A Comparative and Explainable Study of Machine Learning Models for Early Detection of Parkinson's Disease Using Spectrograms

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Abstract: Parkinson's disease (PD) is a progressive neurodegenerative disorder that originally affects the motor system. Therefore, early diagnosis is essential for effective intervention. Classic diagnostic approaches heavily rely on clinical observations and manual feature extraction, limiting the detection of subtle early vocal impairments. This research examines machine learning (ML) techniques, namely Support Vector Machines (SVM), Random Forest (RF), and Extreme Gradient Boosting (XGBoost), for early identification of PD through the analysis of spectrogram images derived from voice recordings. Mel-Frequency Cepstral Coefficients (MFCC), Short-Time Fourier Transform (STFT), and Mel-Spectrograms were extracted. The improvement of the model was introduced by the Synthetic Minority Over-sampling Technique (SMOTE) and hyperparameter tuning using GridSearchCV (Grid Search with Cross-Validation). Implementing the above methods resulted in significant performance improvements, with XGBoost achieving an accuracy of 95 ± 0.02 on the PC-GITA dataset and SVM attaining 90.74 ± 0.04 on the Neurovoz dataset. Local Interpretable Model-agnostic Explanations (LIME) enhanced model transparency by identifying the significant regions in spectrograms that most influence predictions. This analysis illustrates the efficacy of ML models utilizing SMOTE and GridSearchCV, particularly when augmented by LIME for interpretability, in improving early detection of PD, thereby presenting a feasible approach for clinical implementation.

1 INTRODUCTION

Parkinson's disease, or PD, is a neurodegenerative illness that affects about 1% of people over 60 around the world (Dorsey et al., 2018). The condition is marked by a group of motor symptoms, such as tremors, rigidity, and slow movement, as well as a number of non-motor symptoms, such as cognitive decline and changes in speech and voice (Bloem et al., 2021). These symptoms significantly affect the quality of life for patients with PD and provide considerable obstacles for healthcare personnel in the prompt and efficient administration of medication.

Early PD diagnosis is paramount, as it allows for implementing therapeutic interventions that can markedly enhance patient outcome (Murman, 2012). Still, the present diagnostic techniques—which mostly rely on clinical assessments and patient-reported symptoms—often insufficient short for early PD (Gullapalli & Mittal, 2022), particularly in cases of subtle or unrecognized voice impairments.

People with PD show particular changes in their vocal features, including a decrease in pitch variability, changes in speech pace, and articulation problems (Harel et al., 2004). While audio recordings allow one to record these changes, conventional analysis techniques may rely on hand feature extraction, which might not fully capture the intricacy of voice patterns, therefore restricting their efficacy in automated assessments (Klempíř & Krupička, 2024).

Due to technological developments, speech analysis— as a non-invasive and easily available technique for early disease diagnosis—has been developed. Analyzing acoustic features including pitch, jitter, and shimmer shows that it is possible to

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distinguish PD patients from healthy people. However, many research using these features depend on traditional ML models, which need for hand feature engineering and might not be sufficient in capturing the whole spectrum of auditory features (Badhan & Kaur, 2024).

Building on these developments, researchers aim to leverage the strengths of ML methods to assess their performance in identifying early PD signs using spectrogram images of voice recordings. Optimal for ML-based analysis, spectrograms graphically depict audio signals and capture both frequency and time-domain information.

Using the PC-GITA and Neurovoz datasets, this work contrasts the performance of several ML models—including SVM, RF, and XGBoost—to identify early-stage PD from continuous vowel recordings of the vowel "a". We used SMOTE and GridSearchCV hyperparameter adjustment to solve class imbalance and optimize model performance.

To enhance model interpretability, we employed LIME in the best-performing ML models. This method helps to distinguish how ML models interpret speech data for early PD detection and helps to identify which areas of the spectrograms most contributed to the model's capacity. This understanding is crucial for identifying the vocal features that separate PD patients from healthy controls (HC), thus validating the model's predictive capabilities.

This work attempts to evaluate, using voice analysis, whether ML techniques are more effective for early PD identification. This comparison underscores the potential of ML techniques could automatically extract complex properties.

The present paper focuses on:

- The utility of spectrogram images for classification purposes.
- A comparative analysis of ML techniques for the early detection of PD.
- Model interpretability through LIME.

The framework of this research is presented in the next parts. With a focus on spectrogram production, feature extraction, and model training, Section 2 presents the framework for the materials and methodology. Section 3 offers a comprehensive review of the evaluation metrics critical for dataset assessment. Last but not least, Section 4 presents a thorough examination of the results, contrasting the performance of ML models and stressing important results; it also includes the conclusions of the study and suggestions for next studies.

2 MATERIALS AND METHODS

This paper illustrates the proposed framework, which employs a systematic methodology for early classifying PD based on speech datasets, as shown in Figure 1. It entails gathering voice data from patients with PD and HC participants for analysis, followed by data preprocessing. The feature extraction step commences, extracting attributes such as MFCC, STFT spectrogram, and Mel-spectrogram from the audio data, converting them into spectrogram images, and balancing the dataset utilizing SMOTE. Following data balancing, the next step is to employ GridSearchCV to refine the hyperparameters of the ML models and evaluate their efficacy. We organize each phase to guarantee that the models can proficiently discriminate between HC and individuals with PD utilizing speech data, therefore facilitating the early detection and diagnosis of the disease.

