Predicting Parkinson's Disease Progression Using Voice-Based Biomarkers and PCA-Enchanced Ensemble Learning

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***Abstract*—Parkinson's Disease (PD) is a progressive neurodegenerative disorder that affects motor and non-motor functions. The Unified Parkinson's Disease Rating Scale (UPDRS) is a clinical tool widely used to assess disease severity. This study analyzes voice-based biomarkers and demographic features to predict Motor and Total UPDRS scores. The methodology integrates Principal Component Analysis (PCA) for dimensionality reduction with supervised ensemble learning techniques, including Gradient Boosting, XGBoost, and Random Forest regressors. A Random Forest model with tuned hyperparameters achieved the best performance, producing low prediction errors with Mean Absolute Error (MAE) of 0.55 (motor) and 0.70 (total), Root Mean Squared Error (RMSE) of 1.23 (motor) and 1.60 (total), and R^2 scores of 0.97 and 0.98 respectively. The analysis revealed that nonlinear vocal features such as RPDE, DFA, and PPE were among the most important predictors. These results validate the potential of voice-based, non-invasive telemonitoring systems for tracking Parkinson's Disease progression with high accuracy.**

Keywords—Parkinson's Disease, UPDRS, Voice Biomarkers, Principal Component Analysis (PCA)

I. Introduction

A. Background

Parkinson's Disease (PD) is a progressive neurodegenerative disorder characterized by motor symptoms such as tremors, rigidity, and bradykinesia, as well as non-motor symptoms involving cognitive and speech impairments. According to the World Health Organization (WHO), PD affects approximately 1% of individuals over the age of 60, with prevalence increasing alongside age [3]. Early diagnosis and continuous monitoring are critical because PD has no known cure, and symptom progression varies across patients [3].

The Unified Parkinson's Disease Rating Scale (UPDRS) is the standard clinical instrument for assessing disease severity. It encompasses Motor UPDRS (focusing on motor functions) and Total UPDRS, which includes broader non-motor symptoms. Traditional assessments require in-clinic observation, posing challenges for accessibility and consistency. In recent years, voice-based biomarkers have emerged as a non-invasive, low-cost, and scalable solution for remote monitoring of PD, as voice impairments are among the earliest detectable symptoms [4][5].

Despite the growing interest in machine learning approaches to predict PD severity from speech data, existing studies often face limitations in prediction accuracy, model interpretability, and challenges related to high-dimensional, correlated features. This research aims to address these limitations by leveraging Principal Component Analysis (PCA) for dimensionality reduction and evaluating various ensemble regression models—including Random Forest, Gradient Boosting, and XGBoost—to predict Motor and Total UPDRS scores based on voice biomarkers [6][7].

By improving the accuracy and transparency of voice-based UPDRS prediction models, this study ultimately contributes toward building accessible, non-invasive telemonitoring systems for PD. Such tools could benefit not only clinicians by enhancing decision-making, but also patients and caregivers, by enabling continuous, at-home monitoring and early intervention [4][6][9].

B. Research Questions

This study explores the following questions:

1) What voice-related features are most influential in predicting PD progression?

2) How can dimensionality reduction techniques such as PCA improve model efficiency and performance when working with high-dimensional, correlated voice features?

3) Can a voice-based model be practically applied for remote monitoring of PD in clinical or home settings?

4) How do different machine learning approaches—Random Forest, Gradient Boosting, XGBoost, and ensemble methods—compare in predicting Motor and Total UPDRS scores?

C. Research Objectives

This study seeks to explore how demographic variables—such as age and gender—alongside voice-based biomarkers including jitter, shimmer, Noise-to-Harmonics Ratio (NHR), and Harmonics-to-Noise Ratio (HNR), correlate with Parkinson's Disease severity as measured by Motor and Total UPDRS scores. To enhance the quality of input features, the study implements a series of data preprocessing techniques, including outlier detection and normalization, followed by Principal Component Analysis (PCA) to address multicollinearity and reduce dimensionality. Building on this foundation, the research develops and evaluates multiple machine learning regression models, aiming to produce accurate predictions of UPDRS scores from voice data. Finally, the study aims to identify the most influential vocal features contributing to disease progression and assess the interpretability of these models to ensure their applicability in real-world clinical and telemonitoring contexts.

