17. Parkinson's project

/* The Parkinson dataset includes 195 biomedical records of people with 23 varied characteristics. The idea behind this project is to design an ML model that can differentiate between healthy people and those suffering from Parkinson's disease. The model uses the XGboost (extreme gradient boosting) algorithm based on decision trees to make the separation.*/

Parkinson's signs and symptoms may include:

- 1-Tremor. A tremor, or shaking, usually begins in a limb, often your hand or fingers.
- 2-Slowed movement (bradykinesia). Over time, Parkinson's disease may slow your movement, making simple tasks difficult and time-consuming.
- 3-Rigid muscles. Muscle stiffness may occur in any part of your body.
- 4-Impaired posture and balance. Your posture may become stooped, or you may have balance problems as a result of Parkinson's disease.
- 5-Loss of automatic movements. You may have a decreased ability to perform unconscious movements, including blinking, smiling or swinging your arms when you walk.
- 6- speech changes and writting changes...

Classification is a process of categorizing a given set of data into classes, It can be performed on both structured or unstructured data.

Regression analysis is a statistical method to model the relationship between a dependent (target) and independent (predictor) variables with one or more independent variables.

Support Vector Machine(SVM) is a supervised machine learning algorithm used for both classification and regression. Though we say regression problems as well its best suited for classification. The objective of SVM algorithm is to find a hyperplane in an N-dimensional space that distinctly classifies the data points.

The SVM kernel is a function that takes low dimensional input space and transforms it into higher-dimensional space, ie it converts not separable problem to separable problem. It is mostly useful in non-linear separation problems. The tremor fluctuation during kinetic and resting task is used as classification features. The support vector machine is used as a classifier and tested with 10-fold cross-validation. This novel feature provides a perfect PD/ET classification with 100% accuracy, sensitivity and specificity.

XGBoost is an implementation of Gradient Boosted decision trees.

Boosting is an ensemble technique where new models are added to correct the errors made by existing models.

A Bagging classifier is an ensemble meta-estimator that fits base classifiers each on random subsets of the original dataset and then aggregate their individual predictions (either by voting or by averaging) to form a final prediction.

Execution Speed.
Model Performance.

In [1]: pip install numpy pandas sklearn xgboost

```
Requirement already satisfied: numpy in c:\users\personal\anaconda3\lib\site-packages (1.22.2)
Requirement already satisfied: pandas in c:\users\personal\anaconda3\lib\site-packages (1.1.3)
Requirement already satisfied: sklearn in c:\users\personal\anaconda3\lib\site-packages (0.0)
Requirement already satisfied: xgboost in c:\users\personal\anaconda3\lib\site-packages (1.5.2)
Requirement already satisfied: python-dateutil>=2.7.3 in c:\users\personal\anaconda3\lib\site-packages (from pandas) (2.8.1)
Requirement already satisfied: pytz>=2017.2 in c:\users\personal\anaconda3\lib\site-packages (from pandas) (2020.1)
Requirement already satisfied: scikit-learn in c:\users\personal\anaconda3\lib\site-packages (from xgboost) (1.5.2)
Requirement already satisfied: scipy in c:\users\personal\anaconda3\lib\site-packages (from python-dateutil>=2.7.3->pandas) (1.15.0)
Requirement already satisfied: joblib>=0.11 in c:\users\personal\anaconda3\lib\site-packages (from scikit-learn->sklearn) (0.17.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\personal\anaconda3\lib\site-packages (from scikit-learn->sklearn)
Note: you may need to restart the kernel to use updated packages.
```

In [2]: import numpy as np import pandas as pd import os, sys

 $\textbf{from} \ \, \textbf{sklearn.preprocessing} \ \, \textbf{import} \ \, \textbf{MinMaxScaler}$

from xgboost import XGBClassifier

from sklearn.model_selection import train_test_split

from sklearn.metrics import accuracy_score

```
In [3]: #DataFlair - Read the data
    df=pd.read_csv('parkinsons.data')
    df.head()
```

