PARKINSON DISEASE DETECTION USING MACHINE LEARNING WITH EXPLAINABLE AI

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This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project titled **"Parkinson disease detection using machine learning with Explainable AI"**, submitted by Jannatul Ferdaous, ID No: 201-15-3226 to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on *26-01-2024*.

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DECLARATION

I hereby declare that, this project has been done by us under the supervision of **Ms. Nasima Islam Bithi, Lecturer, Department of CSE,** Daffodil International University. I also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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ABSTRACT

Aside from its effects on the nervous system, Parkinson's disease also modifies the physiological functions that the nervous system regulates. The progressive nature of Parkinson's disease makes it a degenerative disorder. A variety of symptoms, such as rigidity, tremor, speech impediment, sluggishness, and trouble walking, can be intentionally induced. These same principles are applicable to issues like depression, anxiety disorders, and similar ailments. We aim to use machine learning algorithms to identify cases of Parkinson's disease (PD) in patient-created audio recordings. Time Frequency Features, Mel Frequency Cepstral Coefficients (MFCCs), Vocal Fold Features, TWQT features, and Wavelet Transform-based Features are some of the speech signal processing methods that were used to extract clinically important data from the audio recordings in order to evaluate PD. In order to glean useful information from the recordings, these methods were employed. The objective of this research endeavour is to assess a number of these models by means of a number of machine learning techniques, such as Logistic Regression, XGBoost, Adaboost, Decision Tree, Support Vector Machine, Naive Bayes, and Random Forest, among others. The application uses voice attribute-based data preparation, which allows for the measurement of effectiveness. By the end of the experimental evaluation, the XGBoost classifier had achieved the maximum achievable accuracy of 88%. The authors of this study used explainable AI to zero in on the problem of creating models that laypeople might understand.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF FORMULA

CHAPTER 1
INTRODUCTION

1.1 Introduction

Deterioration of the neurological system causes Parkinson's disease (PD), a disorder characterised by tremors and stiffness of body parts. When neurons in certain parts of the brain are injured, die, or become weak, it can lead to problems with movement, tremor, or stiffness in the trunk or limbs. Studying the causes of Parkinson's disease (PD) and creating better treatments to help people with the condition live better lives is why this field is so important. Biomarkers for Parkinson's disease (PD) that can be detected early might lead to faster and more effective treatments [1]. On top of that, research can help find new therapeutic targets and create new medicines to stop or delay the disease's course [2]. Participation in research studies by people with Parkinson disease (PD) can increase our knowledge of the disease and lead to the development of new treatments. There are a number of advantages to studying Parkinson's disease. As scientists learn more about what causes Parkinson's disease, they will be able to create more effective drugs, which will improve patients' quality of life. The development of more effective treatments for Parkinson's disease may be possible if biomarkers could be found through scientific research and used for earlier diagnosis. Research can also help find new drug targets, which can lead to innovative treatments that can slow or stop the disease in its tracks. By taking part in studies, people with Parkinson's disease can help researchers better understand the disease and find new ways to treat it. Finding a treatment that works for Parkinson's disease is extremely difficult because the ailment is complex and has many different aspects. A wide variety of motor and non-motor symptoms are brought on by the disease's root cause: the degeneration of dopamine-producing neurons in the brain. The present drugs for Parkinson's disease may alleviate movement symptoms, but they aren't very effective at slowing the disease's course or treating other symptoms [3]. Adding to the difficulty of dealing with the disease is finding effective pharmaceutical therapies to slow its course, which is marked by gradually worsening symptoms. Furthermore, there is still much mystery surrounding the origins of Parkinson's disease (PD), which hinders the development of effective targeted treatments. Still, a lot of work is being put into it to figure out what causes Parkinson's disease (PD) and how to cure it. People living with Parkinson's disease (PD)

who take part in research help expand our understanding of the disease and pave the way for new treatments. In this study, we examined biological voice measurements from 188 Parkinson's disease (PD) patients, ranging in age from 33 to 87 years old. The patients included 107 males and 81 women. The 64 physically fit individuals that made up the control group range in age from 41 to 82 years, with 23 males and 41 females making up the group. Each subject's sustained phonation of the vowel /a/ was recorded three times after the doctor's examination, and the microphone was calibrated to 44.1 KHz as part of the dataset collection process. Time Frequency Features, Mel Frequency Cepstral Coefficients (MFCCs), Vocal Fold Features, TWQT features, and Wavelet Transform based Features are among the speech signal processing algorithms that have been used to process speech recordings from Parkinson's disease (PD) patients in order to extract clinically meaningful data for PD assessment. Many researchers have tried to use machine learning algorithms to detect Parkinson's disease.[21]

1.2 Motivation

Because of it affects so many people, Parkinson's disease is becoming more common and faster every day. Neurons are a type of brain cell that deteriorate or die out in Parkinson disease sufferers over time. The degeneration of dopamine-producing neurons on brain is the root cause of numerous symptoms experienced by people with Parkinson's disease. Previously recorded the six million Parkinson cases reported in 2016, the estimated 9.4 million Parkinson patient cases globally in 2020 is significantly higher.[12] According to various national statistics, the United States has 930K, Germany 266K, Japan 344K, Italy 149K, the United Kingdom 142K, France 157K, and Spain 120K. Here is Figure 1.1. In an effort to foretell the disease, a small number of studies have been conducted. The prognosis of Parkinson's disease is an area that we investigate thoroughly. Their accuracy is improved by the majority of them. As a result, we test a number of different categorization models to find the one that performs the best. Lastly, this project takes a look at explainable AI as a way to predict and comprehend the human brain's exceptionally accurate Parkinson's disease symptoms.

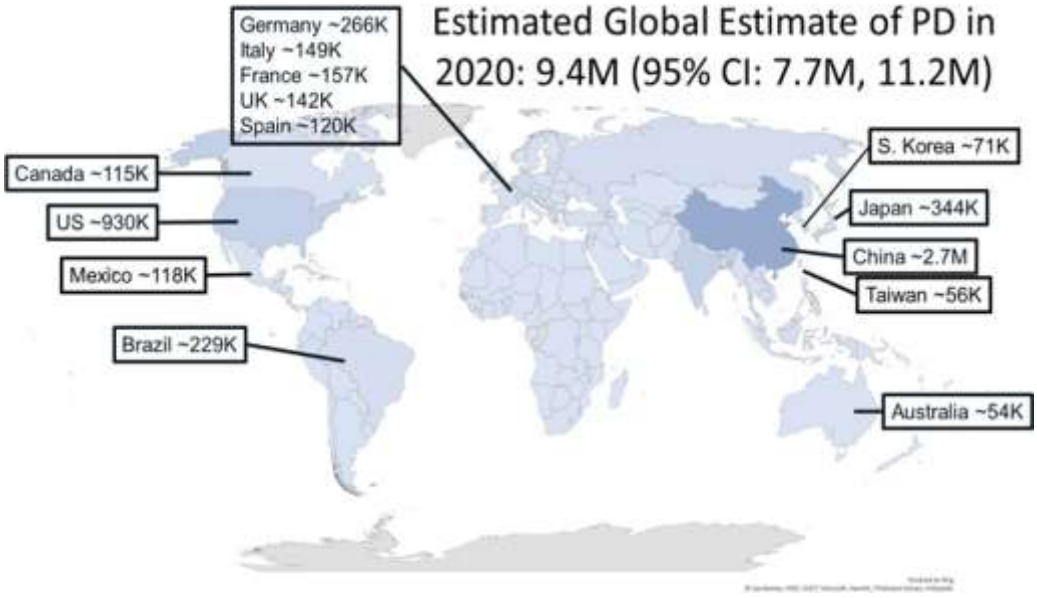


Figure 1.1: Parkinson Patient World Wide

1.3 Research Objective

- To categorize healthy controls and those with Parkinson's disease based on voice records at different frequencies.
- To develop a classical ML model to predict whether a person has Parkinsons disease or not.
- To detect Parkinson disease using multiple machine learning models.
- To introduce more accurate model.
- To Explain the instances for classified output.

1.4 The rationale of the study

A model for predicting the onset of Parkinson's disease in humans is suggested in this research. There has been recent evidence that this illness is sweeping the globe. On the other hand, we learned from our research that diagnostic and awareness technologies are lacking. In our rapidly expanding society, the cost of diagnosing and analyzing a patient's symptoms is high. It is our hope that our machine learning research will help us find a solution to this challenge.

1.5 Research Question

- What is the benefit of this proposed model?
- What is the future plan for this research work?
- Is real life implementation possible?
- Which voice feature important for this disease?

CHAPTER 2
BACKGROUND STUDY

2.1. Preliminaries

Precise Parkinson's disease layout is now possible because to machine learning methods. In this part, we will go over the research and analysis that went into studying the patient's vocal characteristics. Logistic Regression, Random Forest, Boosting, Naïve Bayes, Support Vector Machine, k-NN, Decision Tree and Bagging classification are some of the computations used by these models. A small number of academics have heavily relied on models in their investigations, namely Deep Learning models that are applicable to this area.

2.2 Related works

In order to categorize cases of Parkinson's disease using acoustic voice characteristics, Sharanyaa et al. [5] utilize machine learning techniques. Multiple algorithms, including Naïve Bayes, Random Forest, K-Nearest Neighbours, and Logistic Regression, were evaluated for their performance utilizing parametric and nonparametric machine learning approaches. Results showed that non-parametric models using K-Nearest Neighbours (90.2% accuracy) and Random Forest (87.2% accuracy) performed better in classification. In order to improve the accuracy of diagnoses, the article suggests using deep learning neural networks and adding additional speech qualities for feature extraction. Automated Parkinson's disease diagnosis is beneficial for doctors and other healthcare providers. Although there is currently no treatment or cure for the disease, it can be managed with medication and therapy. The lack of comprehensive methodology is one of the paper's limitations.

Using Big Data (BD) and Machine Learning (ML) technology, Krishna et al. [6] aims to predict and diagnose Parkinson's disease early on. The proposed method improves Parkinson's disease therapy and management by using the Logistic Decision Regression (LDR) algorithm for illness categorization. After cleaning up the Parkinson's disease dataset of irrelevant information, the next step is to use feature selection to identify the most important traits for classification. A prediction of Parkinson's disease is generated from the dataset after the ML and BD algorithms have been applied. Results showing 95% sensitivity, 93% accuracy, and 97% classification efficiency were achieved utilizing the proposed LDR method, which is encouraging.

This research primarily focuses on the building of telemonitoring and telediagnosis models, with an emphasis on speech models used to the analysis of Parkinson disease (Rahman et al., 2007). Researchers drew from a large database of Parkinson's disease patients' voice recordings; among these recordings were a number of variants of the letters "a," "o," and "u" that represent vowels. Two state-of-the-art signal processing methods, Relative SpecTrAl PLP (RASTA-PLP) and Perceptual Linear Prediction (PLP), were employed to extract features from the audio recordings. Afterwards, a Support Vector Machine (SVM) model equipped with four separate kernel types was used to categorize the audio samples. The results showed that the algorithm had a 74% accuracy rate when it came to classifying the voice samples. In addition to auto-regressive modeling and cepstral coefficient adjustment, the study employed liftering techniques for feature extraction.

The accuracy of several machine learning (ML) algorithms used to predict the onset of Parkinson's disease is the subject of a comprehensive analysis by Anila et al. The authors stress the significance of accurately diagnosing and classifying Parkinson's disease early on to stop new symptoms from appearing. The following machine learning methods were employed: Bayes, Support Vector Machines (SVM), the Optimum-Path Forest (OPF) classifier, ResNet-50, an FKNN-centered system with 10-fold cross-validation, and more. There have been several methods for predicting the presence of Parkinson's disease using data collected from various sources, including brain MRI images, speech, posture, writing, and data obtained by sensors. Speech problems, like hypophonia and dysarthria, are common in people with Parkinson's disease. This makes speech or voice data an important part of diagnosing the disease. [8]

The progressive neurodegenerative disease that impacts motor functions and quality of life is Parkinson's disease; Gomathy et al. apply machine learning techniques to identify cases of this disease. Using ML (machine learning) techniques, the scientists trained their model on massive amounts of data from both healthy individuals and those with a history of Parkinson's disease; the model then achieved a disease detection efficacy of 73.8%. According to the results, people with Parkinson's disease may soon be able to enjoy a far higher standard of living thanks to the use of voice-based models and machine learning algorithms for disease detection. In the second module, the data was trained and tested using machine learning methods. It was specifically stated that the XGBoost algorithm is used for accurate Parkinson's disease detection.[9]

Although there have been technical advancements, early prediction of Parkinson's disease is still challenging, thus the researcher examines several machine learning (ML) techniques. In order to find the best classifier for PD classification, the study compared three classifiers (Multilayer Perceptron, SVM, and KNN) on a benchmark speech dataset. The research found that the ANN classifier with the best classification accuracy (95.89%) was the one utilizing the Levenberg-Marquardt algorithm. The research evaluates several classifiers using a machine learning library benchmark speech dataset taken from the University of California, Irvine. In order to choose the best classifier for PD classification, we measure each classifier's classification accuracy. The paper also discusses the quantification and visual measurement of neuron loss in various brain lobes in Parkinson PD patients using neuroimaging techniques like fMRI, SPECT, MRI, and PET.[10]

This paper's research uses wearable accelerometers worn on both knees to track gait data for the purpose of classifying patients with Parkinson disease (PD) into "On" and "Off" stages. The statistical data and spatiotemporal gait features are fed into four separate classifiers—random forest, support vector machine, K Nearest neighbor, and Naïve Bayes—in the study's proposed method. The algorithm's performance was evaluated with twenty PD patients who exhibited characteristic motor fluctuations. With a recall of 97.35%, precision of 96.02%, and accuracy of 96.72%, the random forest classifier outperformed the others. The study's major limitations are its reliance on the "On" and "Off" states and its reliance on data acquired in a controlled laboratory environment. It is recommended that further research confirm the effectiveness in residential environments and use more data to construct a more accurate model. in [13]

In an effort to simplify datasets and improve classification accuracy, the researcher is concentrating on feature extraction from audio signals. Classification of Parkinson's illness using voice signals is accomplished in this article utilizing six separate ML models: Extreme Gradient Boosting (XGB), Stochastic Gradient Descent (SGD) Classifier, LR Classifier, RF Classifier, Decision Tree (DT), and K-Nearest Neighbour (KNN) Classifier. The results showed that when it comes to detecting people with Parkinson's disease using voice signals, the Random Forest attained the maximum accuracy of 97%. Finding important elements in audio signals is crucial for simplifying datasets and improving classification accuracy, according to the study.[14]