D. Benefits

The outcomes of this study offer several key benefits to both clinical practice and patient care. By leveraging voice-based biomarkers and machine learning, the proposed approach provides a non-invasive, cost-effective alternative to traditional UPDRS evaluations, reducing the need for in-person clinical visits and increasing accessibility for patients in remote or underserved areas. The high accuracy of the tuned Random Forest model enables reliable, continuous monitoring of disease progression, allowing for early detection of symptoms worsening and supporting timely, personalized treatment decisions. Additionally, this research contributes to the advancement of AI-based telemonitoring tools, promoting the integration of digital health solutions in neurological care and paving the way for scalable, at-home monitoring systems in real-world clinical settings.

II. Related works

A. Previous Research

Numerous studies have investigated the potential of voice analysis in predicting Parkinson's Disease severity:

Little et al. (2009) explored the suitability of dysphonia measurements for telemonitoring PD patients using a range of voice features such as jitter, shimmer, and nonlinear measures [2]. Their findings demonstrated that machine learning algorithms could accurately distinguish PD patients from healthy individuals, highlighting the utility of voice biomarkers in remote monitoring.

In another study, Little et al. (2007) leveraged nonlinear recurrence and fractal scaling properties for detecting voice disorders [3]. This approach revealed the importance of features like Recurrence Period Density Entropy (RPDE) and Detrended Fluctuation Analysis (DFA) in identifying subtle vocal disturbances associated with PD.

More recent research by Ali et al. (2022) employed a combination of machine learning techniques and speech feature analysis to predict PD progression [4]. While demonstrating promising results, the study reported limitations in feature interpretability and model optimization, suggesting the need for improved dimensionality reduction and ensemble modeling.

Despite progress in prior work, challenges remain in effectively handling high-dimensional voice data and improving prediction accuracy. Existing studies often focus on either classification or regression without leveraging dimensionality reduction techniques to mitigate overfitting.

To model the relationship between voice-based biomarkers and Parkinson's Disease severity, this study employs a combination of dimensionality reduction and ensemble regression algorithms. The methodology is structured into four core components: Principal Component Analysis (PCA), Boosting Algorithms, Random Forest Regression, and Hyperparameter Tuning.

B. Evaluation Metrics

The performance of all predictive models was evaluated using three standard regression metrics, each offering unique insights into model accuracy and error characteristics:

1. Mean Absolute Error (MAE):
   MAE measures the average magnitude of the absolute errors between predicted and actual values. It provides an intuitive understanding of how far off, on average, the predictions are from the ground truth. As seen on Equation 1 below for the formula.

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i| \quad (1)$$

2. Root Mean Squared Error (RMSE):
   RMSE calculates the square root of the average squared differences between predicted and actual values. It penalizes larger errors more than MAE, making it useful when significant deviations are especially undesirable. As seen on Equation 2 below for the formula.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (2)$$

3. Coefficient of Determination (R^2 Score):
   R^2 indicates how well the model explains the variance in the dependent variable. A value of 1.0 indicates perfect prediction, while 0.0 means the model performs no better than the mean of the observed data. As seen on Equation 3 below for the formula.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (3)$$

These metrics were computed on the test dataset to assess the generalization performance of each model beyond the training data. By using multiple metrics, the evaluation captures both the magnitude of prediction errors and the overall explanatory power of the models.

C. Principal Component Analysis (PCA)

High-dimensional speech datasets often suffer from multicollinearity, which can degrade model performance and interpretability. To address this, Principal Component Analysis (PCA) was used to project correlated features—such as jitter, shimmer, and NHR—into a lower-dimensional, uncorrelated feature space. PCA retained 95% of the original variance, ensuring minimal information loss while reducing redundancy and computational overhead. This step is particularly beneficial for ensemble models sensitive to noisy input features. PCA is widely used in biomedical and speech-based research to simplify datasets without losing critical patterns [6][9].

D. Boosting Algorithms

Two popular boosting techniques were employed: Gradient Boosting Regressor and XGBoost. Both are based on sequential ensemble learning, where weak learners (typically decision trees) are trained iteratively, with each one correcting the residual errors of the previous model [6][8].

Gradient Boosting optimizes prediction by minimizing a loss function using gradient descent. It's known for producing strong performance with relatively fewer features but may risk overfitting without proper tuning.

