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Intelligent System for Early Detection of Parkinson's Disease Using ML Techniques

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***Abstract*—Early detection of Parkinson's disease (PD) is critical for timely treatment and better patient outcomes. Medical professionals may now benefit from well-designed procedures that utilize biological voice metrics to help in the diagnosis of PD, thanks to advanced AI and ML capabilities. With the use of the UC Irvine PD dataset, this study introduces a smart ML approach to early PD detection. The planned approach consists of data preprocessing, feature normalization (StandardScaler), addressing class imbalance (Borderline SMOTE) and subject-level stratified data splitting for unbiased model evaluation. A discriminative pattern is learned from the voice-based features using an XGBoost classifier for accurate classification of healthy individuals or Parkinson's patients. The proposed model was evaluated and found to be as accurate as 98.50%, outperforming other machine learning models. Precision (PRE), recall (REC), F1 score (F1), and confusion matrix analysis were used to further evaluate the robustness and reliability of the suggested framework. The results show that the suggested AI system can help doctors make better decisions by simplifying the diagnostic process and allowing for earlier detection, faster treatment, and better clinical management of PD.**

Keywords—Parkinson's disease, Machine Learning, XGBoost, Early Disease Detection, UCI Parkinson's Dataset.

I. INTRODUCTION

Healthcare's "quadruple aim" is to improve public health, make treatment better for patients, improve the experience of caregivers, and lower healthcare costs [1][2]. As a result, global healthcare systems face huge problems. Worldwide, healthcare expenses are on the rise, the population is becoming older, and more and more people are living with chronic diseases. As a result, there is a lot of pressure on governments, payers, regulators, and providers to come up with new ways of delivering healthcare [3][4].

The accumulation of neuronal death in the nigrostriatal region is a hallmark of PD, a prevalent and progressive neurodegenerative movement condition. Many questions concerning the neurodegenerative nature of PD persist, and no cure is currently available [5]. A patient's quality of life is drastically affected when they have significant motor symptoms of PD, such as difficulty moving their hands, or when their muscles are rigid and trembling, making it difficult for them to stand and walk [6]. Motor symptoms include tremor, bradykinesia, postural instability, and stiffness are the most prominent manifestations of PD. Furthermore, non-motor symptoms are typically modest, unnoticed, and might appear years prior to motor symptoms. Among these symptoms are things like autonomic dysfunction, REM sleep behavior disorder, and hyposmia/anosmia, which is a lack of smell or olfactory perception. Diseases including essential tremor, drug-induced parkinsonism, and atypical parkinsonian illnesses such corticobasal degeneration (CBD), progressive supranuclear palsy (PSP), and multiple system atrophy (MSA) can all make a differential diagnosis of PD challenging [7][8].

A lack of precision in predicting the disease's course and the inability of clinicians to provide a firm diagnosis in the early stages of the disease's progression are clinical challenges connected with the condition [9]. Recently, neurocritical research has focused on the unmet need to find sensitive, specific biomarkers for early detection and intervention in PD. Early detection of PD, by methods such as prognostic and pre-symptomatic diagnosis, allows for improvements in clinical treatment and therapy to start in the early stages of the illness. Therefore, it is necessary to develop reliable biomarkers to distinguish PD from other disorders [10]

The use of ML techniques in healthcare is on the rise [11][12]. ML allows computers to learn and semi-automatically make sense of data, just how the name says [13]. Multiple data modalities have been queried using ML models for the goal of PD detection. These include, but are not limited to, patterns of movement, speech, CSF, serum, cardiac scintigraphy, neuroimaging, and OCT. With the use of ML, many imaging modalities, like as SPECT and MRI, may be combined to diagnose PD. Consequently, they can detect PD in its preclinical phases or typical forms by utilizing ML algorithms to discover significant variables that are not often employed in clinical PD diagnoses [14].

A. Motivation and Contribution of the Study

This work is driven by the need to find a better way to diagnose PD, as the condition is becoming more common in older populations and current methods using motor symptoms

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in the latter stages are inadequate. Current ML research has issues with data leakage, class imbalance, poor feature selection, and interpretability, however voice-based screening provides an intrusive and scalable alternative. This study aims to develop a clinically relevant, reliable, and well-established intelligent system for PD detection based on voice biomarkers early in the disease process. This study made the following key contributions:

- Applied a real-world speech biomarker dataset including acoustic recordings from both healthy controls and PD patients (UCI Parkinson's dataset).
- Used Borderline SMOTE to implement thorough data preparation measures, such as cleaning, feature selection, normalization, and class balance.
- Applied Bayesian Optimization for hyperparameter tuning and dynamic F1-threshold optimization for balanced classification.
- Integrated SHAP-based interpretability on a global and regional scale to extract prominent voice characteristics and deliver open-book forecasts.
- ACC, PRE, REC, ROC-AUC, and F1 were used to assess the model's performance.

