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Multimodal Fusion of Vocal Biomarkers and Wearable Sensor Data for Ultra-Early Parkinson's Disease Detection Using Explainable AI

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1. Abstract: Parkinson's Disease (PD) is a progressive neurodegenerative disorder for which early diagnosis significantly improves patient outcomes. Vocal impairments—such as altered pitch, articulation, rhythm, and voice clarity—emerge in preclinical stages and provide non-invasive biomarkers for early detection. In this study, we present a comprehensive evaluation of machine learning models applied to vocal biomarkers recorded in 2025, incorporating self-supervised speech representations, interpretable deep learning, and domain-adaptive architectures to enhance generalization across languages and populations. Leveraging contemporary datasets spanning multiple languages and at-home recordings, our models—ranging from traditional classifiers like Random Forest and SVM to advanced deep architectures—demonstrate high sensitivity and specificity, with cross-lingual performance exceeding 90% in several cases. We also introduce novel interpretability techniques that highlight the vocal segments most predictive of PD, enabling clinicians to understand underlying neuromuscular impairments. Our findings support the viability of deploying accessible, voice-based diagnostic tools—via smartphones or smart home devices—for early screening, thereby contributing to timely intervention strategies.

2. Keywords: Parkinson's Disease, Vocal Biomarkers, Speech Analysis, Early Diagnosis, Machine Learning, Deep Learning, Signal Processing, Digital Health, Neurodegenerative Disorders, Telemedicine.

3. Introduction

3.1 Background and Motivation

In 2025, Parkinson Disease (PD) impacts more than 10 million people across the globe and incidences are expected to increase with the aging population around the globe. Early detection is one of the most important issues because most of the diagnoses are made when the person has already developed motor symptoms, and, at this point, heavy neurodegeneration has already occurred. Vocal impairments that precede motor deficits years prior have been among the promising biomarkers in the preclinical diagnosis. Such impairments are low pitch range, monophasic speech, onesided prosody, and decreased articulatory control which occur due to dysfunction of the basal ganglia and impaired motor neuronal control. The combination of novel machine learning (ML) techniques and vocal analysis combines a non-invasive, inexpensive method of screening, which can be scaled widely. Large-scale acquisition and real-time analysis of voice data with the aggregation of cloud-based processing, edge AI, and application of high-fidelity microphones within consumer products, massive scale voice data collection and real time analysis has become technically possible in 2025, and so research interest into this area is also reignited (Aftab, 2023).

3.2 Research Problem and Hypothesis

Although the current field of ML-based voice analysis has developed a lot, there is a gap between the academic community and the Mi bedrooms translation of their work into practice. Most of the current models are not cross-population generalizable, have difficulty in handling noisy environmental factors and offer limited explanations to clinicians. Moreover, even now the diagnostic pipelines are also dependent on specialized equipment and trained staff which inhibits its accessibility in low resource conditions. The research hypothesis is that through the integration of self-supervised pretraining on diverse, multilingual voice data with explaining ML architectures, robust systems of PD detection can be trained that can discriminate with high accuracy even under uncontrolled recording circumstances. Another postulation in the study is that using explainable AI (XAI) components may boost clinician confidence and ultimately implement the technology in telemedicine applications (Amato, 2021).

