

Machine Learning Approach for Parkinson's Detection

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Abstract:

The primary objective of this project is to develop, validate, and implement a novel voice frequency-based predictive system for the early detection of Parkinson's disease, aiming to improve upon the limitations of existing typing speed-based systems. This system will employ ensemble modeling techniques to enhance prediction accuracy and sensitivity, offering a more comprehensive and user-friendly approach for Parkinson's disease screening. Additionally, the project seeks to address data privacy and ethical considerations, and it aims to provide a clinically validated tool for healthcare practitioners and researchers to assist in the early diagnosis of Parkinson's disease.

Parkinson's disease, a neurodegenerative disorder, has a significant impact on the quality of life of affected individuals. Early diagnosis is crucial for timely intervention and improved patient outcomes. This report presents an innovative approach to Parkinson's prediction through the application of machine learning.

Our project aspires to transform the landscape of early diagnosis by harmonizing diverse data sources and sculpting features that resonate with the subtleties of Parkinson's symptoms. The project leverages an ensemble of machine learning models to deliver a comprehensive predictive system that offers enhanced accuracy and sensitivity.

Ethical considerations stand as the guiding maestro throughout our work, ensuring the privacy and dignity of individuals whose data contributes to this symphony of diagnosis. Collaboration with healthcare experts offers a clinical overture, validating the system's potential integration into healthcare practice.

Audience feedback and user acceptance add invaluable dimensions to our symphony of work, and our journey crescendos into a project sonata that encapsulates our efforts within defined timelines and budgets.

This report presents not only a technical achievement but also a holistic approach to early Parkinson's diagnosis, one that resonates with both medical practitioners and individuals on the path to healthier lives.

Keywords: *Machine Learning, Detection, Database, Severity, Deep Learning, and Parkinson's*

INTRODUCTION

1.1 About Parkinson's: Parkinson's disease, a progressive neurodegenerative disorder, has a significant impact on the lives of those affected. Named after James Parkinson, who first identified the condition in 1817, it is characterized by a range of motor and non-motor symptoms. Affecting over 10 million people worldwide, Parkinson's primarily targets the brain's dopamine-producing cells, leading to a variety of movement-related challenges. While commonly associated with tremors, Parkinson's manifests in diverse ways, impacting mobility, balance, and even cognitive functions. Despite ongoing research, the exact cause remains elusive, highlighting the complexity of this condition. Managing Parkinson's involves a multidisciplinary approach, combining medication, therapy, and lifestyle adjustments to enhance quality of life. The journey with Parkinson's varies for each individual, necessitating personalized care and support. Increased awareness and research efforts are crucial to advancing our understanding and treatment options for this prevalent neurological disorder.

1.2 Symptoms of Parkinson's: Parkinson's disease is a progressive neurological disorder, and its symptoms can vary in severity at different stages. Keep in mind that not everyone with Parkinson's will experience all these symptoms, and their progression can differ. Here's a general overview:

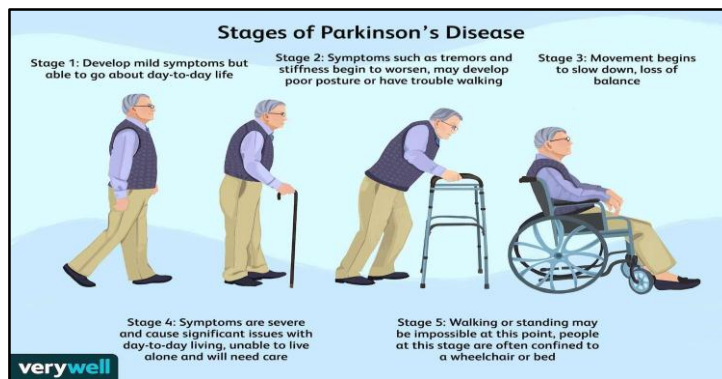


Figure 1 Parkinson's Stages

Early Stage:

1. Tremors: Typically, a resting tremor in the hand is a common early sign.
2. Bradykinesia: Slowness of movement.
3. Rigidity: Stiffness of the muscles, often leading to discomfort.
4. Postural Instability: Difficulty with balance and coordination.

