In [1183]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn.neighbors import KNeighborsClassifier
from scipy.stats import zscore
from sklearn import metrics
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB
from sklearn.impute import SimpleImputer
from sklearn.metrics import confusion_matrix,accuracy_score
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.tree import export_graphviz
from sklearn.externals.six import StringIO
from IPython.display import Image
import pydotplus
import graphviz
from sklearn import model_selection
from mlxtend.classifier import StackingClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.ensemble import BaggingClassifier
from sklearn.ensemble import GradientBoostingClassifier
```

1. Load the dataset

In [1184]:

```
park = pd.read_csv("Data-Parkinsons.csv")
```

In [1185]:

```
park.shape
```

Out[1185]:

```
(195, 24)
```

In [1186]:

```
park.head()
```

Out[1186]:

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

5 rows × 24 columns

2. Studying the data attributes

In [1187]:

```
park.info()
```

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

In [1188]:

```
park.isnull().values.any()
```

Out[1188]:

```
False
```

In [1189]:

```
park.describe()
```

Out[1189]:

	MDVP:Fo(Hz)	MDVP:Fhi(Hz)	MDVP:Flo(Hz)	MDVP:Jitter(%)	MDVP:Jitter(Abs)	MDVP:RAP	MDVP:PPQ	Jitter:DDP	MDVP:Shimm
count	195.000000	195.000000	195.000000	195.000000	195.000000	195.000000	195.000000	195.000000	195.0000
mean	154.228641	197.104918	116.324631	0.006220	0.000044	0.003306	0.003446	0.009920	0.0297
std	41.390065	91.491548	43.521413	0.004848	0.000035	0.002968	0.002759	0.008903	0.0188
min	88.333000	102.145000	65.476000	0.001680	0.000007	0.000680	0.000920	0.002040	0.0095
25%	117.572000	134.862500	84.291000	0.003460	0.000020	0.001660	0.001860	0.004985	0.0165
50%	148.790000	175.829000	104.315000	0.004940	0.000030	0.002500	0.002690	0.007490	0.0229
75%	182.769000	224.205500	140.018500	0.007365	0.000060	0.003835	0.003955	0.011505	0.0378
max	260.105000	592.030000	239.170000	0.033160	0.000260	0.021440	0.019580	0.064330	0.1190

8 rows × 23 columns

> The following can be understood from initial data analysis
>
> - There are 195 entries

- There are no null values.
- There are 22 float,1 integer,1 object column.
- The shape of the data is 8 rows and 23 columns.

3. Univariate analysis

In [1190]:

```
park["MDVP:Fo(Hz)"].describe()
```

Out[1190]:

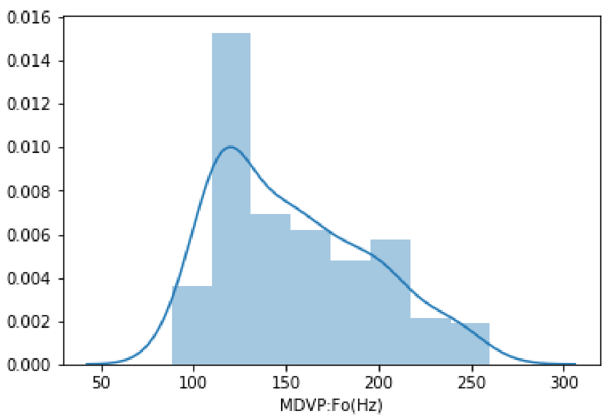
```
count    195.000000
mean     154.228641
std       41.390065
min       88.333000
25%      117.572000
50%      148.790000
75%      182.769000
max      260.105000
Name: MDVP:Fo(Hz), dtype: float64
```

In [1191]:

```
sns.distplot(park["MDVP:Fo(Hz)"])
```

Out[1191]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x202d4d5d288>
```



In [1192]:

```
park["MDVP:Fhi(Hz)"].describe()
```

Out[1192]:

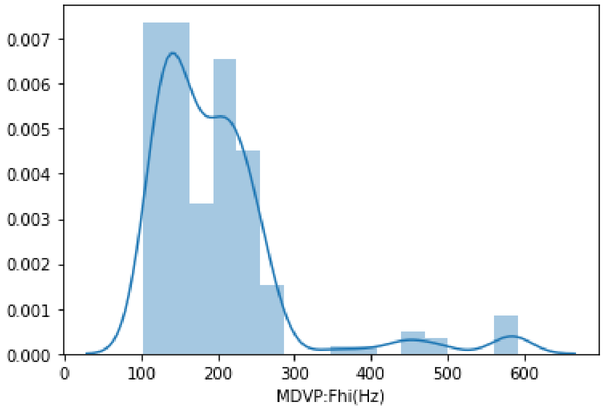
```
count    195.000000
mean     197.104918
std       91.491548
min      102.145000
25%      134.862500
50%      175.829000
75%      224.205500
max      592.030000
Name: MDVP:Fhi(Hz), dtype: float64
```

In [1193]:

```
sns.distplot(park["MDVP:Fhi(Hz)"])
```

Out[1193]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x202d4dce0c8>
```



In [1194]:

```
park["MDVP:Flo(Hz)"].describe()
```

Out[1194]:

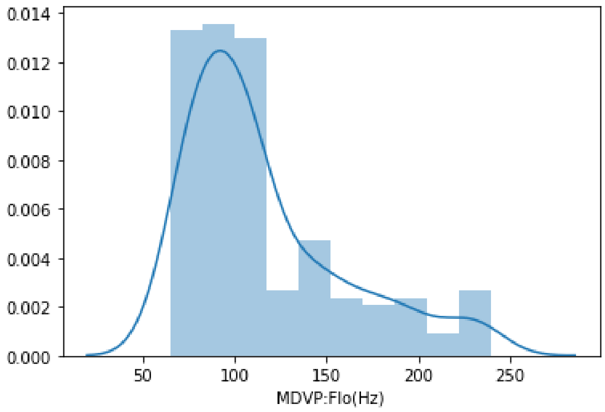
```
count    195.000000
mean     116.324631
std       43.521413
min       65.476000
25%       84.291000
50%      104.315000
75%      140.018500
max      239.170000
Name: MDVP:Flo(Hz), dtype: float64
```

In [1195]:

```
sns.distplot(park["MDVP:Flo(Hz)"])
```

Out[1195]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x202d4e66048>
```



In [1196]:

```
park["MDVP:Jitter(%)"].describe()
```

Out[1196]:

```
count    195.000000
mean       0.006220
std        0.004848
min        0.001680
25%        0.003460
50%        0.004940
75%        0.007365
```

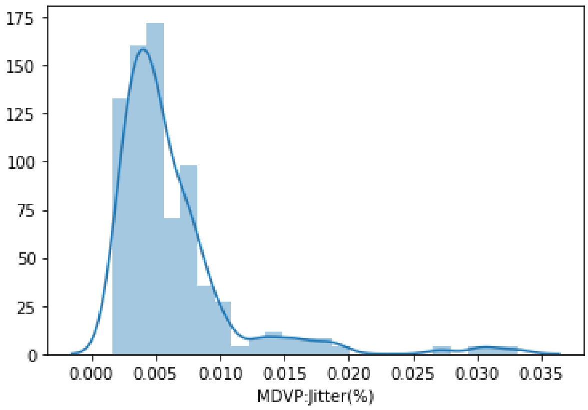
```
max         0.033160
Name: MDVP:Jitter(%), dtype: float64
```

In [1197]:

```
sns.distplot(park["MDVP:Jitter(%)"])
```

Out[1197]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x202d4ed36c8>
```



In [1198]:

```
park["MDVP:Jitter(Abs)"].describe()
```

Out[1198]:

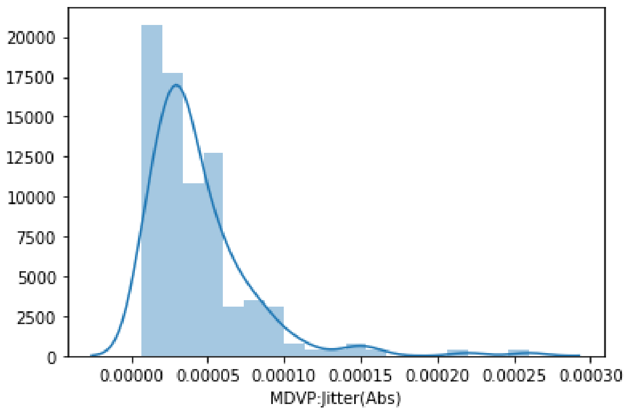
```
count    195.000000
mean       0.000044
std        0.000035
min        0.000007
25%        0.000020
50%        0.000030
75%        0.000060
max        0.000260
Name: MDVP:Jitter(Abs), dtype: float64
```

In [1199]:

