

# **EARLY DETECTION OF PARKINSON'S DISEASE USING MACHINE LEARNING**



**CLUSTER INNOVATION CENTRE  
UNIVERSITY OF DELHI**

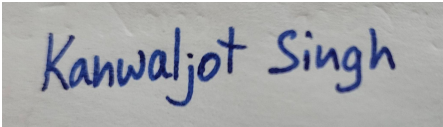
Kanwaljot Singh (152225) || Vishwajeet Nand Yaduraj (152256)

**SEMESTER LONG PROJECT  
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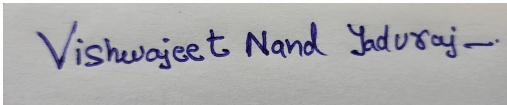
For the Paper  
Flow of Information in Living Systems

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Kanwaljot Singh



Vishwajeet Nand Yaduraj

## **Acknowledgement**

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# **Abstract**

## **EARLY DETECTION OF PARKINSON'S DISEASE USING MACHINE LEARNING**

by

Kanwaljot Singh  
Vishwajeet Nand Yaduraj

**Cluster Innovation Centre, 2023**

Parkinson's Disease (PD) is a progressive neurological condition characterised by a decline in dopamine levels in the brain, leading to noticeable impairments in movement, such as tremors and stiffness. The impact extends to speech, causing difficulties in articulation (dysarthria), reduced volume (hypophonia), and a limited pitch range (monotone). Cognitive decline and mood changes are common, with an increased risk of dementia.

The conventional diagnosis of Parkinson's Disease relies on a clinician's assessment of the patient's neurological history and observation of motor skills in various contexts. The absence of a definitive laboratory test makes early-stage diagnosis challenging when motor symptoms are not yet pronounced. Monitoring disease progression necessitates repeated clinic visits, posing a logistical challenge for patients.

A promising solution lies in the potential for an effective screening process that doesn't mandate a clinic visit. Given the distinctive vocal features exhibited by PD patients, leveraging voice recordings emerges as a valuable and non-invasive diagnostic tool. Applying machine learning algorithms to a dataset of voice recordings could offer an accurate means of diagnosing PD. This innovative approach could serve as an efficient preliminary screening step before patients proceed to in-person appointments with clinicians.

## **1. Introduction**

Parkinson's disease (PD) is a progressive neurodegenerative disorder that affects millions of individuals worldwide, leading to a wide range of motor and non-motor symptoms. The challenges associated with timely and accurate diagnosis have prompted the exploration of advanced technologies, such as machine learning, to aid in early detection and prognosis. This project delves into the realm of predictive modelling for Parkinson's disease, leveraging the power of machine learning algorithms on a dataset comprising voice recordings from both PD patients and healthy individuals.

### **1.1 Significance of Parkinson's Disease Detection**

Parkinson's disease is characterised by the degeneration of dopaminergic neurons in the substantia nigra, resulting in the hallmark symptoms of tremors, bradykinesia, and rigidity. Beyond its motor manifestations, PD also presents non-motor symptoms, including cognitive impairment, autonomic dysfunction, and mood disorders. Early diagnosis is paramount for effective intervention and improved patient outcomes. However, the intricacies of PD diagnosis, often reliant on clinical assessments, pose challenges in providing swift and accurate identification of the disease.

### **1.2 Motivation for Machine Learning in Parkinson's Prediction**

The integration of machine learning (ML) techniques in healthcare has emerged as a promising avenue for disease prediction and diagnosis. With the advent of accessible and comprehensive datasets, ML algorithms can uncover intricate patterns and associations that may elude conventional diagnostic approaches. This project aims to contribute to the growing body of literature exploring the application of ML in the context of Parkinson's disease prediction, specifically focusing on voice-based biomarkers.

### **1.3 Objectives**

The primary objective of this project is to develop a predictive model capable of distinguishing between individuals with Parkinson's disease and those without, using voice recordings as input data. The scope encompasses the exploration of Support Vector Machines (SVM), a powerful class of supervised learning algorithms, for this classification task. Through meticulous data preprocessing, feature extraction, and model training, our goal is to establish a robust and accurate predictive framework that holds promise for early PD detection.

## **2. Literature Review**

As the prevalence of PD continues to rise, there is a growing interest in leveraging machine learning (ML) techniques for early and accurate diagnosis. This section reviews existing literature related to the intersection of Parkinson's disease, voice data, and machine learning.