B. *Justification and Novelty*

This work advances the integration of ML and voice-based biomarker analysis to enhance PD early diagnosis in the elderly population. It provides a detailed pipeline that integrates Borderline SMOTE, Bayesian-optimized XGBoost, dynamic threshold tuning and dual-level SHAP interpretability, unlike conventional ML approaches that suffer from data leakage, static thresholding, and opaque decision making. This strategy is unique because it uses these complementing strategies, together with appropriate preprocessing procedures, on a real-world speech dataset that is extremely unbalanced. In the article, a validated and high-performance prediction model is offered as an AI solution for future Parkinson's screening applications in both remote and clinical settings. The model is both scalable and interpretable.

C. *Structure of the Paper*

This paper is organized as follows: A survey of the research on PD detection is included in Section II. Detailed in Section III, with accompanying flowcharts, was the research approach, Section IV assesses the suggested model's performance and compares it to current models. restrictions and continued efforts. The findings are presented in the last section, V.

II. Literature Review

The most effective ML algorithms for early PD diagnosis have been XGBoost and RF, according to recent research. To make the model more robust and useful in clinical settings, tho, further work is required.

Sarangi et al. (2026) This research aims to compare four popular algorithms for data classification—XGBoost, RF, SVM, and KNN—in their capacity to diagnose PD using acoustical data from the UCI PD dataset. This descriptive ML approach used to explore the topic. Phase one of the study effort was to build a baseline model. Phase two involved stratifying a 10-fold cross-validation. Phase three involved using SMOTE to balance the classes. Phase involved reducing dimensions using PCA. XGBoost outperformed all other models in terms of ACC (97.22%) and Matthews correlation coefficient (top algorithm) when it came to PD classification throughout the whole study [15].

Esan et al. (2025) This study utilized a public ally accessible dataset of 2105 samples that included demographic, medical history, lifestyle, clinical symptoms, cognitive, and functional evaluations. It also employed five ML algorithms: SVM, KNN, LR, RF, XGBoost, and a stacked ensemble approach. For the purpose of preprocessing and feature selection, SMOTE and Sequential Backward Elimination were employed. The combination of RF with Backward Elimination showed the highest predictive ACC (93%), PRE (93%), REC (93%), F1 (93%), and AUC (0.97). UPDRS scores, cognitive impairment and motor symptoms were the main predictors found by SHAP and LIME analysis, making the results easier to interpret for the clinic [16].

W.-H. Guo et al. (2025) Compare the PDAssist app and ML models to UPDRS in order to predict motor symptoms of PD for eight different tasks: resting tremor, postural tremor, finger tapping, facial expressions, rigidity, speech, walking, and pronation/supination. The trial data comes from early de novo PD patients. The prediction model boasted an ACC ranging from 0.87 to 0.93 for resting tremor, postural tremor, finger tapping, facial expressions, and postural stability. As for rigidity, the model had an ACC of 0.81 with a Kappa of 0.74, and for speech, the ACC was 0.79 with a Kappa of 0.61, demonstrating its abilities to detect subtle motor deficits and for remote monitoring [17].

R. Mohammadi et al. (2024) A two-year consecutive one-unit decrease in the Montreal Cognitive Assessment was used to predict CD using data from the Early PD Longitudinal Singapore (2014-2018). By utilizing baseline demographics, clinical assessments, and blood biomarkers, four ML approaches were utilized: AutoScore, RF, KNNs, and NN. Important characteristics that were shown to be predictors of CD were years of schooling, blood pressure readings (lying and standing), BMI, tau levels (phosphorylated and total), Neurofilament light chain, and inhibition of tumorigenicity 2. The most effective method, RF, achieved an AUC of 0.93 (95% CI: 0.89, 0.97) when 10-fold cross-validation was applied [18].

P. John et al.(2023) the goal is to conduct a thorough evaluation of the potential for a cost-effective and reliable wearable device by concentrating on initially noticeable symptoms, such as metrics relating to motor control and gait. Feature selection was carried out using a subset of the PPMI, PPMI Gait dataset, following extensive analysis using multiple ML methods. After that, the identified important characteristics were put to the test using real-time data for early Parkinson Syndrome identification, and the model achieved an ACC rate of 91.9% [19]

Demir et al. (2022) A novel and effective method for PD detection from audio recordings was suggested in this work; it relies on multi-level feature selection. Using Chi-square and L1-Norm SVM algorithms, the initial stage of feature selection was executed. The Relief method was used to integrate the extracted characteristics and pick very unique samples. Among the three methods utilized for classification, KNN outperformed SVM and DT. By using Bayesian optimization to the selection of KNN hyperparameters, the suggested method was able to get a classification ACC of 95.4% thru the use of 10-fold cross-validation [20].