```
sns.distplot(park["MDVP:Jitter(Abs)"])
```

Out[1199]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x202d4f9d208>
```



In [1200]:

```
park["MDVP:RAP"].describe()
```

Out[1200]:

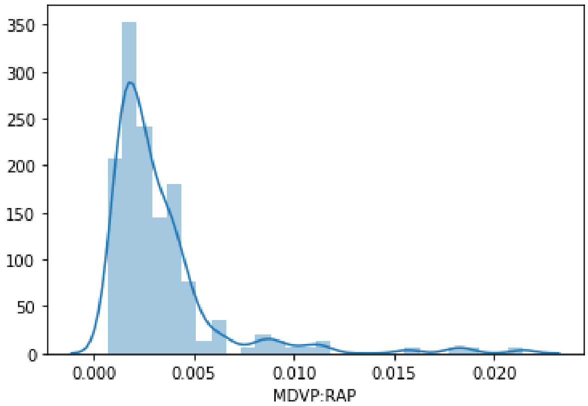
```
count    195.000000
mean       0.003306
std        0.002968
min        0.000680
25%        0.001660
50%        0.002500
75%        0.003835
max        0.021440
Name: MDVP:RAP, dtype: float64
```

In [1201]:

```
sns.distplot(park["MDVP:RAP"])
```

Out[1201]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x202d504c7c8>
```



In [1202]:

```
park["MDVP:PPQ"].describe()
```

Out[1202]:

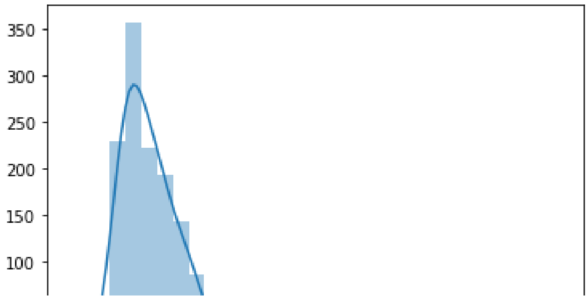
```
count    195.000000
mean       0.003446
std        0.002759
min        0.000920
25%        0.001860
50%        0.002690
75%        0.003955
max        0.019580
Name: MDVP:PPQ, dtype: float64
```

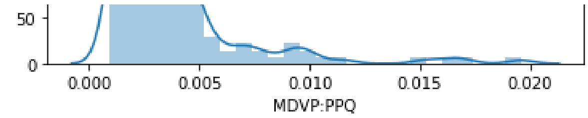
In [1203]:

```
sns.distplot(park["MDVP:PPQ"])
```

Out[1203]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x202d50faa48>
```





In [1204]:

```
park["Jitter:DDP"].describe()
```

Out[1204]:

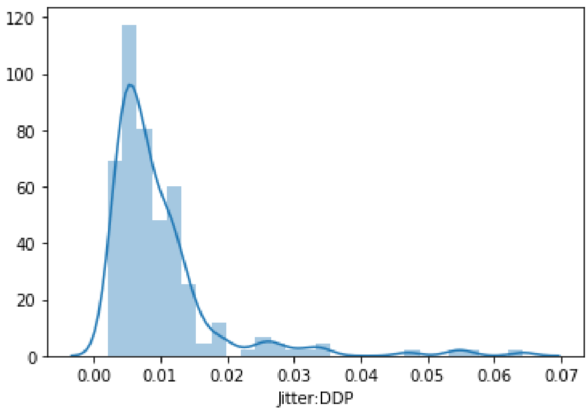
```
count    195.000000
mean       0.009920
std        0.008903
min        0.002040
25%        0.004985
50%        0.007490
75%        0.011505
max        0.064330
Name: Jitter:DDP, dtype: float64
```

In [1205]:

```
sns.distplot(park["Jitter:DDP"])
```

Out[1205]:

<matplotlib.axes._subplots.AxesSubplot at 0x202d51aad08>



In [1206]:

```
park["MDVP:Shimmer"].describe()
```

Out[1206]:

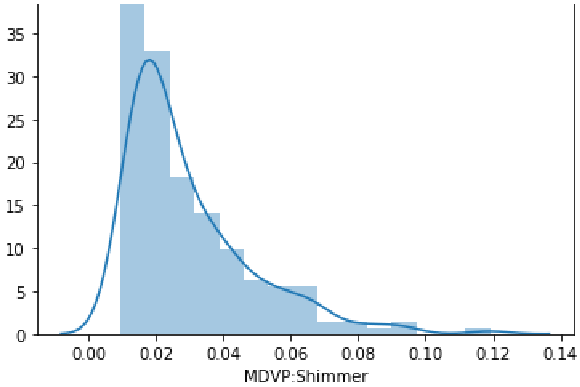
```
count    195.000000
mean       0.029709
std        0.018857
min        0.009540
25%        0.016505
50%        0.022970
75%        0.037885
max        0.119080
Name: MDVP:Shimmer, dtype: float64
```

In [1207]:

```
sns.distplot(park["MDVP:Shimmer"])
```

Out[1207]:

<matplotlib.axes._subplots.AxesSubplot at 0x202d526ca08>



In [1208]:

```
park["MDVP:Shimmer(dB)"].describe()
```

Out[1208]:

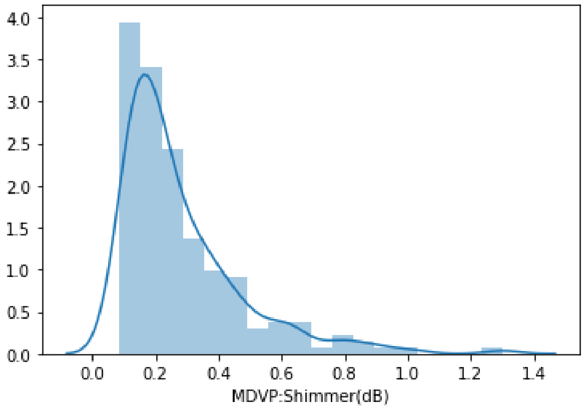
```
count    195.000000
mean       0.282251
std        0.194877
min        0.085000
25%        0.148500
50%        0.221000
75%        0.350000
max        1.302000
Name: MDVP:Shimmer(dB), dtype: float64
```

In [1209]:

```
sns.distplot(park["MDVP:Shimmer(dB)"])
```

Out[1209]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x202d52e6548>
```



In [1210]:

```
park["Shimmer:APQ3"].describe()
```

Out[1210]:

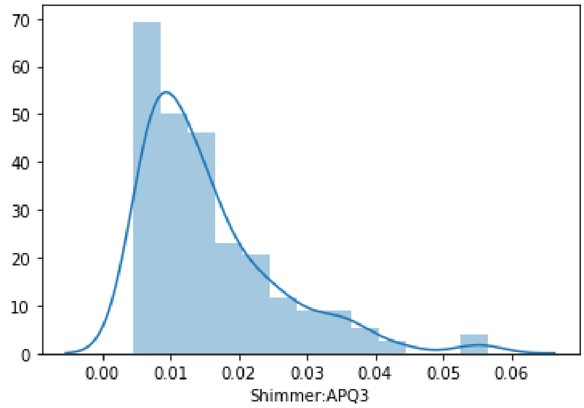
```
count    195.000000
mean       0.015664
std        0.010153
min        0.004550
25%        0.008245
50%        0.012790
75%        0.020265
max        0.056470
Name: Shimmer:APQ3, dtype: float64
```

In [1211]:

```
sns.distplot(park["Shimmer:APQ3"])
```

Out[1211]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x202d5378888>
```



In [1212]:

```
park["Shimmer:APQ5"].describe()
```

Out[1212]:

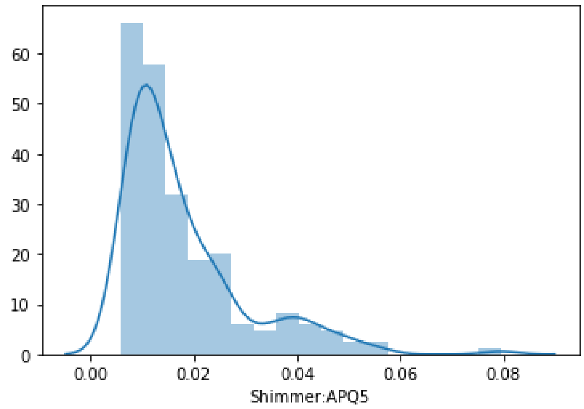
```
count    195.000000
mean       0.017878
std        0.012024
min        0.005700
25%        0.009580
50%        0.013470
75%        0.022380
max        0.079400
Name: Shimmer:APQ5, dtype: float64
```

In [1213]:

```
sns.distplot(park["Shimmer:APQ5"])
```

Out[1213]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x202d53e5908>
```



In [1214]:

