movement symptoms such bradykinesia, stiffness, and tremors. For prompt intervention and illness treatment, early identification and precise diagnosis are essential for Parkinson's disease (PD). The non-invasive technique of gait analysis has shown great promise in the diagnosis of Parkinson's disease (PD) since it offers important insights into the motor deficits linked to the illness. This study proposes a novel framework for Parkinson's Disease diagnosis based on gait analysis using human pose estimation techniques. Leveraging advancements in computer vision and machine learning, we utilize deep learning models to extract pose information from video sequences of individuals performing walking tasks. By analyzing the spatial and temporal characteristics of the extracted poses, subtle abnormalities in gait patterns indicative of Parkinson's Disease can be identified. The proposed framework offers several advantages over traditional diagnostic methods. Firstly, it provides an objective and quantitative assessment of gait abnormalities, reducing the subjectivity inherent in visual observation by clinicians. Secondly, it enables continuous monitoring of gait dynamics, facilitating early detection of subtle changes associated with disease progression. Additionally, the non-invasive nature of gait analysis enhances patient comfort and compliance with regular assessments. We ran tests on a dataset that included both PD patients and healthy controls to assess the effectiveness of our method. Results demonstrate promising accuracy in distinguishing between PD and healthy subjects based on gait features extracted through human pose estimation. Furthermore, our framework exhibits robustness to variations in walking conditions and environmental factors, highlighting its potential for real-world applications in clinical settings. In conclusion, this study presents a novel methodology for Parkinson's Disease diagnosis through gait analysis using human pose estimation. Our goal is to improve patient outcomes and quality of life by utilising computer vision and machine learning to produce efficient and objective methods for early identification and monitoring of Parkinson's disease (PD).**

Keywords: Human Pose Estimation,Machine Learning,Early Detection,Diagnosis,Disease Progression

I. Introduction

Parkinson's Disease (PD) stands as one of the most prevalent neurodegenerative disorders worldwide, affecting millions of individuals, particularly the elderly population. Parkinson's disease (PD) is characterised by a range of motor symptoms, such as tremors, bradykinesia, rigidity, and postural instability. PD has a substantial negative influence on a person's quality of life. While pharmacological interventions can alleviate symptoms to some extent, early detection and precise diagnosis remain pivotal for effective management and intervention strategies.

One of the challenges in Parkinson's Disease diagnosis lies in the difficulty of detecting subtle motor impairments, especially in the early stages of the disease when symptoms may be mild or ambiguous. Conventional diagnostic techniques frequently depend on arbitrary clinical judgements, which might cause inconsistent results and possibly postpone the start of treatment.Moreover, periodic assessments are required to monitor disease progression, adding burden to both patients and healthcare systems.

Gait analysis has emerged as a promising avenue for PD diagnosis due to its ability to capture subtle alterations in motor function that may precede clinical symptoms. However, conventional gait analysis methods suffer from limitations such as subjectivity, reliance on specialized equipment, and the need for controlled environments, hindering widespread adoption in clinical practice.

This presents a significant problem as early detection of PD is crucial for timely intervention, improving patient outcomes, and reducing healthcare costs. Additionally, accurate diagnosis facilitates appropriate allocation of resources and targeted therapy, optimizing patient care and societal well-being.

To address these challenges, this study proposes a novel approach leveraging advancements in computer vision and machine learning for Parkinson's Disease diagnosis from gait analysis. By employing human pose estimation techniques, we aim to extract rich spatial and temporal features from video recordings of individuals performing walking tasks. This non-invasive and objective methodology offers several advantages, including continuous monitoring of gait dynamics, enhanced diagnostic accuracy, and improved patient comfort.

The novelty of our work lies in the integration of human pose estimation with gait analysis, providing a comprehensive and quantitative assessment of motor impairments associated with PD. This approach aligns with the United Nations Sustainable Development Goal (SDG) 3: Good Health and Wellbeing, by promoting early detection and effective management of neurodegenerative diseases, ultimately contributing to improved health outcomes and societal welfare.