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name	MDVP:Fo(Hz)	MDVP:Fhi(Hz)	MDVP:Flo(Hz)	MDVP:Jitter(%)	MDVP:Jitter(Abs)	MDVP:RAP	MDVP:PPQ	Jitter:DDP	MDVP:Shimmer	 Shimn
0 phon_R01_S01_1	119.992	157.302	74.997	0.00784	0.00007	0.00370	0.00554	0.01109	0.04374	
1 phon_R01_S01_2	122.400	148.650	113.819	0.00968	0.00008	0.00465	0.00696	0.01394	0.06134	
2 phon_R01_S01_3	116.682	131.111	111.555	0.01050	0.00009	0.00544	0.00781	0.01633	0.05233	
3 phon_R01_S01_4	116.676	137.871	111.366	0.00997	0.00009	0.00502	0.00698	0.01505	0.05492	
4 phon_R01_S01_5	116.014	141.781	110.655	0.01284	0.00011	0.00655	0.00908	0.01966	0.06425	

5 rows × 24 columns



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

Jitter is defined as the parameter of frequency variation from cycle to cycle, and shimmer relates to the amplitude variation of the sound wave

```
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
```

In [4]: df.tail()

Out[4]:

:		name	MDVP:Fo(Hz)	MDVP:Fhi(Hz)	MDVP:Flo(Hz)	MDVP:Jitter(%)	MDVP:Jitter(Abs)	MDVP:RAP	MDVP:PPQ	Jitter:DDP	MDVP:Shimmer	 Shi
	190	phon_R01_S50_2	174.188	230.978	94.261	0.00459	0.00003	0.00263	0.00259	0.00790	0.04087	
	191	phon_R01_S50_3	209.516	253.017	89.488	0.00564	0.00003	0.00331	0.00292	0.00994	0.02751	
	192	phon_R01_S50_4	174.688	240.005	74.287	0.01360	0.00008	0.00624	0.00564	0.01873	0.02308	
	193	phon_R01_S50_5	198.764	396.961	74.904	0.00740	0.00004	0.00370	0.00390	0.01109	0.02296	
	194	phon_R01_S50_6	214.289	260.277	77.973	0.00567	0.00003	0.00295	0.00317	0.00885	0.01884	

5 rows × 24 columns

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In [5]: df.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
dtype	es: float64(22), i	nt64(1), object(1)

dtypes: float64(22), int64(1), object(1)

memory usage: 36.7+ KB

In [6]: df.describe()

Οι	ıt	[6]	:

	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)	•
count	195.000000	195.000000	195.000000	195.000000	195.000000	195.000000	195.000000	195.000000	195.000000	195.000000	
mean	154.228641	197.104918	116.324631	0.006220	0.000044	0.003306	0.003446	0.009920	0.029709	0.282251	
std	41.390065	91.491548	43.521413	0.004848	0.000035	0.002968	0.002759	0.008903	0.018857	0.194877	
min	88.333000	102.145000	65.476000	0.001680	0.000007	0.000680	0.000920	0.002040	0.009540	0.085000	
25%	117.572000	134.862500	84.291000	0.003460	0.000020	0.001660	0.001860	0.004985	0.016505	0.148500	
50%	148.790000	175.829000	104.315000	0.004940	0.000030	0.002500	0.002690	0.007490	0.022970	0.221000	
75%	182.769000	224.205500	140.018500	0.007365	0.000060	0.003835	0.003955	0.011505	0.037885	0.350000	
max	260.105000	592.030000	239.170000	0.033160	0.000260	0.021440	0.019580	0.064330	0.119080	1.302000	