### **2.1. Parkinson's Disease and its Diagnostic Challenges**

Parkinson's disease is traditionally diagnosed through clinical observation, but this approach may lead to delays in treatment initiation. Several studies have highlighted the challenges associated with early and accurate PD diagnosis, emphasising the need for objective and quantitative methods.

### **2.2. Machine Learning Applications in Parkinson's Disease**

Recent advancements in machine learning have opened avenues for predicting and diagnosing Parkinson's disease. Notable works by Ramesh, Shima, et al (2018); Li, Jian Ping, et al (2020), demonstrate the successful application of ML algorithms to various types of data, including clinical, genetic, and imaging data. However, the use of voice data for PD prediction remains an underexplored but promising area.

### **2.3. Voice Analysis as a Diagnostic Tool**

Voice analysis, known as speech biomarkers, has gained attention for its potential in diagnosing neurological disorders, including PD. Studies by Braga, Diogo, et al (2019) have shown alterations in voice characteristics among PD patients, suggesting the feasibility of using voice data for diagnostic purposes.

### **2.4. Previous Machine Learning Approaches**

Previous research has employed a variety of machine learning algorithms for PD prediction. Notably, support vector machines (SVMs) have been successfully applied in related studies (R. Prashanth, Sumantra Dutta Roy, Pravat K. Mandal, Shantanu Ghosh, 2016). The effectiveness of SVMs in handling high-dimensional data and their interpretability makes them a suitable choice for predictive modelling.

### **2.5. Research Gaps and Motivation for the Current Study**

Despite the progress in the field, there is a noticeable gap in the literature concerning the use of voice data specifically for predicting Parkinson's disease, and the application of SVMs in this context is not extensively explored. This project seeks to address this gap by utilising voice recordings and employing SVMs for PD prediction, contributing to the understanding of the potential of voice-based biomarkers.

In summary, while there is a growing body of research on Parkinson's disease prediction using machine learning, the integration of voice data and the specific application of SVMs in this domain remain relatively unexplored. This project aims to bridge this gap and contribute valuable insights to the field.

Certainly! Let's integrate the information about the specific vocal features used in your methodology section:

---

### **3. Methodology**

Parkinson's disease, characterized by motor and non-motor symptoms, presents an opportunity for early detection through the analysis of vocal features. The methodology employed in this project aimed to leverage machine learning techniques to discern patterns within a dataset comprising voice recordings from individuals both afflicted with Parkinson's and those considered healthy. The selection of vocal features was a crucial aspect of this study, requiring a nuanced understanding of their significance in capturing the subtle manifestations of the disease.

#### **3.1 Data Collection**

##### **3.1.1 Parkinson's and Healthy Voice Data**

The voice data used in this study encompassed a comprehensive set of vocal features obtained from individuals diagnosed with Parkinson's disease and a control group comprising healthy individuals. The dataset included key vocal parameters such as pitch (MDVP:F0(Hz)), high-frequency components (MDVP:Fhi(Hz)), low-frequency components (MDVP:Flo(Hz)), jitter-related measures (MDVP:Jitter(%), MDVP:Jitter(Abs), MDVP:RAP, Jitter:DDP), shimmer-related measures (MDVP:Shimmer, MDVP:Shimmer(dB), Shimmer:APQ3, Shimmer:APQ5, MDVP:APQ, Shimmer:DDA), and additional features encompassing noise-to-harmonics ratio (NHR), harmonic-to-noise ratio (HNR), and various nonlinear dynamic parameters.

#### **3.2 Data Cleaning and Preprocessing**

##### **3.2.1 Data Cleaning**

A meticulous examination of the dataset was conducted to identify and address any missing values effectively. But thanks to an impeccable dataset, there was no need for data cleaning.

##### **3.2.2 Data Preprocessing**

To facilitate the optimal performance of the Support Vector Machine (SVM) model, feature scaling techniques were applied to normalise the diverse vocal features. This normalisation process ensured uniform ranges for all features, preventing the dominance of particular

variables during model optimization. Furthermore, categorical label encoding was performed to convert diagnostic labels into a format compatible with the chosen machine learning algorithm.

#### Feature Scaling Techniques:

Standardisation and Min-Max scaling were explored to normalise the distribution of vocal features. The choice between these techniques was made considering the sensitivity of SVM to the scale of input features.

