

# Implementing a Model to Detect Parkinson Disease using Machine Learning Classifiers

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**Received** 2022 March 15; **Revised** 2022 April 20; **Accepted** 2022 May 10.

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## Abstract

Parkinson disease is a neurodegenerative disorder that affects nervous system and the root cause of it is falling rates of dopamine levels in the forebrain. The machine learning model is implemented to significantly improve diagnosis method of Parkinson disease. In this work it indicates that the ensemble techniques XGBoost classification (Extreme gradient boosting) algorithm achieved the high test accuracy rate (94.8%) compared to different classification algorithm. The performance of the methods has been assessed with a reliable dataset from UCI Machine learning repository

**Index Terms:** Parkinson disease, Random forest, XGBoost Classifier, Data analysis, ANN etc.

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## I. INTRODUCTION

Parkinson's disease is a progressive disorder of the central nervous system affecting movement and inducing tremors and stiffness. It has 5 stages to it and affects more than 1 million individuals every year in India. This is chronic and has no cure yet. It is a neurodegenerative disorder affecting dopamine-producing neurons in the brain. Biomarkers derived from human voice can offer insight into neurological disorders, such as Parkinson's disease (PD), because of their underlying cognitive and neuromuscular function. PD is a progressive neurodegenerative disorder that affects about one million people in the United States, with approximately sixty thousand new clinical diagnoses made each year. Historically, PD has been difficult to quantify and doctors have tended to focus on some symptoms while ignoring others, relying primarily on subjective rating scales. Due to the decrease in motor control that is the hallmark of the disease, voice can be used as a means to detect and diagnose PD. With advancements in technology and the prevalence of audio collecting devices in daily lives, reliable models that can translate this audio data into a diagnostic tool for healthcare professionals would potentially provide diagnoses that are cheaper and more accurate. We provide evidence to validate this concept here using a voice dataset collected from people with and without PD. This paper explores the effectiveness of using supervised classification algorithms, such as deep neural networks, to accurately diagnose individuals with the disease. Our peak accuracy of 94% provided by the machine learning models. The organizational framework of this study divides the research work in the different sections. The Related work is presented in section 2. Further, in section 3 presented Parkinson disease, in section 4 and 5 voice impairment data and data Analysis discussed. in section 6 ,the description of machine learning and Implemen-tation are mentioned. In section 7, experimental work is shown with Machine learning models. Conclusion and future work are presented by last sections 8.

## II. RELATED WORK

Many studies have been conducted on the detection of Parkinson disease using different machine learning algorithms on different datasets containing different features statistical measures. Shivangi[19], has used Deep dense ANNs (Artificial Neural Networks) on the voice recordings and CNNs (Convolutional Neural Networks) on VGFR dataset is used to predict the Parkinson disease. A three layer neural networks is used on the vertical ground force reaction data and a four layer neural network is used on voice data which is in a comma separated values (CSV) format for processing the data and making prediction.

XGBoost and feature selection used by Iqra Nissar[10], and applied various machine learning models on the voice dataset and found that XGBoost with mRMR feature selection gave best results compared to other models. In the study it is observed that feature selection using minimum-Redundancy and maximum-Relevance has produced better accuracy results in making the prediction using XGBoost model.

Wu Wang[25], have used several indicators like rapid eye movement and olfactory loss, dopaminergic imaging markers and cerebrospinal fluid data for making the predictions using several machine learning algorithms KNN, SVM and ensemble techniques for getting better accuracy.

Hadoop and data mining used for data processing by Richa Mathur[15], and presented a data mining methodology using Weka tool and machine learning algorithms ANN and KNN for making predictions on the processed data. In this study a layered big data framework is used for processing the un-structured data and Attribute selection filter provided by Weka tool for feature selection. A 10-fold cross validation technique is used for mining the data.

Shail Raval[18], has used Random Forest(RF) on static spiral for detecting tremor and used Ensemble techniques like RF (Bagging method), AB (Boosting method) and HV (Voting method) for increasing the proposed accuracy.

Securing data using cloud done by Sumathi et.al[22,23], and has published a paper on securing the medical information processing using scheduling strategy in cloud.

### **III. PARKINSON DISEASE**

Parkinson Disease is a brain neurological disorder. It leads to shaking of the body, hands and provides stiffness to the body. No proper cure or treatment is available yet at the advanced stage. Treatment is possible only when done at the early or onset of the disease. These will not only reduce the cost of the disease but will also possibly save a life. Most methods available can detect Parkinson in an advanced stage; which means loss of approx... 60% dopamine in basal ganglia and is responsible for controlling the movement of the body with a small amount of dopamine. More than 145,000 people have been found alone suffering in the U.K and in India, almost one million populations suffers from this disease and it's spreading fast in the entire world.