2.1 Parkinson's Disease Dataset

Two extensively referenced (PD) datasets were employed in this study: PC-GITA (Orozco-Arroyave & Noth, n.d.) and Neurovoz (Mendes-Laureano et al., 2024). Each database comprises individuals with PD and HC subjects. Neurologists have employed the Unified Parkinson's Disease Rating Scale (UPDRS) and the Hoehn and Yahr scale (H&Y) to identify and categorize the Patients. The databases exhibit variations in demographics and sizes, as outlined in Table 1.

All recordings utilized in this study were at an early stage (UPDRS stages 1-2). Under controlled environmental settings, data recordings were conducted in all instances. The staff instructed each participant to execute several speech activities. This study examines sustained phonation of the vowel /a/. Each patient was recorded three times.

Table 1: Demographic information, including gender and age ranges for the PC-GITA and Neurovoz corpora.

Corpus	Subjects				Age (Years)			
	Female		Male		Female		Male	
	PD	HC	PD	HC	PD	HC	PD	HC
Neurovoz	16	23	15	24	56–86	58–86	41–80	53–77
PC-GITA	17	25	19	25	44–75	43–76	33–77	31–86

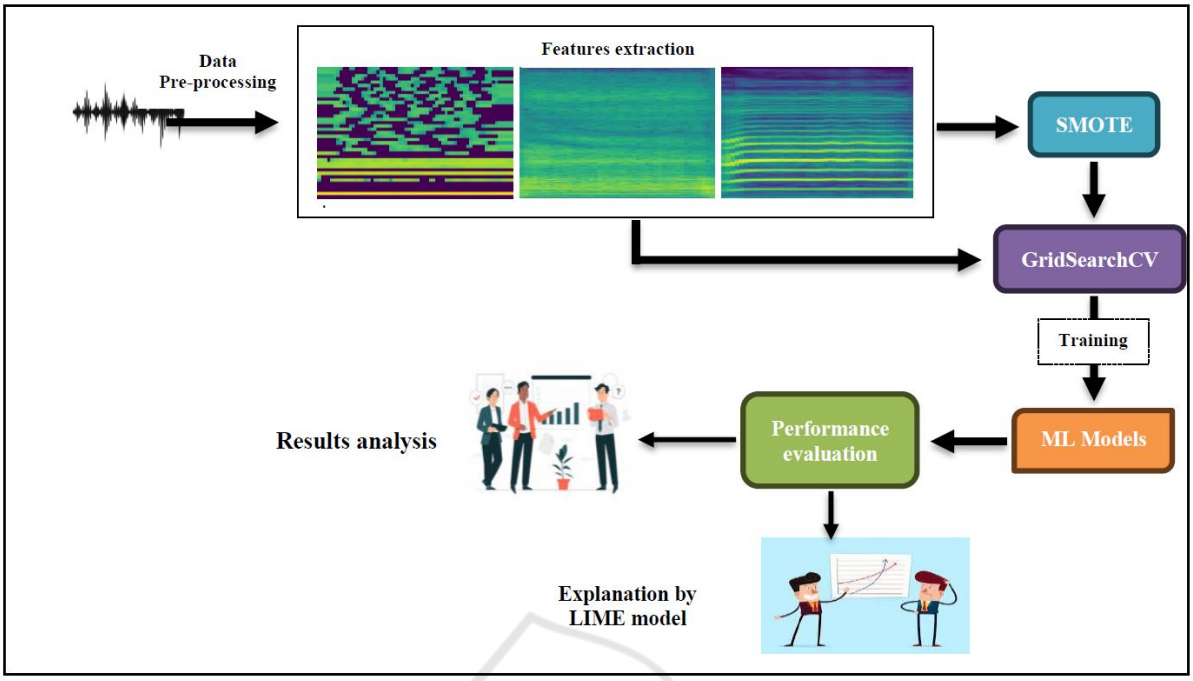


Figure 1: Proposed model for early PD classification.

2.2 Data Pre-Processing

All recordings from the PC-GITA and Neurovoz datasets were resampled to 16 kHz utilizing the librosa library to maintain uniformity in the sampling rate. EBU R128 loudness normalization was implemented utilizing the ffmpeg-normalize library (*Ffmpeg-Normalize*, n.d.) to attain uniform loudness levels, enhancing conventional peak-based normalization.

The spectrogram features were retrieved and saved as 224x224-pixel image files. These images were organized by class label (HC for healthy controls, PD for Parkinson's disease) then normalized to the range [0, 1] by dividing pixel values by 255. 80% of the dataset was used for training, and 20% was used for testing. The dataset was divided into training and test sets at random.

