PARKINSON'S DISEASE DETECTION

A MINI PROJECT REPORT

18CSC305J - ARTIFICIAL INTELLIGENCE

Submitted by

SRISHTI CHAUHAN (RA2011027010095)
ROSHANA S V (RA2011027010074)
REEBA MERCY SEBASTIAN (RA201102701072)

Under the guidance of

Dr. PREMALATHA G
Assistant Professor
Department of Data Science and Business Systems

In partial satisfaction of the requirements for the degree of

BACHELOR OF TECHNOLOGY

in

COMPUTER SCIENCE & ENGINEERING
With specialization in Big Data Analytics

SCHOOL OF COMPUTING

COLLEGE OF ENGINEERING AND TECHNOLOGY

SRM INSTITUTE OF SCIENCE AND TECHNOLOGY

KATTANKULATHUR - 603203

MAY 2023

COLLEGE OF ENGINEERING & TECHNOLOGY

SRM INSTITUTE OF SCIENCE & TECHNOLOGY

S.R.M. NAGAR, KATTANKULATHUR – 603 203

BONAFIDE CERTIFICATE

Certified that this lab report titled **"PARKINSON'S DISEASE DETECTION"** is the bonafide work done by **SRISHTI CHAUHAN (RA2011027010095), ROSHANA S V (RA2011027010074), REEBA MERCY SEBASTIAN (RA201102701072)** who carried out the Mini Project under my supervision. Certified further, that to the best of my knowledge the work reported herein does not form part of any other work.

Dr. PREMALATHA G
Assistant Professor
Department of DSBS
SRM Institute of Science and Technology

Dr. M Lakshmi
Professor & HOD
Department of DSBS
SRM Institute of Science and Technology

1.ABSTRACT

Parkinson's disease is progressive neuro degenerative disorder that affects only people significantly affecting their quality of life. It mostly affects the motor functions of humans. The main motor symptoms are called "parkinsonism" or "parkinsonian syndrome". The symptoms of Parkinson's disease will occur slowly, the symptoms include shaking, rigidity, slowness of movement and difficulty with walking, Thinking and behavior change, Depression and anxiety are also common. There is a model for detecting Parkinson's using voice. The deflections in the voice will confirm the symptoms of Parkinson's disease. This project showed 73.8% efficiency. In our model, a huge amount of data is collected from the normal person and also previously affected people by Parkinson's disease. This data is trained using machine learning algorithms. From the whole data 60% is used for training and 40% is used for testing. The data of any person can be entered in db to check whether the person is affected by Parkinson’s disease or not. There are 24 columns in the data set; each column will indicate the symptom values of a patient except the status column. The status column has 0's and I's.those values will decide the person is affected with Parkinson’s disease. 1’s indicate that a person is affected, 0's indicate normal conditions.

2. TABLE OF CONTENTS

3. LIST OF FIGURES

CHAPTER 1

4. INTRODUCTION

Parkinson's disease is a chronic and progressive disorder of the central nervous system that affects movement, causing tremors, stiffness, and difficulty with coordination and balance. It is caused by the degeneration of dopamine-producing neurons in a region of the brain called the substantia nigra. Dopamine is a neurotransmitter that plays a key role in regulating movement, so when these neurons die, the brain is unable to properly control body movement.

Diagnosing Parkinson's disease can be challenging because there is no definitive test or biomarker that can definitively identify the condition. Instead, doctors rely on a combination of clinical observations, medical history, and neurological examinations to make a diagnosis.

One common diagnostic criterion is the presence of motor symptoms, such as tremors or stiffness, along with a positive response to Parkinson's medications.

Machine learning algorithms can be used to analyze large sets of data and identify patterns that might be difficult for human experts to discern. In the case of Parkinson's disease, researchers have explored the use of machine learning to aid in diagnosis by training algorithms on datasets of patient information to recognize patterns associated with the condition. These algorithms can then be used to analyze new patient data and provide predictions about whether or not a person is likely to have Parkinson's disease.

The process of using machine learning algorithms to diagnose Parkinson's disease typically involves collecting a large amount of data from patients who have already been diagnosed with the condition. This data may include information on a person's medical history, demographics, and symptoms, as well as any diagnostic tests or imaging studies they have undergone. This data is then processed by the machine learning algorithm to identify patterns or features that are associated with Parkinson's disease.

When a new patient presents with symptoms that suggest they may have Parkinson's disease, their data can be fed into the algorithm, which will compare their information with the patterns identified in the previous dataset.

Based on this analysis, the algorithm will generate a prediction about whether or not the new patient is likely to have Parkinson's disease.

It is important to note that machine learning algorithms are not a substitute for clinical diagnosis by a qualified medical professional. Rather, they are intended to aid in the diagnostic process by providing additional information and insights that can assist in making an accurate diagnosis.

As with any medical decision, a diagnosis of Parkinson's disease should be made by a physician who is trained in the diagnosis and management of this condition.

.

