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An Ensemble Learning Driven Voice Investigation for Early Screening of Parkinson's Disease

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Abstract: Parkinson's disease (PD) is a complex and prevalent central nervous syndrome characterized by the emergence of unintended or uncontrollable movements, accompanied by symptoms. The global prevalence of PD has escalated to an estimated 9.4 million individuals, indicating a substantial rise from 6 million. This alarming surge underscores the urgent need for proactive measures to address the growing burden of this neurodegenerative disease and its profound impact on society. The machine learning algorithms used on PD dataset are designed to find the optimum approach for examining the seriousness of the Parkinson disease. The primary focus of this research centers on employing machine learning algorithms to enhance our ability for early prediction of Parkinson's disease accurately. This research attempts to find the best model by investigating a wide variety of classification algorithms. The objective is to enhance early identification and diagnosis, therefore improving patient outcomes and lowering the load on healthcare providers. For this purpose, we have opted various Machine Learning algorithms such as the NB, RF, KNN, GB and XGboost. The evaluation of each algorithm's performance is meticulously conducted through rigorous experimentation, taking into account metrics such as Jaccard similarity, precision, sensitivity, F1score and accuracy. The dataset utilized in this study encompasses valuable clinical and demographic information of PD patients, which enables us to develop and train the mentioned algorithms. We demonstrated the Gradient boosting (GB) algorithm's significant performance across all machine learning algorithms to predict patients with PD. The results are encouraging and reveal the potential for ML algorithms to accurately and efficiently predict symptoms that are undetectable to a medical professional.

Keywords: Parkinson's disease (PD), Machine Learning (ML), Baseline features, fundamental frequency features, Naive Bayes (NB), Random Forest (RF), K-Nearest Neighbors (KNN), Gradient Boosting (GB), XGBoost (XGB).

1. Introduction

Parkinson's disease, which impacts the human motor system, is a chronic degenerative disorder. Named after James Parkinson, this disease shows its symptoms slowly, giving rise to problems with cognition, sleep, behaviour, and the sensory system. PD is usually caused when the nerve cells of the brain, get impaired or die, leading to less secretion of dopamine. Dopamine is one of the important chemicals released by the brain cells and is important for communication between the nerve cells. Along with dopamine, another chemical released at the end of the nerves is norepinephrine, which controls many functions of the body [1]. Parkinson's disease deals with a heavy dataset, for whose analysis various machine learning algorithms have been put to use. ML is a subfield of computer science and artificial intelligence that deals with data and algorithms. It is used for making classifications and predictions when working on data mining projects. Machine learning algorithms are created using an accelerating framework for solution development [2].

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Parkinson Disease is the neurodegenerative illness which occurs due to the combination of genetic and environmental factors. These factors are most likely to generate abnormal aggregation in the selected groups of neurons which cause the misfunctioning and eventually death. The PD can be diagnosed clinically and to exclude other causes of Parkinsonism, high index of suspicion is expected. Methods and surgeries have been introduced to diagnose and treat PD at the earliest stage. Further studies are being carried out to modify the drugs offering neuroprotection against PD and further development in the field of PD treatment is likely to take place [3-4]. The researcher approached to diagnose PD using the acoustic signal feature. They opted machine learning techniques along with deep learning like KNN, Support Vector Machine, Random Forest, and Multilayer Perceptron Amongst all the performed algorithms the researchers found the best results for SVM with accuracy 95% and MLP with accuracy 98.31% [5]. Trained the classifier using the Machine Learning algorithms. The Boosted Logistic Regression was observed by researcher to give the best performance and can thus be used in prediction of PD [6]. Dataset from Parkinson's Progression Markers Initiative (PPMI) was chosen to perform the required Machine Learning Algorithm. Along with biomarkers including tests of CSF fluid and imaging of the dopamine transporter, it also took into account non-motor symptoms. [7].

Authors focused on the early stages of Parkinson's disease, marked by subtle symptoms such as hand tremors, facial rigidity, and speech alterations [8].

Diverse feature extraction methods were employed for binary classification, with KNN, SVM, DT, and RF classifiers. Combining data from various motor tasks, maximum accuracy was obtained by merging the most significant features from both hands [9].

An innovative deep learning technique was introduced to identify PD in its early stage. Comparative analysis with twelve machine learning approaches highlighted the superior performance of the deep learning model. It provided insights into feature importance using the Boosting method [10].