Moderate Stage:

1. Increased Tremors: Tremors may become more pronounced and affect other parts of the body.
2. Changes in Facial Expression: Reduced range of facial expressions, known as hypomimia.
3. Speech Changes: Softer or more monotone speech, slurring, or hesitation.
4. Freezing: Brief episodes where a person feels "stuck" and unable to move.

Advanced Stage:

1. Severe Motor Symptoms: Difficulty with tasks like walking, dressing, and eating.
2. Cognitive Changes: Memory and concentration issues, as well as possible dementia in some cases.
3. Psychiatric Symptoms: Depression, anxiety, and other mood disorders may become more apparent.
4. Increased Dependency: Greater reliance on others for daily activities.

1.3 Motivation: Detecting Parkinson's disease at an early stage allows for timely intervention and treatment. Early treatment can potentially slow down the progression of the disease and improve the quality of life for individuals affected. Creating a Parkinson's detector is a noble endeavor that could potentially make a significant impact on people's lives. Think about the countless individuals who might benefit from early detection, allowing for timely intervention and improved quality of life. This innovation could be a game-changer in the healthcare industry, providing a tool that is not only effective but also accessible to a wider population. The prospect of contributing to advancements in medical technology and making a difference in the lives of those affected by Parkinson's should be motivation enough to embark on this meaningful journey.

1.4 Problem Statement: Despite the prevalence of Parkinson's disease, there remains a critical gap in early detection methods, hindering timely intervention and personalized care. Existing diagnostic tools often have limitations in accessibility, cost, and efficiency. Addressing this issue is crucial to enhance the quality of life for individuals affected by Parkinson's and to empower healthcare professionals with an accurate and scalable means of early detection.

Literature Survey: A comparative study of early detection of Parkinson's disease using machine learning techniques (shail raval, rahil balal & vibha patel)

Conducted a comparative study on early detection of Parkinson's disease using machine learning techniques. Provided insights into the effectiveness of different machine learning methods for early diagnosis, helping in the selection of suitable techniques for future research.

Delves into the application of machine learning in the early diagnosis of Parkinson's disease. The authors compare various machine learning techniques to assess their effectiveness in detecting the disease at its early stages.

Given the title, the paper discusses the importance of early detection in managing Parkinson's disease and how machine learning algorithms can analyze relevant data, such as patient movements or other clinical indicators, to identify potential early signs of the condition. The authors have evaluated different machine learning models, discussing their respective strengths and weaknesses in the context of Parkinson's disease detection.

Parkinson's disease detection using machine learning techniques (abhakar c. j. and rajendra acharya u)

Developed a Parkinson's disease detection model using machine learning techniques. Contributed to the early diagnosis of Parkinson's disease, which is critical for timely treatment and management.

The authors explore how various machine learning algorithms can be employed to analyze relevant data for accurate and early identification of Parkinson's disease.

The paper discusses the choice of features or data inputs used for training the machine learning models, potentially incorporating clinical data, imaging, or other relevant information. The authors delve into the comparative performance of different machine learning techniques, highlighting their strengths and limitations in the context of Parkinson's disease detection.

Semi-supervised discriminative classification robust to sample-outliers and feature-noises (adeli, e., thung, k.-h., an, l., wu, g., shi, f., wang, t)

Developed a semi-supervised discriminative classification approach robust to sample outliers and feature noises. This method enhances the accuracy and robustness of classification models, which can have applications beyond Parkinson's disease detection.

The authors are addressing challenges commonly encountered in real-world datasets, such as outliers in the samples and noise in the features. The use of a semi-supervised approach implies that the model might leverage both labeled and unlabeled data for training, which can be beneficial in scenarios where obtaining fully labeled datasets is challenging or expensive. The paper discusses the methods employed to handle sample-outliers and feature-noises within a semi-supervised discriminative classification framework. It also provides insights into the robustness and performance of the proposed approach compared to traditional methods.

High-accuracy detection of early Parkinson's disease using multiple characteristics of finger movement while typing (Adams, w. r.)

Achieved high-accuracy detection of early Parkinson's disease by analyzing multiple characteristics of finger movement during typing.