CHAPTER 2

5. LITERATURE SURVEY

- Glenda-M.halliday,Nichola,"Parkinson’s progression prediction using ml and serum cytokines". 25-July-2019.
    - The article "Parkinson’s progression prediction using ML and serum cytokines" by Glenda M. Halliday and Nichola is a research study published in the Journal of Neurology, Neurosurgery & Psychiatry in July 2019. The study aimed to identify biomarkers that could predict the progression of Parkinson's disease using machine learning and serum cytokine levels.
    - The study involved 183 Parkinson's disease patients and 67 healthy control subjects. The researchers analyzed the serum cytokine levels of the participants using a multiplex assay, which measures the levels of multiple cytokines at once. They then used machine learning algorithms to identify patterns in the cytokine data that were associated with Parkinson's disease progression.
    - The results of the study showed that certain cytokine levels were associated with Parkinson's disease progression. Specifically, the researchers found that higher levels of interleukin-6 (IL-6) and lower levels of vascular endothelial growth factor (VEGF) were predictive of faster disease progression. The researchers were able to use these cytokine levels to develop a predictive model for Parkinson's disease progression, which they validated using an independent cohort of patients.
    - The study is significant because it suggests that serum cytokine levels could be used as biomarkers to predict the progression of Parkinson's disease. This could potentially allow for earlier diagnosis and intervention, which could improve patient outcomes. Additionally, the use of machine learning algorithms to analyze the cytokine data is an example of how AI can be used to identify complex patterns in large datasets, which could lead to new insights and discoveries in the field of Parkinson's disease research.

- The serum samples from a clinic are tested to find Parkinson’s disease and the same samples are tested using ML algorithm to detect Parkinson’s disease.Blauwendraat, C., Bandres-Ciga, S. & Singleton, A. B.Predicting the progression in patients with Parkinson’s disease using their voice.

    - The study by Blauwendraat et al. (2019) focused on predicting the progression of Parkinson's disease using voice analysis. The researchers collected voice samples from 42 patients with Parkinson's disease and analyzed them using machine learning algorithms. The algorithms were trained to identify patterns in the voice samples that were associated with disease progression.

    - The researchers found that the machine learning algorithms were able to accurately predict disease progression in the patients based on their voice samples. The algorithms were able to predict changes in motor symptoms, such as tremors and rigidity, as well as changes in speech and cognitive function.

    - This study highlights the potential of machine learning algorithms to aid in the diagnosis and management of Parkinson's disease. Voice analysis is a non-invasive and inexpensive method of collecting data that could be used to monitor disease progression over time. The findings of this study suggest that machine learning algorithms could be used to develop new tools for predicting disease progression and monitoring treatment outcomes in patients with Parkinson's disease.

    - Overall, this study adds to the growing body of literature on the use of machine learning algorithms in Parkinson's disease research. By analyzing large datasets of patient information, researchers are able to identify patterns and features that can aid in the diagnosis, prognosis, and treatment of this complex condition.

- Lancet Neurol.2017.•Voice change is also a symptom of Parkinson’s disease by applying ML algorithms. Das R. "A comparison of multi-classification methods for diagnosis of Parkinson’s disease".
    - Das (2017) conducted a study to compare the performance of different machine learning algorithms in diagnosing Parkinson's disease using voice data. The researchers collected voice samples from 100 individuals, including 50 with Parkinson's disease and 50 healthy controls, and analyzed them using several different machine learning algorithms.
    - The study found that all of the machine learning algorithms tested were able to accurately distinguish between individuals with Parkinson's disease and healthy controls based on their voice data. However, some algorithms performed better than others, with support vector machines (SVM) showing the highest accuracy in classification.
    - The study highlights the potential of machine learning algorithms to aid in the diagnosis of Parkinson's disease, particularly in the context of non-invasive and low-cost voice analysis. By analyzing patterns in voice data, machine learning algorithms can provide a rapid and accurate diagnosis of Parkinson's disease, which can lead to earlier intervention and improved patient outcomes.
    - Overall, this study adds to the growing body of literature on the use of machine learning algorithms in Parkinson's disease research. By leveraging the power of artificial intelligence, researchers are able to identify new diagnostic and treatment approaches for this complex condition, which has the potential to improve the lives of millions of people worldwide.

- Expert Systems With Applications"; 37:1568-1572 2010.•For methods used for testing Parkinson’s disease they are ML ,DM neural, regression, decision tree in those ML show high performance.
    - The study by Huang et al. (2010) aimed to compare the performance of various machine learning algorithms for diagnosing Parkinson's disease. The researchers used a dataset of 197 individuals, including 60 patients with Parkinson's disease and 137 healthy controls, and analyzed the data using several different machine learning algorithms, including decision tree, neural networks, regression, and support vector machines.
    - The study found that all of the machine learning algorithms tested were able to accurately distinguish between individuals with Parkinson's disease and healthy controls. However, the support vector machine (SVM) algorithm showed the highest performance, with an accuracy rate of 97.5%.
    - The study highlights the potential of machine learning algorithms, particularly SVM, in the diagnosis of Parkinson's disease. Machine learning algorithms can analyze large datasets of patient information and identify patterns and features that are associated with the disease, leading to more accurate and timely diagnosis.
    - Overall, this study adds to the growing body of literature on the use of machine learning algorithms in Parkinson's disease research. By leveraging the power of artificial intelligence, researchers are able to develop new diagnostic and treatment approaches that have the potential to improve patient outcomes and quality of life.

