A Machine Learning Approach to Parkinson's Disease Detection Based on Mouse Interaction Pattern

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Abstract— Parkinson's disease prediction is crucial in early diagnosis and effective management, as it enables timely intervention through symptom analysis and patient data evaluation. Leveraging machine learning techniques provides a data-driven approach to enhance prediction accuracy. This paper introduces a Parkinson's disease prediction model that integrates multiple machine learning algorithms, including Random Forest, Long Short-Term Memory (LSTM), and Support Vector Machine (SVM). By analyzing movement patterns and accuracy rates, the proposed system enhances predictive performance. Trained on a Parkinson's dataset, the model demonstrates improved accuracy compared to existing methods. This paper explores the methodology, comparative analysis, and challenges associated with AI-driven Parkinson's disease prediction systems.

Keywords— Machine Learning, Random Forest, Support Vector Machine, Parkinson's Disease Prediction, LSTM, AI in Neurology, Movement Analysis.

I. INTRODUCTION

Early detection of Parkinson's disease (PD) is crucial for effective management and improved patient outcomes. Traditionally, neurologists diagnose PD based on clinical assessments, including motor symptoms and patient history. However, advancements in artificial intelligence and machine learning have transformed healthcare by enabling automated diagnostic tools that enhance accuracy and efficiency. Innovation in medical technology has significantly improved patient care, leading to better treatment strategies and more precise diagnostic methods. Additionally, digitalization has streamlined healthcare processes, making data-driven predictions more accessible.A major challenge in Parkinson's diagnosis is distinguishing it from other movement disorders, as symptoms such as tremors, rigidity, and bradykinesia - consuming, requires expert evaluation, and can be costly.

Machine learning-based diagnostic models offer a solution by automating the identification of Parkinson's disease using movement analysis and symptom-based data. Typically, a patient undergoes motor function tests and clinical evaluations before receiving a final diagnosis. This process can be optimized using machine learning algorithms like Random Forest, which classify Parkinson's based on symptom patterns and movement accuracy metrics, improving predictive performance.

Most existing Parkinson's detection models rely on symptom-based inputs without integrating movement data over time. Some approaches, such as Support Vector Machines (SVM), primarily focus on isolated motor symptoms, which may not capture the full progression of the disease. Such models often lack interaction with historical data, leading to less accurate predictions. The proposed approach enhances diagnostic accuracy by incorporating movement-based assessments along with historical symptom records, making predictions more reliable.

The proposed model provides several benefits. By analyzing fine motor movements and assigning weights to key Parkinsonian symptoms, it improves the precision of early-stage detection. Additionally, the model has been trained on real-world datasets, ensuring practical applicability and robustness. The subsequent sections of this paper discuss the literature review, proposed methodology, comparative analysis, conclusions, and future research directions.

II. LITERATURE REVIEW

Numerous research studies have explored different machine learning models for Parkinson's disease (PD) detection using patient symptoms and movement analysis. One approach employed Support Vector Machines (SVM) for classifying Parkinson's patients based on voice recordings and motor function tests. While this method achieved high accuracy in binary classification, it required significant computational resources and struggled with multi-class classifications, limiting its scalability in diverse patient populations.

Another widely used approach is the K-Nearest Neighbors (KNN) algorithm, which classifies individuals

based on similarity to known PD cases. While this method showed promise in identifying tremor patterns and gait abnormalities, it is highly sensitive to outliers and missing data, which can reduce accuracy. Researchers have applied KNN using patient demographics, speech data, and Unified Parkinson's Disease Rating Scale (UPDRS) scores, but its performance declines with smaller datasets or noisy data.