This research paper utilized voice data from both PD and healthy control (HC) groups. ML algorithms, such as SVM, KNN, and RF were compared and PCA was applied to reduce the initial 26 voice features into two principal components, optimizing data for PD and HC classification. This model effectively improved F1 score and AUC, enabling the practical differentiation of PD and HC patients, as indicated by ROC curve values nearing 1. and Random Forest achieved the highest accuracy [11]. This study uses a large dataset from the UCI ML repository of 5876 × 22 fields, which includes details about both Parkinson's and healthy people, to assess how well deep learning and machine learning techniques work in determining the most effective and precise method for diagnosing Parkinson's disease early on [12]. A computer approach based on auditory features extracted from sustained vowel recordings is proposed to distinguish between individuals with PD and healthy individuals [13-14].

This work aims to introduce new techniques in feature engineering and machine learning for vowel phonation-based diagnostics, as well as to update earlier studies. ML approaches and further features were added [15].

Various machine learning models were compared to assess the performance of a range of ML models for the accurate prediction of Parkinson's disease severity [16]. The primary objective was to develop a highly effective and precise model, enabling early disease diagnosis. It contributed to more timely medical interventions and improved recovery opportunities for PD patients [17]. The goal of our research is to increase prediction accuracy by offering a thorough analysis of the factors that contribute to PD. The features of acoustic and their effects on PD are explained in detail in the section that follows.

2. Data Set and Feature Analysis

This section describes about the data set and explains different features. Researchers are able to evaluate the risk variables and connections related to Parkinson's disease by using these features along with other characteristics. The growth of Parkinson's disease management, early detection, and prevention measures is greatly aided by this thorough understanding.

The data used in this research was gathered from Kaggle [18]. The detailed description of data set is given in table 1 and The Figure 1 shows the count of patients with Parkinson disease (PD) and non-Parkinson disease (NPD)

2.1 Feature description and analysis

Total 8 features are used for the diagnosis of Parkinson. Only one feature is having categorical values i.e. Gender. One of the initial signs of PD is speech impairment, which can be automatically assessed to corroborate the finding and evaluate the severity of the condition in both genders.

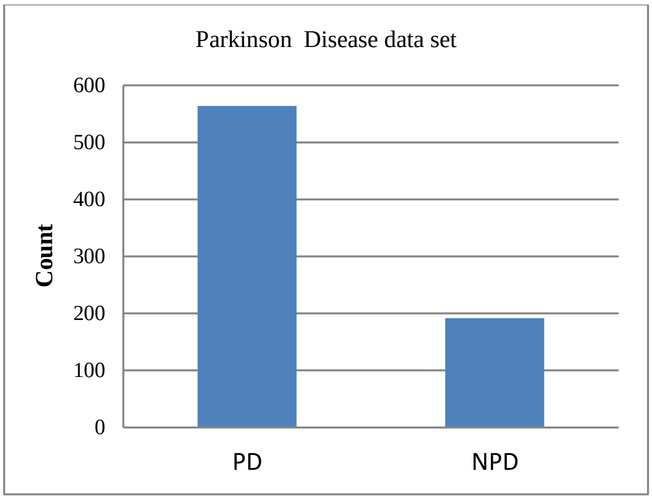


Fig. 1. Patients count with Parkinson disease (PD) and non-Parkinson disease (NPD)

This research examines how voice signals are processed to estimate the prevalence of PD in both women and men. Table I shows Parkinson's data set contains different audio tasks were recorded using microphone. The results indicate that the likelihood of men developing Parkinson's disease is higher than that of women.

Remaining 7 features are pitch period entropy, detrended fluctuation analysis, recurrence period density entropy, number of pulses, mean of periodic pulses, standard deviation of periodic pulses, jitter with values in numerical range shown in Table II.

2.1.1 Pitch Period Entropy (PPE)

It is one of the baseline features which is used to measure of dysphonia for distinguishing PD patients from those in good health. It uses a logarithmic scale to quantify the loss of basic frequency control. Pitch Period Entropy (PPE) may withstand a range of erratic confounding variables, including noisy environments and normal, healthy variations in voice frequency.

Table 1. Data Set Description

	Men	*Women*	*Total*		*Total Data Set Collection*	*Range of Age*
Patients with Parkinson	107	81	188	Each sample is collected with three repetitions.	564	with ages ranging from 33 to 87
Healthy Person	23	41	64		192	with ages varying between 41 and 82

Table 2. shows numerical statistics of feature with the values of its minimum, maximum and mean.