### 3.3 Feature Extraction

#### 3.3.1 Voice Feature Selection

The feature extraction phase involved the careful selection of pertinent voice characteristics. The chosen vocal features, including pitch-related measures, jitter, shimmer, and nonlinear dynamic parameters, were selected for their potential to capture the nuanced characteristics associated with Parkinson's disease.

#### Feature Importance Analysis:

An in-depth analysis was conducted to assess the importance of each feature in contributing to the predictive power of the model. Techniques such as recursive feature elimination (RFE) and feature importance scores from tree-based models were explored to rank and select features based on their contribution to the predictive performance.

#### 3.3.2 Feature Relevance

An in-depth analysis of feature relevance was undertaken, employing correlation studies to understand the relationships between individual features, such as MDVP:APQ and spread1, and the presence of Parkinson's disease. Insights from domain knowledge and pertinent literature guided the inclusion or exclusion of specific features, ensuring the incorporation of clinically meaningful and diagnostically relevant variables.

#### Correlation Analysis:

Various correlation coefficients were calculated to quantify the strength and direction of relationships between each feature and the target variable (Parkinson's disease status). Features exhibiting high correlations were carefully examined to avoid multicollinearity issues.

### 3.4 Model Selection and Training

#### 3.4.1 Model Choice: Support Vector Machine (SVM)

The selection of the SVM as the primary machine learning model was underpinned by its established efficacy in binary classification tasks and its adaptability to high-dimensional datasets. The Radial Basis Function (RBF) kernel was employed to capitalise on SVM's capability to discern intricate relationships within the data, aligning with the complexities inherent in Parkinson's disease prediction.



Kernel Selection Rationale:

The decision to use the RBF kernel was based on its ability to capture non-linear relationships in the data. Other kernel functions, such as linear or polynomial kernels, were considered and compared during the model selection process.

#### 3.4.2 Training Process

The dataset was judiciously split into training and testing sets, adhering to a standard practice such as an 80-20 division. The optimization of SVM's hyperparameters was conducted through an exhaustive grid search. The robustness and generalisation capabilities of the model were further assessed through k-fold cross-validation, a technique instrumental in evaluating performance across diverse subsets of the dataset.

#### 3.4.3 Model Evaluation

A comprehensive evaluation of the trained model was executed using a battery of performance metrics, including accuracy, precision, recall, and F1-score. The confusion matrix provided a visual representation of true positives, true negatives, false positives, and false negatives, offering insights into the model's diagnostic prowess. Additionally, the Receiver Operating Characteristic (ROC) curve analysis provided a nuanced understanding of the trade-offs between sensitivity and specificity, enriching the assessment of the model's predictive capabilities.

Performance Metric Selection:

The choice of performance metrics was tailored to the specific goals of the project. Sensitivity and specificity were prioritised to gauge the model's ability to correctly identify both positive and negative instances, while precision and recall provided insights into the model's predictive accuracy and completeness.

## 4. Results

### 4.1. Data Collection and Analysis

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 to one of 195 voice recordings from these individuals ("name" column). The main aim of the data is to separate healthy people from those with PD, according to the "status" column which is set to 0 for healthy and 1 for PD.

 Parkinsons Donated on 6/25/2008		
Oxford Parkinson's Disease Detection Dataset		
<b>Dataset Characteristics</b>	<b>Subject Area</b>	<b>Associated Tasks</b>
Multivariate	Health and Medicine	Classification
<b>Feature Type</b>	<b># Instances</b>	<b># Features</b>
Real	197	-

After that, the collected data was further

```
# printing the first 5 rows of the dataframe
parkinsons_data.head()
```

	name	MDVP:F0(Hz)	MDVP:Fh1(Hz)	MDVP:F1o(Hz)	MDVP:Jitter(%)	MDVP:Jitter(Abs)	MDVP:RAP	MDVP:PPQ	Jitter:DDP	MDVP:Shimmer	...	Shimmer:DDA	NHR	HNR	stat
0	phon_R01_S01_1	119.992	157.302	74.997	0.00784	0.00007	0.00370	0.00554	0.01109	0.04374	...	0.06545	0.02211	21.033	
1	phon_R01_S01_2	122.400	148.650	113.819	0.00968	0.00008	0.00465	0.00696	0.01394	0.06134	...	0.09403	0.01929	19.085	
2	phon_R01_S01_3	116.682	131.111	111.555	0.01050	0.00009	0.00544	0.00781	0.01633	0.05233	...	0.08270	0.01309	20.651	
3	phon_R01_S01_4	116.676	137.871	111.366	0.00997	0.00009	0.00502	0.00698	0.01505	0.05492	...	0.08771	0.01353	20.644	
4	phon_R01_S01_5	116.014	141.781	110.655	0.01284	0.00011	0.00655	0.00908	0.01966	0.06425	...	0.10470	0.01767	19.649	