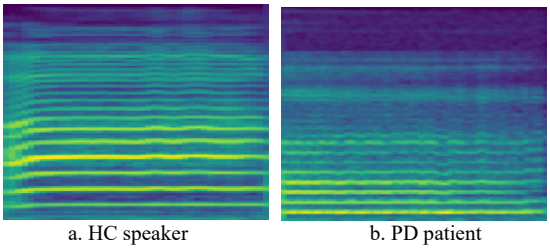
2.3 Feature Extraction

2.3.1 MFCC Coefficients

MFCCs were extracted with 13 MFCC coefficients per frame and their derivatives in order to capture the envelope of a sound's short-term power spectrum (Mishra et al., 2024). These factors are perfect for differentiating between PD patients and HC because they accurately capture the timbral features of speech.

2.3.2 STFT Spectrograms

The STFT spectrogram is an effective tool for analyzing and visualizing time-varying frequency content in audio signals. It converts all recordings into the time-frequency domain, facilitating the examination of the dynamic evolution of frequency content in a given signal (Xuan, 2023). In this work, windows (n-fft) of 32 milliseconds in length were computed using STFT representations chosen to achieve a balance between computing efficiency and sufficient temporal and frequency precision. To ensure constant signal length, the hop length was set at 8 milliseconds and the maximum padding length (max_pad_len) was changed to 100. The time-frequency representation extracted was used as input to feed to the ML model.



a. HC speaker b. PD patient

Figure 2: STFT spectrograms of the vowel /a/speech signal pronounced by HC speaker (a) and a patient with PD (b).

2.3.3 Mel-Spectrograms

The Mel-spectrogram is a popular used representation of audio data that measures the power of a signal on the Mel scale, which more accurately approximates the human auditory system's reaction to different frequencies. This work created Mel-spectrograms with a filter bank of 40 Mel bands. This method transforms the power spectrogram to a log scale, resulting in a reliable representation of audio features relevant for speech analysis and disease detection.

After extracting features from the MFCC with their derivatives, STFT and Mel-spectrograms, the spectrograms were flattened into one-dimensional vectors, thus ensuring compatibility with ML models. In this stage, the two-dimensional spectrograms are converted into a format that numerical array-input models may use. A full feature set representing each audio sample was created by merging the resulting flattened vectors. To make sure that all relevant auditory features were used for classification, these feature vectors were fed into the ML pipeline.

2.4 Classification Methods

Following previous stages, we used ML techniques, including SVM, RF, and XGBoost, to identify early PD, building on earlier stages. To improve the performance of the model and find the ideal hyperparameters, SMOTE and GridsearchCV were used to all of the ML models. Kernel types, the number of estimators, and learning rates were explored to determine the most effective models for the early detection of PD.

2.4.1 Support Vector Machine (SVM)

A supervised ML algorithm that is widely utilized for classification tasks. It works by finding a hyperplane that optimally differentiates data points belonging to disparate classes within a high-dimensional space. SVM is efficacious in high-dimensional settings and exhibits resilience to overfitting, particularly when the number of features surpasses the number of observations. Employing an array of kernel functions (linear, polynomial, radial basis function) can handle both linear and non-linear classification (Bind et al., 2015).

2.4.2 Random Forest (RF)

An ensemble learning method based on decision trees. During the training phase, it builds multiple trees, each using a random subset of the data. The outputs of these trees are then combined using majority voting, resulting in an improved classification. The method is versatile, capable of handling large datasets with high dimensionality, and resistant to noise and overfitting (Breiman, 2001).

2.4.3 Extreme Gradient Boosting (XGBoost)

A robust gradient-boosting algorithm that builds models stage-wise, with each new tree correcting errors from the previous ones by focusing on misclassified examples. It uses regularization to minimize overfitting and use optimization techniques such as parallelization and tree pruning to improve performance and speed. XGBoost excels at processing structured data and consistently outperforms other algorithms in ML contests (Wang et al., 2022).

2.4.4 Synthetic Minority Over-sampling Technique (SMOTE)

There are few PD samples than HC samples in the dataset, which creates an imbalance. A solution to this problem is to oversample members of the minority class in order to achieve distributional parity. Improving the class distribution is possible via instance replication, but it does not provide any new information. SMOTE addresses this issue by producing new samples using linear interpolation of existing minority class instances, hence generating synthetic data points along the trajectory of the feature space (Brownlee, 2020). For a certain minority instance x_i a synthetic sample x_{new} is generated by interpolating between x_i and one of its k-nearest neighbors x_{neighbor}, where λ is a random value within the interval [0,1].

$$x_{new} = x_i + \lambda(x_{\text{neighbor}} - x_i) \quad (1)$$

2.4.5 Hyperparameter Tuning (GridSearchCV)

GridSearchCV is a widely utilized method for hyperparameter optimization in ML models. Hyperparameters are predefined configurations set prior to model training, encompassing the Kernel, C, gamma, number of estimators, learning rate, and max_depth. Determining the ideal values for these parameters can substantially enhance model performance (Jumanto et al., 2024).

GridSearchCV is a method for systematically exploring a predefined set of hyperparameter values to identify the optimal configuration. It requires three key elements:

- The estimator represents the model to be trained.

