Attribute Information:

1. **name** - ASCII subject name and recording number
2. **mdvp_fo_hz** - Average vocal fundamental frequency (Actualy column name MDVP:Fo(Hz))
3. **mdvp_fhi_hz** - Maximum vocal fundamental frequency (Actualy column name MDVP:Fhi(Hz))
4. **mdvp_flo_hz** - Minimum vocal fundamental frequency (Actualy column name MDVP:Flo(Hz))
5. **mdvp_jitter_in_percent, mdvp_jitter_abs, mdvp_rap, mdvp_ppq, jitter_ddp** - Several measures of variation in fundamental frequency (Actualy column names MDVP:Jitter(%), MDVP:Jitter(Abs), MDVP:RAP, MDVP:PPQ, Jitter:DDP respectively)
6. **mdvp_shimmer, mdvp_shimmer_db, shimmer_apq3, shimmer_apq5, mdvp_apq, shimmer_dda** - Several measures of variation in amplitude (Actualy column names MDVP:Shimmer, MDVP:Shimmer(dB), Shimmer:APQ3, Shimmer:APQ5, MDVP:APQ, Shimmer:DDA respectively)
7. **nhr, hnr** - Two measures of ratio of noise to tonal components in the voice (Actualy column names NHR, HNR respectively)
8. **rpde, d2** - Two nonlinear dynamical complexity measures (Actualy column names RPDE, D2 respectively)
9. **dfa** - Signal fractal scaling exponent (Actualy column name DFA)
10. **spread1, spread2, ppe** - Three nonlinear measures of fundamental frequency variation (Actualy column names spread1, spread2, PPE respectively)
11. **status** - Health status of the subject (one) - Parkinson's, (zero) - healthy (**Target Varibale / attribute**)

```
# Importing the necessary libraries
import numpy                            as np
import pandas                           as pd
import seaborn                          as sns
import matplotlib.pyplot                as plt
import warnings


%matplotlib inline
warnings.filterwarnings('ignore')

import statsmodels.api                  as sm
from sklearn import model_selection
from sklearn.model_selection            import train_test_split

# getting methods for confusion matrix, F1 score, Accuracy Score
from sklearn import metrics
from sklearn.metrics                    import confusion_matrix,f1_score,accuracy_score,classification_report,roc_curve,auc,average_precision_score
from sklearn.linear_model               import LogisticRegression
from sklearn.naive_bayes                import GaussianNB
from sklearn.neighbors                  import KNeighborsClassifier
from sklearn.svm                        import SVC


from sklearn.preprocessing import StandardScaler
```

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import StackingClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import AdaBoostClassifier
```

```
pdDataOrg = pd.read_csv("Parkinsson disease.csv")
pdDataOrg.head()
```

	name	MDVP:Fo(Hz)	MDVP:Fhi(Hz)	MDVP:Flo(Hz)	MDVP:Jitter(%)	MDVP:Jitter(Abs)	MDVP:RAP
0	phon_R01_S01_1	119.992	157.302	74.997	0.00784	0.00007	0.00370
1	phon_R01_S01_2	122.400	148.650	113.819	0.00968	0.00008	0.00465
2	phon_R01_S01_3	116.682	131.111	111.555	0.01050	0.00009	0.00544
3	phon_R01_S01_4	116.676	137.871	111.366	0.00997	0.00009	0.00502
4	phon_R01_S01_5	116.014	141.781	110.655	0.01284	0.00011	0.00655

5 rows × 24 columns

```
pdData = pdDataOrg.copy()

targetCol = 'status'
targetColDf = pdData.pop(targetCol)
pdData.insert(len(pdData.columns),targetCol, targetColDf)

# deleting variables that were used for changing column position of target column
del targetCol
del targetColDf

# converting column names into lower case
pdData.columns = [c.lower() for c in pdData.columns]
# replacing spaces in column names with '_'
pdData.columns = [c.replace(' ', '_') for c in pdData.columns]
# replacing ':' in column names with '_'
pdData.columns = [c.replace(':', '_') for c in pdData.columns]
# replacing '(' in column names with '_'
pdData.columns = [c.replace('(', '_') for c in pdData.columns]
# replacing ')' in column names with '' i.e blank
pdData.columns = [c.replace(')', '') for c in pdData.columns]
# replacing '%' in column names with 'in_percent'
pdData.columns = [c.replace('%', 'in_percent') for c in pdData.columns]

# to check the above printing top 5 rows
pdData.head()
```

	name	mdvp_fo_hz	mdvp_fhi_hz	mdvp_flo_hz	mdvp_jitter_in_percent	mdvp_jitter_abs	mdvp
0	phon_R01_S01_1	119.992	157.302	74.997	0.00784	0.00007	0.0
1	phon_R01_S01_2	122.400	148.650	113.819	0.00968	0.00008	0.0
2	phon_R01_S01_3	116.682	131.111	111.555	0.01050	0.00009	0.0
3	phon_R01_S01_4	116.676	137.871	111.366	0.00997	0.00009	0.0
4	phon_R01_S01_5	116.014	141.781	110.655	0.01284	0.00011	0.0

5 rows × 24 columns

```
print('\033[1mThe Parkinson\'s disease dataset having "{0}" rows and "{1}" columns\033[0m.'.format(pdData.shape[0],pdData.shape[1]))
```

The Parkinson's disease dataset having "195" rows and "24" columns.