8 rows × 23 columns

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In [7]: df.shape

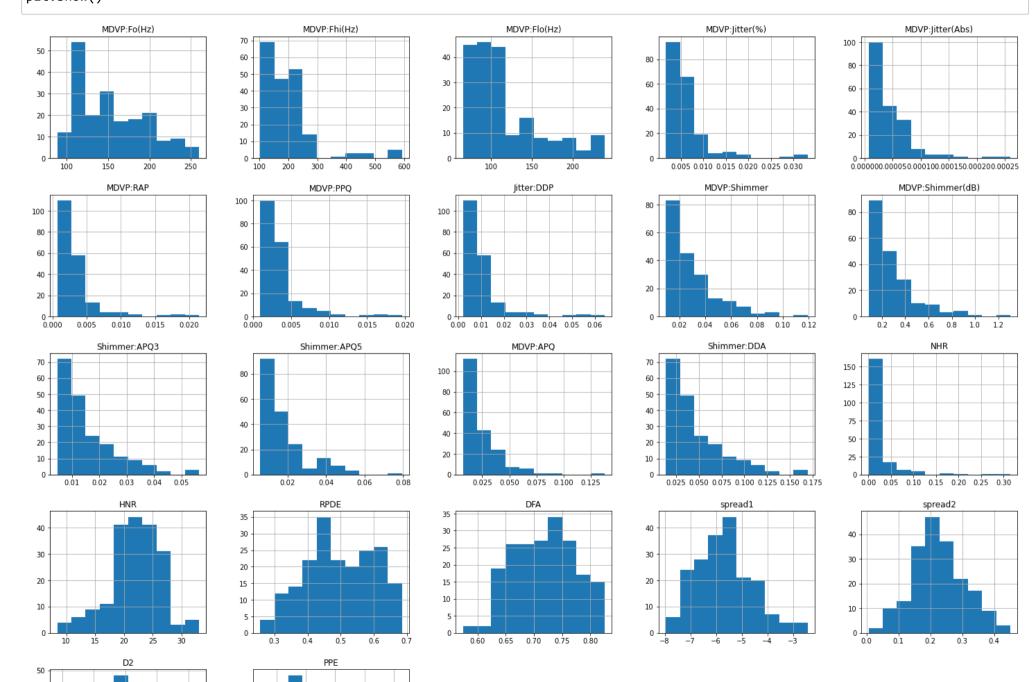
Out[7]: (195, 24)

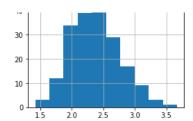
```
df.mean()
 In [8]:
Out[8]: MDVP:Fo(Hz)
                             154.228641
         MDVP:Fhi(Hz)
                             197.104918
         MDVP:Flo(Hz)
                             116.324631
                               0.006220
         MDVP:Jitter(%)
         MDVP:Jitter(Abs)
                               0.000044
         MDVP: RAP
                               0.003306
         MDVP:PPO
                               0.003446
         Jitter:DDP
                               0.009920
         MDVP:Shimmer
                               0.029709
         MDVP:Shimmer(dB)
                               0.282251
         Shimmer:APO3
                               0.015664
         Shimmer:APO5
                               0.017878
         MDVP:APO
                               0.024081
         Shimmer:DDA
                               0.046993
         NHR
                               0.024847
         HNR
                               21.885974
                               0.753846
         status
         RPDE
                               0.498536
         DFA
                               0.718099
         spread1
                               -5.684397
         spread2
                               0.226510
         D2
                               2.381826
         PPE
                               0.206552
         dtype: float64
         df.columns
In [10]:
Out[10]: Index(['name', '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'],
               dtvpe='object')
In [11]: #DataFlair - Get the features and labels
         features=df.loc[:,df.columns!='status'].values[:,1:]
         labels=df.loc[:,'status'].values
```

