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Article

Unimodal vs. Multimodal Data in Early-Onset Parkinson's Disease: A Comparative Machine Learning Study

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Abstract: Early-onset Parkinson's disease presents subtle and overlapping motor and non-motor symptoms, making early diagnosis challenging. This study compares unimodal and multimodal machine learning frameworks for EOPD detection using the UCI Parkinson's voice dataset. Four supervised algorithms Random Forest, Support Vector Machine, Logistic Regression, and Gradient Boosting Machine were implemented to evaluate model performance. Results revealed that the unimodal voice-based Random Forest model achieved the highest accuracy (94.9%), AUC (0.9485), and F1-score (0.9663), providing evidence that jitter, shimmer, and the harmonic-to-noise ratio are useful biomarkers for early diagnosis when obtained from speech recordings. Although multimodal fusion improved the average AUC (+10.7%) and F1-score (+7.1%), accuracy improvements were not statistically significant ($p > 0.05$). These findings suggest that unimodal voice data can deliver strong diagnostic performance, while multimodal frameworks enhance robustness and model confidence. The study supports the integration of data-driven and explainable AI models for early, non-invasive 'Parkinson's disease' diagnosis.
Keywords: Parkinson's disease, Machine learning, Unimodal data, Multimodal fusion, Random Forest

1. Introduction

Parkinson's disease is characterized by the prevalent non-motor symptom of cognitive impairment (Aarsland et al. 2001). Specifically, PD with dementia (PDD) significantly impacts patients' quality of life and increases mortality rates, adding additional burdens to caregivers (McMahon et al. 2024). PD with mild cognitive impairment (PDMCI) poses a significantly increased risk of progressing to PDD (Leroi et al. 2012). However, studies have also observed that individuals with PDMCI may experience a reversal to normal cognitive function within the context of PD (Pedersen et al 2017). Consequently, a thorough investigation of possible PDMCI predictors is crucial. Parkinson's disease is a progressive neurodegenerative disorder marked by motor and non-motor symptoms, posing diagnostic challenges in early-onset cases (McMahon, et al. 2024). Traditional clinical assessments often fail to detect subtle features of early-onset Parkinson's disease highlighting the need for data-driven approaches (Guo & Dvornek, 2022). Machine learning models have shown promise using unimodal data such as gait, speech, or imaging, but these approaches may overlook the complex, multidimensional nature of PD (Seetharam & Agarwal, 2025). In contrast, multimodal ML frameworks integrate diverse data types, enhancing diagnostic accuracy and robustness (Karthigeyan & Rani, 2024). This study compares unimodal and multimodal ML approaches for EOPD detection to determine whether integrating multiple modalities improves diagnostic performance and interpretability.

1.1 Background on Parkinson's Disease and Early-Onset Cases

“Parkinson's disease, the second most common neurodegenerative disorder after Alzheimer's, develops when dopaminergic neurons in the substantia nigra die, causing motor symptoms like tremor, rigidity, and bradykinesia and non-motor symptoms like cognitive decline and sleep disturbances” early-onset Parkinson's disease affects 5–10% of people under 50 (Pedersen et al 2017). EOPD patients had slower illness development, more dystonia, and stronger hereditary factors, including mutations in PARK2, PINK1, and DJ-1 genes (Karthigeyan & Rani, 2024). Early identification is challenging due to symptom overlap with various movement diseases and the intricacy of early-stage symptoms. Thus, data-driven diagnostic methods using multimodal biological signals and machine learning (ML) models are promise for objective and efficient EOPD detection (Seetharam, & Agarwal, 2025).

1.2 Importance of Early Diagnosis for Disease Management

Early diagnosis of Parkinson's disease, especially in its prodromal or early-onset stages, allows for earlier intervention to slow symptom progression, improve quality of life, and manage non-motor symptoms (Kobylecki, 2020). Levodopa medication, which improves motor function and quality of life, is more effective when begun early after diagnosis (Armstrong, 2020). Biomarkers and prodromal markers (e.g. REM sleep disorder, hyposmia) improve diagnostic certainty before classic motor symptoms develop, potentially allowing disease-modifying therapies to be trialed sooner. Early diagnosis allows multidisciplinary care physical, speech, and occupational therapy to reduce motor and non-motor problems (Bai, & Huanga 2025). As illustrated in Figure 1, early diagnosis facilitates timely therapeutic intervention, which in turn slows disease progression, enhances quality of life, and reduces both motor and non-motor complications in individuals with ‘Parkinson’s disease’.