```
pdData.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_in_percent  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  rpde                    195 non-null    float64
 18  dfa                     195 non-null    float64
 19  spread1                 195 non-null    float64
 20  spread2                 195 non-null    float64
 21  d2                      195 non-null    float64
 22  ppe                     195 non-null    float64
 23  status                  195 non-null    int64  
```

```
dtypes: float64(22), int64(1), object(1)
memory usage: 36.7+ KB
```

```
# setting name column as index column
pdData.set_index('name',inplace=True)
```

```
# after setting column 'name' as index now we have less columns to confirm that printing number of rows and column once again
print('\033[1mAfter setting \'name\' column as index of the Dataset,\033[0m now there are \033[1m"{0}"\033[0m Rows and \033[1m"{1}"\033[0m Columns in the given Dataset.'.format(pdDa
```

After setting 'name' column as index of the Dataset, now there are **"195"** Rows and **"23"** Columns in the given Dataset.

```
pdData.head()
```

	mdvp_fo_hz	mdvp_fhi_hz	mdvp_flo_hz	mdvp_jitter_in_percent	mdvp_jitter_abs	mdvp_ra
name						
phon_R01_S01_1	119.992	157.302	74.997	0.00784	0.00007	0.0037
phon_R01_S01_2	122.400	148.650	113.819	0.00968	0.00008	0.0046
phon_R01_S01_3	116.682	131.111	111.555	0.01050	0.00009	0.0054
phon_R01_S01_4	116.676	137.871	111.366	0.00997	0.00009	0.0050
phon_R01_S01_5	116.014	141.781	110.655	0.01284	0.00011	0.0065

5 rows × 23 columns

```
# printing datatypes of each columns of the dataset

print("\033[1m*"*100)
print("a.\nColumn_Names        Data_Types")
print("*"*30)
print("\033[0m{0}\033[1m".format(pdData.dtypes))
print("*"*30)
print()

# printing No of Columns having different Types of Datatype

print("*"*100)
print("b.\nNumber of Columns with each DataTypes as follows :")
print("*"*50)
print("Column_Names     No_of_Columns\033[0m")
print("*"*30)
print(pdData.dtypes.value_counts())
print("\033[1m*"*30)
```

```
print("\033[0m")

# printing Different Column Names of the dataset

print("\033[1m*"*100)
print("c.\nEach Column Names of the dataset")
print("*"*80)
print("\033[0m{0}\033[1m".format(pdData.columns))
print("*"*80)
print("\033[0m")
```

```
****************************************************************************************************
a.
Column_Names        Data_Types
******************************
mdvp_fo_hz                float64
mdvp_fhi_hz               float64
mdvp_flo_hz               float64
mdvp_jitter_in_percent    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
rpde                      float64
dfa                       float64
spread1                   float64
spread2                   float64
d2                        float64
ppe                       float64
status                      int64
dtype: object
******************************

****************************************************************************************************
b.
Number of Columns with each DataTypes as follows :
**************************************************
Column_Names     No_of_Columns
******************************
float64    22
int64       1
dtype: int64
******************************

****************************************************************************************************
c.
```

```
Each Column Names of the dataset
********************************************************************************
Index(['mdvp_fo_hz', 'mdvp_fhi_hz', 'mdvp_flo_hz', 'mdvp_jitter_in_percent',
       'mdvp_jitter_abs', 'mdvp_rap', 'mdvp_ppq', 'jitter_ddp', 'mdvp_shimmer',
       'mdvp_shimmer_db', 'shimmer_apq3', 'shimmer_apq5', 'mdvp_apq',
       'shimmer_dda', 'nhr', 'hnr', 'rpde', 'dfa', 'spread1', 'spread2', 'd2',
       'ppe', 'status'],
      dtype='object')
********************************************************************************
```

After observing the dataset and column description given we can conclude the followings:

- **Columns having only two datatypes, int64, float64. (column 'name' was object datatype which was set as index of the dataframe)**
- **Column 'status' is only having int64 datatype, remaining all columns datatype is float64.**
- **All columns except 'status' are Numeric column.**
- **Columns 'status' is Nominal Categorical column with binary response.**

```
# checking missing values in dataset for each attributes / columns

print("\033[1m*"*100)
print("Column_Name       No_of_Missing_Values")
print("*"*50)
print("\033[0m{0}".format(pdData.isnull().sum()))
print("\033[1m*"*50)
print()

# checking if any duplicate rows available in the dataset

print("*"*100)
print("Showing Duplicate rows if any in the dataset: ")
print("*"*50)
print("\033[0m{0}".format(pdData[pdData.duplicated()]))
print("\033[1m*"*100)
print("\033[0m")
```

```
****************************************************************************************************
Column_Name       No_of_Missing_Values
**************************************************
mdvp_fo_hz                0
mdvp_fhi_hz               0
mdvp_flo_hz               0
mdvp_jitter_in_percent    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
rpde                    0
dfa                     0
spread1                 0
spread2                 0
d2                      0
ppe                     0
status                  0
dtype: int64
**************************************************

****************************************************************************************************
Showing Duplicate rows if any in the dataset:
**************************************************
Empty DataFrame
Columns: [mdvp_fo_hz, mdvp_fhi_hz, mdvp_flo_hz, mdvp_jitter_in_percent, mdvp_jitter_abs, mdvp_rap, mdvp_ppq, jitter_ddp, mdvp_shimmer, mdvp_shimmer_db, shimmer_apq3, shimmer_ap
Index: []

[0 rows x 23 columns]
****************************************************************************************************
```

As shown above,

(a.) There are no missing values

and (b.) No duplicate rows in the given dataset