Parkinson's disease symptoms can be different for everyone. Early signs are mild that goes unnoticed. Symptoms usually begin on one side of your body and gets worsen on that side, afterwards it affects both the sides.

Parkinson's symptoms may include

- Tremor
- Slowed movement
- Rigid muscles.
- Impaired posture and balance.
- Loss of automatic movements
- Speech changes
- Writing changes
- Depression
- Anxiety
- Sleeping, and memory-related issues
- Loss of sense of smell along with balance problems.
- What causes Parkinson's disease is still unclear, but researchers found that several factors are responsible for triggering the disease.

The Parkinson's disease is due to a loss of neurons that produce a chemical messenger in the brain called dopamine. When there is a decrease in level of the amino acid named dopamine it leads to the abnormal brain activity, which leads to Parkinson's disease.

The cause of Parkinson's disease is still a question mark, but several factors appear to play a role, including:

1. *Genes*- Certain mutation genes have been found by research that are very rare. The gene variants often increase the risk of Parkinson's disease but have a lesser effect on each genetic marker.
2. *Environment*- Due to certain harmful toxins or chemical substances found in the environment can trigger the disease but have a lesser effect.
3. *Triggers*

As a result people suffer from this disease for many years before diagnosis. The estimated results have shown that there are 7-10 million people are affected by Parkinson's disease worldwide. People with age above 50 are the one's who has

the higher possibility of getting Parkinson’s disease but still an estimated 4 percentage of people who are under the age 50 are diagnosed with Parkinson’s disease. There is no cure or prevention for PD. However, the disease can be controlled in early stage. The data mining techniques is used as a effective way for early detection and diagnosis of the disease. Data mining techniques in medicine is a research area that combines sophisticated representational and computing techniques with the insights of expert physicians to produce tools for improving healthcare. Data mining is a statistical method for finding hidden patterns in datasets by constructing predictive or classification models that can be learned from past experience and applied in future cases, so there is a need for a more accurate, objective means of early detection, ideally one which can be used by individuals in their home setting.

**IV. VOICE IMPAIRMENT DATA**

**• Data Set Information:**

This dataset is composed of a range of biomedical voice measurements from 31 people, 23 with Parkinson's disease (PD). Each column in the table is a particular voice measure, and each row corresponds one of 195 voice recording from these individuals ("name" column). The main aim of the data

Is to discriminate healthy people from those with PD, according to "status" column which is set to 0 for healthy and 1 for PD. Table4.1 explains the list of features description in dataset.

**• Dataset Description**

Attribute	Description
MDVP:Fo(Hz)	Average vocal fundamental frequency
MDVP:Fhi(Hz)	Maximum vocal fundamental frequency
MDVP:Flo(Hz)	Minimum vocal fundamental frequency
MDVP:Jitter(%),MDVP Jitter(Abs),MDVP:RAP,MDVP:P PQ,Jitter:DDP	Several measures of variation in fundamental frequency
MDVP:Shimmer,MDVP:Shimmer(dB),Shimmer:APQ3,Shimmer:APQ5,MDVP:APQ,Shimmer:DDA	Several measures of variation in amplitude
NHR,HNR	Two measures of ratio of noise to tonal components in the voice
Status	Health status of the subject (one) - Parkinson's, (zero) – healthy
RPDE,D2	Two nonlinear dynamical complexity measures
DFA	Signal fractal scaling exponent spread1,spread2
PPE	Three nonlinear measures of fundamental frequency variation