```
park["MDVP:APQ"].describe()
```

Out[1214]:

```
count    195.000000
```

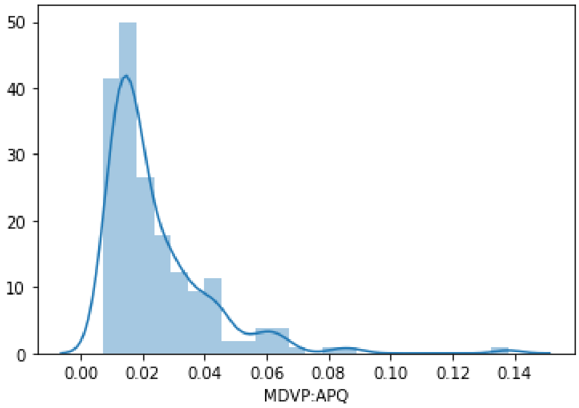
```
mean        0.024081
std         0.016947
min         0.007190
25%         0.013080
50%         0.018260
75%         0.029400
max         0.137780
Name: MDVP:APQ, dtype: float64
```

In [1215]:

```
sns.distplot(park["MDVP:APQ"])
```

Out[1215]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x202d54cfc88>
```



In [1216]:

```
park["Shimmer:DDA"].describe()
```

Out[1216]:

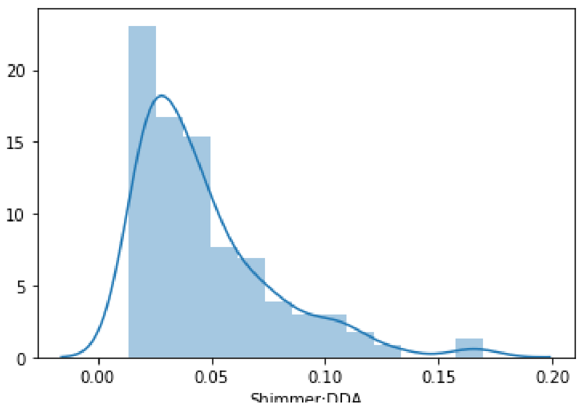
```
count     195.000000
mean        0.046993
std         0.030459
min         0.013640
25%         0.024735
50%         0.038360
75%         0.060795
max         0.169420
Name: Shimmer:DDA, dtype: float64
```

In [1217]:

```
sns.distplot(park["Shimmer:DDA"])
```

Out[1217]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x202d5578608>
```



Shimmer:DDA

In [1218]:

```
park["NHR"].describe()
```

Out[1218]:

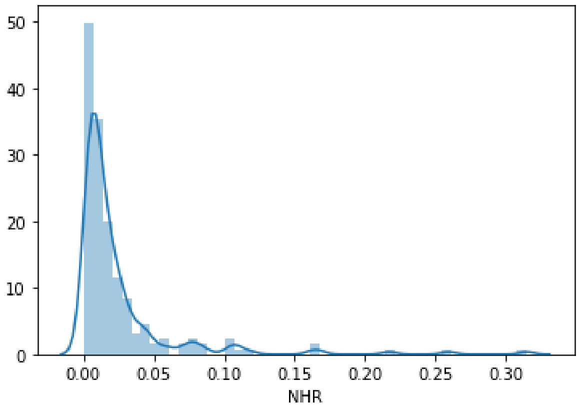
```
count    195.000000
mean       0.024847
std        0.040418
min        0.000650
25%        0.005925
50%        0.011660
75%        0.025640
max        0.314820
Name: NHR, dtype: float64
```

In [1219]:

```
sns.distplot(park["NHR"])
```

Out[1219]:

<matplotlib.axes._subplots.AxesSubplot at 0x202d65c53c8>



In [1220]:

```
park["HNR"].describe()
```

Out[1220]:

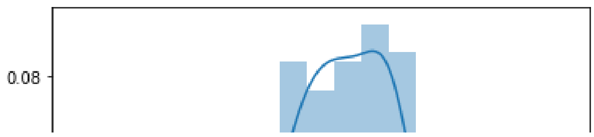
```
count    195.000000
mean      21.885974
std        4.425764
min        8.441000
25%       19.198000
50%       22.085000
75%       25.075500
max       33.047000
Name: HNR, dtype: float64
```

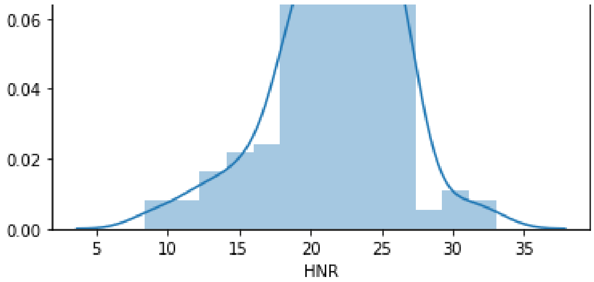
In [1221]:

```
sns.distplot(park["HNR"])
```

Out[1221]:

<matplotlib.axes._subplots.AxesSubplot at 0x202d666ef08>





In [1222]:

```
park["status"].describe()
```

Out[1222]:

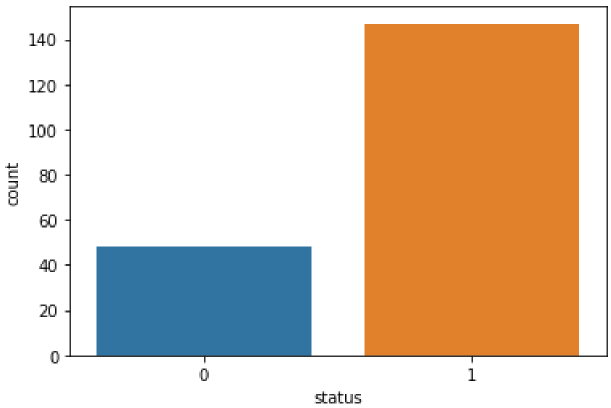
```
count    195.000000
mean       0.753846
std        0.431878
min        0.000000
25%        1.000000
50%        1.000000
75%        1.000000
max        1.000000
Name: status, dtype: float64
```

In [1223]:

```
sns.countplot(park["status"])
```

Out[1223]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x202d66f93c8>
```



In [1224]:

```
park["RPDE"].describe()
```

Out[1224]:

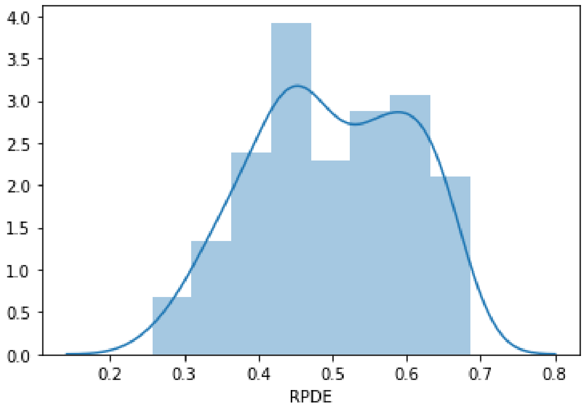
```
count    195.000000
mean       0.498536
std        0.103942
min        0.256570
25%        0.421306
50%        0.495954
75%        0.587562
max        0.685151
Name: RPDE, dtype: float64
```

In [1225]:

```
sns.distplot(park["RPDE"])
```

Out[1225]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x202d67922c8>
```



In [1226]:

```
park["DFA"].describe()
```

Out[1226]:

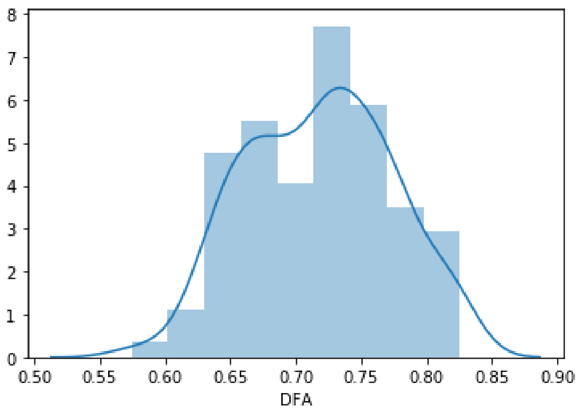
```
count    195.000000
mean       0.718099
std        0.055336
min        0.574282
25%        0.674758
50%        0.722254
75%        0.761881
max        0.825288
Name: DFA, dtype: float64
```

In [1227]:

```
sns.distplot(park["DFA"])
```

Out[1227]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x202d680afc8>
```



In [1228]:

```
park["spread1"].describe()
```

Out[1228]:

```
count    195.000000
mean      -5.684397
std        1.090208
min       -7.964984
25%       -6.450096
```