```
# Five point summary of each attribute
pdData.describe().T
```

	count	mean	std	min	25%	50%	75%	
mdvp_fo_hz	195.0	154.228641	41.390065	88.333000	117.572000	148.790000	182.769000	260.10
mdvp_fhi_hz	195.0	197.104918	91.491548	102.145000	134.862500	175.829000	224.205500	592.03
mdvp_flo_hz	195.0	116.324631	43.521413	65.476000	84.291000	104.315000	140.018500	239.17
mdvp_jitter_in_percent	195.0	0.006220	0.004848	0.001680	0.003460	0.004940	0.007365	0.03
mdvp_jitter_abs	195.0	0.000044	0.000035	0.000007	0.000020	0.000030	0.000060	0.00
mdvp_rap	195.0	0.003306	0.002968	0.000680	0.001660	0.002500	0.003835	0.02
mdvp_ppq	195.0	0.003446	0.002759	0.000920	0.001860	0.002690	0.003955	0.01
jitter_ddp	195.0	0.009920	0.008903	0.002040	0.004985	0.007490	0.011505	0.06
mdvp_shimmer	195.0	0.029709	0.018857	0.009540	0.016505	0.022970	0.037885	0.11
mdvp_shimmer_db	195.0	0.282251	0.194877	0.085000	0.148500	0.221000	0.350000	1.30
shimmer_apq3	195.0	0.015664	0.010153	0.004550	0.008245	0.012790	0.020265	0.05
shimmer_apq5	195.0	0.017878	0.012024	0.005700	0.009580	0.013470	0.022380	0.07
mdvp_apq	195.0	0.024081	0.016947	0.007190	0.013080	0.018260	0.029400	0.13

```
# checking skewness of the data
pdData.skew().sort_values(ascending=False)
```

```
nhr                        4.220709
jitter_ddp                 3.362058
mdvp_rap                   3.360708
mdvp_jitter_in_percent     3.084946
mdvp_ppq                   3.073892
mdvp_jitter_abs            2.649071
mdvp_apq                   2.618047
mdvp_fhi_hz                2.542146
mdvp_shimmer_db            1.999389
shimmer_apq5               1.798697
mdvp_shimmer               1.666480
shimmer_dda                1.580618
shimmer_apq3               1.580576
mdvp_flo_hz                1.217350
ppe                        0.797491
mdvp_fo_hz                 0.591737
spread1                    0.432139
d2                         0.430384
spread2                    0.144430
dfa                       -0.033214
rpde                      -0.143402
hnr                       -0.514317
status                    -1.187727
dtype: float64
```

As from above we understand the following:

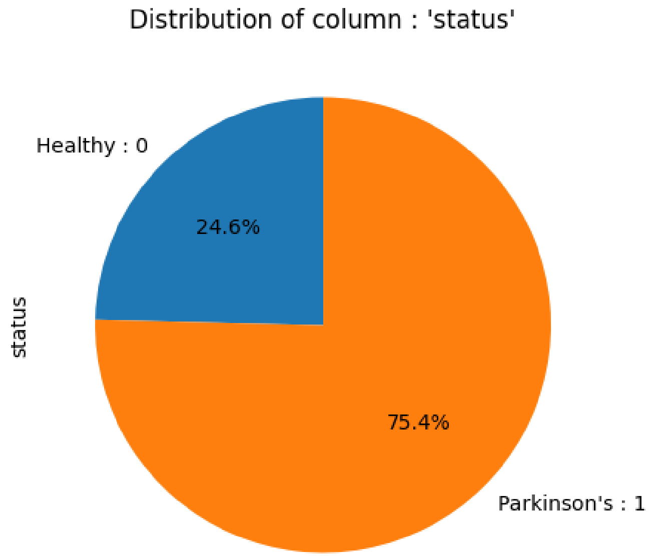
- Independent variables are measured in different units e.g. Hz, dB, % and absoulute etc i.e variation in units of data exists and gap between feature values extreamly high. Requires data scalling techniques to scale different quantities of measurements.
- Symmetrical distribution : Values close to 0 MDVP:Fo(Hz) spread1 spread2 PPE
- Negative skewness and Tail is larger towards the left hand side of the distribution HNR status RPDE DFA
- Positive skewness and Tail is larger towards the Right hand side of the distribution All other attributes have a very high distribution towards right of the median

```
plt.figure(figsize=(10,5))                                 # setting figure size with width = 10 and height = 5
# seaborn count catplot to examine distribution of the status
ax = sns.catplot(x='status', kind="count", data=pdData)
plt.title("Distribution of column : 'Status'")      # setting title of the figure
y = []                                                     # creating a null or empty array
for val in range(pdData.status.nunique()):        # looping for number of unique values in the status
    # appending count of each unique values from status to array y
    y.append(pdData.groupby(pdData.status,sort=False)['status'].count()[val])
for i, v in enumerate(y):                                  # looping count of each unique value in the status
    # including count of each unique values in the plot
    plt.annotate(str(v), xy=(i,float(v)), xytext=(i-0.1, v+3), color='black', fontweight='bold')
```

```
<Figure size 1000x500 with 0 Axes>
```

```
plt.figure(figsize=(5,5))                              # setting figure size with width = 10 and height = 5
# seaborn pie chart to examine distribution of the status
pdData.groupby(['status']).status.count().plot(kind='pie',labels=['Healthy : 0','Parkinson\'s : 1'],
                                                              startangle=90, autopct='%1.1f%%')
plt.title("Distribution of column : 'status'")   # setting title of the figure
```

```
Text(0.5, 1.0, "Distribution of column : 'status'")
```



From above we can see out of 195 patients, 48 patients (24.6 %) are healthy and 147 patients (75.4%) patients are having Parkinson's disease.