For the purpose of predicting Parkinson's disease using voice data sets, Celik et al. conducted research. The study assesses a number of different classification algorithms, such as logistic regression, Extreme gradient boosting, support vector machines, Decision trees, and random forests. For the purpose of expanding the feature space, the Information Gain (IG) and Principal Component Analysis (PCA) techniques are utilized in the process of feature extension. Additionally, the most significant features that were discovered by Information Gain are expanded and features that were selected by principal component analysis are expanded by employing the Correlation Heatmap (CH) technique. In the process of classification, the Random Forest (RF) technique is implemented. Using a bootstrapping operation on the training set, this method constructs each tree using a randomly chosen subset of characteristics for splitting. The authors recommend that future studies investigate other feature reduction or selection strategies to enhance classification accuracy in Parkinson disease Detection. [15]

The goal of this research is to find out how effective supervised classification algorithms like deep neural networks are at detecting people with Parkinson's disease (PD) and how speech biomarkers fare in this area of diagnostics. Researchers gathered audio recordings from people with and without Parkinson's disease (PD) to use in their dataset. The raw audio data was preprocessed using VoiceBox's Voice Activation Detection (VAD) technology to eliminate background noise. The feature extraction process made use of two distinct methods: the AVEC 2013 audio features and the Geneva Minimalistic Acoustic Parameter Set (GeMaps). These algorithms were in charge of sifting through the audio data for the pertinent information. The SVM machine learning models outperform both professionals and non-experts in clinical diagnosis of movement disorders, reaching a peak accuracy of 85%. This is in line with what the research found. The research shows that voice analysis and machine learning can be used to make Parkinson's disease diagnoses more accurate and faster.[16]

The objective of this research is to underscore the potential of innovative biomarkers and machine learning methodologies in the context of clinical decision-making. The research center’s on the utilization of machine learning algorithms to classify individuals as having Parkinson's disease or as healthy controls. The authors examined the outcomes, dataset types, machine learning (ML) algorithms, data sources, and objectives associated with them by analyzing 112 distinct research articles. A study was conducted to investigate the potential of newly developed biomarkers and machine

learning approaches to improve the diagnosis of Parkinson's disease and to assist in clinical decision-making. For the purpose of diagnosing Parkinson disease, machine learning algorithms were evaluated by analyzing speech characteristics, gait patterns, and handwriting patterns. With the help of bagging ensemble for handwritten patterns, L1-Norm SVM with K-fold cross-validation, and SVM for gait analysis, we were able to achieve the greatest accuracy rates for speech characteristics. The goal of this research is to lay out the groundwork for how novel biomarkers and machine learning approaches could improve Parkinson's disease diagnosis. The report also includes recommendations for future studies and developments in this area. [17]

Through the utilization of hand movement data obtained from a Leap Motion sensor in conjunction with machine learning techniques, the research endeavor is centered on the detection of Parkinson's disease (PD). The hand motions of Parkinson's disease (PD) patients and a control group were recorded for the purpose of the study, which examined 25 kinematic features for each and every motor task. Training and evaluation of four different classifiers (KNN, SVM, Decision Tree, and Random Forest) were carried out with the use of 8-fold cross-validation. The most successful results were achieved by combining the most significant qualities of both hands. The comparable accuracy for each motor task was 95.3% for FT, 93.8% for PS, and 90.6% for OC for the corresponding time period. It was determined that the total characteristics result across all motor tasks was 98.4%. When attempting to differentiate between people who have Parkinson's disease (PD) and those who do not have the disease, it was discovered that kinematic features and feature extraction selections were helpful.[18]

In the paper, the method for identifying Parkinson's disease is described. This method makes use of training examples and incremental decision trees. The method takes use of decision forest algorithms such as SysFor, ForestPA, and Random Forest in order to achieve the highest possible level of detection accuracy while simultaneously taking advantage of the smallest possible number of trees. Voice recordings are used to extract acoustic information using this technique, which makes use of 2 contemporary datasets consisting of persons with control participants and Parkinson's disease . Classification model such as k-nearest neighbor, C4.5, decision forest approaches, logistic regression, Naive Bayes and back-propagation neural network are utilized in this process. The ForestPA method reaches 95% accuracy with two decision trees on the Spanish dataset,

it reaches a maximum detection accuracy of 94.12% on the Istanbul acoustic dataset. You can get both of these outcomes by using the ForestPA technique.[19]

For the purpose of classifying Parkinson's disease (PD) based on voice feature sets, the research makes use of Convolutional Neural Networks (CNN) as the major method. There are two different convolutional neural network (CNN) designs that are proposed. The second framework makes use of parallel convolution layers in order to extract profound properties from each feature set before merging them in the merge layer. For the purpose of determining whether or not the proposed CNN frameworks are effective, Support Vector Machines (SVM) are utilized in conjunction with CNN as a reference model. The models are trained and validated with the help of a dataset obtained from the repository of machine learning at the University of California, Irvine. Methods such as the F-measure, the Matthews correlation coefficient, and accuracy metrics are utilized in order to assess their performance. According to the results of the experiments, the second framework, which is comprised of parallel convolution layers, is capable of effectively extracting profound properties from each feature set and enhancing the classifiers' capacity to differentiate between different categories. [22]

Through the usage of machine learning techniques, the purpose of the study was to classify persons who were diagnosed with Parkinson's disease (PD) and healthy individuals who did not have the condition. This was accomplished by analyzing speech recordings. Patients diagnosed with Parkinson's disease were classified with an accuracy rate of 84.21% thanks to the machine learning models' ability to effectively classify them. The performance, on the other hand, was increased through the implementation of the pipeline technique, which led to an increase in accuracy of 85.09%. It was determined that the pipeline technique was more effective in detecting relevant characteristics and accurately classifying those who had Parkinson's disease and those who did not have the disorder. The implementation of this methodology is a viable option for the rapid diagnosis of Parkinson's disease.[23]

Table 2.1: Summary of Related Works

Sn	Source	Used Model	Accuracy
1	[5]	Random Forest (RF), Naïve Bayes, Logistic Regression (LR) K-Nearest Neighbours (KNN)	90.2%
2	[7]	Support Vector Machine	74%
3	[9]	XGBoost	73.8%
4	[10]	ANN, MLP, KNN, SVM	95%
5	[13]	Random Forest, Naïve Bayes, Support vector machine, K-Nearest Neighbours,	96.72%
6	[14]	XGB, SGD, RF, LR, KNN, DT	97%
7	[16]	Support Vector Machine	85%
8	[19]	ForestPA, and Random Forest and SysFor.	95%

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Research Subject and Instrument

In the course of the research, a number of algorithms utilizing the ensemble technique were built in order to ascertain the accuracy of the dataset. The use of a few tools, such as high-quality configuration machines that were outfitted with the most powerful GPUs, was necessary for us. The programming language Python, the Jupiter Notebook, and Google Collaboratory have all been deployed by our team. It makes it possible to write and run Python code under any circumstances through the use of a web browser. This testing was conducted on a Windows 11 64-bit laptop, namely an Inspiron 15 T GL 3000,3511. It also had an 8 gigabytes of data storage and AMD Ryzen 5 3600 6-core processor operating at 3.59 GHz.

3.2 Data Collection Procedure

The data was practically ready for use because it was collected via Kaggle. One hundred eighty-eight persons with Parkinson's disease (PD) and sixty-four healthy controls make up this dataset. The participants in this study ranged in age from 33 to 87 and included 107 males and 81 females. Beyond that, out of sixty-four healthy individuals that make up the control group, forty-one are female and twenty-three are male. They are between the ages of 41 and 82. When the dataset was being collected, the microphone was set to record at a 44.1 kilohertz frequency. After the doctor finished his examination, the sustained phonation of the vowel /a/ was recorded three times for each individual. Several speech signal processing techniques have been applied to audio recordings of PD patients in order to extract clinically relevant data with the aim of PD evaluation. Features based on the Wavelet Transform, Vocal Fold, Mel Frequency Cepstral Coefficients (MFCCs), Time Frequency, and TWQT are all part of this set of algorithms.[21] [21] The dataset is described in Table 3.1, and the features derived from the audio samples are listed in Table 3.2.

Table 3.1: Dataset Class and Instances

Class	Age Ranges	Instance
Healthy (64)	41-82	192
Patients (188)	33-87	564

Table 3.2: Parkinson Disease Dataset Voice Feature Description

Feature	Feature set	Number of features
Time Frequency Features (24-34)	Intensity Parameter (24-26)	3
	Formant Frequencies (27-30)	4
	Bandwidth (31-34)	4
Baseline Features (3-23)	Jitter variants	5
	Shimmer variants	6
	Fundamental frequency parameters	5
	Harmonicity parameters	2
	RPDE	1
	DFA	1
	PPE	1
Mel Frequency Cepstral Coefficients (57-140)	MFCCs	84
Wavelet Transform based Features (141-322)	Wavelet Transform (WT)	182
Vocal fold feature (35-56)	Glottis Quotient (GQ)	3
	Glottal to Noice Excitation (GNE)	6
	Vocal Fold Excitation Ratio (VFER)	7
	Empirical Mode Decomposition (EMD)	6
Tunable Q-factor Wavelet Transform (323-754)	TQTW features	432

The audio recordings are primarily intended for use in illness prediction. You can see the percentage of PD patient in figure 3.1. After that, we display all of the provided data in fig 3.2,

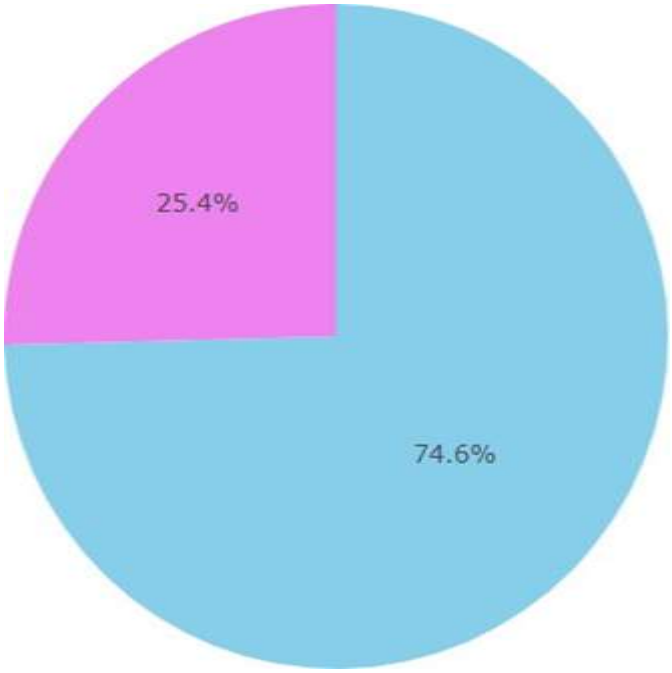
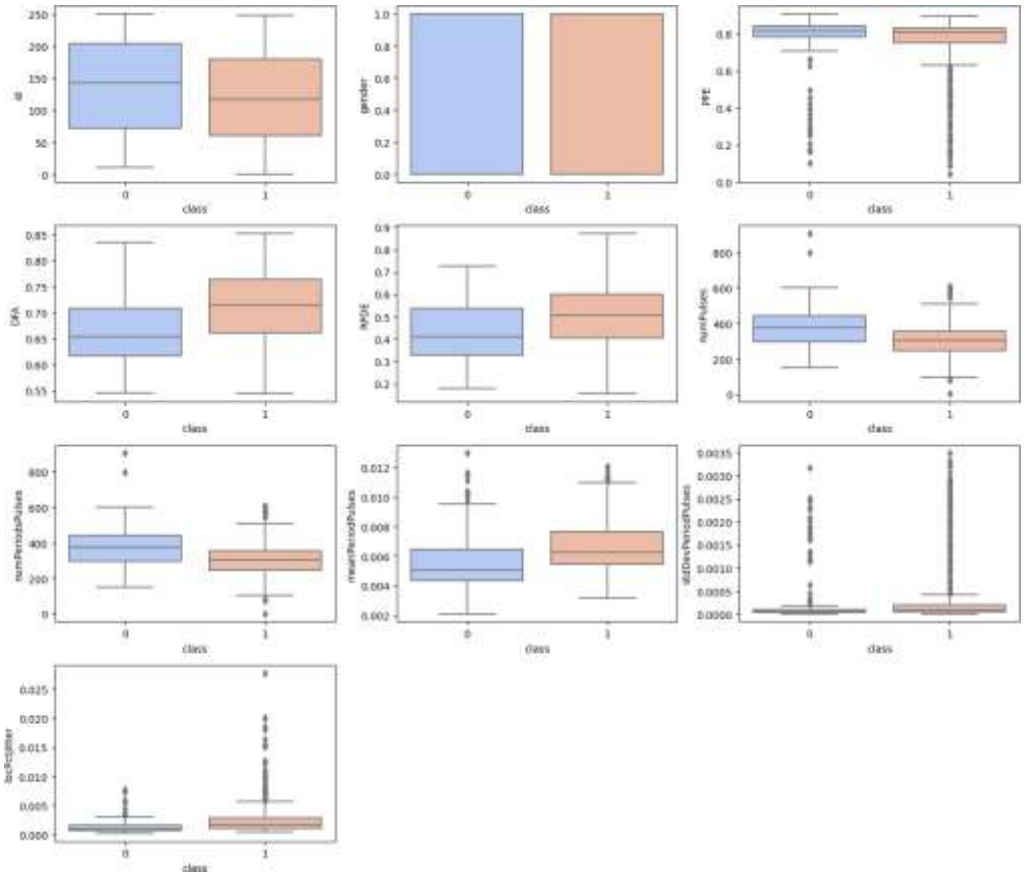


Figure 3.1: Parkinson Patient percentage

As seen in Figure 3.1, 74.6% of the individuals in our sample are afflicted with Parkinson's disease, while 25.4% are not. Fig. 3.2 displays all data visualizations.