- A parameter grid is a list of hyperparameters and their potential values.
- CV: The number of folds in K-fold cross-validation. We set k = 5.

3 EVALUATION METRICS

The key evaluation metrics for classification models are accuracy, precision, recall, and F1-score:

- **Accuracy** measures the proportion of correctly classified instances:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (2)$$

- **Precision** indicates the proportion of predicted positives that are positive:

$$\text{Precision} = \frac{TP}{TP + FP} \quad (3)$$

- **Recall** measures the proportion of actual positives correctly identified:

$$\text{Recall} = \frac{TP}{TP + FN} \quad (4)$$

- **F1-score** balances precision and recall, particularly for imbalanced datasets:

$$\text{F1} - \text{score} = \frac{2\,TP}{2\,TP + FP + FN} \quad (5)$$

4 RESULTS AND DISCUSSION

Tables 2 and 3 present a comparative performance of ML models for early PD detection from the two disjoint datasets without and with the application of SMOTE. The analysis is based on performance metrics, including accuracy, F1 score, precision, and recall, all with standard deviation, to highlight the strengths and weaknesses of the models across these datasets.

The models showed different success over the two datasets according to the results acquired without applying SMOTE (Table 2). The XGBoost model showed the best level of accuracy in the PC-GITA dataset—82.85 ± 0.05 Followed by the SVM (80.77 ± 0.05). While the XGBoost model showed the highest precision (86.67 ± 0.08), the SVM model also had the highest F1-score (77.27 ± 0.08) and recall (73.42 ± 0.09). Its F1-score and recall were, however, rather lower than those of SVM and RF. The results imply that XGBoost shows a superior balance between accuracy and precision. With an accuracy of 78.85 ± 0.07 and a recall of 59.09 ± 0.14 RF model showed the lowest performance among the three. The results show that the RF model showed more trouble than the other models handling class imbalance.

With an accuracy of 72.09 ± 0.06, an F1 score of 70 ± 0.04, and a recall of 66.67 ± 0.12, SVM displays the best performance in the Neurovoz dataset. With XGBoost attaining the lowest accuracy (69.37 ± 0.04) and recall (52.38 ± 0.10), the results for XGBoost and RF were inferior; yet, its precision was greater than those of other models with 78.57 ± 0.04. These results show that although SVM showed superior performance in handling data without SMOTE, XGBoost, and RF showed more amazing difficulty in addressing the class imbalance, especially with the recall.

Table 2: Performance results without SMOTE from each dataset using the ML models for the early prediction of PD.

Dataset	Model	Accuracy	F1_score	Precision	Recall
PC-GITA	SVM	80.77 ± 0.05	77.27 ± 0.08	79.86 ± 0.11	73.42 ± 0.09
	RF	78.85 ± 0.07	70.27 ± 0.13	85.91 ± 0.09	59.09 ± 0.14
	XGBoost	82.85 ± 0.04	70.27 ± 0.08	86.67 ± 0.08	59.68 ± 0.06
Neurovoz	SVM	72.09 ± 0.06	70 ± 0.04	73.68 ± 0.03	66.67 ± 0.08
	RF	70.79 ± 0.05	66.67 ±0.05	72.22 ± 0.07	61.90 ±0.12
	XGBoost	69.37 ± 0.04	62.86 ± 0.07	78.57 ± 0.04	52.38 ± 0.10

Table 3: Performance results with SMOTE from each dataset using the ML models for the early prediction of PD.

Dataset	Model	Accuracy	F1_score	Precision	Recall
PC-GITA	SVM	90 ± 0.03	89.60 ± 0.04	96.30 ± 0.05	83.87 ± 0.06
	RF	86.66 ± 0.05	86.14 ± 0.06	96 ± 0.03	77.42 ± 0.07
	XGBoost	95 ± 0.02	95.08 ± 0.03	96.67 ± 0.02	93.55 ± 0.04
Neurovoz	SVM	90.74 ± 0.04	90.71 ± 0.05	96.15 ± 0.04	86.21 ± 0.05
	RF	83.33 ± 0.06	84.21 ± 0.07	85.71 ± 0.05	82.76 ± 0.06
	XGBoost	80.62 ± 0.07	81.36 ± 0.06	80 ± 0.08	82.76 ± 0.03

When SMOTE (Table 3) was used, the performance of all models improved, especially SVM and XGBoost, across both datasets. When tested on the PC-GITA dataset, the SVM was enhanced. Its accuracy went from 80.77 ± 0.05 to 90 ± 0.03 and its F1 score went from 77.27 ± 0.08 to 89.60 ± 0.04. The accuracy went up a lot, from 79.86 ± 0.08 to 96.30 ± 0.05, and the recall went up a lot, too, from 73.42 ± 0.09 to 83.87 ± 0.06. It's clear from these results that SMOTE facilitated enhanced the SVM's performance by reducing class mismatch, which is a key part of finding rare PD cases in the dataset.