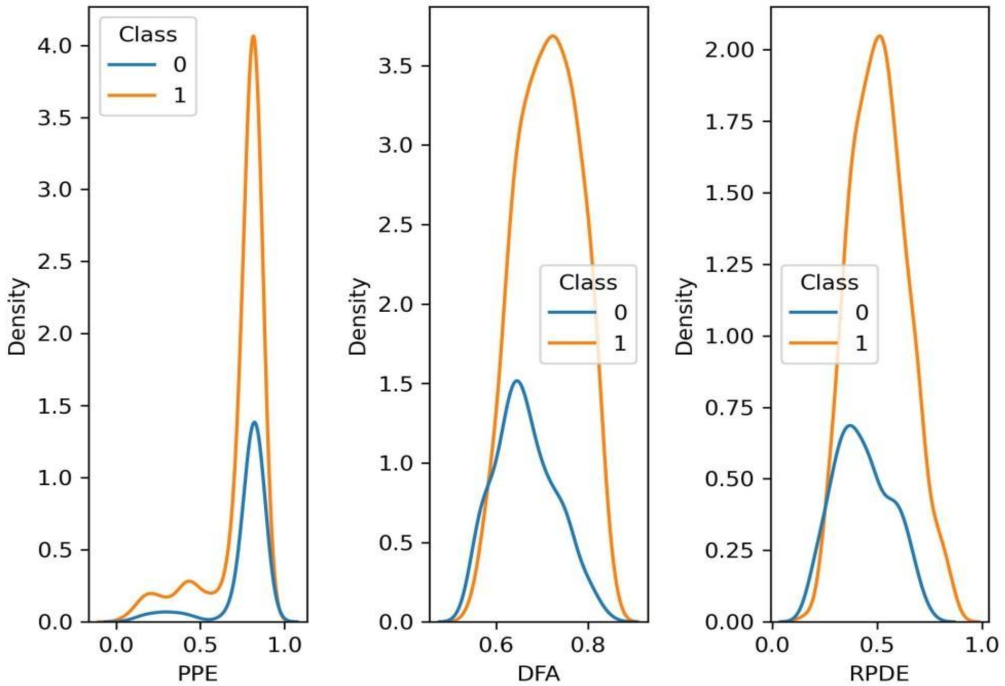
SN	*Baseline features/fundamental frequency features*	*Minimum Value*	*Maximum Value*	*Mean Value*
1.	Pitch Period Entropy (PPE)	0.041551	0.907660	0.746284
2.	Detrended Fluctuation Analysis (DFA)	0.543500	0.852640	0.700414
3.	Recurrence Period Density Entropy (RPDE)	0.154300	0.871230	0.489058
4.	Number of pulses and periods	2.000000	907.000000	323.972222
5.	Mean periodic pulses	0.002107	0.012966	0.006360
6.	Standard deviation of periodic pulses	0.000011	0.003483	0.000383
7.	Jitter	0.000210	0.027750	0.002324

2.1.2 Detrended Fluctuation Analysis (DFA)

It is an essential baseline element for the investigation of far-reaching temporal correlations in time series for electrophysiological recordings. In DFA, data are linearly detrended and separated into segments of length L. As a function of L, fluctuation of the slackened data is examined [19]. A linear relationship between the logarithm of the fluctuation and the logarithm of L can be used to show that the spectrum exhibits power law behavior.

2.1.3 Recurrence period density entropy (RPDE)

It is a baseline feature which characterizes the periodicity of a signal. Given the noise caused by turbulent airflow, these restrictions are anticipated to be less stringent for speakers who have dysphonia. Using the information-theoretic concept of entropy, RPDE measures the uncertainty in the calculation of the vocal fold cycle time. It has been used effectively to find anomalies in speech signals [20].



(a) **(b)** **(c)**

Fig.2. Estimated probability density functions of (a) Pitch Period Entropy (b) Detrended Fluctuation Analysis (c) Recurrence period density entropy for patients with PD and healthy person.

The Figure 2 illustrates the estimated probability density curves of PPE, DFA and RPDE respectively. Plots of the probability density curves for Parkinson disease patients and healthy individuals are shown in blue and orange, respectively.

It is observed from Figure 2(a) the probability density curve of PPE is reached to 4.0 for patients with PD while it is less than 1.5 for the case of non-PD. Whereas from Figure 2(b) the probability density curve of DFE is greater than 3.5 for patients with PD while it is 1.5 for the case of non-PD. From the figure 2(c) The probability density curves suggest that PD patients' mean RPDE values are higher than those of normal people.