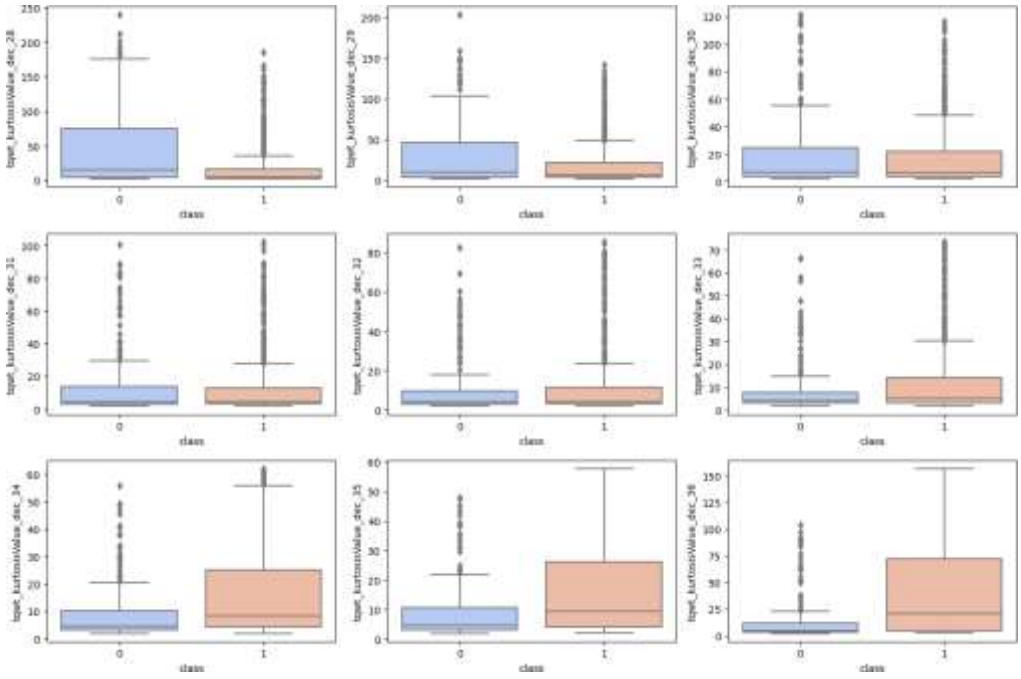


Figure 3.2: Dataset Feature Visualization

Using a heatmap, we can see the Pearson correlation. Numerous correlations between the features are displayed by the heatmap. The correlation between the variables is shown in Figure 3.3 heatmap.

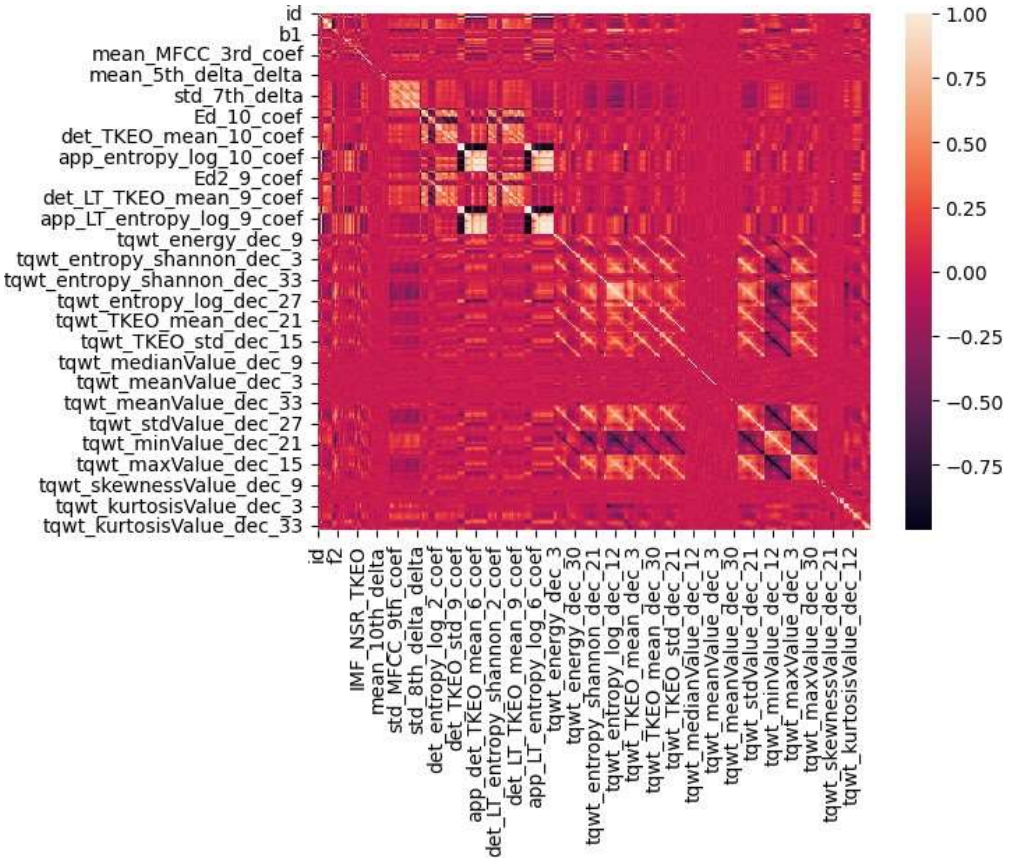


Figure 3.3: Heatmap variable

3.3 Data Pre-Processing

This is the initial step in making the data more refined and intelligible, and it is accomplished by applying preprocessing techniques to the raw dataset once it has been collected. Due to the fact that it entails making raw data more advanced and comprehensible, data preparation is the most crucial aspect of the data analysis process. Data collected from the real world is, in the majority of instances, unreliable, inconsistent, redundant, imprecise, and noisy. Data preparation is a tried-and-true method that has been shown to be effective in addressing these difficulties and improving the data. During the normalizing procedure, the min-max normalization algorithm is utilized in order to successfully complete the typical feature scaling operation. The utilization of feature scaling is one method that can be utilized to standardize the range of independent variables or data components involved. Scaling features make it simple to compare quantities that are not directly comparable by allowing the numbers to be changed throughout the comparison process. Precision of the model is improved as a result of this. Application of the Principal Component Analysis (PCA) approach is recommended in order to further reduce the number of

features or variables contained within the dataset while preserving as much of its initial variability as is practically possible. This becomes an exceptionally advantageous situation when working with high-dimensional datasets that contain a number of characteristics.

Regularization is the process of altering numerical values so that they fall within the range of zero to one. The name "normalization" refers to this process. It is often referred to by the name "min-max scaling." When scaling numerical column attributes to a standard, data normalization is the method that is utilized. Considering that the attribute values contained in the dataset that was incorporated into this investigation lie within a wide range of numerical values, it was required to carry out this normalization technique. In addition to this, it reduces the amount of redundant data and enhances the integrity of the data.

Follow this formula in order to normalize:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}}$$

Formula 3.3.1: For Normalization

3.4 Proposed Methodology

Following the loading of the audio voice dataset into the system, we proceeded to preprocess the data by employing Principal Component Analysis (PCA) and min-max normalization. Obtain two different sets of data: one for testing and one for training purposes. A phenomenon known as overfitting occurs in the field of machine learning when classifiers are trained on an entire dataset without ever being exposed to new data. A method of evaluating machine learning (ML) classification models that we named cross-validation was utilized by us in order to rectify this situation. Following the development and testing of a machine learning classification model on each subset of the data, the data was then separated into subgroups according to the ratios that were predetermined during the process. The calculation of the average error rate is a useful tool for gaining a better understanding of the performance of the model in terms of classification accuracy. In a typical configuration, testing consumes approximately thirty percent of the data, whereas training consumes approximately seventy percent of the data. Following that, we put a variety of machine learning techniques through their

paces to determine how well they perform. Afterwards, ensemble algorithms were utilized in order to get the highest possible level of accuracy in the forecasting process. The algorithms that are used for bagging and boosting in ensembles. After that, an analysis was performed on the outcomes of the ensemble methods that were utilized. Explainable artificial intelligence was the subject of our inquiry, which culminated in an analysis of its potential as a tool for giving people with explanations that are both clear and concise. The design of the system that has been proposed is shown in Figure 3.4,

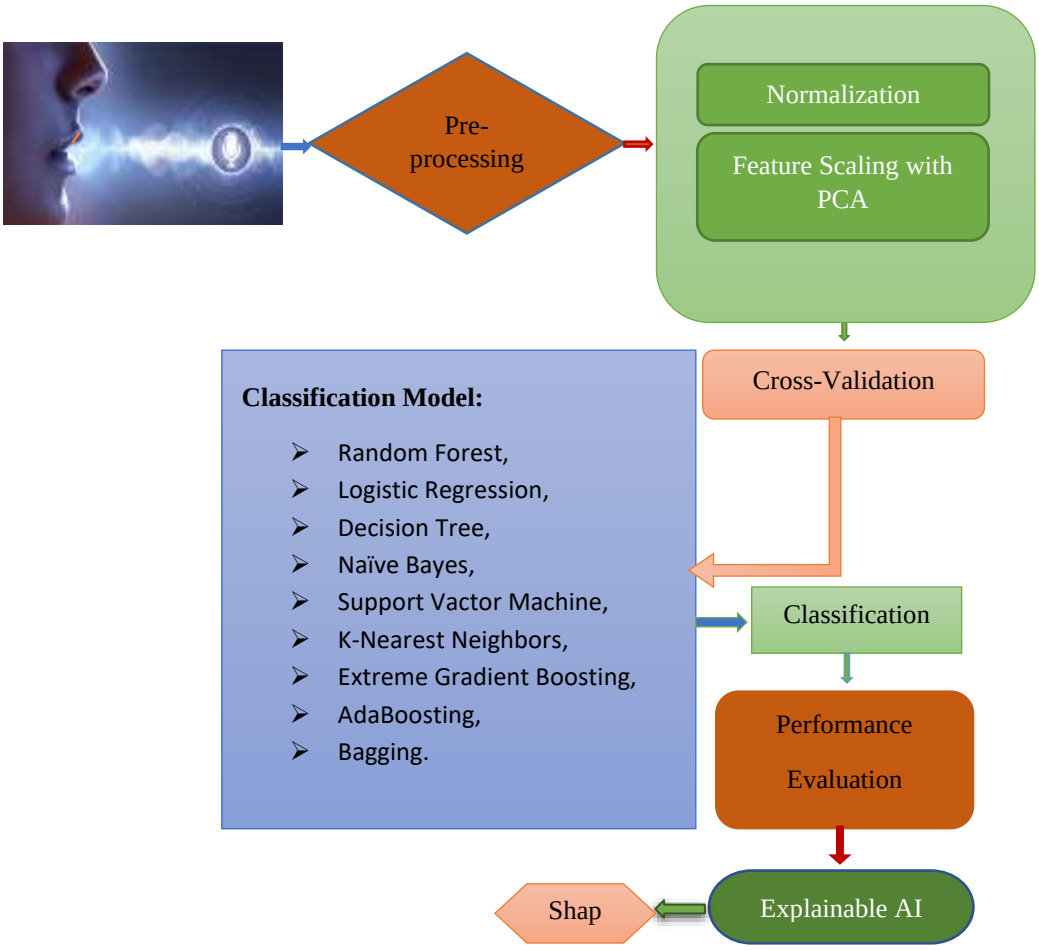


Figure 3.4: Working Principle of this proposed work

3.5 Classifier Algorithms

3.5.1 Logistic Regression

Logistic regression (LR) divides the class label into two yes/no binary (0/1) categories as a machine learning (ML) based classifier technique. Because of the connection between the discrete variables, logistic regression can be used. It is often known that numerical data values produce superior results from regression analysis. However,

discrete variables can also be predicted using a combination of continuous and discrete predictor values. Although they serve comparable purposes, multiple regressions and discriminant function analysis do not assume anything about the distribution of the resulting predictors.[4] Figure 3.5, which is attached to this text, illustrates the concept.

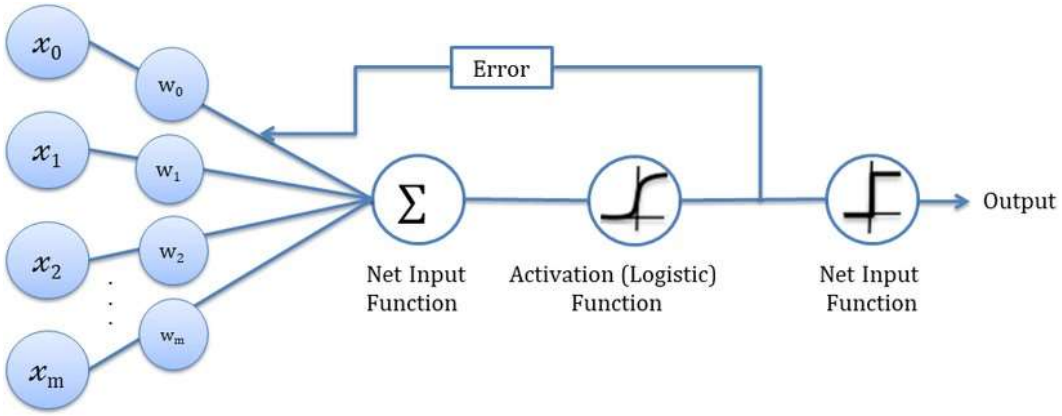


Figure 3.5: Logistic Regression

3.5.2 Random Forest

An ensemble learning approach that improves a model's performance, the Random Forest algorithm makes use of several classifiers. In supervised machine learning, Random Forest is a method that uses decision trees. It solves problems with both regression and classification. Using Random Forest to build many decision trees and then combining them allows for a more accurate prediction. The premise upon which the Random Forest model rests is that numerous independent decision trees, or models that are not associated with one another, perform very well when used together. At each node, a random selection of K variables has been made from a pool of M accessible variables.[5] Figure 3.6 is included for your reference.

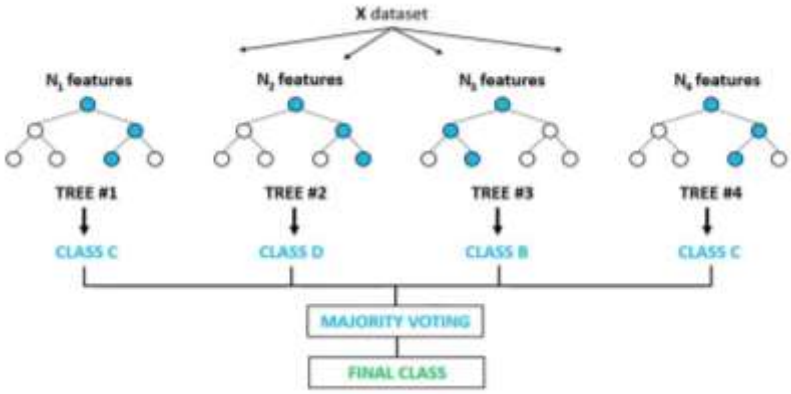


Figure 3.6: Random Forest

3.5.3 Naive Bayes

One generative learning method for text categorization is the Naive Bayes classifier, which works under the conditional independence assumption. Rapid and precise forecasts are possible because to its supervised learning methodology. The Naive Bayes classifier assigns the MAP class to new instances based on the assumption of conditional independence between attributes. Naïve Bayes relies on the independence assumption, which necessitates straightforward and rapid training. It is imperative that each and every class's attributes be considered separately. Table searches and computations of conditional probabilities based on normal distributions make up the exam.[5] Below figure 3.7, you can see the concept.