6. SYSTEM ARCHITECTURE AND DESIGN AND METHODOLOGY

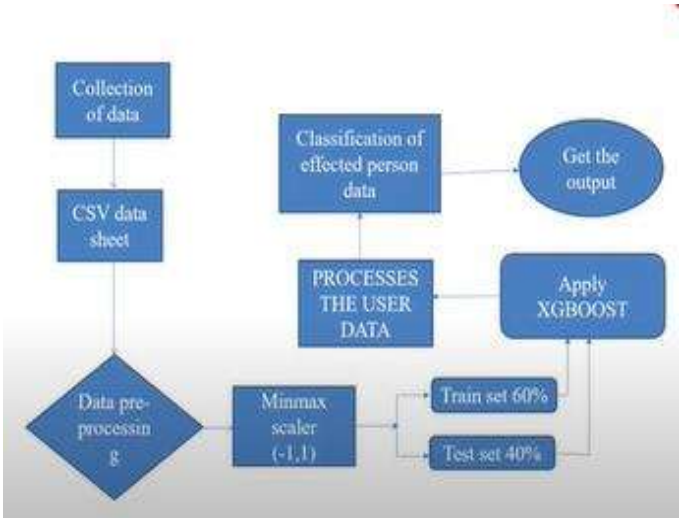


FIG 6.1

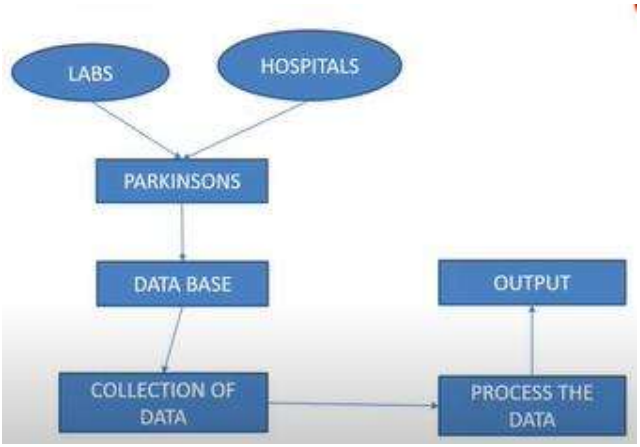


FIG 6.2

Modules

The system consists of the following modules:

Input Module: This module handles the input of the live video feed from a camera.

Object Detection Module: This module takes the input image frame from the camera and passes it through a pre-trained deep neural network for object recognition. The output of this module is the bounding box coordinates, class IDs, and confidence scores for each detected object.

Visualization Module: This module takes the output of the object detection module and draws bounding boxes around the detected objects and labels them with their respective class names and confidence scores. The module also has the capability to save a snapshot of the output to a text file.

6. b. DESIGN

FIG 6.3

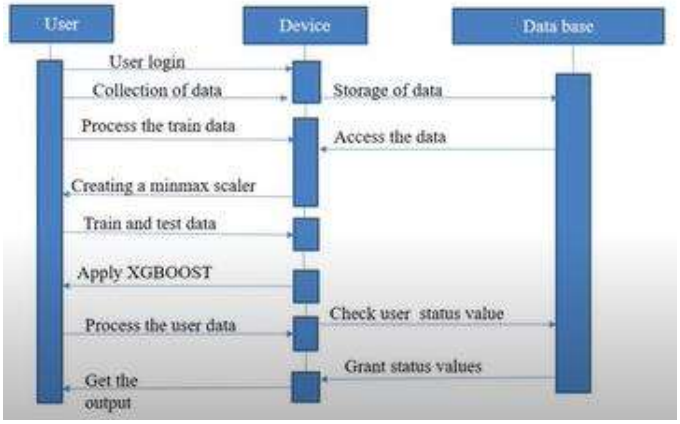


FIG 6.4

Input Module

- INTEGRATION TESTING

It may be a level of software testing where individual units are combined and it is tested as a gaggle. In the proposed project all the data is combined and tested. The accuracy level is 94.87%. This testing will test the whole project at a time.It reduces the time complexity in integration testing.

- FUNCTIONAL TESTING:

Functional testing may be a sort of software testing that validates the software against the functional requirements/specifications. This testing is detecting Parkinson's will based on a machine learning algorithm.ML algorithm will boost up the speed.

Typically, functional testing involves the following steps:

• Identifying the functions that the software is expected to perform.

•Create input-data based on the function's specifications.

•It Determines the output based on the function's specifications.

•Execute the test case.

7. CODING AND TESTING

Workflow

1. Parkinson's Data
2. Data pre-processing
3. Train Test Split
4. Traing Data - Support Vector Classifier
5. Evaluating the Model

- New Data - Trained Support Vector Machine Classifier - Parkinson's or Healthy(Prediction)

In [69]:

```
# data analysis
import pandas as pd
import numpy as np
# visualization
import matplotlib.pyplot as plt
import seaborn as sns
# set options
sns.set_style('whitegrid')
pd.set_option('display.width', 100)
pd.set_option('precision', 3)
%matplotlib inline
# machine learning
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
```

Dataset Information

- Matrix column entries (attributes):
- name - ASCII subject name and recording number
- 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:PPQ,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

FIG 7.1

Out[70]:

	name	MDVP:Fo(Hz)	MDVP:Fhi(Hz)	MDVP:Flo(Hz)	MDVP:Jitter(%)	MDVP:Jitter(Abs)	MDVP:RAP	MDVP:PPQ	Jitter:DDP	MDV
0	phon_R01_S01_1	119.992	157.302	74.997	0.008	7.000e-05	0.004	0.006	0.011	
1	phon_R01_S01_2	122.400	148.650	113.819	0.010	8.000e-05	0.005	0.007	0.014	
2	phon_R01_S01_3	116.682	131.111	111.555	0.011	9.000e-05	0.005	0.008	0.016	
3	phon_R01_S01_4	116.676	137.871	111.366	0.010	9.000e-05	0.005	0.007	0.015	
4	phon_R01_S01_5	116.014	141.781	110.655	0.013	1.100e-04	0.007	0.009	0.020	