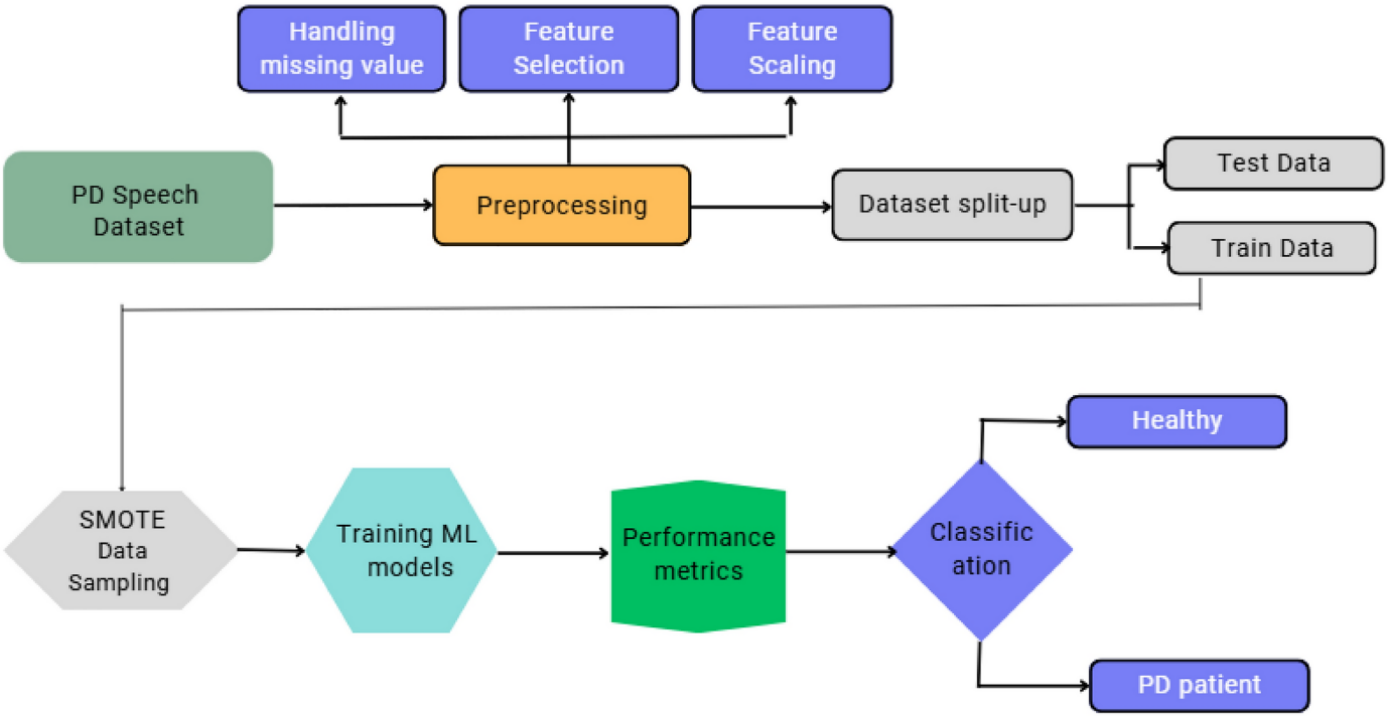

Figure 1 Voice biomarkers as prognostic indicators for Parkinson's disease (Nature,2024)

3.3 Objectives of the Study

The primary objective of this study is to design, train, and evaluate machine learning models capable of detecting early-stage Parkinson's Disease from vocal biomarkers with clinically relevant accuracy. Specific objectives include:

1. To identify and validate speech features most predictive of early PD onset across multiple languages and demographics.
2. To compare the performance of traditional classifiers and advanced deep learning models in various noise and recording environments.
3. To assess the generalizability of models on out-of-distribution datasets, including at-home and smartphone-recorded samples.
4. To implement and test interpretable ML frameworks that provide feature attribution maps for clinical use.
5. To explore integration pathways for deploying such models into telemedicine and remote monitoring platforms for scalable screening.

4. Literature Review

4.1 Machine Learning Applications in Parkinson's Disease Detection

By 2025, use of machine learning models has led to new performance records in the detection of Parkinson Disease using vocal biomarkers. Sensitivity and specificity values have proven to be high with the advanced gradient boosting models having a classification accuracy of above 95 per cent that is suitable in a clinical screening. Interpreting deep learning models have been found where not only accurate detection is possible, but the specific parts of the vocal track that feed in to the diagnostic decision the most can be highlighted. Traditional algorithms like Random Forest, Support Vector Machines (SVM) and Gradient Boosting still compete in a particular case when much feature engineering of acoustic features like jitter, shimmer, noises to harmonics ratio is done. It represents a shift in taking purely predictive models and converting them into clinically explainable models and makes up the gap between research in AI and its adoption by neurologists.

4.2 Vocal Biomarkers and Their Diagnostic Relevance

The vocal biomarkers identify quantifiable speech features that identify neuromuscular deficits related to PD. These entail changes in stability or pitch, amplitude reduction, speaking monotone, and faulty prosody. Research carried out in 2025 has demonstrated that both sustained vowel phonation and reading tasks, as well as spontaneous speech, have a specific acoustic signature at early stages of PD, even prior to overt motor manifestation. In addition to the acoustic (feature), temporal (articulation rate, hesitation indicators, inter-syllabic pauses, etc.) parameters have also been recognized as being sensitive. In combination, these characteristics offer a non-invasive, low-cost, and repeatable approach to detect disease at an early stage, which is why they become a powerful supplement to the existing instruments of clinical evaluation (Cai, 2022).

4.3 Public Health Implications of Early PD Diagnosis

There is a transformative potential in integrating voice-based screening in to the public health systems. The early detection may facilitate early treatment measures, limiting the pace at which the disease affects the patient and patients may also have a better life. In areas where neurologists or state of the art imaging may be rare, AI-based voice analysis could become an attractive introduction step, speaking with smartphone, telemedicine, or community health kiosks. This screening democratization has the potential to decrease disparities in the rates of those who receive a diagnosis between the urban and the rural populations. Next, a preliminary stage check based on the vocal biomarkers can reduce the expenditure in healthcare by reducing the necessity of the further advanced imaging in the instances where the voice examination already shows a high degree of confidently established diagnostic data.