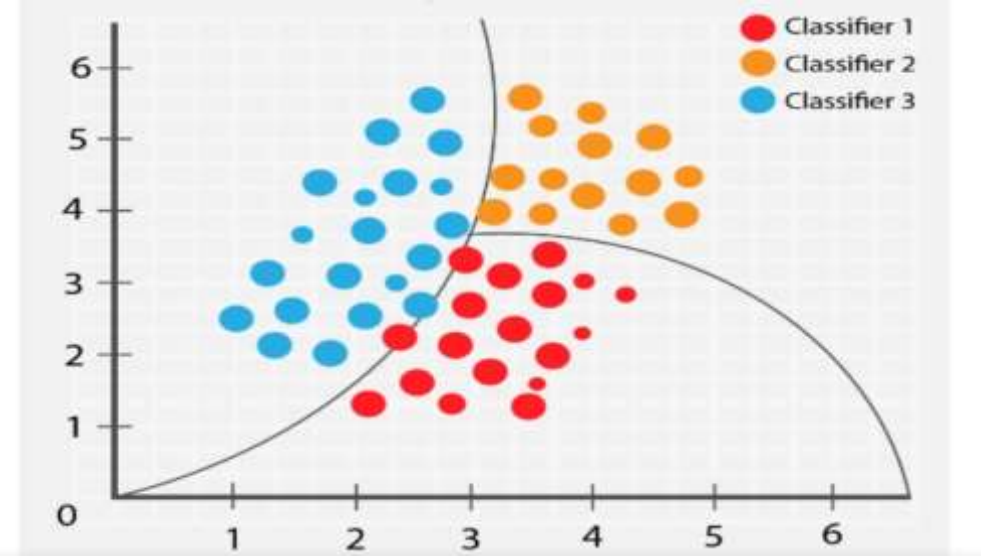


Figure 3.7: Naive Bayes

3.5.4 K-Nearest

This is a non-parametric supervised learning classifier called the k-nearest neighbors algorithm, also written as KNN or k-NN. It classifies or predicts data points based on their closeness to one another. According to the results obtained from the majority voting method, the optimal value of k for producing accurate predictions is 5. The reason for this is that a lower K number might change the model's exceptions.[5] The idea is shown in fig 3.8,

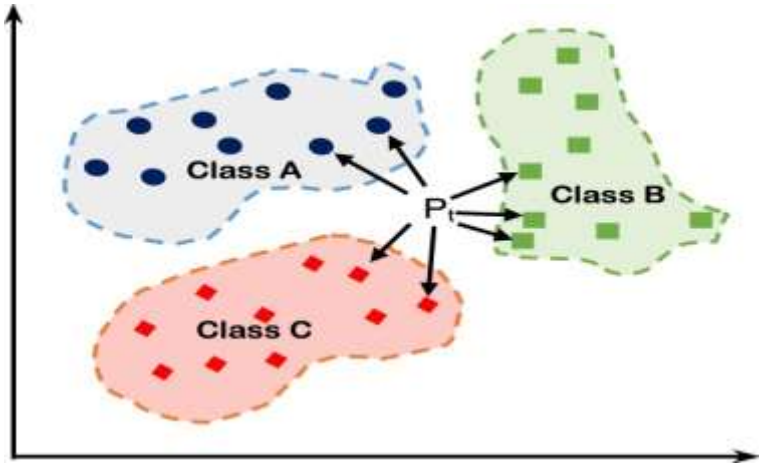


Figure 3.8: k-nearest neighbors

3.5.5 Decision Tree (DT)

In machine learning, a decision tree algorithm is an example of an algorithm that uses a decision tree to generate predictions. The program uses a graphical representation of choices and their outcomes, similar to a tree. At each node in the tree, the method's most significant property is used to divide the data into subsets. Building a model that can predict, given a set of input variables, the value of a target variable is the main objective. Figure 3.9 below illustrates the basic idea of this model.

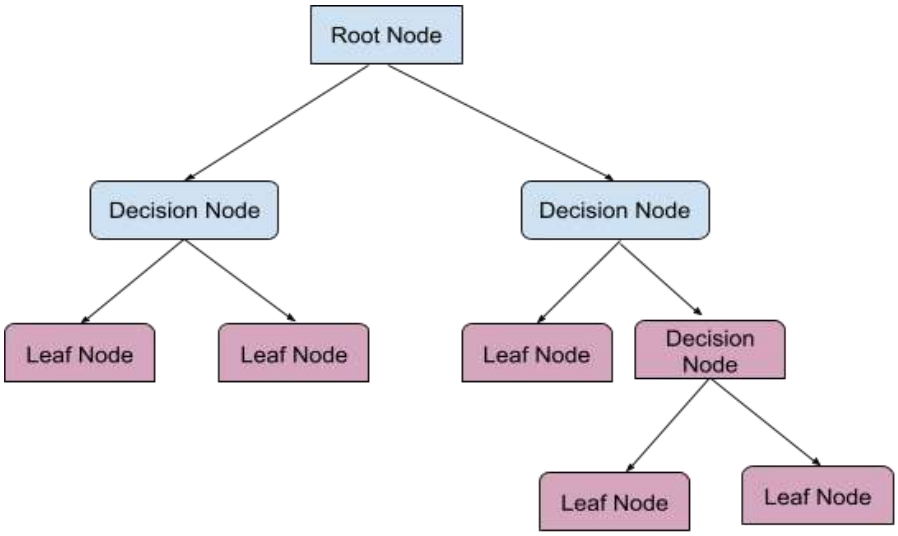


Figure 3.9: Decision Tree

3.5.6 Support Vector Machine (SVM)

Support vector machine (SVM) is an effective supervised method that excels at handling complex, smaller datasets. While support vector machines (SVMs) can be useful for classification tasks as well as regression ones, the former is typically where

they shine. It can solve both nonlinear and linear regression classification problems. Dual convex quadratic programmers were the result of applying them to the optimization problem in order to avoid the problems with linear functions in a high-dimensional feature space. The following is the idea behind this model's figure 3.10,

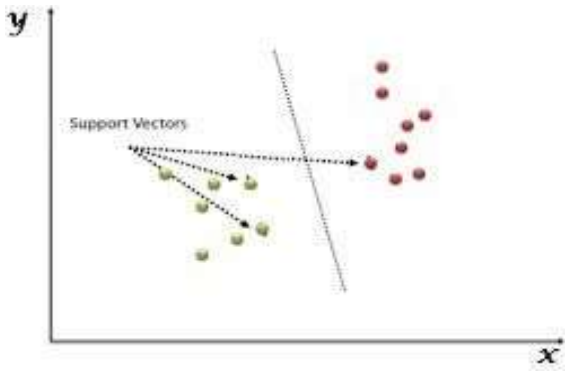


Figure 3.10: Support Vector Machine

3.5.7 Extreme Gradient Boosting Model

One important method for developing supervised regression models is Extreme Gradient Boosting (XGBoost). One boosting method employed by XGBoost is bagging, which comprises training a number of decision trees and then combining their outputs. It gives XGBoost an edge in scenarios when there are several attributes to think about and allows it to learn more quickly than other algorithm.

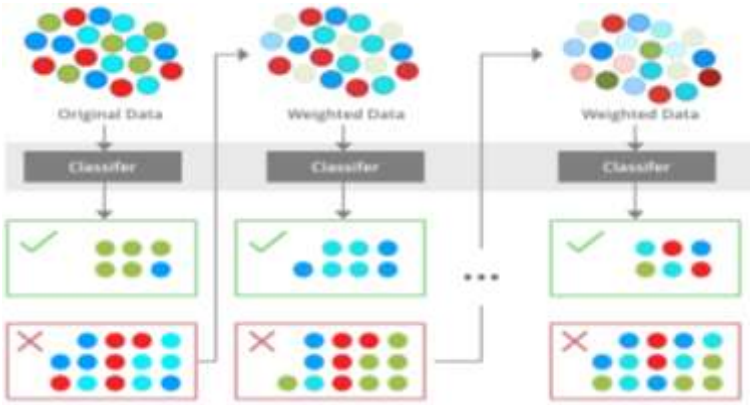


Figure 3.11: XGBoost

3.5.8 Bagging Classifier

Bagging, alternatively known as Bootstrap aggregation, is an ensemble learning methodology that involves the concurrent and independent training of numerous base models on distinct subsets of the training data. The process of bootstrap sampling with replacement is utilized to indiscriminately select data points for the formation of each subset. The ultimate forecast produced by the Bagging classifier is determined by aggregating predictions from the all-base model via majority voting. Bagging regression is a type of regression wherein the final prediction is obtained through the process of aggregating the predictions made by the entire base model.

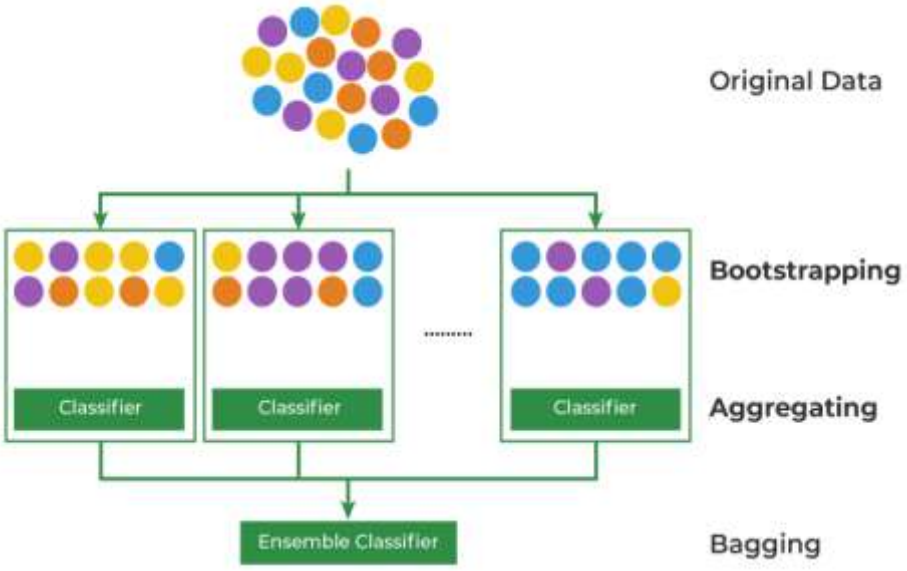


Figure 3.12: Bagging Classifier

3.5.9 Classification Report

The model's performance in each class is thoroughly analyzed in the classification report, which also highlights the trade-off between recall and precision. There may be an imbalance in the data set or between the classes because the amount of instances (support) for each class is also displayed. Machine learning models that focus on categorization use it as one of their performance measures. It shows your model's F1 score, recall, and precision. Improving one's comprehension of the trained model's overall performance is a worthwhile endeavor.

3.5.10 Accuracy

Specifically, it addresses the percentage of accurate data prediction. Accuracy, on the other hand, is a factor that determines how easily available the measurements are when actual measurements are being used. The only variable that it is based on is one. Only errors that are made on purpose are considered accurate. Any model can benefit from this measurement strategy because it is one of the simplest. All of our models need to be as accurate as we possibly can make them.

$$\text{Accuracy} = \frac{TruePositive + TrueNegative}{True\ Positives + True\ Negatives + False\ Positives + False\ Negatives}$$

Formula 3.5.10.1: Formula for Accuracy

3.5.11 PRECISION

With regard to the scope of this conversation, we are going to look into the proportion of real positive observations that were anticipated to take place. As a result of their precision, they are able to successfully compute the real fraction of all the possible outcomes that they correctly expected. A best recall for any model might occasionally be deceptive.

$$\text{Precision} = \frac{TruePositive}{TruePositive + FalsePositive}$$

Formula 3.5.11.2: Formula for Precision

3.5.12 Recall

Recall is the percentage of positive objects divided by true positives in a model. It's used to estimate anticipated positives to all positive labels, but high precision can lead to erroneous conclusions. This context explores the use of recall.

$$\text{Recall} = \frac{TruePositive}{TruePositive + FalseNegative}$$

Formula 3.5.12.3: Formula for Recall

3.5.13 F-1 Score

The F1 score, often known as the F-measure, is calculated as the harmonic mean of a classification model's precision and recall. Because both metrics contribute equally to the final result, the F1 metric is a more exact indicator of a model's reliability. In terms

of quality, the memory to accuracy ratios are extremely good. A drop in the harmonic mean most often indicates the absence of quality features in the model.

$$\text{F-1 score} = 2 * \frac{Recall + Precision}{Recall + Precision}$$

Formula 3.5.13.4: Formula for F-1 score

Explainable AI

The topic of explainable AI (XAI) has expanded dramatically in recent years. For example, deep learning models, which are widely used, are extremely accurate but infamously difficult to understand. According to [20], "explainable AI" refers to a set of strategies that seek to clarify and understand the rationale behind AI and ML models' decisions. "Explainable AI" is a significant subfield of AI that aims to develop models that non-specialists can understand. Explainable AI aims to increase public trust in AI decision-making by providing more transparency. Given the weight of the repercussions that AI decisions may have on human lives, this is a top priority in the healthcare industry. Explainable AI uses a variety of algorithms, including decision trees, LIME, SHAP, and others. This study makes use of the form technique. SHAPE is an abbreviation for "Shapley Additive Explanations," and it is used by AI developers and machine learning (ML) professionals to comprehend ML algorithms' predictions. It allows for a better understanding of any model's predictions.

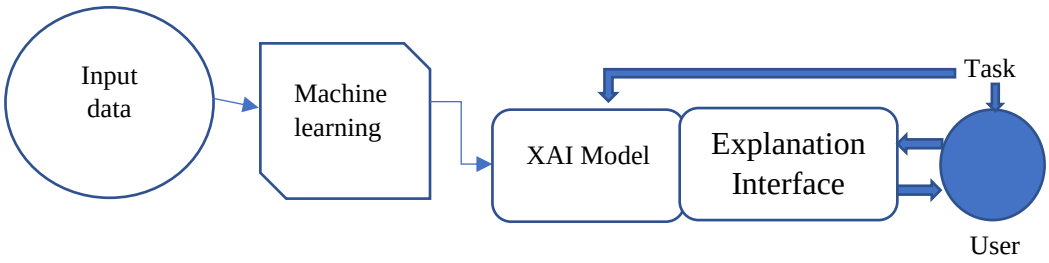


Figure 3.13: Explainable AI

CHAPTER 4
EXPERIMENTAL RESULT AND ANALYSIS

4.1 Configuration for Experiments

Here, we employed a classification model strategy based on testing and training. The experimental model is built from the training dataset. in order to get the desired output. We used classification model in our work, including Random Forest (RF), K-Nearest Neighbours (KNN), Naive Bayes (NB), Logistic Regression (LR) and Decision Tree (DT). Next, we look at group approaches like bagging Classification and Extreme Gradient Boosting (XGB) Classification , followed by explainable AI.

