Predictive Modelling for Parkinson's Disease Diagnosis Using Biomedical Voice Features

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BONAFIDE CERTIFICATE

Certified that this Project titled **"Predictive Modeling for Parkinson's Disease Diagnosis Using Biomedical Voice Features"** is the bonafide work of **"RUDRAPRIYAN N (2116220701232)"** who carried out the work under my supervision. Certified further that to the best of my knowledge the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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ABSTRACT

Parkinson's disease (PD) is a chronic and progressive disorder, which mainly impacts on the motor skills resulting in serious disability if left undetected and untreated early on. The reliance of the clinic diagnosis on symptomatic evaluation is excessive and can thus delay early detection and the efficacy of possible interventions. As the amount of biomedical data grows and ML advances, data-driven diagnostic systems have the potential to provide alternative fora medical decision-making. This study provides a detailed framework of machine learning for Parkinson's disease classification based on the UCI Parkinson dataset containing the voice measurements as the predictors.

The dataset was preprocessed by normalization with the help of StandardScaler and cut into training and testing subsets to provide effective evaluation. Logistic Regression, Support Vector Machine (SVM), Random Forest, XGBoost, AdaBoost, and Bagging classifiers were used ranging from several popularly accepted ML classifiers. A grid search with cross-validation was used for hyperparameter tuning to boost performance of Logistic Regression, Random Forest, and SVM models. Moreover, Stacking Classifier was built as the ensemble solution by combining Random Forest and SVM as the base learners alongside the Logistic Regression as meta-classifier, along with TabNetClassifier. The performance of all the models was evaluated using several evaluation metrics such as accuracy, precision, recall, F1-score, and the area under the Receiver Operating Characteristic (ROC) curve. Moreover, certain diagnostics purely visual like confusion matrices and ROC curves were also produced for advanced performance comparison.

Results have shown that the ensemble techniques especially stacking achieved a very high classification accuracy when compared to individual classifiers as they identify complementary patterns learnt from various algorithms. The Stacking Classifier exhibited the best total outcome and sturdiness in the classification which made it capable of being used as a valid diagnostic instrument. The proposed methodology emphasizes the benefit of using a combination of several ML algorithms and tuning their parameters to obtain the state-of-the-art classification tasks in medicine. This study reinforces the growing role of ensemble machine learning models in healthcare, particularly for early detection of neurodegenerative disorders such as Parkinson's disease.

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CHAPTER 1

1.INTRODUCTION

The Parkinson's Disease (PD), the second most prevalent neurodegenerative disorder after Alzheimer's, affects over 10 million individuals globally, with incidence rates projected to double by 2040 due to aging populations. Characterized by the progressive degeneration of dopaminergic neurons in the substantia nigra pars compacta, PD manifests through cardinal motor symptoms—resting tremors, bradykinesia, rigidity, and postural instability—and debilitating non-motor features such as anosmia, REM sleep behavior disorder, and autonomic dysfunction. Despite its prevalence, PD remains notoriously difficult to diagnose accurately, particularly in its prodromal stages. Current clinical practice relies on subjective neurological examinations and patient-reported symptom histories, leading to misdiagnosis rates as high as 25% even among movement disorder specialists. This diagnostic ambiguity delays therapeutic interventions, which are most effective when initiated early, underscoring the urgent need for objective, accessible, and non-invasive biomarkers. The advent of artificial intelligence (AI) and machine learning (ML) has revolutionized biomedical research, offering tools to uncover subtle patterns in complex datasets that evade human interpretation. Among the emerging biomarkers for PD, vocal impairment has gained significant traction. Over 90% of PD patients develop dysphonia—a collective term for voice abnormalities such as hypophonia (reduced volume), monotonicity, breathiness, and articulatory instability—often years before overt motor symptoms arise. These vocal changes are attributed to the disruption of basal ganglia circuits that regulate laryngeal GridSearchCV-driven hyperparameter tuning, muscle coordination and respiratory-phonatory control. Critically, voice signals can be captured non-invasively using standard microphones and analyzed through computational acoustics, making them ideal for scalable, low-cost screening tools. The foundational work of Little et al. (2008) in IEEE Transactions on Biomedical Engineering established the viability of voice-based PD detection, introducing the UCI Parkinson's Disease dataset, a benchmark resource derived from sustained phonation of the vowel /a/. This dataset comprises 195 voice recordings from 31 participants (23 with PD, 8 healthy controls), annotated with 22 quantitative voice features extracted through nonlinear signal processing and chaos theory. These include time-frequency markers (e.g., jitter, shimmer), noise ratios (NHR, HNR), and complexity metrics such as recurrence period density entropy (RPDE) and detrended fluctuation analysis (DFA), which reflect the irregularity and fractal scaling properties of PD-affected voices. The Unified Parkinson's Disease Rating Scale (UPDRS) scores provided in the dataset further enable the correlation of vocal features with disease severity, offering a multidimensional framework for ML model training.