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Table I summarizes the approaches, findings, constraints, and research requirements of ongoing ML studies for PD early detection. Overall, it shows the need for more robust, explainable, and generalizable diagnostic models.

TABLE I. COMPARATIVE ANALYSIS OF RECENT MACHINE LEARNING-BASED STUDIES FOR EARLY PARKINSON'S DISEASE DETECTION

Author (Year)	Methodology	Key Findings	Challenges	Limitations	Research Gap
Sarangi et al. (2026)	Compared XGBoost, RF, SVM, and KNN using UCI Parkinson's voice dataset with SMOTE, PCA, and 10-fold cross-validation.	XGBoost achieved the highest accuracy of 97.22% and the best MCC.	Dependence on handcrafted acoustic features and dataset quality.	Evaluated only a single voice dataset with limited real-world diversity.	Requires validation on larger multimodal datasets and clinically diverse populations to improve generalizability.
Esan et al. (2025)	Applied SVM, KNN, LR, RF, XGBoost, and stacked ensemble with SMOTE, Sequential Backward Elimination, SHAP, and LIME.	Random Forest achieved 93% accuracy and 0.97 AUC with interpretable predictions.	Integrating heterogeneous clinical features while maintaining model interpretability.	Focused on one public dataset without external clinical validation.	Future work should develop generalized, real-time, explainable models validated across multiple healthcare datasets.
W.-H. Guo et al. (2025)	Smartphone-based motor assessment using ML models on eight PD motor tasks.	Achieved 0.87–0.93 accuracy for most motor symptoms, enabling remote monitoring.	Accurate assessment of subtle symptoms under varying real-world conditions.	Evaluated only motor symptoms in early-stage PD patients.	Future research should integrate voice, gait, and clinical biomarkers for comprehensive early diagnosis.
R. Mohammadi et al. (2024)	Used AutoScore, RF, KNN, and Neural Networks on longitudinal clinical and biomarker data with 10-fold cross-validation.	Random Forest achieved AUC = 0.93 for cognitive decline prediction.	Longitudinal data collection is costly and time-consuming.	Dataset was limited to a single regional cohort (Singapore).	Multi-center validation and multimodal learning are required for robust prediction across populations.
P. John et al. (2023)	Feature selection and ML analysis using the PPMI gait dataset for wearable-device-based detection.	Achieved 91.9% accuracy for early Parkinson's detection.	Reliable acquisition of wearable sensor data in daily environments.	Focused primarily on gait-related features.	Combining gait with speech, handwriting, and clinical features may improve early detection performance.
Demir et al. (2022)	Multi-level feature selection using Chi-square, L1-SVM, ReliefF, and KNN with Bayesian optimization.	KNN achieved 95.4% accuracy using voice recordings.	Selecting optimal features while avoiding redundant information.	Used only voice recordings and a relatively small dataset.	More robust deep learning and multimodal approaches should be explored using larger, diverse datasets.

III. METHODOLOGY

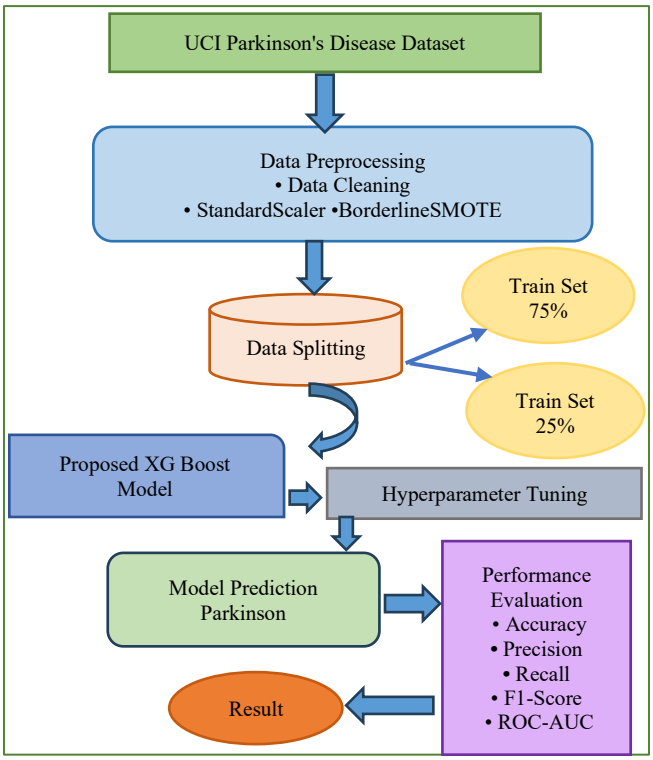


Fig. 1. Proposed Machine Learning Framework for Parkinson's Disease Detection

An intelligent ML system for early identification of PD is proposed using the UCI PD dataset. After collecting data, the technique performs a plethora of preprocessing steps, including feature normalization with StandardScaler and class imbalance management using Borderline SMOTE. In order to guaranty accurate model evaluation, the processed dataset is then divided into a training set and a testing set using subject level stratified sampling. The optimized XGBoost classifier is trained for disease classification, and the optimal hyperparameter settings are optimized using Bayesian optimization. Lastly, the model's performance is evaluated through ACC, PRE, REC, F1 and ROC-AUC for the effectiveness in detecting early PD. Fig. 1 shows the entire process of the proposed framework.