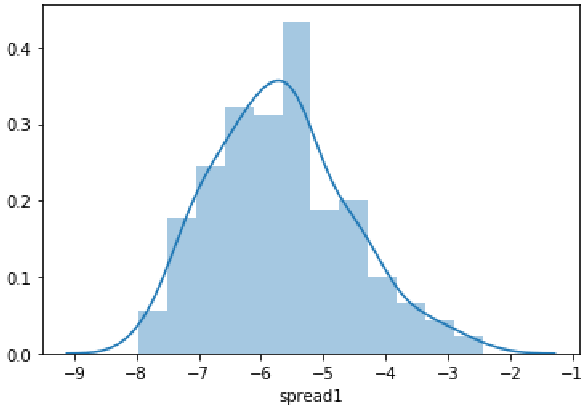
```
50%        -5.720868
75%        -5.046192
max        -2.434031
Name: spread1, dtype: float64
```

In [1229]:

```python
sns.distplot(park["spread1"])
```

Out[1229]:

```
&lt;matplotlib.axes._subplots.AxesSubplot at 0x202d687b108&gt;
```



In [1230]:

```python
park["spread2"].describe()
```

Out[1230]:

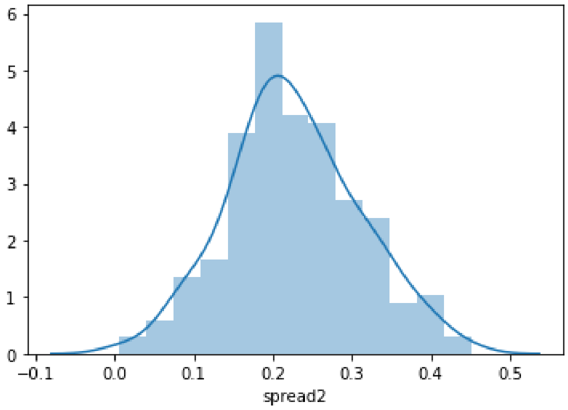
```
count    195.000000
mean       0.226510
std        0.083406
min        0.006274
25%        0.174351
50%        0.218885
75%        0.279234
max        0.450493
Name: spread2, dtype: float64
```

In [1231]:

```python
sns.distplot(park["spread2"])
```

Out[1231]:

```
&lt;matplotlib.axes._subplots.AxesSubplot at 0x202d312e908&gt;
```



In [1232]:

```
park["D2"].describe()
```

Out[1232]:

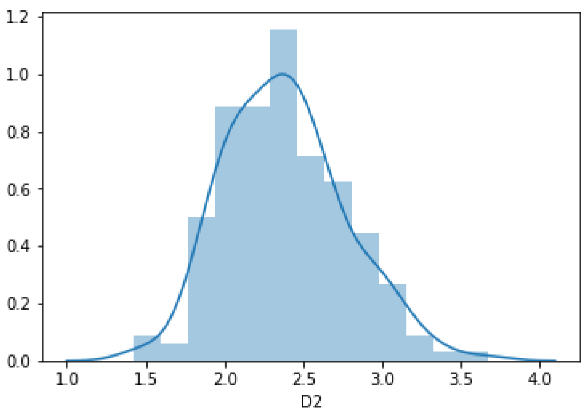
```
count    195.000000
mean       2.381826
std        0.382799
min        1.423287
25%        2.099125
50%        2.361532
75%        2.636456
max        3.671155
Name: D2, dtype: float64
```

In [1233]:

```
sns.distplot(park["D2"])
```

Out[1233]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x202d6983308>
```



In [1234]:

```
park["PPE"].describe()
```

Out[1234]:

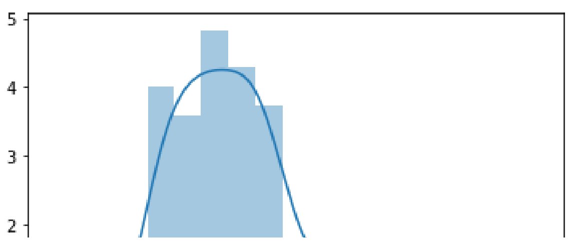
```
count    195.000000
mean       0.206552
std        0.090119
min        0.044539
25%        0.137451
50%        0.194052
75%        0.252980
max        0.527367
Name: PPE, dtype: float64
```

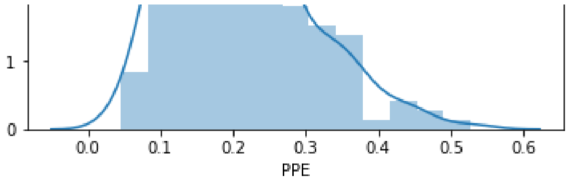
In [1235]:

```
sns.distplot(park["PPE"])
```

Out[1235]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x202d6a4a5c8>
```





From the univariate analysis, the following can be inferred

- From count plot out of 195 patients checked around 140 patients are suspected to have Parkinson.
- The columns D2,spread2,spread1 have a normal bell-shaped curve.
- The columns DFA, HNR are skewed towards the right.
- The rest of all columns are skewed towards left.
- The spread, mean, IQR, etc have been calculated.

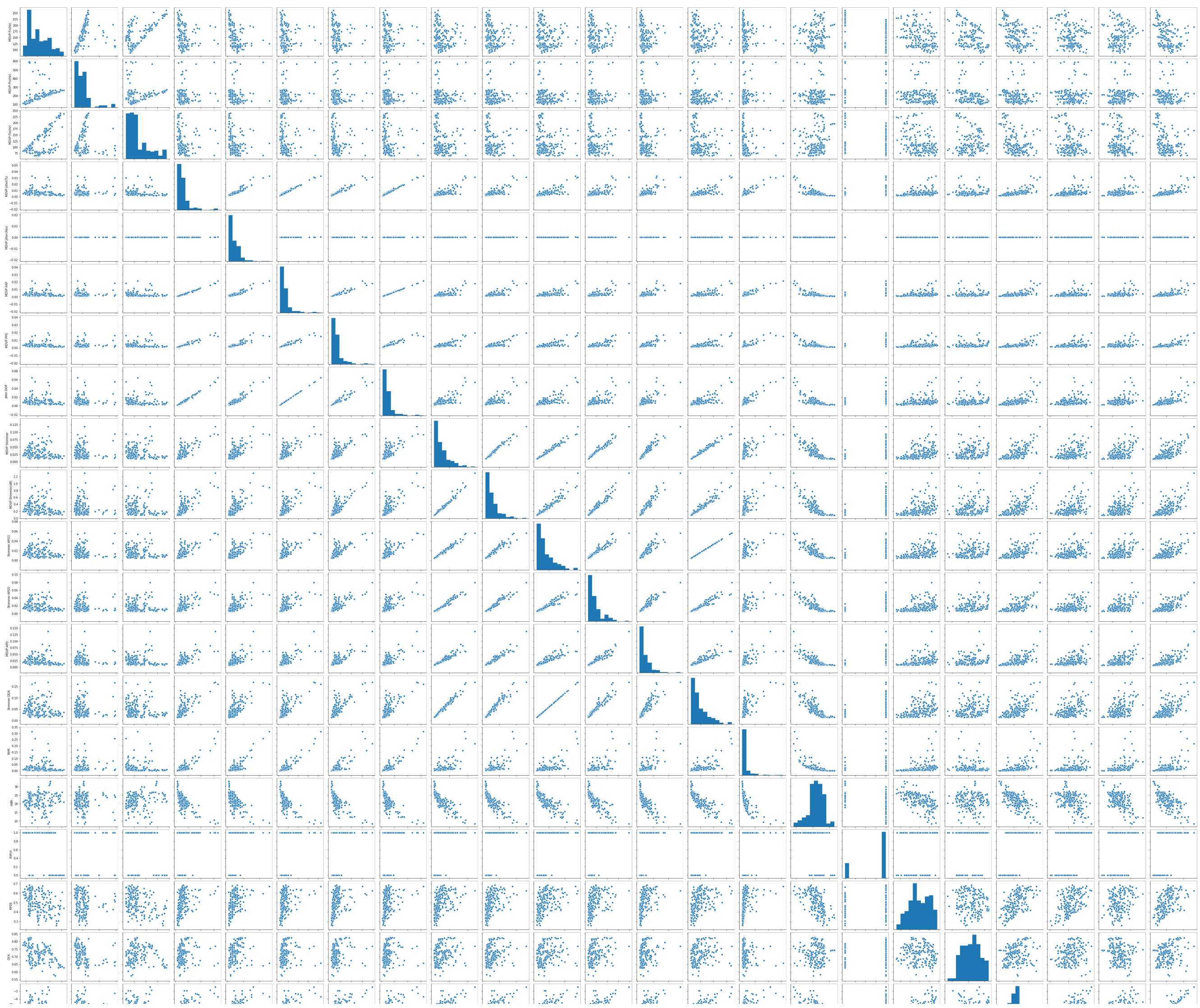
Bivariate Analysis

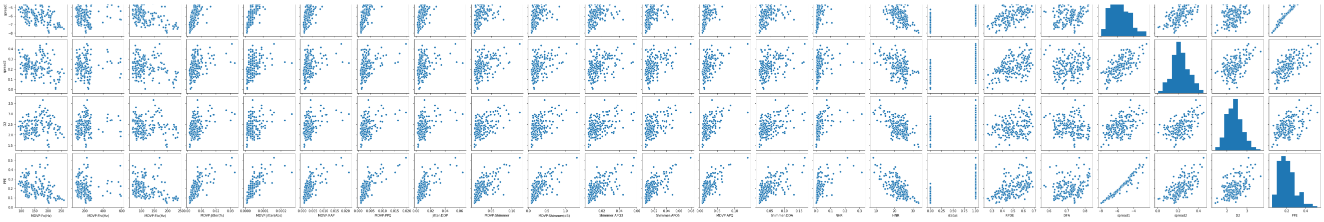
In [1236]:

```
sns.pairplot(park[["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"]])
```