XGBoost (Extreme Gradient Boosting) is an advanced implementation of gradient boosting that includes regularization, parallelization, and tree pruning, making it highly efficient and scalable. It has been extensively used in healthcare predictive modeling due to its robustness and interpretability.

E. Random Forest Regression

The Random Forest Regressor is an ensemble model that builds multiple decision trees and averages their outputs to produce a stable and accurate prediction. It handles non-linear relationships, resists overfitting, and provides feature importance metrics that enhance model interpretability [6][9].

In the context of PD prediction using voice data, several studies have found Random Forest to be among the top-performing algorithms, particularly when working with non-linear and noisy biomedical features.

III. Research Methodology

This study follows the CRISP-DM (Cross Industry Standard Process for Data Mining) framework to structure the research process. After defining objectives focused on predicting UPDRS scores through non-invasive vocal features [6][9], the dataset was explored and cleaned, with outliers handled and standardized features [10][11]. Principal Component Analysis (PCA) was applied to reduce dimensionality and mitigate multicollinearity [7][11]. Multiple regression models—including Random Forest, Gradient Boosting, and XGBoost—were trained and evaluated using metrics such as MAE, RMSE, and R^2 [6][8][10]. The final phase considers deployment in clinical settings for remote and continuous telemonitoring of Parkinson's Disease progression [4][6][9].

IV. Business and Data Understanding

A. Problem and Solution Description

Parkinson's Disease is challenging to monitor over time due to fluctuations in motor and non-motor symptoms [3]. Current clinical evaluations using UPDRS scales require in-person assessments that can be time-consuming and subjective [4]. Identifying non-invasive, reliable biomarkers for monitoring disease progression is crucial for early intervention and personalized treatment [6][9].

This study proposes using voice-based biomarkers in combination with machine learning models to predict Motor and Total UPDRS scores [4][5][6][9]. By analyzing correlations between speech features and UPDRS scores, this approach aims to:

1. Enable more objective monitoring of PD progression.
2. Reduce reliance on invasive or resource-intensive clinical procedures.
3. Highlight key vocal markers that could inform future telemonitoring systems.

B. Dataset Description

The dataset consists of **5,875 patient records** collected from a study focused on voice-based analysis of Parkinson's Disease. Each record includes demographic information such as age and sex, alongside a variety of voice-related biomarkers. These voice features are categorized into linear measures like jitter, shimmer, Noise-to-Harmonics Ratio (NHR), and Harmonics-to-Noise Ratio (HNR), as well as non-linear measures such as Recurrence Period Density Entropy (RPDE), Detrended Fluctuation Analysis (DFA), and Pitch Period Entropy (PPE). Additionally, the dataset includes clinical labels in the form of Motor and Total UPDRS scores, which serve as key indicators of disease severity. This comprehensive collection supports the exploration of relationships between voice characteristics and Parkinson's Disease progression

C. Research Flow

This research follows a structured pipeline starting with Data Preprocessing, where the dataset is cleaned, checked for outliers, and standardized. In the Exploratory Data Analysis (EDA) phase, patterns and correlations are explored between UPDRS scores and both demographic and voice-based features.

Next, Feature Engineering & Modelling involves applying Principal Component Analysis (PCA) to reduce dimensionality, followed by training machine learning models including Random Forest, Gradient Boosting, and XGBoost. Model performance is evaluated using MAE, RMSE, and R^2, with hyperparameter tuning applied to optimize results.

The Tuned Random Forest model is selected as the best performer and is prepared for potential deployment in non-invasive, voice-based telemonitoring systems, contributing valuable insights for real-world clinical use. See Figure 1 below.