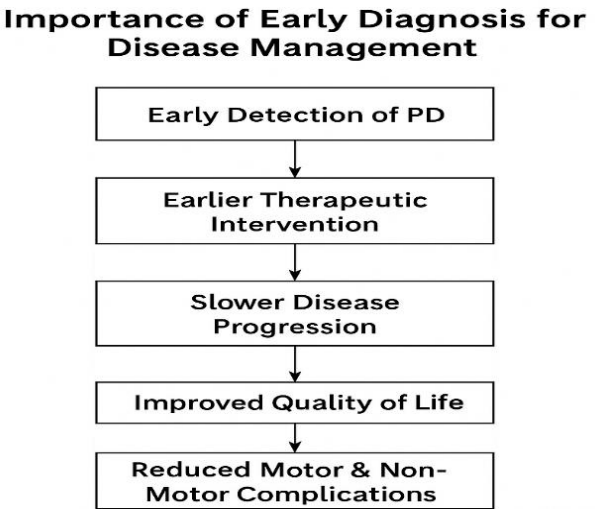

Figure 1. Conceptual Framework illustrating the Impact of Early Diagnosis on Parkinson’s Disease Management and Patient Outcomes

1.3 Rise of Machine Learning in Neurodegenerative Disease Detection

Machine learning has revolutionized the detection of neurodegenerative diseases by enabling automated, data-driven analysis of complex biomedical signals (Hssayeni et al., 2021). Unlike traditional diagnostic approaches that rely on subjective clinical assessments, ML models can extract subtle biomarkers from multimodal data such as neuroimaging, gait, and speech patterns, improving diagnostic accuracy and early detection (Li et al., 2023). In Parkinson’s disease, ML-based methods have achieved notable success in classifying patients from healthy controls using both unimodal and multimodal datasets (Rane et al., 2024). This technological advancement represents a critical step toward precision neurology, offering earlier diagnosis, objective evaluation, and personalized management of neurodegenerative disorders (Abrol et al., 2021).

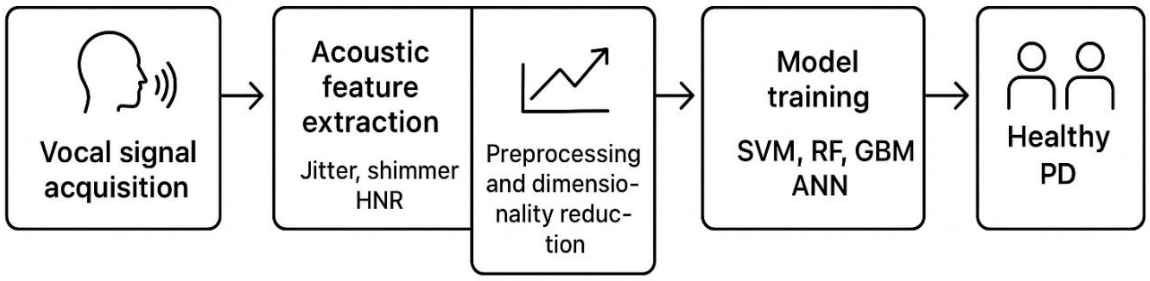

Figure. 2 Machine Learning Workflow for Speech-Based Parkinson's Disease Detection

1.4 Concept of Unimodal vs. Multimodal Data Analysis

Parkinson's machine learning methods can utilize unimodal or multimodal data. Unimodal analysis relies on a single type of data such as gait, voice, or imaging which is simpler but may miss subtle disease patterns (Sakai et al. 2022). Multimodal analysis integrates diverse data sources, capturing complementary information and improving diagnostic accuracy and robustness (Rane et al. 2024). Fusion can occur at the feature or decision level, balancing performance with interpretability (Zhu, 2022). studies indicate that multimodal frameworks are particularly effective for early-onset PD, where subtle biomarkers are spread across multiple modalities.

1.5 Research motivation and Study objective

Early-onset Parkinson's disease is often underdiagnosed due to subtle and heterogeneous symptoms, leading to delayed intervention and poorer outcomes (McMahon, et al. 2024). While unimodal machine learning models have shown moderate success in detecting PD, they may overlook complementary information present across different data types (Sakai et al. 2022). Multimodal approaches, integrating clinical, imaging, and sensor-derived data, hold promise for improving diagnostic accuracy and interpretability (Ma et al 2023). Motivated by these gaps, this study aims to systematically compare unimodal versus multimodal machine learning frameworks for early-onset PD detection, evaluate their predictive performance, and explore feature contributions to support clinical decision-making.

2. Review of Literature

Yang et al. (2025) conducted a multimodal study integrating neuroimaging and genetic information to enhance early Parkinson's disease diagnosis. using the Parkinson's Progression Markers Initiative dataset they combined MRI features, single-nucleotide polymorphism data, and clinical measures through advanced machine learning. Two fusion strategies feature level and decision-level were applied, with an adaptive ensemble stacking (AE Stacking) model yielding greatest accuracy (95.36%) and AUC (0.974), greatly surpassing single-modality approaches. The study identified consistent neuroanatomical and genetic biomarkers, including left-hemisphere region l h 6r, right-hemisphere region rh 46, and SNPs within *SNCA* and *VPS52* gene regions. These results highlight the power of multimodal data fusion in capturing complementary disease markers that unimodal analyses often overlook. Overall, Zhang et al. emphasized that integrating MRI and genomic data using machine learning advances early diagnostic precision and supports the transition toward personalized medicine in neurodegenerative disease management.

