Comparison of different Machine Learning algorithms for Parkinson's disease detection

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Abstract— Parkinson's disease (PD) is a progressive neurodegenerative condition that affects millions worldwide, and early diagnosis remains critical for effective treatment. Over the past few years, multiple innovative types of machine learning approaches have been developed for PD diagnosis based on data in the form of speech patterns, handwriting samples, sensor data, and many more. However, the performance of these algorithms varies significantly with the choice of data and features used.

In this paper, authors have compared the performance of a number of machine learning algorithms to diagnose Parkinson's disease. The dataset for this study was acquired from Oxford UCI Machine repository. We obtained the dataset for the study from the Oxford UCI Machine repository. After preprocessing the data and extracting relevant features, we applied various algorithms, including logistic regression, support vector machines, random forests to classify individuals as either PD patients or healthy controls.

The performance evaluation parameters, including accuracy, precision, recall, F1 score, and Precision-Recall curve (PR curve), were used to compare the algorithms. Our findings revealed that random forests achieved the highest accuracy and other performance metric scores, while logistic regression and support vector machines offered greater interpretability. Overall, our research underscores the potential of machine learning in early PD detection and emphasizes the importance of comprehensive datasets and effective feature selection. The long-term goal of this work is to increase the sensitivity and

specificity diagnostic methods and potentially improve the quality of life for individuals with Parkinson's disease along with better patient outcomes.

Comparison of the classification results of Logistic Regression, Decision Tree, Random Forest, Support Vector Machine, KNN, Gaussian Naive Bayes, and Bernoulli Naive Bayes led to the conclusion of Random Forest as an ideal machine learning (ML) technique for the detection of Parkinson’s Disease. The detection accuracy of the Random Forest model is 98.3051%

Keywords — Classification Algorithms, Data Analysis, Machine Learning, Parkinson’s Disease.

# Introduction

Parkinson's disease has destroyed the lives of 10 million people around the world and is the second most deadly neurodegenerative disease after Alzheimer’s disease. The symptoms include: "frozen" facial expression, bradykinesia or slowness of movement, akinesia or impairment of voluntary movement, tremor, and impairment of the voice. By the time a diagnosis is made, typically 60% of nigrostriatal neurons have degenerated, as does 80% of striatal dopamine.

There is no single test in which this condition can be diagnosed. Doctors must perform careful clinical analysis of the patient's medical history. However, this result was inaccurate. According to the National Institute of Neurological Disorders, early diagnosis (with symptoms for ≤ 5 years) is only 53% accurate. This is hardly much better than expected, but early diagnosis makes all the differences in the world for effective treatment.

These problems motivated us to investigate a machine learning approach to accurately diagnose Parkinson's, using a dataset of various speech features (a non-invasive yet characteristic tool) from the University of Oxford.

The purpose of this project is to discover a machine learning technique that can be effectively used for the prediction of Parkinson's disease using relevant data. This study will conduct a comparative analysis of feature selection and representation techniques to identify the most relevant and enlightening features from the available data useful in the treatment of patients.

# Methodology

## Dataset

We have collected the required Parkinson's disease dataset, created by the University of Oxford, called the Oxford Parkinson's Disease Detection dataset, containing 197 recordings and 23 features, created by Max Little from the University of Oxford, along with the National Centre for Voice and Speech, Denver, Colorado, who recorded the speech signals.

The data contains biomedical voice recordings from 31 individuals, 23 of whom had Parkinson's disease (PD). Each column in the table is a voice measurement, and each row corresponds to one of the 195 voices recorded by that individual ("name row"). For patients with Parkinson's disease, the "Status" column is set to 0 for healthy patients and 1 for Parkinson's disease. The file is in ASCII CSV format. The rows of the CSV file contain examples for a recording. There are approximately six entries for each patient, and the patient's name is identified in the first row.