2.1.4 Fundamental frequency features

Parkinson's disease identification relies heavily on finding features of voice samples. Four different types of dysphonia features were used in this research. These traits were identified based on the finding that vocal fold vibrations are regular in healthy persons but irregular in PD patients. In PD patients, fundamental frequency variability considerably increased.
The number of pulses and periods, mean, standard deviation, and jitter parameters are utilized to determine the frequency of the voice signal [21].
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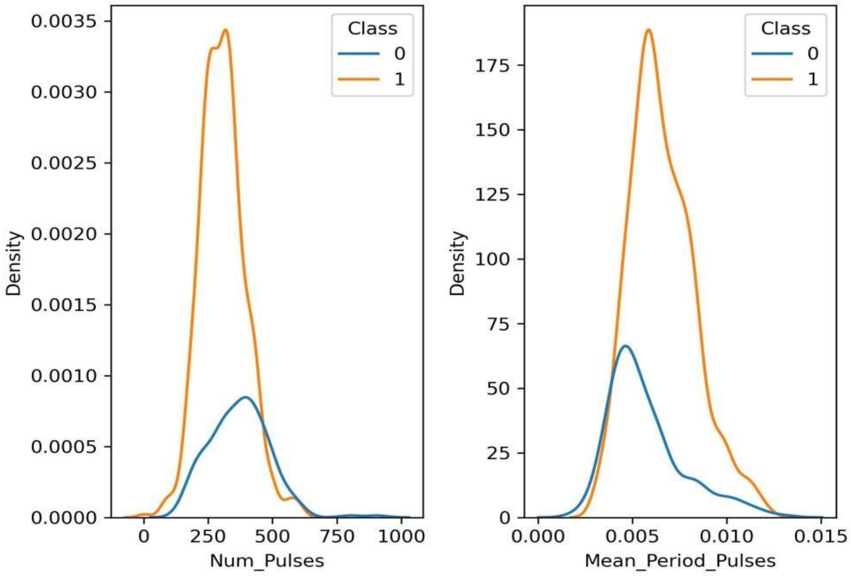
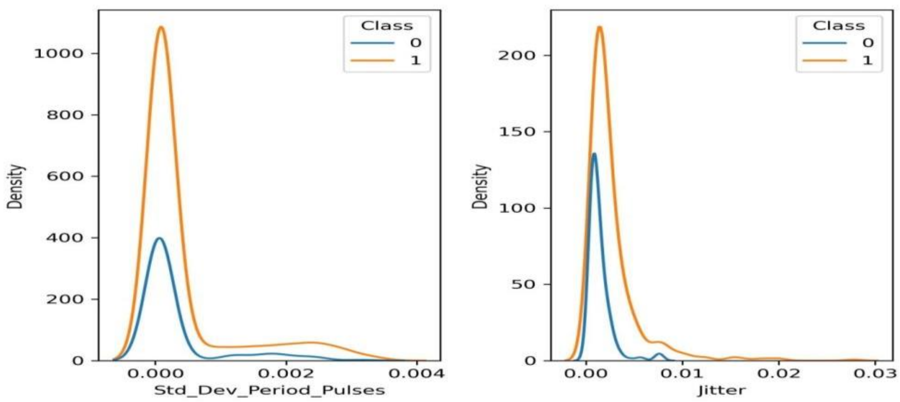
Jitter variants are used to record instabilities in the oscillation pattern of the vocal folds, and this feature sub-set measures the fundamental frequency fluctuations from cycle to cycle.
The dataset showed that, as compared to healthy individuals, patients with Parkinson's disease had a striking change in these characteristics.



(a) (b)

Fig. 3. Estimated probability density functions of (a) Number of pulses (b) Mean Periodic pulses



(a) **(b)**

Fig. 4. Estimated probability density functions of (a) Standard deviation of periodic pulses (b) Jitter

It is depicted from Figure 3 (a) In PD patients, the probability density curve for the number of pulses reaches 0.0035, whereas in non-PD patients, it is less than 0.0010. and from Figure 3 (b) For patients with PD, the probability density curve of mean periodic pulses exceeds 175 while going below 75 in the case of non-PD patients. The graphical analysis demonstrated that the aforementioned features exhibit greater variability in patients with Parkinson’s.