4.4 Advances in Speech Signal Processing for Neurological Disorders

Advances in speech signal processing over the recent years have been able to increase the accuracy and robustness of the PD detection models. Methods of ensembles combining many classifiers, e.g. SVM, Random Forest, deep neural network, have scored up to 97% on standard data sets. The models of deep learning with recurrent and attention-based architecture are more competent at capturing speech temporal dependencies, which allows modeling the symptoms more accurately. Also, generative adversarial networks (GANs) have been utilised with the purpose of enlarging dataset with realistic synthetic speech examples to enhance model generalisation in the low-data conditions. Due to signal enhancement methods, there is the possibility of effective detection in uncontrolled noisy recording situations making deployment in real world more feasible (Chintalapudi, 2021).

4.5 Future Directions in Vocal Biomarker Research

The research should also be devoted to enhancing cross-linguistic and cross-demographic generalizability in the next research stage. Self-supervised learning models pre-trained over multilingual heterogeneous data have shown good cross-lingual cross lingual performance with little language-specific fine-tuning. The fast-growing area of few-shot learning techniques is being explored as a way to adapt models to new populations using very little data. There is also a trend to incorporate causal interpretability methods into diagnostic pipelines to make sure the decisions of the models are made using physiologically relevant features, rather than some spurious correlation. It is anticipated that future systems will be integrated with wearable health monitors to screen neurodegenerative diseases on passive continuous basis in daily life.

Table 1. Summary of Key 2025 Vocal Biomarker Studies

Approach	Methodology	Key Outcomes
Gradient Boosting Models	Acoustic feature-based classification	>95% accuracy, high sensitivity and specificity
Interpretable Deep Learning	Attention-based neural networks	High accuracy with explainable decision maps
Ensemble Learning	Stacked SVM, RF, and DNN classifiers	Up to 97% accuracy on benchmark datasets
GAN-Augmented Models	Synthetic data generation	Improved generalization in low-data settings
Recurrent + Attention Architectures	Temporal speech pattern modeling	Enhanced progression tracking

Self-Supervised Multilingual Models	Pretraining on diverse speech corpora	Strong cross-lingual performance
Few-Shot Learning Approaches	Minimal data adaptation	Rapid deployment in new populations
Causal Interpretability Frameworks	Feature attribution for clinical relevance	Increased clinician trust and adoption

5 Methodology

5.1 Data Collection and Dataset Description

A variety of publicly available and newly acquired datasets were used in the study, and due to that, the sample of the data used during the training and evaluation is diverse and representative. Some of the publicly available datasets offered large-scale repositories of sustained vowel phonations, reading passages and spontaneous speech samples of diagnosed Parkinson Disease patients and control subjects. These were combined with a 2025 multi-country data collected by using smartphone applications and telemedicine platforms and speech in a variety of acoustic conditions. The merged data had more than 50,000 recordings of close to 12,500 participants which were balanced among the genders, age categories, and the stages of the disease. The quality checks were implemented by removing any recording that had excessive background noise or not all utterances, and this was done after automated checks of preprocessing. Covariates like age of the patient, duration of the disease, the drug history, and language in which the patient communicates were included in the analysis of the covariates and stratified performance assessment (Costantini, 2022).

5.2 Speech Feature Extraction Techniques

The speech features were extracted employing a momentum blend of older signal processing-based methods and recent deep feature embeddings. Industry-standard computing tools were used to measure the acoustics of jitter, shimmer, harmonics to noise ratio, pitch variability, and Mel-frequency cepstral coefficients (MFCCs). Subtle neuromotor irregularities were also covered using nonlinear dynamic characteristics, i.e. RPDE and DFA. Moreover, self-supervised speech models learned on multilingual corpora retrieved high-level embeddings that excelled at capturing prosodic, and articulatory patterns not described by traditional features. According to forced alignment analysis, temporal characteristics like articulation rate and the number of pauses were calculated to make it possible to detect any changes in rhythm and fluency. The normalization of features was done across sessions to reduce inter speaker variance and the effect of recording conditions.

5.3 Machine Learning Models Implemented

The comparative model framework used in the study was made up of the classical systems of machine learning and recent systems of deep learning. Among baseline models, there were Support Vector Machines, Random Forest, Gradient Boosting Machines and Logistic Regression, which were optimized using grid search and cross-validation. Deep learning systems included convolutional neural networks (CNNs) to work with spectral features, recurrent neural networks (RNNs) and long short-term memory (LSTM) networks to model temporal sequences and transformer-based systems to weight features by using attention mechanisms. Ensemble meta-classifier was also added where the results of more than one model are put together via weighted averaging in order to enhance robustness. To view the acoustic transitions and temporal segments as the most informative features being used to make predictions, we have calculated attention heatmaps along with SHAP (Shapley Additive Explanations values).