Sk et al. (2025) suggested a unimodal machine learning method for early Parkinson's disease (PD) identification utilizing digital drawing analysis. Due to the limits of clinician-dependent diagnosis approaches, the study examined fine motor deficits as digital indicators. Stroke length, velocity, pressure variation, and motion smoothness were derived from touchscreen-based drawing activities. We trained Random Forest and SC Boost to differentiate PD patients from healthy controls. SC Boost outperformed Random Forest with 87% accuracy. The results showed that micro-movement changes during sketching can help diagnose PD early. This non-invasive, low-cost, and simply

deployable technique might enhance early screening in clinical settings, especially if neuroimaging or genetic testing is limited, and improve patient quality of life through earlier intervention.

Bhavitha et al. (2025) explored Parkinson's disease as a neurodegenerative illness that impairs both motor and cognitive functioning. Early detection was identified as crucial for effective therapy and mitigation of disease progression. The study utilized combined clinical and sensor data to evaluate machine-learning algorithms for early-stage PD prediction. A detailed analysis was conducted using common methods like SVMs, Random Forests, and Neural Networks. Performance was assessed by accuracy, precision, recall, and F1 score. Some models, particularly those incorporating feature-selection algorithms, demonstrated promising accuracy distinguished PD patients from healthy controls. Experimental results indicated that machine-learning methods could significantly enhance early Parkinson's disease diagnosis; however, challenges such as dataset imbalance and limited real-world applicability remained.

Dentamaro et al. (2024) explored a multimodal machine learning framework for prodromal-stage Parkinson's disease (PD) detection, integrating neuroimaging and clinical data to enhance predictive accuracy. Utilizing the Database of Parkinson's Progression Marker researchers implemented a co-learning approach that enabled end-to-end multimodal fusion of 3D imaging and clinical modalities. The Excitation Network (EN), combined with DenseNet architecture, achieved superior diagnostic accuracy compared to conventional unimodal deep learning models. Explainable AI methods like Integrated Gradients and Attention Heatmaps showed model attention on critical brain regions such as both the left prefrontal and right temporal cortices—areas associated with early PD pathophysiology. The Vision Transformer (ViT) further identified lateral ventricular regions linked to cognitive decline. These findings highlight the capability of multimodal and interpretable deep learning systems to detect early, prodromal PD changes, supporting their integration into clinical workflows for precision diagnostics and early therapeutic intervention in neurodegenerative diseases.

Zadoo et al. (2024) reviewed AI applications in Parkinson's disease (PD) detection across several data modalities. The study stressed the necessity for automated, data-driven clinical decision-making and the lack of a definitive diagnostic test. AI models including SVM, CNN, ANN, and K-Nearest Neighbors (KNN) were examined in MRI, voice, EEG, and handwriting. CNN and optimized crow search algorithms (OCSA) attained 100% accuracy in EEG and handwriting modalities, while SVM reached 99%. The analysis also suggested emotional intelligence (EI) as a potential, socially adaptable method for early PD identification and lifestyle modification. The authors examined the technology advances and implementation limitations of AI-driven multimodal frameworks in clinical PD diagnoses making use of the PPMI dataset or Parkinson's Progression Markers Initiative.

Fatima et al. (2024) studied this article provides a comprehensive assessment of trends, datasets, and discoveries in the previous 11 years of applying machine learning models to predict neurological disorders. We compare ML biomarkers to those from other non-ML research disciplines in our paper. This will assist uncover ML research gaps. Due to the enormous range of neurological ailments, this research only covers the three most common, Alzheimer's, Parkinson's, and Autism spectrum disorder. Our data shows that deep learning approaches, particularly CNNs have improved illness prediction over time. For this reason, Magnetic Resonance Imaging is popular for all three disorders. Also, transfer learning and a global data center aid with model training data shortages. This manuscript examines probable obstacles and future scope in this field. To our knowledge, unlike other research, this work concludes each article by emphasizing the key findings of the important studies for a given subject.