It can be seen in Figure 4 (a) The probability density curve for the standard deviation of periodic pulses is larger than 1000 in PD patients compared to less than 400 in non-PD patients. and from Figure 4 (b) The probability density curve of jitter reaches 200 for Parkinson's disease patients**,** while it drops to below 150 for people without PD. The statistical study revealed that the above features were more variable in the PD patients.

3. Methodology

This section evaluates the ability of five distinct machine learning algorithms to detect and diagnose Parkinson's disease using a consistent methodology. The steps included in the evaluation process are shown in the figure 5:

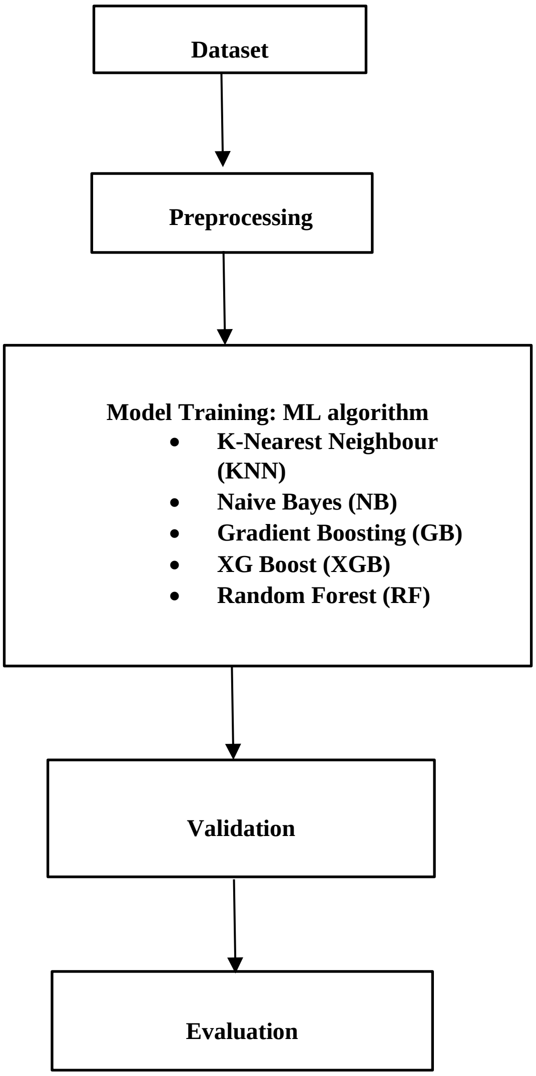


Fig.5. Steps for evaluation of Machine Learning models

3.1. Preprocessing

A large-scale dataset was acquired that included clinical and demographic data from people with and without Parkinson's disease. The machine learning models were trained and assessed using this dataset as the basis. Preprocessing was done in order to get the data ready for model training. In order to make training the algorithms easier, the processes for preparing made sure the data was presented correctly. In preprocessing first step is splitting the data and second is feature scaling. The dataset was split into training and evaluation sets in order to facilitate efficient model training and precise performance evaluation. This division allowed the model to learn patterns from a portion of the data and assess its ability to generalize to unseen data. In addition, feature scaling was performed to normalize the numerical features within the dataset. This crucial step aimed to bring the features to a comparable scale, preventing any particular feature from overpowering the learning process due to differences in magnitudes.

Common techniques employed for feature scaling include standardization or normalization. The choice of scaling technique depended on the characteristics of the features and the requirements of the machine learning algorithm being employed.

3.2. Model Training

Five distinct machine learning algorithms were utilized in this study: K-Nearest Neighbors (KNN), Naive Bayes (NB), Random Forest, Gradient Boosting, and XGBoost. Each algorithm was trained on the preprocessed dataset using a designated portion of the data for the training phase.

3.2.1 KNN

K-Nearest Neighbors (KNN) is different because it doesn't make assumptions about the data and relies on the examples in the dataset to make predictions. When it encounters a new data point, it looks at the closest existing data points and takes a vote to decide which category the new point belongs to. Preprocessed data that has been set aside expressly for training is used to train the KNN algorithm. To get the greatest results with KNN, like with any machine learning algorithm, it is crucial to carefully preprocess the data, choose the right hyperparameters, and assess its performance.