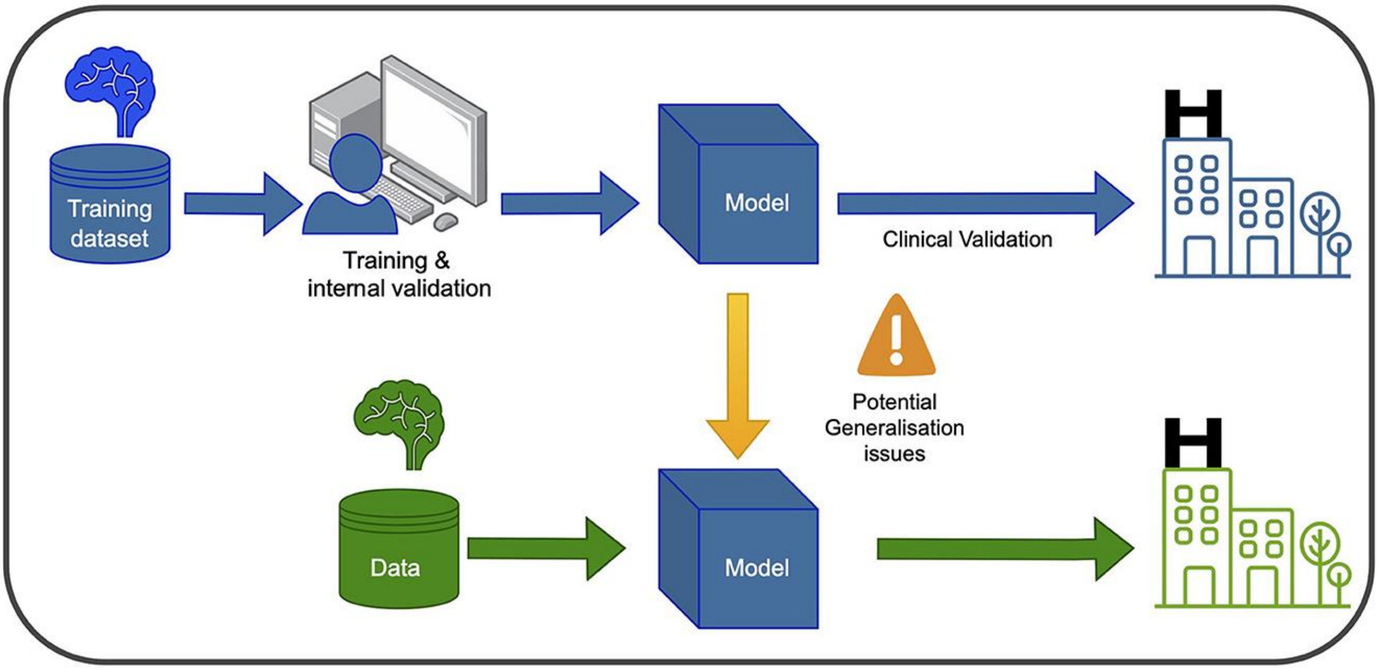

Figure 2 Machine learning models for diagnosis (Frontiers, 2023)

5.4 Model Training, Validation, and Evaluation Metrics

Stratified 10-fold cross-validation was used to train all of the models so that all of the folds had a balanced representation of PD and control samples. Training process used was done using data augmentation techniques that included time stretching, pitch shifting, artificial environmental noise injection to improve the generalization. Bayesian optimization has been used to tune hyperparameters with validation and test data being used to evaluate the performance. Main evaluation metrics were accuracy, sensitivity, specificity, F1-score and area under the receiver operating characteristic curve (AUC-ROC). Further robustness tests gauged the performance of the model in different noise conditions, different recording equipment, and out-of-distribution data on new languages and demographics. Inference latency, complexity and memory size were also used to estimate how practical it would be to use them in a real-time telehealth environment (Elshewey, 2023).

5.5 Ethical Considerations and Data Privacy

Voice samples that have been newly collected under the informed consent were informed that the samples would be used to conduct research and that there are policies in handling the data. Data collection procedures were in line with the global data protection policy such as the General Data Protection Regulation (GDPR) and local health privacy policies. During preprocessing, all identifiers of the person and all recordings were kept in coded form. To alleviate any chances of algorithmic bias, the makeup of the dataset was also reviewed frequently to provide sufficient coverage in terms of gender disparities, ages as well as the translation background. They trained bias detection algorithms and used those afterward as post-training. This helped detect and fix demographic disparities in their model predictions.