A. Data Collection

An exhaustive collection of biomedical speech data from both PD patients and healthy controls, acquired by DSP, is housed in the UCI PD dataset. Data is used to gauge performance and predictive modelling to optimise early PD detection, enabling clinicians to identify at-risk patients, reduce misdiagnosis, improve referral processes, and ultimately improving time to neuroprotective treatment. This dataset is consistent with the popular UCI Parkinson's dataset found in the UCI ML Repository, healthcare diagnostics optimization.

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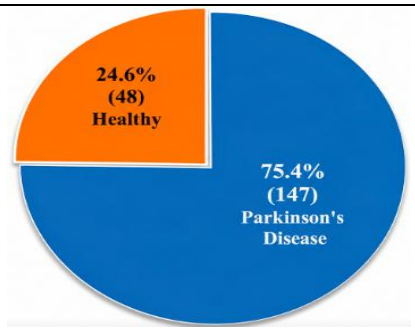


Fig. 2. Class Distribution of UCI Parkinson's Disease Dataset

The UCI PD data set employed in this study is shown in the class distribution in Fig. 2. A total of 195 voice recordings are used, which are divided into the voice recordings of 147 people with PD (75.4%) and 48 healthy individuals (24.6%). The pie chart graphically illustrates the relative frequency of each category, indicating that most of the data set consists of cases of PD. This imbalance can affect the learning process of ML models, as predictions are made towards the dominant class. In the pre-processing phase, a balanced training set was created using Borderline SMOTE method, which reduces and improves this problem and makes the data better classified. The figure shows the composition of the dataset, which highlights the class imbalance and the need for robust solutions to address it to ensure accurate and fair detection of PD.

B. *Data Preprocessing*

The preprocessing step ensures that the voice data used for processing is clean, consistent, and suitable for analysis by ML and statistics algorithms. This is especially important because medical data can include missing, erroneous, or outliers that can affect the results of models. The pre-processing operations conducted are:

1) *Missing Value Analysis*

Data completeness and consistency were checked before applying any preprocessing techniques, by checking for missing and null values. The absence of data may impact the learning experience and the ACC of ML models for prediction. UCI Parkinson's dataset was examined for any missing values and none were found. Hence, there was no need to impute or replace any data and all available samples could be used for subsequent analysis.

2) *Duplicate Data Removal*

The data set was checked for duplicate observations to remove duplicate data that may be a source of bias in the training of the model. The classifier's performance could be exaggerated if a duplicate test set is used. It was determined through the duplication checking method that there were no instances of duplicate data in the UCI PD dataset. To facilitate subsequent pre-processing and model construction, all samples were subsequently archived.

3) *StandardScaler for Feature Normalization:*

The use of StandardScaler was critical in ensuring that lesser features did not be overshadowed by bigger ones. This research uses the z-score normalization technique to standardize all variables to a mean of 0 and a standard deviation of 1. This method is given by the following Equation (1):

$$x' = \frac{x - \mu_{train}}{\sigma_{train}} \quad (1)$$

4) *BorderlineSMOTE for Class Imbalance Handling:*

Synthetic minority oversampling was the method that was used to solve the problem of class imbalance in the dataset. focused order to reduce the likelihood of misclassification, Borderline SMOTE focusses focused on minority cases that are near the decision boundary [21]. Unlike SMOTE, which evenly distributes its artificial minority samples over the feature space, Borderline SMOTE concentrates augmentation efforts on these critical borderline samples, avoiding the addition of spurious noise from well-separated minority samples. Synthetic samples that captured the exact features of borderline Parkinson's patients were produced as a result of the process. The pre and post class distribution sample are presented in Fig.3 before and after applying Borderline SMOTE respectively.