XGBoost significantly improved performance, with accuracy increasing from 82.85 ± 0.04 to 95 ± 0.02, F1 score went from 70.27 ± 0.08 to 95.08 ± 0.03, and recall went from 59.68 ± 0.06 to 93.55 ± 0.04. Based on these results, it looks like the synthetic data that SMOTE created helped XGBoost a lot, especially when it came to memory. This means that the model became better at finding positive cases of PD. Even though RF's accuracy went up from 78.85 ± 0.07 to 86.66 ± 0.05, its F1 score and recall went up less than those of SVM and XGBoost. As expected, the recall went up from 59.09 ± 0.14 to 77.42 ± 0.07. This indicates that SMOTE enhanced performance for RF, albeit not to the same extent as for SVM and XGBoost.

The enhancements on the Neurovoz dataset were more modest but still significant. The SVM's recall improved from 66.67 ± 0.08 to 86.21 ± 0.05, and its accuracy increased from 72.09 ± 0.06 to 90.74 ± 0.04. These results indicate that SVM experienced substantial benefits from SMOTE, as evidenced by its improved generalization across the entire dataset and significant increases in recall. In addition, XGBoost exhibited an increase, with accuracy increasing from 69.37 ± 0.04 to 80.62 ± 0.07 and recall increasing from 52.38 ± 0.10 to 82.76 ± 0.03. However, the model's susceptibility to the challenge was suggested by the fact that the XGBoost enhancement was less pronounced on Neurovoz than on PC-GITA.

Figure 3 illustrates the ROC-AUC curves of the three ML models—SVM, RF, and XGBoost—generated on the PC-GITA dataset. In subplot (a), the AUCs for SVM and XGBoost are 0.90 and 0.88, respectively, indicating excellent discriminatory performance without SMOTE. Nevertheless, the RF model exhibits slightly superior predictive capacity, with an AUC of 0.90. These findings show that all three models can efficiently identify PD patients from HC, with RF doing the best without SMOTE. In subplot (b), the use of SMOTE improved the performance of all three models. The SVM and XGBoost models both have a good AUC of 0.96, suggesting exceptional classification skill across thresholds.

Moreover, RF has superior performance, with an AUC of 0.91, highlighting its capacity to tackle class imbalance via SMOTE. The observed enhancement across models demonstrates that oversampling using SMOTE significantly improves the model's robustness, especially in datasets with class imbalance. Both SVM and XGBoost exhibit exceptional and consistent performance on the PC-GITA dataset, rendering them optimal choices for early PD identification.

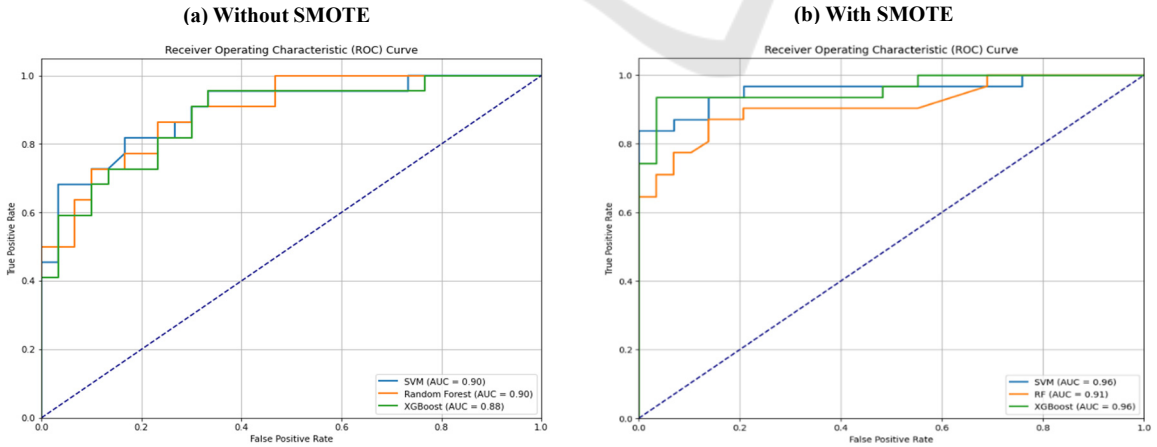


Figure 3: AUC-ROC curve of the three ML models in PC-GITA dataset without and with SMOTE.