**Table 4.1: showing attribute information of dataset**

Feature	Mean	Std	Min	25%	50%	75%	Max
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<b>MDVP:Fo(Hz)</b>	195.0	154.22864	41.39006	88.33300	117.57200	148.79000	182.76900	260.10500
<b>MDVP:Fhi(Hz)</b>	195.0	197.10491	91.49154	102.15400	134.86250	175.82900	224.20550	592.03000
<b>MDVP:Flo(Hz)</b>	195.0	116.32463	43.52141	65.47600	84.29100	104.01850	140.01850	239.17000
<b>MDVP:Jitter(%)</b>	195.0	0.00622	0.00484	0.00168	0.00346	0.00494	0.00736	0.03316
<b>MDVP:Jitter(%)</b>	195.0	0.00622	0.00484	0.00168	0.00346	0.00494	0.00736	0.03316
<b>MDVP:RAP</b>	195.0	0.00330	0.00296	0.00068	0.00166	0.00250	0.00383	0.02144
<b>MDVP:RAP</b>	195.0	0.00330	0.00296	0.00068	0.00166	0.00250	0.00383	0.02144
<b>MDVP:RAP</b>	195.0	0.00330	0.00296	0.00068	0.00166	0.00250	0.00383	0.02144
<b>MDVP:Shimmer</b>	195.0	0.02970	0.01885	0.00954	0.01650	0.02297	0.03788	0.11908
<b>MDVP:Shimmer(dB)</b>	195.0	0.28225	0.19487	0.08500	0.14850	0.22100	0.35000	1.30200
<b>Shimmer:DDA</b>	195.0	0.04699	0.03045	0.01364	0.02473	0.03836	0.06079	0.16942
<b>NHR</b>	195.0	0.02484	0.04041	0.00065	0.00592	0.01166	0.02564	0.31482
<b>HNR</b>	195.0	21.88597	4.42576	8.44100	19.19800	22.08500	25.07550	33.04700
<b>RPDE</b>	195.0	0.49853	0.10394	0.25657	0.42130	0.49595	0.58756	0.68515
<b>DFA</b>	195.0	0.71809	0.05533	0.57428	0.67475	0.72225	0.76188	0.82528
<b>Spread1</b>	195.0	-5.68439	1.09020	-7.96498	-6.45009	-5.72086	-5.04619	-2.43403
<b>Spread2</b>	195.0	0.22651	0.08340	0.00627	0.17435	0.21888	0.27923	0.45049

**Table 4.2: Showing statistical measures of dataset**

The dataset which is used for analysis is created by Max Little of the University of oxford, in collaboration with the National Centre for Voice and speech, Denver, Colorado, who recorded the speech signals. This data set consists of a range of biomedical voice measurement with 195 samples of features from 31 people, 23 with Parkinson’s disease (PD) and 8 of them are the control group. The data is in ASCII CSV format. A series of features was extracted which can be categorized as : name of the patients, three types of fundamental frequency(high, low and average),several measures of variation in fundamental frequency(jitter and its type)several measures of variation of amplitude(shimmer and its type),two measures of ratio of noise to tonal components in the voice(NHR and HNR),Two nonlinear dynamically complexity measure-es(RPDE,D2),DFA is a signal fractal scaling exponent, and Three nonlinear measures of fundamental frequency variation(spread1,spread2,PPE). The statistical measures of features in dataset are shown in table4.2. The main aim of the data is to discriminate healthy people from those with PD, according to "status" column which is set to 0 for healthy and 1 for PD. There are around 6 recording per patients. The data set has about 75% of cases suffering from Parkinson disease and 25% of cases which are healthy as shown in the fig.4.1 with the help of bar plot.

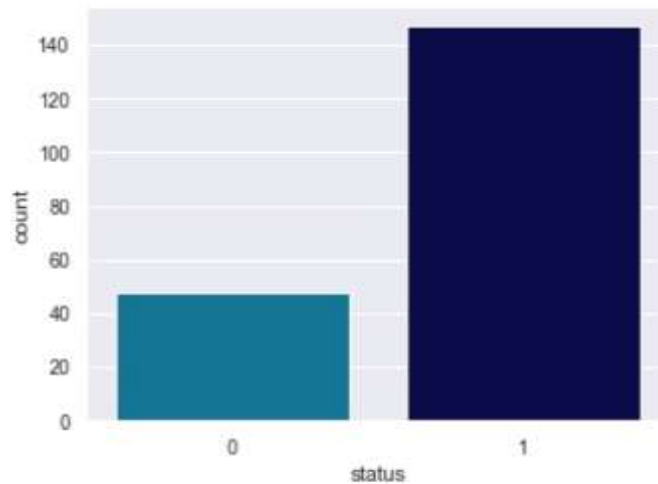


Fig.4.1: Show value counts for two categorical 0 for healthy and 1 for Parkinson's

• Feature Analysis

Feature importance refers to a class of techniques for assigning scores to input features to a predictive model that indicates the relative importance of each features when making a prediction. Feature important analysis provide insight into the dataset. The relative scores can highlight which features can be more relevant to the target. Feature importance analysis can provide insight into the model. Most important scores are calculated by a predictive model that has been fit on the dataset. In fig.4.2. it describes how different features in the Parkinson's disease dataset correlated to each other.