1. Overview of Vocal Analysis Attributes and Their Purposes

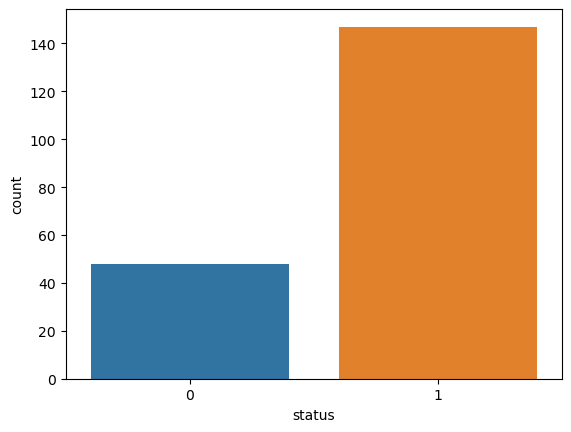
|  |  |
| --- | --- |
| Attribute | Purpose |
| Name | Data is stored in ASCII CSV format where patient name and recording number is stored |
| MDVP: Fo (Hz) | Fundamental frequency of pitch period |
| MDVP: Fhi (Hz) | Upper limit of fundamental frequency or maximum threshold of voice modulation |
| MDVP: Flo (Hz) | Lower limit or minimal vocal fundamental frequency |
| MDVP: Jitter, Abs, RAP, PPQ, DDP | Various measures from Kay Pentax’s multi-dimensional voice program (MDVP), assessing frequency of vibrations in vocal folds at pitch periods |
| Jitter and Shimmer | Measures of absolute difference between frequencies of each cycle, after normalizing the average |
| NHR and HNR | Signal to noise and tonal ratio measures that indicate robustness of the environment to noise |
| Status | 0 indicates healthy person while 1 indicates person with Parkinson's disease (PWP) |
| D2 | Correlation dimension used to identify dysphonia in speech using fractal objects; a nonlinear, dynamic attribute |
| RPDE | Recurrence Period Density Entropy quantifies the extent to which the signal is periodic |
| DFA | Detrended Fluctuation Analysis measures the extent of stochastic self-similarity of noise in speech signals |
| PPE | Pitch Period Entropy is used to assess abnormal variations in speech on a logarithmic scale |
| Spread1, Spread2 | Analysis of extent or range of variations in speech with respect to MDVP: Fo (Hz) |

## Data Analysis

The data analysis process aims to provide an understanding of the data set showing important relationships, distributions and features. This knowledge will guide preprocessing steps and contribute to the development of effective machine learning models for diagnosing Parkinson's disease.

**Distribution Analysis**

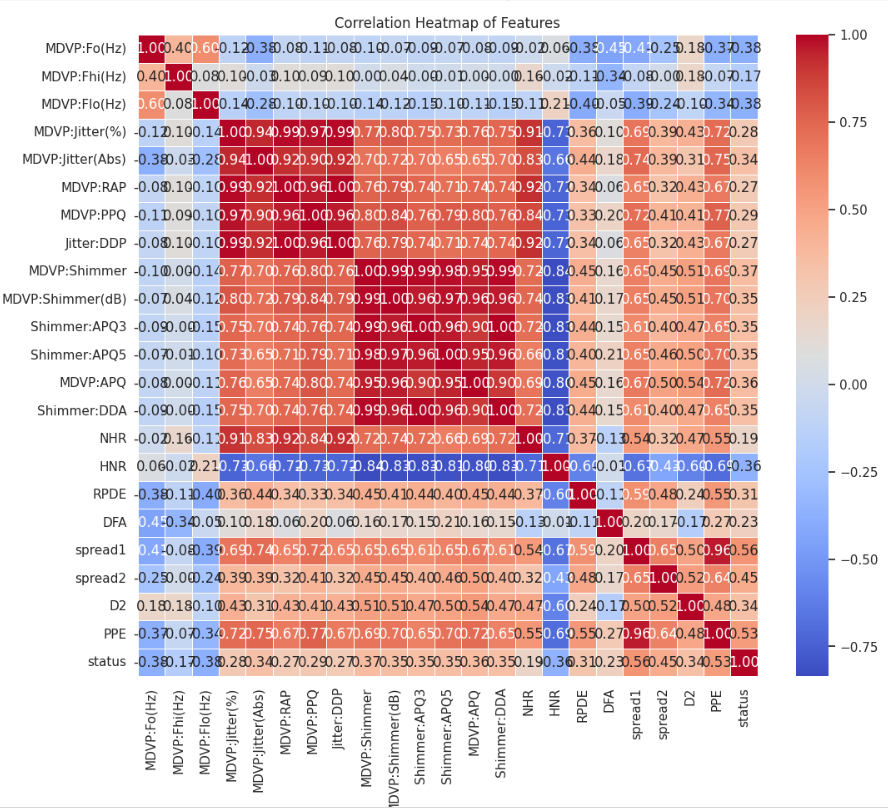
Analyzing the distribution of target variable values (1 and 0) to understand the prevalence of patients with Parkinson's disease in the dataset and identify abnormalities that will affect model training and evaluation.