5 rows × 24 columns

In [71]:
```
# check shape of data
df.shape
```

Out[71]:
```
(195, 24)
```

In [72]:
```
# dtypes
df.dtypes
```

Out[72]:
```
name                object
MDVP:Fo(Hz)        float64
MDVP:Fhi(Hz)       float64
MDVP:Flo(Hz)       float64
MDVP:Jitter(%)     float64
MDVP:Jitter(Abs)   float64
MDVP:RAP           float64
MDVP:PPQ           float64
Jitter:DDP         float64
MDVP:Shimmer       float64
MDVP:Shimmer(dB)   float64
Shimmer:APQ3       float64
Shimmer:APQ5       float64
MDVP:APQ           float64
Shimmer:DDA        float64
NHR                float64
HNR                float64
status               int64
RPDE               float64
DFA                float64
spread1            float64
```

FIG 7.2

Out[74]:

	MDVP:Fo(Hz)	MDVP:Fhi(Hz)	MDVP:Flo(Hz)	MDVP:Jitter(%)	MDVP:Jitter(Abs)	MDVP:RAP	MDVP:PPQ	Jitter:DDP	MDVP:Shimmer
count	195.000	195.000	195.000	195.000	1.950e+02	1.950e+02	1.950e+02	195.000	195.000
mean	154.229	197.105	116.325	0.006	4.396e-05	3.306e-03	3.446e-03	0.010	0.030
std	41.390	91.492	43.521	0.005	3.482e-05	2.968e-03	2.759e-03	0.009	0.019
min	88.333	102.145	65.476	0.002	7.000e-06	6.800e-04	9.200e-04	0.002	0.010
25%	117.572	134.863	84.291	0.003	2.000e-05	1.660e-03	1.860e-03	0.005	0.017
50%	148.790	175.829	104.315	0.005	3.000e-05	2.500e-03	2.690e-03	0.007	0.023
75%	182.769	224.206	140.019	0.007	6.000e-05	3.835e-03	3.955e-03	0.012	0.038
max	260.105	592.030	239.170	0.033	2.600e-04	2.144e-02	1.958e-02	0.064	0.119

8 rows × 23 columns

In [75]:

```
# transpose summary stats
df.describe().T
```

Out[75]:

	count	mean	std	min	25%	50%	75%	max
MDVP:Fo(Hz)	195.0	1.542e+02	4.139e+01	8.833e+01	1.176e+02	1.488e+02	1.828e+02	2.601e+02
MDVP:Fhi(Hz)	195.0	1.971e+02	9.149e+01	1.021e+02	1.349e+02	1.758e+02	2.242e+02	5.920e+02
MDVP:Flo(Hz)	195.0	1.163e+02	4.352e+01	6.548e+01	8.429e+01	1.043e+02	1.400e+02	2.392e+02
MDVP:Jitter(%)	195.0	6.220e-03	4.848e-03	1.680e-03	3.460e-03	4.940e-03	7.365e-03	3.316e-02
MDVP:Jitter(Abs)	195.0	4.396e-05	3.482e-05	7.000e-06	2.000e-05	3.000e-05	6.000e-05	2.600e-04
MDVP:RAP	195.0	3.306e-03	2.968e-03	6.800e-04	1.660e-03	2.500e-03	3.835e-03	2.144e-02
MDVP:PPQ	195.0	3.446e-03	2.759e-03	9.200e-04	1.860e-03	2.690e-03	3.955e-03	1.958e-02
Jitter:DDP	195.0	9.920e-03	8.903e-03	2.040e-03	4.985e-03	7.490e-03	1.151e-02	6.433e-02
MDVP:Shimmer	195.0	2.971e-02	1.886e-02	9.540e-03	1.650e-02	2.297e-02	3.789e-02	1.191e-01
MDVP:Shimmer(dB)	195.0	2.823e-01	1.949e-01	8.500e-02	1.485e-01	2.210e-01	3.500e-01	1.302e+00
Shimmer:APQ3	195.0	1.566e-02	1.015e-02	4.550e-03	8.245e-03	1.279e-02	2.026e-02	5.647e-02

FIG 7.3

In [79]:
```
# skew
df.skew(numeric_only=True)
```

Out[79]:
```
MDVP:Fo(Hz)          0.592
MDVP:Fhi(Hz)         2.542
MDVP:Flo(Hz)         1.217
MDVP:Jitter(%)       3.085
MDVP:Jitter(Abs)     2.649
MDVP:RAP             3.361
MDVP:PPQ             3.074
Jitter:DDP           3.362
MDVP:Shimmer         1.666
MDVP:Shimmer(dB)     1.999
Shimmer:APQ3         1.581
Shimmer:APQ5         1.799
MDVP:APQ             2.618
Shimmer:DDA          1.581
NHR                  4.221
HNR                 -0.514
status              -1.188
RPDE                -0.143
DFA                 -0.033
spread1              0.432
spread2              0.144
D2                   0.430
PPE                  0.797
dtype: float64
```