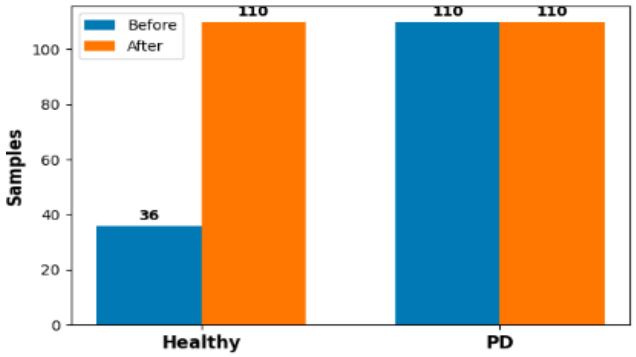


Fig. 3. Class Distribution Before and After Borderlinesmote

C. *Data Splitting*

The ACC of the model was evaluated by dividing the dataset into a training set and a test set. The data has been divided into two groups: 75% for training and parameter estimation, and 25% for testing and performance assessment. Stratified sampling at the subject level was used to meticulously select and split each subject's recordings into a training set and a test set. This made guaranteed that each class was fairly represented and stopped information from seeping through the partitions.

D. *Proposed XGBoost Model*

Predictive classification for early identification of PD is performed using the XGBoost technique [22]. The XGBoost method optimizes a regularized objective function while learning from previous mistakes, and it then constructs a set of additive regression trees. A mathematical representation of this objective function is given by Equation (2), which incorporates a regularization factor and a differentiable loss function:

$$\mathcal{L} = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} (\gamma T_k + \tfrac{1}{2}\lambda \sum_{j=1}^{Tk} \omega_{kj}^2) \quad (2)$$

The loss function, usually the logistic loss for binary classification, is represented as *l(yi, ŷi)* and quantifies the difference between the actual label *yi* and the anticipated likelihood *ŷi*. All of the trees in the ensemble are subject to a regularization term, which is the second part of the total. Tk represents the number of leaf nodes at the k-th tree, while ωkj stands for the score at the j-th leaf of the k-th tree. The two regularization parameters γ and λ regulate the complexity of the model by making the trees prune and by shrinking the leaf weights, respectively, to avoid overfitting.

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E. Hyperparameter Tuning

The first XGBoost model was constructed and pruned to its most informative attributes, then underwent an intensive optimization process to enhance the model's predictive power while ensuring its generalizability. Bayesian optimization iteratively models the goal function by leveraging prior evaluation results. This method finds a happy medium between under- and over-sampled regions by using an acquisition function to choose the next sampling point and constructing a surrogate function probability model [23]. After testing a range of thresholds from 0.1 to 0.9 with a 0.01% step size, the sweet spot was found at 0.43. The search ranges for the hyperparameters that were tuned during this optimization phase are presented in Table II. Learned parameter values encompass maximum tree depth, gamma, subsample ratio, column sampling ratio, and number of boosting cycles.

TABLE II. OPTIMAL HYPERPARAMETER VALUES

Hyperparameter	Optimal Value
colsample_bytree	0.62
gamma	0.00
learning rate	0.29
max_depth	5
estimators	500
reg_alpha	0.00
reg_lambda	5.00
subsample	0.60

F. Performance Metrics

Evaluation metrics are crucial in ML for gaging the efficacy of models. They give numerical evaluations of the model's efficacy by means of ROC-AUC, F1, REC, PRE, and ACC. Researchers can use these measures to pick the optimal method for a certain job and verify that the selected model satisfies clinical standards.

- **True Positive (TP):** The model successfully diagnosed an individual with PD.
- **True Negative (TN):** A healthy individual was correctly recognized as not having PD by the algorithm.
- **False Positive (FP):** The mistaken diagnosis of PD in a healthy individual might lead to unwarranted anxiety and more diagnostic procedures.
- **False Negative (FN):** A person suffering from PD who was mistakenly diagnosed as not having the condition, which might have caused a delay in diagnosis and treatment.

Accuracy: The ACC of a model is proportional to the number of healthy persons and PD cases well identified. When there is an equal number of PD and healthy samples in the dataset, it reliably depicts how well the model predicted the outcomes. Equation (3) provides the formula.

$$Accuracy = \frac{\mathrm{TN} + \mathrm{TP}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}} \quad (3)$$

Precision: The ACC of a model for diagnosing PD is the percentage of real diagnoses that were backed by the model's predictions. This metric measures how well the algorithm can reduce FP and guaranty that the PD patients it predicts severely impacted by the illness. The formula for it is Equation (4).