4.2 Experimental Result & Analysis

This task necessitates generating an analysis report on the experimental results of our proposed models using the specific dataset for Parkinson's illness. Initially, we employed the dataset we selected, rectified any absent or incorrect figures (our dataset is devoid of any missing values), executed a range of algorithms, and evaluated their efficacy. We computed the confusion matrices' Accuracy, Precision, Recall, and F-1 Score for the strategies we put forward. The confusion matrices were assessed using conventional methodologies. We conducted an assessment of various machine learning algorithms, including Random Forest (RF), K-Nearest Neighbors (KN), Decision Tree (DT), Support Vector Machine (SVM), Extreme Gradient Boosting (XGB), Naive Bayes (NB) and Logistic Regression (LR) and Bagging classification . Furthermore, we have observed numerous ensemble methodologies that employ confusion matrices. An examination is conducted on the ensemble strategies for Bagging and Boosting. Subsequently, we employ explainable artificial intelligence. Our research on Explainable AI Systems for Patient conclusion has the capacity to enhance trust between medical practitioners and AI systems, contingent upon the doctor's comprehension of the rationale behind the system's conclusion.

Logistic Regression (LR)

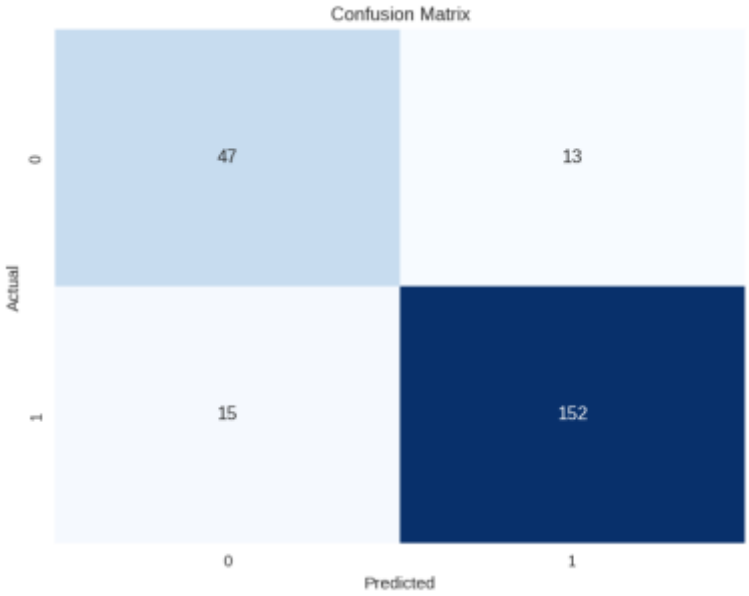


Figure 4.1: Logistic Regression Confusion matrix

A tabular format that gives a full explanation of a classification model's performance is the confusion matrix, which is shown in figure 4.1. With 47 positive data points correctly predicted and 152 negative data points correctly detected, this model performed admirably. The model also made a number of mistakes, including incorrectly classifying 13 negative data points as positive and 15 positive data points as negative. The experimental results of the classifier model are shown in Fig 4.2,

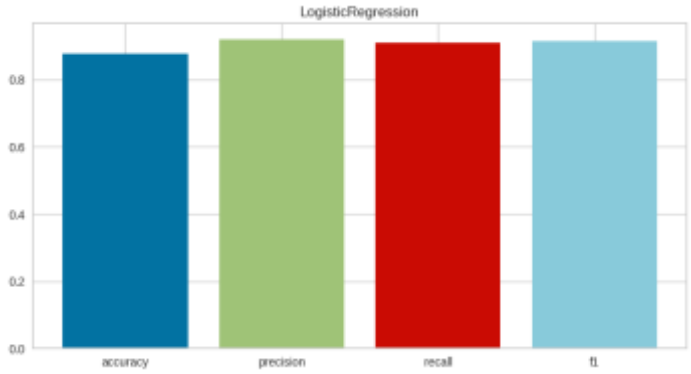


Figure 4.2: Result for Logistic Regression

The model's accuracy is 87%, precision is 92%, recall is 91%, and the F1 score is 91%, as shown in Figure 4.2. You can also find the ROC curve for this model in fig 4.3,

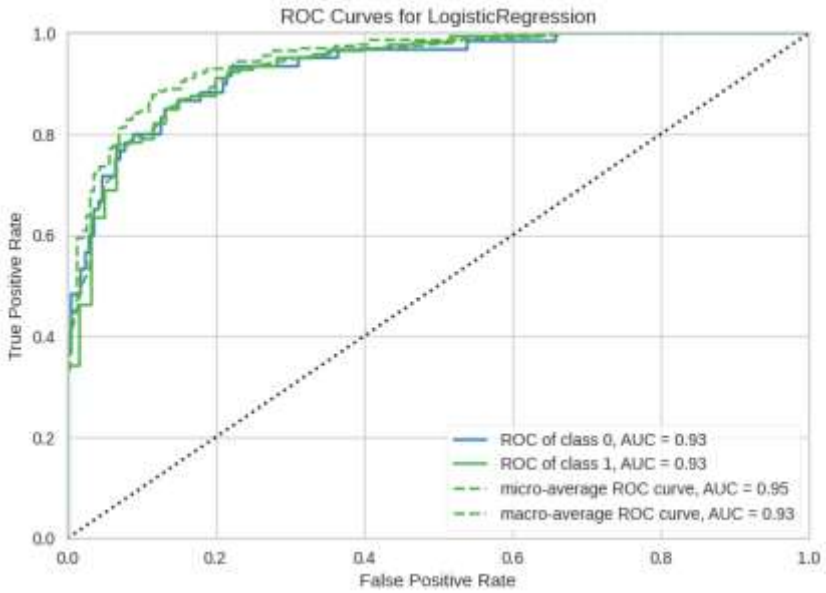


Figure 4.3.: ROC Curve for Logistic regression

As shown in the area under the receiver operating characteristic curve (AUC-ROC) in Figure 4.3, Logistic Regression (LR) achieved a success rate of 93% for class 0 and 93% for class 1, respectively. To add insult to injury, the average ROC curve for micro is 95%, whereas the average ROC curve for macro is 93%.

Naive Bayes (NB)

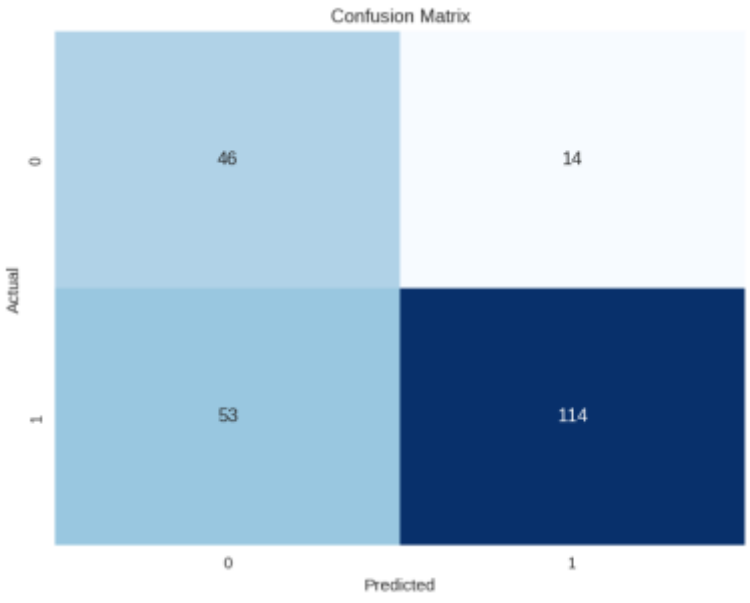


Figure 4.4: Naive bayes Confusion Matrix

The confusion matrix in Figure 4.4 showed that our model correctly projected 46 positive data points and found 114 negative data points. Besides that, the model got 14 negative data points wrongly marked as positive and 53 positive data points wrongly

marked as negative. The experiment results for the classifier model are shown in Figure 4.5.

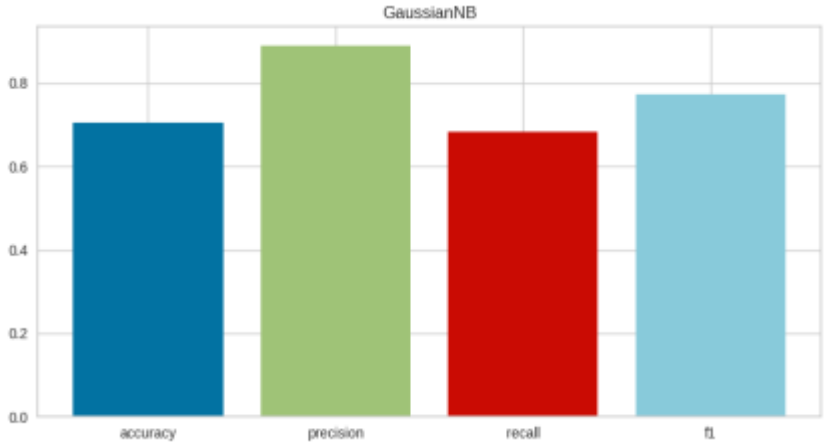


Figure 4.5: Result of Naive Bayes

Figure 4.5 shows that this model is 70% accurate and 89% precise. Remember: 68% Score for F1: 77%. This model's ROC curve is also shown. fig 4.6,

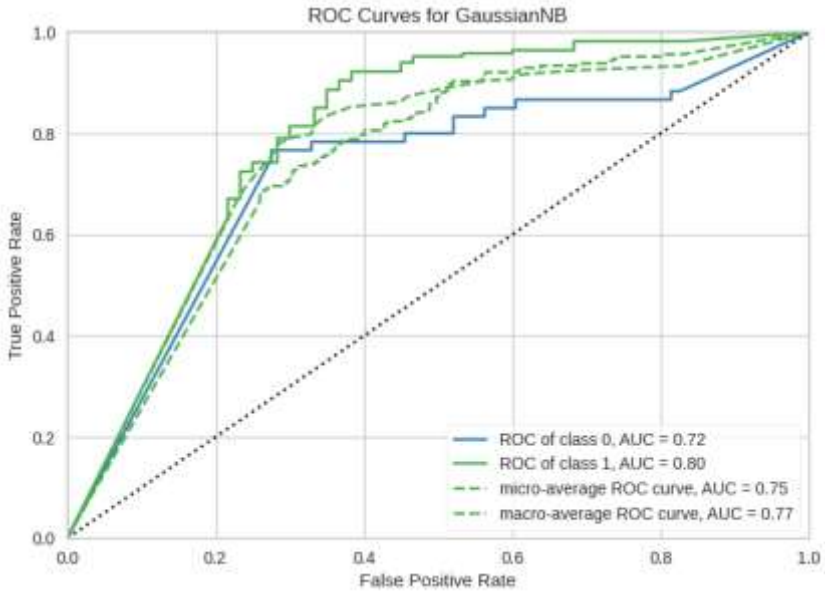


Figure 4.6: ROC Curve for Naive Bayes

The AUC-ROC Curve is displayed in Figure 4.6. For class 0 and 1, Naive Bayes (NB) achieved scores of 72% and 80%, respectively. On average, the micro ROC curve is 75% while the macro ROC curve is 77%.

K Nearest Neighbors (KNN)

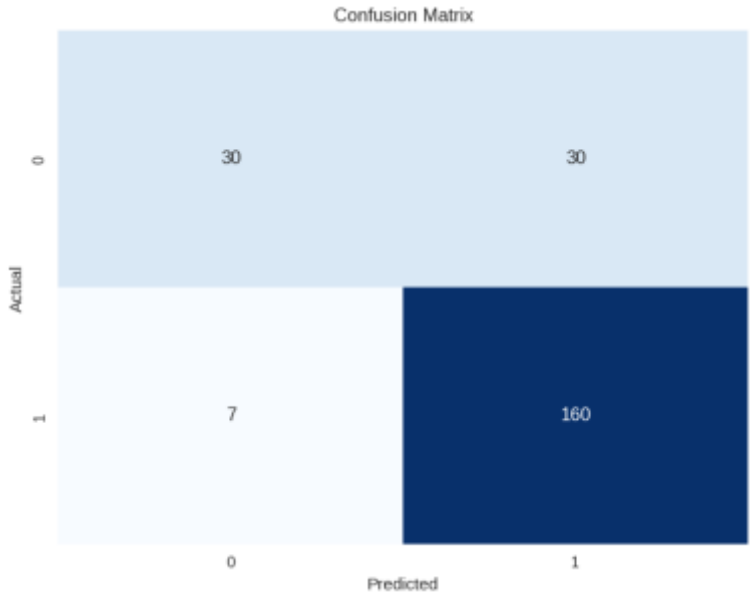


Figure 4.7: K-nearest neighbors Confusion Matrix

Figure 4.7 is a visual representation of a classification model's performance. For every one hundred negative data points, this model correctly predicted thirty positive ones. In addition, there was an error in grouping 30 negative data points with positive data points and 7 positive data points with negative data points. As illustrated in Figure 4.8, the classifier model underwent a battery of testing.

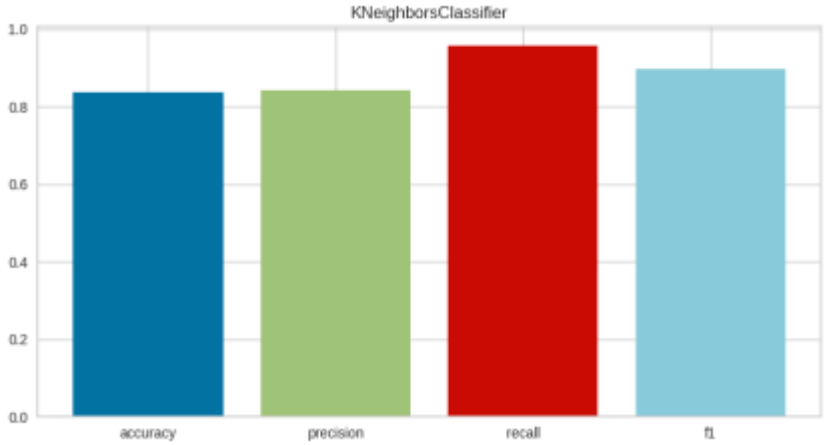


Figure 4.8: Result for Classifier k-nearest neighbors

Figure 4.8 demonstrates that the model achieves 83% accuracy, 84% precision, 95% recall, and an 89% F-score. This model includes a ROC curve. Figure 4.9,

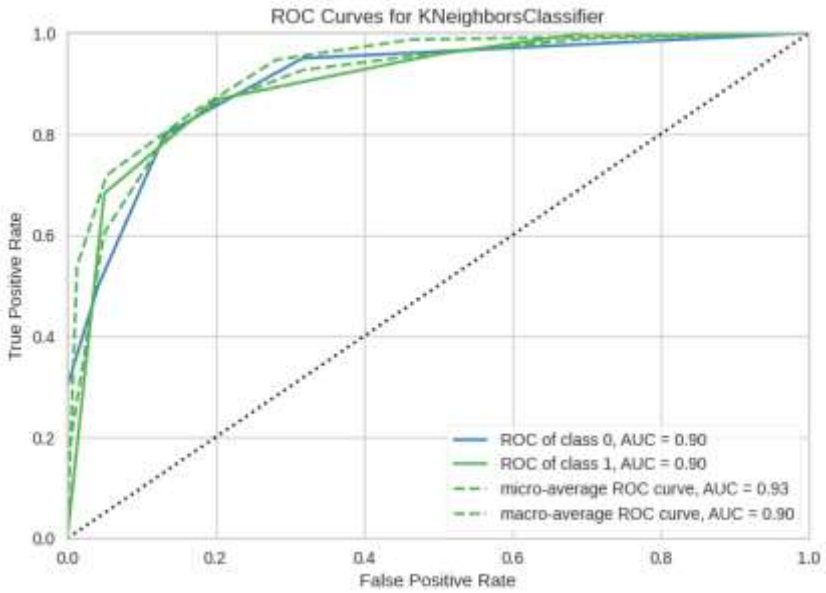


Figure 4.9: ROC Curve for K-nearest neighbors

Figure 4.9's area under the receiver operating characteristic (AUC-ROC) curve shows that k-nearest neighbours (KNN) obtained 90% accuracy for class 0 and 90% accuracy for class 1, respectively. On average, the micro ROC curve is 93% while the macro ROC curve is 90%.