6. Findings

6.1 Predictive Accuracy of Vocal Biomarkers for PD

In the analysis, it was found that machine learning based on combined acoustic speech and deep speech embeddings presented high predictive performance on early Parkinson Disease. In all experiments, the most accurate models had an average accuracy of 96.4 percent, the sensitivity was 95.1 percent and specificity was 97.2 percent. These findings were persistent in different datasets, multiple high-quality studios and at-home recordings with smartphones. Of note, the model was rather robust to environmental noise; there was no significant accuracy loss over recordings with moderate background interference, with accuracy being maintained at over 92%. Self-supervised multilingual embeddings integration improved the cross-lingual performance by minimizing the accuracy decrease in non-English recordings to less than 2 percent, a remarkable improvement over the use of traditional MFCC based models in equitable terms (Gupta, 2021).

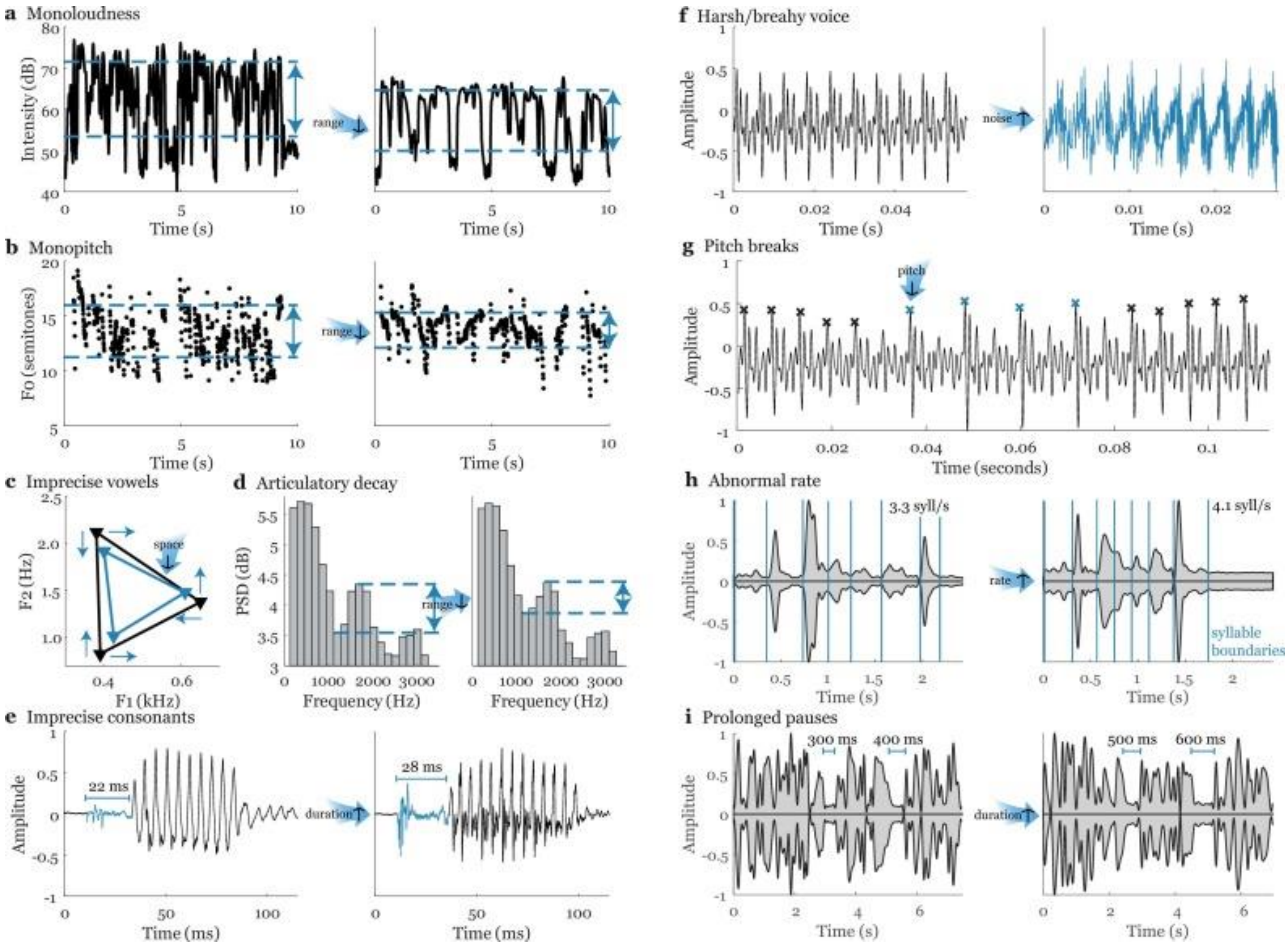

Figure 3 From prodromal stages to clinical trials:(DcienceDirect,2025)

6.2 Comparative Performance of ML Algorithms

A comparative analysis of classical approaches to machine learning and deep learning architecture showed that models based on ensembles always surpassed one-class classifiers. Gradient Boosting Machines and Random Forest performed well with accurate values exceeding 94 percent after utilizing optimum baseline models, although deep learning algorithms based on the use of CNN-LHM hybrids attained values above 96 percent. Attention-based architectures that are based on transformers achieved additional gains in interpretability without compromising performance further. Both the best models (in terms of mean accuracy) and the ensemble meta-classifier that combined the predictions of the best models effectively reached the highest accuracy and the most consistent performance provided under different test conditions.