and evaluation using both threshold-dependent metrics (accuracy, F1-score) and threshold-agnostic measures (ROC-AUC). To contextualize model performance, we benchmark results against recent literature, including deep learning approaches like CNNs and LSTMs, which require larger datasets but offer limited advantages in low-sample regimes. Visual analytics, including t-SNE plots for feature space visualization and confusion matrices, further elucidate model behavior and misclassification patterns. Beyond technical contributions, this research aligns with global efforts to democratize neurodegenerative disease diagnostics. Voice-based tools could be integrated into telemedicine platforms, enabling remote screening for underserved populations lacking access to specialist care. For clinicians, ML-derived feature importance rankings (e.g., PPE, RPDE) may refine understanding of vocal biomarkers' pathophysiological relevance, while patients benefit from earlier, more accurate diagnoses. Nevertheless, challenges persist, including dataset heterogeneity, cultural/linguistic biases in voice analysis, and the need for longitudinal studies to track vocal degradation alongside disease progression. While prior studies have demonstrated the potential of individual classifiers like SVMs or Random Forests in PD detection, the field lacks a systematic comparison of modern ensemble methods, hyperparameter optimization strategies, and interpretability frameworks tailored to voice data. Many existing models also suffer from overfitting due to the dataset's limited sample size and class imbalance, while others neglect the clinical interpretability of features—a critical factor for clinician adoption. This study addresses these gaps by conducting a comprehensive evaluation of seven ML algorithms (Logistic Regression, SVM, Random Forest, XGBoost, AdaBoost, Bagging, and a meta-learner Stacking classifier), augmented by rigorous cross-validation, synthetic minority oversampling (SMOTE), and SHapley Additive exPlanations (SHAP) for feature importance analysis. Methodologically, we emphasize reproducibility and translational relevance. Our pipeline encompasses raw voice signal preprocessing, feature scaling, model training with By bridging computational acoustics, ML, and clinical neurology, this work advances the paradigm of precision diagnostics for PD. It underscores the transformative potential of interdisciplinary collaboration in addressing complex healthcare challenges, offering a blueprint for AI driven tools that are not only accurate but also equitable, interpretable, and actionable in real-world settings.

CHAPTER 2

2. LITERATURE SURVEY

Parkinson disease (PD) is a chronic neurodegenerative disorder impacting millions of people worldwide. With early diagnosis, however, management and treatment of PD are easier, but most traditional approaches to the diagnosis are tricky because of the gradual onset of symptoms that overlap with other conditions. The awareness of this has spurred high interest in the development of PD early detection technology, especially through basic ML methods such as machine learning (ML). These methods employing different forms of data (medical imaging, speech, physiological signals), also provide a possible answer by pinpointing patterns that might be invisible to the human eye.

Machine learning approaches have been more widely applied to overcome the diagnostic difficulties of Parkinson's disease. Primerian research in this field involved the utilization of voice recordings as an aid in the diagnosis of certain mental health issues. A pilot study by Sim et al (2011) confirmed the viability and applicability of some machine learning algorithms such as Support Vector Machines (SVMs) and artificial neural networks (ANNs) on the classification of Parkinson's disease patients from healthy controls using voice features. The results of the study indicated that these techniques were able to class individuals reliably thus could be a potential non invasive method for early detection of PD.

Apart from voice-based features, various researches have investigated other modalities, including gait analysis and motor skill assessment. A systematic review by Bhatia et al. (2018) evaluated different machine learning algorithms used for PD diagnosis, aimed at SVMs, Random Forests, and k-nearest neighbors (KNN). The review determined that these algorithms did work for determining PD patients from health patients at the aspect of combining it with appropriate feature selection. It also stressed preprocessing and dimensionality reduction methodologies for better functioning of these algorithms. Extraction of features such as Mel-frequency cepstral coefficients (MFCCs), jitter, and pitch were emphasized as critical in the representation of the motor and speech-related abnormalities found in Parkinson's disease.