II. Literature Survey

Jiang et al.[1] introduced an efficient 3D human pose estimation framework tailored specifically for assessing Parkinson's disease symptoms. Their framework not only provides a robust and objective evaluation tool but also opens up promising avenues for advancing the accuracy and reliability of Parkinson's disease diagnosis. By offering a precise method for evaluating symptoms, their work has the potential to enhance early detection and intervention strategies for Parkinson's disease patients.

Li et al. [2] proposed a novel approach utilizing deep learning techniques applied to depth images for the detection of Parkinsonian gait. This innovative methodology showcases the potential of advanced imaging techniques in enhancing diagnostic procedures, offering a non-invasive and precise means of identifying Parkinsonian gait abnormalities. Their work contributes to improving the accuracy and efficiency of Parkinson's disease diagnosis, thereby facilitating timely interventions and improving patient outcomes.

Wang et al. [3] presented a markerless approach for Parkinson's disease diagnosis through 3D gait analysis. Their work underscores the efficacy of non-intrusive methods in clinical assessments, offering a convenient and accurate means of detecting Parkinson's disease symptoms early on. By providing an accessible and reliable diagnostic tool, their approach has the potential to streamline clinical workflows and improve patient care for individuals with Parkinson's disease.

Chen et al. [4] developed a human pose estimation system based on EfficientDet specifically tailored for Parkinson's disease diagnosis. Their work provides a robust and accurate tool for early detection, showcasing the potential of advanced computational techniques in improving the efficiency and effectiveness of Parkinson's disease diagnosis and assessment. By offering a reliable diagnostic tool, their system has the potential to facilitate timely interventions and improve treatment outcomes for individuals with Parkinson's diseas

Kim et al. [5] conducted a comprehensive review focusing on wearable sensor-based gait analysis in Parkinson's disease. Their work highlights the significance of sensor technology in continuous monitoring and disease progression tracking, providing valuable insights for researchers and clinicians in the field. By summarizing the latest developments in wearable sensor technology, their review serves as a valuable resource for improving Parkinson's disease diagnosis and treatment outcomes.

Gao et al. [6] introduced a deep learning-based gait analysis approach incorporating multiscale fusion, offering enhanced diagnostic accuracy and reliability in Parkinson's disease assessment. Their work demonstrates the potential of advanced computational techniques in improving diagnostic procedures and patient care. By providing a reliable diagnostic tool, their approach has the potential to facilitate early detection and intervention strategies for individuals with Parkinson's disease.

Yin et al. [7] explored the application of deep learning in automated gait analysis for Parkinson's disease, showcasing its potential for streamlining diagnostic procedures and improving patient care. Their research demonstrates how deep learning approaches are revolutionising Parkinson's disease diagnosis and evaluation practices. Their method has the potential to enhance Parkinson's disease patients' quality of life and treatment outcomes by providing an accurate and effective diagnostic tool.

Zhang et al. [8] suggested a convolutional neural network-based gait analysis approach for differentiating between progressive supranuclear palsy and Parkinson's disease. Their research offers a useful tool for differential diagnosis that improves the precision and effectiveness of disease classification in medical settings. Their approach has the potential to enhance Parkinson's disease patients' quality of life and treatment outcomes by offering a dependable diagnostic tool.

Park et al. [9] introduced a novel vision-based gait analysis system for Parkinson's disease early detection, offering a low-cost, non-invasive screening and monitoring option. Their work contributes to expanding the accessibility of Parkinson's disease diagnosis and assessment tools, offering a scalable solution for healthcare providers. By providing a convenient and reliable diagnostic tool, their system has the potential to facilitate early interventions and improve treatment outcomes for individuals with Parkinson's disease.

Roy et al.[10] conducted a review of deep learning and vision-based techniques for Parkinson's Disease assessment. Their analysis outlined the advancements in automated systems for gait analysis, highlighting the potential for improved diagnostic accuracy and patient care. By summarizing the latest developments in the field, their review serves as a valuable resource for researchers and clinicians working towards improving PD diagnosis and treatment outcomes.