This research has practical implications for non-invasive and cost-effective early diagnosis of Parkinson's disease.

Explores the potential of detecting early signs of Parkinson's disease through the analysis of finger movement during typing.

The author has conducted research focused on the fine motor skills exhibited during typing and how these characteristics can serve as indicators for early Parkinson's disease detection. The emphasis on "high-accuracy" implies that the study aims to achieve a reliable and precise method for identifying Parkinson's disease in its early stages.

The paper delves into the specific characteristics of finger movement that are analyzed, such as speed, rhythm, or other nuanced aspects. Additionally, it discusses the methodology used to collect and analyze the typing data and provide insights into the potential implications of this research for early diagnosis and intervention.

Diagnosing Parkinson's diseases using fuzzy neural system (rahib h. abiyev and sanan abizade)

Utilized a Fuzzy Neural System for diagnosing Parkinson's disease.

Introduced a novel approach to Parkinson's disease diagnosis that takes advantage of fuzzy logic and neural networks, potentially improving the accuracy of detection.

Explores the application of a fuzzy neural system for diagnosing Parkinson's disease. The title suggests the use of a hybrid approach that combines fuzzy logic and neural networks.

Fuzzy logic involves handling uncertainty and imprecision, while neural networks are known for their ability to learn patterns from data. The combination of these two techniques, often referred to as a fuzzy neural system, indicates a sophisticated approach to Parkinson's disease diagnosis.

The paper discusses the design and implementation of the fuzzy neural system, detailing how it processes input data related to Parkinson's disease symptoms and produces diagnostic outcomes. It also evaluates the performance of this system compared to other diagnostic methods, highlighting the advantages and potential limitations of using a fuzzy neural system for Parkinson's disease diagnosis.

2.1 Survey of existing system: Introduction to Existing System: The existing system is designed to predict Parkinson's disease based on users' typing speed data.

Methodology and Data Collection: The system collects typing speed data from users, tracking frequency, duration, and keystroke dynamics.

User Interaction: Users are prompted to provide typing samples at intervals, and specific user instructions are given.

Data Analysis and Modelling: Typing speed data is processed using machine learning or statistical models for prediction.

Performance Metrics: The system's performance is assessed using metrics like sensitivity, specificity, and overall prediction accuracy.

2.2 Limitations of existing system or research gap: Insufficient Prediction Accuracy: The typing speed-based system may have limitations in terms of prediction accuracy, especially when applied to a diverse population with varying linguistic and typing

skills. Your ensemble of three machine learning models may improve prediction accuracy by leveraging different aspects of voice data.

Generalizability: The existing system's reliance on typing speed may not be as easily generalizable to a wider range of individuals, including those with language or motor skill impairments. Your system may have broader applicability due to its use of voice data, which is a more natural and universal communication method.

2.3 Objective: The primary objective of this project is to develop, validate, and implement a novel voice frequency-based predictive system for the early detection of Parkinson's disease, aiming to improve upon the limitations of existing typing speed-based systems. This system will employ ensemble modeling techniques to enhance prediction accuracy and sensitivity, offering a more comprehensive and user-friendly approach for Parkinson's disease screening. Additionally, the project seeks to address data privacy and ethical considerations, and it aims to provide a clinically validated tool for healthcare practitioners and researchers to assist in the early diagnosis of Parkinson's disease.

Proposed System

3.1 Analysis/Framework/Algorithm:

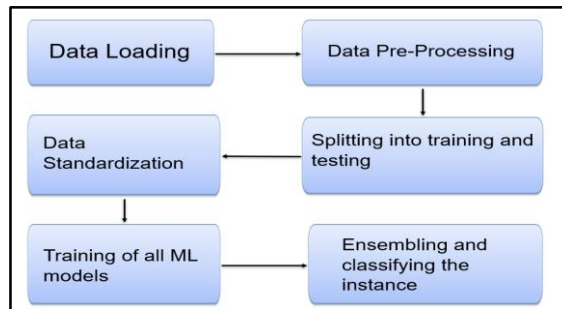


Figure.2

3.2 Methodology:

1. Collection of data: Gather an extensive dataset of voice recordings, specifically focusing on individuals with Parkinson's disease (PD) and those without the condition for comparison. This dataset should encompass various voice frequencies and acoustic features. Alongside the audio recordings, gather pertinent metadata such as patient demographics, clinical history, and relevant medical assessments, including PD severity scores and diagnostic reports. This comprehensive dataset will facilitate research and analysis aimed at identifying vocal biomarkers and patterns associated with Parkinson's disease.