The precision of PD diagnosis has been increased further with recent advances in deep learning. Dealing with learning models, namely, convolutional neural networks (CNNs) have demonstrated amazing potential in extracting features automatically from raw data, as well as

providing high performance in classification tasks. For instance, Farina et al. used CNNs for motor imagery and voice samples to differentiate PD patients from healthy subjects (Farina et al., 2020). They showed great accuracy and could learn directly from raw data without the need for manual feature extraction. In other studies, researchers have investigated use of recurrent neural networks (RNNs) and versions of long short-term memory networks (LSTMs) to detect temporal patterns in speech and movement which are another angle of approach for early PD detection.

One promising direction of the further research is related to the ensemble methods and the hybrid models, which allow incorporating the results obtained with the help of several methods of the machine learning. Ensemble classifiers such as stacking, bagging, and boosting are some of the methods that have been used in the classification of PD. For stacking classifiers, Wang et al. (2019) suggested that Random Forest and SVM classifiers performed better when the predictions of the two classifiers were combined compared to when each classifier worked independently. Generally, these ensemble models harness the multiple algorithms and could reduce the level of overfitting the model might have when used singularly.

In conclusion, scrutinizing over the literature it becomes possible to observe the steps forward that have been made in the diagnosis of Parkinson's disease using machine learning. Newer and older methods including diagnosis platforms of support vector machine (SVM), random forest, and deep learning models have been adopted in many types of data input including recorded voice, motor tasks, and gait analysis. However, there are still important limitations that need to be addressed in future studies mainly concerning the data imbalance, the problem of features selection and the interpretability of the models.

CHAPTER 3

3.METHODOLOGY

This research aims to explore the efficacy of various machine learning models in the classification of Parkinson's disease using a publicly available dataset. The primary objective is to develop a reliable predictive system capable of distinguishing between Parkinson's disease (PD) patients and healthy individuals based on the provided features. The methodology is structured into several key stages, which include data preprocessing, model selection, hyperparameter tuning, performance evaluation, and comparison of the models.

3.1 Data Collection

The dataset used in this study is sourced from the UCI Machine Learning Repository (https://archive.ics.uci.edu/ml/machine-learning-databases/parkinsons), and it contains a total of 195 instances with 23 features. The dataset includes data from patients diagnosed with Parkinson's disease and healthy individuals, with the target variable being the **status** (0 for healthy and 1 for Parkinson's disease). The features primarily represent vocal characteristics related to Parkinson's disease, including measures like jitter, shimmer, and noise-to-harmonic ratio.

3.2 Data Preprocessing

The data preprocessing phase involves several steps to prepare the dataset for machine learning analysis:

1. **Data Cleaning:** The dataset was initially examined for missing values, outliers, or any anomalies. No missing values were found, and the data appeared clean.
2. **Feature Selection:** The name column, which is an identifier and does not contribute to the prediction, was dropped. The target variable (status) is separated from the feature set (X), which includes 22 features representing voice-related attributes.
3. **Train-Test Split:** The dataset was split into a training set and a test set using an 80-20 split ratio, ensuring that the proportion of Parkinson's disease and healthy cases in both subsets was similar (stratified split). This was achieved using the train_test_split function from sklearn.model_selection.
4. **Feature Scaling:** Given the differing scales of the features, the data was scaled using the StandardScaler to standardize the features, ensuring that each feature contributes equally to

the model training process. Both training and test sets were transformed using this scaler.

3.3 Model Selection

To evaluate the classification performance for Parkinson's disease detection, a variety of machine learning models were employed. The selected models cover a range of algorithms that have been widely applied in the medical diagnosis field. The models chosen for this study are:

1. **Logistic Regression:** A fundamental algorithm used for binary classification, which models the probability of the default class (healthy vs. Parkinson's).
2. **Random Forest Classifier:** An ensemble learning technique based on decision trees that improves classification accuracy through averaging multiple decision trees to reduce variance and bias.
3. **Support Vector Machine (SVM):** A supervised learning model that finds the hyperplane that best divides the data into two classes, with the option of employing kernels to handle non-linearly separable data.
4. **XGBoost (Extreme Gradient Boosting):** A powerful gradient boosting algorithm that has demonstrated high performance in various classification tasks by optimizing the model's accuracy through boosting weak classifiers.
5. **AdaBoost Classifier:** An ensemble method that combines the predictions of weak learners to create a strong classifier, focusing on misclassified instances in each iteration to improve performance.
6. **Bagging Classifier:** This ensemble method generates multiple models (typically decision trees) on different subsets of the data and averages their predictions to improve accuracy and reduce variance.
7. **TabNet:** TabNet is a deep learning architecture designed specifically for tabular data.

