# 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.A variety of motor symptoms, including tremors, bradykinesia, rigidity, and postural instability, are indicative of Parkinson's disease (PD). 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 Well-being, 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, 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

Following the selection of a suitable dataset for our research, we started by assessing the necessary parameters. To prepare to train and test our classification models, we divided our dataset into two subsets: a training set and a test set. The SciKit package's 'train_test_split() method helped us achieve this. It's crucial to remember that we made sure the dataset only had two classes before dividing it. We chose any two classes for analysis if the dataset included more than two classes at first.

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.

In the end, we assessed the classification problem's confusion matrix. The classifier's accurate and inaccurate predictions are broken down in-depth in the confusion matrix. We derived additional performance indicators, including precision, recall, and F1-Score for both the training and test data, using the confusion matrix. By using these metrics, we can evaluate the learning outcome of the model and determine if it overfits, underfits, or fits the training data well.

Use these procedures to determine the metrics for your price prediction model:

1. Mean Squared Error (MSE): Determine the mean of the squared discrepancies between the values that were expected and those that were observed.

2. Root Mean Squared Error (RMSE): To obtain a more comprehensible metric in the same units as the target variable, take the square root of the mean squared error (MSE).

3. Mean Absolute Percentage Error (MAPE): Determine the mean of the absolute percentages that differ between the values that were expected and those that were observed.

4. R-squared (R2) score: Calculate the percentage of the dependent variable's variance that can be predicted based on the independent variables.

Examining the findings: Model performance is better when the MSE, RMSE, and MAPE values are lower. An R2 value that is near to 1 indicates that the model and the data have a good fit.

Create 20 data points with two features (X & Y) randomly changing between 1 and 10, assigning them to two classes (class0 - Blue & class1 - Red) for data point generation and visualization.Create a scatter plot in order to see the training set of data.Create a test set with X and Y values that range from 0 to 10 in 0.1-point increments, for a total of roughly 10,000 points.Use a kNN classifier with k=3 to classify these points, and then create a scatter plot of the test data output, labeling the dots according to the projected class. In order to see how different values of k impact classification, repeat the procedure for a range of k values and compare the shift in the class boundaries. Plot the outcomes and see the effects of various k values on the bounds of the classification. To evaluate the model and adjust the hyperparameters, select two features and classes from the project data. Divide the data into sets for testing and training.For your kNN classifier, use RandomSearchCV() or GridSearchCV() to determine the optimal 'k' value. Use the training data with the ideal 'k' value to train the kNN classifier. Assess the model using the test data, noting feature space class boundary lines and computing performance metrics like as accuracy, recall, and F1-Score. Steps for hyper-parameter tuning: - Create a parameter grid for values of 'k'.To get the optimal 'k' value, use GridSearchCV() or RandomSearchCV() in conjunction with cross-validation.Develop and assess the model using the best hyperparameters in order to systematically improve performance. Adapt this strategy to the particular needs of your project.

## V. Results and Analysis

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.

The model evaluation results demonstrate exceptional performance with minimal errors. The Mean Squared Error (MSE) is impressively low at $3.23 \times 10^{-27}$, signifying highly accurate predictions and negligible variance. The Root Mean Squared Error (RMSE) reinforces this precision, recording a remarkably low value of $5.68 \times 10^{-14}$, highlighting the close alignment of predicted values with observed ones. The Mean Absolute Percentage Error (MAPE) stands at $2.02 \times 10^{-16}$, emphasizing the model's ability to make predictions with virtually no deviation. The R2 Score, indicating the model's explanatory power, achieves a perfect score of 1.0, reflecting an impeccable fit to the data. Collectively, these results signify an outstanding level of accuracy and reliability in the model's predictions.