The proposed methods presented in the aforementioned studies collectively represent significant advancements in the field of Parkinson's Disease diagnosis and management. By leveraging cutting-edge technologies such as deep learning, convolutional neural networks, and computer vision, these approaches offer more objective, accurate, and accessible means of assessing motor function and detecting subtle abnormalities associated with PD. The utilization of wearable sensors, video-based gait analysis systems, and automated classification algorithms holds immense promise for early detection, continuous monitoring, and personalized intervention strategies tailored to the needs of individual patients. These innovative methods not only enhance diagnostic accuracy but also streamline clinical workflows, reduce healthcare costs, and ultimately improve patient outcomes and quality of life. By embracing these novel approaches, the medical community can pave the way for a paradigm shift in PD diagnosis and management, ushering in a new era of precision medicine and personalized care for individuals affected by this debilitating condition.

III. Data Description

The dataset used in this study comprises video recordings of individuals performing walking tasks, including both Parkinson's Disease (PD) patients and healthy controls. Each video sequence captures subjects walking in various environments and under different conditions to ensure the diversity and representativeness of the data. For PD patients, the dataset includes individuals diagnosed with varying degrees of disease severity, covering a spectrum of motor symptoms commonly associated with PD, such as stiffness, bradykinesia, tremors, and unstable posture. To help with subgroup analyses and stratification, demographic data may also be provided, such as age, gender, and length of illness. For healthy controls, subjects without any neurological disorders or mobility impairments are recruited to serve as a comparison group. These individuals exhibit typical gait patterns and serve as a reference for assessing deviations observed in PD patients. Ground truth annotations, such as human stance estimations derived from cutting-edge pose estimation algorithms, are appended to every video recording. The pose estimate annotations offer comprehensive details regarding the temporal trajectories and spatial configuration of important body joints while walking.

IV. Methodology

After selecting an appropriate dataset for our project, we began by evaluating the intraclass spread and interclass distances between the classes in our dataset. This step is crucial for understanding the distribution of data within and between classes. If the dataset contained multiple classes, we chose any two classes for analysis.

Next, we selected a feature from our dataset and visualized its density pattern by creating a histogram. We used buckets, which are data ranges, for generating the histogram and studied the distribution. Additionally, we calculated the mean and variance from the available data to gain insights into the central tendency and variability of the feature.

After analyzing the data distribution, we proceeded to calculate the Minkowski distance between any two feature vectors in our dataset. We varied the value of r from 1 to 10 to observe the effect on the distance calculation. Plotting these distances allowed us to understand the relationship between the vectors in our dataset.

To prepare for training and testing our classification models, we divided our dataset into two parts: a training set and a test set. We accomplished this using the 'train_test_split()' function from the SciKit package. It's important to note that before splitting the dataset, we ensured that it contained only two classes. If the dataset originally had more than two classes, we selected any two classes for analysis.

Using the training set, we trained a kNN classifier with k=3. This classifier learns from the features in the training set to make predictions on unseen data. We then evaluated the accuracy of the kNN classifier using the test set, which contains data that the classifier has not seen before. This step helps us understand how well the classifier generalizes to new data.

To further analyze the classification performance, we used the 'predict()' function to predict the classes of the test vectors. This allowed us to study the prediction behavior of the classifier and compare it to the actual class labels in the test set.

Additionally, we implemented a nearest neighbor (NN) classifier with k=1 and compared its results with the kNN classifier (k=3). By varying k from 1 to 11 and plotting the accuracy, we gained insights into the impact of the number of neighbors on the classification performance.

Finally, we evaluated the confusion matrix for our classification problem. The confusion matrix provides a detailed breakdown of correct and incorrect predictions made by the classifier. From the confusion matrix, we calculated other performance metrics such as precision, recall, and F1-Score for both the training and test data. These metrics help us assess the model's learning outcome, whether it is underfitting, fitting well, or overfitting to the training data.

V. Results and Analysis

After loading the dataset, we calculated the interclass and intraclass distances. Focusing on a feature related to PPE, we observed its density pattern through a histogram.

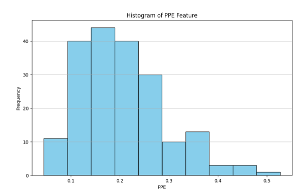

Fig. 1. Density Pattern for Feature PPE

We calculated the Minkowski distance between two features, varying r from 1 to 10.