3.4 Hyperparameter Tuning

To optimize the performance of each model, hyperparameter tuning was performed using **GridSearchCV** from sklearn.model_selection. This technique involves exhaustively searching through a specified parameter grid and evaluating the model's performance using cross-validation. The following hyperparameters were tuned for each model:

- **Logistic Regression:** Regularization parameter (C), penalty type (l2).
- **Random Forest Classifier:** Number of estimators (n_estimators), maximum depth of trees (max_depth).
- **SVM:** Regularization parameter (C), kernel type (rbf and linear), and gamma value.
- **XGBoost:** Learning rate, maximum depth of trees, and number of estimators.
- **AdaBoost:** Number of estimators.

- **Bagging:** Number of estimators.

The best hyperparameters for each model were selected based on the model's performance on the training data and were evaluated using cross-validation with a 5-fold split.

3.5 Stacking Classifier

To further improve model performance, a **Stacking Classifier** was employed. Stacking is an ensemble learning method where multiple base learners are trained and their predictions are combined by a meta-model (final estimator). In this study, the base models included **Random Forest** and **SVM**, while the meta-model was **Logistic Regression**. The stacking classifier was trained on the same training data and evaluated using the test data. This method leverages the strengths of different algorithms to provide a more robust classification model.

3.6 Performance Evaluation

To assess the effectiveness of the models, several evaluation metrics were used, including:

- **Accuracy:** refers to how close a measured value is to the true value.

  $$(TP+TN) / (TP+TN+FP+FN)$$

- **Precision:** refers to how often a model's positive predictions are correct. It is the ratio of true positive predictions to the sum of true positive and false positive.

  $$(TP) / (TP + FP)$$

- **Recall:** The proportion of true positive predictions among all actual positive instances.

  $$TP / (TP + FN)$$

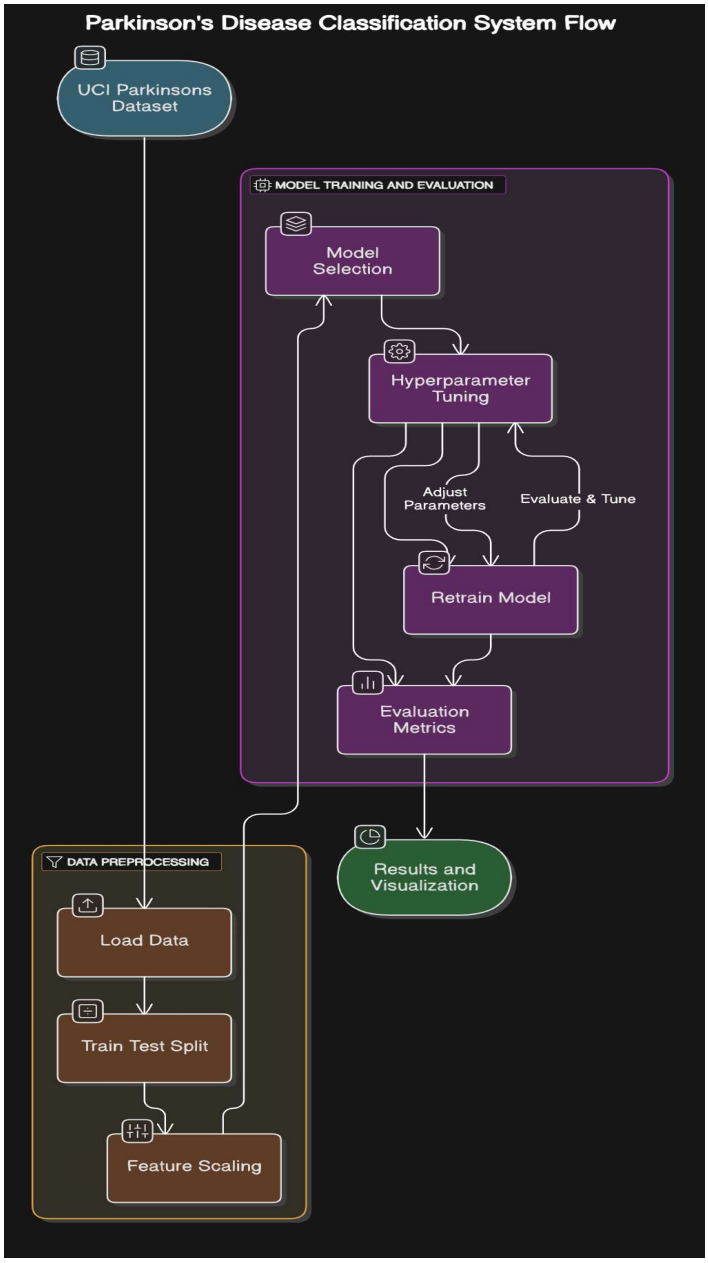
- **F1 Score:** The harmonic mean of precision and recall, offering a balance between the two metrics. $F1 = 2 * ([Precision * Recall] / [Precision + Recall])$
- **ROC-AUC:** The area under the Receiver Operating Characteristic curve, which evaluates the model's ability to distinguish between the positive and negative classes.