```
#Split the data into training and test set in the ratio of 70:30 respectively
X = pdData.drop(['status'],axis=1)
y = pdData['status']

# split data into train subset and test subset
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=47)

# checking the dimensions of the train & test subset
# printing dimension of train set
print(X_train.shape)
# printing dimension of test set
print(X_test.shape)
```

```
(136, 22)
(59, 22)
```

```
X_train.drop(['mdvp_jitter_in_percent'],axis=1,inplace=True)
X_test.drop(['mdvp_jitter_in_percent'],axis=1,inplace=True)
```

```
X_train.drop(['mdvp_shimmer'],axis=1,inplace=True)
X_test.drop(['mdvp_shimmer'],axis=1,inplace=True)
```

```
X_train.drop(['hnr'],axis=1,inplace=True)
X_test.drop(['hnr'],axis=1,inplace=True)
```

```
# printing dimension of train set
print(X_train.shape)
# printing dimension of test set
print(X_test.shape)
```

```
(136, 19)
(59, 19)
```

```
# Let us scale train as well as test data using StandardScaler
scaler = StandardScaler()

X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.fit_transform(X_test)
```

```
# Train and Fit model
lr = LogisticRegression(random_state=0)
lr.fit(X_train_scaled, y_train)

#predict status for X_test_scaled dataset
lr_y_pred = lr.predict(X_test_scaled)

# Confusion Matrix for the Logistic Regression Model
print("Confusion Matrix : Logistic Regression")
print(confusion_matrix(y_test,lr_y_pred))

# Classification Report for the Logistic Regression Model
classRep = classification_report(y_test, lr_y_pred, digits=2)
print(classRep)
```

```
Confusion Matrix : Logistic Regression
[[ 9  4]
 [ 4 42]]
              precision    recall  f1-score   support

           0       0.69      0.69      0.69        13
```

```
              1       0.91      0.91      0.91        46

       accuracy                           0.86        59
      macro avg       0.80      0.80      0.80        59
   weighted avg       0.86      0.86      0.86        59
```

From the above Logistic Regression Model, we can find out the following details:

- **Accuracy of the model:- 86%**
- **Re-call of the model:- 91%**
- **Precision of the model:- 91%**
- **F1-Score of the model:- 91%**

```
# creating odd list of K for KNN
myList = list(range(3,40,2))

# creating empty list for F1 scores od different value of K
f1ScoreList = []

# perform accuracy metrics for values from 3,5....29
for k in myList:
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train_scaled, y_train)
    # predict the response
    y_pred = knn.predict(X_test_scaled)
    # evaluate F1 Score
    f1Score = f1_score(y_test, y_pred)
    f1ScoreList.append(f1Score)

# changing to misclassification error
MSE = [1 - x for x in f1ScoreList]

# determining best k
bestk = myList[MSE.index(min(MSE))]
print("The optimal number of neighbors is %d" % bestk)
```

```
The optimal number of neighbors is 29
```

```
# instantiate learning model (k = 29)
knn = KNeighborsClassifier(n_neighbors = 29, weights = 'uniform', metric='euclidean')

# fitting the model
knn.fit(X_train_scaled, y_train)

# predict the response
knn_y_pred = knn.predict(X_test_scaled)
```

```
# Confusion Matrix for the K-nearest neighbors Model
print("Confusion Matrix : K-nearest neighbors")
print(confusion_matrix(y_test,knn_y_pred))

# Classification Report for the K-nearest neighbors Model
classRep = classification_report(y_test, knn_y_pred, digits=2)
print(classRep)
```

```
Confusion Matrix : K-nearest neighbors
[[ 8  5]
 [ 0 46]]
              precision    recall  f1-score   support

           0       1.00      0.62      0.76        13
           1       0.90      1.00      0.95        46

    accuracy                           0.92        59
   macro avg       0.95      0.81      0.86        59
weighted avg       0.92      0.92      0.91        59
```

From the above K-nearest neighbors Model, we can find out the following details:

- **Accuracy of the model:- 92%**
- **Re-call of the model:- 100%**
- **Precision of the model:- 90%**
- **F1-Score of the model:- 95%**

```
svm = SVC(gamma=0.05, C=70,random_state=47)
svm.fit(X_train_scaled , y_train)

# predict the response
svm_y_pred = svm.predict(X_test_scaled)

# Confusion Matrix for the Support Vector Machine Model
print("Confusion Matrix : Support Vector Machine")
print(confusion_matrix(y_test,svm_y_pred))

# Classification Report for the Support Vector Machine Model
classRep = classification_report(y_test, svm_y_pred, digits=2)
print(classRep)
```

```
Confusion Matrix : Support Vector Machine
[[10  3]
 [ 0 46]]
              precision    recall  f1-score   support

           0       1.00      0.77      0.87        13
           1       0.94      1.00      0.97        46
```

```
    accuracy                           0.95        59
   macro avg       0.97      0.88      0.92        59
weighted avg       0.95      0.95      0.95        59
```

From the above Support Vector Machine Model, we can find out the following details:

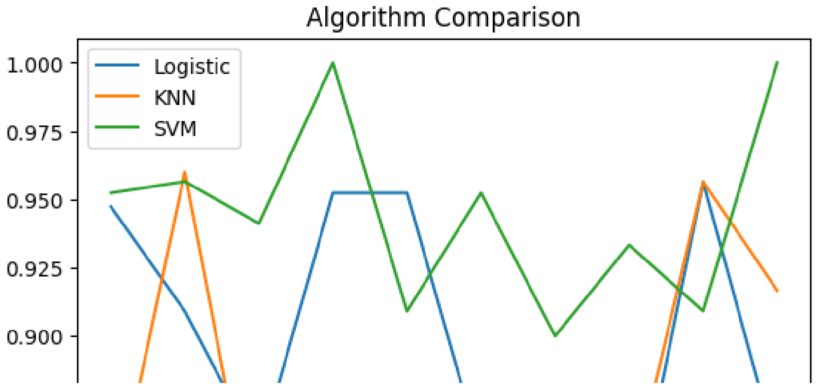
- **Accuracy of the model:- 95%**
- **Re-call of the model:- 100%**
- **Precision of the model:- 94%**
- **F1-Score of the model:- 97%**