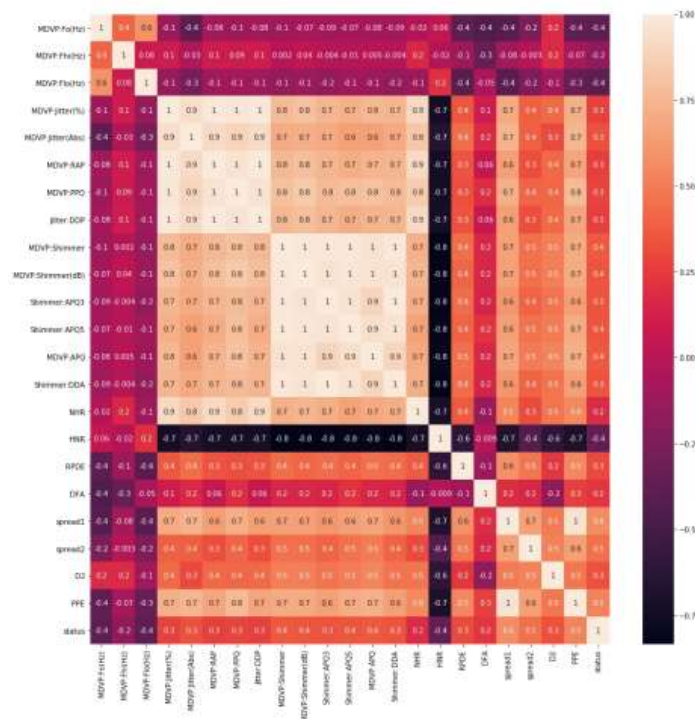


Fig.4.2: Correlation between features of parkinson's disease

V. ANALYSIS

Data Analysis is the methodical approach of applying the statistical measures to describe, analyse, and evaluate data. The researchers analyse patterns and relationships among variables. Univariate, Bivariate, and Multivariate are the major statistical techniques of data analysis.

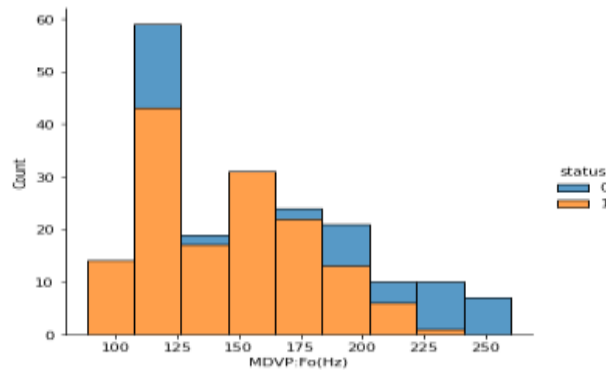
**A. UNIVARIATE ANALYSIS**

Univariate analysis is the easiest methods of quantitative data analysis. As the name suggests, “Uni,” meaning “one,” in univariate analysis, there is only one dependable variable. It is used to test the hypothesis and draw inferences. The objective is to derive data, describe and summarize it, and analyse the pattern in it.

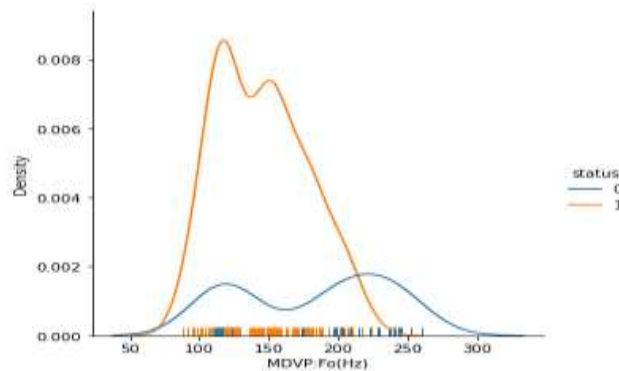
MDVP:Fo(Hz) Mean - Median = 5.4386

MDVP:Fo(Hz) 3 Standard Deviation below mean 30.0584

MDVP:Fo(Hz) 3 Standard Deviation above mean 278.3988



**Fig. 5.a.1: Histogram Plot for MDVP:FO(Hz) feature**



**Fig. 5.a.2: KDE for MDVP:FO(Hz) feature**

Measures of variation of fundamental frequency is positively skewed. For some people, average vocal fundamental frequency is higher than the average. Mainly because it is higher for healthy persons as seen in fig.5.a.2. Frequencies ranging from 100Hz to 200Hz are the ones of persons with PD. Especially 145Hz to around 160Hz frequency ranges are for PD persons only. There is good separation between two kde graphs indicating that this is a good indicator. As we can observe in Kde rug, values are denser near 150Hz on both sides suggesting need to look more here. Also two peaks suggests that this data might have come from two different sources. There are no outliers here.