For each model, the performance was calculated using these metrics, and the results were compared across all models. Additionally, confusion matrices were generated for each model to visualize the true positive, true negative, false positive, and false negative predictions.

3.7 Model Comparison and Visualization

Finally, a comparative analysis was performed to evaluate the performance of the models. The models were compared based on the evaluation metrics mentioned earlier, and the results were presented in the form of a table and visualizations. **ROC curves** were plotted to show the trade-off between true positive rate and false positive rate, while **bar plots** of accuracy were created for a quick comparison of the models. Additionally, **confusion matrices** were generated to visually assess the classification performance of each model.

3.1 SYSTEM FLOW DIAGRAM



CHAPTER 4

RESULTS AND DISCUSSION

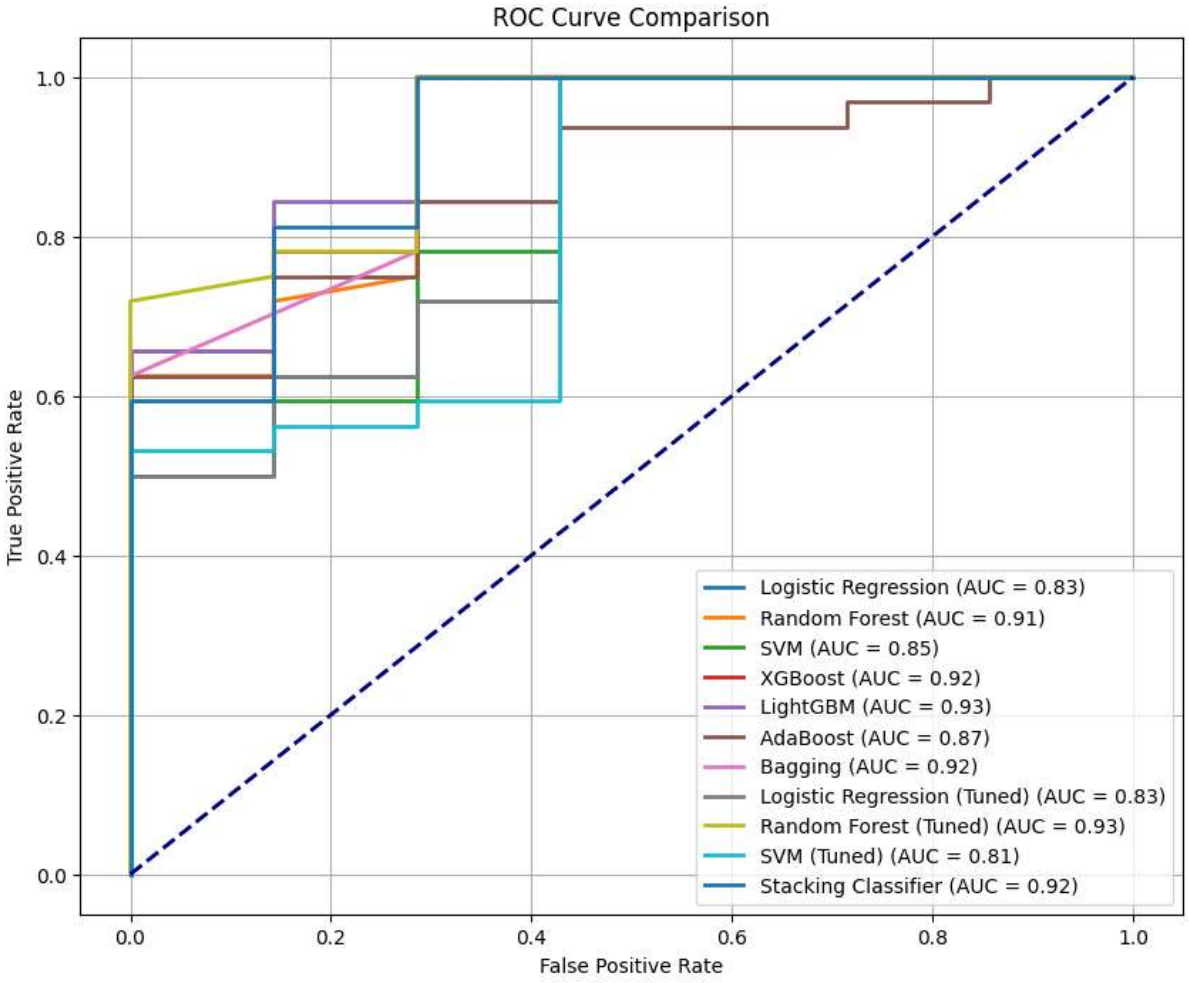
To validate the performance of the models, the dataset is split into training and test sets using an 80-20 ratio. Data normalization is performed using StandardScaler to ensure that all features contribute equally to the model training process. Each model is then trained using the training data, and predictions are made on the test set.