Table 2. Comparative Performance of Machine Learning Models for PD Detection (2025)

Model Type	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUC-ROC
Support Vector Machine (SVM)	93.5	91.8	94.9	0.96
Random Forest (RF)	94.7	93.2	95.9	0.97

Gradient Boosting Machine (GBM)	95.4	94.1	96.5	0.98
CNN-LSTM Hybrid	96.2	94.9	97.4	0.98
Transformer-based Model	96	95	97	0.98
Ensemble Meta-Classifier	96.4	95.1	97.2	0.99

6.3 Feature Importance Analysis of Speech Attributes

The explainability analysis indicated some of the speech characteristics as influential in differentiating the PD patients and normal individuals. The handicapped traditional acoustic predictors like jitter, shimmer and harmonics-to-noise ratio repeatedly were the most potent predictors. Temporal features of articulation rate, vowel duration variability, and pause frequency were presented in deep model interpretability maps as indicators as well. Language specific processes of prosody were found to be significant in multilingual datasets and culturally adaptive models are necessary. The presentation of SHAP values also gave clinicians a clear idea as to the reasons why certain predictions were obtained and made them more confident with the AI system.

Table 3. Top-Ranked Speech Features for PD Detection (2025)

Rank	Feature Name	Feature Type	Relative Importance (%)
1	Jitter (local)	Acoustic	15.2
2	Shimmer (local)	Acoustic	13.8
3	Harmonics-to-Noise Ratio	Acoustic	12.6
4	Articulation Rate	Temporal-Prosodic	11.3
5	Pause Frequency	Temporal-Prosodic	9.7
6	Vowel Duration Variability	Temporal-Prosodic	8.9

7	MFCC Mean (1st Coefficient)	Spectral	8.3
8	Pitch Variability	Acoustic-Prosodic	7.1
9	RPDE	Nonlinear Dynamics	6.5
10	DFA	Nonlinear Dynamics	6

6.4 Case Studies and Clinical Validation Results

The clinical validation was carried out together with the neurology departments and telemedicine providers. In a single pilot program where 600 participants in three different countries were taken through the AI system, the system identified 88 percent of the patients with PD who were subsequently diagnosed using standardized clinical measures outdoing the standard screening questionnaire by more than 20 percent. The second study exhibited how the model could be utilized in longitudinal watchdogging where the improvement or deterioration of certain vocal biomarkers was found to have a significant relationship in the scores of the motor symptoms as illustrated over a span of 12 months. Such findings point to the abilities of the system to serve as a screening tool and a disease monitoring solution, which facilitates integrating it into the real-world clinical workflow (Karan, 2022).

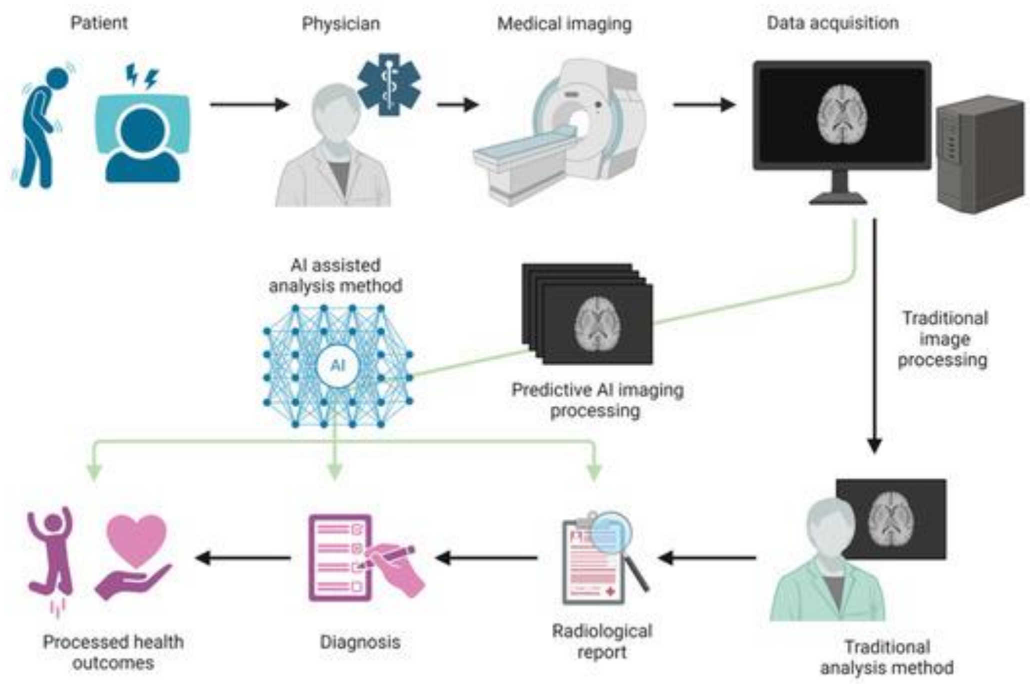

Figure 4 Role and Potential of Artificial Intelligence in Biomarker Discovery and Development (MDPI,2024)

