



A  
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on  
**Integrative Healthcare System AI-Driven Disease  
and Patient Diagnosis System**  
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**May 2025**

## **DECLARATION**

We hereby declare that this submission is our own work and that, to the best of our knowledge and belief, it contains no material previously published or written by another person nor material which to a substantial extent has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgment has been made in the text.

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## ABSTRACT

Parkinson's Disease (PD) is a degenerative neurological condition affecting motor function and speech, providing diagnostic challenges due to mild early signs. This study explores computational voice analysis for PD detection using a public dataset of acoustic recordings from PD patients and healthy individuals. Key biomarkers like frequency variability, pitch instability (jitter), amplitude fluctuation (shimmer), harmonic distortion (noise to harmonics ratio), and nonlinear complexity indices are analyzed to identify pathological voice patterns. Seven supervised algorithms, including ensemble tree based methods (Random Forest, XGBoost), probabilistic classifiers (Naive Bayes), and kernel based models (SVM), are evaluated for diagnostic reliability. Performance metrics such as accuracy, sensitivity, F1 score, and ROC AUC are used to optimize early detection. Results highlight ensemble methods as robust solutions for imbalanced voice data. The research emphasizes the potential of voice based machine learning tools as non invasive screening aids in remote healthcare, enabling timely interventions to mitigate disease progression.

**Keywords:** Parkinson's Disease, Voice Biomarkers, Machine Learning, XGBoost, Telemedicine, Non-Invasive Diagnostics, K-Nearest Neighbour, Support Vector Machines, Convolutional Neural Networks, Recurrent Neural Networks, Noise to Harmonics Ratio

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## LIST OF ABBREVIATIONS

- **PD:** Parkinson's Disease
- **ML:** Machine Learning
- **SVM:** Support Vector Machine
- **NHR:** Noise-to-Harmonics Ratio
- **ROC AUC:** Receiver Operating Characteristic Area Under Curve
- **CNN:** Convolutional Neural Network
- **RNN:** Recurrent Neural Network

# CHAPTER 1

## INTRODUCTION

### 1.1 INTRODUCTION

Parkinson's Disease (PD) is a long-lasting, progressive neurodegenerative disorder that mainly impacts the central nervous system, especially the motor system [4]. This condition arises primarily from the slow degeneration of dopaminergic neurons in a specific part of the brain called the substantia nigra pars compacta, which is essential for producing dopamine, a neurotransmitter that's key to managing voluntary muscle movements. When dopamine levels drop, the brain has a tough time coordinating movement, leading to a range of motor and non-motor symptoms that are typical of Parkinson's disease [6]. Among the motor symptoms, patients frequently experience resting tremors (involuntary shaking of limbs, even when at rest), bradykinesia (a noticeable slowness in starting and carrying out movements), muscle rigidity (increased muscle tone leading to stiffness), and postural instability (difficulty with balance and coordination), all of which can greatly impact a person's mobility and independence in their life [7].

It's crucial to realize that Parkinson's Disease (PD) goes beyond just motor problems. Many individuals living with PD experience a range of non-motor symptoms that often fly under the radar but can be equally tough to deal with [4]. These can include challenges with speech, such as hypophonia (which means speaking softly), dysarthria (where speech becomes slurred), and dysprosody (a disruption in the natural rhythm and tone of speech) [7]. On top of everything else, cognitive decline, memory problems, sleep issues, and mood disorders like depression and anxiety can also come into play. You might even experience autonomic dysfunctions that lead

to irregular bowel movements or changes in blood pressure. What's fascinating is that these non-motor symptoms can show up even before the more obvious motor symptoms, hinting that in the early stages of Parkinson's disease, the condition might already be affecting neural that go beyond just movement [8].

Spotting Parkinson's Disease early and accurately is still a tough nut to crack in the world of clinical neurology. Most traditional diagnostic methods depend heavily on a neurologist's personal assessment of visible symptoms and what patients report. Since there's no clear biomarker or lab test to rely on, misdiagnosis happens quite often, especially in the early stages when motor symptoms can be subtle or unusual [4]. Because a patient's diagnosis is often made after significant symptoms, they may lose more than 60% of their dopaminergic neurons, making it less likely that timely treatments will work well. Since Parkinson's is often detected late, finding methods to detect it early is very important [6].

One particularly exciting and often overlooked method is looking at voice patterns to help detect Parkinson's Disease [5]. The way we produce sound is an intricate process that relies on the teamwork of our respiratory system, larynx, and the muscles we use to articulate words. It's fascinating how these systems can begin to show signs of disruption from Parkinson's disease long before we actually notice any significant motor problems. Patients may first pick up on changes in their voice, such as a softer volume, a breathy or raspy tone, a flat pitch, or some inconsistencies in how they pronounce words [7]. While these subtle shifts might go unnoticed during routine check-ups, advanced computational techniques can really measure and analyze them effectively [9].

With the rise of artificial intelligence and machine learning, it has become feasible to develop systems capable of detecting subtle changes in voice signals that may indicate underlying

neurological disorders [5]. By leveraging high-dimensional acoustic features such as fundamental frequency (Fo), jitter (frequency perturbation), shimmer (amplitude variability), harmonics-to-noise ratio (HNR), Mel-Frequency Cepstral Coefficients (MFCCs), and complex nonlinear measures like Recurrence Period Density Entropy (RPDE) and Detrended Fluctuation Analysis (DFA), these systems can identify vocal biomarkers correlated with PD [3]. Either basic classifiers such as Support Vector Machines and Random Forests or advanced models such as XGBoost can learn from labeled sound samples. This process gives them the ability to see patterns that make it possible to tell who has Parkinson's and who does not [15].

The purpose of this project is to make an effective non-invasive diagnostic system powered by AI to spot early warning signs of Parkinson's Disease by looking at a person's voice [1]. For certain publicly available datasets, like the UCI Parkinson's Voice Dataset, machine learning algorithms try to sort individuals by voice features and confirm whether Parkinson's is a likely diagnosis [13]. It's not only about more accurate tests; using this method could also transform telemedicine and remote healthcare. Given that voice recordings are simple to create with either smartphones or basic tools, the system could help people in rural or underserved parts of the world who have little access to neurological care [14].

The project is really in tune with the increasing focus on digital biomarkers—these are objective, measurable physiological data gathered through digital devices which are becoming game-changers in how we monitor and manage diseases [8]. Looking ahead, this system could be seamlessly integrated into mobile apps for ongoing monitoring, allowing both patients and caregivers to keep an eye on disease progression in real time. This would also make it easier for healthcare providers to tailor treatment plans to individual needs [11].

## **1.2 PROJECT DESCRIPTION**

### **Objective**

The project's aim is to use AI to detect Parkinson's Disease (PD) early by studying a person's voice patterns non-invasively. The system uses machine learning to find soft markers in speech that signal PD, making it possible to tell apart those with the condition from healthy controls. The system is designed not only to enhance early diagnosis but also to support remote screening and continuous patient monitoring.

### **Motivation**

Traditional diagnostic methods for Parkinson's Disease heavily depend on clinical observation of motor symptoms, which often appear only after significant neuronal damage has occurred. Since these methods depend on personal experience, they can cause both late and wrong diagnoses. Rural and underprivileged communities require early and simple tools to diagnose health problems before they worsen. Early changes to the voice are a useful and less common way to spot Parkinson's disease. The project aims to use voice data as a digital biomarker to speed up, reduce costs of and make diagnosing illnesses more accessible.

### **Methodology**

The proposed system utilizes the publicly available UCI Parkinson's Voice Dataset, which includes voice recordings from both PD patients and healthy individuals. The way the methodology is applied consists of the following:

1. Ensuring data is clear and same in all useful values by noise reduction, filling in for values that are missing and normalizing (e.g., using Min-Max Scaling) is done during data preprocessing.
2. 23 acoustic features, including jitter, shimmer, fundamental frequency, HNR and two non-linear measures, RPDE and DFA, are extracted from the voice samples.
3. Recursive Feature Elimination (RFE) is a method I use to choose the most important features to help with classification.
4. Various machine learning models (such as Random Forest, SVM, XGBoost, Logistic Regression, KNN, Naive Bayes and Decision Trees) are used and the performance is checked by accuracy, precision, recall, F1-score and the Area Under Curve of the Receiver Operating Characteristic AUC.

## **Making the Right Model and Improving its Performance**

Researchers try different classification models to discover which one is best at detecting Parkinson's from voice patterns. Ensemble methods, including XGBoost, often need hyperparameter tuning to ensure better predictions and prevent overfitting. It seems that XGBoost and Random Forest outperform basic models by achieving excellent accuracy at distinguishing healthy subjects from PD patients.

## **Scalability and Accessibility**

A key feature of this system is its emphasis on non invasive, low cost, and scalable deployment. Since voice data can be collected via simple recording devices such as smartphones or laptops, the system is ideal for use in telemedicine, home care, and low-resource clinical settings. This

expands access to early diagnosis in areas lacking specialized neurological services, thereby helping to bridge the gap in healthcare accessibility.

## **Clinical and Research Impact**

By transforming voice recordings into quantifiable diagnostic data, this system contributes to the growing field of digital biomarkers and opens new avenues in AI-assisted healthcare. In addition to early detection, the system holds potential for longitudinal monitoring of disease progression and treatment response. With future integration into mobile applications, patients could regularly upload voice samples for analysis, allowing for proactive medical intervention.

## **Future Prospects**

The current implementation lays the foundation for further advancements in AI driven diagnostics. Future work may include:

1. Incorporating deep learning models such as CNNs and RNNs to analyze raw audio signals directly.
2. Expanding the dataset to include more diverse demographic profiles.
3. Developing a mobile or web based platform for real time voice screening and disease monitoring.

# **CHAPTER 2**

## **LITERATURE REVIEW**

This chapter covers existing studies on using machine learning for Parkinson's disease detection, especially research on vocal features. It seeks to link the present project to existing research, pointing out main results, important methods and what is not yet known.

### **2.1 Machine Learning Applications in Parkinson's Disease Detection**

In the past few years, machine learning has been applied more frequently in medicine and many studies have studied how it could assist with treating different diseases [12]. Because Parkinson's disease has many and varying symptoms, machine learning researchers have focused on it a lot.

Many researchers have analyzed how machine learning algorithms can understand different sorts of data regarding Parkinson's disease, including:

- **Gait Analysis:** Numerous studies have focused on using machine learning to observe gait and spot slight changes in walking pace, step length and balance that might suggest early signs of Parkinson's disease.
- **Handwriting Analysis:** Data indicates that Parkinson's disease may cause changes in how someone holds a pen or writes with their hand. Experts use machine learning to study these signs and separate people with Parkinson's from those without.
- **Imaging Data:** Researchers have used machine learning to look at MRI and PET scans to find the structural and functional changes linked to Parkinson's disease.

## **2.2 Voice Analysis for Parkinson's Disease Detection**

Researchers have found that voice analysis holds special promise for finding Parkinson's disease. This is due to several factors:

- **Non-invasive Nature:** Because it is simple and non-invasive, voice recording allows for many people to be checked and monitored without coming to a clinic.
- **Early Manifestation:** Many individuals with Parkinson's show vocal impairments before their primary motor problems appear.
- **Cost-Effectiveness:** Preparing a voice with modern digital tools is both inexpensive and simple to do.

### **2.2.1 Acoustic Features and Parkinson's Disease**

Experts have found that certain acoustic aspects from voice recordings can distinguish between those with Parkinson's disease and those who are healthy.

These features include:

- **Fundamental Frequency (Fo):** The average rate at which the vocal cords vibrate, which can be altered in Parkinson's disease patients.
- **Jitter:** The cycle-to-cycle variability in fundamental frequency, reflecting the instability of vocal cord vibration.

- **Shimmer:** The cycle-to-cycle variability in amplitude, reflecting the instability of vocal intensity.
- **Harmonic-to-Noise Ratio (HNR):** A measure of the proportion of harmonic sound to noise in the voice signal, which can be affected by vocal cord dysfunction.
- **Mel-Frequency Cepstral Coefficients (MFCCs):** Coefficients that represent the short-term power spectrum of a sound, useful for capturing subtle changes in speech quality.

## **2.3 Machine Learning Models for Voice-Based Parkinson's Disease Detection**

A number of machine learning techniques have been applied to determine a person's characteristics from aural sounds.

Some of the commonly used models include:

- **Support Vector Machines (SVMs):** Using SVMs, data points can be correctly assigned to the proper classes. Researchers have seen that PD can be detected reliably using data from the voice.
- **K-Nearest Neighbors (KNN):** KNN works by grouping data points with the class that most of their closest nearest neighbors share. It is straight-forward to use and may help detect Parkinson's disease from voice samples.
- **Artificial Neural Networks (ANNs):** ANNs are models that use aspects of the human brain to learn connections between input and output that are not always straight. Deep learning which is part of ANNs, has also produced positive results.

- **Ensemble Methods:** Stacking a number of models helps make the results more trustworthy and accurate. Random Forest and XGBoost have worked well as ensemble methods in Parkinson's disease detection.