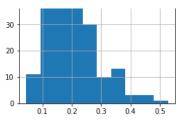
```
In [12]: #DataFlair - Get the count of each label (0 and 1) in labels
         print(labels[labels==1].shape[0], labels[labels==0].shape[0])
         147 48
In [13]: #DataFlair - Scale the features to between -1 and 1
         scaler=MinMaxScaler((-1,1))
         x=scaler.fit transform(features)
         v=labels
In [14]: #DataFlair - Split the dataset
         x train,x test,y train,y test=train test split(x, y, test size=0.2, random state=7)
In [15]: #DataFlair - Train the model
         model=XGBClassifier()
         model.fit(x train,y train)
         C:\Users\personal\anaconda3\lib\site-packages\xgboost\sklearn.py:1224: UserWarning: The use of label encoder in XGBClassifier is
         deprecated and will be removed in a future release. To remove this warning, do the following: 1) Pass option use label encoder=Fa
         lse when constructing XGBClassifier object; and 2) Encode your labels (y) as integers starting with 0, i.e. 0, 1, 2, ..., [num cl
         ass - 1].
           warnings.warn(label encoder deprecation msg, UserWarning)
         [12:00:06] WARNING: C:/Users/Administrator/workspace/xgboost-win64 release 1.5.1/src/learner.cc:1115: Starting in XGBoost 1.3.0,
         the default evaluation metric used with the objective 'binary:logistic' was changed from 'error' to 'logloss'. Explicitly set eva
         1 metric if you'd like to restore the old behavior.
Out[15]: XGBClassifier(base score=0.5, booster='gbtree', colsample bylevel=1,
                       colsample bynode=1, colsample bytree=1, enable categorical=False,
                       gamma=0, gpu id=-1, importance type=None,
                       interaction constraints='', learning rate=0.300000012,
                       max delta step=0, max depth=6, min child weight=1, missing=nan,
                       monotone constraints='()', n estimators=100, n jobs=8,
                       num parallel tree=1, predictor='auto', random state=0,
                       reg alpha=0, reg lambda=1, scale pos weight=1, subsample=1,
                       tree method='exact', validate parameters=1, verbosity=None)
```

```
In [16]: # DataFlair - Calculate the accuracy
         y_pred=model.predict(x_test)
         print(accuracy score(y test, y pred)*100)
         94.87179487179486
In [17]: from sklearn.metrics import confusion matrix
         pd.DataFrame(
             confusion matrix(y test, y pred),
             columns=['Predicted Healthy', 'Predicted Parkinsons'],
             index=['True Healthy', 'True Parkinsons']
Out[17]:
                        Predicted Healthy Predicted Parkinsons
             True Healthy
                                     6
                                                       1
          True Parkinsons
                                                      31
In [18]: #Determining Dependent & Independent Variables
         # get features and labels
         x=df.loc[:,df.columns!='status'].values[:,1:]
         x1=df.loc[:,df.columns!='status']
         y=df.loc[:,'status'].values
         y1=df.loc[:,'status']
In [24]: import matplotlib.pyplot as plt
         import seaborn as sns
         import warnings
         warnings.filterwarnings('ignore')
```

In [123]: #Analyzing Features
x1.hist(figsize=(25,20))
plt.show()





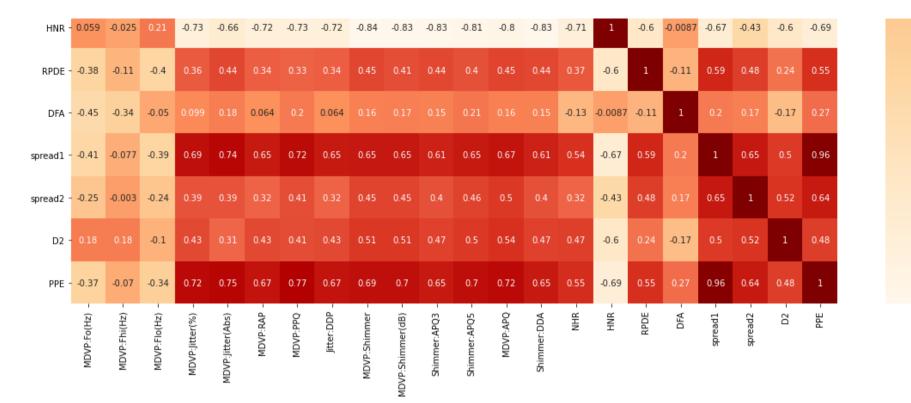


In [25]: correl=x1.corr()
 plt.figure(figsize=(20,20))
 sns.heatmap(correl,annot=True,cmap='OrRd')
 plt.show()