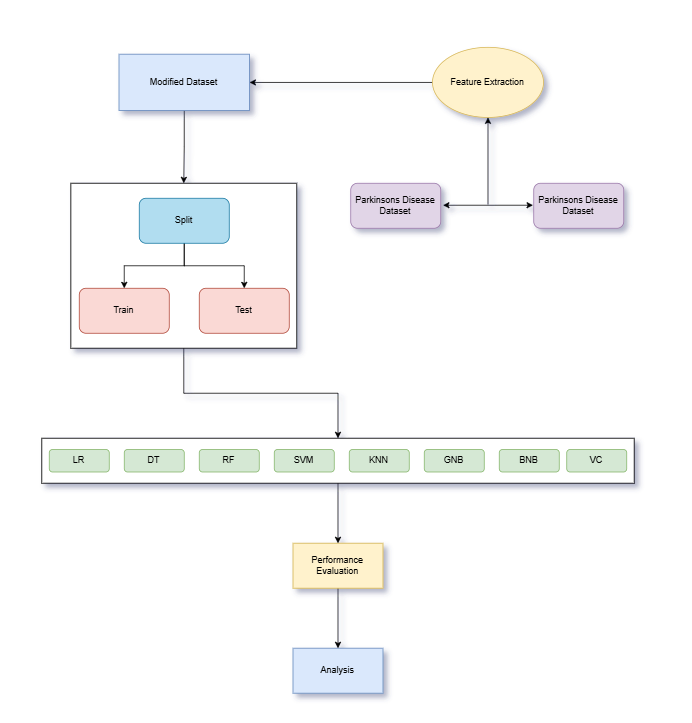
1. Comparison of Data Distribution by Count

**Correlation Analysis:**

Analyzing the correlation between the different features and the target variable values (status 1 and 0) and finding out features that have a very strong correlation, because they can play an important role in the diagnostic process.



1. Correlation Heatmap of features



1. Proposed architecture

The flowchart in Fig. 3. represents a pipeline for a machine learning approach on multi-classification models that can predict Parkinson's disease.

1. Parkinson's Disease Dataset: This process begins with the acquisition of the dataset for Parkinson's disease. The dataset contains features such as voice recordings and other form of clinical data relevant to Parkinson's symptoms.

2. Feature Extraction: Here, features are extracted from the dataset by selecting only the most relevant attributes for the prediction task. Here, the idea is to ensure that it will be features only that make a difference in order to improve the performance of the model. This is the modified dataset after this step.

3. Dataset Split: The adapted dataset is split into two subsets: training data and testing data. The set of train data is employed for training the machine learning models, and the test set is utilized for model performance evaluation and generalization capability.

4. Model Training: Several machine learning models are implemented within the pipeline. They are:

* LR (Logistic Regression)
* DT (Decision Tree)
* RF (Random Forest)
* SVM (Support Vector Machine)
* KNN (K-Nearest Neighbors)
* GNB (Gaussian Naive Bayes)
* BNB (Bernoulli Naive Bayes)
* VC (Voting Classifier)

All these models are fitted with the training dataset, and each model attempts to predict whether the subject is diagnosed with the disease of Parkinson's.

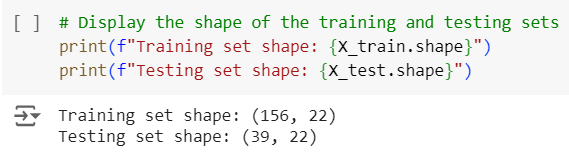
5. Performance Evaluation: Finally, the performance of each model is tested against the test dataset. Performance evaluation metrics include accuracy, precision, recall, and F1-score, among others.

6. Analysis: Finally, the results of the evaluation are analyzed. This involves a direct comparison of the various models and selection of the best model to deploy or use further in research.

A systematic method ensures that there exists a robust comparison for the best predictive model to apply for Parkinson's disease.

**Splitting the dataset:**

The data is split into 80% training and 20% testing data as our applied ML algorithms first train themselves based on the data of the training dataset whereas the remaining testing dataset is used to text and predict the outcome.