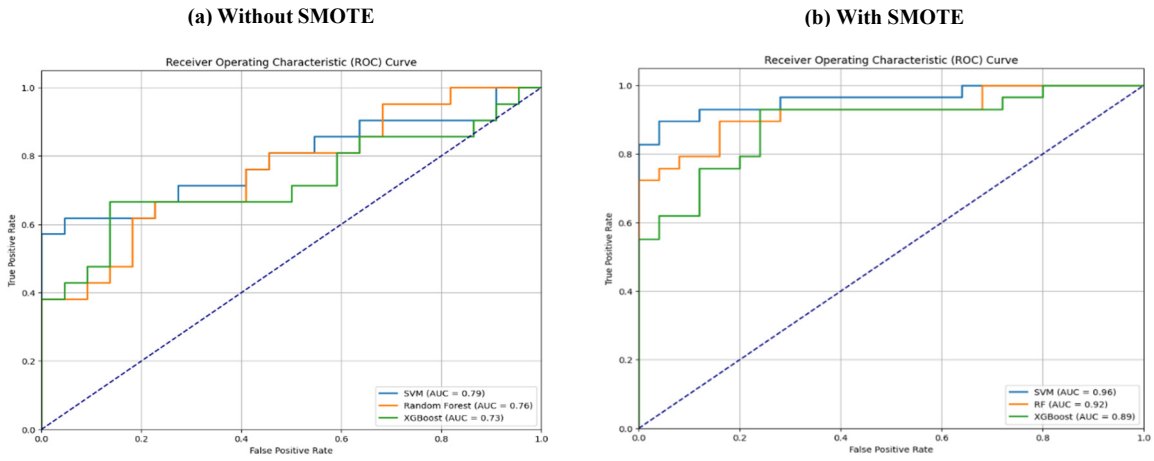


Figure 4: AUC-ROC curve of the three ML models in Neurovoz dataset without and with SMOTE.

Figure 4 demonstrates the effectiveness of the models on the Neurovoz dataset, as evidenced by the AUC-ROC curves. In subplot (a), before to the application of SMOTE, the SVM attains a maximum AUC of 0.79, which, although satisfactory, indicates a reduction in performance relative to PC-GITA. XGBoost achieves an AUC of 0.73, whereas RF has the lowest performance at 0.70. These findings indicate that the Neurovoz dataset poses additional hurdles, most likely due to variability and underlying characteristics in patient data. Subplot (b) shows that applying SMOTE improves AUC scores significantly across all models, illustrating the relevance of resolving class imbalance. SVM once again earns the highest AUC (0.96), demonstrating its resilience and reliability. The RF model shows a significant improvement, with an AUC of 0.92, demonstrating that it can adjust to class-balanced data. XGBoost has an AUC of 0.89, which indicates improved performance in this context.

The importance of SMOTE in addressing class imbalance is emphasized by these findings, particularly in the context of the Neurovoz dataset. GridSearchCV was also instrumental in the optimization of hyperparameters for all models, which exacerbated the performance enhancements observed with SMOTE. Furthermore, fine-tuning parameters such as kernel type and regularization strength improved SVM's capacity to generalize, contributing to the model's consistently high AUC. Similarly, with XGBoost, GridSearchCV enhanced the learning rate and maximum tree depth, allowing the model to catch more complicated patterns in the data. After applying SMOTE, RF gained much improved performance from optimal tree depth and the number of estimators. These hyperparameter adjustments highlighted the joint effectiveness of SMOTE and GridSearchCV by helping the models match their performance with the features of every dataset. Several significant observations arise from results analysis. The application of SMOTE, illustrated in subplot (b), significantly enhanced AUC values for all models and datasets, thereby addressing class imbalance concerns. Second, SVM's dependability for early PD identification was confirmed by its consistent achievement of the greatest AUC across datasets (0.96). XGBoost demonstrated exceptional efficacy, particularly on PC-GITA, despite minor performance fluctuations. RF, despite its initial subpar performance, successfully adjusted to SMOTE and achieved impressive results on the Neurovoz dataset. Nonetheless, SMOTE facilitated the recovery of all models, resulting in robust outcomes.

In summary, the SVM model proves to be the most resilient and reliable across both datasets and situations, positioning it as a formidable candidate for clinical applications. XGBoost and RF exhibit potential, especially when customized to the distinct features of certain datasets. The synergistic effect of SMOTE and GridSearchCV underscores their significance in improving model efficacy for unbalanced datasets, especially with early PD detection.

4.1 Local Interpretable Model-Agnostic Explanations (LIME)

In this study, we employed LIME to interpret the best model, XGBoost, predictions in classifying PD in early-stage and HC patients. A post-hoc interpretability method was developed to explain

every prediction complex and black-box model. It achieves this by constructing local, interpretable models that approximate the behavior of the black-box ML models within some small neighborhood around the data point being explained (Molnar, 2020).

LIME was selected for this work because it is a model-agnostic technique. Hence, it can be easily applied to any ML algorithm (e.g. XGBoost, SVM). It will also provide local explanations that will enable the analysis of exactly which features of the input data- namely, Mel-spectrograms- the model is considered most influential for classifying each patient as either PD or HC. This capability is critical when applied clinically, for which there is an urgent need to understand the underlying decision-making process of ML models to build trust among health professionals and ensure the validity of model outputs.

LIME works by perturbing the input data, slightly modifying the spectrogram, and observing how the model's prediction changes. Then, it builds a more straightforward interpretable model example; a linear model approximates the decision boundary of the complex model in the vicinity of the input data point. Formally, this can be presented as:

$$\xi(x) = argmin\, L(f, g, \pi_x) + \Omega(g) \quad (6)$$

Where :

- f is the original black-box model (XGBoost in our study).
- g is the interpretable local surrogate model.
- π_x is a proximity measure that assigns higher weights to data points close to the instance x.
- L (f, g, π_x) ensures that the local surrogate model g approximates the complex model f behavior.
- Ω(g) enforces interpretability by ensuring the surrogate model remains simple.