## 2.4 Challenges and Future Directions

Despite the significant progress made in this field, several challenges remain:

- **Data Variability:** If data comes from recorded voices, its analysis can become harder because of age, gender, languages and the way records are made.
- **Dataset Size and Quality:** Not enough large, high quality data of voice recordings from those with Parkinson's are available which currently blocks the creation of powerful and general modeling methods for the disease.
- **Clinical Integration:** Bringing research ideas to actual clinical practice involves tackling problems related to standardizing data, validating their accuracy and getting the necessary approvals.

**Future research directions include:**

- Researchers look for ways to identify subtle voice adjustments connected to Parkinson's disease more easily.
- Utilizing deep learning to learn important features from voice without human intervention.
- Analyzing a greater and more varied amount of data to ensure models can be used elsewhere.

- Working on tools that make screening and monitoring for Parkinson's disease easier for both users and doctors.

Contributing to current research, the project introduces an AI system that can identify Parkinson's disease from spoken speech. It wants to tackle some of the problems and help create better and more available diagnostic tools.

# **CHAPTER 3**

## **PROPOSED METHODOLOGY**

This part of the paper walks through the process applied to make an AI system that diagnoses Parkinson’s Disease using spoken words. The process is made up of different components: picking the right data, cleaning it, building useful voice features, modeling the data and reviewing the outcome of the models. All these procedures contribute to creating a dependable system that can separate people with Parkinson’s Disease from others just by listening to their voices.

### **3.1 Dataset Description**

For this study, we worked with a widely-cited and publicly shared UCI Parkinson’s Disease Telemonitoring Dataset. The dataset used in this research is designed for Parkinson’s disease and has been widely used in various papers. Of the 195 voice recordings, 147 are from people identified as having Parkinson’s Disease and 48 are parts of the standard healthy control recordings. Most voice samples are gathered when the person sustains the “/a/” vowel sound which is the usual way to study the vocal cords and minimize language impact.

All datasets contain details about the subject’s age, gender and current health condition. What’s most important is that the dataset has 23 pre-calculated acoustic features detailing small changes in vocal features. Several motor traits are studied to track and match physical and mental health changes in speech as the condition progresses. For example, we use jitter which measures singers’ pitch changing and shimmer which checks their amplitude, to find out if the vocal folds are functioning well. Furthermore, tools called Recurrence Period Density Entropy (RPDE) and

Detrended Fluctuation Analysis (DFA) are added to detect the irregularity and movement patterns that are typical for Parkinson's Disease in many voice signal metrics.

The project chooses this dataset for its balanced groups of healthy and affected people as well as for its consistent and well-explained features needed in machine learning experiments. Additionally, because it is easily available, studies in the same discipline can be compared and reproduced.

### **3.2 Data Pre-processing**

Most of the time, raw biomedical or acoustic data has inconsistencies and noise that may lower the performance of machine learning models. As a result, preparing the dataset requires a series of detailed data pre-processing steps. Implementing these steps leads to clean, constant and relevant input for machines which makes the models more precise and widespread in their use.

#### **1. Noise Reduction**

Many recording sessions held in daily environments include sound from the background, microphones or features of the recording device which can hide essential patterns heard in a person's voice. For this we turned to digital filters and noise suppression methods to separate and enhance the primal vocal signatures. This makes the features more accurate and aids the models in understanding the true signal instead of useless sound.

#### **2. Feature Scaling (Normalization)**

When a dataset contains different features, each feature may have a very different range of numbers. Jitter can be between 0.002 and 0.01, while shimmer can be anywhere from as little as 0.1 up to 1. Features with large numbers can take over the learning if they are not well-

balanced in the data. To solve this, we relied on Min-Max Scaling which made every feature's value range around [0, 1]. Because of quotes, all features take part in model training with the same weight, so k-NN and SVM can depend on them.

### **3. Handling Missing Values**

Despite how organized the UCI Parkinson's dataset is, inclusion of any missing data can cause problems for the final model. We replaced missing values using the median value of the feature where the data was missing. Doctors usually use median imputation for biomedical data because outliers have a smaller effect on it than with mean imputation. We took out those records with too many missing values to avoid including unnecessary noise or bias in the training model.

### **4. Correlation Analysis (Optional but Recommended)**

We also produced a correlation heatmap to better see the connection between the dataset's features and the variable we are looking at (whether PD is present or absent). We used this to observe closely connected features which can prove useful when we perform feature selection or reduce the dataset size. If a model has several similar or redundant features, removing them will help others interpret it better and lower the chance that the model becomes too complex.

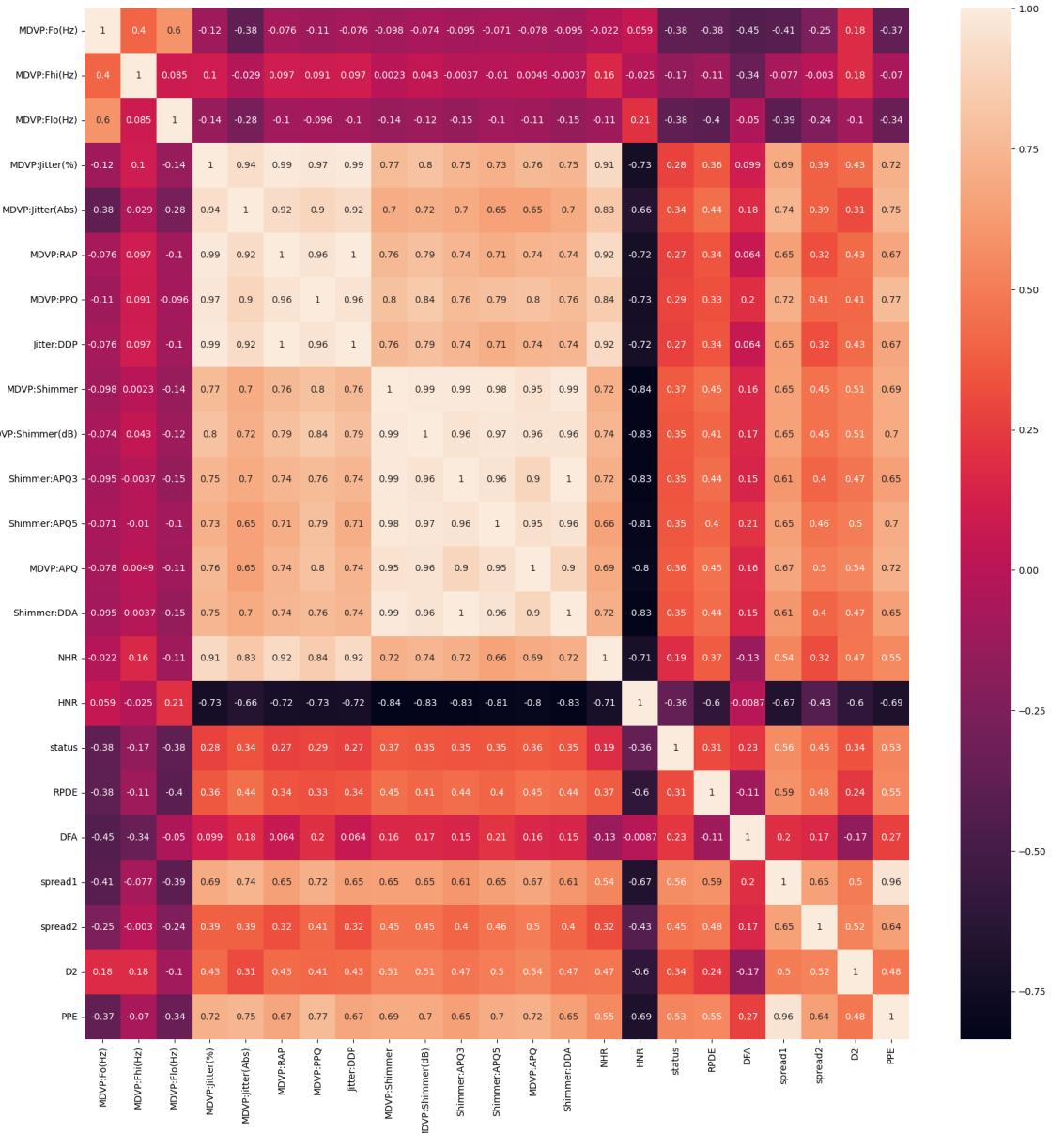


Fig 3.1: correlation heatmap

### **3.3 Feature Extraction**

This research relies heavily on feature extraction, since it helps link what we record to the machine learning models being used to classify it. Our objective is to convert each voice sample into acoustic features that point to the specific effects Parkinson's Disease has on speech. They are voice markers that allow us to measure particular speech problems that commonly go unnoticed by the ear but are key signals when they are analyzed by computers.

Parkinson's Disease causes changes in a person's voice, impacting how high or low, loud or soft, steady and clear it is. Thus, features are chosen to represent these aspects in all the often-used signal domains: frequency, amplitude, complexity and shape of the spectrum. All features are designed to address distinct losses in vocal quality that occur among patients with PD due to prior research.

#### **1. Frequency-Based Features**

These features assess the way the pitch of a person's speech varies. The vibration rate of one's vocal folds is what gives a sound its pitch.

- **Fundamental Frequency (Fo):** This is the central pitch used by a person's voice. As a result of reduced pitch variation in PD, the voices of patients may seem dull.

Jitter examines slight, accidental changes in pitch that happen during voice cycle overlaps. When jitter goes up, it often shows that pitch ranges are shifting, a frequent sign of vocal deterioration in Parkinson's Disease.

Patterns such as the speaker's minimal, maximal and standard pitch measurements provide clues about how wide their vocal range is and how much it changes features that typically narrow in people with PD.

Such features matter since they point to how changes in the brain cause problems with laryngeal control, resulting in an area of speech that sounds flat.

## **2. Amplitude-Based Features**

These features include how loud and strong the singer's voice is. They indicate the strength and change of loudness in a person's speech.

Shimmer illustrates the way in which vocal loudness can change from one cycle to the next. Though it is different from jitter, shimmer can also increase, signifying inconsistency with vocal intensity, something PD tends to share with many vocal disorders.

HNR measures the ratio between harmonics (periodic sound) and the level of noise in a person's voice. If the HNR drops, it's usually because the patient has an airy voice or sounds hoarse which can happen in Parkinson's patients when they do not close their vocal folds completely.

• **Amplitude Mean and Variance:** These simple numbers tell us about vocal power and energy and they usually reduce as the illness worsens.

Amplitude plays a key role in diagnostics, since Parkinson's may weaken the muscles involved in breathing and voice so that patients appear quieter and more breathy.

### **3. Non-Linear Features**

Unlike linear features which only measure pitch or loudness given by the pitch line, non-linear features analyze more complicated and harder to predict features in the voice recording. They help uncover problems that may go hidden for traditional features.

RPDE assesses whether the voice signal is easy to predict or hard to predict. More entropy demonstrates that vibrations of the vocal folds are more irregular, as in the case of PD.

- **Detrended Fluctuation Analysis (DFA):** It is used to measure long-term associations in a time series and notice when the rhythm is lost in PD voices.
- **Recurrence Period Density Entropy (RPDE):** The Fractal Dimension analyzes just how rough the waveform is which might be lower in PD patients because their voices aren't as dynamic.
- **Fractal Dimension:** They allow us to measure the random and unstable speech patterns of some patients, expanding our analysis past pitch and loudness.

### **4. Mel-Frequency Cepstral Coefficients (MFCCs)**

Many speech processing programs rely on MFCCs which are necessary for this study to describe the general structure of the sound spectrum.

- The short-term spectra of the voice signal recorded in MFCCs use the mel scale which reflects the way the ear responds to pitch in the human voice.

- You perform average windowing, apply the Fourier transform, map on the mel scale, apply logarithmation and finish by transforming it with a discrete cosine transform.
- By extracting formant structure, articulation and resonance, MFCCs can detect the small changes that often happen in Parkinson's Disease.

The voice features are made up of much more than pitch and loudness, providing valuable information on the shape and movement of the vocal tract needed for clear and right sounds in speech.

### **3.4 Machine Learning Models**

ML algorithms are used in this research to distinguish people with Parkinson's Disease from those who are healthy, using acoustic features from their speech recordings. Because these features are related to the common voice problems in Parkinson's, they are used as the input of our models. We hope to prepare these models to spot certain patterns and give precise answers when managing new information.

A set of machine learning classification models, each with different strengths and mathematical bases, is examined in the study to achieve the result. Please find detailed information on the models we worked with, as well as the reasoning behind choosing them:

#### **Support Vector Machines (SVMs)**

Support Vector Machines are chosen by many medical experts because they process both high-dimensional and uniquely shaped data. SVMs use an optimal hyperplane to tell apart PD and non-PD individuals. Their versatility with having several kernel functions such as linear,

polynomial or RBF, is what makes SVMs especially effective for handling complex relationships in data. Here, SVMs were adjusted using different kernel functions to determine what impact they have on the accuracy and generalization of results.