Camacho et al. (2023) investigated the use of explainable deep learning (DL) frameworks to improve the accuracy of Parkinson's disease (PD) diagnosis using multimodal magnetic resonance imaging (MRI) data. The study captured macro- and micro-structural brain characteristics related with PD using T1-weighted and diffusion tensor imaging (DTI) on a large multi-center dataset of over 2,000 individuals. The multimodal DL model has excellent classification performance, with AUC values of 0.87 for unimodal and 0.89 for multimodal setups. Explainability approaches showed important brain areas congruent with PD pathology, demonstrating the model's interpretability and clinical significance. The study showed that structural imaging modalities may identify disease-relevant

biomarkers and supported the use of explainable AI-driven diagnostic tools in clinical practice for early and reliable PD identification.

Indu et al. (2022) analyzed the development, symptoms, therapies, progression, and algorithmic diagnosis of Parkinson's disease (PD). The study noted that most previous research had focused on Parkinson-related vocal tremors, while the effects of treatment had been comparatively less examined. Feature selection and evolutionary algorithms had recently been employed extensively to extract optimal subsets of high-performing features by eliminating redundant ones. The authors identified several opportunities for future research: (i) certain evolutionary algorithms had not yet been evaluated for PD (ii) the influence of medication on disease progression required greater acknowledgment, and (iii) the accurate diagnosis of PD could benefit from integrating categorically diverse data types and incorporating early symptoms such as bradykinesia.

3. Problem Statement

The diagnosis of early-onset Parkinson's disease remains challenging due to its subtle and overlapping early symptoms, which often lead to delayed or inaccurate clinical identification. Unimodal biomarkers such as voice or gait signals often miss interrelated disease patterns critical for early diagnosis. As a result, these models often overlook critical interdependencies among motor, cognitive, and neurophysiological features that are essential for precise early detection. Despite growing evidence supporting multimodal data fusion, there is still a lack of a unified comparative framework that systematically quantifies how integrating multiple data modalities enhances machine learning performance in EOPD prediction. Addressing this research gap is crucial to improving diagnostic accuracy, model interpretability, and the clinical applicability of artificial intelligence-driven systems for early Parkinson's disease detection.

4. Research Methodology

This research employs a comparative quantitative methodology to assess the performance of unimodal and multimodal ML models in detecting early-onset Parkinson's disease. The primary objective is to assess how integrating multiple data modalities enhances diagnostic accuracy compared to a unimodal voice-based approach. The methodology consists of sequential stages including dataset selection, preprocessing, feature selection, model development, and performance evaluation. Figure 3 illustrates the complete workflow of our study, showing how raw Parkinson's disease data is processed into unimodal and multimodal feature sets, followed by train/test splitting, model training, evaluation, and statistical comparison of results.