In our analysis, LIME has been applied to explain the predictions made through XGBoost upon spectrograms from PC-GITA and Neurovoz datasets. The spectrograms represent time-frequency representations of speech recordings, where XGBoost was tasked with classifying the spectrograms as belonging to either PD or HC patients. With LIME, we can visualize those regions within the Mel-spectrograms that contribute the most toward model predictions and, in turn, provide an interpretable explanation for each decision made by this class.

Figures 5 and 6 present LIME explanations for PD and HC patients of the PC-GITA and Neurovoz datasets, respectively.

Figure 5 illustrates that the XGBoost model utilized four essential regions inside the Mel-spectrogram to categorize PD patients in the PC-GITA dataset. The locations marked in red signify areas where the model identified auditory traits indicative of PD, including diminished frequency variability, lower vocal intensity, and delayed speech. These features signify vocal abnormalities typically linked to PD, such as monotone speech and dysarthria. The localized features of these emphasized regions indicate that the model concentrates on distinct portions of the spectrogram to discern PD-specific speech patterns.

Furthermore, the model found five separate areas that assisted with sort the PC-GITA dataset into groups of HC patients. The red areas show the sound features that show a healthy vocal system. These include changing pitches quickly and clearly, and regular speech. These traits show normal speaking range and flow, which is very different from the stiff and repetitive speech patterns seen in people with PD. Focusing on these key areas shows that the model uses variations in frequency and intensity to tell the difference between normal and Parkinsonian speaking.

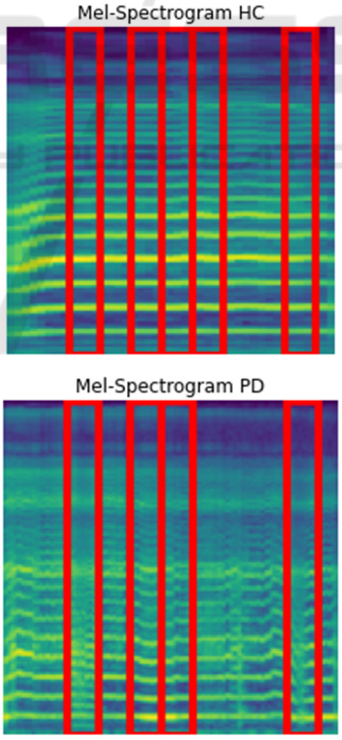


Figure 5: LIME explanations for both PD and HC from PC-GITA dataset.

By contrast, in the case of the Neurovoz dataset, XGBoost depended on a broader set of regions in both PD and HC Mel-spectrograms. In the case of the HC patients from this dataset, three regions were underlined by the model within the spectrogram. This wider distribution of salient regions reflects the greater complexity and variability inherent in healthy speech patterns. Healthy subjects thus had dynamic pitch modulation, more variance over time, and a wider range of vocal frequencies, while the dependence of the model on several regions indicates that this is a level at which complexity needs to be captured for accurate classification.

The model also focused on three salient regions in the Mel-spectrogram for PD patients in the Neurovoz dataset. These will highlight the spectrogram parts that the model focused on because of speech features typical for a PD, such as reduced tempo and frequency modulation. More regions suggest that Neurovoz contains more subtle or dispersed Parkinsonian features, and the model needs to consider more significant parts of the spectrograms to make a more confident classification.

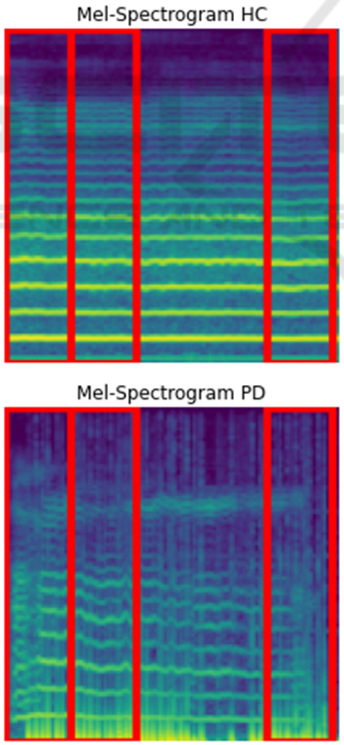


Figure 6: LIME explanations for both PD and HC from Neurovoz dataset.

Comparing the results from the PC-GITA with the Neurovoz datasets, it is apparent that this model requires fewer regions in the dataset on which it was trained to differentiate between PD and HC patients. This fact could support the claim that the acoustic features are more salient in the PC-GITA dataset; therefore, the model can rely on fewer key areas for classification. In contrast, the intensive distribution of important regions in the Neurovoz dataset suggests that more dispersed and subtle features need to be captured by the model. These differences are likely attributable to variations in the demographics of speakers, languages, or recording conditions between the two datasets.