Out[1236]:

```
<seaborn.axisgrid.PairGrid at 0x202d6ae13c8>
```





In [1237]:

```
core=park.corr()
park.corr()
```

Out[1237]:

	MDVP:Fo(Hz)	MDVP:Fhi(Hz)	MDVP:Flo(Hz)	MDVP:Jitter(%)	MDVP:Jitter(Abs)	MDVP:RAP	MDVP:PPQ	Jitter:DDP
MDVP:Fo(Hz)	1.000000	0.400985	0.596546	-0.118003	-0.382027	-0.076194	-0.112165	-0.076213
MDVP:Fhi(Hz)	0.400985	1.000000	0.084951	0.102086	-0.029198	0.097177	0.091126	0.097150
MDVP:Flo(Hz)	0.596546	0.084951	1.000000	-0.139919	-0.277815	-0.100519	-0.095828	-0.100488
MDVP:Jitter(%)	-0.118003	0.102086	-0.139919	1.000000	0.935714	0.990276	0.974256	0.990276
MDVP:Jitter(Abs)	-0.382027	-0.029198	-0.277815	0.935714	1.000000	0.922911	0.897778	0.922913
MDVP:RAP	-0.076194	0.097177	-0.100519	0.990276	0.922911	1.000000	0.957317	1.000000
MDVP:PPQ	-0.112165	0.091126	-0.095828	0.974256	0.897778	0.957317	1.000000	0.957319
Jitter:DDP	-0.076213	0.097150	-0.100488	0.990276	0.922913	1.000000	0.957319	1.000000
MDVP:Shimmer	-0.098374	0.002281	-0.144543	0.769063	0.703322	0.759581	0.797826	0.759555
MDVP:Shimmer(dB)	-0.073742	0.043465	-0.119089	0.804289	0.716601	0.790652	0.839239	0.790621
Shimmer:APQ3	-0.094717	-0.003743	-0.150747	0.746625	0.697153	0.744912	0.763580	0.744894
Shimmer:APQ5	-0.070682	-0.009997	-0.101095	0.725561	0.648961	0.709927	0.786780	0.709907
MDVP:APQ	-0.077774	0.004937	-0.107293	0.758255	0.648793	0.737455	0.804139	0.737439
Shimmer:DDA	-0.094732	-0.003733	-0.150737	0.746635	0.697170	0.744919	0.763592	0.744901
NHR	-0.021981	0.163766	-0.108670	0.906959	0.834972	0.919521	0.844604	0.919548
HNR	0.059144	-0.024893	0.210851	-0.728165	-0.656810	-0.721543	-0.731510	-0.721494
status	-0.383535	-0.166136	-0.380200	0.278220	0.338653	0.266668	0.288698	0.266646
RPDE	-0.383894	-0.112404	-0.400143	0.360673	0.441839	0.342140	0.333274	0.342079
DFA	-0.446013	-0.343097	-0.050406	0.098572	0.175036	0.064083	0.196301	0.064026
spread1	-0.413738	-0.076658	-0.394857	0.693577	0.735779	0.648328	0.716489	0.648328
spread2	-0.249450	-0.002954	-0.243829	0.385123	0.388543	0.324407	0.407605	0.324377
D2	0.177980	0.176323	-0.100629	0.433434	0.310694	0.426605	0.412524	0.426556
PPE	-0.372356	-0.069543	-0.340071	0.721543	0.748162	0.670999	0.769647	0.671005

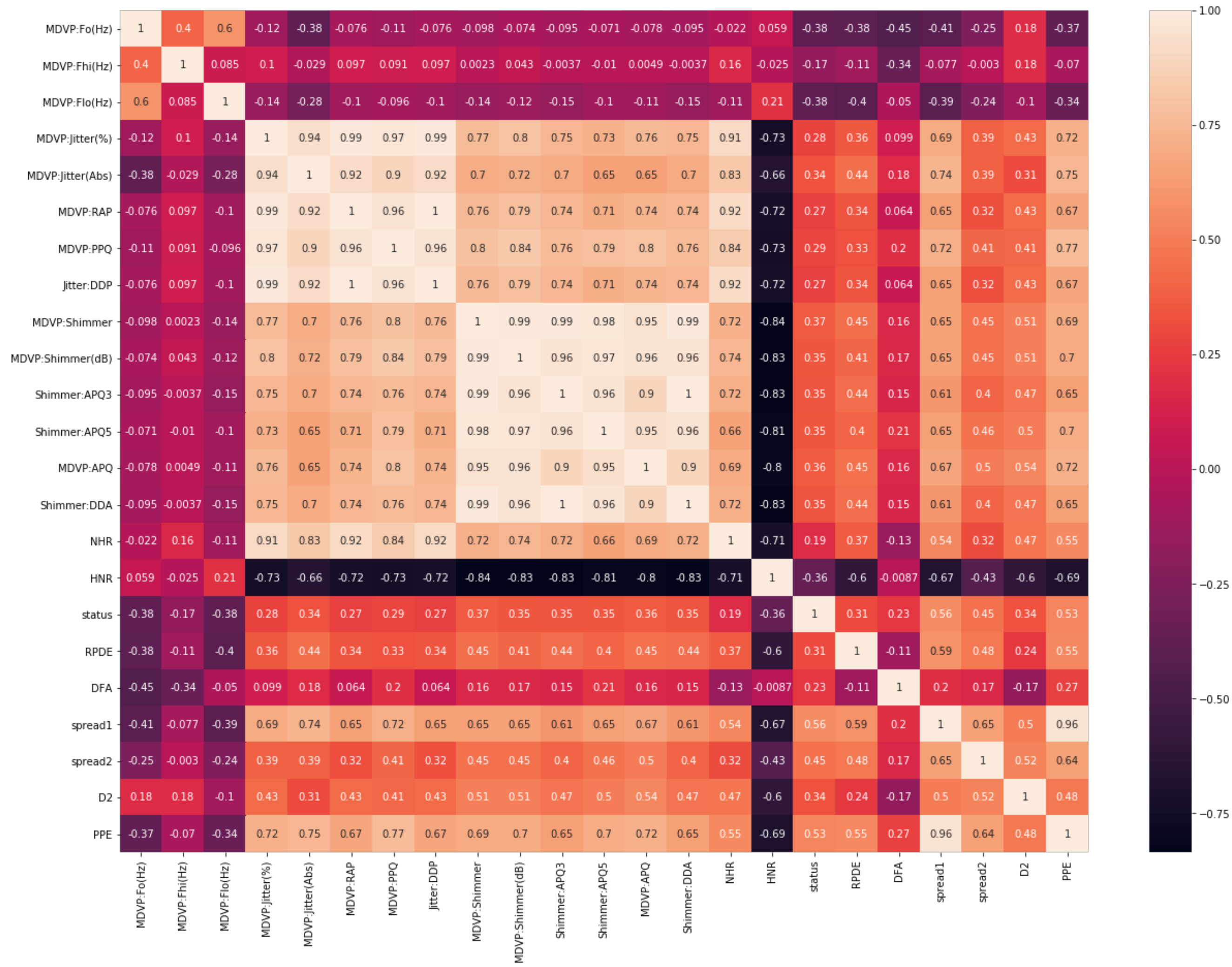
23 rows × 23 columns

In [1238]:

```
plt.figure(figsize = (21,15))
sns.heatmap(core,annot=True)
```

Out[1238]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x202eb0ed648>
```



> From the bivariate analysis, the following can be inferred
>
> - Around 10 variables have a strong correlation.
> - The pair plot of all the variables is plotted.
> - The columns Jitter: DDP, DFA, MDVP: Fhi, NHR are deleted due to least significant of the variables.

In [1239]:

```
park.drop("name",axis=1,inplace=True)
park.drop("Jitter:DDP",axis=1,inplace=True)
park.drop("DFA",axis=1,inplace=True)
park.drop("MDVP:Fhi(Hz)",axis=1,inplace=True)
park.drop("NHR",axis=1,inplace=True)
```

4. Split the dataset into training and test set in the ratio of 70:30

In [1240]:

```
X= park.drop("status",axis=1)
Y= park["status"]
x_train,x_test,y_train,y_test = train_test_split(X,Y,test_size=0.3,random_state=1)
```

```
x_train,x_test,y_train,y_test = train_test_split(X,Y,test_size=0.3,random_state=1)
x_train.head()
```

Out[1240]:

	MDVP:Fo(Hz)	MDVP:Flo(Hz)	MDVP:Jitter(%)	MDVP:Jitter(Abs)	MDVP:RAP	MDVP:PPQ	MDVP:Shimmer	MDVP:Shimmer(dB)	Shim
42	237.226	225.227	0.00298	0.00001	0.00169	0.00182	0.01752	0.164	
17	168.778	75.603	0.00718	0.00004	0.00284	0.00387	0.03327	0.348	
5	120.552	113.787	0.00968	0.00008	0.00463	0.00750	0.04701	0.456	
120	128.940	88.251	0.00581	0.00005	0.00241	0.00314	0.02008	0.221	
98	125.791	96.206	0.01378	0.00011	0.00826	0.00655	0.04689	0.422	

In [1241]:

```
rep_0 = SimpleImputer(missing_values=0, strategy="mean")
cols=x_train.columns
x_train = pd.DataFrame(rep_0.fit_transform(x_train))
x_test = pd.DataFrame(rep_0.fit_transform(x_test))

x_train.columns = cols
x_test.columns = cols

x_train.head()
```

Out[1241]:

	MDVP:Fo(Hz)	MDVP:Flo(Hz)	MDVP:Jitter(%)	MDVP:Jitter(Abs)	MDVP:RAP	MDVP:PPQ	MDVP:Shimmer	MDVP:Shimmer(dB)	Shimm
0	237.226	225.227	0.00298	0.00001	0.00169	0.00182	0.01752	0.164	
1	168.778	75.603	0.00718	0.00004	0.00284	0.00387	0.03327	0.348	
2	120.552	113.787	0.00968	0.00008	0.00463	0.00750	0.04701	0.456	
3	128.940	88.251	0.00581	0.00005	0.00241	0.00314	0.02008	0.221	
4	125.791	96.206	0.01378	0.00011	0.00826	0.00655	0.04689	0.422	

6. Train at least 3 standard classification algorithms

In [1242]:

```
model = LogisticRegression(solver="liblinear")
model.fit(x_train, y_train)
y_predict = model.predict(x_test)
coef_df = pd.DataFrame(model.coef_)
coef_df['intercept'] = model.intercept_
print(coef_df)
```

```
          0         1         2         3        4         5         6  \
0 -0.012963 -0.001277  0.007513  0.000066  0.00741  0.006545  0.110842

          7         8         9        10        11        12        13  \
0  1.049264  0.059919  0.067636  0.086584  0.179732  0.081816  0.53297

         14        15        16        17  intercept
0  0.952267  0.445513  2.576728  0.561887   0.754797
```

In [1243]:

```
model_score = model.score(x_test, y_test)
```

```
print(model_score)
```

```
0.7966101694915254
```

In [1244]:

```
confusion_matrix(y_test, y_predict)
```

Out[1244]:

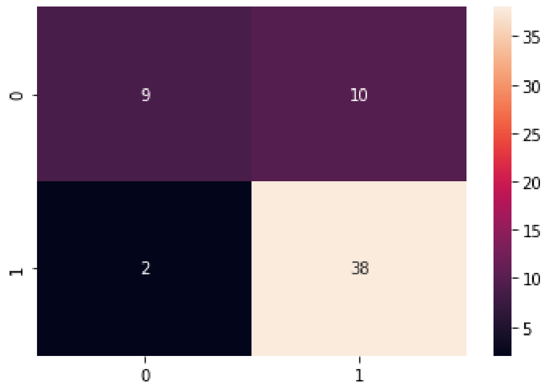
```
array([[ 9, 10],
       [ 2, 38]], dtype=int64)
```

In [1245]:

```
cm=confusion_matrix(y_test, y_predict)
sns.heatmap(cm, annot=True)
```

Out[1245]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x202d35d7388>
```



In [1246]:

```
print("Classification Report")
print(metrics.classification_report(y_test,y_predict, labels=[1, 0]))
```

```
Classification Report
              precision    recall  f1-score   support

           1       0.79      0.95      0.86        40
           0       0.82      0.47      0.60        19

    accuracy                           0.80        59
   macro avg       0.80      0.71      0.73        59
weighted avg       0.80      0.80      0.78        59
```

KNN Classifier

In [1247]:

```
park.groupby(["status"]).count()
```

Out[1247]:

	MDVP:Fo(Hz)	MDVP:Flo(Hz)	MDVP:Jitter(%)	MDVP:Jitter(Abs)	MDVP:RAP	MDVP:PPQ	MDVP:Shimmer	MDVP:Shimmer(dB)	Sl
status									
0	48	48	48	48	48	48	48	48	
1	147	147	147	147	147	147	147	147	

In [1248]:

```
XScaled  = X.apply(zscore)
XScaled.describe()
```

Out[1248]:

	MDVP:Fo(Hz)	MDVP:Flo(Hz)	MDVP:Jitter(%)	MDVP:Jitter(Abs)	MDVP:RAP	MDVP:PPQ	MDVP:Shimmer	MDVP:Shimmer(dB)
count	1.950000e+02	1.950000e+02	1.950000e+02	1.950000e+02	1.950000e+02	1.950000e+02	1.950000e+02	1.950000e+02
mean	-2.277381e-18	6.148928e-17	-2.127927e-17	2.562053e-18	-1.380662e-16	9.351494e-17	2.829645e-16	-1.369275e-16
std	1.002574e+00	1.002574e+00	1.002574e+00	1.002574e+00	1.002574e+00	1.002574e+00	1.002574e+00	1.002574e+00
min	-1.596162e+00	-1.171366e+00	-9.389487e-01	-1.064103e+00	-8.872543e-01	-9.180440e-01	-1.072340e+00	-1.014787e+00
25%	-8.879183e-01	-7.379376e-01	-5.708520e-01	-6.898141e-01	-5.561906e-01	-5.764609e-01	-7.020291e-01	-6.881025e-01
50%	-1.317379e-01	-2.766579e-01	-2.647942e-01	-4.018994e-01	-2.724216e-01	-2.748504e-01	-3.583019e-01	-3.151160e-01
75%	6.913210e-01	5.458200e-01	2.366858e-01	4.618447e-01	1.785683e-01	1.848331e-01	4.346898e-01	3.485429e-01
max	2.564598e+00	2.829908e+00	5.570985e+00	6.220139e+00	6.125892e+00	5.862742e+00	4.751617e+00	5.246243e+00

In [1249]:

```
X_train, X_test, Y_train, Y_test = train_test_split(XScaled, Y, test_size=0.30, random_state=42)
```

In [1250]:

```
NNH = KNeighborsClassifier(n_neighbors= 5 , weights = 'distance' )
```

In [1251]:

```
NNH.fit(X_train, Y_train)
```

Out[1251]:

```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                     metric_params=None, n_jobs=None, n_neighbors=5, p=2,
                     weights='distance')
```

In [1252]:

```
predicted_labels = NNH.predict(X_test)
NNH.score(X_test, Y_test)
```

Out[1252]:

```
0.9152542372881356
```

In [1253]:

```
a=confusion_matrix(Y_test, predicted_labels)
print("confusion matirx of KNN classifier = \n",a)
```

```
confusion matirx of KNN classifier =
 [[10  5]
 [ 0 44]]
```

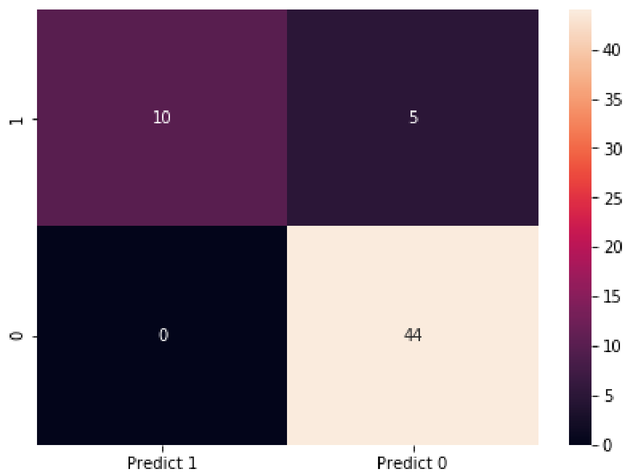
In [1254]:

```
knnm=metrics.confusion_matrix(Y_test, predicted_labels)
knn_m = pd.DataFrame(knnm, index = [i for i in ["1","0"]],columns = [i for i in ["Predict
1","Predict 0"]])
plt.figure(figsize = (7,5))
```

```
sns.heatmap(knn_m, annot=True)
```