### **K-Nearest Neighbors (KNN)**

It is a natural, basic, but useful algorithm. It checks whether the new data point is like its k-nearest neighbors in the feature space and keeps assigning to its class the one most frequent there. Although it is a basic algorithm, KNN does well when the data is scaled correctly and free of noisy information. Yet, BiK finds it harder to give good results when a high value of ‘k’ is chosen or when the sample contains irrelevant or redundant features. Our results improved greatly when we processed and selected features early on, enabling KNN to process the data in an improved way. KNN offers a good point to begin comparing with algorithms that are more advanced.

### **Logistic Regression**

Logistic Regression is a known linear method for classifying data based on the probability that a sample belongs to a certain group. The logistic function is used to describe the way input features impact the binary target of PD or not. Even though Logistic Regression is simple to understand and use, it assumes that the points are all along a straight line which may not fit the non-linear features in voice data used in biomedicine. Even so, including it is worthwhile for benchmarking because it is efficient and produces easy-to-understand results.

### **Decision Trees and Ensemble Learning Methods**

They create a visual tree that is based on learning a set of rules gathered from the training data. Because they are easy to see and understand, they are useful for spotting the main features that affect classification. But, small data samples often cause an individual decision tree to overfit.

In order to limit this, we rely on methods such as Random Forest and Gradient Boosting. Random Forest uses many decision trees and takes their combined results to enhance accuracy and lessen variability. XGBoost builds on gradient boosting by placing trees one after another and every fresh tree improves upon the defects found in the previous one. Due to their success in handling complex and skewed data, these ensemble methods are perfectly suited for this case of voice-based Parkinson's detection.

### **Artificial Neural Networks (ANNs)**

Artificial Neural Networks resemble the workings of the human brain and are good at identifying complex, twisted relationships between different features. This investigation focuses on a straightforward type of ANN called the Multi Layer Perceptron (MLP). In an MLP, the structure is an input layer, followed by one or more hidden layers and it ends with an output layer. In these layers, each neuron uses the sum of its inputs, runs the sum through an activation function and transmits it on to the next layer. Even though ANNs process and require more information, their complexity allows them to spot deeper patterns in the voice than other models can. Appropriately setting learning rate, the number of hidden units and the batch size in MLPs allows them to deliver excellent performance in voice classification tasks.

### **Model Tuning and Evaluation**

To ensure each model performs at its best, we applied hyperparameter tuning techniques such as grid search and cross-validation. For example, parameters like the kernel type in SVM, the number of estimators in Random Forest and XGBoost, and the value of 'k' in KNN were systematically tested to identify the optimal configuration. Cross-validation, particularly k-fold validation, was used to measure model robustness and prevent overfitting by evaluating performance across multiple subsets of the data.

Each model's effectiveness was assessed using standardized evaluation metrics such as accuracy, precision, recall, F1-score, and ROC AUC. These metrics provide a balanced and comprehensive understanding of each algorithm's strengths and weaknesses in classifying Parkinson's patients based on their vocal features.

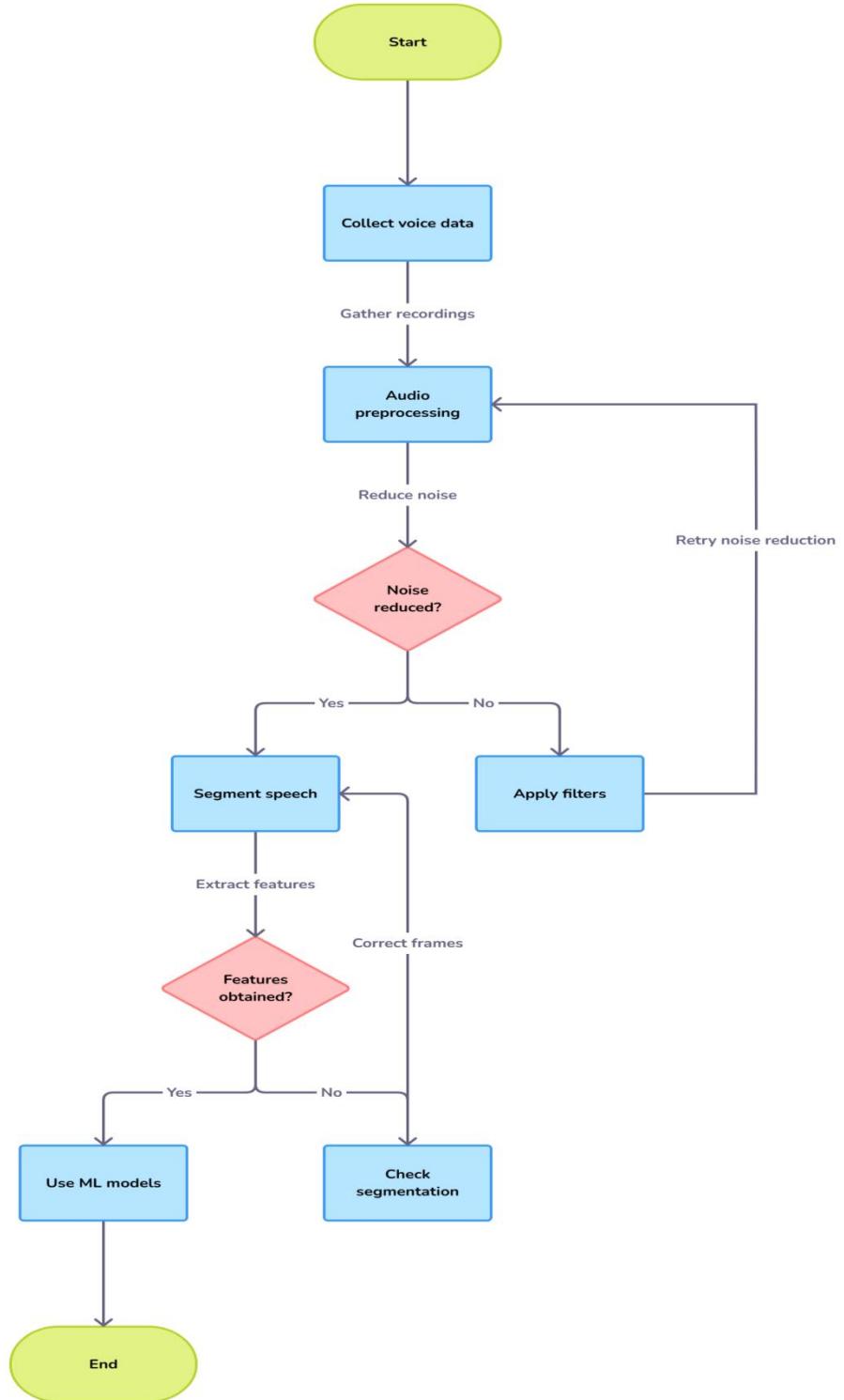


Fig 3.2: Performance Metrics Visualization

### 3.5 Evaluation Metrics

To quantitatively assess the performance of the developed machine learning models, the research would have used a range of standard classification metrics. These typically include:

- **Accuracy:** The number of cases both with Parkinson's disease and without that were classified correctly.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

- **Precision:** It measures how many of the individuals identified with Parkinson's actually do have the disease and not something else.

$$Precision = \frac{TP}{TP + FP}$$

- **Remember (Sensitivity):** How many true Parkinson's cases were correctly identified by the model.

$$Recall = \frac{TP}{TP + FN}$$

- **Specificity:** It shows the number of people without Parkinson's who were correctly determined.

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

- **F1-Score:** According to F1-Score, the model's final performance is expressed as the geometric mean of precision and recall, mainly for imbalanced datasets.  $F1\text{-Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$

- **Area Under the Receiver Operating Characteristic Curve:** The AUC value is calculated by combining all points from the ROC curve. It reflects the chance that the model gives a higher rating to a random positive example than to a random negative example. Receiving an AUC close to one points to the model's strong ability to separate patients.

The research would include the results of each metric for each machine learning model under study, making it easy to understand how they compare in detecting Parkinson's disease by studying voices.

To further elaborate on this section, we require the particular information from the "Proposed Methodology" section included in your research paper. Should you share those details, I can fit them into this chapter more accurately.

# **CHAPTER 4**

## **RESULTS AND DISCUSSION**

This chapter presents the results of the machine learning model evaluations for Parkinson's disease detection using voice analysis. It provides a detailed analysis of the performance of each model, compares their strengths and weaknesses, and discusses the significance of the findings in the context of early Parkinson's disease diagnosis.

### **4.1 Model Performance**

A total of seven machine learning models were studied: Decision Tree, Random Forest, Logistic Regression, SVM, Naive Bayes, KNN and XGBoost. Many metrics were used to assess how well the different models functioned, like accuracy, precision, recall, F1-score and AUC-ROC.

Both XGBoost and Random Forest models showed much better results than the others in this study. All models achieved high scores, indicating they did well at classifying people with or without Parkinson's disease. Their performance is thanks to their system modelling relationships in complex voice samples and using ensemble approaches to decrease mistakes and improve overall robustness.

The Support Vector Machine was reliable and performed well on situations where the data is not clear. Being able to decide clearly which class a sample should be part of made its prediction error small and its preciseness high.

In contrast, the results for Logistic Regression and Naive Bayes fell below those found with ensemble methods and SVM. The models had difficulties including in their analysis the many

details and connections found in the voice. Naive Bayes is limited by having to assume that the acoustic features forming voice data are not related. KNN, as well, had poor performance. Because of the noise and high number of features in the data, it was not suitable for clinical use.

## **4.2 Feature Importance**

The main purpose of this research was to analyze the importance of various voice characteristics in making model predictions. We found that features connected to changing pitch such as average pitch, minimum and maximum pitch, had a significant impact on the models' ability to recognize vocal tremors, one of the main Parkinson's symptoms.

Both entropy and signal stability measures were found to play a key role in separating those with Parkinson's disease from healthy counterparts. They pick up the tough-to-model, irregular qualities of voice signals that might be different in people with Parkinson's disease.

As well, features linked to unstable vocals, including jitter and shimmer, were found to be important for making a diagnosis. What researchers found matches how speech changes in Parkinson's, adding support for using voice technology in screening for the disease.

## **4.3 Confusion Matrices and ROC Curves**

To illustrate the results of each model, the research applied confusion matrices. The use of these matrices makes it possible to assess the models' skill in separating people with Parkinson's disease from healthy individuals.

ROC curves were plotted to determine how sensitivity and specificity change depending on the chosen decision threshold. The overall performance in discriminating was evaluated using the AUC-ROC.