```
#Using K fold to check how the above algorighms varies throughout the dataset with 10 different subset of equal bins
models = []
models.append(('Logistic Regression', LogisticRegression(random_state=47)))
models.append(('K-NN', KNeighborsClassifier(n_neighbors = 29, weights = 'uniform', metric='euclidean')))
models.append(('SVM', SVC(gamma=0.05, C=70,random_state=47)))

# evaluate each model
results = []
names = []
scoring = 'f1'
for name, model in models:
    kfold = model_selection.KFold(n_splits=10, random_state=47,shuffle=True)
    cv_results = model_selection.cross_val_score(model, X_train_scaled, y_train, cv=kfold, scoring=scoring)
    results.append(cv_results)
    names.append(name)
    print("\033[1m{0}\033[0m model have \033[1mmean F1-Score\033[0m of {1} and \033[1mSD F1-Score\033[0m of {2}".format(name, cv_results.mean(), cv_results.std()))
```

Logistic Regression model have **mean F1-Score** of 0.8930882775410977 and **SD F1-Score** of 0.05346316304648212
K-NN model have **mean F1-Score** of 0.8805069690035365 and **SD F1-Score** of 0.04633386023424363
SVM model have **mean F1-Score** of 0.9453975265995727 and **SD F1-Score** of 0.033233692576697435

```
plt.title('Algorithm Comparison')
plt.plot(results[0],label='Logistic')
plt.plot(results[1],label='KNN')
plt.plot(results[2],label='SVM')
plt.legend()
```

```
<matplotlib.legend.Legend at 0x7f2578d65430>
```



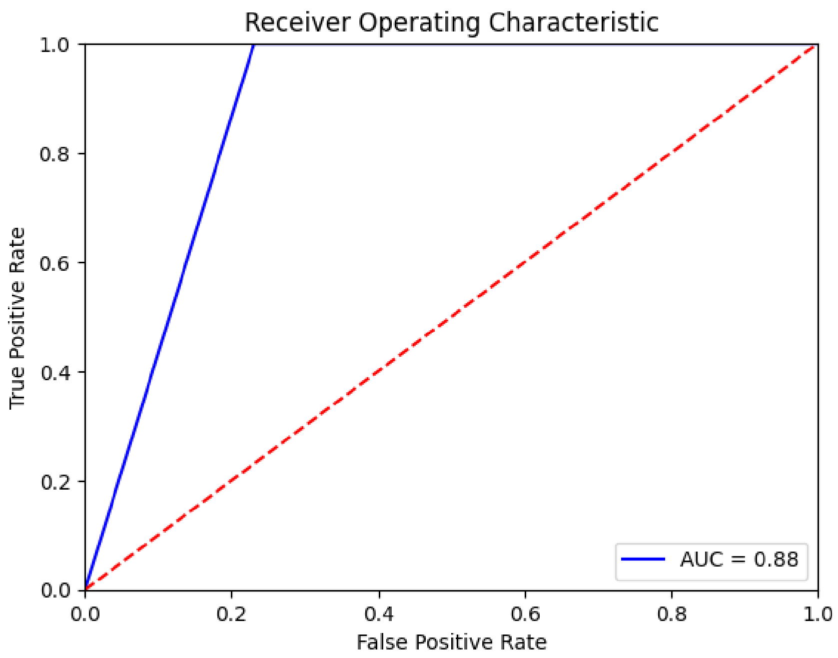
From the above comparision of different algorithms (Logistic Regression, K-nearest neighbors and Support Vector Machine) we can conclude that SVM (Support Vector Machine) performed slightly better than other algorithms.

```
# defining level hetrogenious model
level0 = list()
level0.append(('lr', LogisticRegression(random_state=47)))
level0.append(('knn', KNeighborsClassifier(n_neighbors = 29, weights = 'uniform', metric='euclidean')))
level0.append(('cart', DecisionTreeClassifier()))
level0.append(('svm', SVC(gamma=0.05, C=70,random_state=47)))
level0.append(('bayes', GaussianNB()))

# define meta learner model
level1 = SVC(gamma=0.05, C=3,random_state=47)

# define the stacking ensemble with cross validation of 5
Stack_model = StackingClassifier(estimators=level0, final_estimator=level1, cv=5)

# predict the response
Stack_model.fit(X_train_scaled, y_train)
prediction_Stack = Stack_model.predict(X_test_scaled)

# Confusion Matrix for the Stacking Model
print("Confusion Matrix : Stacking")
print(confusion_matrix(y_test,prediction_Stack))

# Classification Report for the Stacking Model
print(classification_report(y_test, prediction_Stack, digits=2))
```

```
Confusion Matrix : Stacking
[[10  3]
 [ 0 46]]
              precision    recall  f1-score   support

           0       1.00      0.77      0.87        13
```

```
           1       0.94      1.00      0.97        46

    accuracy                           0.95        59
   macro avg       0.97      0.88      0.92        59
weighted avg       0.95      0.95      0.95        59
```

```
#determining false positive rate and True positive rate, threshold
fpr, tpr, threshold = metrics.roc_curve(y_test, prediction_Stack)
roc_auc_stack = metrics.auc(fpr, tpr)

#plotting ROC curve
plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc_stack)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



From the above Stacked meta classifier Model, we can find out the following details:

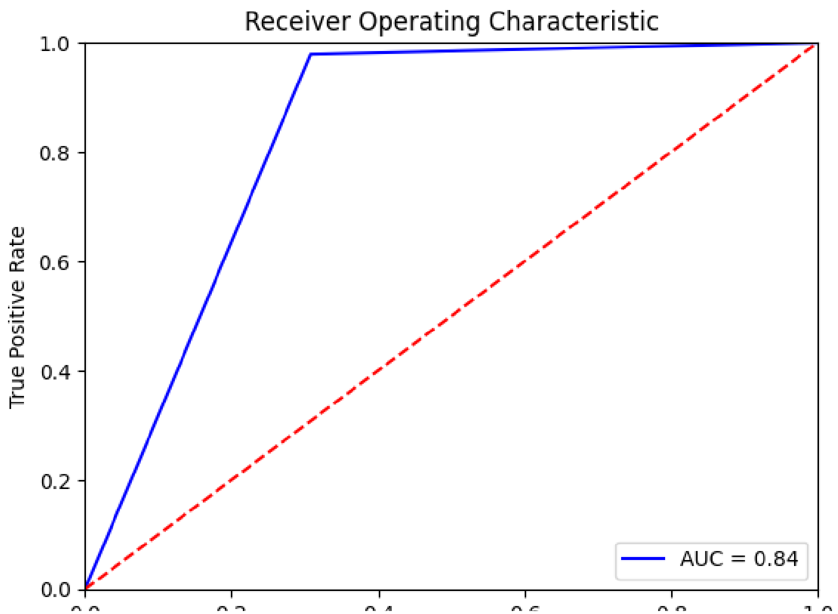
- **Accuracy of the model:- 95%**

- **Re-call of the model:- 100%**
- **Precision of the model:- 94%**
- **F1-Score of the model:- 97%**
- **ROC-AUC : 88%**

```
#creating model of Random Forest
RandomForest = RandomForestClassifier(n_estimators = 100,criterion='entropy',max_features=10,random_state=47)
RandomForest = RandomForest.fit(X_train_scaled, y_train)

# predict the response
RandomForest_pred = RandomForest.predict(X_test_scaled)

# Confusion Matrix for the Random Forest Model
print("Confusion Matrix : Random Forest")
print(confusion_matrix(y_test,RandomForest_pred))

# Classification Report for the Randome Forest Model
print(classification_report(y_test, RandomForest_pred, digits=2))
```

```
Confusion Matrix : Random Forest
[[ 9  4]
 [ 1 45]]
              precision    recall  f1-score   support

           0       0.90      0.69      0.78        13
           1       0.92      0.98      0.95        46

    accuracy                           0.92        59
   macro avg       0.91      0.84      0.86        59
weighted avg       0.91      0.92      0.91        59
```

```
#determining false positive rate and True positive rate, threshold
fpr, tpr, threshold = metrics.roc_curve(y_test, RandomForest_pred)
roc_auc_rf = metrics.auc(fpr, tpr)

#plotting ROC curve
plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc_rf)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



From the above Random Forest Model, we can find out the following details:

- **Accuracy of the model:- 92%**
- **Re-call of the model:- 98%**
- **Precision of the model:- 92%**
- **F1-Score of the model:- 95%**
- **ROC-AUC : 84%**

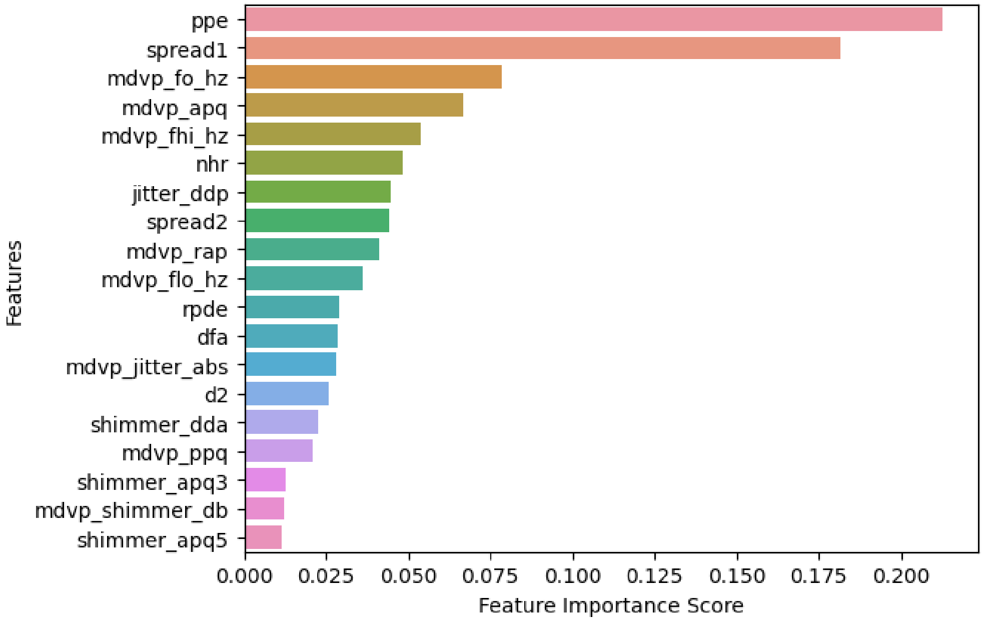
```
# Lets check features importance
feature_imp = pd.Series(RandomForest.feature_importances_,index=X_train.columns).sort_values(ascending=False)
feature_imp
```

```
ppe                 0.212646
spread1             0.181815
mdvp_fo_hz          0.078539
mdvp_apq            0.066849
mdvp_fhi_hz         0.053630
nhr                 0.048251
jitter_ddp          0.044719
spread2             0.044320
mdvp_rap            0.041004
mdvp_flo_hz         0.036010
rpde                0.029126
dfa                 0.028516
mdvp_jitter_abs     0.028306
d2                  0.025957
shimmer_dda         0.022860
```