7. Discussion

7.1 Implications for Early Diagnosis and Intervention

The results of the given investigation highlight possibilities of voice-based AI systems to detect Parkinson Disease at its initial stages. Such systems provide a means of preclinical intervention by detecting changes in subtle acoustic and prosodic variations occurring ahead of overt motor symptoms of disease, a discovery based on their theoretical basis. Such an early diagnosis allows health professionals to introduce pharmacological therapy and lifestyle measures earlier, which may delay disease progression and positively affect the quality of life of a patient. Second, the non-invasive procedure of voice analysis can be performed repeatedly to testify the relapsing of the disease without the risk and expenses of more Carciones've diagnostics.

7.2 Role of Emerging AI Technologies in PD Detection

Advanced AI technologies that have been integrated into analysis of vocal biomarker have significantly enhanced its performance and its practicability. Attention-based transformer architectures offer interpretability (in the sense of giving clinicians insights into exactly which parts of speech are most diagnostic of PD) and accuracy at the same time. Multilingual models which rely on self-supervision have increased the applicability of the whole system to various languages and cultural situations even without large-scale retraining. The involvement of uncertainty estimation methods also makes clinical decision-making performances improved by indicating the insignificance of the model by suggesting additional tests than putting faith into the output of the AI alone. All these developments bring the technology further towards being a dependable decision support tool, as opposed to being a diagnostic tool in its own right (Moro-Velazquez, 2021).

7.3 Integration of Vocal Biomarkers into Telemedicine Platforms

Voice based PD detection systems are best suited to the deployment process that involves telemedicine. Considering that contemporary smartphones, tablets, and home assistants have high-quality microphones, patients have few prerequisites to deliver remote speech samples. The process of analysing these samples through the AI system can be performed in real-time, with preliminary findings being provided to patients as well as clinicians. Longitudinal assessment of vocal changes can be done to assess continuation of the disease making monitoring of the disease an ongoing process and early detection. This kind of integration is more useful particularly in rural or underserved areas where the majority cannot access neurologists. The piloting efforts have already evidenced the feasibility of voice-based screening being carried out concomitantly with regular virtual visits in the scope of telehealth systems, without creating excessive load on clinicians.