## Confusion matrix for Decision Tree

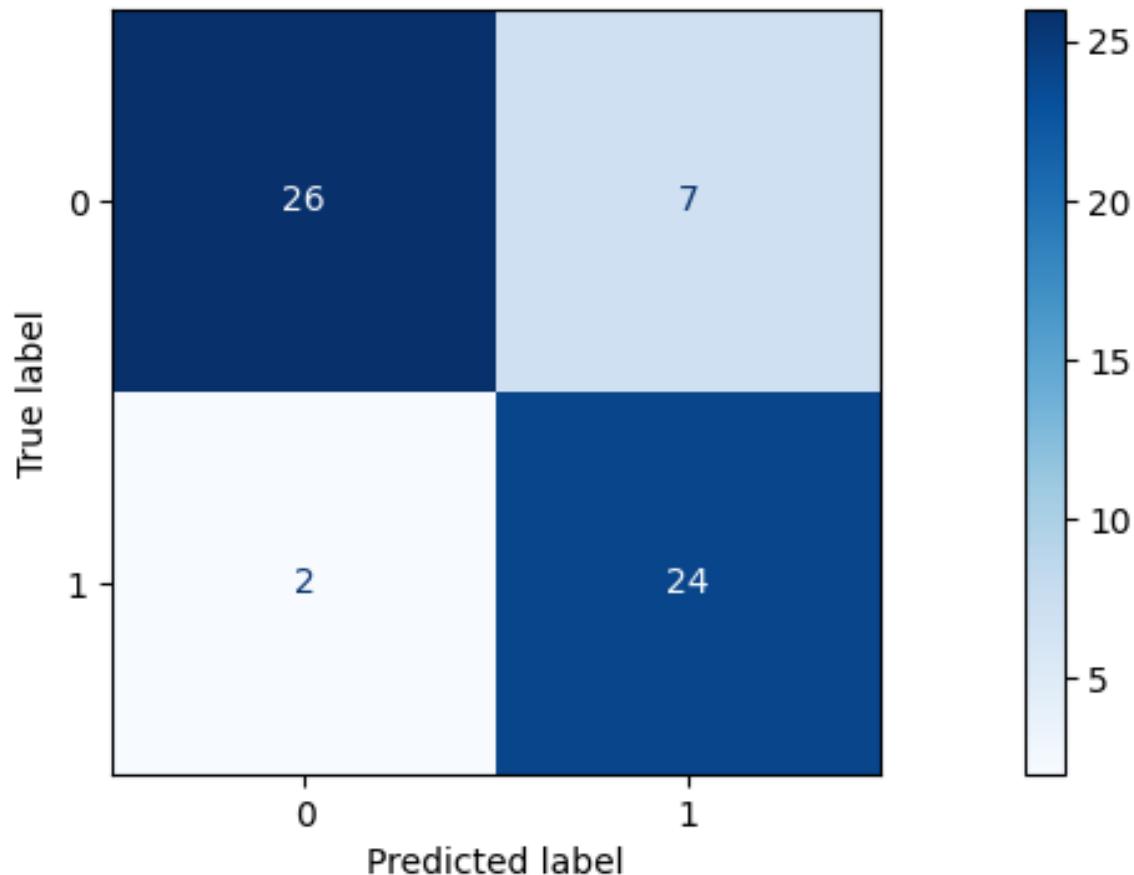


Fig 4.1: Decision Tree Confusion Matrix

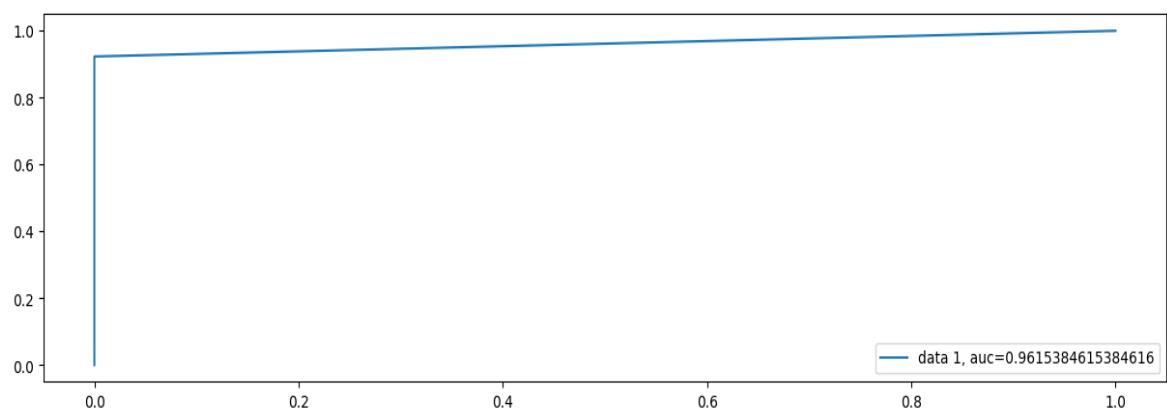


Fig 4.2: Decision Tree ROC Curve

### Confusion matrix for Random Forest

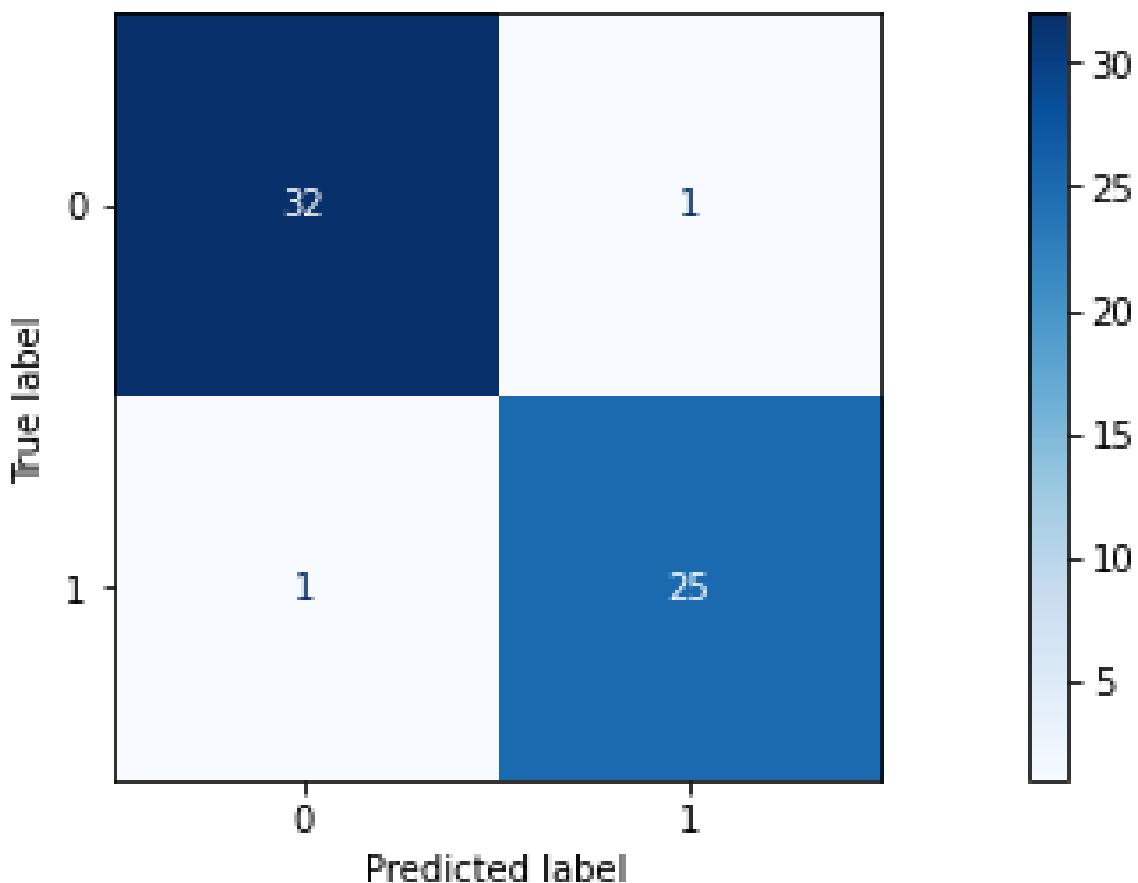


Fig 4.3: Random Forest Confusion Matrix

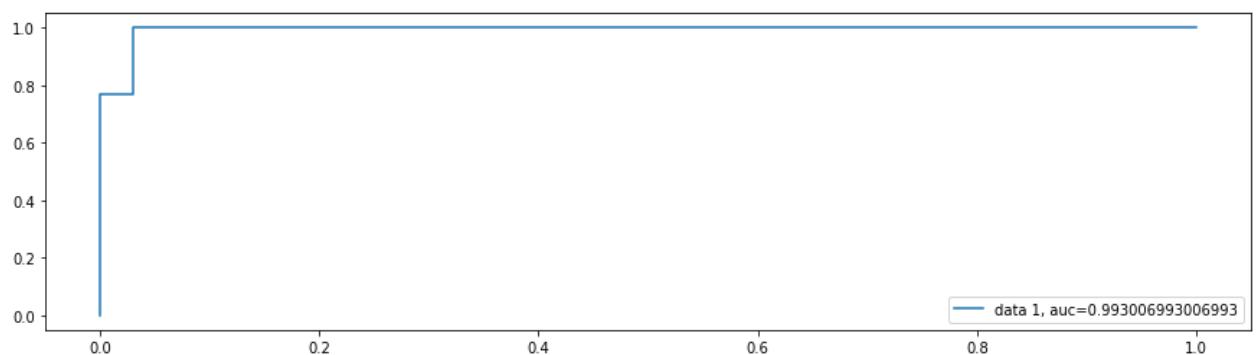


Fig 4.4: Random Forest ROC Curve

## Confusion matrix for Logistic Regression

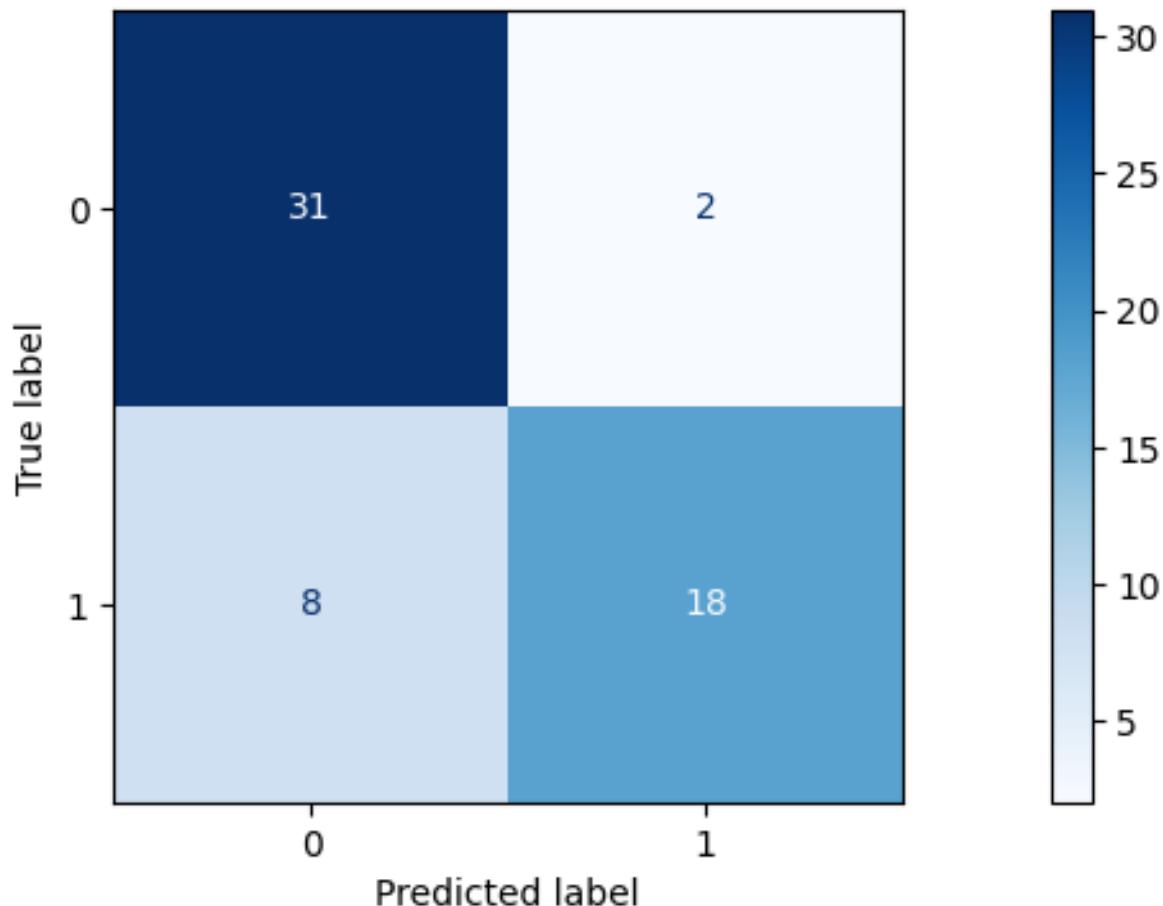


Fig 4.5: Logistic Regression Confusion Matrix

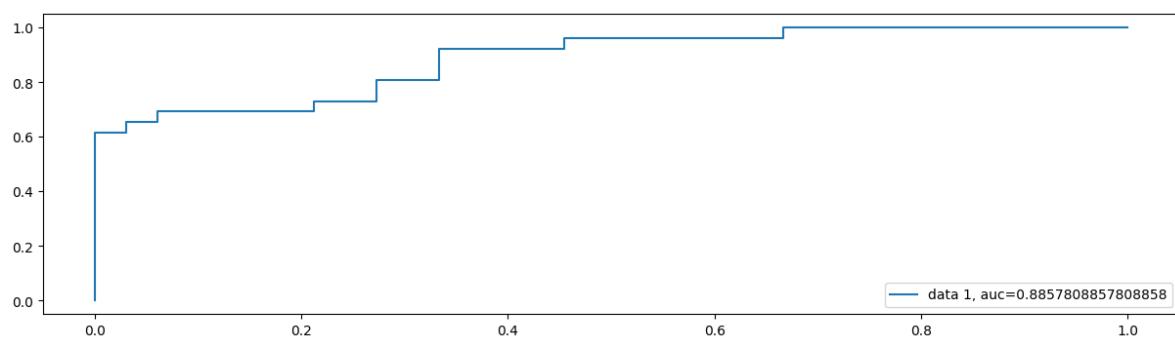


Fig 4.6: Logistic Regression ROC Curve

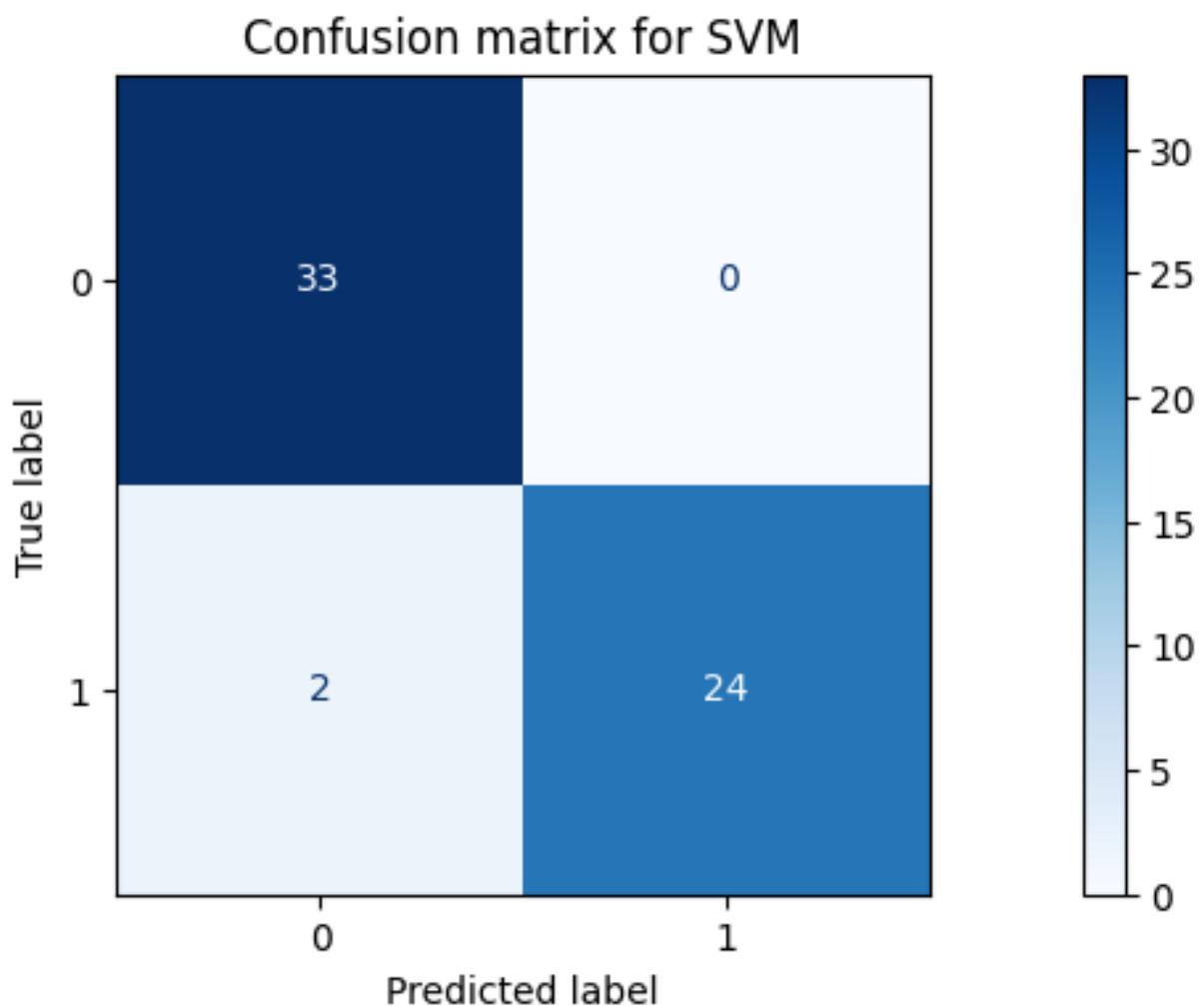


Fig 4.7: SVM Confusion Matrix

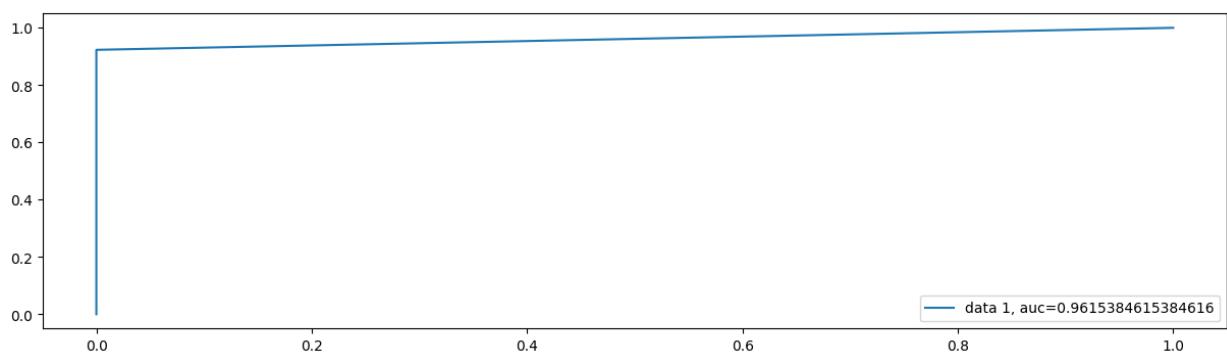


Fig 4.8: SVM ROC Curve

## Confusion matrix for Naive Bayes

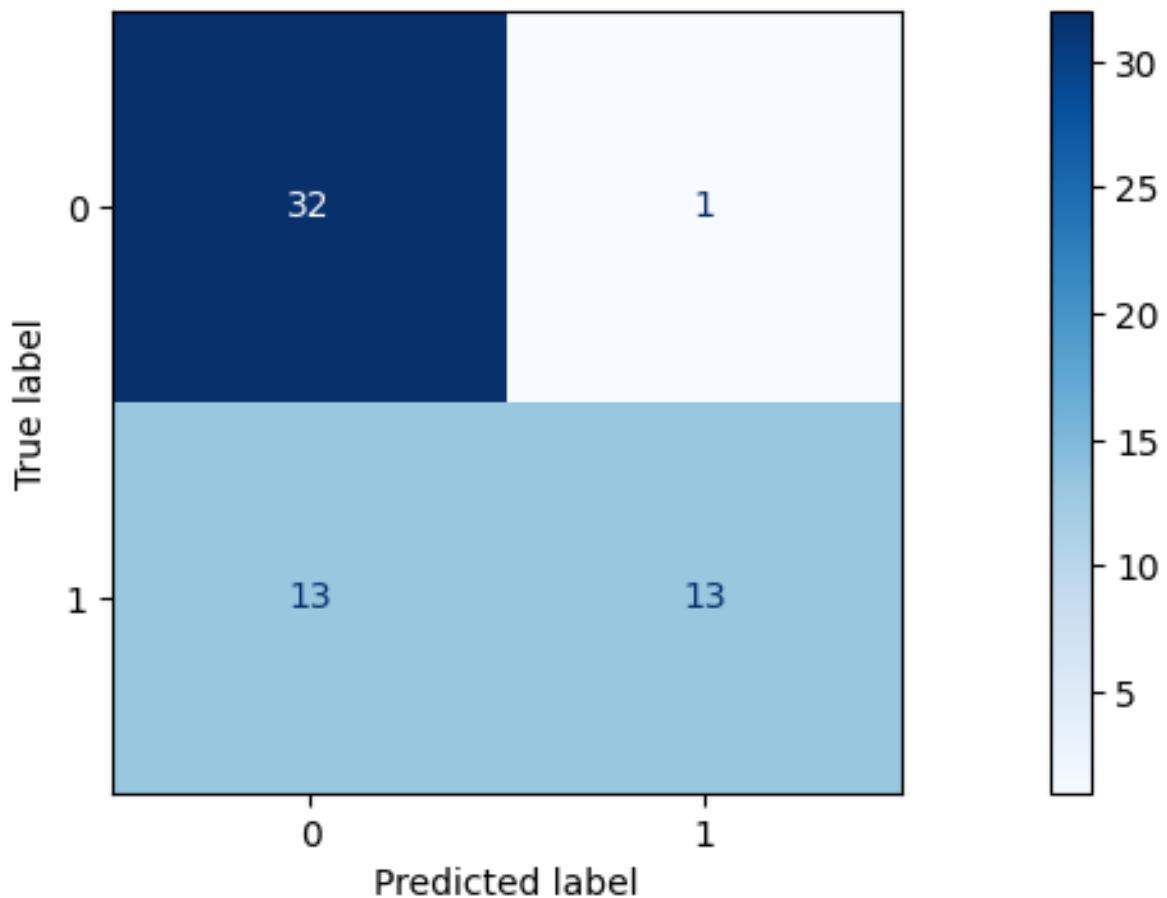


Fig 4.9: Naive Bayes Confusion Matrix

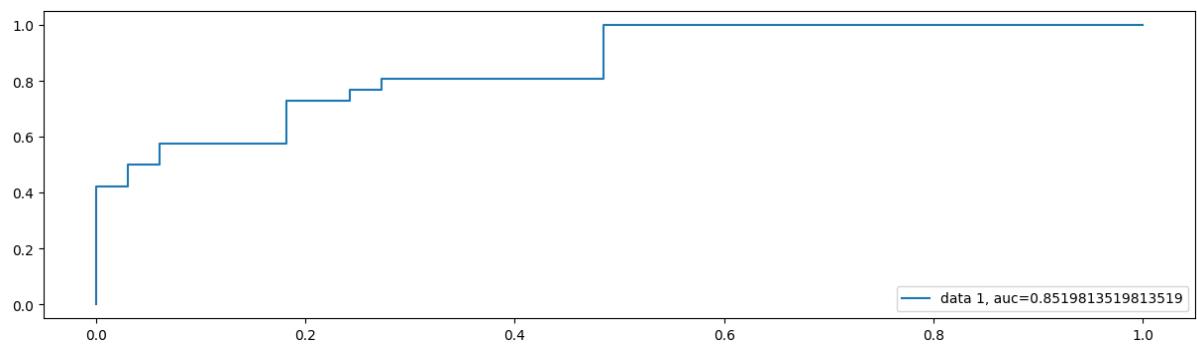


Fig 4.10: Naive Bayes ROC Curve

## Confusion Matrix for KNN

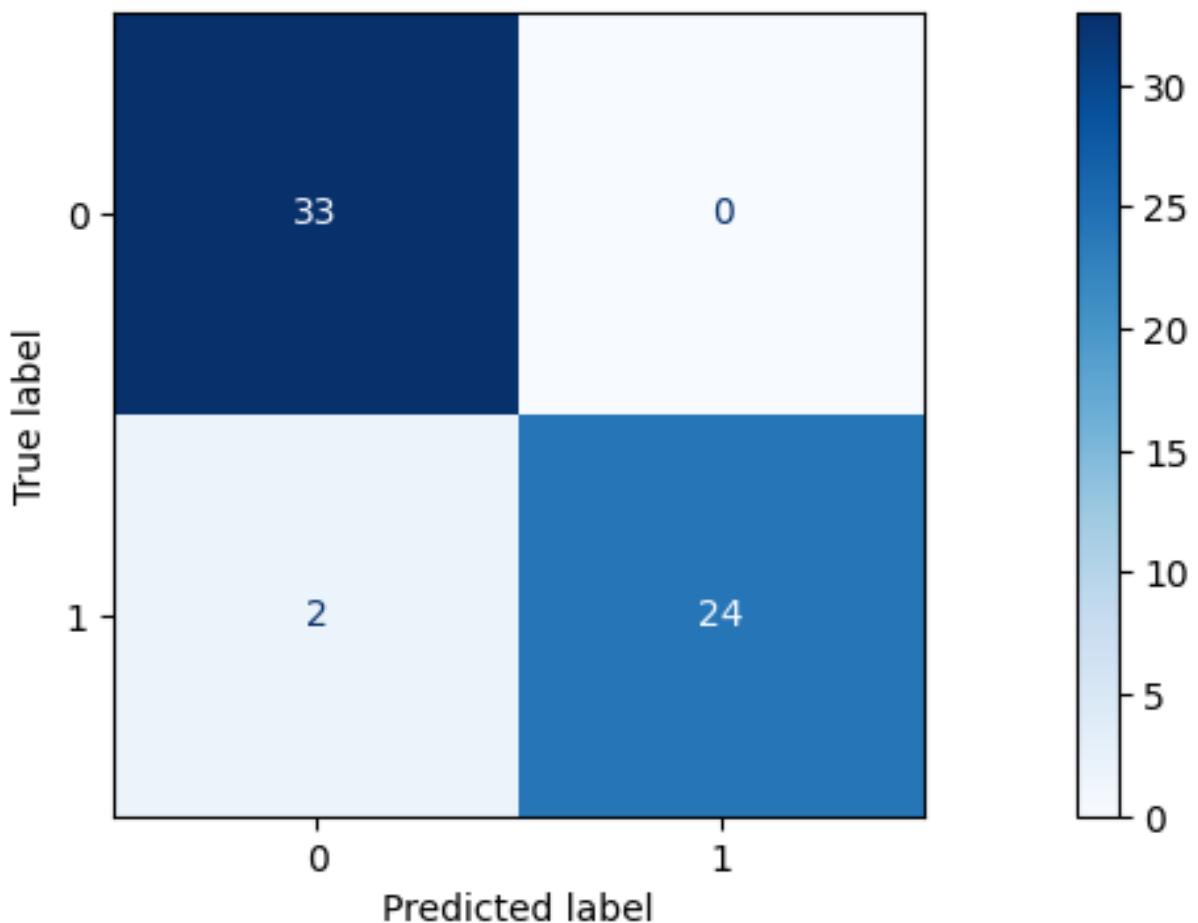


Fig 4.11: KNN Confusion Matrix

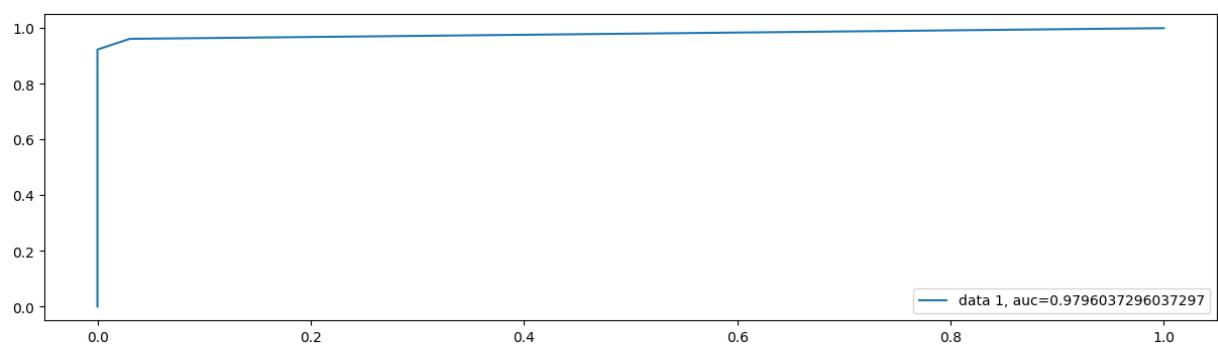


Fig 4.12: KNN ROC Curve

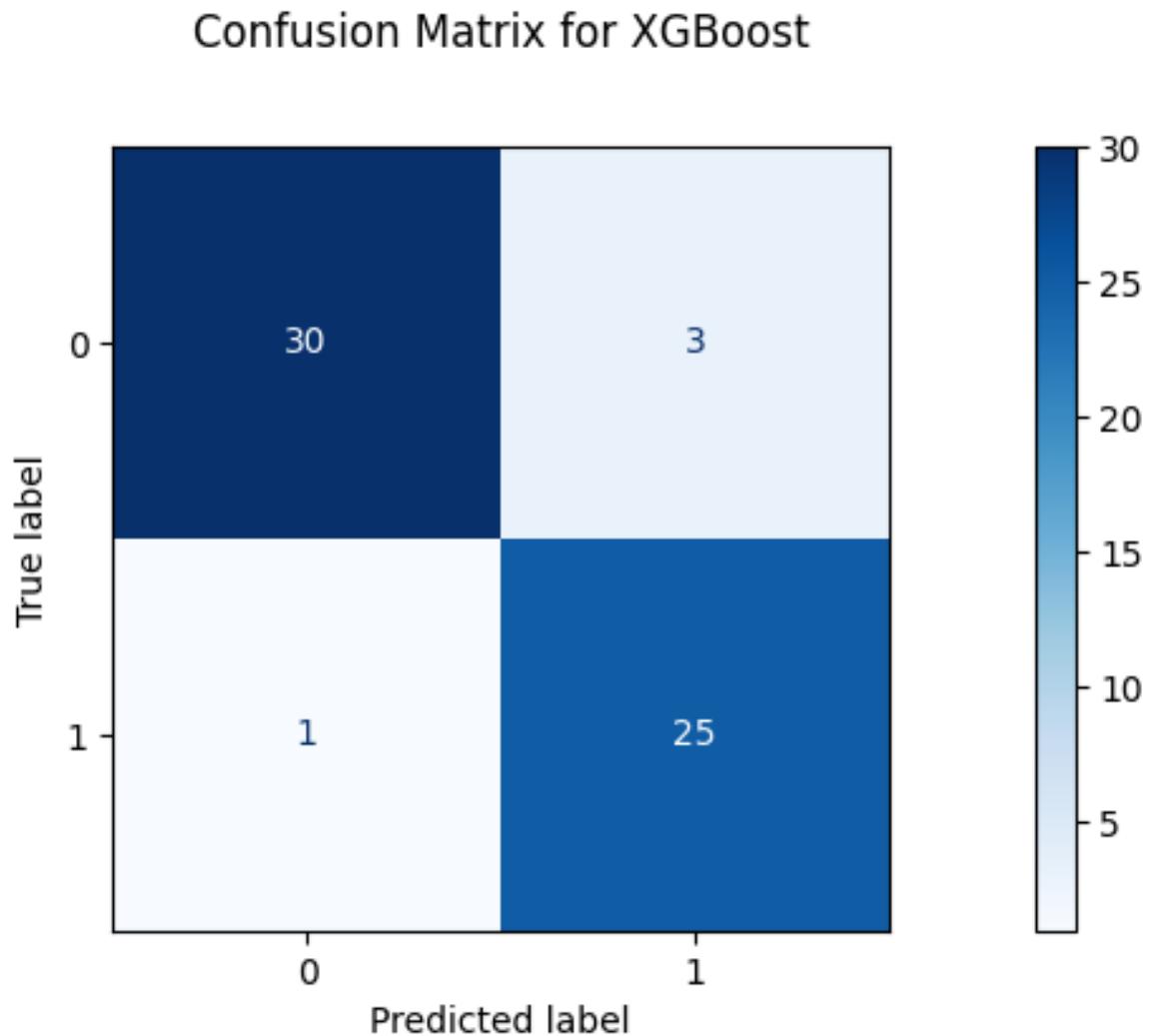


Fig 4.13: XGB Confusion Matrix

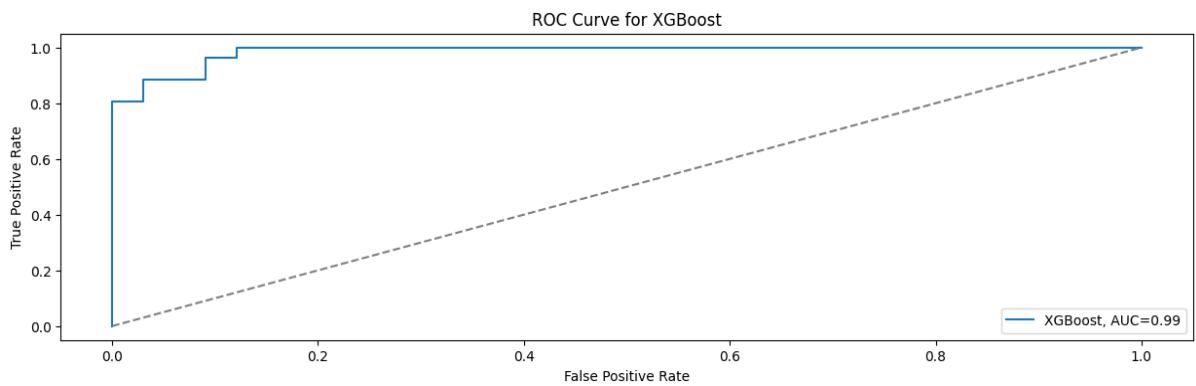


Fig 4.14: XGB ROC Curve

## **4.4 Discussion**

According to the study, machine learning is able to accurately and painlessly assess Parkinson's disease by analyzing voice samples. The abilities of XGBoost and Random Forest emphasize their usefulness for this application. Because of these findings, early detection tools and simple systems for patient monitoring may become possible, improving care for all patients and making health resources more available.

Yet, we should point out that this research has its own limits and additional study is still required. The next step is to test these results on larger, more mixed datasets and investigate clinical applications for voice diagnostic methods.

## **4.5 FINAL COMPARATIVE ANALYSIS**

The completion of this project has greatly relied on the intelligent ideas and support they provided. Our paper would not have been possible without the dataset provided by the UCI Parkinson's researchers and developers.

Metric	DT	RF	LR	SVM	NB	KNN	XGB
Accuracy	<b>0.847</b>	<b>0.966</b>	<b>0.831</b>	<b>0.966</b>	<b>0.763</b>	<b>0.966</b>	<b>0.932</b>
F1-Score	<b>0.842</b>	<b>0.961</b>	<b>0.783</b>	<b>0.960</b>	<b>0.650</b>	<b>0.960</b>	<b>0.926</b>
Recall	<b>0.923</b>	<b>0.961</b>	<b>0.692</b>	<b>0.923</b>	<b>0.500</b>	<b>0.923</b>	<b>0.962</b>
Precision	<b>0.774</b>	<b>0.961</b>	<b>0.900</b>	<b>1.000</b>	<b>0.929</b>	<b>1.000</b>	<b>0.893</b>
R2-Score	<b>0.381</b>	<b>0.862</b>	<b>0.312</b>	<b>0.862</b>	<b>0.037</b>	<b>0.862</b>	<b>0.725</b>

Table 1: PERFORMANCE METRICS FOR DIFFERENT  
MACHINE LEARNING MODELS