MDVP_Fin(Hz) = 04	MDVP:Fo(Hz)	1	0.4	0.6	-0.12	-0.38	-0.076	-0.11	-0.076	-0.098	-0.074	-0.095	-0.071	-0.078	-0.095	-0.022	0.059	-0.38	-0.45	-0.41	-0.25	0.18	-0.37
MDVP-Jitter(Abs) - 0.12	MDVP:Fhi(Hz)	0.4	1	0.085		-0.029	0.097		0.097	0.0023	0.043	-0.0037	-0.01	0.0049	-0.0037		-0.025	-0.11	-0.34	-0.077	-0.003	0.18	-0.07
MDVP-Jitter(Abs) - 0.38	MDVP:Flo(Hz)	0.6	0.085	1	-0.14	-0.28	-0.1	-0.096	-0.1	-0.14	-0.12	-0.15	-0.1	-0.11	-0.15	-0.11	0.21	-0.4	-0.05	-0.39	-0.24	-0.1	-0.34
MDVP-RAP - 0.076 0.097 0.1 0.99 0.92 1 0.96 1 0.96 0.8 0.8 0.8 0.8 0.76 0.79 0.74 0.71 0.74 0.74 0.92 0.72 0.34 0.064 0.65 0.32 0.43 0.67 0.77 0.77 0.77 0.78 0.78 0.78 0.78 0.7	MDVP:Jitter(%)	-0.12	0.1	-0.14	1	0.94	0.99	0.97	0.99	0.77	0.8	0.75	0.73	0.76	0.75	0.91	-0.73	0.36		0.69	0.39	0.43	0.72
MDVP:Shimmer -0.098 0.0037 0.15 0.75 0.75 0.75 0.74 0.75 0.75 0.75 0.75 0.75 0.75 0.75 0.75	MDVP:Jitter(Abs)	-0.38	-0.029	-0.28	0.94	1	0.92	0.9	0.92	0.7	0.72	0.7	0.65	0.65	0.7	0.83	-0.66	0.44	0.18	0.74	0.39	0.31	0.75
Jitter:DDP - 0.076 0.097 0.1 0.99 0.92 1 0.96 1 0.76 0.79 0.74 0.71 0.74 0.74 0.74 0.92 0.72 0.34 0.064 0.65 0.32 0.43 0.67 0.65 0.74 0.75 0.75 0.75 0.75 0.75 0.75 0.75 0.75	MDVP:RAP -	-0.076		-0.1	0.99	0.92	1	0.96	1	0.76	0.79	0.74	0.71	0.74	0.74	0.92	-0.72	0.34	0.064	0.65	0.32	0.43	0.67
MDVP:Shimmer - 0.098 0.0023 0.14 0.77 0.7 0.76 0.8 0.76 1 0.99 0.99 0.98 0.95 0.99 0.72 0.84 0.45 0.16 0.65 0.45 0.51 0.69 MDVP:Shimmer(dB) - 0.074 0.043 0.12 0.8 0.72 0.79 0.84 0.79 0.99 1 0.96 0.97 0.96 0.96 0.96 0.74 0.83 0.41 0.17 0.65 0.45 0.51 0.79 0.96 Shimmer:APQ3 - 0.095 0.0037 0.15 0.75 0.7 0.74 0.76 0.74 0.99 0.96 0.96 1 0.96 0.96 0.96 0.96 0.96 0.81 0.44 0.15 0.61 0.4 0.47 0.65 0.97 0.96 0.98 0.99 0.99 0.99 0.99 0.99 0.99 0.99	MDVP:PPQ -	-0.11		-0.096	0.97	0.9	0.96	1	0.96	0.8	0.84	0.76	0.79	0.8	0.76	0.84	-0.73	0.33	0.2	0.72	0.41	0.41	0.77
MDVP:Shimmer(dB) - 0.074	Jitter:DDP -	-0.076		-0.1	0.99	0.92	1	0.96	1	0.76	0.79	0.74	0.71	0.74	0.74	0.92	-0.72	0.34	0.064	0.65	0.32	0.43	0.67
Shimmer:APQ3 - 0.095	MDVP:Shimmer -	-0.098	0.0023	-0.14	0.77	0.7	0.76	0.8	0.76	1	0.99	0.99	0.98	0.95	0.99	0.72	-0.84	0.45		0.65	0.45	0.51	0.69
Shimmer:APQ50.071	MDVP:Shimmer(dB)	-0.074	0.043	-0.12	0.8	0.72	0.79	0.84	0.79	0.99	1	0.96	0.97	0.96	0.96	0.74	-0.83	0.41	0.17	0.65	0.45	0.51	0.7
MDVP:APQ - 0.078 0.0049 -0.11 0.76 0.65 0.74 0.8 0.74 0.95 0.96 0.9 0.95 1 0.9 0.69 -0.8 0.45 0.16 0.67 0.5 0.54 0.72 Shimmer:DDA - 0.095 -0.0037 -0.15 0.75 0.7 0.74 0.76 0.74 0.99 0.96 1 0.96 0.9 1 0.72 -0.83 0.44 0.15 0.61 0.4 0.47 0.65	Shimmer:APQ3 -	-0.095	-0.0037	-0.15	0.75	0.7	0.74	0.76	0.74	0.99	0.96	1	0.96	0.9	1	0.72	-0.83	0.44	0.15	0.61	0.4	0.47	0.65
Shimmer:DDA0.095 -0.0037 -0.15 0.75 0.7 0.74 0.76 0.74 0.99 0.96 1 0.96 0.9 1 0.72 -0.83 0.44 0.15 0.61 0.4 0.47 0.65	Shimmer:APQ5 -	-0.071	-0.01	-0.1	0.73	0.65	0.71	0.79	0.71	0.98	0.97	0.96	1	0.95	0.96	0.66	-0.81	0.4	0.21	0.65	0.46	0.5	0.7
	MDVP:APQ -	-0.078	0.0049	-0.11	0.76	0.65	0.74	0.8	0.74	0.95	0.96	0.9	0.95	1	0.9	0.69	-0.8	0.45		0.67	0.5	0.54	0.72
NHR - 0.022 0.16 -0.11 0.91 0.83 0.92 0.84 0.92 0.72 0.74 0.72 0.66 0.69 0.72 1 -0.71 0.37 -0.13 0.54 0.32 0.47 0.55	Shimmer:DDA -	-0.095	-0.0037	-0.15	0.75	0.7	0.74	0.76	0.74	0.99	0.96	1	0.96	0.9	1	0.72	-0.83	0.44	0.15	0.61	0.4	0.47	0.65
	NHR -	-0.022		-0.11	0.91	0.83	0.92	0.84	0.92	0.72	0.74	0.72	0.66	0.69	0.72	1	-0.71	0.37	-0.13	0.54	0.32	0.47	0.55