```
mdvp_ppq           0.020985
shimmer_apq3       0.012780
mdvp_shimmer_db    0.012384
shimmer_apq5       0.011302
dtype: float64
```

```
# Creating a bar plot
sns.barplot(x=feature_imp, y=feature_imp.index)
# Add labels to your graph
plt.xlabel('Feature Importance Score')
plt.ylabel('Features')
```

```
Text(0, 0.5, 'Features')
```




```
#creating model of Adaptive Boosting
AdBs = AdaBoostClassifier( n_estimators= 50)
AdBs  = AdBs.fit(X_train_scaled, y_train)

# predict the response
AdBs_y_pred = AdBs.predict(X_test_scaled)

# Confusion Matrix for the Adaptive Boosting Model
print("Confusion Matrix : Adaptive Boosting")
print(confusion_matrix(y_test,AdBs_y_pred))

# Classification Report for the Adaptive Boosting Model
print(classification_report(y_test, AdBs_y_pred, digits=2))
```

```
Confusion Matrix : Adaptive Boosting
[[ 9  4]
 [ 2 44]]
              precision    recall  f1-score   support

           0       0.82      0.69      0.75        13
           1       0.92      0.96      0.94        46

    accuracy                           0.90        59
   macro avg       0.87      0.82      0.84        59
weighted avg       0.89      0.90      0.90        59
```

```
#determining false positive rate and True positive rate, threshold
fpr, tpr, threshold = metrics.roc_curve(y_test, AdBs_y_pred)
roc_auc_ada = metrics.auc(fpr, tpr)

#plotting ROC curve
plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc_ada)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```

Receiver Operating Characteristic

From the above Adaptive Boosting Model, we can find out the following details:

- **Accuracy of the model:- 90%**
- **Re-call of the model:- 96%**
- **Precision of the model:- 92%**
- **F1-Score of the model:- 94%**
- **ROC-AUC : 82%**

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=47)
```

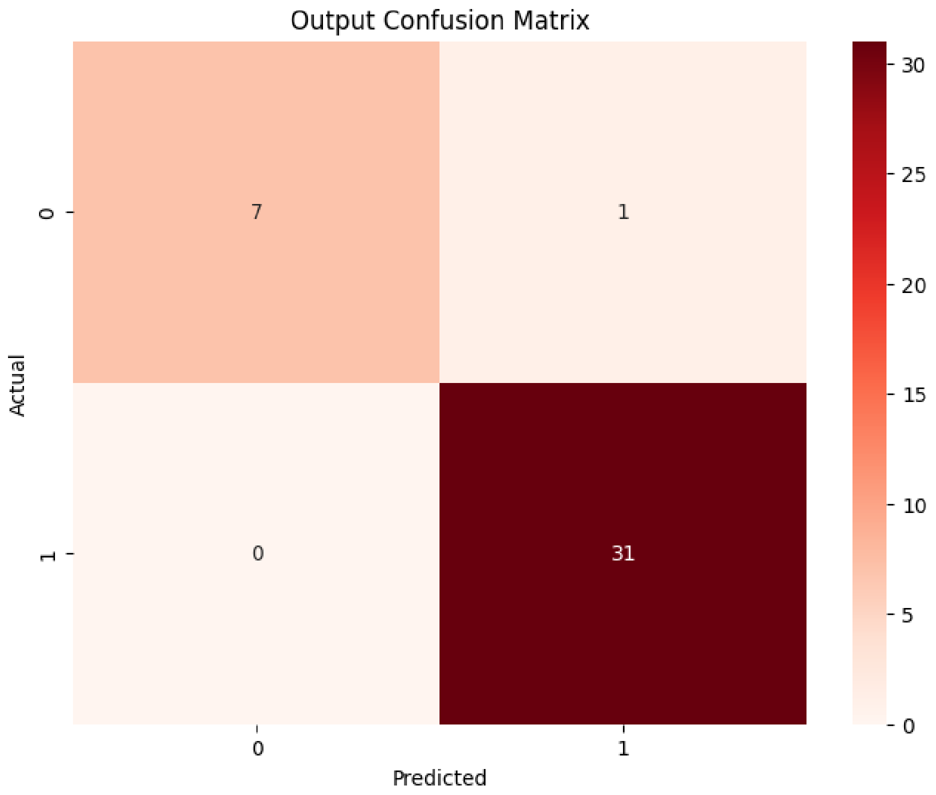
```
# Train the model
from xgboost import XGBClassifier


model=XGBClassifier()
model.fit(X_train,y_train)
predict=model.predict(X_test)

print(accuracy_score(y_test,predict)*100)

# Confusion Matrix for the XGBoosting Model
print("Confusion Matrix : XGBoosting")
print(confusion_matrix(y_test,predict))

# Classification Report for the XGBoosting Model
print(classification_report(y_test, predict, digits=2))
```

```
97.43589743589743
Confusion Matrix : XGBoosting
[[ 7  1]
 [ 0 31]]
              precision    recall  f1-score   support

           0       1.00      0.88      0.93         8
           1       0.97      1.00      0.98        31

    accuracy                           0.97        39
   macro avg       0.98      0.94      0.96        39
weighted avg       0.98      0.97      0.97        39
```