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP+FP}} \quad (4)$$

Recall: The sensitivity or REC of the model is its capacity to accurately detect real-life PD instances. An important factor in reducing FN, it indicates the percentage of real cases of PD that the model correctly detects. Equation (5) provides the value.

$$\mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP+FN}} \quad (5)$$

F1-score: The F1 is a harmonic hybrid of the REC and ACC. An all-encompassing evaluation of the model is achieved by including both true positives (individuals mistakenly diagnosed as having PD) and false negatives (individuals with PD improperly recognized as healthy). One way to find it is by using Equation (6).

$$\mathrm{F1} = 2 * \frac{(\mathrm{precision} * \mathrm{recall})}{\mathrm{precision+recall}} \quad (6)$$

AUC-ROC: The AUC-ROC is a measure of a model's ability to distinguish between healthy individuals and those with PD. An AUC of about 1 improves both classification accuracy and generalizability. According to the ROC curve:

- **True Positive Rate (TPR):** The correctly identified Parkinson patients in Equation (7) divided by the total number of actual Parkinson patients (TP).

$$TPR = \frac{TP}{TP+FN} \quad (7)$$

- **False Positive Rate (FPR):** FPR refers to the percentage of non-Parkinson individuals that are mistakenly classified as Parkinson in Equation (8).

$$FPR = \frac{FP}{FP+TN} \quad (8)$$

AUC is also a critical model evaluation metric in the range [0.5,1] and the larger the value, the stronger the generalization and classification ability.

IV. RESULTS & DISCUSSION

A controlled experiment setup in Python, using the provided Jupyter Notebook and Google Collab, was used to test the proposed framework for the detection of PD. Data was preprocessed and analyzed using pandas, NumPy, and Scikit-learn. The feature normalization was performed with StandardScaler, class balancing by Borderline SMOTE and feature selection by XGBoost Gain Importance for the most informative vocal features. The hyperparameters of XGBoost were optimized using Bayesian Optimization, and the optimization of the threshold value was performed to maximize the F1. The data was split into a training set and a test set, with 75% used for training and 25% for testing. The model's performance was assessed using ACC, PRE, REC, F1, ROC-AUC, confusion matrix, and interpretability analysis with SHAP values.

A. Experiment Result

This optimization approach has been tested and proven to be effective in previous experiments. When it comes to the improved XGBoost model's ultimate performance, Table III displays its classification ACC results. A total of 98.50% ACC, 99.99% PRE, 98.04% REC, 99.01% F1, and 99.10% ROC-AUC were attained by the classifier. The results demonstrate a high level of generalizability and discriminative capability in detecting PD.

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TABLE III. PERFORMANCE EVALUATION METRICS OF THE XGBOOST MODEL

Performance Metric	Proposed XGBoost
Accuracy (%)	98.50
Precision (%)	99.99
Recall (%)	98.04
F1-Score (%)	99.01
ROC-AUC (%)	99.30

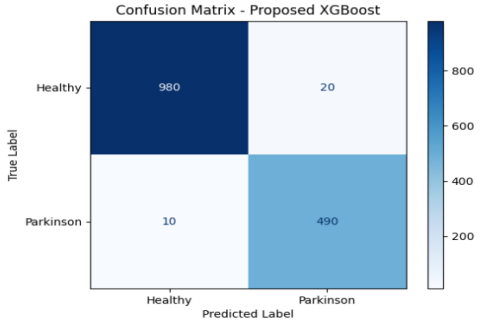


Fig. 4. Confusion Matrix of Xgboost.

The proposed XGBoost model's classification results for PD detection are displayed in Fig. 4. The model has an impressive ACC rate and almost no misclassifications in both healthy and PD patients. This model's low rates of false positives and negatives, together with its high rates of true positives and true negatives, make it an excellent choice for the early detection of PD.

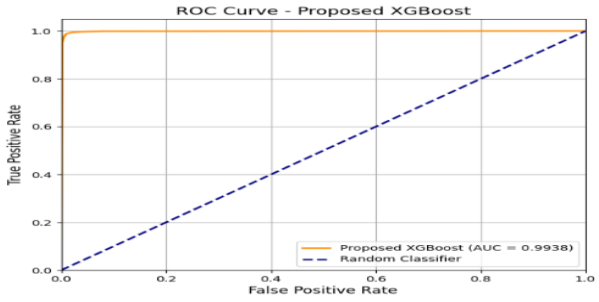


Fig. 5. Roc Curve of XGBoost

The proposed XGBoost model for PD detection is shown in Fig. 5. along with its ROC curve. An AUC of 99.38% indicates that the model has strong discriminative ability and consistently produces accurate results when separating healthy controls from Parkinson's patients.

TABLE IV. COMPARATIVE ANALYSIS FOR PARKINSON DETECTION BETWEEN EXISTING MODELS' PERFORMANCE

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
LSTM[24]	88.94	0.90	0.88	-
SVM [25]	85.05	-	70 .00	66.67
Random Forest [26]	86.89	94.09	89.11	84.18
Deep Neural Network	96.87	-	95.83	-
Proposed XGBoost	98.50	99.99	98.04	99.01

Table IV compares the proposed XGBoost model to other ML and DL methods for PD identification. When contrasted with LSTM, SVM, RF, and DNN models, the suggested XGBoost model achieves better results with respect to ACC (98.50%), PRE (99.99%), REC (98.04%), and F1 (99.01%). According to the findings, XGBoost is a powerful tool for early PD identification as it accurately detects PD and decreases misclassification.