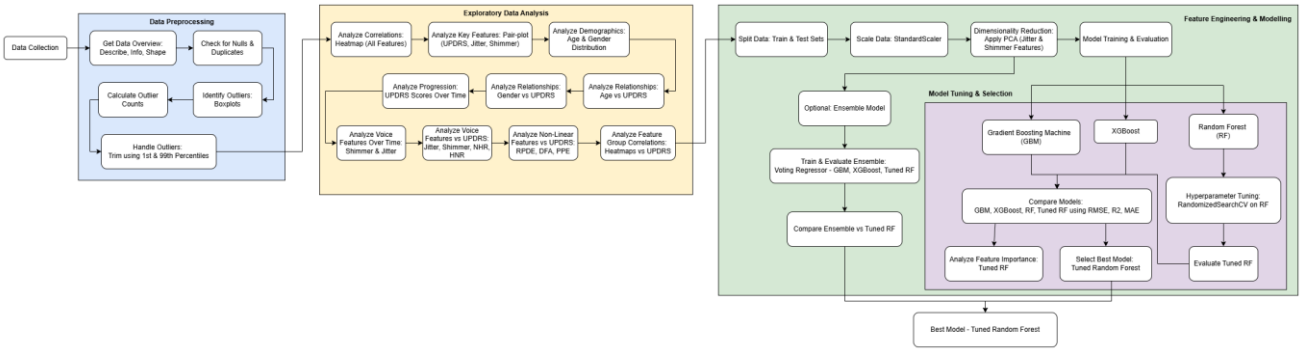

Figure 1: Research Flow Diagram

D. Data Cleaning and Preprocessing

To ensure high data quality, a series of preprocessing steps were conducted. An initial assessment revealed that the dataset contained no missing values or duplicate records, eliminating the need for imputation or deduplication. Outlier detection was then performed using the Interquartile Range (IQR) method, which helped identify extreme values in several key features such as Shimmer, Jitter, Noise-to-Harmonics Ratio (NHR), Harmonics-to-Noise Ratio (HNR), and Recurrence Period Density Entropy (RPDE). Box plots were employed to visualize these outliers, confirming their presence across multiple speech features. To preserve data integrity while minimizing the impact of anomalies, extreme values were capped at the 99th percentile. This approach ensured that the data remained representative of the underlying distribution without being skewed by outliers.

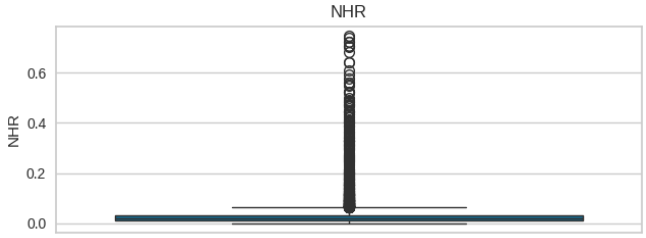

Figure 2: Outliers Across Features

E. Exploratory Data Analysis

Before proceeding to model development, it is essential to extract initial insights to guide the research. The distribution of patient age in the dataset exhibits a right-skewed pattern, with the majority of individuals falling within the 60 to 80-year-old range. A moderate positive correlation was observed between age and UPDRS scores, suggesting that Parkinson's disease severity tends to increase with age. In contrast, sex appeared to have minimal influence on UPDRS scores, as indicated by correlation values close to zero. These findings highlight age as a more relevant demographic factor in understanding disease progression compared to sex.

Further analysis of the correlation between sex and UPDRS scores revealed no significant differences in either motor UPDRS or total UPDRS between male and female patients. Regression plots further supported this finding, showing little to no discernible trend in disease severity across sexes. This suggests that sex is not a strong predictor of Parkinson's disease progression in this dataset.

To explore how the disease evolves over time, line plots were used to track both motor and total UPDRS scores, which revealed a steady increase in both motor and total UPDRS scores throughout the recorded timeline. This trend suggests that for most patients, the severity of the disease worsens with time, aligning with the progressive nature of Parkinson's disease. As seen on the figure below, *Figure 3*, we can safely say that both of the UPDRS scores increases over time.