3.2.2 Naive Bayes

The popular classification algorithm Naive Bayes, which is known for its ease of use and effectiveness, uses Bayes' theorem to generate predictions. When evaluating the class label, it presumes that a dataset's features are independent of one another. When working with high-dimensional data and text classification jobs, this statistical technique is quite helpful. Operating on the basis of prior knowledge about each class, the algorithm estimates the probability that features belong to distinct classes. It determines, given the observable features, the conditional probability of a certain class. Despite its simplicity, the algorithm often delivers competitive results and serves as a strong baseline for more complex classification models.

3.2.3 Gradient Boosting

Gradient Boosting is an advanced and powerful machine learning algorithm that has gained widespread popularity due to its exceptional predictive capabilities. The fundamental principle behind Gradient Boosting lies in its ability to construct accurate predictive models by effectively combining multiple weak models, often decision trees.

Through an iterative process, the algorithm continuously trains new models on the training data, with a primary focus on correcting errors made by previous models. It actively pays extra attention to data points that were previously not accurately predicted, resulting in remarkable model performance improvements.

The essence of Gradient Boosting is to iteratively minimize a special loss function, which serves as a crucial driving force for its continuous refinement.

For instance, mean squared error is commonly used for regression tasks, where the objective is to predict numerical values, while log loss is frequently employed for classification tasks, involving the categorization of data points into discrete classes. Throughout the boosting process, Gradient Boosting meticulously seeks to minimize the loss function.

3.2.4 XG Boost

XGBoost, also known as Extreme Gradient Boosting, is an advanced machine learning algorithm used for regression and classification tasks. It builds upon the gradient boosting algorithm and integrates additional techniques to enhance its performance and efficiency.

Like gradient boosting, XGBoost trains weak models, such as decision trees, in a sequential manner to rectify the mistakes made by previous models.

However, XGBoost introduces several improvements to make the training process more powerful. It incorporates regularisation techniques to prevent overfitting, parallelization to accelerate training, and a specialised loss function to optimise the model's performance.

3.2.5 Random Forest

By randomly choosing a subset of each tree's characteristics and training data, Random Forest creates a number of decision trees. This randomization is beneficial because it helps prevent overfitting and enables the model to generalize well to unseen data. In the training process, the Random Forest algorithm grows numerous decision trees, each one learning patterns and making predictions independently. In classification tasks, this is achieved through majority voting, while in regression tasks, the predictions are averaged.
The Gini Index is a statistical measure that quantifies the degree of impurity or disorder in a set of elements. They are capable of handling high-dimensional data effectively, capturing intricate interactions between features, and providing estimates of feature importance.

4. Experimental Results

The results of an experiment to identify Parkinson's disease are covered in this section. using the given dataset and five different machine learning methods. The following list of quantitative metrics is used to evaluate the methods

4.1 Confusion Matrix

There are N target classes in this N x N confusion matrix. We contrast the ML model's predicted values with the target values in the matrix. The confusion matrix for PD classification is shown in table 3

that require rejection. This indicates that FN = FP = 0 for a classifier with 100% accuracy. Accuracy is an aggregate measure of classifier performance.

- Precision is the number of cases generated that were actually applicable. To find the value of precision, we divide the total number of correctly identified positive data by the entire number of projected positive data. It measures the ratio of actual samples that are positive to expected healthy samples. The relationship provides precision.
- Sensitivity is the model's accuracy in identifying positive instances.
- Jaccard Similarity compares the individuals in two sets to identify the similarities and differences between them. It is calculated using y as the expected labels and y as the actual labels.
- Log Loss one of the key measures used to evaluate the effectiveness of any classification task, which is based on probabilities. The statistic that is accurately predicted for each instance is the negative average of the log of probabilities.
- In essence, the AUC ROC curve is a tool for evaluating an ML model's performance. AUC is a summary of the ROC curve that indicates a binary classifier's capacity to discriminate between classes. ROC stands for the receiver operating characteristic curve is a graph that displays a classification model's performance over all categorization levels. The FP rate and TP rate can be plotted on the horizontal axis and vertical axis, respectively

All five ML algorithm's performance is evaluated using all the quantitative indicators. Table 4 present results.

As can be seen from Table 4 that Gradient Boosting recorded the highest accuracy of 94.07%, followed by Random Forest, XGBoost, KNN, and Naive Byes with accuracy of 90.78%, 84.81%, 82.83%, and 79.53%, respectively.

Jaccard similarity index of 86.44%, 82.44%, 82.35%, 80.74% and 75.59% is obtained by Gradient boosting, XGboost, Random Forest, KNN and Naïve bayes respectively.

Gradient Boosting reported the highest F1-Score of 88% followed by 85%, 84%, 81% and 80% with Random Forest, XGboost, KNN and Naive Bayes respectively.