V. CONCLUSION & FUTURE WORK

Early diagnosis is key to ensuring that patients start treatment early, can slow the progression of Parkinson's and can live a better life. BVA has become an effective support for clinical diagnosis using AI/ML techniques. The proposed smart framework successfully produced a model for PD identification by combining several techniques such as data preprocessing, feature scaling, control of class imbalance, subject-level data separation, and the XGBoost algorithm. With a REC, ACC, and F1 of 98.50%, the suggested technique successfully distinguished between normal volunteers and PD patients in experiments. The model outperformed some other well-known ML techniques, showing the supremacy of the XGBoost model in this classification problem. The framework should be evaluated in larger and more diverse datasets collected from multiple healthcare organizations to improve its applicability for future studies. Multimodal clinical information (gait data, handwriting, signals from wearable sensors, and neuroimaging data) can complement this for better diagnostic ACC. Further, XAI approaches can make forecasts clearer and easier to understand, which increases physicians' confidence in the system. The proposed framework for developing a real-time clinical decision support application could help to implement the system in clinical applications, thus improving the ACC and accessibility of PD diagnosis.

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REFERENCES

[1] R. Snehamrutha, "Patient Engagement Strategies in Community Pharmacies and their Effect on Vaccination Uptake and Medication Synchronizations," *ESP J. Eng. Technol. Adv.*, vol. 3, no. 3, pp. 163–173, 2023, doi: 10.56472/25832646/JETA-V3I7P120.

[2] A. Warrier, "Real-Time AI Integration Architectures for HIPAA-Compliant Healthcare Data Interoperability," in *International Conference on Recent Trends in Computer Science and Information Technology*, ScienceTech Xplore, 2025, pp. 74–81. doi: 10.63282/3050-9246/ICRTCSIT-140.

[3] S. Mahmud, K. K. Mohammed, V. R. Jain, and S. A. Shah, "Artificial Intelligence-Driven Predictive Models for Identifying Risk Factors of Chronic Diseases," in *2026 14th International Symposium on Digital Forensics and Security (ISDFS)*, Boston, MA, USA: IEEE, Mar. 2026, pp. 01–06. doi: 10.1109/ISDFS69419.2026.11459003.

[4] C. S. Pareek, "Testing for the Unexpected: Ensuring Insurance System Stability During COVID-19," *J. Artif. Intell. Mach. Learn. Data Sci.*, vol. 1, no. 1, pp. 1680–1684, Nov. 2022, doi: 10.51219/JAIMLD/Chandra-shekhar-pareek/375.

[5] S. K. Madishetty, "Cyber Resilience and DevOps in Operating

Rooms: Securing Connected Embedded Medical Devices in High Risk Clinical Environments," *J. Electr. Syst.*, vol. 19, no. 3, pp. 244–253, Jan. 2024, doi: 10.52783/jes.9597.

[6] J. Zhang, "Mining imaging and clinical data with machine learning approaches for the diagnosis and early detection of Parkinson's disease," *npj Park. Dis.*, vol. 8, no. 1, p. 13, Jan. 2022, doi: 10.1038/s41531-021-00266-8.

[7] S. Mukherjee, "AI-Driven Deep Learning System for Alzheimer's Disease (AD) Detection Via MRI Imaging," in *2026 International Conference on Intelligent Computing, Networks, and Security (IC-ICNS)*, Bhubaneswar, India: IEEE, Mar. 2026, pp. 1–6. doi: 10.1109/IC-ICNS68863.2026.11537765.

[8] S. A. D. Poovaiah and P. K. Pareek, "AI-Optimized Multimodal Neuroimaging Pipelines for Early Alzheimer's Disease Detection: A System-Level Perspective," in *Alzheimer's Disease - Diagnostics, Pathogenesis, and Treatment [Working Title]*, IntechOpen, 2026. doi: 10.5772/intechopen.1015774.

[9] M. Mittal and S. Balamurugan, "Ethical Challenges In Ai-Based Healthcare: Balancing Innovation With Patient Privacy And Fairness," *Int. J. Artif. Intell. Med.*, vol. 3, no. 2, pp. 1–20, Jul. 2025, doi: 10.34218/IJAIMED_03_02_001.

[10] S. Das and H. Ramteke, "A Comprehensive Review of the Role of Biomarkers in Early Diagnosis of Parkinson's Disease," *Cureus*, pp. 1–11, Feb. 2024, doi: 10.7759/cureus.54337.

[11] R. Lingam, "Agentic AI and Federated Learning for Privacy-Preserving Dental Imaging," in *2026 Innovations in Machine, Engineering, and Digital Conference (IMED)*, Kota Kinabalu, Malaysia: IEEE, Mar. 2026, pp. 1–6. doi: 10.1109/IMED68921.2026.11484887.