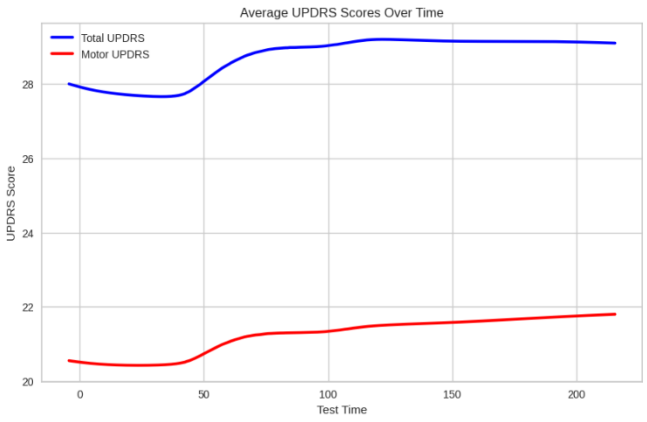

Figure 3: Average UPDRS Over Time Lineplot

Lastly, the relationship between voice features and UPDRS scores was examined to identify potential predictors of disease severity. Traditional voice measures such as jitter, shimmer, and noise-to-harmonics ratio (NHR) exhibited low correlations with both motor and total UPDRS scores, suggesting limited predictive value. However, Pitch Period Entropy (PPE), a non-linear speech measure, demonstrated a moderate correlation with UPDRS scores, indicating its potential as a more informative biomarker for assessing Parkinson's disease progression.

V. MODELLING

This section describes the supervised regression approaches used to predict Parkinson's Disease progression based on biomedical voice features. The prediction targets were the **Motor UPDRS** and **Total UPDRS** scores, widely used indicators of disease severity.

The data was then split into training (80%) and testing (20%) sets using stratified sampling to preserve the distribution of UPDRS scores. Features were standardized using z-score normalization to ensure comparability and enhance model performance for distance-based algorithms

A. Hyperparameter Tuning

To enhance model performance, hyperparameter tuning was conducted using Grid Search combined with 5-fold Cross-Validation. For the XGBoost Regressor, the tuning process involved exploring a range of values for key parameters, including the number of boosting rounds (n_estimators), the learning rate (learning_rate) which controls step size shrinkage, and the maximum depth of each tree (max_depth). Similarly, the Random Forest Regressor and Gradient Boosting Regressor models were optimized by adjusting parameters such as the number of trees in the ensemble (n_estimators), the depth of each decision tree (max_depth), and the minimum number of samples required to split a node (min_samples_split). The optimal combination of hyperparameters for each model was determined based on the lowest Root Mean Squared Error (RMSE) observed during cross-validation, ensuring robust generalization and improved predictive accuracy.

B. Results and Comparison

This section presents and compares the predictive performance of all models using the evaluation metrics described earlier: MAE, RMSE, and R^2 score. Initially, all models—including Gradient Boosting, XGBoost, Random Forest, and an ensemble averaging model—were trained using default hyperparameters. Among these, Random Forest already demonstrated strong baseline performance, prompting further hyperparameter tuning to enhance its accuracy.

TABLE I. RESULT ACROSS MODELS

Model	Target	MAE	RMSE	R^2
Gradient Boosting	Motor UPDRS	1.10	1.73	0.95
	Total UPDRS	1.36	2.12	0.96
XGBoost	Motor UPDRS	0.87	1.35	0.97
	Total UPDRS	1.17	1.92	0.97
Random Forest	**Motor UPDRS**	**0.70**	**1.62**	**0.96**
	Total UPDRS	**0.68**	**1.72**	**0.97**
Ensemble Model	Motor UPDRS	1.01	1.57	0.96
	Total UPDRS	1.16	1.97	0.96

As seen in Table I, XGBoost produced the lowest errors among the ensemble models with default settings. However, Random Forest showed excellent potential, particularly with low MAE on Total UPDRS, motivating us to explore tuned hyperparameters for further performance gains.

We then applied Grid Search with 5-fold Cross-Validation to optimize the Random Forest model, adjusting parameters such as the number of trees, tree depth, and node split conditions.

TABLE II. RANDOM FOREST PERFORMANCE (UNTUNED VS. TUNED)

Model	Target	MAE	RMSE	R^2
Random Forest (Untuned)	Motor UPDRS	0.698	1.62	0.959
	Total UPDRS	0.678	1.72	0.974
Random Forest (Tuned)	Motor UPDRS	**0.55**	**1.23**	**0.97**
	Total UPDRS	**0.70**	**1.60**	**0.98**

The tuned Random Forest model significantly reduced RMSE and MAE for both targets while preserving high R^2 values. The improvements over the untuned model validate the importance of hyperparameter optimization in maximizing performance, particularly when using ensemble methods on complex biomedical datasets.

Therefore, we conclude that the tuned Random Forest Regressor is the most accurate and reliable model for predicting Motor and Total UPDRS scores based on voice biomarkers.