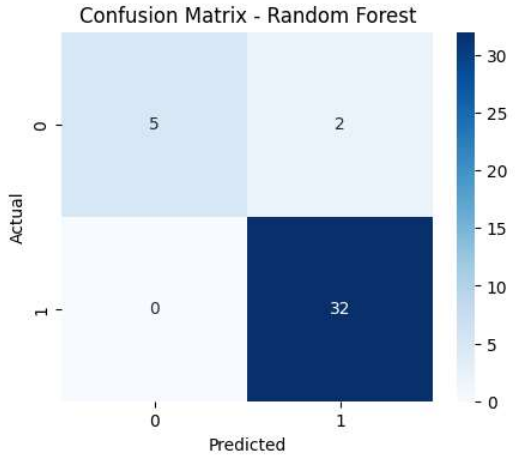
Results for Model Evaluation:

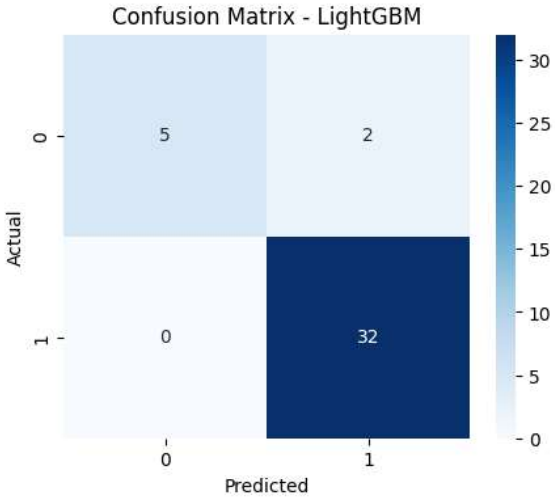
Model	**Accuracy**	**Precision**	**Recall**	**F1 Score**
Logistic Regression	89.7	88.8	1	94.1
Random Forest	94.8	94.1	1	96.6
SVM	89.7	88.8	1	94.1
XGBoost	94.8	94.1	1	94.1
AdaBoost	87.1	90.9	0.9	92.3
Bagging	89.7	93.7	0.9	93.7