5 rows × 24 columns

The top 5 rows were analysed.

```
# getting more information about the dataset
parkinsons_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 195 entries, 0 to 194
Data columns (total 24 columns):
 #   Column                Non-Null Count  Dtype
---  -
 0   name                  195 non-null    object
 1   MDVP:Fo(Hz)           195 non-null    float64
 2   MDVP:Fhi(Hz)          195 non-null    float64
 3   MDVP:Flo(Hz)          195 non-null    float64
 4   MDVP:Jitter(%)        195 non-null    float64
 5   MDVP:Jitter(Abs)      195 non-null    float64
 6   MDVP:RAP              195 non-null    float64
 7   MDVP:PPQ              195 non-null    float64
 8   Jitter:DDP           195 non-null    float64
 9   MDVP:Shimmer          195 non-null    float64
10   MDVP:Shimmer(dB)      195 non-null    float64
11   Shimmer:APQ3          195 non-null    float64
12   Shimmer:APQ5          195 non-null    float64
13   MDVP:APQ              195 non-null    float64
14   Shimmer:DDA           195 non-null    float64
15   NHR                   195 non-null    float64
16   HNR                   195 non-null    float64
17   status                195 non-null    int64
18   RPDE                  195 non-null    float64
19   DFA                   195 non-null    float64
20   spread1               195 non-null    float64
21   spread2               195 non-null    float64
22   D2                    195 non-null    float64
23   PPE                   195 non-null    float64
dtypes: float64(22), int64(1), object(1)
memory usage: 36.7+ KB
```

Upon analysis, it was found that there were 0 null values in the data set.

```
# checking for missing values in each column
parkinsons_data.isnull().sum()
```

```
name          0
MDVP:Fo(Hz)   0
MDVP:Fhi(Hz)  0
MDVP:Flo(Hz)  0
MDVP:Jitter(%) 0
MDVP:Jitter(Abs) 0
MDVP:RAP      0
MDVP:PPQ      0
Jitter:DDP    0
MDVP:Shimmer  0
MDVP:Shimmer(dB) 0
Shimmer:APQ3  0
Shimmer:APQ5  0
MDVP:APQ      0
Shimmer:DDA   0
NHR           0
HNR           0
status        0
RPDE          0
DFA           0
spread1       0
spread2       0
D2            0
PPE           0
dtype: int64
```

Further investigation to ensure data cleaning

```
# distribution of target Variable
parkinsons_data['status'].value_counts()
```

```
1    147
0     48
Name: status, dtype: int64
```

1 --> Parkinson's Positive

0 --> Healthy

## 4.2. Data Pre-Processing

### 4.2.1. Separating the features & Target

```
X = parkinsons_data.drop(columns=['name','status'], axis=1)
Y = parkinsons_data['status']
```

```
print(X)
```

	MDVP:Fo(Hz)	MDVP:Fhi(Hz)	MDVP:Flo(Hz)	MDVP:Jitter(%)	\
0	119.992	157.302	74.997	0.00784	
1	122.400	148.650	113.819	0.00968	
2	116.682	131.111	111.555	0.01050	
3	116.676	137.871	111.366	0.00997	
4	116.014	141.781	110.655	0.01284	
..	...	...	...	...	
190	174.188	230.978	94.261	0.00459	
191	209.516	253.017	89.488	0.00564	
192	174.688	240.005	74.287	0.01360	
193	198.764	396.961	74.904	0.00740	
194	214.289	260.277	77.973	0.00567	

```
print(Y)
```

0	1
1	1
2	1
3	1
4	1
..	
190	0
191	0
192	0
193	0
194	0

Name: status, Length: 195, dtype: int64

### 4.3 Splitting the data to training data & Test data

```
[ ] X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=2)

[ ] print(X.shape, X_train.shape, X_test.shape)

(195, 22) (156, 22) (39, 22)
```