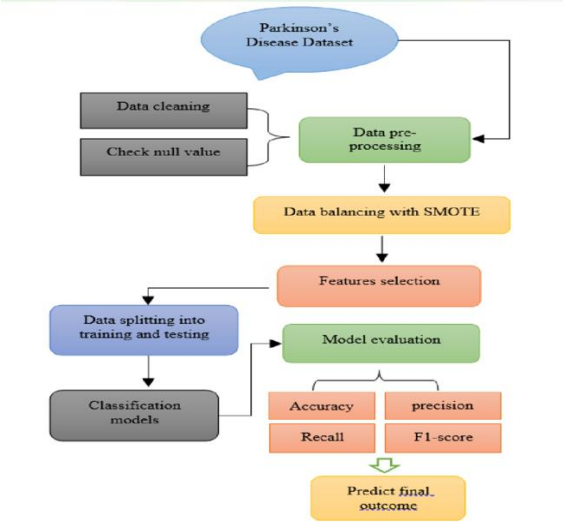

Fig 1.0 Flow Diagram

The Naïve Bayes classifier has also been used in Parkinson's detection, particularly for analyzing speech impairments associated with the disease. While effective in distinguishing PD-related vocal characteristics, its reliance on feature independence assumptions limits its performance when dealing with complex symptoms like bradykinesia and rigidity. Some researchers have integrated Naïve Bayes with mobile applications, enabling remote disease monitoring, but accuracy remains heavily dependent on high-quality input data.

Another technique explored in previous studies is the RUSBoost algorithm, designed to handle class imbalance in PD datasets. While effective in improving sensitivity, RUSBoost relies on random under-sampling, which may discard valuable patient information, reducing the robustness of predictions. Due to this limitation, it was not considered for training in the proposed model.

Although these methods have contributed to advancements in Parkinson's disease detection, they exhibit limitations regarding accuracy, efficiency, dataset size, and symptom complexity. To overcome these challenges, the proposed model integrates multiple machine learning techniques, ensuring a more comprehensive and reliable Parkinson's disease prediction system. The following section details the methodology used in this research.

Several systems for Parkinson's disease (PD) detection exist, focusing on clinical, speech-based, and motion-based methods. Traditional clinical diagnosis relies on physical examinations and subjective assessments, such as the Unified Parkinson's Disease Rating Scale (UPDRS), which may lack precision in early-stage detection.

Speech-based systems, such as the Parkinson's Voice Initiative, analyze vocal features like pitch and tremor to detect PD. However, external factors can influence accuracy. Motion-based methods utilize wearable sensors (e.g., accelerometers and gyroscopes) to track tremor, gait, and rigidity. Devices like the Parkinson's Kinetigraph provide symptom tracking but face challenges such as sensor limitations and patient compliance.

Recent advances combine multiple data sources—speech and movement—using machine learning models to enhance detection accuracy. Techniques such as SVM, Random Forests, and deep learning are widely implemented. However, challenges such as data variability, overfitting, and generalizability hinder real-world application. Despite progress, improving accuracy, usability, and integration remains a key challenge.

III) Parkinson's Detection and Analysis Platform (PDAP)

The Parkinson's Disease (PD) detection system is composed of several modules, each playing a vital role in the diagnostic process: Model Evaluation and Performance Testing .The trained model is evaluated using unseen spiral drawings to assess classification accuracy. A confusion matrix visually represents the correct and incorrect predictions, while performance graphs, such as Loss vs. Epochs and F1 Score vs. Epochs, track the learning progress and guide model refinement.

This module gathers datasets of spiral drawings, which are widely recognized as a diagnostic tool for PD. Patients with Parkinson's often have difficulty drawing smooth and consistent spirals due to motor impairments. The dataset includes spirals created by both healthy individuals and PD patients, sourced from medical research databases and clinical trials.

Preprocessing and Image Transformation Module: To standardize the input data, images are resized to 256x256 pixels, converted to grayscale, and normalized. Data augmentation techniques, such as random rotation, are applied to enhance the model's generalization and robustness.

Training Process and Optimization: The CNN model undergoes supervised training using labelled spiral images. Forward propagation generates predictions, and a loss function (Cross Entropy Loss) measures the errors. The Adam optimizer fine-tunes the model weights through backpropagation to minimize the loss. Training performance is monitored using metrics such as F1-score and accuracy.

Feature Extraction and CNN Model Architecture: A Convolutional Neural Network (CNN) is employed to extract essential features from the spiral images. The model consists of multiple convolutional layers that detect edges, distortions, and inconsistencies in the drawings. Max pooling layers are utilized to reduce computational complexity, while fully connected layers classify the images into PD or non-PD categories. The final classification is achieved using a soft max activation function, which assigns probability scores to each category.