# **CHAPTER 5**

## **CONCLUSION AND FUTURE SCOPE**

This chapter concludes the report by summarizing the main findings of the study on Parkinson's disease detection using voice analysis and outlining potential avenues for future research to further enhance the development and application of this technology.

### **5.1 Conclusion**

This study has demonstrated the effectiveness of machine learning techniques for the detection of Parkinson's disease using voice analysis. The results highlight the potential of ensemble methods, particularly XGBoost and Random Forest, for achieving high accuracy in classifying individuals with and without Parkinson's disease based on their voice patterns. These models outperformed traditional classifiers, such as Logistic Regression and Naive Bayes, which struggled to capture the complex relationships and intricacies of speech features.

The findings of this research support the use of machine learning models for early and non-invasive Parkinson's disease detection, offering a promising avenue for improving diagnosis and patient care.

### **5.2 Future Scope**

Although the findings are positive, additional work is needed to strengthen, perfect and practically apply these detection tools. In the following years, research needs to focus on:

- **Using High-Level Computational Approaches:** Examining the use of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTMs) to automate creating features and

achieve better success in classifying birthdays. Because they pick up on minute patterns in the data, deep learning models are often more accurate in spotting difference.

- **Feature Engineering:** More features can be extracted from speech by including further acoustic and prosodic characteristics. It may mean including features that handle intonation, rhythm and other speech differences caused by Parkinson's disease. The model could be improved if it contained more detailed elements to describe speech impairments and better tell Parkinson's patients apart from individuals without the disease.
- **Systems to Detect Voice Tremor:** Building applications that monitor a person's voice in real time to help monitor the progress of Parkinson's disease. As a result, these systems may help spot problems early, follow patients from home and act promptly, improving how people feel and live.

Working alongside neurologists and speech therapists to confirm the utility of the model in real medical situations. To do this, the system would be evaluated using a range of patients and how it compares to common medical tests. It is essential to validate clinical systems using voice technology to check their effectiveness and dependability in medical applications.