Table 3. Confusion Matrix

		Predicted Class	
		Healthy Person	Patients with Parkinson
Actual Class	Healthy Person	True Positive (TP)	False Negative (FN)
	Patients with Parkinson	False Positive (FP)	True Negative (TN)

Table 4. Assessment of Machine Learning Algorithms through Diverse Quantitative Metrics

	Percentage (%) of results obtained with ML algorithms				
Evaluation Parameters	***KNN***	***RF***	***NB***	***XGB***	***GB***
Jaccard Similarity	80.74	82.35	75.59	82.44	86.77
Precision	83	85	80	84	89
Sensitivity	83	85	80	95	89
F1 Score	81	85	80	84	88
Accuracy	82.83	90.78	79.53	84.81	94.07

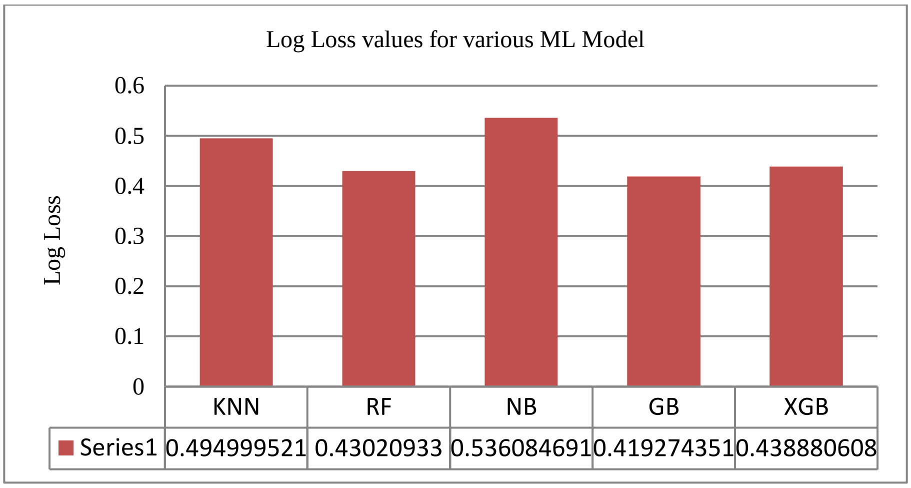


Fig. 6. Log loss values for various Machine Learning Model

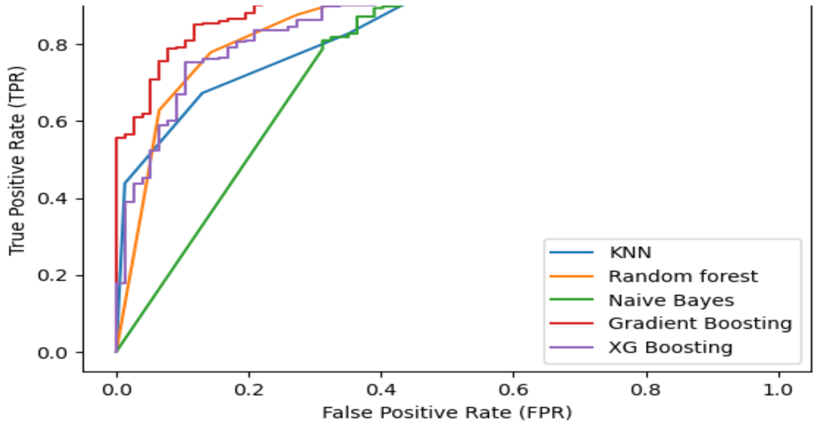


Fig. 7. AUC ROC Curve for various ML algorithms

Gradient Boosting showed the highest precision of 89%, followed by Random Forest, XGBoost, KNN, and Naive Bayes with corresponding precisions of 85%, 84%, 83%, and 80%. The figure 6 shows the graphical values of log loss that were acquired using various techniques.

Gradient Boosting yielded the lowest log loss of 0.4192, which was followed by Random Forest, XGBoost, KNN, and NB with relative log losses of 0.4302, 0.4388, 0.4949, and 0.5360.

The figure 7 illustrates that AUC ROC value for Gradient Boosting is highest (93.92%) is near to 1 hence GB performed better as compared to other ML algorithms such as 88.48% for XGB, 88.44% for RF, 85.83% for KNN and 76.47% for NB.