[12] S. R. Chanthati, "Integrating Large Language Models (LLMs) in Cognitive Medical Robotics," in *Proceedings of the International Conference on AI and Robotics (AIR 2025)*, May 2025. doi: 10.5281/zenodo.20316245.

[13] R. Palwe, "Three Layers of Trust in AI Interfaces: Interface, Behavior, and Organization," *Int. J. Sci. Res.*, vol. 15, no. 1, pp. 1152–1160, Jan. 2026, doi: 10.21275/SR26112072531.

[14] J. Mei, C. Desrosiers, and J. Frasnelli, "Machine Learning for the Diagnosis of Parkinson's Disease: A Review of Literature," *Front. Aging Neurosci.*, vol. 13, no. May, pp. 1–41, 2021, doi: 10.3389/fnagi.2021.633752.

[15] P. K. Sarangi *et al.*, "Enhancing prediction accuracy for Parkinson's disease using advanced machine learning models," *Sci. Rep.*, vol. 16, no. 1, p. 22533, Jun. 2026, doi: 10.1038/s41598-026-54057-3.

[16] A. O. Esan, D. B. Olawade, A. A. Soladoye, B. A. Omodunbi, I. A. Adeyanju, and N. Aderinto, "Explainable AI for Parkinson's disease prediction: A machine learning approach with interpretable models," *Curr. Res. Transl. Med.*, vol. 73, no. 4, p. 103541, Dec. 2025, doi: 10.1016/j.retram.2025.103541.

[17] W.-H. Guo *et al.*, "Early detection of Parkinson's disease: Machine learning-based prediction of UPDRS Part III scores in de novo patients using smartphone assessments," *J. Park. Dis.*, vol. 15, no. 6, pp. 1099–1110, Sep. 2025, doi: 10.1177/1877718X251359494.

[18] R. Mohammadi *et al.*, "Machine Learning for Early Detection of Cognitive Decline in Parkinson's Disease Using Multimodal Biomarker and Clinical Data," *Biomedicines*, vol. 12, no. 12, p. 2758, Dec. 2024, doi: 10.3390/biomedicines12122758.

[19] P. John, S. Rani, and Alex, "Early Detection of Parkinson's Disease using Motor Symptoms and Machine Learning," 2023. doi: 10.48550/arXiv.2304.09245.

[20] F. Demir, K. Siddique, M. Alswaitti, K. Demir, and A. Sengur, "A Simple and Effective Approach Based on a Multi-Level Feature Selection for Automated Parkinson's Disease Detection," *J. Pers. Med.*, vol. 12, no. 1, p. 55, Jan. 2022, doi: 10.3390/jpm12010055.

[21] V. Rajput and N. Maheswari, "EEFSA-SECM: an enhanced ensemble feature selection and stacking ensemble classifier to detect Parkinson's disease," *Front. Neurol.*, vol. 17, Mar. 2026, doi: 10.3389/fneur.2026.1717252.

[22] M. Oumaima, B. Achraf, J. Abdelilah, and H. Ahmed, "Non-invasive detection of Parkinson's disease using voice analysis and machine learning techniques," *Int. J. Speech Technol.*, vol. 29, no. 1, p. 3, Mar. 2026, doi: 10.1007/s10772-025-10231-y.

[23] S. Fouladi, A. A. Safaei, D. Alayari, and D. Bell, "Advanced Parkinson's disease diagnosis: leveraging deep learning and machine learning with vowel analysis," *Neural Comput. Appl.*, vol. 38, no. 4, p. 76, Feb. 2026, doi: 10.1007/s00521-025-11727-z.

[24] A. N. Mir, I. Nissar, M. Ahmed, S. Masood, and D. R. Rizvi, "Parkinson's Disease Diagnosis Through Deep Learning: A Novel LSTM-Based Approach for Freezing of Gait Detection," in *Lecture Notes in Networks and Systems*, 2024, pp. 201–215. doi: 10.1007/978-981-97-3523-5_16.

[25] M. A. Sayed *et al.*, "Parkinson's Disease Detection through Vocal Biomarkers and Advanced Machine Learning Algorithms," *J. Comput. Sci. Technol. Stud.*, vol. 5, no. 4, pp. 142–149, Dec. 2023, doi: 10.32996/jcsts.2023.5.4.14.

[26] S. Srinivasan, P. Ramadass, S. K. Mathivanan, K. Panneer Selvam, B. D. Shivahare, and M. A. Shah, "Detection of Parkinson disease using multiclass machine learning approach," *Sci. Rep.*, vol. 14, no. 1, p. 13813, 2024, doi: 10.1038/s41598-024-64004-9.