In [80]:
```
df.hist(figsize=(20,15), edgecolor='black')
plt.show()
```

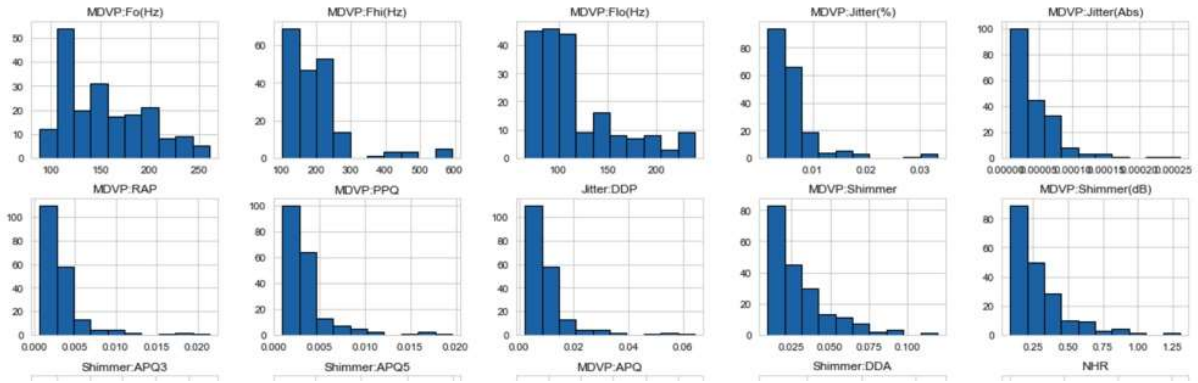