- 0.75 - 0.50 - 0.25 - 0.00

- -0.25



- -0.50

- -0.75

```
In [26]: #Scale the features to between -1 and 1
    scaler=MinMaxScaler((-1,1))
    x1=scaler.fit_transform(x)
    y1=y
```

In [27]: #Split the dataset

xtrain,xtest,ytrain,ytest=train_test_split(x1, y1, test_size=0.2)

```
In [28]: # Train the model
from xgboost import XGBClassifier

model=XGBClassifier()
model.fit(xtrain,ytrain)
predict=model.predict(xtest)
```

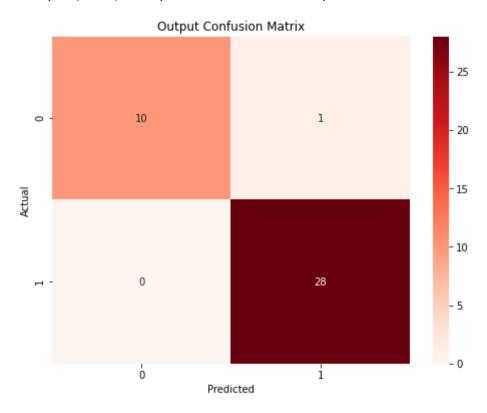
[12:04:04] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.5.1/src/learner.cc:1115: Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed from 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.

In [29]: print(accuracy_score(ytest,predict)*100)

97.43589743589743

```
In [30]: from sklearn.metrics import confusion_matrix
    cm=confusion_matrix(ytest,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")
```

Out[30]: Text(0.5, 1.0, 'Output Confusion Matrix')



In [31]: pd.DataFrame({'actual':ytest,'predict':predict})

Out[31]:		actual	predict
	0	1	1
	1	1	1
	2	1	1
	3	1	1
	4	1	1
	5	1	1
	6	0	0
	7	0	0
	8	0	1
	9	1	1
	10	1	1
	11	1	1
	12	1	1
	13	0	0
	14	1	1
	15	1	1
	16	1	1
	17	0	0
	18	1	1
	19	0	0
	20	1	1
	21	0	0
	22	1	1
	23	1	1
	24	0	0
	25	0	0

	actual	predict
26	0	0
27	1	1
28	1	1
29	0	0
30	1	1
31	1	1
32	1	1
33	1	1
34	1	1
35	1	1
36	1	1
37	1	1
38	1	1