PPE Mean - Median = 0.0125

PPE 3 Standard Deviation below mean -0.0638

PPE 3 Standard Deviation above mean 0.477

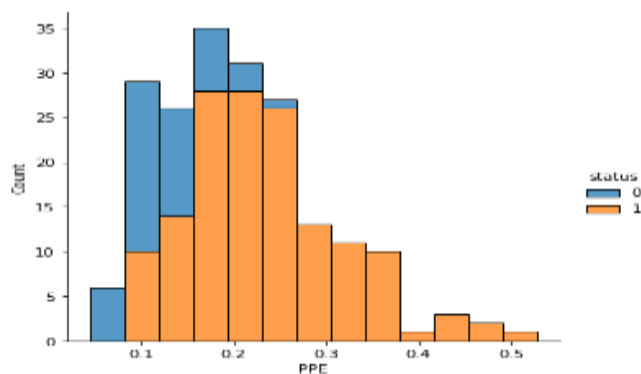


Fig. 5.a.3: Histogram Plot for PPE feature

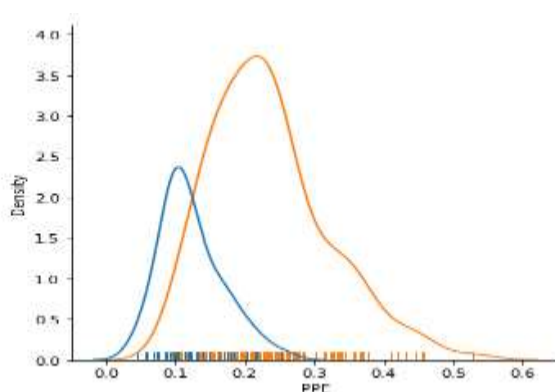


Fig. 5.a.4: KDE for PPE feature

It is a nonlinear measure of fundamental frequency variation. From 0.1 to 0.5 is the range which correlates to persons with PD. This is a good indicator as there is separation. As we can observe in fig.5.a.4, values are denser between 0.2 & 0.3 suggesting need to look more here. It might have outliers.

So out of all independent features only PPE, spread2, spread1, MDVP:Fo(Hz) are the features which look like good indicators as of now

**B. BIVARIATE ANALYSIS**

In Bivariate Analysis, there are two variables wherein the analysis is related to cause and the relationship between the two variables.

**Analysis Of Bar Plots:**

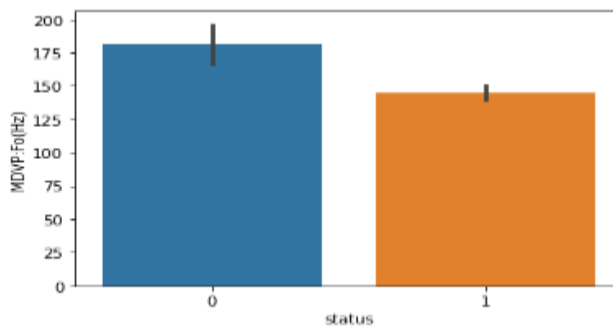


Fig. 5.b.1: Bar Plot for MDVP:Fo(Hz) feature





In this Python machine learning project, using the Python libraries scikit-learn, numpy, pandas, and XGBoost, a model is built using an XGB Classifier. The data is loaded, got the features and labels, scaled the features, then the dataset is split, built an XGB Classifier, and then calculated the accuracy of our model. It is a disease which is a disorder in the nervous system. Parkinson's disease affects the movement of the human body. In today's world, around 1 million people are suffering from this disease. This is a disorder which produces neurodegenerative dopamine-producing neurons in the brain. The following system will detect Parkinson's symptoms in the human body.

The project will be made by a new machine learning algorithm called the XGBoost. XGBoost is a new Machine Learning algorithm designed with speed and performance in mind. XGBoost stands for Extreme Gradient Boosting and is based on decision trees. In this project, we will import the XGB Classifier from the XGBoost library; this is an implementation of the scikit-learn API for XGBoost classification. To build a model to accurately detect the presence of Parkinson's disease in an individual.