LIME has provided much more insight for the clinician into the model's decision-making process, and the highlighted regions in the Mel-spectrograms point to specific vocal features relevant in a clinical sense for distinguishing PD from HC patients. For instance, monotonic speech, reduced articulation, or slowed speech are well-established indicators of PD and parameters that the model has paid much attention to agree with the clinical expectation. With interpretable explanations, LIME ensures the XGBoost model provides transparent predictions that the patient can clinically validate. This interpretability is necessary for embedding the ML model into clinical decision-making to enable early detection of PD.

4.2 Comparative Analysis with Previous Studies

Results obtained with the proposed model are compared to several recent related works on the early detection of PD using ML models and speech features, focusing on the accuracy achieved in detecting PD from the sustained phonation of the vowel /a/ across different models and datasets outlined in Table 4. During the last few years, various studies have investigated the potential of ML models in diagnosing PD through speech signal processing. These works have extracted different acoustic features from voice records and applied various ML techniques to attain higher diagnostic accuracy.

Recently, Wodzinski et al. (Wodzinski et al., 2019) conducted a serious study on the use of MFCC features that were then converted into spectrogram images for analysis. The method was based on a ResNet convolutional neural network model, which treated the problem as an image classification task. This research utilized the PC-GITA dataset for its study and powered an accuracy of 91.7% regarding detecting PD on the sustained phonation of the vowel sound /a/. They have used deep learning techniques to show how voice data can generally be analyzed to detect diseases.

Table 4: Comparison of performance of the proposed model with previous studies.

References	Input	Model	Dataset	Accuracy
Wodzinski M. et al.	MFCCs transforming them into Spectrogram images	ResNet	PC-GITA	91.7%
Nayak S. S. et al.	MFCC + Mel-spectrogram + Spectralcontrast + Chromagram + Tonnetz with GA	SVM	PC-GITA	94%
Ibarra E. J. et al.	Mel-scale spectrograms	2D-CNN	Neurovoz	74.9%
Our work	MFCCs with their derivatives+ STFT spectrograms + Mel-spectrograms transforming them into Spectrogram images	XGBoost	PC_GITA	95%
		SVM	Neurovoz	90.74%

Similarly, another work by Nayak et al. (Nayak et al., 2023) featured a much higher dimensionality feature set upon combining MFCC, Mel-spectrogram, Spectral Contrast, Chromagram, and Tonnetz features. These features were optimized by GA so that the features traits of voice signals would not go unnoticed. For this ML model, SVM was applied with an accuracy as high as 94% on the PC-GITA dataset. The current study underlined the effectiveness of conventional ML models once combined with optimized feature selection methods.

Meanwhile, Ibarra et al. (Ibarra et al., 2023) applied deep learning by using Mel-spectrograms as the input to the 2D CNN model. Their research was done with the Neurovoz dataset, which has voice recordings in many different languages; thus, it is more diverse than PC-GITA on the one hand. The model, however, performed worse, with a performance accuracy of 74.9%. This decrease in the accuracy could be due to difficulties the model has faced with generalizing due to the various languages and features of the voices. Nevertheless, the presented study gave insight into the perspective of performing a language-independent PD screening.

This work adopted a representation combining MFCCs with their derivatives, STFT spectrograms, and Mel-spectrograms. Adopting the SMOTE technique to overcome the data imbalance and GridSearch for hyperparameter tuning resulted in the proposed XGBoost, trained on PC-GITA, reaching an accuracy of 95%, outperforming the state-of-the-art ML algorithms. On the other hand, our SVM model, trained on Neurovoz, yielded an accuracy of 90.74%, proving the benefits of using intense feature extraction and balancing techniques.

Our approach tends to outperform other types in the proposed PC-GITA dataset, showing the effectiveness of incorporating ML with rich acoustic features and a strong preprocessing technique. This comparison underlines our approach's potential for enhancing early PD detection by voice analysis and ML.

5 CONCLUSION

The examination performed in this paper outlines the capability of ML algorithms focused on SVM and XGBoost for early detection of PD by analyzing spectrograms extracted from speech recordings. Feature extraction techniques were enhanced based on MFCCs with their derivatives, STFT, and Mel-Spectrograms combined with class balancing through SMOTE and hyperparameter tuning via GridSearchCV, allowing our models to produce promising results for two datasets. XGBoost was the top classifier with an AUC of 95% in the PC-GITA dataset. On no account did SVM fail to prove its worth in both datasets and qualify as one of the ideal candidates for clinical usage. By applying LIME, the interpretability of the models was advanced and provided helpful insight into the most predictive vocal features, catering to a significant requirement for the model's clinical deployment. Nonetheless, variations in model performance across different datasets outline the necessity of optimization for particular datasets and further exploration of feature extraction techniques. Subsequent efforts should prioritize enhancing dataset variety, refining models, and including more acoustic cues to augment generalization and the precision of early PD detection systems. These discoveries will facilitate the development of non-invasive diagnostic instruments that allow for early identification and prompt intervention in PD.

DATA AVAIBILITY STATEMENT

The PC-GITA and Neurovoz datasets are available from the authors upon request.

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