4.2 Result Discussion

The performance of various machine learning algorithms was evaluated for the prediction of Parkinson’s disease from voice recordings in this research. The goal of the investigation was to examine the baseline features and fundamental frequency features of speech signal through the prognostic capacities of various algorithms in order to determine the most accurate and efficient technique of predicting Parkinson's disease.

In this research, each algorithm's performance utilizing a complete set of evaluation criteria such as accuracy, precision, sensitivity, Jaccard similarity, F1-score, and AUC-ROC. Individual classifier predictions were merged with ensemble stacking and voting procedures, and a comparative study of these ensemble accuracies is presented to reduce classifier bias. The final results verified the algorithms' performance, confirming their ability to accurately predict the patient with or without Parkinson's disease. From the result observed that the model Gradient boosting performed best as compared with other ML models such as KNN, Random Forest, Naive Byes and XGboost.

GB achieved the greatest accuracy, F1-score, precision, and Jaccard similarity among the algorithms, suggesting its overall excellence in accurately classifying instances. The sensitivity of a machine learning model assesses its ability to recognize positive instances. It is sometimes referred to as the True Positive Rate. The model XGB achieved high sensitivity as compare to other ML models hence XGB has ability to recognize positive instances. The cross entropy of the error between two probability distributions is measured by the log loss function. The model GB showed less log loss values, indicates better predictor model with best performance.

The AUC-ROC metric assesses the algorithm's ability to distinguish between positive and negative cases. The greatest AUC-ROC scores were obtained by GB, suggesting their significant discriminatory capability. The models XGB and RF had lower AUC-ROC values, indicating less ability to discriminate amongst the two classes efficiently.

Along with predicted performance, we assessed the algorithm's computational efficiency and interpretability. KNN and NB are simple algorithms with low computing efficiency that are easier to interpret. On the other hand, RF, GB, and XGB are ensemble approaches that need more computational resources and are more difficult to interpret. When selecting an algorithm for Parkinson's disease prediction, computational efficiency should be considered.

This research presents a complete analysis of speech signal using various machine learning algorithms for detecting Parkinson's disease. Although GB demonstrated the best overall accuracy for prediction, XGB and RF also performed well. Researchers and medical practitioners may select the suitable algorithm based on the relationship between accuracy, precision, Jaccard similarity, sensitivity, AUC-ROC, and computing efficiency.

5. Conclusion

This research concludes that the values of probability density curves of fundamental frequency features and baseline features of speech signal recorded higher for patients with PD while less for the healthy person. In conclusion we can say that the best algorithms that can be performed to give earlier predictions of Parkinson's Disease using speech signal are Gradient Boosting and Random Forest. Gradient Boosting provides the highest accuracy of 94.07 and log loss of 0.4192 while Random Forest provides the accuracy of 90.78 and log loss of 0.4302. The algorithms with highest accuracy and low log loss prove to be the most satisfying and efficient for earlier predictions of Parkinson's Disease. We also observed that Naive Bayes comes with least accuracy and highest log loss proving the algorithm to be not suitable to carry out PD's earliest prediction. Naive Bayes comes with an accuracy of 79.53 and log loss of 0.5360. This model can serve as the learning tool in the medical field and better accuracy and predictions can be obtained by introducing the necessary improvements.

This demonstrates that for earlier predictions of Parkinson's Disease, Gradient Boosting and Random Forest emerge as the most promising algorithms. Both these algorithms exhibit competitive performance in terms of accuracy and log loss, making them highly effective choices for early detection of PD. Furthermore, the superior performance of Gradient Boosting over Random Forest in terms of accuracy and log loss reaffirms the power of ensemble methods like boosting in improving prediction accuracy.

In summary, a comprehensive analysis of machine learning algorithms for the diagnosis of Parkinson's disease advances medical knowledge. By utilizing the power of these algorithms, healthcare professionals may provide specific treatment plans and make well-informed decisions, which will eventually improve patient outcomes.

Author contributions

Megha Chakole[1]: Conceptualization, Methodology, investigation, writing—review and editing, supervision. **Yogita Dubey[2]:** Conceptualization, Methodology, investigation, visualization. **Sayalee Joshi[3]:** software, validation, resources writing—original draft preparation. **Usha Ambule[4]:** software, data curation, formal analysis, writing—original draft preparation. **Sanskruti Kayarkar5:** formal analysis, writing—original draft preparation. **Roshan Umate[6]:** funding acquisition.

Conflicts of interest

The authors declare no conflicts of interest.

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