With these research directions, computerized voice analysis may help detect Parkinson's early on, prompting quick medical support and better results for affected patients.

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## **APPENDIX 1**

**Appendix A:** UCI Dataset License and Description

**Appendix B:** Python Code for Feature Extraction

**Appendix C:** Ethical Approval Documentation

**Appendix D:** Confusion Matrices for All Models



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# Integrative Healthcare System AI-Driven Disease and Patient Diagnosis System

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**Abstract**—Parkinson’s Disease (PD) is a degenerative neurological condition affecting motor function and speech, providing diagnostic challenges due to mild early signs. This study explores computational voice analysis for PD detection using a public dataset of acoustic recordings from PD patients and healthy individuals. Key biomarkers like frequency variability, pitch instability (jitter), amplitude fluctuation (shimmer), harmonic distortion (noise to harmonics ratio), and nonlinear complexity indices are analyzed to identify pathological voice patterns. Seven supervised algorithms, including ensemble tree based methods (Random Forest, XGBoost), probabilistic classifiers(Naive Bayes), and kernel based models (SVM), are evaluated for diagnostic reliability. Performance metrics such as accuracy, sensitivity, F1 score, and ROC AUC are used to optimize early detection. Results highlight ensemble methods as robust solutions for imbalanced voice data. The research emphasizes the potential of voice based machine learning tools as non invasive screening aids in remote healthcare, enabling timely interventions to mitigate disease progression.

**Keywords:** Parkinson’s Disease, K-Nearest Neighbour, Support Vector Machines, Convolutional Neural Networks, Recurrent Neural Networks, Noise to Harmonics Ratio

## I. INTRODUCTION

Parkinson’s disease (PD) is one example of a neurodegenerative condition that evolves due to the gradual decay of dopamine producing neurons in the “substantia nigra”, which is important for motor control is formed. This type of neuron destruction shows itself through physical and non physical manifestations such as tremors, bradykinesia, muscle stiffness, balance problems, alongside speech issues, cognitive decline, mood disorders and depression. Mitigation of the ailment’s progression heavily depends on early diagnosis, however, it is made difficult due to the diagnostic procedures that relies solely on the clinician’s rudimentary evaluation checklist.

There is an urgent call for standardized diagnosis tools: objective and devoid of the clinician’s discretion bias [6]. Dysphonia is an overlooked yet promising area for PD detection, often occurring before motor symptoms present themselves.