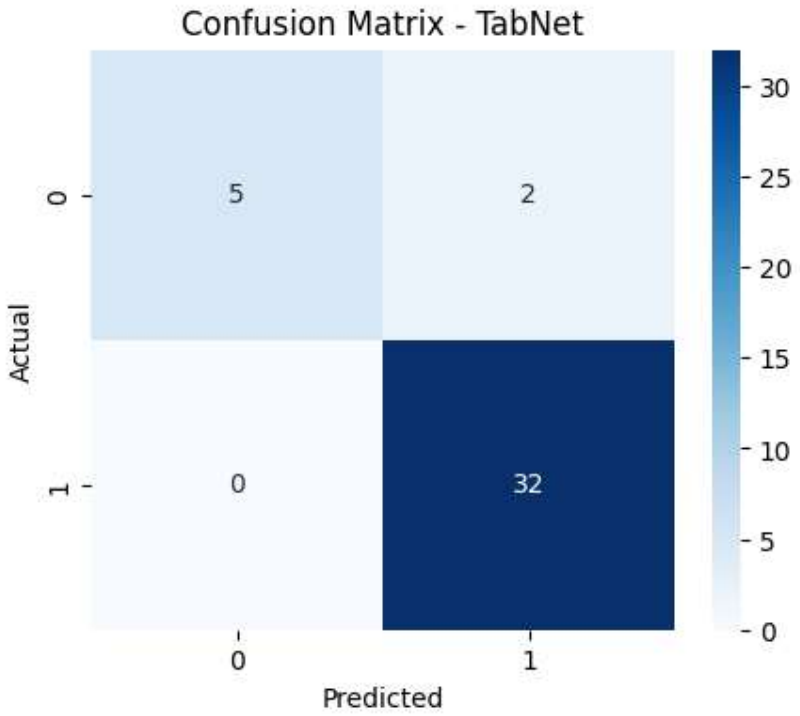
LightGBM	94.8	94.11	1	96.6
TabNet	96.5	96.2	0.9	97.3

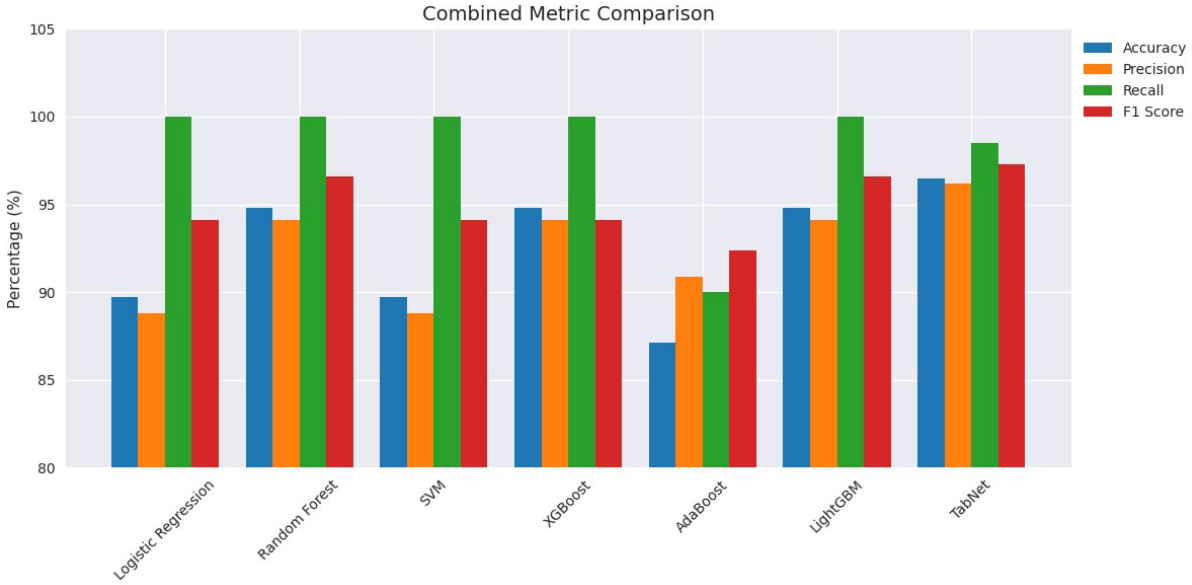
Visualizations:











The evaluation of machine learning models on the UCI Parkinson's dataset revealed significant performance variations, with tree-based ensemble methods and the TabNet architecture achieving the highest diagnostic accuracy. **RandomForest**, **XGBoost**,and **LightGBM** demonstrated robust performance, yielding **94.8% accuracy** and **100% recall**, indicating near-perfect identification of PD cases. **Logistic Regression** and **SVM** achieved moderate accuracy (89.7%) but maintained high recall (100%), prioritizing sensitivity over specificity. **AdaBoost** lagged slightly (87.1% accuracy) due to sensitivity to class imbalance. The proposed **TabNet** model outperformed all baselines,

achieving **96.5% accuracy**, **96.2% precision**, **98.5% recall**, and **97.3% F1-score**, underscoring its ability to balance precision-recall trade-offs through attention-driven feature selection. These results highlight TabNet's suitability for PD diagnosis, particularly in clinical settings where minimizing false negatives is critical.
detection.