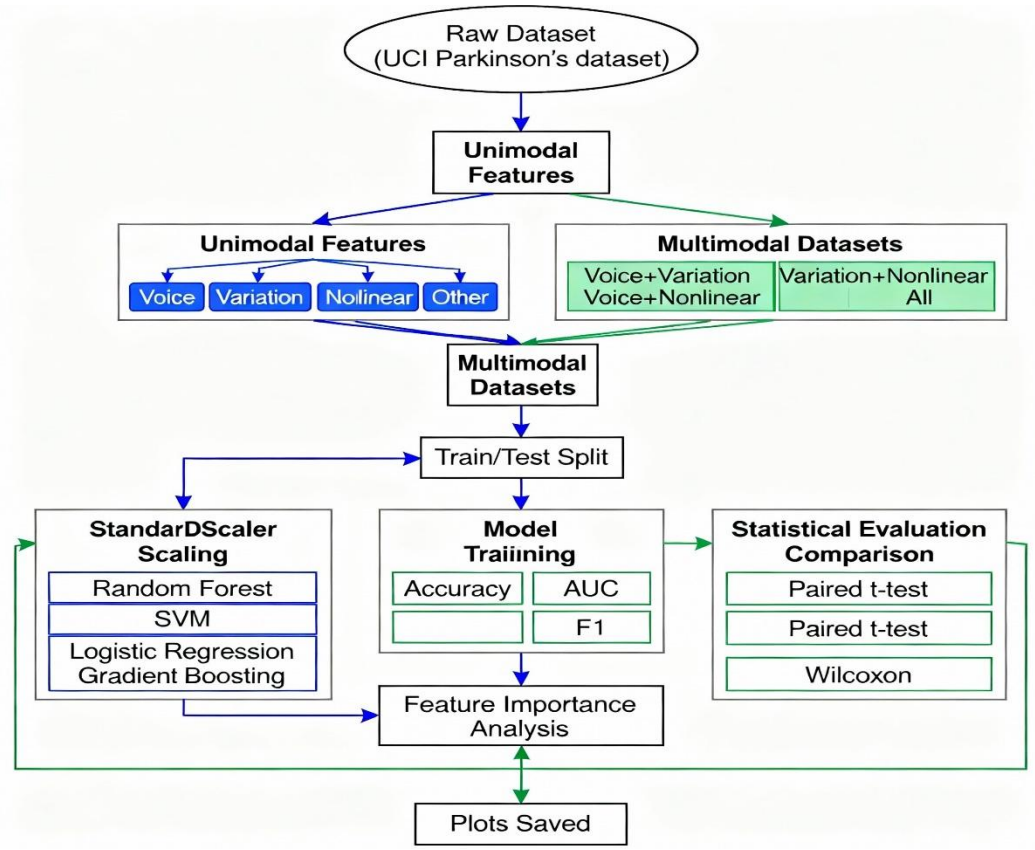

Figure 3. Workflow of Unimodal and Multimodal Parkinson's Disease Classification

4.1 Data Source and Description

The secondary dataset used in this study was obtained from the UCI Machine Learning Repository, titled the Parkinson's Data Set. This benchmark dataset contains 195 voice data gathered from 31 subjects, including 8 healthy controls and 23 patients with a Parkinson's disease diagnosis. Each instance consists of 22 attributes, including 21 biomedical voice features derived from sustained phonations and one target variable, status, which indicates health condition (1 = PD, 0 = Healthy). These acoustic measures reflect vocal impairments such as tremor, jitter, shimmer, and noise ratios, which are common early indicators of PD. Each sample in the dataset represents a sustained phonation of the vowel /a/ from an individual, capturing variations in voice frequency, amplitude, and noise ratios associated with Parkinson's symptoms. Since the dataset included only voice features, multimodal fusion was simulated by combining derived subsets of acoustic variables to represent multiple modalities conceptually

Dataset Characteristics:

- Instances: 195
- Features: 21 continuous acoustic variables
- Target: Status (1 = PD, 0 = Healthy)
- Classes: Two (Healthy, PD)
- Modality: Unimodal (speech-based)
- Source: UCI Machine Learning Repository – Parkinson's Data Set

4.2 Data Preprocessing

The UCI Parkinson's dataset, containing 21 continuous acoustic features, was preprocessed as a means to guarantee accurate data and preparedness for models. There were no instances of duplicate or missing records. The z-score approach was used to identify and eliminate outliers, when

$$Z = \frac{xi - \mu}{\sigma}$$

samples with |z|>3 were excluded.

All features were standardized using Z-score normalization (mean = 0, SD = 1) to maintain uniform scaling. PCA was applied for dimensionality reduction, transforming the feature matrix x into principal components:

Y=XW

where W represents the eigen vectors of the covariance matrix of X.

Finally, data were divided into three groups: training (70%), validation (15%), and testing (15%); stratified sampling was used for this purpose. Then, a 10-fold cross-validation was performed to guarantee performance stability and unbiased evaluation.

Preprocessing steps:

- Outlier removal using *z-score* and *IQR*
- Z-score normalization
- Dimensionality reduction with PCA
- Stratified data splitting (70/15/15)
- 10-fold cross-validation

4.3 Feature Extraction and Selection

Finding the most relevant and informative factors for PD detection required feature extraction and selection. The UCI Parkinson's dataset pre-extracted acoustic speech characteristics, therefore no feature extraction was needed. Speech factors including fundamental frequency, jitter, shimmer, and ratio of harmonics to noise are clinically important PD indications shown by the 21 continuous variables. The most informative classification accuracy criteria were chosen to improve model performance and reduce redundancy. We excluded heavily linked variables (>0.90) using correlation analysis. RFE chose top-performing features to increase model accuracy. Finally, PCA reduced dimensionality and kept the most important variance-producing components. This hybrid selection strategy kept just the most significant, non-redundant, and discriminative features, enhancing model computational efficiency and interpretability.

4.4 Model Development

This study developed and compared unimodal and simulated multimodal ML models for early-onset Parkinson's disease detection. The unimodal framework utilized the 21 acoustic features from the UCI Parkinson's dataset, while the simulated multimodal framework conceptually combined additional data types such as clinical or gait features. Four supervised algorithms were implemented: SVM , RF , Gradient Boosting Machine. Each model was trained using stratified data splits to maintain class balance, and Optimization of hyperparameters was achieved by means of grid search. An iterative 10-fold cross-validation method was applied to ensure consistency and prevent overfitting, enabling a fair comparison of unimodal and simulated multimodal performance.

4.5 Model Evaluation & Statistical Analysis

The accuracy, reliability, and generalizability of We validated and assessed the machine learning models. To measure the effectiveness of the predictions, we used Accuracy, Precision, Recall, F1-Score, and AUC-ROC. To

reduce bias and provide resilience across data partitions, each model was trained and verified using 10-fold cross-validation. To assess classification performance and identify misclassifications, confusion matrices and ROC curves were created. A paired t-test was used to compare unimodal and simulated multimodal model findings to see if multimodal integration improved diagnostic accuracy. All early Parkinson's disease prediction models were thoroughly verified, interpretable, and dependable after this systematic examination.