Decision Tree (DT)

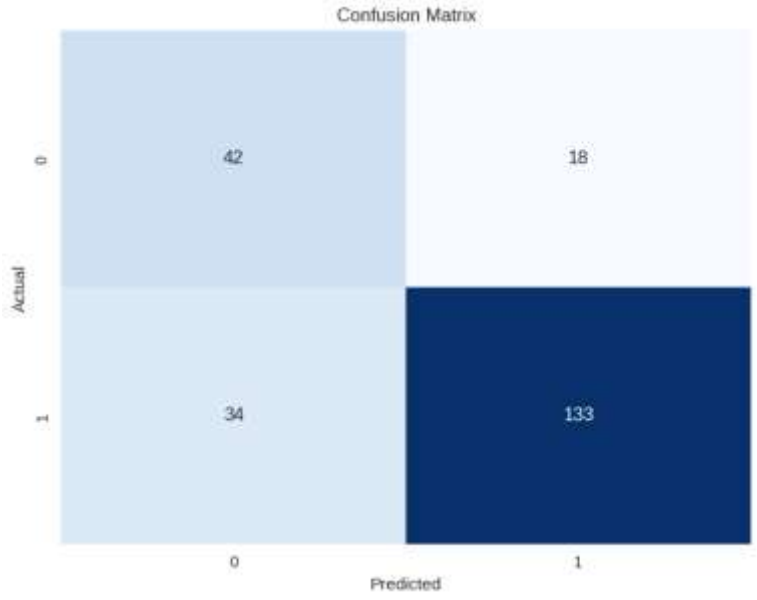


Figure 4.10: Decision Tree Confusion Matrix

The performance of a classification model is illustrated by the confusion matrix (Fig. 4.10). While correctly identifying 133 negative data points, this model correctly forecasted 42 positive data points. Also, out of a total of forty-four data points, the

model incorrectly classified 18 as positive and thirty-four as negative. You can see the classifier model's experimental results in Figure 4.11.

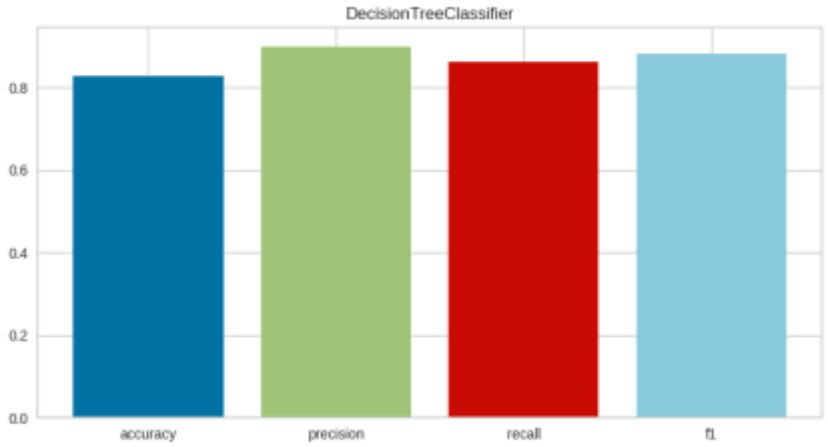


Figure 4.11: Result for Decision Tree

Figure 4.11 shows that the model has an 82% accuracy rate, a 90% precision rate, an 86% recall rate, and an 88% F-score. There is also a ROC curve provided for this model. image 4.12,

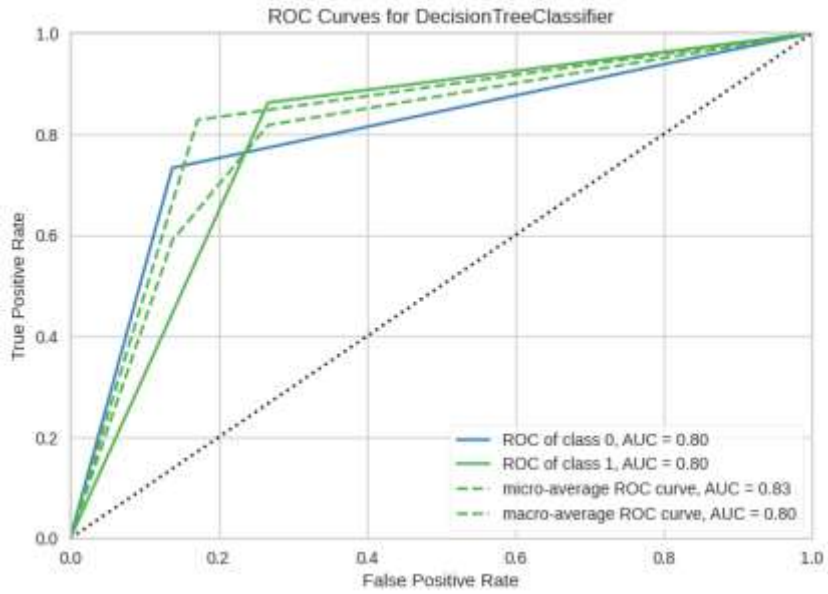


Figure 4.12: Decision Tree ROC curve

Figure 4.12 shows the area under the receiver operating characteristic (ROC) curve, which Decision Tree (DT) hit at 80% for class 0 and 80% for class 1. Also, the average ROC curves for micro and macro are 83% and 80%, respectively.

Random Forest (RF)

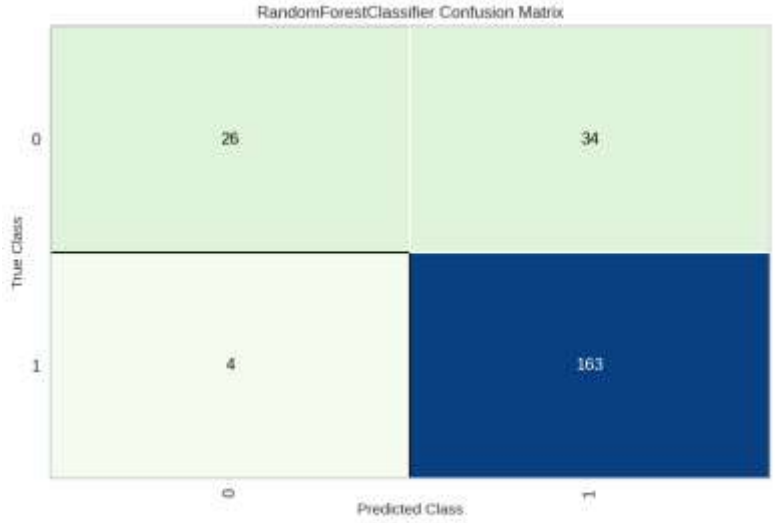


Figure 4.13: Random Forest Confusion matrix

The confusion matrix, depicted in Figure 4.13, is a metric for evaluating the performance of a classification model. Our model was very accurate, with 26 correct predictions and 163 incorrect classifications. More than that, the model incorrectly classified 34 negative data items as positive and 4 positive data points as negative. The experimental results of the classifier model are shown in fig 4.14,

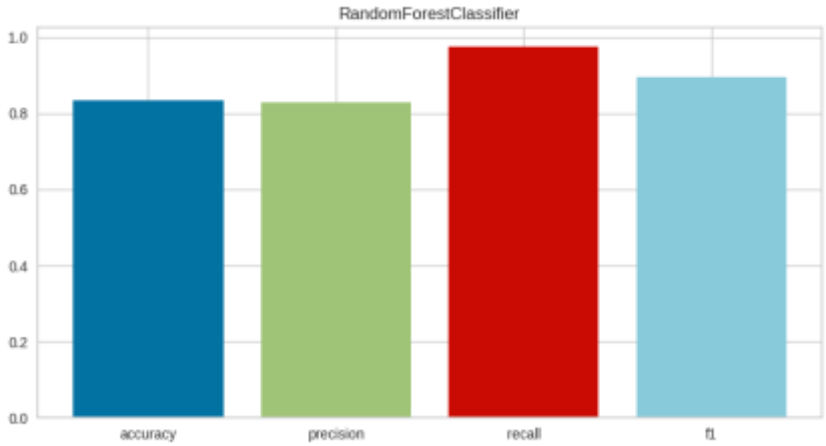


Figure 4.14: Result for Random Forest

We can observe that the model has an F1 Score of 89%, an Accuracy of 83%, a Precision of 82%, and a Recall of 97%. Fig. 4.15 also displays the ROC curve for this model.

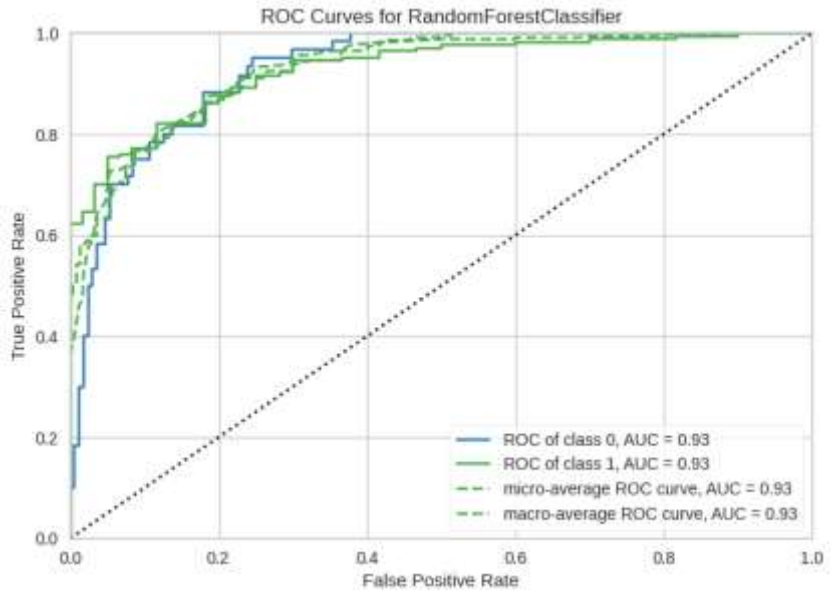


Figure 4.15: Random Forest ROC curve

Area under the receiver operating characteristic (AUC) curve, as shown in figure 4.15, also shows that Random Forest (RF) had a 93% success rate for class 0 and 93% success rate for class 1. There is a 93% agreement between the micro and macro-ROC curves.

Support Vector Machine (SVM)

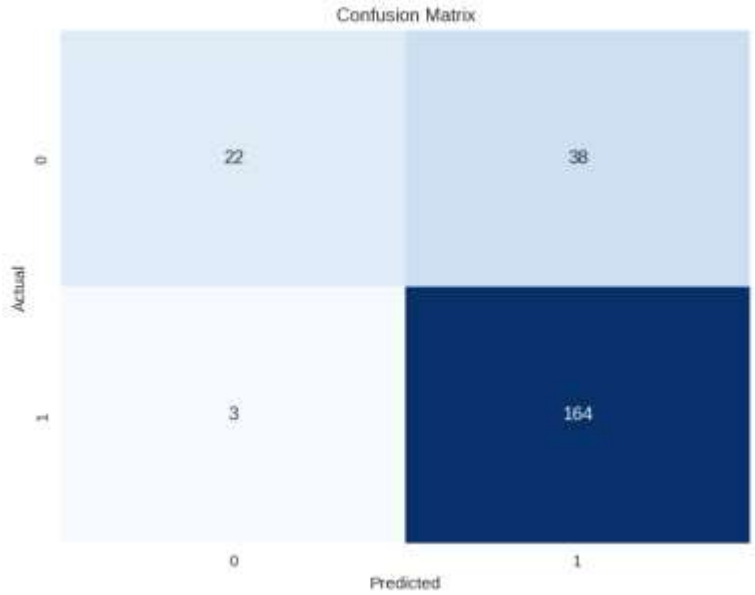


Figure 4.16: Support Vector Machine Confusion matrix

Figure 4.16 shows the confusion matrix, which shows how well this model performed. With 22 positive predictions and 164 negative classifications, this model proved successful. Additionally, the model made a mistake by mistakenly assigning three positive data points to the negative category and 38 negative data points to the positive category. As shown in figure 4.17, the classifier model's experimental results.

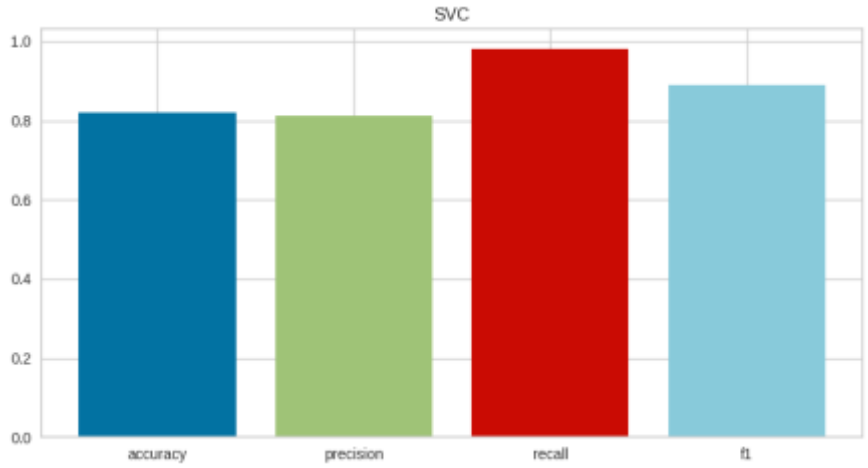


Figure 4.17: Result for Support Vector Machine

We observe the model Accuracy is 81% and Precision: 81% Recall: 98%, F1 Score: 88%.