Out[1254]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x202f1c61fc8>
```



In [1255]:

```
print("Classification Report")
print(metrics.classification_report(Y_test, predicted_labels, labels=[1, 0]))
```

```
Classification Report
              precision    recall  f1-score   support

           1       0.90      1.00      0.95        44
           0       1.00      0.67      0.80        15

    accuracy                           0.92        59
   macro avg       0.95      0.83      0.87        59
weighted avg       0.92      0.92      0.91        59
```

SVM classifier

In [1256]:

```
x_train, x_test, y_train, y_test = train_test_split(X, Y, test_size=0.3, random_state=42)
```

In [1257]:

```
svc_model = SVC(C= .1, kernel='linear', gamma= 1)
svc_model.fit(x_train, y_train)

prediction = svc_model .predict(x_test)
```

In [1258]:

```
print(svc_model.score(x_train, y_train))
print(svc_model.score(x_test, y_test))
```

```
0.8455882352941176
0.864406779661017
```

In [1259]:

```
print("Confusion Matrix:\n",confusion_matrix(y_test,prediction))
```

```
Confusion Matrix:
 [[ 8  7]
```

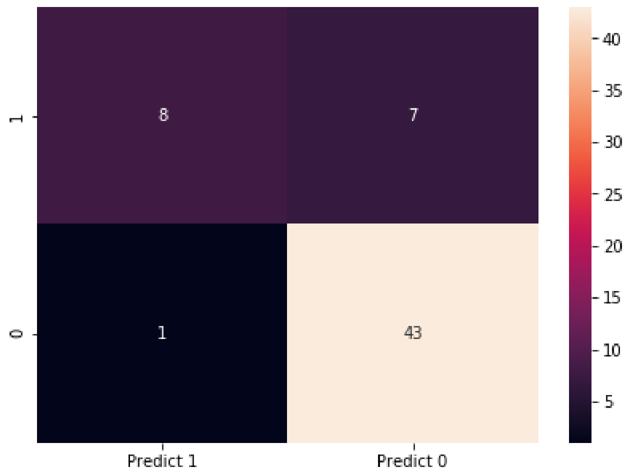
```
 [ 1 43]]
```

In [1260]:

```
knnm=metrics.confusion_matrix(y_test,prediction)
knn_m = pd.DataFrame(knnm, index = [i for i in ["1","0"]],columns = [i for i in ["Predict
1","Predict 0"]])
plt.figure(figsize = (7,5))
sns.heatmap(knn_m, annot=True)
```

Out[1260]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x202f141e188>
```



In [1261]:

```
print("Classification Report")
print(metrics.classification_report(y_test,prediction, labels=[1, 0]))
```

```
Classification Report
              precision    recall  f1-score   support

           1       0.86      0.98      0.91        44
           0       0.89      0.53      0.67        15

    accuracy                           0.86        59
   macro avg       0.87      0.76      0.79        59
weighted avg       0.87      0.86      0.85        59
```

In [1262]:

```
svc_model = SVC(kernel='rbf')
svc_model.fit(x_train, y_train)
```

Out[1262]:

```
SVC(C=1.0, break_ties=False, cache_size=200, class_weight=None, coef0=0.0,
    decision_function_shape='ovr', degree=3, gamma='scale', kernel='rbf',
    max_iter=-1, probability=False, random_state=None, shrinking=True,
    tol=0.001, verbose=False)
```

In [1263]:

```
svc_model  = SVC(kernel='poly')
svc_model.fit(x_train, y_train)

prediction = svc_model.predict(x_test)

print(svc_model.score(x_train, y_train))
print(svc_model.score(x_test, y_test))
```

```
0.8529411764705882
0.8305084745762712
```

In [1264]:

```
svc_model = SVC(kernel='sigmoid')
svc_model.fit(x_train, y_train)

prediction = svc_model.predict(x_test)

print(svc_model.score(x_train, y_train))
print(svc_model.score(x_test, y_test))
```

```
0.7573529411764706
0.7457627118644068
```

8.Ensemble model

Decision Tree

In [1265]:

```
feature_cols = ['MDVP:Fo(Hz)',' MDVP:Flo(Hz)','MDVP:Jitter(%)','MDVP:Jitter(Abs)','MDVP:RAP','MDVP:
PPQ','MDVP:Shimmer',
                'MDVP:Shimmer(dB)','Shimmer:APQ3','Shimmer:APQ5','MDVP:APQ','Shimmer:DDA','HNR','RP
DE','spread1','spread2','D2','PPE']
clf = DecisionTreeClassifier()

clf=clf.fit(x_train,y_train)

y_pred = clf.predict(x_test)
```

In [1266]:

```
print("Accuracy:",metrics.accuracy_score(y_test, y_pred))
```

```
Accuracy: 0.864406779661017
```

In [1267]:

```
print("Confusion Matrix:\n",confusion_matrix(y_test,y_pred))
```

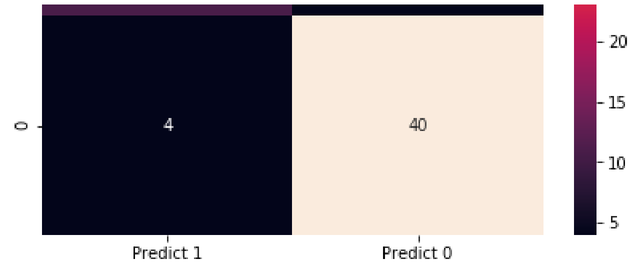
```
Confusion Matrix:
 [[11  4]
 [ 4 40]]
```

In [1268]:

```
tree=metrics.confusion_matrix(y_test,y_pred)
tree_m = pd.DataFrame(tree, index = [i for i in ["1","0"]],columns = [i for i in ["Predict
1","Predict 0"]])
plt.figure(figsize = (7,5))
sns.heatmap(tree_m, annot=True)
```

Out[1268]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x202f13fbcc8>
```



In [1269]:

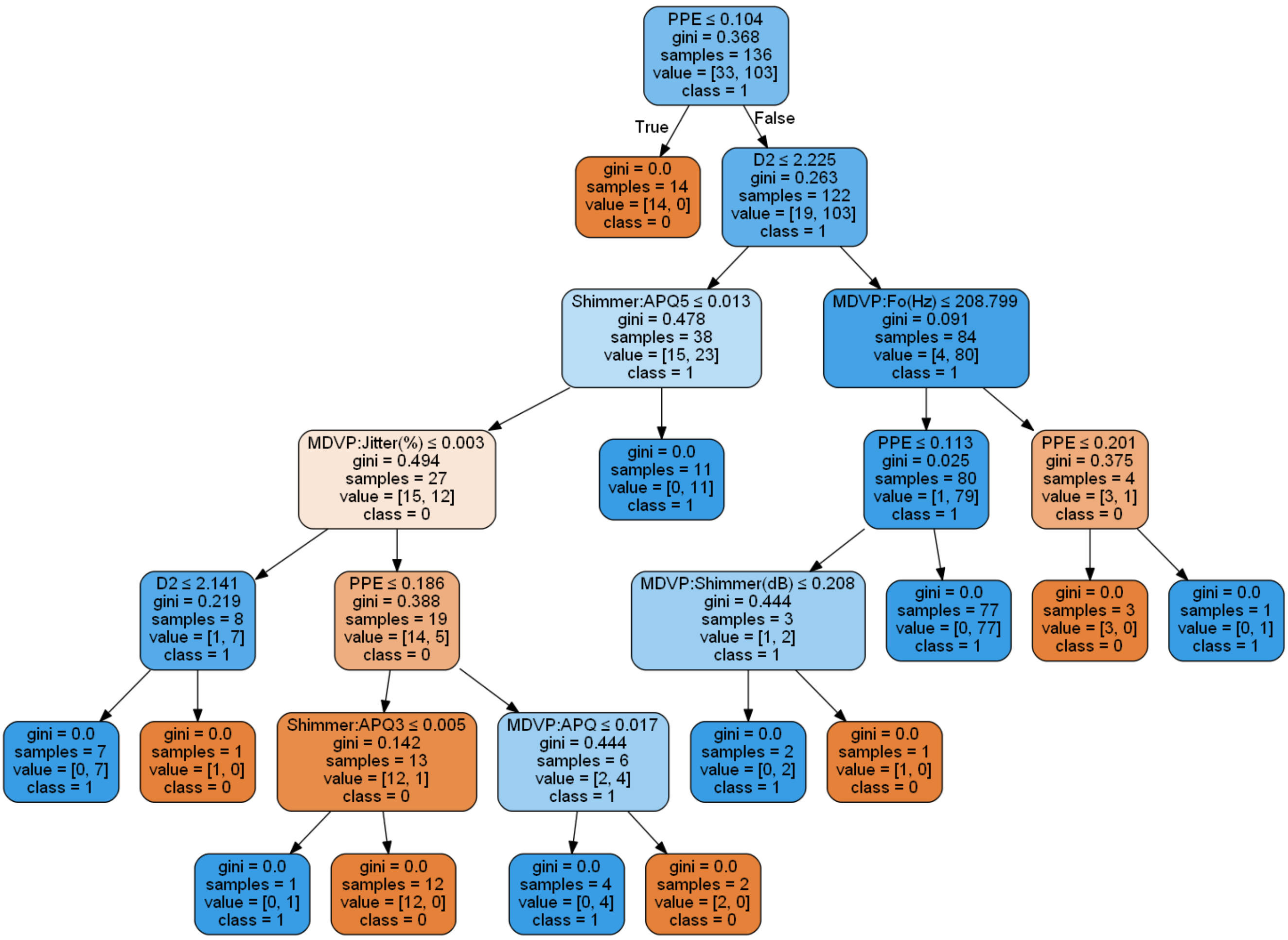
```
print("Classification Report")
print(metrics.classification_report(y_test,y_pred, labels=[1, 0]))
```