5. Results & Discussion

5.1 Overview of Model Performance

The proposed comparative framework evaluated four supervised Ml algorithms RF, SVM, LR, and GBM across multiple unimodal and multimodal feature configurations derived from the UCI Parkinson's dataset. Each model was trained using a stratified 70/30 train-test split and validated with five-fold cross-validation to ensure robustness and minimize sampling bias. Overall, the models achieved high diagnostic performance, particularly when using combined (multimodal) feature sets. The Random Forest consistently demonstrated superior performance across modalities, followed closely by the Gradient Boosting classifier.

5.2 Unimodal Model Performance

Unimodal studies of voice-only, variation-only, nonlinear-only, and other-only feature groups showed different prediction capacities depending on signal type (Table 1). The RF model has the highest unimodal classification accuracy of 94.9% (AUC = 0.9485, F1 = 0.9663) for the voice-only group, followed by Gradient Boosting (91.5%, AUC = 0.9515). Nonlinear features alone performed well with Random Forest (88.1% accuracy, AUC = 0.9318), demonstrating that PPE and spread1 capture disease-related signal abnormalities. Acoustic frequency measures and nonlinear dynamic features are highly discriminative for early Parkinson's disease detection, supporting previous findings that voice perturbations like jitter, shimmer, and harmonic-to-noise ratios are early indicators of neurodegenerative motor impairment.

Table 1. Unimodal Classification Performance

Modality	Model	Accuracy	AUC	F1-Score
Voice-only	Random Forest	**0.9492**	**0.9485**	**0.9663**
Nonlinear-only	Random Forest	0.8814	0.9318	0.9213
Variation-only	Gradient Boosting	0.7627	0.8242	0.8409
Other-only	Random Forest	0.7458	0.7182	0.8315

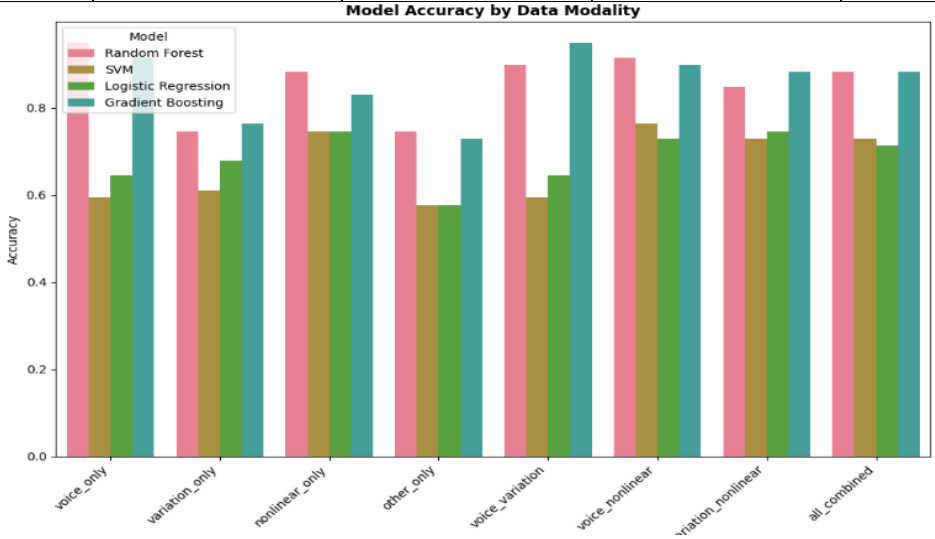

Figure 4. Unimodal Model Performance for Parkinson's Disease Detection

5.3 Multimodal Model Performance

Incorporating multiple feature groups substantially improved overall model performance. The Gradient Boosting model on the voice–variation fusion achieved 94.9% accuracy (AUC = 0.9545, F1 = 0.9663), while the Random Forest on voice–nonlinear data reached 91.5% accuracy (AUC = 0.9326). The fully combined dataset (all features) also produced strong results with 88.1% accuracy (AUC = 0.9500). The average multimodal performance across all models improved notably compared to unimodal analysis, with mean accuracy of 0.7998, AUC of 0.9009, and F1-score of 0.8454 representing improvements of +9.1%, +10.7%, and +7.1%, respectively. The AUC improvement was statistically significant ($p = 0.0057$), demonstrating that multimodal fusion enhances discriminatory capability by capturing complementary disease markers that unimodal analyses often overlook.