FIG 7.4

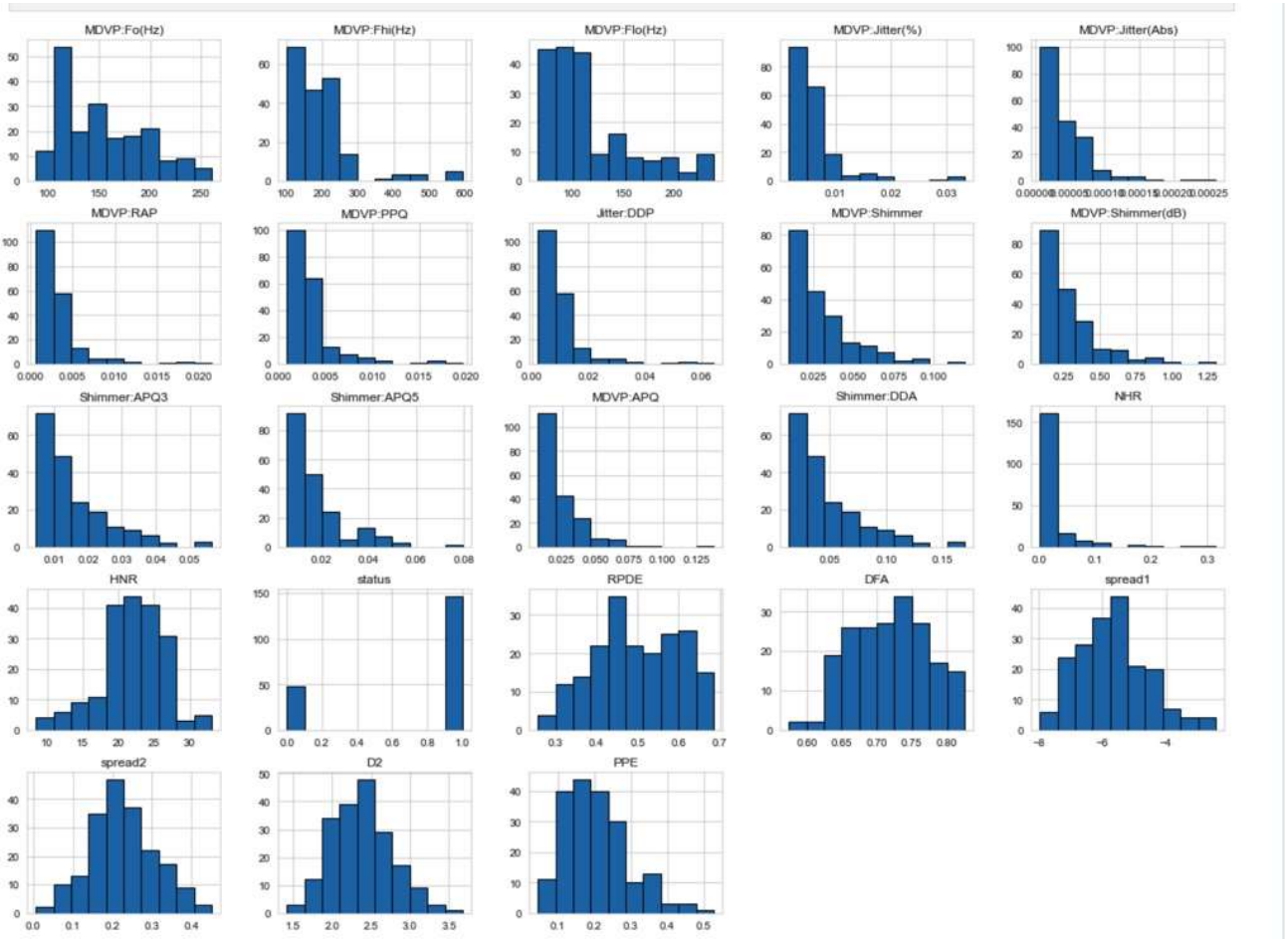
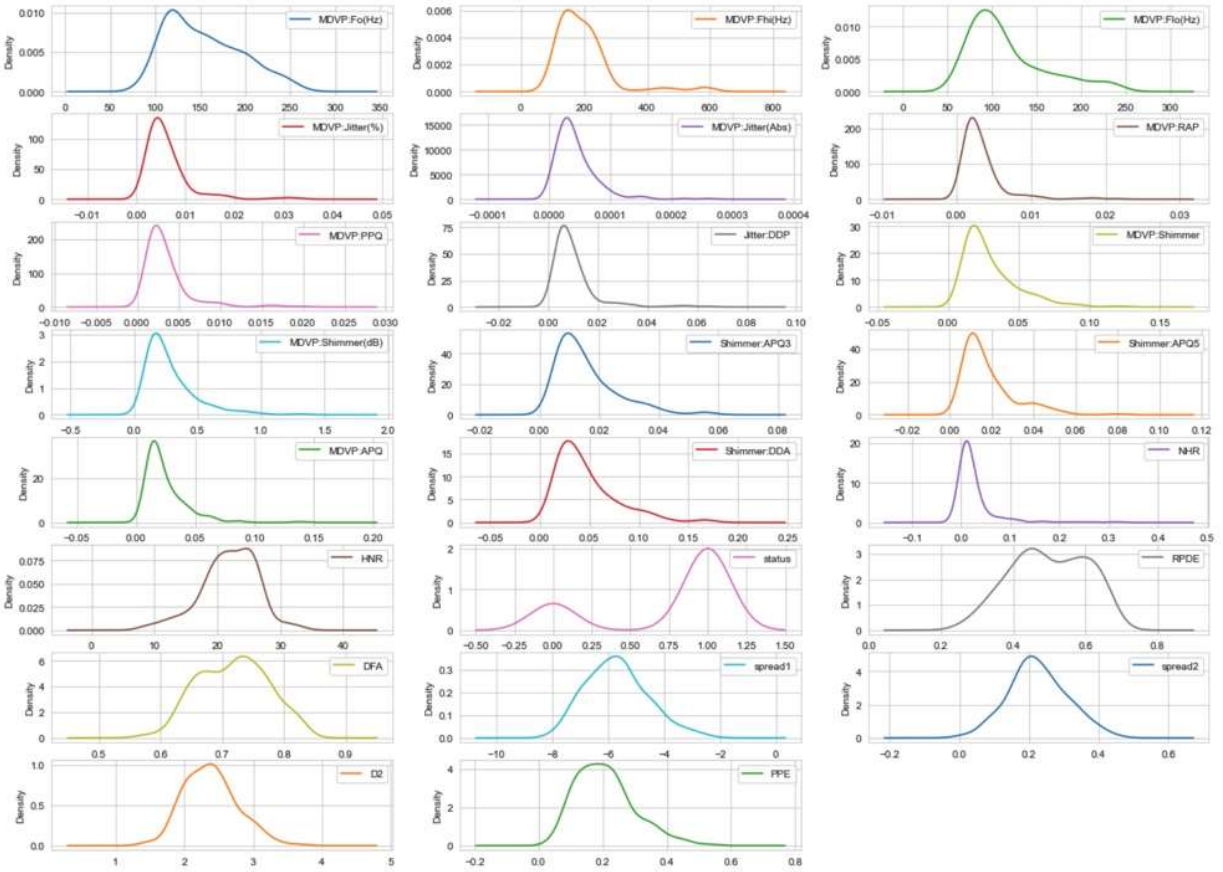