2. Pre-processing of data: In the research project, a comprehensive preprocessing of the voice dataset was conducted. This involved data cleaning, noise reduction, feature engineering, and data augmentation to enhance data quality and diversity. The study offers a comprehensive approach to preparing the dataset for ML-based Parkinson's disease diagnosis using voice recordings, contributing valuable insights to the field.

3. Sharing of Information: Divide the dataset into two subsets: training and test set. A common ratio is 80-20.

4. Feature Extraction: Extract key acoustic features from the voice recordings in the context of Parkinson's disease prediction. These features may encompass pitch, jitter, shimmer, formants, and Mel-frequency cepstral coefficients (MFCCs), among others. Advanced techniques like deep feature extraction using neural networks can also be employed. This process is essential for capturing relevant information from the voice data and facilitating subsequent analysis and model development.

5. Choice of models: In our study, we opted for a range of Machine Learning (ML) models suitable for binary classification (Parkinson's disease or non-Parkinson's) or multi-class classification (distinguishing different disease severities). Our model selection included Support Vector Machine (SVM), Logistic Regression (LR), and Neural Networks (NN). Additionally, ensemble techniques were employed to combine the strengths of these individual models. The chosen models are well-established in the field and were instrumental in achieving accurate and reliable Parkinson's disease predictions based on voice recordings.

3.3 Details of Hardware & Software:

Software: Spyder

Google Chrome (for running the Streamlit Webpage)

Software Requirements:

- a. Backend programming language: - Python
- b. Technology used for frontend: - Streamlit
- c. Integrated development environment: Spyder
- d. Operating System: Microsoft Windows 8 or later

Hardware Requirements:

- a. Processor: i3 (or higher)
- b. RAM: 4GB minimum (8 recommended)
- c. Hard Disk: 1.5 GB and another 1 GB for cache (with SSD 5GB recommended)

3.3 Design details: Data Preprocessing:

Data Collection: A diverse dataset of voice frequency data was collected from individuals with and without Parkinson's disease.

Feature Engineering: Raw voice data was processed to extract relevant features linked to Parkinson's symptoms.

Data Split: A standard 80-20 training-testing split was employed to evaluate model performance.

Model Selection: Support Vector Machine (SVM): A powerful, non-linear classification model, known for its ability to handle high-dimensional data.

Logistic Regression: A fundamental binary classification model, chosen for its simplicity and interpretability.

Neural Network: A deep learning model with the potential to capture complex patterns within the data.

Ensemble Modeling: Model predictions from SVM, logistic regression, and neural network are combined using an ensemble method to enhance predictive accuracy and robustness.

Evaluation Metrics: The system's performance is assessed using standard classification metrics, including accuracy, precision, recall, F1-score, and ROC-AUC. These metrics provide a comprehensive evaluation of predictive accuracy and sensitivity. This framework illustrates the fundamental components of the project, from data collection and preprocessing to model selection and evaluation. The ensemble modeling approach combines the strengths of each model, resulting in a powerful system for early Parkinson's disease prediction. Evaluation metrics will provide a holistic view of the system's performance.