1. Shape of the Training Set

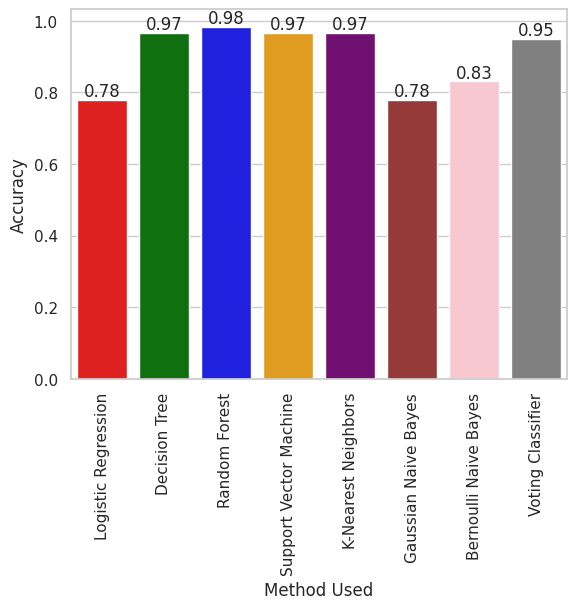
## Performance Measure

To compare the prediction performance of the algorithms, 4 metrics are used, namely precision, accuracy, recall, and f1 score respectively.

# Results and Discussions

### **Model Comparison:**

In our study, we compared several machine learning algorithms for the classification of Parkinson's Disease using vocal biomarkers from the Oxford UCI dataset. The models evaluated include [Shrey to insert names of models here], each applied to a standardized dataset with the same preprocessing pipeline. The comparison was conducted based on a variety of performance metrics, including accuracy, precision, recall, F1 score, and area under the ROC curve (AUC).