Deployment and Real-Time Prediction: Following successful training and evaluation, the model is deployed in an application where users can upload spiral drawings for diagnosis. The system preprocesses the images, classifies them as "Healthy" or "Parkinson's Detected," and provides instant results. This efficient and automated approach supports early PD detection, facilitating timely medical intervention.

IV. PROPOSED METHODOLOGY

The existing system is a task-based analyzer designed to assist in the detection of Parkinson's disease through the evaluation of motor control tasks. The application is built using Python's Tkinter library, providing a graphical user interface (GUI) that allows users to engage in three distinct tests: following a line, drawing a square, and clicking on moving targets. Each test is aimed at assessing different aspects of motor control, which are critical in identifying potential symptoms of Parkinson's disease.

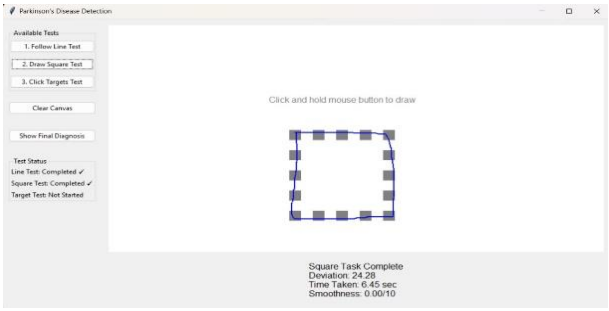

Fig 1.1 Output

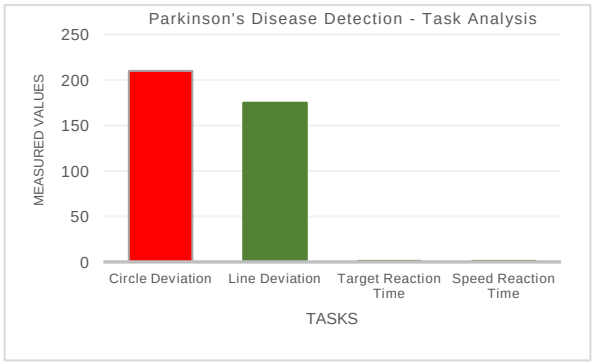

Fig 1.2 Task Analysis

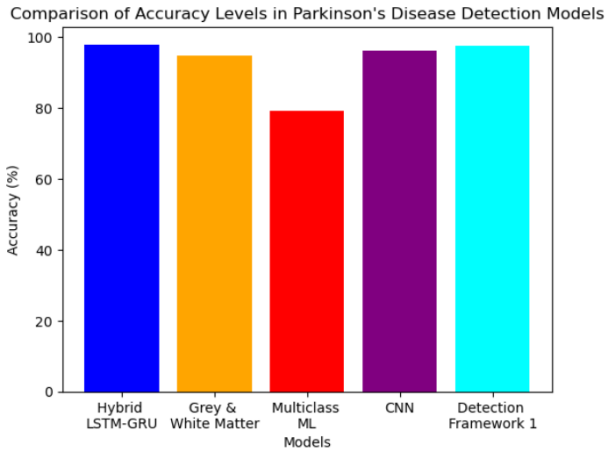

Figure 1.5 Result and E

User Interface (UI): The UI consists of a control panel on the left side and a main canvas on the right. The control panel includes buttons to initiate each test, clear the canvas, and display results. Status indicators provide real-time feedback on the progress of each test.

1)Task Implementation:

Follow Line Test: Users are prompted to draw along a predefined horizontal line. The application records the user's movements and calculates metrics such as mean squared error (MSE), time taken, and smoothness of the drawing.

Draw Square Test: In this task, users are instructed to draw a square. The system analyzes the deviation from the ideal square shape, calculating MSE and smoothness to evaluate performance.

Click Targets Test: This test involves clicking on moving targets that appear randomly on the canvas. The application measures reaction times and tracks the number of successful clicks versus missed targets.

2)Data Collection and Analysis

The application records user interactions, capturing the coordinates of mouse movements and clicks along with timestamps. This data is used to compute various performance metrics:

Mean Squared Error (MSE): Measures the average squared deviation from the target path or shape.