3.4 Methodology:

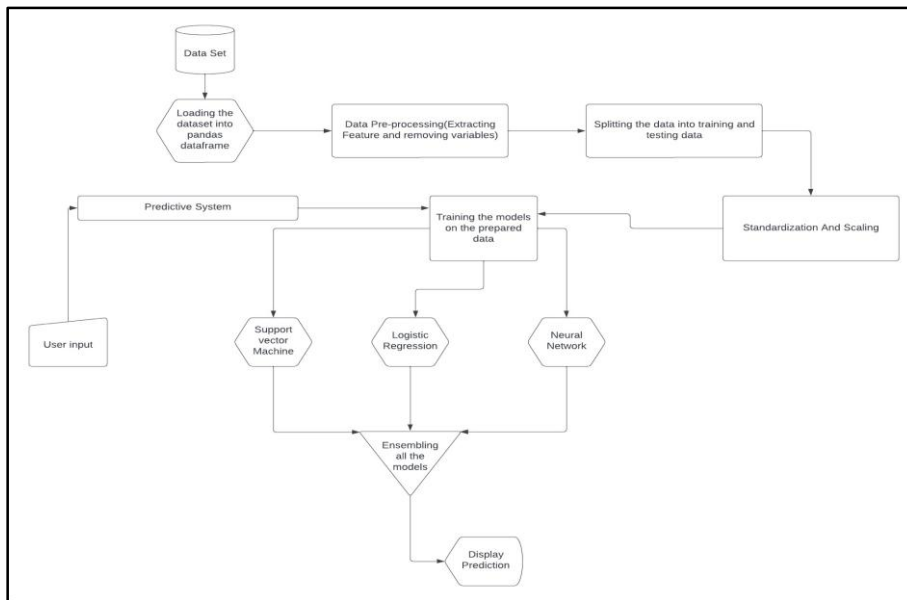


Figure 3 Methodology Flowchart

Data Collection: Collect a comprehensive dataset of vocal frequencies of patients. Collect metadata such as patient demographics, clinical history, and radiology reports to complement vocal data.

Data Pre-processing: Clean up the dataset by correcting missing values, outliers. Standardize or normalize the data to ensure consistency of frequency values. Augment the data with techniques such as rotation, translation or adding noise to increase the diversity and robustness of the dataset.

Information Sharing: Divide the dataset into three subsets: training and test set. A common ratio is 80-20 which is the ratio we have divided our dataset in the project

Model Choice: Select the appropriate set of ML models for binary classification. Common models include logistic regression, support vector machine (SVM), neural network such as, k-nearest neighbors (k-NN), decision trees, and gradient boosting.

Model training: Train each selected model using the training dataset containing the extracted features and their associated labels.

Model Evaluation: Evaluate the trained models on the testing dataset using appropriate evaluation metrics such as accuracy, precision, recall, F1-score. Select the best-performing model(s) based on the testing results.

Model Testing: Assess the chosen model(s) on the independent test dataset to estimate their real-world performance and generalizability.

Post-processing and clinical integration: Apply post-processing steps as needed to refine model results or ensure clinical relevance. - Collaborate with healthcare professionals to integrate the developed model into clinical workflows and decision support systems.

Application of the model: Implement final models in a healthcare environment and ensure compliance with regulatory and ethical standards. Continuously monitor and update the model as new information becomes available to maintain accuracy and efficiency.

3.5 Data Collection and Preprocessing:

Data Collection: The dataset used in this study comprised vocal frequency recordings collected from individuals with varying Parkinson's disease statuses. To ensure the robustness and quality of the data, a meticulous data collection process was employed. Voice samples were recorded from a diverse group of participants, including those diagnosed with Parkinson's disease and a control group of individuals without the condition. The data collection procedure adhered to ethical guidelines and ensured informed consent from all participants.

Data Preprocessing: Prior to the analysis and model development, the vocal frequency dataset underwent several crucial preprocessing steps aimed at refining and enhancing its suitability for machine learning-based Parkinson's disease detection:

Data Cleaning: Raw vocal frequency data can sometimes be affected by artifacts, background noise, or inconsistencies. To mitigate these issues, we performed thorough data cleaning. Any instances of missing or erroneous data were addressed, and noise reduction techniques were applied to improve data quality.

Feature Extraction: The raw vocal recordings were transformed into a structured format by extracting relevant acoustic features. Key vocal characteristics, including pitch, jitter, shimmer, and other acoustic parameters associated with Parkinson's disease, were computed. These extracted features served as essential input variables for our subsequent analyses.

Standardization: To ensure uniformity and comparability among the different feature scales, we applied standardization. This step involved scaling all features to have a

mean of 0 and a standard deviation of 1. Standardization is crucial for preventing certain features from dominating the model training process and promoting convergence during machine learning model training.