### **A. Methodology**

XGBoost is an implementation of gradient boosted decision trees designed for speed and performance that is dominative competitive machine learning. XGBoost provides a wrapper class to allow models to be treated like classifiers or regressors in the scikit-learn framework. This means we can use the full scikit-learn library with XGBoost models.

#### **XGB Classifier**

The XGBoost model for classification is called XGB Classifier. Initialize an XGB Classifier and train the model. This classifies using eXtreme Gradient Boosting- using gradient boosting algorithms for modern data science problems. It falls under the category of Ensemble Learning in ML, where we train and predict using many models to produce one superior output. We can create and fit it to our training dataset. Models are fit using the scikit-learn API and the `model.fit()` function. To detect the presence of Parkinson's Disease in individuals using various factors. We used an XGB Classifier for this and made use of the sklearn library to prepare the dataset.

### **Training Features**

1. When searching for best feature value for node split, XGBoost provides an option to search on the feature value's quantiles or histogram instead of try all the feature values to split node.
2. When building feature histogram, XGBoost may split feature data into multiple computers to calculate histogram, then merge back to generate a aggregate histogram, this like Hadoop Map-reduce operation, and the generated histogram will be cached for next split.
3. XGBoost can automatically handle missing values in feature. In tree node split step, XGBoost will either assign all missing value instances to left or right child, depend on which side has larger gain.
4. XGBoost provide lots hyper-parameters to deal with overfitting

### **B. XGBoost Analysis**

XGBoost is a decision-tree-based ensemble Machine Learning algorithm that uses a gradient boosting framework. In prediction problems involving unstructured data (images, text, etc.) artificial neural networks tend to outperform all other algorithms or frameworks. However, when it comes to small-to-medium structured/tabular data, decision tree based algorithms are considered best-in-class right now. Please see the chart below for the evolution of tree-based algorithms over the years.

**Step1:** Finding similarity scores for each groups (left and right) using the equation

$$\text{Similarity score} = \frac{(\sum \text{Residual}_i)^2}{\sum [P_i \times (1 - P_i) + \lambda]}$$

**Step2:** Calculating Gain to decide the thresholds for better split  
 Gain = Left similarity + Right similarity- Root similarity

**Step3:** Calculating Cover for each leaf node to determine minimum number of residuals in a node in the tree using the Cover equation  
 Cover =  $\sum [P_i \times (1 - P_i)]$

**Step4:** Tree Pruning is made based on Gain value, using the below equation  
 Gain -  $\gamma$   
 Pruning is made if difference is Negative

**Step5:** Output values are calculated for every leaf node in the tree  
 Output =  $\sum [P_i \times (1 - P_i) + \lambda]$

**Step6:** Calculating new prediction for the constructed tree  
 New prediction = Initial predicted value + learning rate ( $\epsilon$ )  $\times$  Output value

**Fig 6.1: Algorithm for XGBoost Decision Tree**

We could simply compare the new residuals and found that whether we have taken a small step in the right direction. We keep building other trees based on new residuals and make new prediction gives smaller residuals until residuals are small or reached maximum number.

**VII. EXPERIMENTAL RESULTS**

This section shows the analysis of different learning models through the experimental work. The paper conducts the experiments on different well known learning models using Voice impairment data taken.

The Table 7.1. Presents the comparison of various learning models used in the experiment. All the learning models are doing well with minimum accuracy of 82.05 % gained by SVC and 94.87 % gained by XGBoost classifier.

Models	Samples	ML Classifier	Test Accuracy
Existing Method	50	SVM	81.16
		XGBoost	77
Proposed Method	50	XGBoost Classifier	94.87
	50	Logistic Regression	
	50	SVC	89.74
	50		82.05

**Table 7.1: The Comparison tables of different models**

**VIII. CONCLUSION**

The analysis of which algorithm provide the high accuracy of prediction for the Parkinson’s disease dataset, here the classification accuracy was studied and compared, with good performance and fast implementation XGBoost with multiple fold data achieved a high accuracy with 94.87%. This system provides the comparison between machine learning classifiers of LR and XGBoost in PD disease diagnosis with high dimensional data.

**Future work**

In future work, we can focus on different techniques to predict the Parkinson disease using different datasets. In this research, we using binary attribute (1- diseased patients, 0-non-diseased patients) for patient’s classification. In the future we will use different types of attributes for the classification of patients and also identify the different stages of Parkinson's disease

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