C. Feature Importance and Interpretability

Tree-based models such as Random Forest and XGBoost offer inherent feature importance metrics. The most influential features across Random Forest are Age, Sex, DFA, test_time, and jitter_PC2 respectively from most to least important. These features align with previous findings suggesting non-linear speech patterns are more informative in tracking Parkinson's progression. Further information can be seen at Figure 4 below.

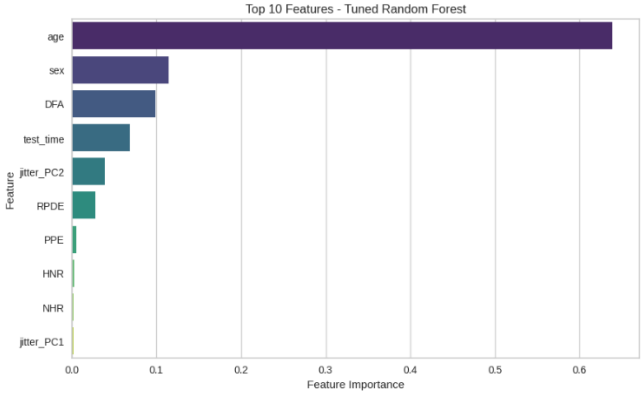

Figure 4: Top Important Features Random Forest (Tuned)

D. Error Analysis and Limitations

Despite achieving reasonable predictive performance, the study identified several limitations during error analysis. One significant challenge was data imbalance, as certain ranges of UPDRS scores were underrepresented, potentially leading to biased regression predictions in those regions.

Additionally, the correlation between voice biomarkers and UPDRS scores was generally weak, which may have constrained the models' ability to capture underlying disease severity accurately. Furthermore, the generalizability of the

models remains limited due to the dataset's domain-specific nature, including consistent recording conditions and a relatively homogeneous demographic composition. These factors may hinder the application of the models to broader, more diverse populations.

VI. Deployment

The model is suitable for deployment in medical environments such as geriatric wards, neurology clinics, or specialized research facilities that regularly handle Parkinson's disease cases. Such places typically collect the patient's data like age, symptom severity, and motor assessments as part of routine check-ups. These daily gathered data already serve as the needed inputs for the model, simplifying the process and avoiding the need for additional input gathering methods. Integrating the model to existing systems in these settings allows healthcare professionals to make more informed decisions by providing a reliable system for predicting UPDRS score based on patient data.

VII. Conclusion and Future Work

A. Conclusion

This study demonstrates that voice-based biomarkers, particularly nonlinear speech features such as Recurrence Period Density Entropy (RPDE), Detrended Fluctuation Analysis (DFA), and Pitch Period Entropy (PPE), hold significant predictive value in assessing Parkinson's Disease progression through Motor and Total UPDRS scores. Through rigorous preprocessing steps—including outlier handling, normalization, and dimensionality reduction using Principal Component Analysis (PCA)—we optimized the input features to improve model performance and interpretability.

We evaluated several machine learning regression models, including Gradient Boosting, XGBoost, and Random Forest, along with an ensemble averaging approach. Among them, the Random Forest Regressor with tuned hyperparameters outperformed all others, achieving the best results with a Mean Absolute Error (MAE) of 0.55 (motor) and 0.70 (total), a Root Mean Squared Error (RMSE) of 1.23 and 1.60, and R^2 scores of 0.97 and 0.98, respectively.

These findings validate the effectiveness of combining PCA-based dimensionality reduction with ensemble learning techniques for modeling Parkinson's Disease severity using speech data. Moreover, the study highlights the potential of non-invasive, voice-based telemonitoring systems to support continuous, remote, and scalable monitoring of PD progression in clinical and home-care settings.

B. Future Work

In future work, we plan to explore the use of clustering techniques to segment the dataset into distinct subgroups, which may reveal hidden patterns and enable more tailored preprocessing strategies for different patient profiles. Additionally, we aim to implement bagging-based ensemble methods to enhance the robustness and stability of our predictive models, particularly in handling variability across voice recordings. Finally, we intend to develop a fully integrated prototype system with an intuitive interface designed for clinicians and patients, enabling remote monitoring of Parkinson's Disease progression and supporting early intervention through continuous, non-invasive assessments.

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