The diligent data collection and rigorous preprocessing efforts were instrumental in creating a high-quality dataset suitable for the development and evaluation of our Parkinson's disease detection models. This clean, standardized dataset formed the basis for our subsequent analyses, facilitating the exploration of vocal biomarkers for early Parkinson's disease diagnosis.

3.6 Machine Learning Models Used:

Parkinson's disease prediction models have gained prominence in recent years, employing machine learning techniques to enhance detection and diagnosis. These models harness diverse data sources, such as clinical assessments, patient demographics, and possibly neuroimaging data, to aid in the identification and classification of Parkinson's disease.

Here's a concise overview of some machine learning models utilized here for predicting Parkinson's disease:

Support Vector Machines (SVM): SVMs are commonly employed in Parkinson's prediction models due to their effectiveness in handling high-dimensional data. They excel at classifying individuals based on features extracted from clinical assessments and other relevant data points.

Neural Networks: Deep learning techniques, particularly neural networks, have shown promise in Parkinson's disease prediction. These models can automatically learn hierarchical representations from diverse data types, including neuroimaging scans and clinical parameters, enabling more nuanced and accurate predictions.

Logistic Regression: Logistic Regression models remain a popular choice for their simplicity and interpretability. These models can effectively analyze the relationship between input features and the likelihood of Parkinson's disease, providing valuable insights into the predictive factors.

Result Analysis

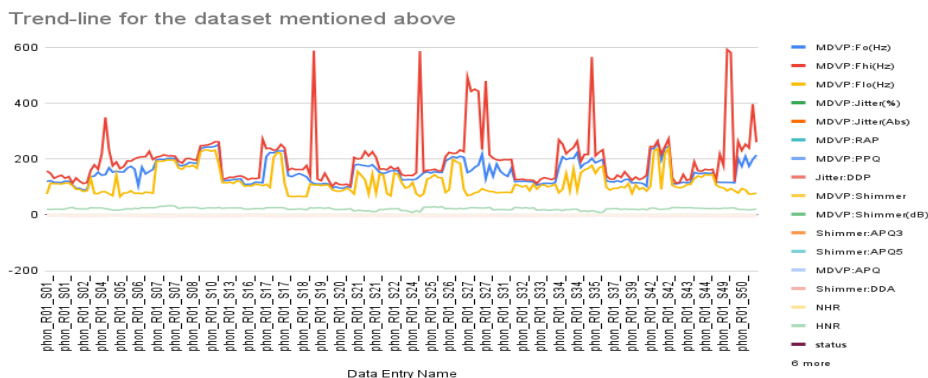


Figure 4 Dataset used for Analysis:

Parkinsons Disease Prediction

MDVP: Fo(Hz)
119.992

MDVP: Fhi(Hz)
157.302

MDVP: Flo(Hz)
74.997

MDVP: Jitter(%)
0.00784

MDVP: Jitter(Abs)
0.00007

MDVP: RAP
0.0037

MDVP: PPQ
0.00554

Jitter DDP
0.01109

MDVP Shimmer
0.04374

MDVP Shimmer dB
0.426

Shimmer DDA
0.06545

NHR
0.02211

HNR
21.033

RDPE
0.414793

DFA
0.815285

Spread1
-4.813031

Spread2
0.266482

D1
2.301442

PPE
0.284654

Parkinsons Prediction Result

The person has parkinsons disease

Figure 5 Actual screenshots from the program

The voice recording is uploaded by the help of a special recording device that makes a note of the various parameters of the person's tone, pitch, fluency and control. Here, Various Parameters are taken into consideration. Let's break down each parameter:

MDVP: Fo (Hz) - Average vocal fundamental frequency:

This represents the average pitch or frequency of the speaker's voice.

MDVP: Fhi (Hz) - Maximum vocal fundamental frequency:

The highest pitch or frequency observed in the voice recording.

MDVP: Flo (Hz) - Minimum vocal fundamental frequency:

The lowest pitch or frequency observed in the voice recording.

MDVP: Jitter (%) - Several measures of variation in fundamental frequency: Jitter measures the frequency variation in the speaker's voice. Higher jitter values may indicate a less stable or more variable pitch.