```
from sklearn.metrics import confusion_matrix
cm=confusion_matrix(y_test,predict)
plt.figure(figsize=(8,6))
fg=sns.heatmap(cm,annot=True,cmap="Reds")
figure=fg.get_figure()
```

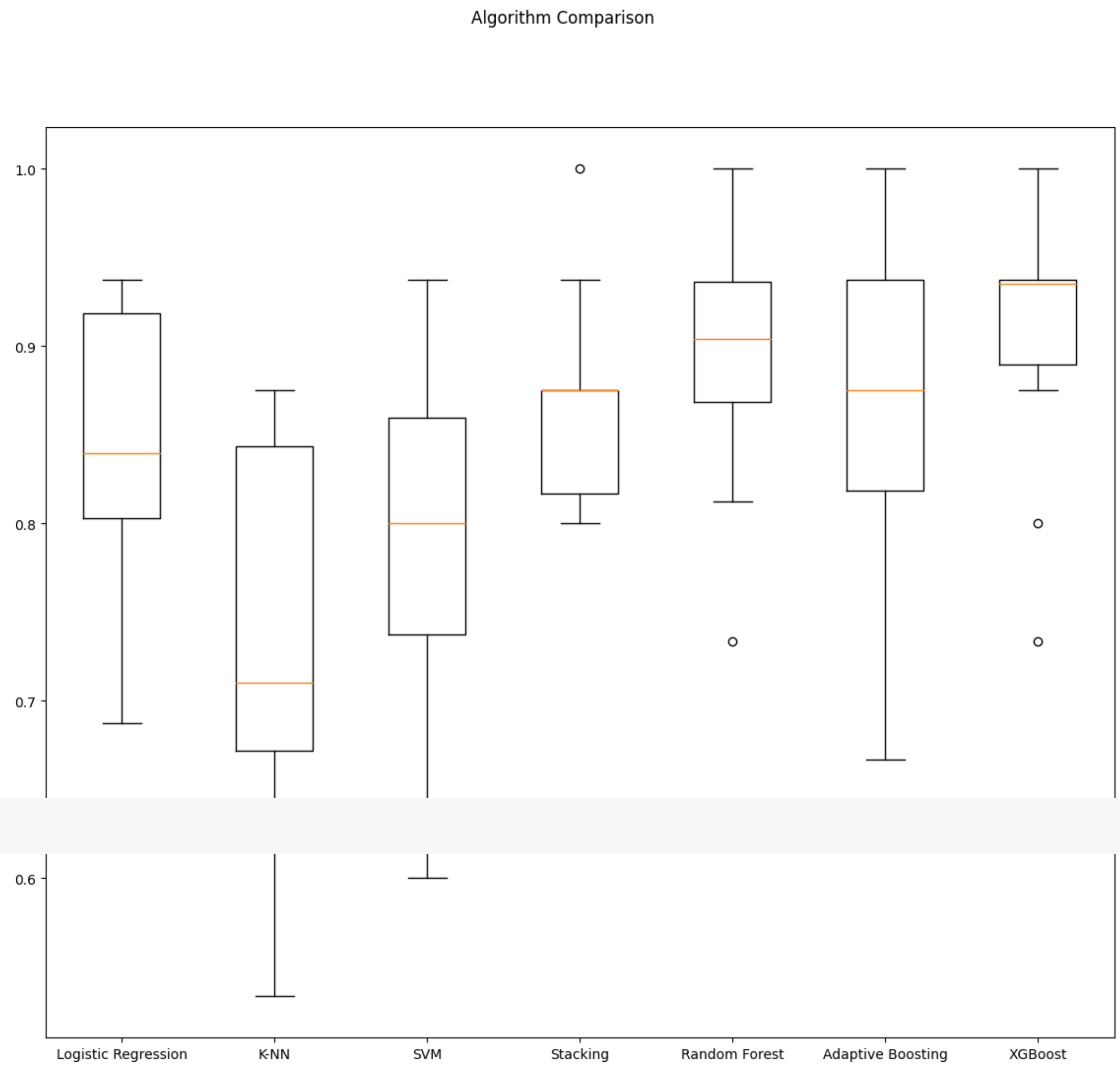
```
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title("Output Confusion Matrix")
```

```
Text(0.5, 1.0, 'Output Confusion Matrix')
```




```
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
# The baseline

# Test options and evaluation metric
num_folds = 10
seed = 7
scoring = 'accuracy'

# Spot-Check Algorithms
models = []
models.append(('Logistic Regression', LogisticRegression(random_state=47)))
models.append(('K-NN', KNeighborsClassifier(n_neighbors = 29, weights = 'uniform', metric='euclidean')))
models.append(('SVM', SVC(gamma=0.05, C=70,random_state=47)))
models.append(('Stacking', StackingClassifier(estimators=level0, final_estimator=level1, cv=5)))
```

```
models.append(('Random Forest', RandomForestClassifier(n_estimators = 100,criterion='entropy',max_features=10,random_state=47)))
models.append(('Adaptive Boosting', AdaBoostClassifier( n_estimators= 50)))
models.append(('XGBoost',XGBClassifier()))

def eval_algorithms(models, show_boxplots=True):
    # Evaluate each model in turn
    # Setup the test harness to use 10-fold cross validation
    results = []
    names = []
    for name, model in models:
        kfold = KFold(n_splits=10, random_state=seed,shuffle=True)
        cv_results = cross_val_score(model, X_train, y_train, cv=kfold, scoring=scoring)
        results.append(cv_results)
        names.append(name)
        #print("Estimated accuracy of {} with the mean of {} and std. dev. {}".format(name, cv_results.mean()*100.0, cv_results.std()*100.0))
        #print("{}: {} ({})".format(name, cv_results.mean()*100.0, cv_results.std()*100.0))

    if show_boxplots:
        # Create a plot of the model evaluation results to compae the spread
        # and the estimated mean accuracy of each model
        fig = plt.figure(figsize=(14,12))
        fig.suptitle('Algorithm Comparison')
        ax = fig.add_subplot(111)
        plt.boxplot(results)
        ax.set_xticklabels(names)
        plt.show()

eval_algorithms(models)
```



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