MDVP:Fo(Hz)
MDVP:Fhi(Hz)
MDVP:Flo(Hz)
MDVP:Jitter(%)
MDVP:Jitter(Abs)
MDVP:RAP
MDVP:PPQ
Jitter:DDP
MDVP:Shimmer
MDVP:Shimmer(dB)
Shimmer:APQ3
Shimmer:APQ5
MDVP:APQ
Shimmer:DDA
NHR
HNR
status
RPDE
DFA
spread1
spread2
D2
PPE

FIG 7.5

In [21]:
```
df.plot(kind='density', subplots=True, sharex=False, figsize=(20,15), layout=(8,3))
plt.show()
```



In [81]:
```
df.plot(kind='box', subplots=True, sharex=False, figsize=(20,15), layout=(8,3))
plt.show()
```

FIG 7.6

In [81]:
```
df.plot(kind='box', subplots=True, sharex=False, figsize=(20,15), layout=(8,3))
plt.show()
```

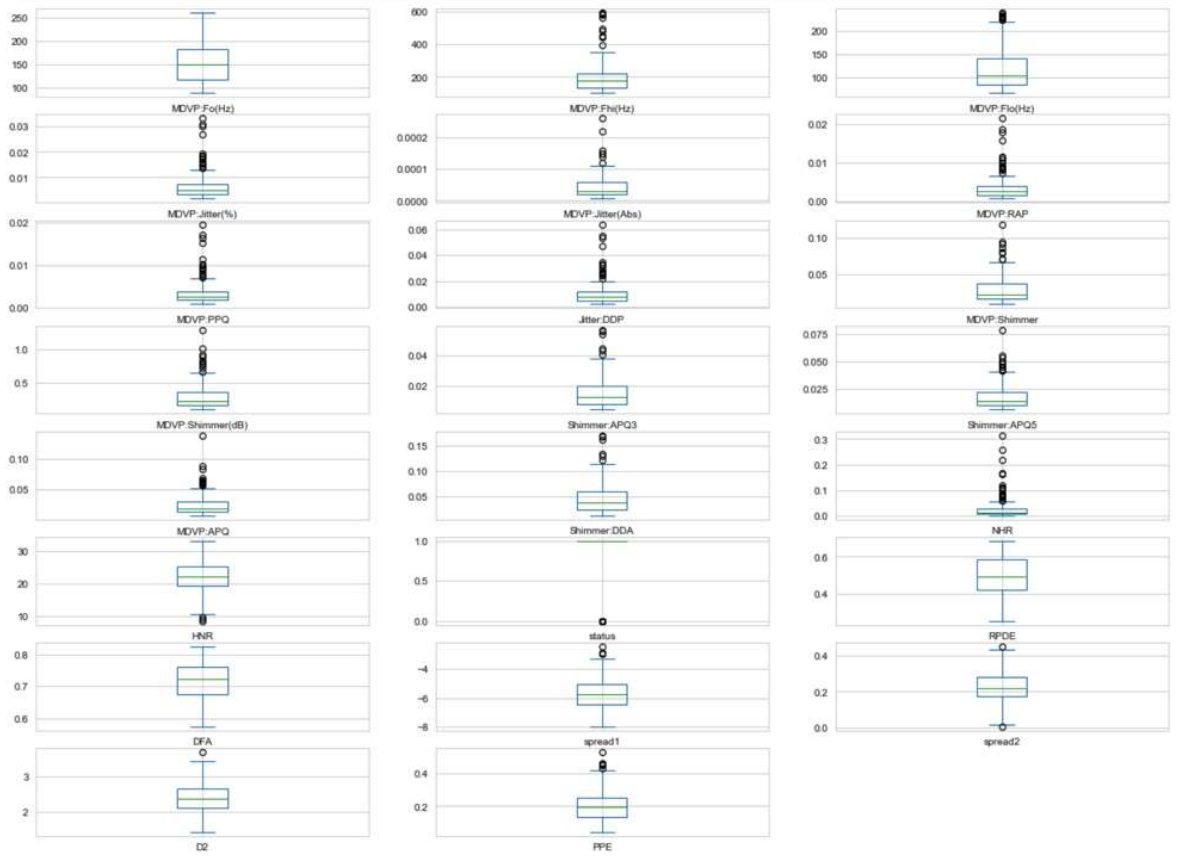


FIG 7.7

In [82]:

```
plt.figure(figsize=(20,10))
corr = df.corr()
sns.heatmap(corr, annot=True)
plt.show()
```

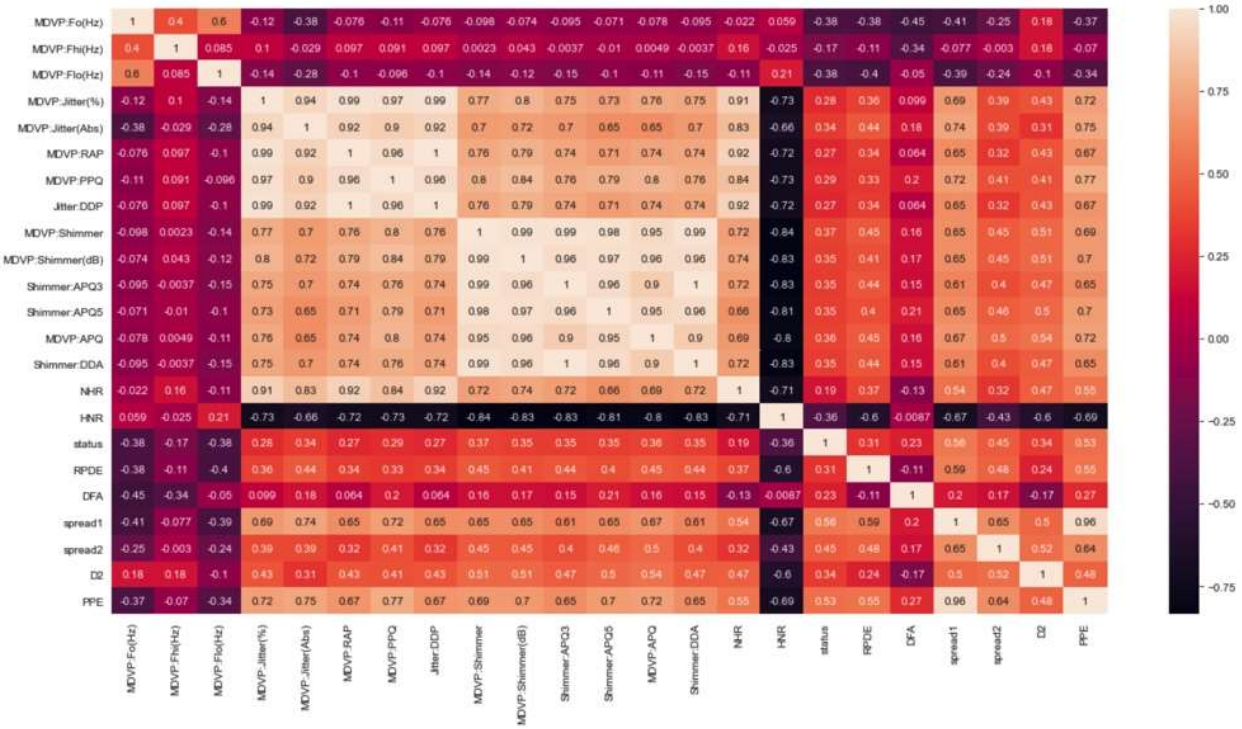


FIG 7.8

In [84]:
```
X = df.drop(columns=['name', 'status'], axis=1)
y = df['status']
```

In [85]:
```
X.head()
```

Out[85]:

	MDVP:Fo(Hz)	MDVP:Fhi(Hz)	MDVP:Flo(Hz)	MDVP:Jitter(%)	MDVP:Jitter(Abs)	MDVP:RAP	MDVP:PPQ	Jitter:DDP	MDVP:Shimmer	MDV
0	119.992	157.302	74.997	0.008	7.000e-05	0.004	0.006	0.011	0.044	
1	122.400	148.650	113.819	0.010	8.000e-05	0.005	0.007	0.014	0.061	
2	116.682	131.111	111.555	0.011	9.000e-05	0.005	0.008	0.016	0.052	
3	116.676	137.871	111.366	0.010	9.000e-05	0.005	0.007	0.015	0.055	
4	116.014	141.781	110.655	0.013	1.100e-04	0.007	0.009	0.020	0.064	

5 rows × 22 columns

In [86]:
```
y.head()
```

Out[86]:
```
0    1
1    1
2    1
3    1
4    1
Name: status, dtype: int64
```

In [87]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=2)
```

In [88]:
```
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