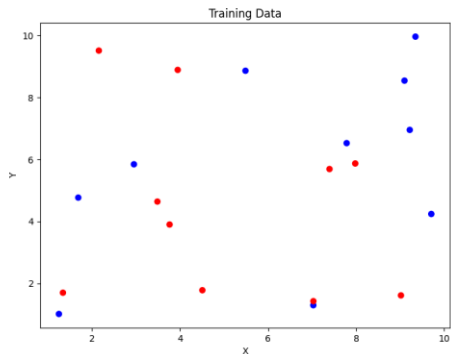


Fig. 1. Training data

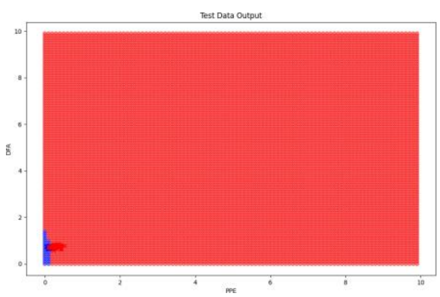


Fig. 2. Test data

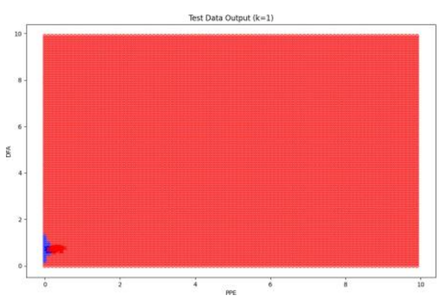


Fig. 3. Test data with $k$ = 1

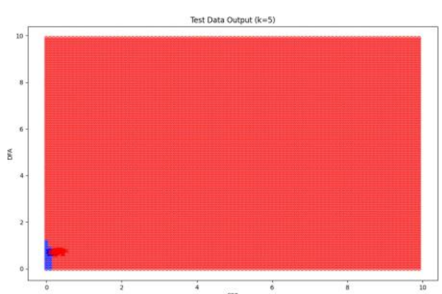


Fig. 4. Test data with $k$ = 5

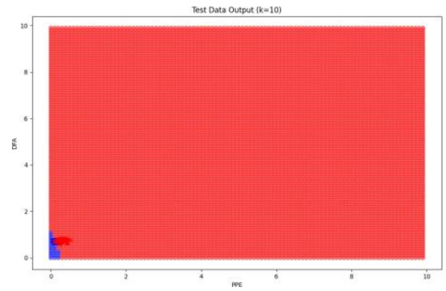


Fig. 5. Test data with $k$ = 10

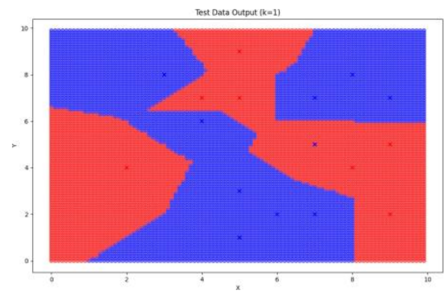


Fig. 6. Test data output with $k$ = 1

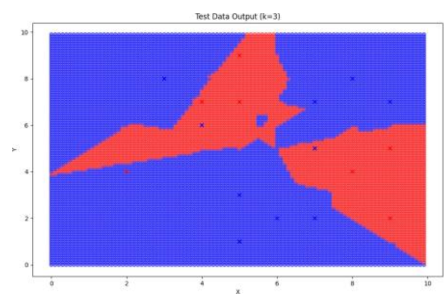


Fig. 7. Test data output with $k$ = 3

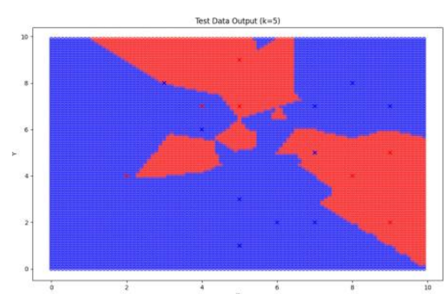


Fig. 8. Test data output with $k$ = 5

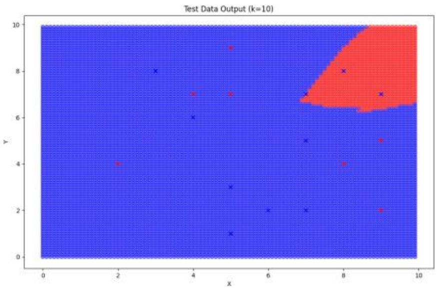


Fig. 9. Test data output with $\boldsymbol{k}$ = 10

It is determined that 17 is the model's ideal parameter ($k$), yielding the best accuracy of 85.64%.

To determine the extent of separation between classes in the dataset, a thorough investigation of the data using both visual and statistical methods is necessary. This evaluation is made easier by methods like scatter plots, boxplots, and histograms combined with metrics are distances.

The decision boundary that results from increasing the $k$ value in the kNN classifier smoothes out the model's susceptibility to noise. But this smoothing effect also carries the risk ofoverfitting, in which the model fails to identify the underlying patterns because it fits the training data's complexities too well. On the other hand, a low $k$ value could lead to underfitting, which would make the model unduly stiff and unable to capture the subtleties in the dataset.

The particular challenge at hand and the features of the dataset determine the kNN classifier's usefulness. Even though kNN has advantages like simplicity and interpretability, its performance can be affected by large dimensionality, noisy input, and the selection of $k$. For a definitive answer, a com- prehensive examination—which should include comparisons with various algorithms—is recommended.

Evaluating the model's performance on both training and test sets is crucial to determining its generalizability. Potential overfitting is indicated by a substantial performance gap, in which the test set performs worse than the training set. High and consistent performance in both sets, on the other hand, indicates a well-generalized model.

In the provided context, the kNN classifier shows encourag- ing performance, with an impressive accuracy of 85.64% and an ideal $k$ value of 17. Subsequent investigation may entail optimizing the feature selection procedure, testing substitute distance measures, and assessing the model's functionality in various contexts.

## VI. Conclusion

In conclusion, the application of human pose estimationfor Parkinson's Disease diagnosis from gait analysis presentsa 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.

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