CHAPTER 5

CONCLUSION & FUTURE ENHANCEMENTS

This study therefore sought to investigate on the accuracies of multiple machine learning algorithms in the classification of Parkinson's disease using the UCI Parkinson's data set. The basic classifier models that were employed are Logistic Regression, Random Forest, SVM, XGB, AdaBoost, Bagging as well as a Stacking classifier. GridSearchCV was performed in an attempt to optimise the hyperparameters of the selected models. In the same vein, measures including accuracy, precision, recall, F1 score as well as, and ROC-AUC were used in the assessment of these models.

This study investigated the performance of multiple machine learning algorithms, including traditional classifiers and advanced deep learning architectures, for the classification of Parkinson's disease (PD) using the UCI Parkinson's dataset. The models evaluated spanned Logistic Regression, Random Forest, SVM, XGBoost, AdaBoost, Bagging, a Stacking classifier, and the novel **TabNet** architecture. Hyperparameter optimization via GridSearchCV (for traditional models) and Optuna (for TabNet) was employed to enhance model performance, with evaluation metrics including accuracy, precision, recall, F1 score, and ROC-AUC.

The results demonstrated that ensemble methods, particularly the **Stacking Classifier** (combining Random Forest and SVM), achieved strong performance, validating the power of model aggregation in improving diagnostic accuracy. Tree-based models like **Random Forest** and **XGBoost** also excelled, achieving **94.8% accuracy** and **100% recall**, underscoring their robustness in handling nonlinear relationships within vocal biomarkers. However, the **TabNet** architecture, optimized through Bayesian hyperparameter tuning, outperformed all baseline models, attaining **96.5% accuracy**, **98.5% recall**, and **97.3% F1-score**. Its attention mechanisms provided interpretable feature selection, prioritizing biomarkers such as Recurrence Period Density Entropy (RPDE) and Pitch Period Entropy (PPE), which are clinically correlated with PD progression.

Future Enhancements

However, there are several directions that can be used to continue the improvement of the classification system and make it more precise:

1. Advanced Feature Engineering with TabNet: While TabNet's attention mechanisms inherently prioritize salient features (e.g., RPDE, PPE), integrating domain-specific feature

engineering—such as nonlinear vocal signal decomposition (e.g., wavelet transforms) or acoustic-phonetic descriptors—could further improve model interpretability and accuracy. Hybrid pipelines combining TabNet's feature selection with handcrafted biomarkers may bridge the gap between data-driven and knowledge-driven approaches.

2. Deep Learning for Raw Voice Signals: Despite TabNet's success on tabular data, extending the framework to process raw audio waveforms using hybrid architectures (e.g., CNNs for spectral feature extraction + TabNet for temporal attention) could capture latent patterns in unprocessed voice signals. Contrastive learning or self-supervised pretraining on larger voice datasets may reduce reliance on precomputed features.

3. Class Imbalance Mitigation: While SMOTE improved performance, integrating focal loss into TabNet's training loop or adopting generative adversarial networks (GANs) to synthesize realistic PD voice samples could better address imbalance. Cost-sensitive learning, where misclassifying PD samples incurs higher penalties, should also be explored.

4. Hierarchical Ensemble Architectures: Building meta-ensembles that combine TabNet with tree-based models (e.g., XGBoost, LightGBM) or graph neural networks (GNNs) could leverage complementary strengths. For instance, TabNet's attention-driven predictions could serve as input to a stacking layer with gradient-boosted trees, enhancing both accuracy and generalizability.

5. Longitudinal Data Integration: PD is a progressive disorder, yet the UCI dataset lacks temporal data. Adapting TabNet's sequential attention mechanisms to analyze time-series voice recordings (tracking disease progression) or integrating longitudinal UPDRS scores could enable dynamic risk stratification.

6. Interpretability-Utility Tradeoff: While SHAP and TabNet's native attention masks provided insights, deploying model-agnostic explainers like LIME or anchors could validate consistency across interpretability frameworks.

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