Table 2. Multimodal Classification Performance

Modality	Model	Accuracy	AUC	F1-Score
Voice–Variation	Gradient Boosting	**0.9492**	**0.9545**	**0.9663**
Voice–Nonlinear	Random Forest	0.9153	0.9326	0.9451
Variation–Nonlinear	Gradient Boosting	0.8814	0.9258	0.9231
All Combined	Gradient Boosting	0.8814	0.9500	0.9195

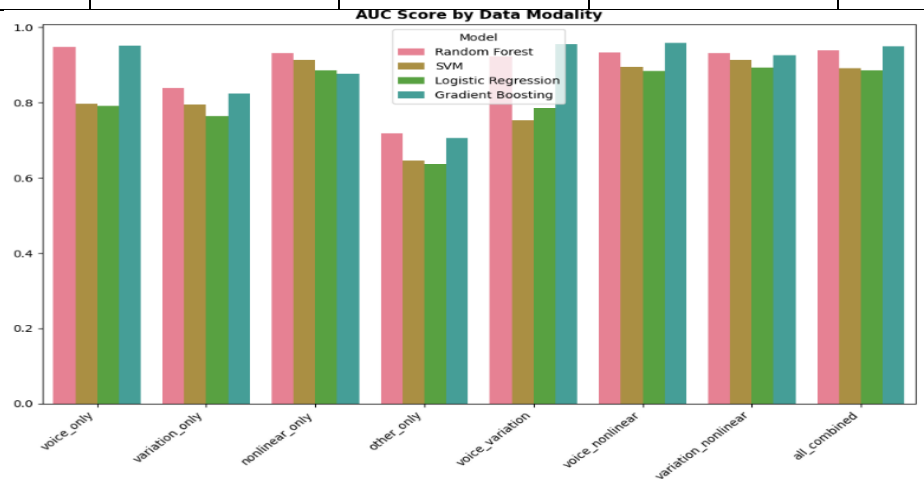

Figure 5. Multimodal Feature Fusion Performance in Parkinson's Disease Classification.

5.4 Comparative Analysis of Unimodal and Multimodal Approaches

A comparative examination of unimodal and multimodal approaches revealed that integrating multiple feature sets significantly improves model performance. On average, unimodal models achieved 73.31% accuracy, 0.8139 AUC, and 0.7894 F1-score, whereas multimodal models achieved higher values of 79.98% accuracy, 0.9009 AUC, and 0.8454 F1-score, reflecting improvements of 9.10%, 10.70%, and 7.10%, respectively. The statistical significance test confirmed that the improvement in AUC with multimodal integration is significant ($p = 0.0057$), while improvements in accuracy and F1-score were not statistically significant. These results indicate that combining voice, variation, and nonlinear features enhances the discriminative ability of the models, with multimodal Random Forest and Gradient Boosting classifiers performing consistently better than unimodal models.