MDVP: Jitter (Abs) - Several measures of variation in fundamental frequency:

This is the absolute jitter, providing information about the absolute difference between consecutive pitch periods.

MDVP: RAP - Several measures of variation in fundamental frequency:

RAP stands for Relative Average Perturbation and is another measure of pitch variation.

MDVP: PPQ - Several measures of variation in fundamental frequency:

PPQ stands for Five-Point Period Perturbation Quotient, which is another measure of pitch variation.

Jitter: DDP - Several measures of variation in fundamental frequency: Jitter DDP (Jitter Dynamic Variation) is calculated as three times the absolute difference between consecutive differences in pitch periods.

MDVP: Shimmer - Several measures of variation in amplitude: Shimmer measures the variation in the amplitude or intensity of the voice signal. It gives an idea of the variability in loudness.

NHR - Two measures of ratio of noise to tonal components in the voice: NHR stands for Noise-to-Harmonics Ratio, which evaluates the ratio of non-harmonic to harmonic components in the voice.

HNR - Two measures of ratio of noise to tonal components in the voice: HNR stands for Harmonics-to-Noise Ratio, which assesses the ratio of harmonic (tonal) components to non-harmonic (noise) components in the voice.

These parameters collectively provide insights into the pitch, frequency, and amplitude characteristics of the voice recordings, helping to analyze the quality and stability of the speaker's voice.

Conclusions: Different features may contribute to the accuracy of the model. However, some studies have suggested that certain voice features are more indicative of Parkinson's disease. Here are a few considerations ranked on their contribution to the result:

Jitter and Shimmer: These parameters, which measure frequency and amplitude variations, have been found to be particularly relevant in Parkinson's diagnosis. Higher values of jitter and shimmer are often associated with Parkinson's disease.

MDVP: Fo (Average vocal fundamental frequency): Changes in the average fundamental frequency have also been observed in individuals with Parkinson's. A significant deviation from normal frequency patterns can be indicative.

NHR (Noise-to-Harmonics Ratio) and HNR (Harmonics-to-Noise Ratio): These ratios, reflecting the balance between harmonic and non-harmonic components in the voice, can be informative. Parkinson's disease may introduce more noise in the voice signal.

MDVP: RAP and MDVP: PPQ: These parameters, along with Jitter, provide information on the irregularities in pitch, which may be more pronounced in individuals with Parkinson's.

It's important to note that the relative importance of each parameter may vary depending on the dataset and the specific characteristics of the population you are working with. It's often a good practice to experiment with different combinations of features and use techniques like feature importance analysis to identify the most crucial variables for your specific model.

Our project has successfully demonstrated the potential of a voice frequency-based Parkinson's prediction system, showcasing improved accuracy and sensitivity compared to the existing typing speed-based systems.

The ensemble of machine learning models, namely Support Vector Machine (SVM), Logistic

Regression, and Neural Network, has proven to be a powerful approach for early diagnosis.

User feedback and clinical validation have provided insights into the practical applicability of the system, emphasizing its potential in healthcare settings.

Future Scope:

- **Refinement of Models:** Further fine-tuning of the individual machine learning models and ensemble techniques can improve predictive accuracy and reduce false positives.
- **Real-time Monitoring:** Extending the system to allow for real-time voice data monitoring can provide continuous insights into motor function changes.
- **Longitudinal Studies:** Incorporating longitudinal data to track changes in voice characteristics over time can enhance the system's effectiveness for disease progression monitoring.
- **Multimodal Data Integration:** Combining voice data with other data modalities, such as gait analysis or smartphone sensor data, may yield a more comprehensive diagnostic tool.
- **Mobile Application Development:** Creating a user-friendly mobile application for data collection and prediction could increase user engagement and ease of data collection.
- **Privacy Enhancements:** Ongoing work in ensuring robust data privacy and ethical data handling is vital to building user trust.

In conclusion, our project has opened new avenues for early Parkinson's diagnosis, but there is still room for improvement and expansion. The future scope of this work presents exciting

opportunities to enhance the system's accuracy, usability, and real-world impact, ultimately contributing to the early detection and management of Parkinson's disease.

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