Time Taken: The duration taken to complete each task, providing insight into user efficiency.

Smoothness: Assessed through the calculation of velocity changes during drawing tasks, indicating the fluidity of movement.

Reaction Time: In the target clicking task, the time taken to click on a target after it appears is recorded, providing a measure of responsiveness.

Upon completion of each test, the application presents the results to the user, including detailed metrics and visual feedback. The results are displayed in a dedicated section of the UI, allowing users to review their performance and understand the implications of their scores in relation to potential Parkinson's disease symptoms.

The existing system serves as a foundational tool for assessing motor control through interactive tasks. By leveraging user input and analyzing performance metrics, the application aims to provide valuable insights into motor function, which can be indicative of Parkinson's disease. Future enhancements could include more sophisticated analysis techniques and integration with machine learning algorithms to improve diagnostic accuracy.

B. MODULE DESCRIPTION

The PD detection system consists of multiple modules, each contributing to different stages of the diagnostic process.

1.Data Collection Module: The system gathers datasets of spiral drawings, which serve as a widely recognized diagnostic tool. Parkinson's patients often struggle to draw smooth, consistent spirals due to motor impairments. The dataset includes spirals drawn by both healthy individuals and PD patients, sourced from medical research databases and clinical trials.

2. Preprocessing and Image Transformation Module: To standardize input data, images are resized to 256x256 pixels, converted to grayscale, and normalized. Data augmentation techniques, such as random rotation, enhance model generalization and robustness.

3. Feature Extraction and CNN Model Architecture: A Convolutional Neural Network (CNN) extracts essential features from spiral images. The model comprises multiple convolutional layers, which detect edges, distortions, and inconsistencies in drawings. Max pooling layers reduce computational complexity, and fully connected layers classify images into PD or non-PD categories. The final classification is performed using a soft max activation function, assigning probability scores to each category.

4. Training Process and Optimization: The CNN model undergoes supervised training using labeled spiral images. Forward propagation generates predictions, while a loss function (Cross Entropy Loss) measures errors. The Adam optimizer fine-tunes model weights through backpropagation to minimize loss. Training performance is tracked using F1-score and accuracy metrics.

5. Model Evaluation and Performance Testing: The trained model is tested using unseen spiral drawings to measure classification accuracy. A confusion matrix visually represents correct and incorrect predictions, while performance graphs, such as Loss vs. Epochs and F1 Score vs. Epochs, monitor learning progress and guide model refinement.

6. Deployment and Real-Time Prediction: After successful training and evaluation, the model is deployed in an application where users can upload spiral drawings for diagnosis. The system preprocesses images, classifies them as "Healthy" or "Parkinson's Detected," and provides instant results. This efficient, automated approach aids in early PD detection, facilitating timely medical intervention.

V. RESULT

The Task-Based Analyzer is a graphical user interface (GUI) application developed using Python's Tkinter library, designed to assess motor control impairments associated with Parkinson's Disease (PD) through interactive drawing and target-clicking tasks. The application features three primary tests: a Follow Line Test, a Draw Square Test, and a Click Targets Test. Each test is initiated through dedicated buttons, allowing users to engage in tasks that simulate common motor functions.

Fig 1.3 Frequency Analysis

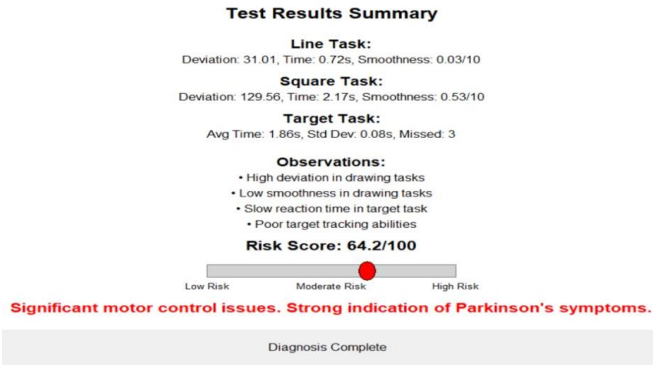

Fig 1.4 Result

Upon starting a test, the application provides real-time instructions and visual feedback. For the Follow Line Test, users are prompted to draw along a predefined line, while the Draw Square Test requires them to trace a square outline. The Click Targets Test involves clicking on moving targets, with the speed and timeout settings adjustable via sliders to accommodate varying difficulty levels. The application records user movements, reaction times, and accuracy, storing this data for analysis.