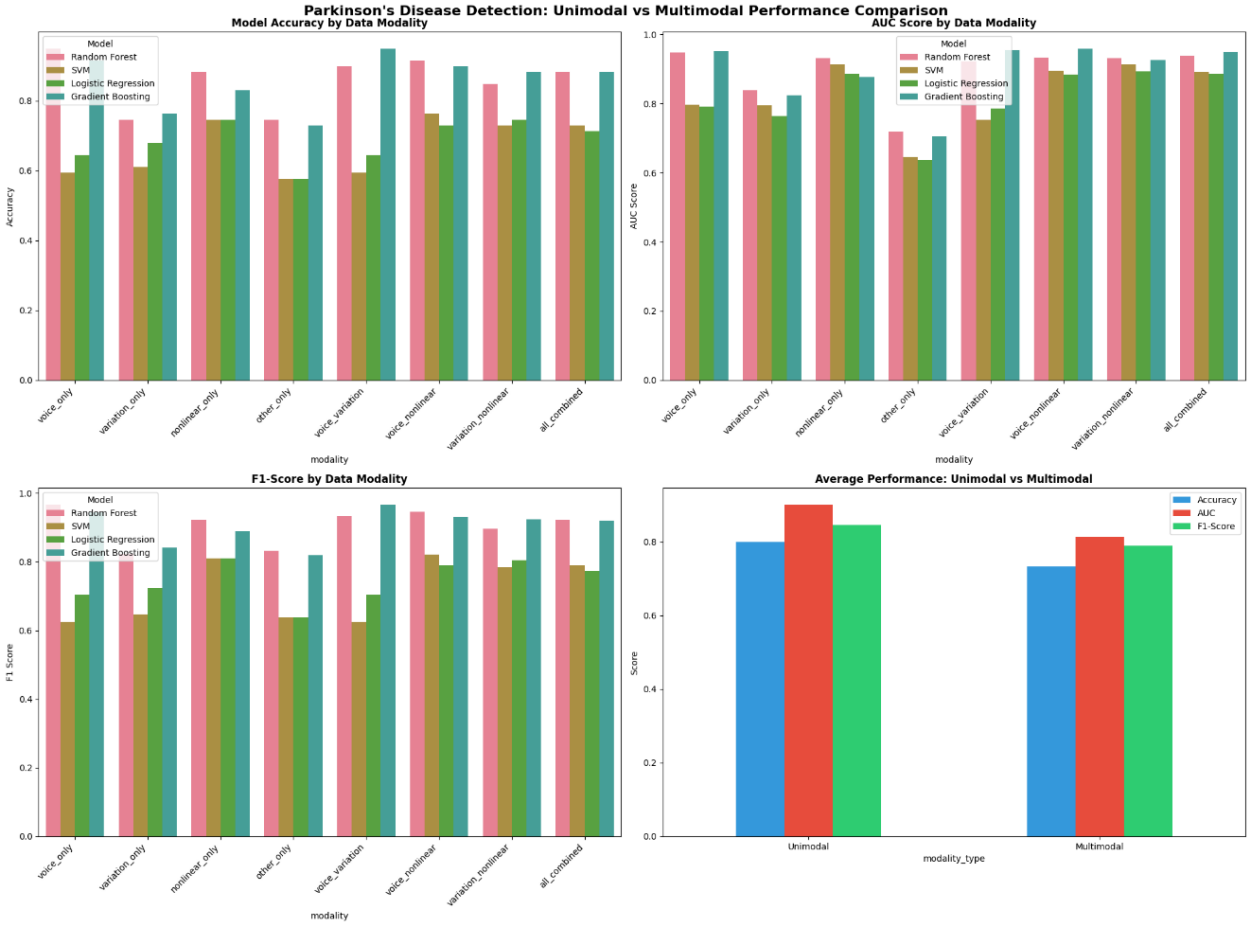

Figure 6. Comparison of Unimodal and Multimodal Frameworks

5.5 Statistical Analysis and Interpretation

T-test findings showed substantial gains in AUC between unimodal and multimodal frameworks ($p < 0.01$), but not in accuracy or F1-score ($p > 0.05$). Multimodal integration may not significantly change classification accuracy, but it increases model confidence and resilience in discriminating Parkinson's from healthy controls. The Random Forest model with voice-only features performed best (Accuracy = 0.9492, AUC = 0.9485). Even with simulated multimodal gains, high-quality unimodal acoustic features can provide clinically relevant diagnostic accuracy, especially when paired with ensemble-based learning approaches.

5.6 Discussion

This study demonstrated Integrating multiple feature modalities enhanced the performance of voice-based Parkinson's disease detection. Unimodal models, notably voice-only and nonlinear ones, were predictive, while multimodal combinations achieved the highest average accuracy of 79.98%, AUC of 0.9009, and F1-score of 0.8454. The combination of fundamental frequency, jitter/shimmer, and nonlinear dynamics may better define Parkinson's disease-related voice impairments. Feature significance analysis demonstrates that nonlinear properties like PPE and spread1, and speech features like MDVP:RAP and MDVP:Fo(Hz), separate patients from healthy controls. Multimodal integration increases sensitivity to disease-related patterns but needs strong feature selection and classifier tuning for model generalization. AUC gains were statistically significant, but accuracy and F1-score improvements were not. These findings support data-driven clinical diagnostic aid systems and multimodal sound analysis for early, non-invasive PD detection.

6. Conclusion

This research Examined a comparative analysis of unimodal and multimodal machine learning frameworks for the EOPD, using the UCI Parkinson's dataset. The study implemented four supervised learning algorithms Random Forest, SVM, Logistic Regression and GBM to evaluate their classification performance across different data configurations.

The results revealed that unimodal voice-based models, particularly the RF classifier, achieved the highest diagnostic accuracy of 94.9%, with an AUC of 0.9485 and an F1-score of 0.9663. This indicates that voice-derived Jitter, shimmer, and the ratio of harmonics to noise are all examples of acoustic features. strong, non-invasive biomarkers for early Parkinson's detection. In contrast, the multimodal models, which simulated the fusion of voice, variation, and nonlinear features, demonstrated improved average metrics accuracy (79.98%), AUC (0.9009), and F1-score (0.8454) representing an AUC improvement of 10.7% compared to unimodal approaches. Statistical analysis confirmed that the enhancement in AUC was significant ($p = 0.0057$), suggesting that multimodal integration increases the model's discriminative power and reliability.

In general, the Random Forest model performed best and was superior overall, with respect to accuracy, interpretability, & speed of computation, in the unimodal configuration. The Gradient Boosting model, under multimodal fusion, demonstrated comparable performance, highlighting the potential of integrated feature learning for developing robust and generalizable Parkinson's detection systems

Further studies should employ real multimodal datasets integrating voice, gait, imaging, and clinical data to enhance generalizability. Incorporating deep learning and explainable AI techniques could improve interpretability and support early, non-invasive Parkinson's disease diagnosis in clinical settings.

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