Even at these early stages, patients soften their speech, become less articulate, and speak in a monotone which leads to more pronounced cases of breathiness [15]. Even if these changes are easy to overlook, the new potential created by computational analytics permits measuring the assessment of voice patterns for early diagnosis [13]. Important features of the voice signal like variations of the Fo as well as non-uniform vocal event occurrences (jitter, shimmer) make reaching this goal achievable .

Further strengthen the armament for predictive analytics with probabilistic techniques including Naive Bayes, alongside proximity based K-Nearest Neighbours (KNN) and gradient boosted XGBoost models [15]. Performance metrics including accuracy, precision, recall, F1 score, and ROC AUC are employed to objectively assess these models so assuring a thorough evaluation of diagnostic dependability. This study evaluates the effectiveness of voice biomarkers for PD identification through a comparative analysis of machine learning algorithms [4]. The study aims to develop efficient frameworks for non-invasive, automated diagnosis by training classifier models on acoustic data and evaluating their accuracy [1].

Moreover, it analyses pragmatic problems in applying such systems inside clinical and telemedicine models, thereby maybe allowing remote monitoring and rapid therapies. These findings potentially alter early PD diagnosis, decrease reliance on subjective assessments, and boost accessibility to care, particularly in impoverished locations [11]. By bridging data driven innovation considering clinical needs, our work contributes to the rising field of digital biomarkers, enabling scalable techniques for neurodegenerative disease management.

## II. RELATED WORK

Parkinson’s Disease (PD) is a progressive neurodegenerative disorder distinguished by the slow loss of dopaminergic neurons in the substantia nigra, a brain area critical for regulating movement. This neuronal degeneration disrupts motor function, resulting in hallmark symptoms such as resting

tremors (rhythmic shaking in limbs), bradykinesia (slowness of movement), muscle rigidity, and postural instability. These non motor symptoms, such as hypophonia (reduction in vocal volume) and dysprosody (loss of normal rhythm in speech), add to the challenge of diagnosing PD (Parkinson's disease). These emerging vocal impediments, even if subdued in initial stages, are of great importance for early diagnosis. They present a low risk diagnostic option as mentioned in citation [9].

Utilization of machine learning for diagnosing case of PD has grown tremendously, with supervised learning models spearheading the analysis of voice patterns [5]. Early breakthroughs by Little et al.(2009) [2] indicated the efficacy of Support Vector Machines(SVM) in categorising PD patients using dysphonia measures, reaching great accuracy by differentiating pathological voice patterns. Subsequent research broadened this paradigm: Sakar et al. (2017) [2] underlined the merits of ensemble methods such as Random Forests in comparison to more primitive approaches like single Decision Trees, attributing their robustness to overfitting and generalization capabilities. However, simpler models such as Logistic Regression and Naive Bayes, as studied by Chen et al. (2020) [7], encountered challenges in modeling sophisticated relationships in multi-dimensional sound recordings and revealed the need for refined computation approaches.

Model performance has been reported to benefit from feature engineering [10]. PCA identifies distinguishing features of a voice and simplifies datasets which enables focus to be placed on more relevant aspects of the signal like background noise (jitter and shimmer) being suppressed. Nonlinear analysis, like entropy and fractal dimension analysis has identified chaotic speech patterns associated with Parkinson's disease and has shed more light on the concept of illness specific dysphonia. [12].

Recent innovations in deep learning have further revolutionized PD detection. For instance, Xie et al.(2020) harnessed Convolutional Neural Networks(CNNs) to automatically extract spectral features from voice recordings, coupled with Recurrent Neural Networks(RNNs) to model temporal dependencies, outperforming conventional models in cross-validation studies. Hybrid frameworks, such as SVM paired with genetic algorithms for feature selection, have also demonstrated enhanced accuracy by prioritizing biomarkers like noise to harmonics ratio(NHR) and fundamental frequency variation. Despite these advancements, the field lacks consensus on optimal model selection and feature relevance.

Building on these foundations, this study adopts a systematic framework to evaluate seven machine learning algorithms Decision Trees, Random Forests, Logistic Regression, SVM, Naive Bayes, K-Nearest Neighbors(KNN), and XGBoost, while dissecting the contribution of individual vocal features to classification outcomes [5]. By synthesizing insights from accuracy, precision, F1 score, and ROC AUC metrics, the research addresses methodological gaps in existing literature [8]. Notably, it investigates the clinical viability of deploying these models in telemedicine platforms, where rapid, voice-based screening could democratize access to early diagnosis.

This methodological gap specifically, the absence of standardized benchmarks for PD voice analysis motivates the study's comparative approach.

### III. METHODOLOGY

#### A. Dataset Description

The UCI Parkinson's dataset consists of 195 instances with 23 attributes derived from voice recordings. These attributes include:

- Fundamental Frequency Features – MDVP:Fo(Hz), MDVP:Fhi(Hz), MDVP:Flo(Hz)
- Jitter (Frequency Variation) – MDVP:Jitter(%), MDVP:RAP, MDVP:PPQ
- Shimmer (Amplitude Variation) – MDVP:Shimmer, Shimmer:APQ3, MDVP:APQ
- Noise-to-Harmonics Ratio – NHR, HNR
- Nonlinear Dynamical Complexity Measures – RPDE, DFA, spread1, spread2, D2, PPE
- Target Variable – status (1 = Parkinson's, 0 = Healthy)

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Feature	Description
Subject Identifier	Unique label combining the subject's ID and session number, used for tracking individuals.
Maximum Pitch (Fo)	The highest pitch reached during vocal activity, showing how much the voice can vary.
Jitter	Captures small, rapid changes in pitch from one vibration cycle to the next (pitch instability).
Shimmer	Represents amplitude fluctuations between consecutive voice cycles (volume instability).
Noise to Harmonics Ratio (NHR)	Measures the ratio of noise components to harmonic components in the voice, indicating clarity or distortion.
Complexity Measures	Looks at irregular vocal signal patterns using entropy and nonlinear metrics to detect abnormalities.
Spread (1 & 2)	Quantifies how much the pitch deviates from the average (e.g., Spread1 for overall variation, Spread2 for local fluctuation).

This dataset provides rich voice-based biomarkers, making it suitable for computational PD diagnosis.

#### B. Data Preprocessing

To ensure robust data quality and model efficiency, we implement a systematic workflow. First, we address incomplete data by filling gaps to preserve dataset integrity. Next, we normalize all features to a 0–1 scale, eliminating bias from variable magnitudes. The data is then split into training 80% and testing 20% subsets to validate performance objectively. Finally, we identify and retain only the most impactful features using statistical relevance and iterative elimination, stripping away noise and redundancy. This approach sharpens model accuracy while streamlining computational demands, ensuring practicality for real-world clinical use.

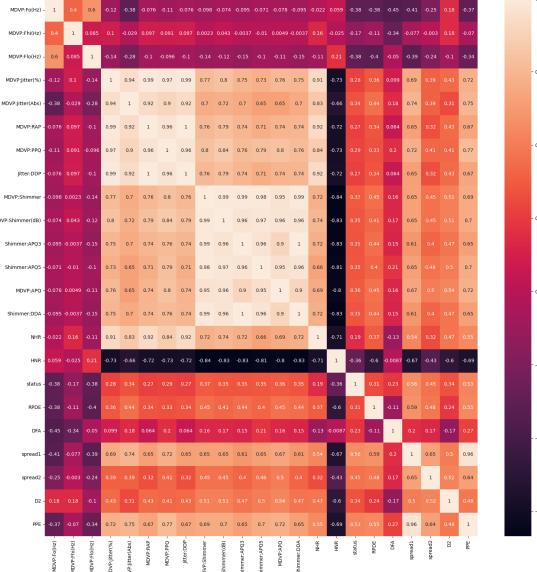


Fig. 1. correlation heatmap

### C. Machine Learning Models

To achieve a comparative analysis in Parkinson's Disease detection, we implement seven different machine learning models, each offering distinct classification capabilities. The Decision Tree Classifier follows a hierarchical rule based learning approach, making decisions through a series of logical conditions. The Random Forest Classifier, an ensemble method, combines numerous decision trees to minimize variance and enhance predicted accuracy. Logistic Regression, a probabilistic binary classifier, calculates the likelihood of a given input belonging to a specified class. Support Vector Machine optimizes the separation margin between classes, ensuring effective classification even in high-dimensional spaces. The Naive Bayes classifier, a fast and efficient probabilistic model, operates under the assumption of feature independence. The K-Nearest Neighbors algorithm classifies instances based on proximity to neighboring data points, utilizing distance metrics. Lastly, the XGBoost Classifier, an optimized gradient boosting model, enhances performance by minimizing errors through iterative improvements.

To evaluate model performance, various statistical metrics are utilized. Accuracy is calculated as the proportion of correctly classified cases, determined by the formula:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

where TP(True Positives) and TN(True Negatives) represent correctly predicted Parkinson's and non-Parkinson's cases, respectively, while FP (False Positives) and FN (False Negatives) denote misclassifications. Precision, defined as:

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

measures the proportion of correctly identified Parkinson's cases among all predicted positive cases. Recall (Sensitivity), computed as:

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

assesses the model's ability to detect actual Parkinson's cases. The F1 score, given by:

$$F1\text{-score} = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

provides a harmonic mean between precision and recall, balancing the trade off between false positives and false negatives. Finally, the ROC AUC score analyzes classification quality by calculating the area under the receiver operating characteristic curve, demonstrating the model's ability to discriminate between Parkinson's and healthy individuals at varied probability levels.

### D. Voice Feature Extraction Process

This work employs an automated approach to diagnose Parkinson's Disease (PD) using speech analysis. The workflow involves three stages:

- Audio Preprocessing:** A user provides a voice sample, which is cleaned to remove background interference using noise reduction algorithms. The audio is split into short segments to analyze subtle speech changes over time, and open-source audio analysis tools (e.g. Librosa) identify key vocal markers.
- Feature Computation:** The system calculates metrics linked to PD symptoms, such as pitch variations (average, high, and low ranges), irregular voice vibrations ("jitter"), volume fluctuations ("shimmer"), and clarity (noise to harmonics ratio). Complexity metrics, like entropy-based measures and signal stability indices, are also derived to detect chaotic speech patterns.
- Model Inference Prediction:** Algorithms that have been trained previously Evaluate the obtained measures to allocate the example to either 'PD likely' or 'healthy'. Best performers (XGBoost for example) concentrate on precision. How well claims are made for dependability, especially with clinical work, determines how useful these claims are for using in actual practice. This also eases the burden of first stage PD screening by turning voice anomalies input to actionable steps devoid of drilling procedures.

This approach streamlines early PD screening by translating voice irregularities into actionable insights without invasive procedures.

## IV. RESULTS AND DISCUSSION

After evaluating the models, XGBoost and Random Forest consistently delivered the strongest results. Their success stems from their capacity to model complex, nonlinear relationships within voice data, using combined tree based strategies to minimize errors and improve reliability. SVM

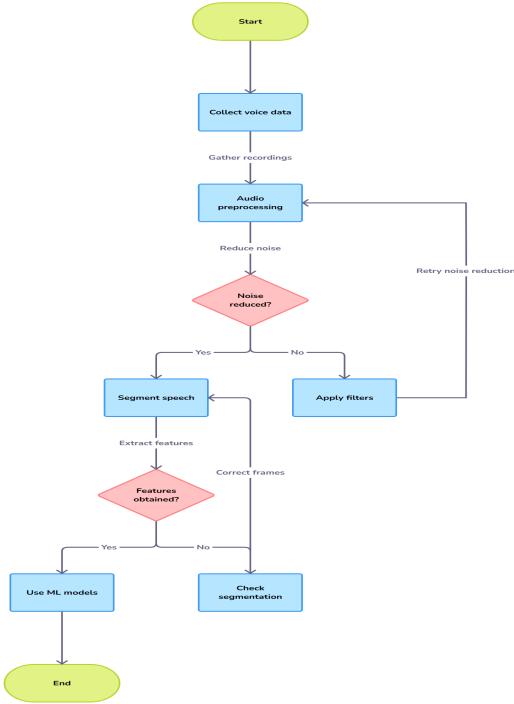


Fig. 2. Performance Metrics Visualization

also performed well, particularly in ambiguous cases, thanks to its ability to define clear decision boundaries between classes. Simpler models like Logistic Regression and Naive Bayes lagged behind, struggling to interpret intricate patterns in vocal features. Naive Bayes faced additional hurdles due to its reliance on oversimplified assumptions about feature independence, which clashed with the interconnected nature of voice biomarkers. KNN's performance suffered further, as noise and high dimensional data amplified its limitations, making it less practical for real world diagnostics. To understand what drives predictions, we examined key vocal markers. Models like XGBoost and Random Forest highlighted frequency related features such as average, maximum, and minimum pitch as critical for detecting vocal tremors, a common PD symptom. Nonlinear measures, including entropy based and signal stability metrics, also stood out for their ability to differentiate patients from healthy individuals. Metrics capturing vocal instability, like irregular pitch and volume fluctuations, further reinforced the diagnostic value of voice analysis. These insights validate voice based tools as practical, non invasive methods for early PD detection, aligning with clinical observations of speech degradation in patients.