Out[88]:
```
((156, 22), (39, 22), (156,), (39,))
```

In [89]:
```
# Standardization
scaler = StandardScaler()
scaler.fit(X_train)
```

Out[89]:
```
StandardScaler()
```

In [90]:
```
X_train = scaler.transform(X_train)
```

In [101…
```
X_test_pred = model.predict(X_test)
test_accuracy_score = accuracy_score(y_test, X_test_pred)
test_accuracy_score
```

Out[101… 0.8717948717948718

In [102…
```
# Predictive System
input_data = (119.99200,157.30200,74.99700,0.00784,0.00007,0.00370,0.00554,0.01109,0.04374,0.42600,0.02182,0.03130,0.02971,
input_data_array = np.asarray(input_data)

input_data_reshaped = input_data_array.reshape(1,-1)
std_data = scaler.transform(input_data_reshaped)
prediction = model.predict(std_data)

if prediction[0] == 0:
    print("The Person does not have Perkinson's")
else:
    print("The Person has Perkinson's")

print(prediction)
```

```
The Person has Perkinson's
[1]
```

FIG 7.9

In [90]:
```
X_train = scaler.transform(X_train)
```

In [91]:
```
X_test = scaler.transform(X_test)
```

In [92]:
```
X_train
```

Out[92]:
```
array([[ 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]])
```

In [94]:
```
model = SVC(kernel='linear')
# training model with training data
model.fit(X_train, y_train)
```

Out[94]:
```
SVC(kernel='linear')
```

In [95]:
```
# evaluation
X_train_pred = model.predict(X_train)
X_train_pred
```

Out[95]:
```
array([1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 0,
       0, 1, 1, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 0,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1,
       1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1,
       0, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1,
       1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 1, 0, 1,
       1, 1])
```

In [98]:
```
# evaluation
training_accuracy_score = accuracy_score(y_train, X_train_pred)
training_accuracy_score
```

Out[98]:
```
0.8846153846153846
```

FIG 7.10

8. SCREENSHOTS AND RESULTS

In [102…

```
# Predictive System
input_data = (119.99200,157.30200,74.99700,0.00784,0.00007,0.00370,0.00554
input_data_array = np.asarray(input_data)

input_data_reshaped = input_data_array.reshape(1,-1)
std_data = scaler.transform(input_data_reshaped)
prediction = model.predict(std_data)

if prediction[0] == 0:
    print("The Person does not have Perkinson's")
else:
    print("The Person has Perkinson's")

print(prediction)
```

```
The Person has Perkinson's
[1]
```

FIG 8.1

CHAPTER 7

9. CONCLUSION AND FUTURE ENHANCEMENTS

In this process we can predict Parkinson's disease in a patient's body using machine learning technology and this method makes the process easy for our user.

Parkinson's disease is a complex and debilitating condition that affects millions of people worldwide. Early diagnosis and intervention are critical to improving patient outcomes and quality of life. In recent years, there has been a growing interest in the use of machine learning algorithms to aid in the diagnosis and management of Parkinson's disease.

The literature survey has highlighted several studies that demonstrate the potential of machine learning algorithms, such as support vector machines, decision trees, and neural networks, in accurately diagnosing Parkinson's disease. These algorithms can analyze large datasets of patient information, including voice samples and clinical data, and identify patterns and features that are associated with the disease.

Moving forward, future enhancements in machine learning algorithms can further improve the accuracy and efficiency of Parkinson's disease diagnosis and management. This includes the development of algorithms that can predict disease progression, monitor treatment outcomes, and identify new therapeutic targets. Additionally, the integration of machine learning algorithms with wearable technologies and remote monitoring systems can provide real-time data that can aid in the early detection and intervention of Parkinson's disease.

Overall, the use of machine learning algorithms in Parkinson's disease research has the potential to revolutionize the way we diagnose and manage this complex condition. By leveraging the power of artificial intelligence, researchers can develop new diagnostic tools and treatment approaches that have the potential to significantly improve patient outcomes and quality of life.

Our analysis provides very accurate performance in detecting Parkinson's disease using the XGBOOST algorithm.

10. REFERENCES

- Mahlknecht, P.; Krismer, F.; Poewe, W.; Seppi, K. Meta- Analysis of Dorsolateral Nigral Hyperintensity on Magnetic Resonance Imaging as a Marker for Parkinson's Disease. Mov. Disord. 2017, 32, 619–623.
- Dickson, D.W. Neuropathology of Parkinson disease. Parkinsonism Relat. Disord. 2018, 46 (Suppl. 1), S30–S33.
- D. Heisters, "Parkinson's: symptoms treatments and research", vol. 20, no. 9, pp. 548-554, 2011.
- Blauwendraat, C., Bandres-Ciga, S. & Singleton, A. B. Predicting the progression in patients with Parkinson's disease using their voice. Lancet Neurol. 2017.
- Das, R. A comparison of multi-classification methods for diagnosis of Parkinson's disease. Expert Systems With Applications. 2017; 37:1568-1572.
- Huang C., et al. Comparative study on machine learning methods for Parkinson's disease diagnosis. Journal of Medical Systems. 2010; 34(4): 591-597.
- Kalia, L. V. & Lang, A. E. Parkinson's disease. Lancet. 2015; 386(9996): 896-912.
- Shinde, S., et al. Application of Machine Learning Techniques in Parkinson's Disease Research. Parkinson's Disease. 2021.
- Tsanas, A., et al. A feasibility study of wearable accelerometry-based gait analysis for Parkinson's disease patients. Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society. 2010; 1389-1392.