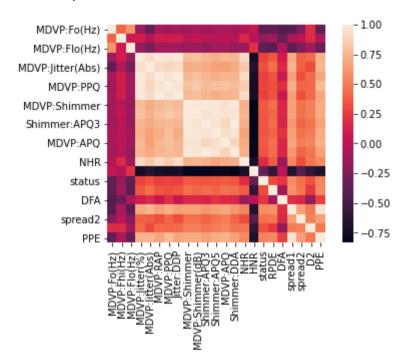
```
In [54]: df.columns
Out[54]: Index(['name', 'MDVP:Fo(Hz)', 'MDVP:Fhi(Hz)', 'MDVP:Flo(Hz)', 'MDVP:Jitter(%)',
                 'MDVP:Jitter(Abs)', 'MDVP:RAP', 'MDVP:PPQ', 'Jitter:DDP',
                'MDVP:Shimmer', 'MDVP:Shimmer(dB)', 'Shimmer:APQ3', 'Shimmer:APQ5',
                'MDVP:APQ', 'Shimmer:DDA', 'NHR', 'HNR', 'status', 'RPDE', 'DFA',
                'spread1', 'spread2', 'D2', 'PPE'],
               dtype='object')
In [55]: #DataFlair - Get the count of each label (0 and 1) in labels
         print(label[label==1].shape[0], label[label==0].shape[0])
         147 48
In [56]: df.shape
Out[56]: (195, 24)
In [57]: #DataFlair - Scale the features to between -1 and 1
         scaler=MinMaxScaler((-1,1))
         a=scaler.fit transform(feature)
         b=label
In [61]: #DataFlair - Split the dataset
         x train1,x test1,y train1,y test1=train test split(x, y, test size=0.2, random state=7)
```

```
In [62]: #DataFlair - Train the model
         model=XGBClassifier()
         model.fit(x train1,y train1)
         [15:13:01] WARNING: C:/Users/Administrator/workspace/xgboost-win64 release 1.5.1/src/learner.cc:1115: Starting in XGBoost 1.3.0,
         the default evaluation metric used with the objective 'binary:logistic' was changed from 'error' to 'logloss'. Explicitly set eva
         1 metric if you'd like to restore the old behavior.
Out[62]: XGBClassifier(base score=0.5, booster='gbtree', colsample bylevel=1,
                       colsample bynode=1, colsample bytree=1, enable categorical=False,
                       gamma=0, gpu id=-1, importance type=None,
                       interaction_constraints='', learning_rate=0.300000012,
                       max delta step=0, max depth=6, min child weight=1, missing=nan,
                       monotone constraints='()', n estimators=100, n jobs=8,
                       num parallel tree=1, predictor='auto', random state=0,
                       reg alpha=0, reg lambda=1, scale pos weight=1, subsample=1,
                       tree method='exact', validate parameters=1, verbosity=None)
In [64]: # DataFlair - Calculate the accuracy
         v pred1=model.predict(x test1)
         print(accuracy score(y test1, y pred1)*100)
         94.87179487179486
In [66]: from sklearn.svm import SVC
         classifi2 = SVC()
In [68]: #fitting the model in SVM
         classifi2.fit(x train,y train)
         print(accuracy score(y test, y pred1)*100)
```

94.87179487179486

In [87]: import seaborn as sb corr_map=df.corr() sb.heatmap(corr_map,square=True)

Out[87]: <AxesSubplot:>



```
RangeIndex: 195 entries, 0 to 194
          Data columns (total 24 columns):
                                 Non-Null Count Dtype
           #
               Column
               _____
           0
                                 195 non-null
                                                 object
               name
               MDVP:Fo(Hz)
                                 195 non-null
                                                 float64
           1
                                 195 non-null
                                                 float64
           2
               MDVP:Fhi(Hz)
              MDVP:Flo(Hz)
           3
                                 195 non-null
                                                 float64
                                 195 non-null
                                                 float64
               MDVP:Jitter(%)
              MDVP:Jitter(Abs) 195 non-null
           5
                                                 float64
               MDVP:RAP
                                 195 non-null
                                                 float64
               MDVP:PPO
                                 195 non-null
                                                 float64
                                 195 non-null
                                                 float64
           8
               Jitter:DDP
               MDVP:Shimmer
                                 195 non-null
                                                 float64
           10 MDVP:Shimmer(dB) 195 non-null
                                                 float64
           11 Shimmer:APO3
                                 195 non-null
                                                 float64
           12 Shimmer:APO5
                                 195 non-null
                                                 float64
           13 MDVP:APO
                                 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
In [115]: # split the dataset into input and output attribute.
          a1=df['status']
          #cols=['MDVP:RAP','Jitter:DDP','DFA','NHR','MDVP:Fhi(Hz)','name','status']
          #b1=df.drop(cols,axis=1)
          b1=df['spread1']
```

df.info()