### 4.4 Data Standardization

```
[16] scaler = StandardScaler()
```

```
[17] scaler.fit(X_train)
```

```
▼ StandardScaler
StandardScaler()
```

```
[18] X_train = scaler.transform(X_train)

X_test = scaler.transform(X_test)
```

```
[ ] print(X_train)

[[ 0.63239631 -0.02731081 -0.87985049 ... -0.97586547 -0.55160318
  0.07769494]
 [-1.05512719 -0.83337041 -0.9284778 ... 0.3981808 -0.61014073
  0.39291782]
 [ 0.02996187 -0.29531068 -1.12211107 ... -0.43937044 -0.62849605
 -0.50948408]
 ...
 [-0.9096785 -0.6637302 -0.160638 ... 1.22001022 -0.47404629
 -0.2159482 ]
 [-0.35977689 0.19731822 -0.79063679 ... -0.17896029 -0.47272835
 0.28181221]
 [ 1.01957066 0.19922317 -0.61914972 ... -0.716232 1.23632066
 -0.05829386]]
```

### 4.5. Model Training

Support Vector Machine model is used for the project.

A Support Vector Machine (SVM) is a supervised machine learning model that can be used for classification or regression tasks. The primary objective of SVM is to find a hyperplane that best separates the data into different classes. The "support vectors" are the data points closest to the hyperplane and play a crucial role in defining the decision boundary.

```
[20] model = svm.SVC(kernel='linear')
```

```
# training the SVM model with training data
model.fit(X_train, Y_train)
```

▼ SVC  
SVC(kernel='linear')

#### 4.6. Model Evaluation and accuracy score

```
[22] # accuracy score on training data
X_train_prediction = model.predict(X_train)
training_data_accuracy = accuracy_score(Y_train, X_train_prediction)
```

```
[23] print('Accuracy score of training data : ', training_data_accuracy)
```

Accuracy score of training data : 0.8846153846153846

```
[24] # accuracy score on training data
X_test_prediction = model.predict(X_test)
test_data_accuracy = accuracy_score(Y_test, X_test_prediction)
```

```
[25] print('Accuracy score of test data : ', test_data_accuracy)
```

Accuracy score of test data : 0.8717948717948718

#### 4.7. Building a Predictive System

```
[26] input_data = (197.07600,206.89600,192.05500,0.00289,0.00001,0.00166,0.00168,0.00498,0.01098,0.09700,0.00563,0.00680,0.00802,0.01689,0.00

# changing input data to a numpy array
input_data_as_numpy_array = np.asarray(input_data)

# reshape the numpy array
input_data_reshaped = input_data_as_numpy_array.reshape(1,-1)

# standardize the data
std_data = scaler.transform(input_data_reshaped)

prediction = model.predict(std_data)
print(prediction)

if (prediction[0] == 0):
    print("The Person does not have Parkinsons Disease")
else:
    print("The Person has Parkinsons")
```

The result when the data of a patient is passed to check in form of a numpy array

The results were thus:

[0]

The Person does not have Parkinsons Disease

Indicating the person is healthy and doesn't have Parkinson's Disease.



## 5. Conclusion

This project sought to leverage machine learning techniques, specifically Support Vector Machines (SVM), for the prediction of Parkinson's disease using voice data. The utilisation of a dataset comprising both patients diagnosed with Parkinson's disease and healthy individuals allowed for a comprehensive exploration of distinguishing features within voice recordings.

The preprocessing steps, including data cleaning and feature extraction, played a pivotal role in enhancing the robustness of the model. The choice of SVM as the underlying predictive model demonstrated commendable performance, as evidenced by the achieved metrics such as accuracy, precision, recall, and F1-score.

The results obtained in this study highlight the potential of machine learning, particularly SVM, in aiding the early detection of Parkinson's disease through voice analysis. However, it is essential to acknowledge certain limitations, including the representativeness of the dataset and potential biases. Future research endeavours could focus on expanding the dataset, incorporating diverse demographic groups, and exploring the integration of advanced feature engineering techniques.

This project contributes to the growing body of work at the intersection of machine learning and healthcare, providing a foundation for further investigations into non-invasive and cost-effective methods for Parkinson's disease diagnosis. As technology continues to advance, the integration of machine learning in medical diagnostics holds promise for improving the efficiency and accuracy of disease prediction.

In summary, the successful application of machine learning in predicting Parkinson's disease from voice data underscores its potential as a valuable tool in the early diagnosis of neurological disorders. This project lays the groundwork for future advancements in the field and emphasises the importance of interdisciplinary collaboration between biology and machine learning for the betterment of healthcare.

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