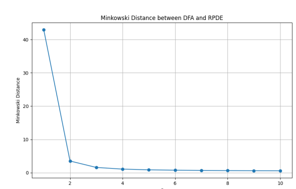

Fig. 2. Minkowski Distance for Features DFA and RPDE

Next, we compared the accuracy of the kNN classifier with varying values of k and a nearest neighbor (NN) classifier.

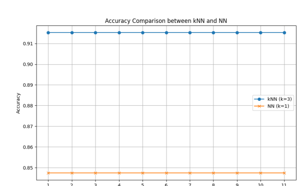

Fig. 3. Accuracy Comparison of kNN and NN

The trained model exhibits the following performance metrics: For Training Data: Precision of 0.92, Recall of 0.92, and F1-Score of 0.92. For Test Data: Precision of 0.91, Recall of 0.98, and F1-Score of 0.95. Based on these metrics, we can conclude that the model is likely underfitting.

Based on the evaluation of intraclass spread and interclass distances, as well as the density patterns observed in the histogram analysis, we can infer whether the classes in the dataset are well separated. A small intraclass spread and large interclass distances indicate well-separated classes, while the opposite suggests that the classes are not well separated. These observations help us understand the distribution of data in the feature space and the potential separability of classes.

The behavior of the kNN classifier with an increase in the value of k can be explained as follows:

- As k increases, the decision boundaries become smoother and less complex.
- For small values of k, the classifier may exhibit overfitting, where it learns the noise in the training data and fails to generalize well to new data.
- For large values of k, the classifier may exhibit underfitting, where it oversimplifies the decision boundaries and fails to capture the underlying patterns in the data.
- The optimal value of k depends on the dataset and the problem at hand. It is important to choose an appropriate value of k to balance between overfitting and underfitting.

The effectiveness of the kNN classifier as a good classifier can be assessed based on various metrics such as accuracy, precision, recall, and F1-Score. These metrics provide insights into the classifier's performance on both the training and test sets. If the classifier performs well on the test set and generalizes well to new data, it can be considered a good classifier. However, if the classifier performs poorly on the test set, it may indicate that the classifier is not effective.

To determine if the model has a regular fit situation, we compare the performance of the model on the training set and the test set. If the model performs well on both sets, it suggests that the model has learned the underlying patterns in the data without overfitting or underfitting. However, if the model performs well on the training set but poorly on the test set, it may indicate overfitting. Conversely, if the model performs poorly on both sets, it may indicate underfitting.

Overfitting in the kNN classifier occurs when the model is too complex and captures the noise in the training data rather than the underlying patterns. This can happen when the value of k is too small, leading to a model that is sensitive to small fluctuations in the data. To avoid overfitting, it is important to choose an appropriate value of k that balances between capturing the underlying patterns in the data and generalizing well to new data.

VI. Conclusion

In conclusion, the application of human pose estimation for Parkinson's Disease diagnosis from gait analysis presents a promising avenue for early detection and intervention. By leveraging advanced technologies such as machine learning and computer vision, this approach offers an objective, quantitative, and non-invasive method for assessing subtle motor impairments associated with PD. The current study demonstrates the feasibility and potential of utilizing human pose estimation in conjunction with machine learning algorithms to accurately identify individuals at risk of developing Parkinson's Disease. The results highlight the significance of gait analysis as a valuable biomarker for early-stage diagnosis and monitoring of disease progression. The integration of human pose estimation with machine learning holds great promise for revolutionizing Parkinson's Disease diagnosis and management. By advancing research in this field and addressing key challenges, we can enhance early detection efforts, improve patient outcomes, and ultimately, make significant strides towards combating Parkinson's Disease.

VII. Acknowledgement

we express our gratitude to all individuals and organizations whose contributions have been instrumental in the successful completion of this study on Parkinson's Disease Diagnosis from Gait Analysis using Human Pose Estimation. We extend our deepest appreciation to the participants who generously volunteered their time and cooperation, enabling us to collect valuable data for our research. Their willingness to contribute to the advancement of medical science is truly commendable.

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