<class 'pandas.core.frame.DataFrame'>

In [75]:

```
In [116]: # Splitting the dataset into trianing and test set
          train size=0.80
          test size=0.20
          seed=5
          from sklearn.model selection import train test split
          x tr2,x te2,y tr2,y te2=train test split(a1,b1,train size=train size,test size=test size,random state=seed)
In [117]: #DataFlair - Train the model
          model=XGBClassifier()
          model.fit(x tr2,y tr2)
          [15:59:31] WARNING: C:/Users/Administrator/workspace/xgboost-win64 release 1.5.1/src/learner.cc:1115: Starting in XGBoost 1.3.0,
          the default evaluation metric used with the objective 'binary:logistic' was changed from 'error' to 'logloss'. Explicitly set eva
          l metric if you'd like to restore the old behavior.
Out[117]: XGBClassifier(base score=0.5, booster='gbtree', colsample bylevel=1,
                        colsample bynode=1, colsample bytree=1, enable categorical=False,
                        gamma=0, gpu id=-1, importance type=None,
                        interaction_constraints='', learning_rate=0.300000012,
                        max delta step=0, max depth=6, min child weight=1, missing=nan,
                        monotone constraints='()', n estimators=100, n jobs=8,
                        num parallel tree=1, predictor='auto', random state=0,
                        reg alpha=0, reg lambda=1, scale pos weight=1, subsample=1,
                        tree method='exact', validate parameters=1, verbosity=None)
In [118]: # DataFlair - Calculate the accuracy
          y pred2=model.predict(x te2)
          print(accuracy score(y te2, y pred2)*100)
          100.0
 In [89]: # split the dataset into input and output attribute.
          s2=df['status']
          cols=['MDVP:RAP','Jitter:DDP','DFA','NHR','MDVP:Fhi(Hz)','name','status']
          s1=df.drop(cols,axis=1)
```

```
In [125]: # Splitting the dataset into trianing and test set
```

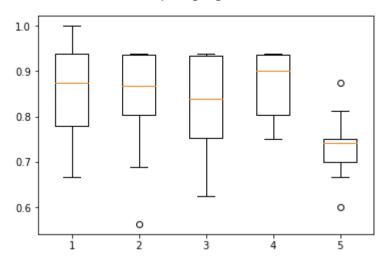
```
train_size=0.80
test_size=0.20
seed=5
```

```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(s1,s2,train_size=train_size,test_size=test_size,random_state=seed)
```

```
In [126]: n neighbors=5
          import matplotlib.pyplot as plt
          from sklearn.linear model import LogisticRegression
          from sklearn.neighbors import KNeighborsClassifier
          from sklearn.svm import SVC
          from sklearn.tree import DecisionTreeClassifier
          from sklearn.naive bayes import GaussianNB
          # keeping all models in one list
          models=[]
          models.append(('LogisticRegression',LogisticRegression()))
          models.append(('knn',KNeighborsClassifier(n neighbors=n neighbors)))
          models.append(('SVM',SVC()))
          models.append(("XGBOOST",DecisionTreeClassifier()))
          models.append(('Naive Bayes',GaussianNB()))
          # Evaluating Each model
          from sklearn.model selection import KFold
          from sklearn.model selection import cross val score
          names=[]
          predictions=[]
          error='accuracy'
          for name,model in models:
              fold=KFold(n splits=10,random state=0)
              result=cross val score(model,x train,y train,cv=fold,scoring=error)
              predictions.append(result)
              names.append(name)
              msg="%s : %f (%f)"%(name,result.mean(),result.std())
              print(msg)
          # Visualizing the Model accuracy
          fig=plt.figure()
          fig.suptitle("Comparing Algorithms")
          plt.boxplot(predictions)
          plt.show()
          LogisticRegression: 0.865833 (0.106275)
          knn: 0.834167 (0.118714)
          SVM: 0.821667 (0.117951)
```

XGBOOST : 0.865833 (0.076508) Naive Bayes : 0.735833 (0.071715)

Comparing Algorithms



In [127]: #Determining Dependent & Independent Variables

In []:

```
# get features and Labels

x=df.loc[:,df.columns!='status'].values[:,1:]
x1=df.loc[:,df.columns!='status']
y=df.loc[:,'status'].values
y1=df.loc[:,'status']
In []:
```