XGBoost Model

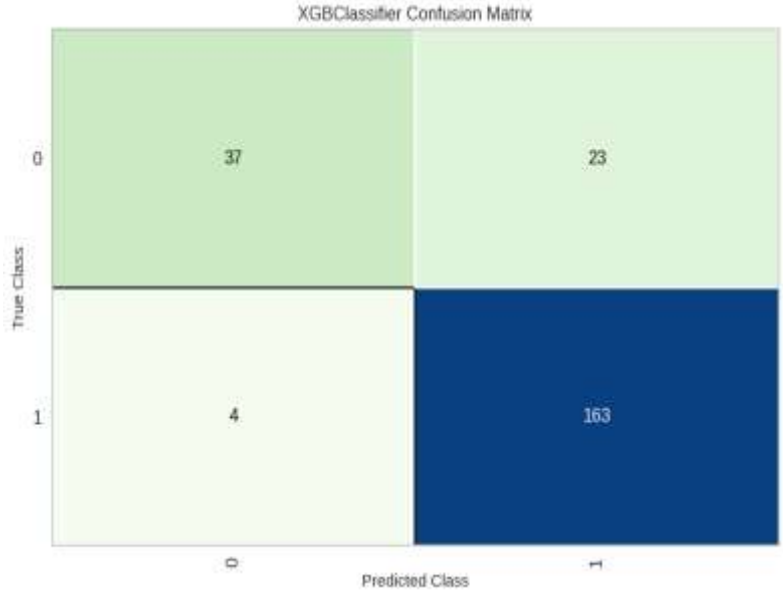


Figure 4.18: XGBoost Confusion Matrix

Figure 4.18 shows a table that shows how well a categorization model did. A total of 37 positive data points and 163 negative data points were accurately predicted by this model. In addition, the model had 4 positive data points wrongly labelled as negative and 23 negative data points wrongly labelled as positive. Figure 4.19 displays the classifier model's experimental results.

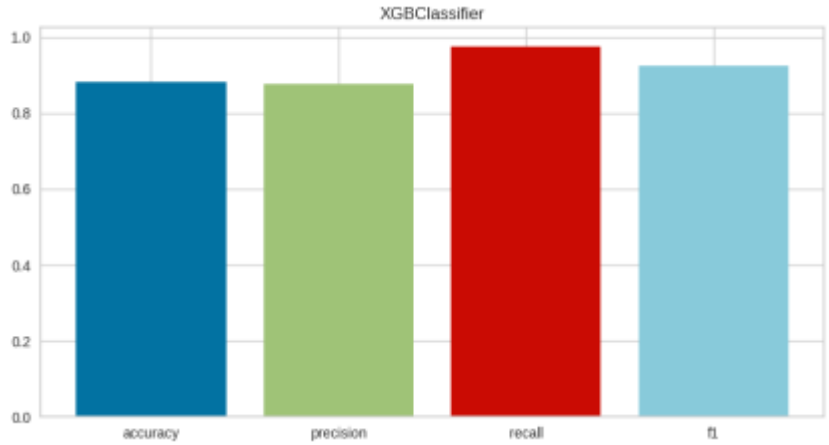


Figure 4.19: Result for XGBoost

The model has an F1 Score of 92%, an Accuracy of 88%, a Precision of 87%, and a Recall of 97%. Below figure 4.20, you can see the ROC Curve of the model that was Assessed.

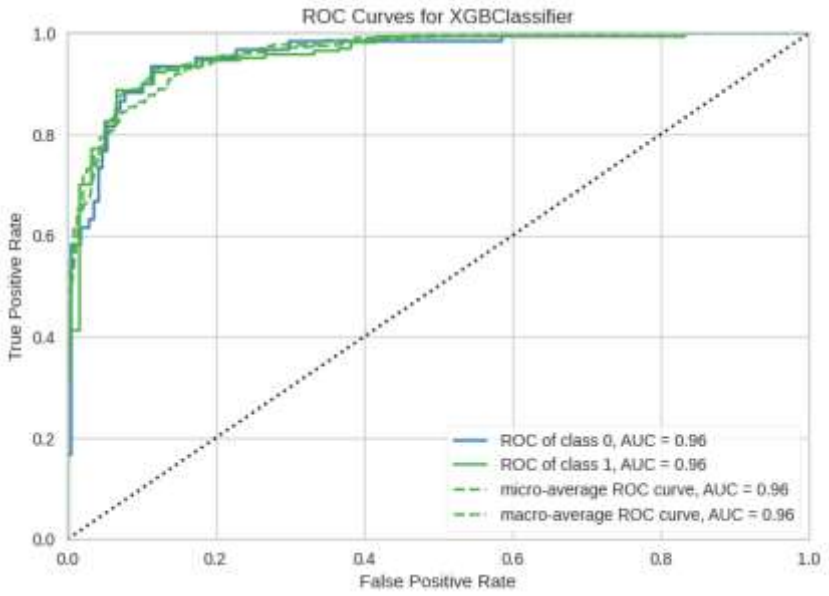


Figure 4.20: XGBoost ROC Curve

Figure 4.20 shows the area under the receiver operating characteristic (ROC) curve, which further demonstrates that XGBoost classification achieved 96% for class 0 and 96% for class 1. Moreover, the average ROC curve for micro and macro is 96% and 96%, respectively.

AdaBoost Classifier

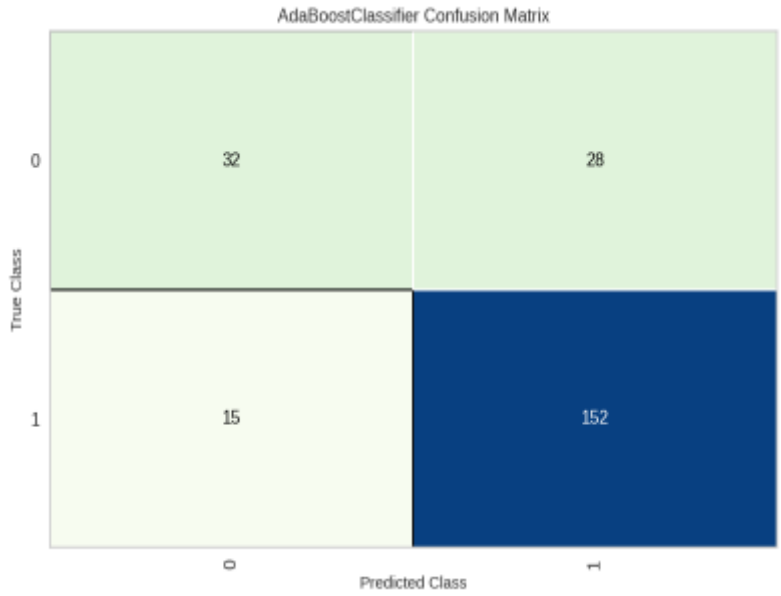


Figure 4.21: AdaBoost Confusion Matrix

Figure 4.21 shows the confusion matrix, which is a table that indicates the performance of a classification model. Of the 152 negative data points, the model accurately predicted 32. Furthermore, the model mistakenly labelled thirty-eight negative data points as positive and fifteen positive data points as negative. Figure 4.22 shows the experimental results of the classifier model.

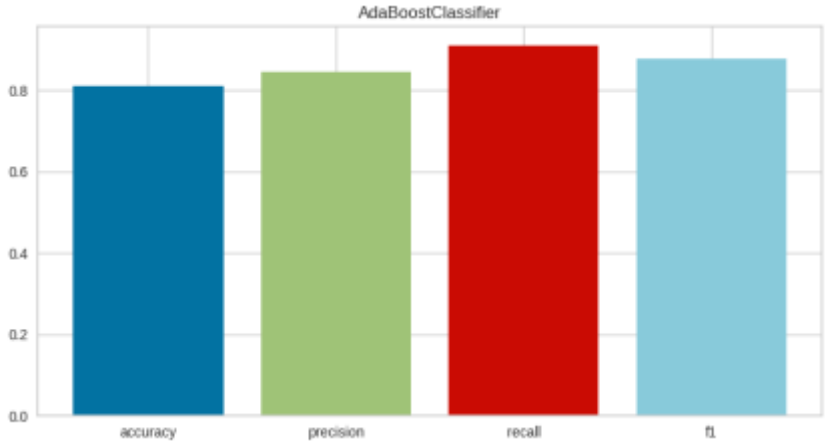


Figure 4.22: Result for AdaBoost

This model has an F1 score of 87%, an accuracy of 81%, a precision of 84%, a recall of 91%, and so on. Below figure 4.23, you can see the ROC Curve of the model that was assessed.

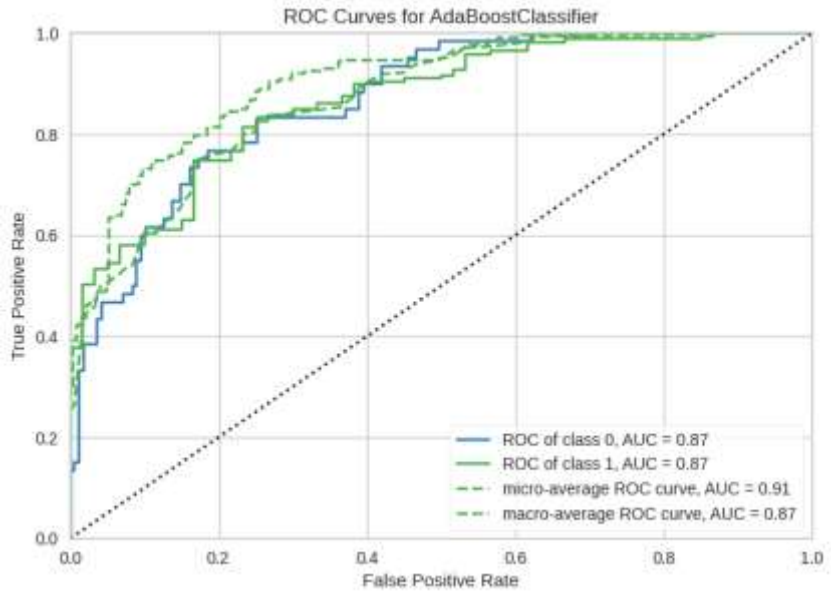


Figure 4.23: ROC curve of AdaBoost

The AdaBoost classification achieved a score of 87% for class 0 and 87% for class 1, as seen in the AUC-ROC Curve in figure 4.23. The average ROC curve for micro and macro is 91% and 87%, respectively.

Bagging Classifier

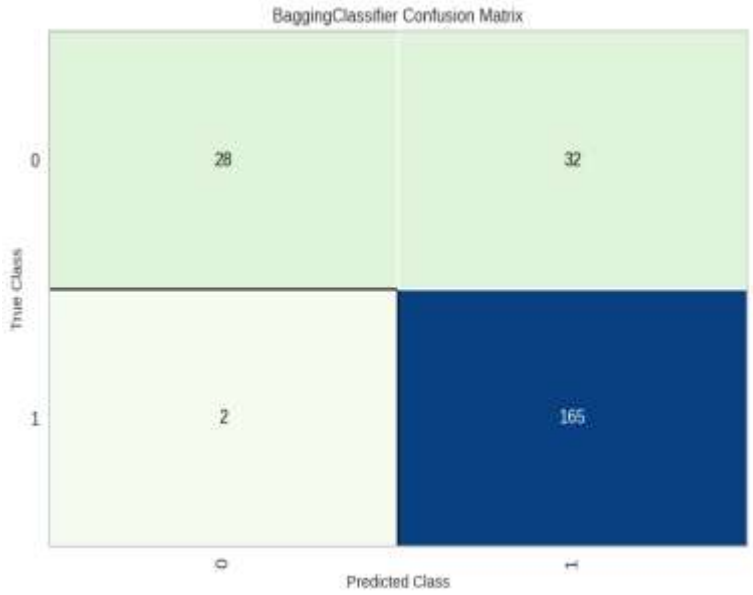


Figure 4.24: Confusion matrix of Bagging Classifier

In figure 4.24, we can see the confusion matrix, which shows how well a classification model performed. A total of 28 positive data points and 165 negative data points were accurately predicted by this model. Additionally, the model made a mistake by mistakenly assigning 2 positive data points to the negative class and 32 negative data

points to the positive class. As shown in figure 4.25, the classifier model's experimental results.

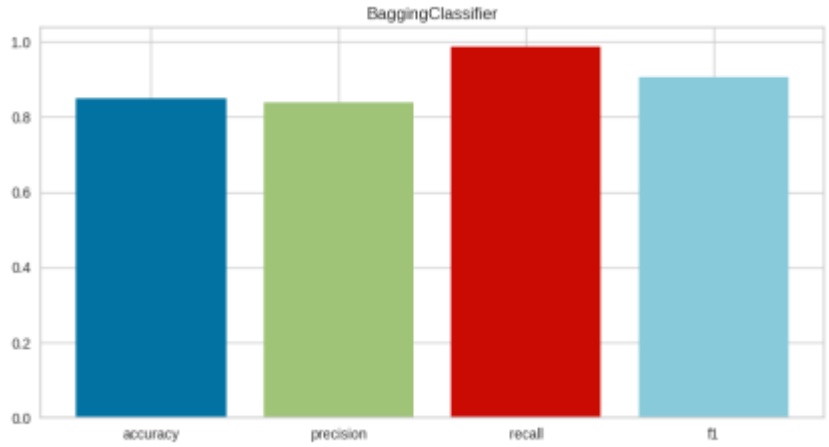


Figure 4.25: Experimental Result of Bagging Classifier

The model has an F1 Score of 92%, an Accuracy of 88%, a Precision of 87%, and a Recall of 97%. Below figure 4.20, you can see the ROC Curve of the model that was assessed.