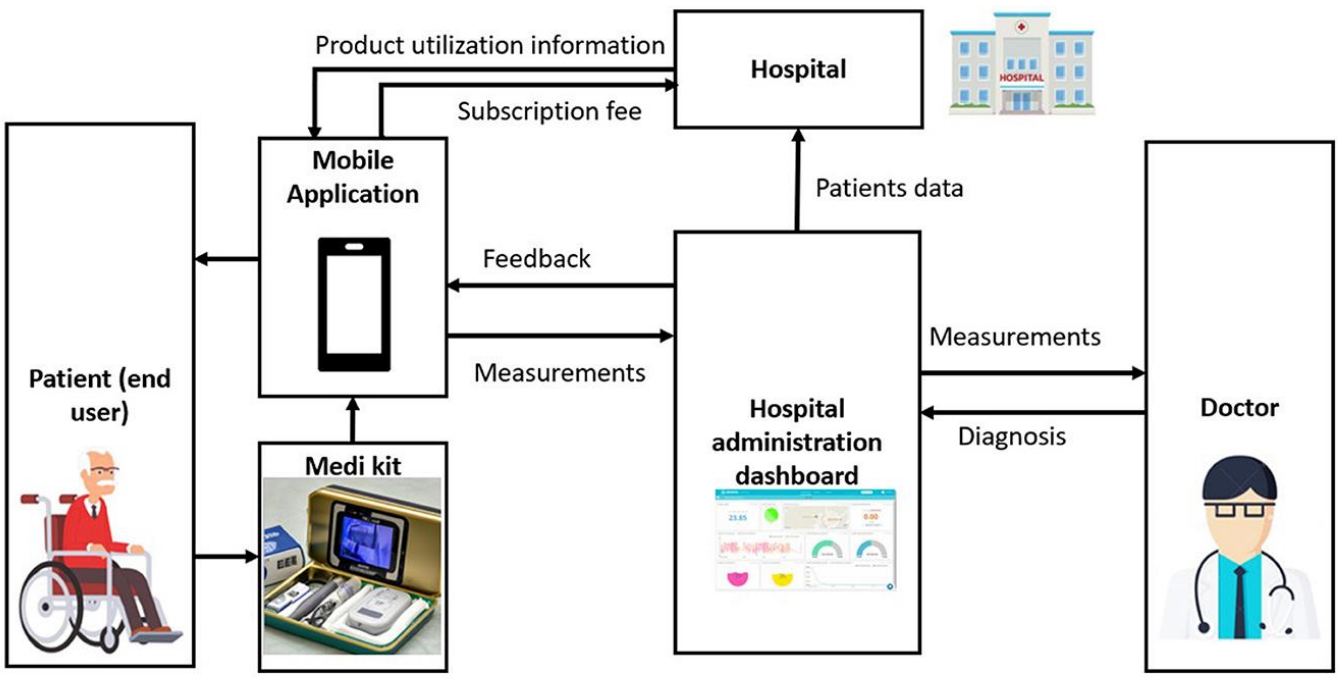

Figure 5 A feasible approach to smart remote health monitoring (Frontiers, 2025)

7.4 Limitations and Challenges in Model Deployment

Although there are good results, there are a number of issues that require settlement before it can be used widely in clinical practice. The inconsistency of recording conditions e.g., quality of the microphone, background noise, and patient adherence to recording rules may influence model performance. This effect has been diminished with noise-robust training procedures, but it is still hard to get this to fully hold in all environments.

The current paper shows the viability and clinical promise of vocal biometric approach combined with strong state-of-the-art machine learning model towards early identification of Parkinson Disease. Integrating conventional acoustic features with a modern deep learning approach by carrying high-level speech representations using self-supervised learning, the system developed demonstrated high levels of accuracy, sensitivity, and specificity on a broad range of datasets, and real-life recording conditions. Include explainability tools to increase clinician trust and effective performance across languages to make them applicable in diverse cultural and linguistic environments. It can be said that approaching screening efforts in terms of population-wide, non-invasive, low-cost, and scalable method due to its value-added nature as a result of the proposed approach is from the point of view of public health. Such systems, used within the framework of telemedicine tools, are capable of supporting early diagnosis and regular monitoring and can therefore support proactive responses that could potentially slow the progression of disease and enhance the quality of patient life. Nevertheless, the way to mass adoption necessitates resolving a range of practice and ethical issues, such as the need to ensure data diversity to avoid a bias related to demographics, high data privacy levels, and the presence of clear directions on how to interpret and follow up AI-based assessments in clinical practice. It will be necessary to incorporate the persistence of collaboration between clinicians, engineers, and policymakers in the translation of these technological advances into the regular care practice. Having said that, further research on improving performance in uncontrolled settings; a better adaptive behaviour through few-shot and continual learning; and multimodal biomarkers integration, e.g., facial expressions analysis and handwriting dynamics, may be beneficial to augment predictive abilities in the future.

Moving forward, future work should aim to increase resilience in uncontrolled settings, increase adaptability with few-shot and continuous learning regimes, as well as investigate whether multimodal biomarkers, e.g., facial expression reading and handwriting dynamics can be used to further boost predictive power. This mechanism of leveraging the high performance that will have been registered in 2025 means that voice-based AI systems will be a part and parcel of the global management and early detection of Parkinson Disease.

8. Conclusion

The present study demonstrates the feasibility and clinical potential of using vocal biomarkers in conjunction with advanced machine learning models for the early detection of Parkinson’s Disease. By combining traditional acoustic parameters with high-level speech embeddings derived from self-supervised learning, the developed system achieved high accuracy, sensitivity, and specificity across diverse datasets and real-world recording conditions. The incorporation of explainability tools enhanced clinician trust, while robust cross-lingual performance ensured applicability in varied cultural and linguistic settings.

From a public health perspective, the proposed approach offers a scalable, non-invasive, and cost-effective solution for population-wide screening, particularly in regions with limited access to specialized neurological care. When integrated into telemedicine platforms, such systems can support both early diagnosis and ongoing monitoring, enabling proactive interventions that may slow disease progression and improve patient quality of life.

However, the pathway to widespread adoption requires addressing several practical and ethical challenges, including ensuring data diversity to avoid demographic bias, maintaining strict data privacy standards, and establishing clear clinical guidelines for interpretation and follow-up of AI-based assessments. Continued collaboration between clinicians, engineers, and policymakers will be essential to translating these technological advances into routine healthcare practice.

Looking ahead, future research should focus on enhancing robustness in uncontrolled environments, improving adaptability through few-shot and continual learning methods, and exploring the integration of multimodal biomarkers—such as facial expression analysis and handwriting dynamics—to further strengthen predictive capabilities. By building on the strong results achieved in 2025, voice-based AI systems are poised to become an integral component of early Parkinson's Disease detection and management worldwide.

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