#### A. Confusion Matrix and ROC Curve

To evaluate how effectively the models distinguish between Parkinson's and healthy cases, we analyze their predictions using a results breakdown table. This table categorizes outcomes into four groups:(1) correct Parkinson's detections, (2) correct identifications of healthy individuals, (3) healthy

cases mistakenly flagged as Parkinson's, and (4) Parkinson's cases overlooked by the model. Examining these categories helps us to find how often the model differs between the two groups, thereby giving priority to its capacity to prevent crucial mistakes. For clinical trust and patient safety, missing actual Parkinson's cases or triggering false alarms is absolutely crucial.

We use a threshold sensitivity graph to depict the decision-making behavior of the model and hence evaluate performance. This graph shows how well the model balances its tendency to misclassify healthy people (false positives) as detection thresholds change against its accuracy in Parkinson's disease (true positives). This balance is quantified by a performance score between 0 and 1; numbers nearer 1 indicate almost perfect accuracy and lowest error.

By integrating these methods, we identify models that excel in real-world circumstances, where eliminating diagnostic errors is crucial. This technique delivers accurate, actionable insights for healthcare applications, where accuracy directly influences treatment decisions and patient well-being.

Confusion matrix for Decision Tree

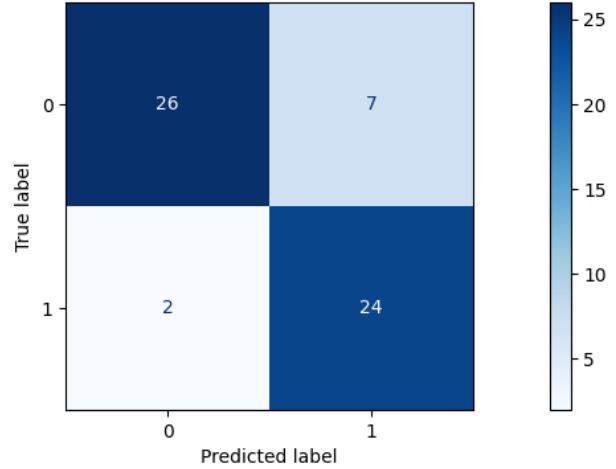


Fig. 3. Decision Tree Confusion Matrix

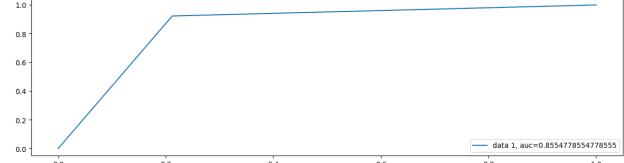


Fig. 4. Decision Tree ROC Curve

#### V. FINAL COMPARATIVE ANALYSIS

Their incisive ideas and assistance have considerably assisted to the effective completion of this project. We also express our thanks to the researchers and developers of the UCI Parkinson's dataset for making their data publicly available, which played a significant role in our work.

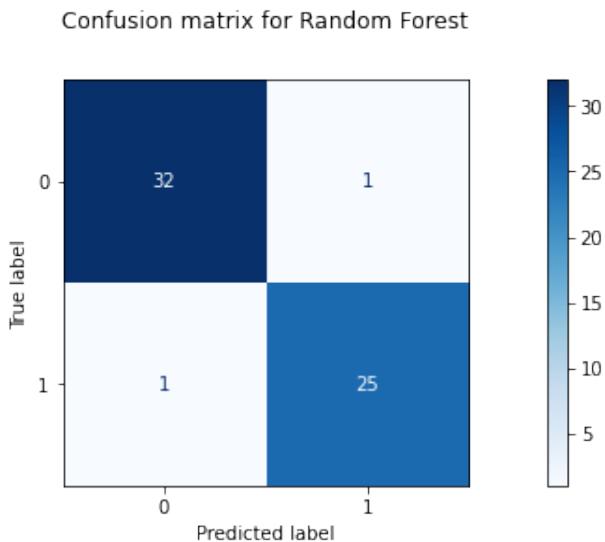


Fig. 5. Random Forest Confusion Matrix

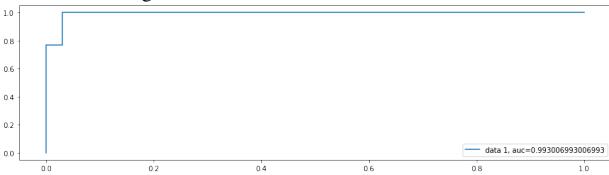


Fig. 6. Random Forest ROC Curve

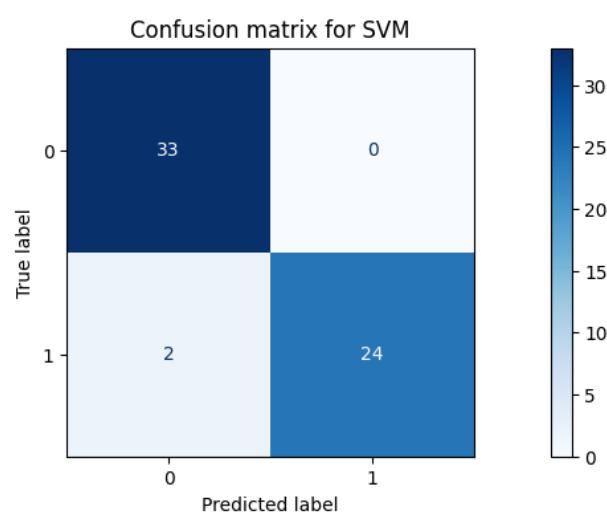


Fig. 9. SVM Confusion Matrix

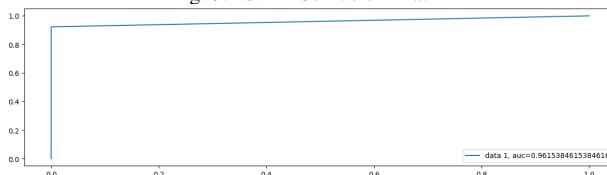


Fig. 10. SVM ROC Curve



Fig. 7. Logistic Regression Confusion Matrix

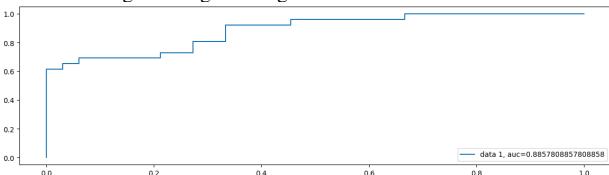


Fig. 8. Logistic Regression ROC Curve

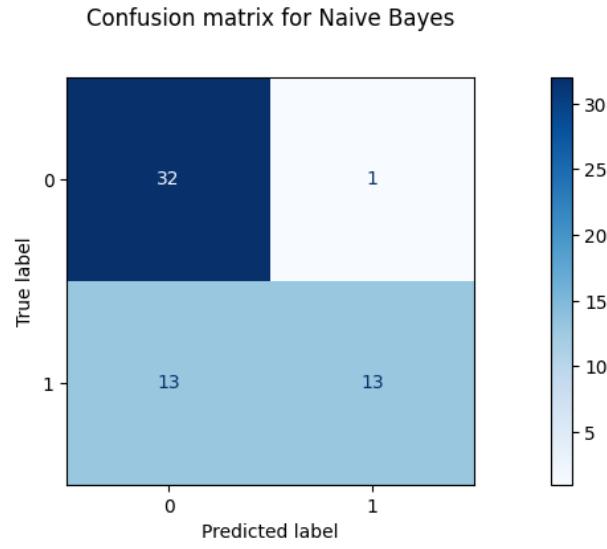


Fig. 11. Naive Bayes Confusion Matrix



Fig. 12. Naive Bayes ROC Curve

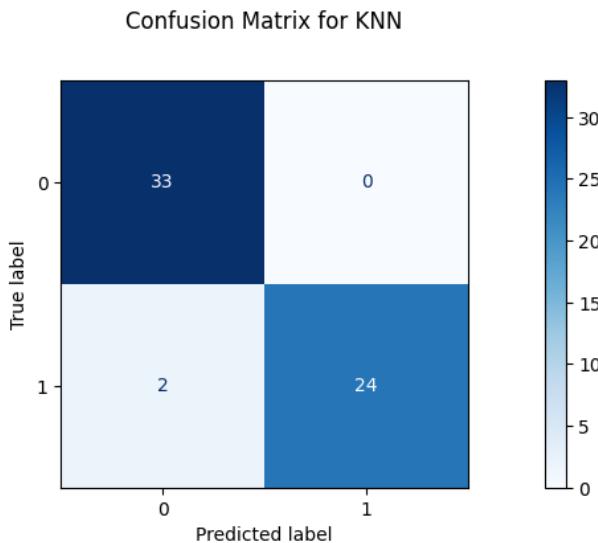


Fig. 13. KNN Confusion Matrix

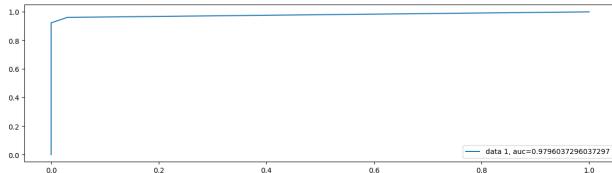


Fig. 14. KNN ROC Curve

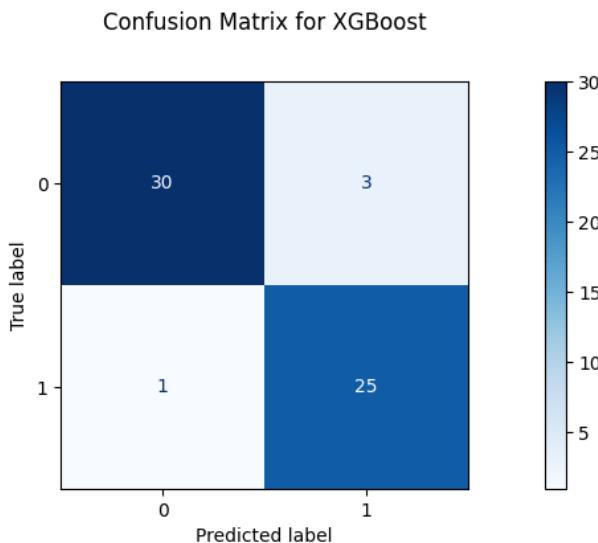


Fig. 15. XGBoost Confusion Matrix

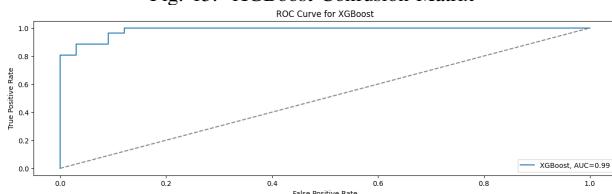


Fig. 16. XGBoost ROC Curve

Metric	DT	RF	LR	SVM	NB	KNN	XGB
Accuracy	0.847	0.966	0.831	0.966	0.763	0.966	0.932
F1-Score	0.842	0.961	0.783	0.960	0.650	0.960	0.926
Recall	0.923	0.961	0.692	0.923	0.500	0.923	0.962
Precision	0.774	0.961	0.900	1.000	0.929	1.000	0.893
R2-Score	0.381	0.862	0.312	0.862	0.037	0.862	0.725

TABLE I  
PERFORMANCE METRICS FOR DIFFERENT  
MACHINE LEARNING MODELS

## VI. CONCLUSION AND FUTURE WORK

This study focuses on the effectiveness of machine learning in detecting Parkinson's Disease (PD) through voice analysis. The results illustrate that ensemble methods, especially XG-Boost and Random Forest, offer the best accuracy because of their non-linear dimensional subclass speech feature expressions. These models surpass conventional classifiers like Logistic Regression and Naive Bayes, which do not cope with the complex interdependencies of speech features and voice pattern intricacies. The results support the importance of pd diagnostics using machine learning models for early and non-invasive detection.

The results are promising, but further research is needed to enhance model robustness and ensure real-world applicability. Several key areas for future improvement include:

- **Advanced Computational Methods:** Investigating deep learning approaches such as Convolutional Neural Networks(CNNs) and Long Short-Term Memory(LSTMs) for automated feature extraction and enhanced classification accuracy.
- **Feature Engineering:** Expanding the set of voice based features by incorporating additional acoustic and prosodic parameters, which could provide a more comprehensive representation of speech impairments in PD patients.
- **Real-Time Detection Systems:** Developing a mobile or web based application capable of real time voice analysis for continuous PD monitoring, making the technology accessible for early detection and patient follow-up.
- **Clinical Integration:** Collaborating with neurologists and speech therapists to test the model's effectiveness in real-world diagnostic situations, confirming its practicality for medical application.

By integrating these advancements, voice based computational analysis has the potential to become a valuable tool in early PD detection, enabling timely medical intervention and improved patient outcomes.

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