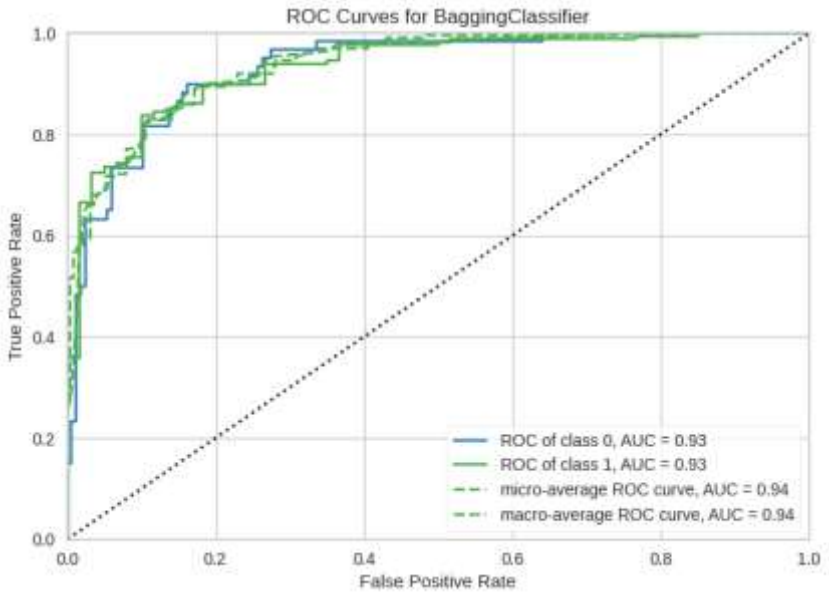


Figure 4.26: ROC Curve for Bagging Classifier

The Bagging classification achieved a score of 93% for class 0 and 93% for class 1, as seen in the AUC-ROC Curve in figure 4.26. On average, the ROC curve for micro and macro is 94% and 94%, respectively.

Result Discussion:

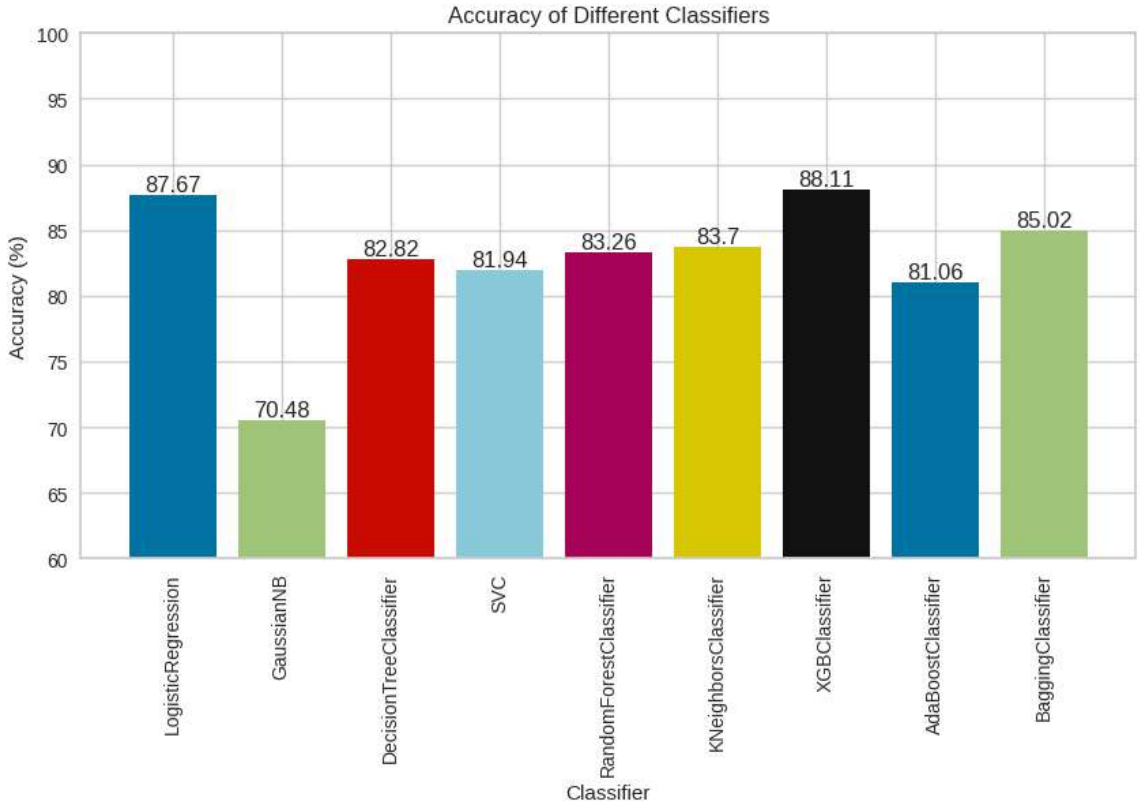


Figure 4.27: Proposed models result comparison

In (fig 4.27), we examined the algorithmic classifier performance. The Extreme Gradient Boosting method achieved the highest accuracy of 88.11%. The results are shown below fig 4.27. The Logistic Regression Classifier achieved the greatest precision score of 92%. The following Classification model achieved varying degrees of precision: Bagging Classifier, Decision Tree (DT), Naive Bayes (NB), XGB Classifier, Support Vector Machine (SVC), AdaBoosting and K-Nearest (KNN) and Random Forest (RF): 83%, 90%, 81%, 89%, 84%, and 87% and 82%. The Support Vector Machine (SVC) and Bagging classifier produced the highest recall score of 98%. The Logistic Regression (LR), K-Nearest (KNN), Random Forest (RF), Adaboosting, Naive Bayes (NB), Decision Tree (DT), and Extreme Gradient Boosting Classifier algorithms had recalls of 91%, 95%, 97%, 91%, 68%, 86%, and 97%, respectively. Using the XGBoost Classifier, the highest F-1 score of 92% was achieved. Random Forest (RF), Logistic Regression (LR), Bagging Classifier, Support Vector Machine (SVM), Naive Bayes (NB), Decision Tree (DT), AdaBoost Classifier, and KNN) Classification model achieved F-1 scores of 89%, 91%, 90%, 88%,77%, 88%, 87%, and 89%, respectively. We can see (fig. 4.35) that our proposed Extreme Gradient Boosting model provides the maximum accuracy. Because XGBoost is designed for

excellent computational efficiency, it enables quick model training on large datasets. It can handle a variety of data types and applications, including regression, classification, and ranking tasks. XGBoost uses a block structure to enable parallel learning. It streamlines the process of boosting capacity on machines with multiple cores or clusters. Additionally, it uses cache awareness to reduce memory consumption during model training with large datasets. XGBoost allows computations to be performed using disk-based data structures rather than in-memory ones, enabling out-of-core computing.

Table 4.2.1: Proposed model result comparison with related work

Sl No	Source	Model	Accuracy
1	[9] Gunduz *et. al*	SVM, CNN	TQTW 82%
2	[10] Hossain *et. al*	SVM, LR, KNN, DT, RF, AdaBoost, Gradient Boost, MLP. LSVC & RF, LSVC & LR, LSVC &KNN, LSVC & DT, LSVC &AdaBoost, LSVC & Gradient BOOST, LSVC & MLP	AdaBoost (84.21%) LSVC & Gradient BOOST (85.09%)
3	**Proposed Model**	Random Forest, Logistic Regression, Naïve Bayes, Decision Tree, Support Vector Machine, K-nearest neighbors, Extreme Gradient Boosting, AdaBoost and Bagging	Extreme Gradient Boosting (XGBoost) 88.11%

Explainable AI

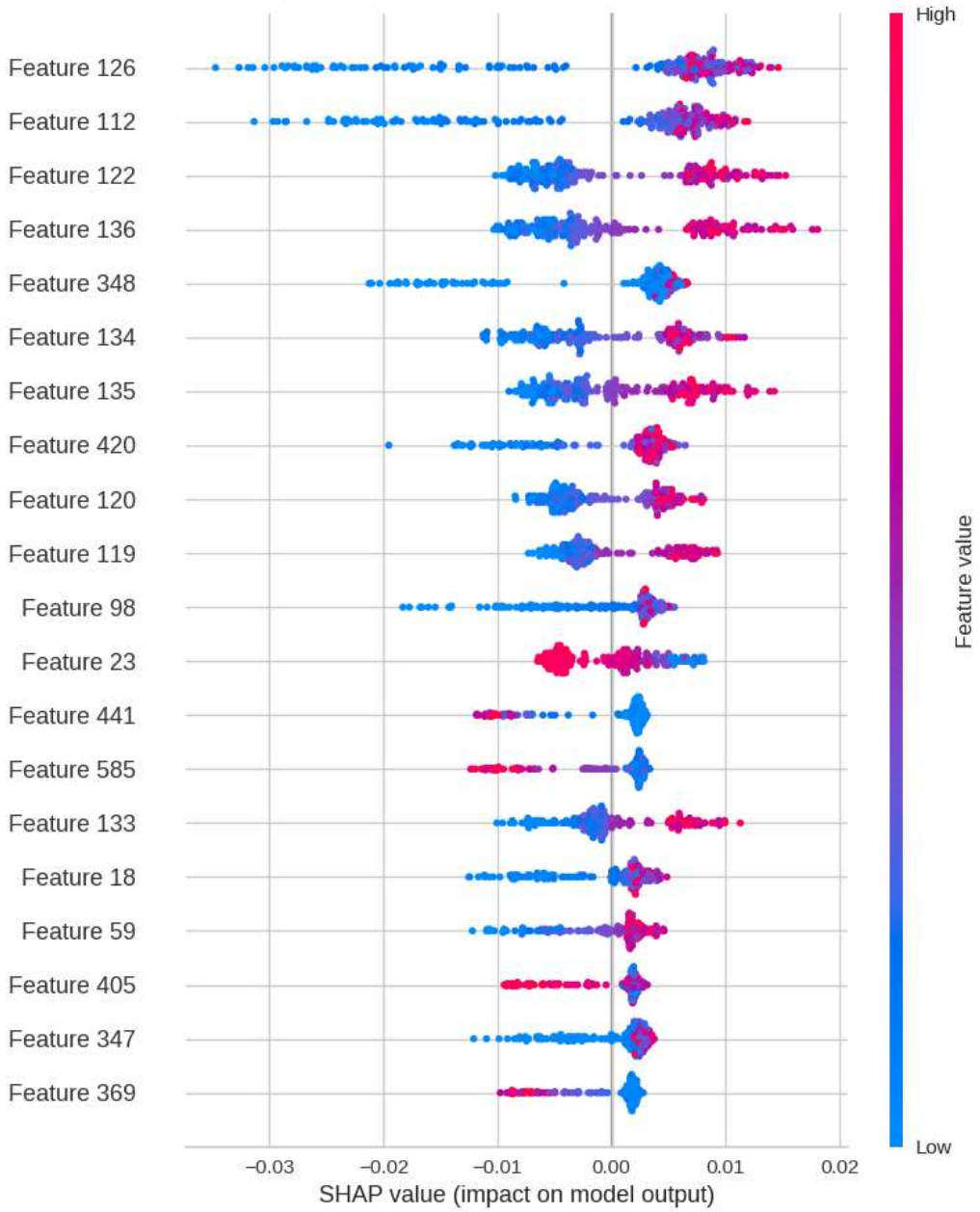


Figure 4.28: Shape value

In this Section (fig 4.29) we can see, feature importance score. We use best accurate model to evaluate the high important feature.

CHAPPTER 5

IMPACT ON SOCIETY, ENVIRONMENT & SUSTAINABILITY

5.1 Impact on Society

Both the economy and society stand to gain a great deal from our suggested approach. By analyzing a real-world dataset, our method deduces the patient's primary worry. This work has societal value since it has the potential to inform young people about the prevalence of Parkinson's disease and how to take steps to avoid getting the disease. We can advise early treatment and regular checkups based on the results of the diagnostic. Why? Because they have excellent eyes for Parkinson's disease symptoms and can quickly assess their risk of developing the disease. The most accurate model is the one we recommend. Consequently, the illness can be accurately and simply foretold. We looked at the dataset that our model was based on to find out which one is the most accurate. Next, we implement AI that is easy for humans to understand. We hope that people will accept and use our proposed paradigm in practical social settings.

5.2 Impact on Environment

Our proposed system is well-suited for implementation in remote regions due to its uncomplicated diagnostic procedures. This model allows us to reduce both complexity and time. We can confidently assert that our model will have a positive environmental impact due to its straightforward implementation and absence of any detrimental effects on the planet. It is possible to receive a Parkinson's disease diagnosis without traveling to major metropolitan areas. The prognostic model can effortlessly validate the patient's reported diagnosis and evaluate the potential outcomes. As a result of the diagnostic's low cost, the patient will not be required to be concerned with Parkinson's disease or local remedies. Because of its user-friendly nature, it is appropriate for people of all age groups. Using our proposed procedure, patients who may have Parkinson's disease can be identified more precisely. The economic and social contexts will both benefit from the paradigm we propose. We guarantee that if our proposed model is effectively implemented, medical technology and research will advance significantly.

5.3 Ethical Aspects

Before the system may be used, the examination of personal data needs to be clearly defined. Additional ethical considerations include the disclosure of personal

information, the use of humor, the accuracy of diagnoses, and the reporting of breaches. The method we have developed is not only applicable to future study, but also to the practical diagnosis of Parkinson's disease. It has been ascertained that the problem extends beyond the particular geographical area and impacts the entire planet. People with knowledge or experience of Parkinson's disease can utilize the recommended approach to predict the signs of the condition.

5.4 Sustainability plan

It is our firm belief that the proposed study will be employed in Parkinson's disease research on a global scale. When applied to female patients, we are confident that the suggested methodology can reliably predict the likelihood of Parkinson's disease. If given the opportunity and the means, we are capable of being motivated and ready to assist rural areas right now. We believe our proposed paradigm will be applicable in the real world and stand the test of time.

CHAPTER 6

CONCLUSION

6.1 Summary of the Study

We may use algorithms to look at our population's effect rate in this fascinating study. Our model allows us to make very accurate forecasts. If the diagnostic technique works, the prediction system might be even better. When people get information about how they will be impacted, it helps them. Maybe they have a strong sense of duty to learn about Parkinson's disease. Our proposal makes it easy to identify the various phases of Parkinson's disease. Assuming our proposal can also benefit individuals responsible for diagnosis. Several time-honored techniques were employed; each of these is simple to construct, accurate, and efficient.

6.2 Conclusion

When applied to the dataset, the results produced through the use of machine learning techniques reveal that the performance of model algorithms is dependent upon the particular characteristics of the dataset. The results of this study show that compared to logistic regression, Random Forest, Naive Bayes, Decision tree, KNN, SVM, Bagging, and Adaboost, Extreme Gradient Boosting algorithms can achieve a higher level of classification accuracy (88.11%). The study also included an analysis that was carried out with the help of the Explainable AI model SHAP. This analysis was successful in determining which feature in this dataset was the most influential. SHAP, which stands for SHapley Additive Explanations, is an effective instrument that may be used to evaluate the explainability of a model. In order to accomplish this, it makes use of straightforward charts such as summary and force.

6.3 Implication for Future Study

Kaggle dataset represents the foundation upon which the research work that is now being carried out is built. Actual data collection is something that we intend to do at some time in the future. Additionally, we make an effort to anticipate the emergence of Parkinson disease by utilizing deep learning techniques and app-based solutions at our disposal. In the event that the work that has been planned is permitted, we will proceed with this examination in a manner that is more complete.

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