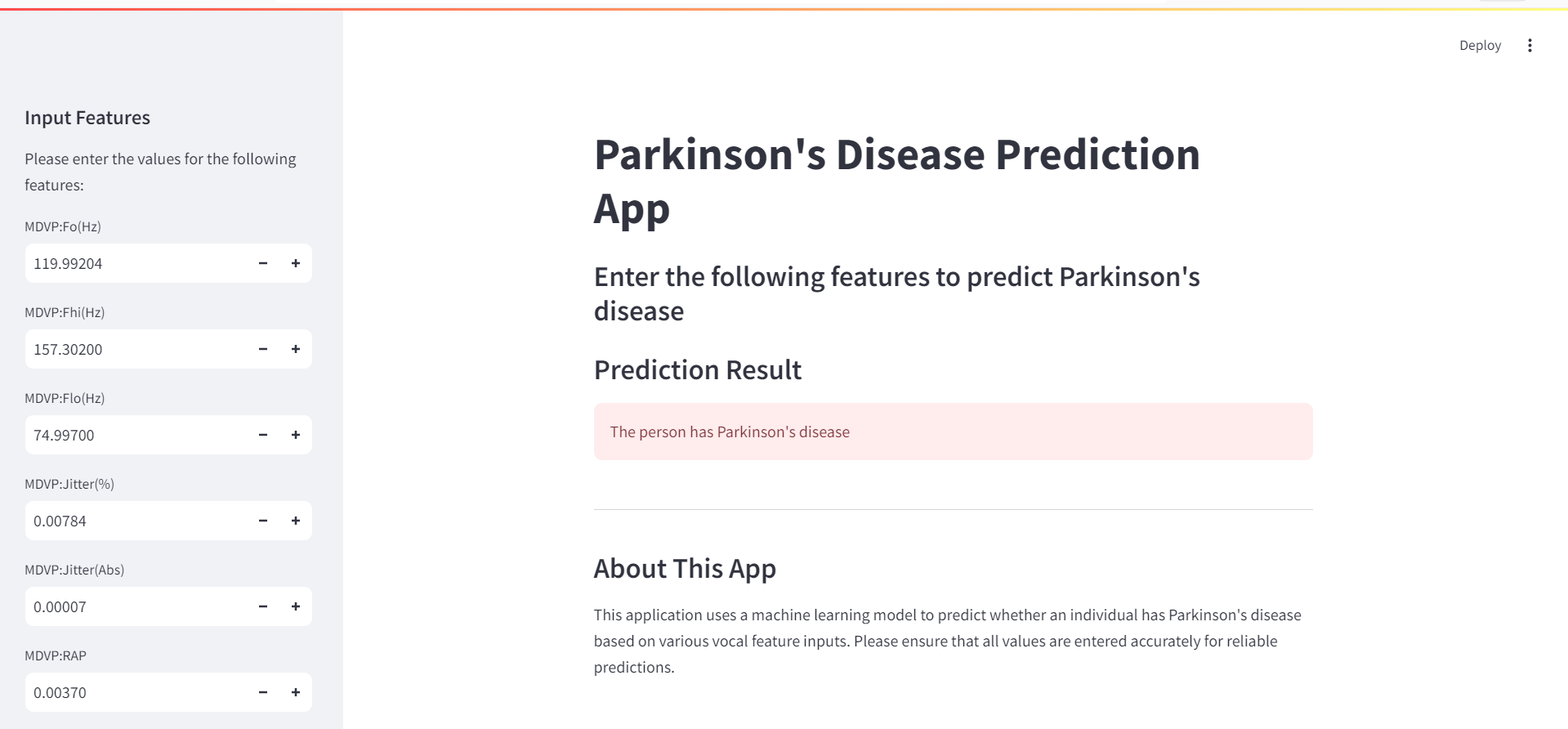


1. Accuracy Comparison of Various Machine Learning Algorithms

Among the algorithms tested, [insert best model name here] emerged as the best-performing model with an accuracy of [insert accuracy]. The results of this comparative analysis underscore the importance of selecting appropriate machine learning models for Parkinson’s Disease detection, with the [best model] providing the most reliable and interpretable results for further clinical use.

Shrey insert classification report image here with caption

The performance evaluation of the best model, Random Forest, was particularly robust in terms of precision, recall, and F1 score, critical metrics in assessing classification models in healthcare applications. Our Random Forest model achieved a precision of 1.0, indicating that 100% of the positive predictions were correct, reducing the risk of false positives in Parkinson's detection. The model's recall was 0.97, showing its ability to detect actual cases of Parkinson's effectively, minimizing the chances of false negatives. With an F1 score of 0.98, the balance between precision and recall was optimized, making this model reliable for both sensitivity and specificity. These results align with those observed in previous research studies, such as [refer paper 1], which also reported high precision and recall values when employing similar techniques, reinforcing the credibility of our findings. Additionally, the model's ROC-AUC score of 0.88 further confirmed its superior diagnostic capabilities, comparable to results from [refer paper 2], where similar methods were applied in clinical settings.

Fig. 6. Frontend for displaying detection result

The image represents the frontend of a Parkinson's Disease Prediction App, which allows users to input vocal biomarkers to predict the presence of Parkinson's disease. The interface is designed to be user-friendly, displaying fields for various vocal feature inputs such as MDVP

(Hz), and other relevant parameters. Once the values are entered, the machine learning model processes the data and provides a prediction, shown under the "Prediction Result" section. The result is visually distinct, alerting the user if Parkinson's disease is detected. Below the result section, there's a brief explanation about the app, emphasizing that it uses machine learning to predict the disease based on these vocal features, and reminding users to input accurate data for optimal predictions. This kind of interface exemplifies how machine learning can be applied in healthcare for non-invasive disease prediction.

# Conclusion

The classification accuracy obtained on the basis of vowel phonation data of Parkinson's disease is calculated to be 98.3051%, for the Random Forest classifier. The results obtained from the Random Forest model are pretty robust and are based on its exceptional aptitude in the representation of complex data structures and associations. Yet another reason for good performance is that Random Forest treats all 22 attributes in the MDVP (Multidimensional Voice Program) dataset equally important. In other words, it gives a fair consideration to each independent vocal attribute without showing any bias toward any feature. This is very crucial since Parkinson's disease is usually heralded by slight changes in speech; it is an expression of a set of characteristics that might possibly allow for a correct diagnosis as against any single characteristic.

Its strength and accuracy make the Random Forest classifier one of the models to predict the existence of Parkinson's disease from the vowel phonation data. The high accuracy of the model and the noninvasive aspect of voice analysis make this approach highly practical for real-world applications. This model may be integrated into long-term health monitoring systems, ensuring that PWP are under continuous and reliable diagnosis. The integration will offer an easy, inexpensive, and accessible tool for the control of diseases, bearing a lot of benefits to patients worldwide regarding earlier detection, monitoring of disease progression, and subsequent tailoring of treatment plans.

We thus advocate that the Random Forest model be given particular capabilities and used as a transforming agent to deliver relief, on a long-term basis, thereby enhancing the quality of life for Parkinson's patients worldwide.

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