The results of each test are computed using metrics such as mean squared error (MSE) for deviation from target paths, time taken to complete tasks, and average reaction times for target clicks. The application also calculates smoothness of movements based on velocity changes, providing a comprehensive assessment of motor control. After completing all tests, users receive a final diagnosis based on their performance, which includes a risk score indicating the likelihood of motor impairments. This score is visually represented on a gauge, enhancing interpretability**.**

The Task-Based Analyzer serves as an experimental tool for early detection of Parkinson's Disease, offering a user-friendly interface for both patients and clinicians**.** emphasize the importance of interactive assessments in understanding motor function and provides a foundation for further research into automated diagnostic tools for neurodegenerative disorders**.**

VI. CONCLUSION

This project successfully implements a movement-based task analyzer using Tkinter to aid in the early detection of Parkinson's Disease. By evaluating a user's ability to follow a line, draw a square, and perform alternating clicks, we extract key motor performance metrics such as deviation (MSE), smoothness, and reaction time. These metrics provide insights into fine motor control, coordination, and tremor severity—key indicators in Parkinson's diagnosis.

The system quantifies movement accuracy and efficiency, helping identify deviations that may signal motor impairment. While not a standalone diagnostic tool, it can serve as a preliminary screening method, assisting neurologists and researchers in identifying potential cases for further medical evaluation.

Future improvements may include integrating machine learning models to enhance accuracy, incorporating additional tests for comprehensive assessment, and collecting real-world patient data to validate the system's effectiveness. This project demonstrates the potential of technology-driven assessments in neurology and highlights how computational tools can contribute to early disease detection and monitoring.

VII. FUTURE SCOPE

The proposed system can be enhanced by incorporating additional movement patterns like clicking and scrolling behavior for improved accuracy. Tracking long-term user interactions can aid in early-stage detection of Parkinson's. Future advancements may include deep learning models for better pattern recognition and mobile/web-based applications for real-time monitoring. The approach can also be extended to detect other neurological disorders. With continuous improvements, this system can become a cost-effective and accessible tool for early disease detection.

Future iterations of the Task-Based Analyzer could significantly benefit from the integration of machine learning algorithms to enhance diagnostic accuracy. By training models on a larger dataset of motor control tasks, the system could analyze user performance metrics more effectively, leading to more precise predictions regarding the likelihood of Parkinson's Disease. Additionally, expanding the variety of tests to include assessments of fine motor skills, hand-eye coordination, and cognitive functions would provide a more comprehensive evaluation of the symptoms associated with the disease. This multifaceted approach would not only enrich the user experience but also yield more valuable data for clinicians.

Another promising enhancement involves the development of a mobile application version of the Task-Based Analyzer, which would increase accessibility and convenience for users. By leveraging mobile device sensors, such as accelerometers, the app could gather additional data on motor control in various environments. Furthermore, incorporating real-time feedback mechanisms and adaptive difficulty levels would allow users to receive immediate guidance during tasks, thereby improving their performance and engagement. Customization options, such as selecting specific tasks or adjusting parameters, would further enhance user satisfaction and ensure that assessments are tailored to individual needs.

Lastly, collaboration with healthcare professionals is essential for refining the Task-Based Analyzer's clinical relevance. Engaging neurologists and occupational therapists during the development process would help align the tests with current diagnostic standards and ensure that the assessment criteria are robust. Additionally, integrating the analyzer with telehealth platforms could facilitate remote monitoring, allowing clinicians to access user data in real-time and make timely interventions. By conducting longitudinal studies, the system could also track changes in motor function over time, providing valuable insights into the progression of Parkinson's Disease and the effectiveness of various interventions. These enhancements would position the Task-Based Analyzer as a vital tool in the early detection and ongoing management of Parkinson's Disease.

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