```
Classification Report
              precision    recall  f1-score   support

           1       0.91      0.91      0.91        44
           0       0.73      0.73      0.73        15

    accuracy                           0.86        59
   macro avg       0.82      0.82      0.82        59
weighted avg       0.86      0.86      0.86        59
```

In [1270]:

```
dot_data = StringIO()
export_graphviz(clf, out_file=dot_data,
                filled=True, rounded=True,
                special_characters=True,feature_names = feature_cols,class_names=['0','1'])
graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
graph.write_png('park.png')
Image(graph.create_png())
```

Out[1270]:



Pruned decision Tree

In [1271]:

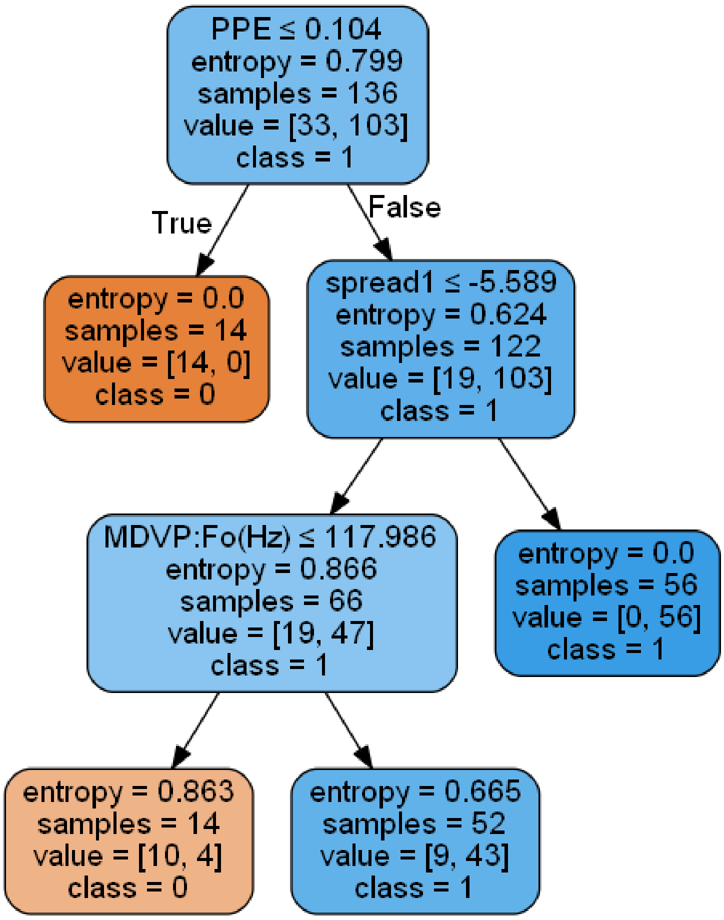
```
clf = DecisionTreeClassifier(criterion="entropy", max_depth=3)
clf = clf.fit(x_train,y_train)
y_pred = clf.predict(x_test)
print("Accuracy:",metrics.accuracy_score(y_test, y_pred))
```

```
Accuracy: 0.847457627118644
```

In [1272]:

```
dot_data = StringIO()
export_graphviz(clf, out_file=dot_data,
                filled=True, rounded=True,
                special_characters=True, feature_names = feature_cols,class_names=['0','1'])
graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
graph.write_png('park1.png')
Image(graph.create_png())
```

Out[1272]:



Random Forest

In [1273]:

```
rf = RandomForestClassifier(n_estimators = 70,criterion="entropy")
rf = rf.fit(x_train, y_train)
```

In [1274]:

```
predrf= rf.predict(x_test)
```

```
accrf = accuracy_score(y_test, predrf)
print(accrf)
```

```
0.8983050847457628
```

In [1275]:

```
print("Confusion Matrix:\n",confusion_matrix(y_test,predrf))
```

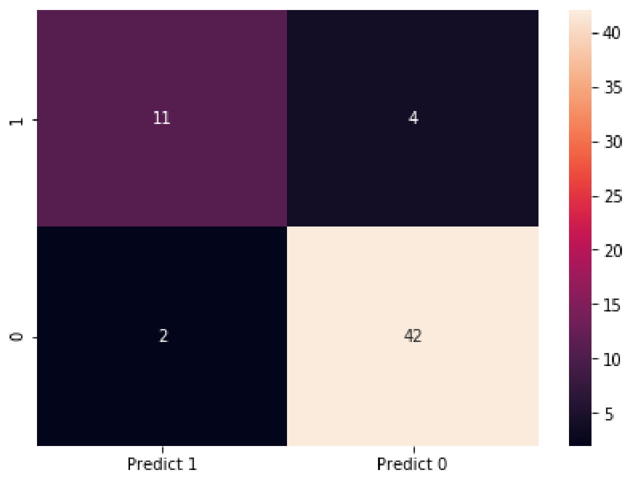
```
Confusion Matrix:
 [[11  4]
 [ 2 42]]
```

In [1276]:

```
rf1=metrics.confusion_matrix(y_test,predrf)
rf1_m = pd.DataFrame(rf1, index = [i for i in ["1","0"]],columns = [i for i in ["Predict
1","Predict 0"]])
plt.figure(figsize = (7,5))
sns.heatmap(rf1_m, annot=True)
```

Out[1276]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x202f155dc08>
```



In [1277]:

```
print("Classification Report")
print(metrics.classification_report(y_test,predrf, labels=[1, 0]))
```

```
Classification Report
              precision    recall  f1-score   support

           1       0.91      0.95      0.93        44
           0       0.85      0.73      0.79        15

    accuracy                           0.90        59
   macro avg       0.88      0.84      0.86        59
weighted avg       0.90      0.90      0.90        59
```

AdaBoost

In [1278]:

```
abc = AdaBoostClassifier(n_estimators=100,learning_rate=1)
model = abc.fit(x_train, y_train)
y_pred = model.predict(x_test)
print("Accuracy:",metrics.accuracy_score(y_test, y_pred))
```

```
Accuracy: 0.864406779661017
```

In [1279]:

```
print("Confusion Matrix:\n",confusion_matrix(y_test,y_pred))
```

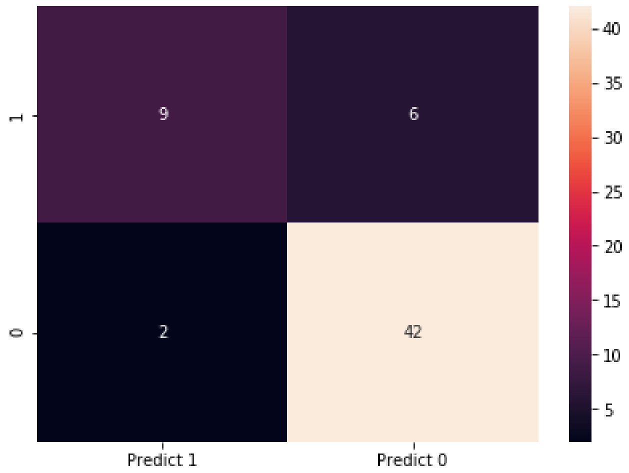
```
Confusion Matrix:
 [[ 9  6]
 [ 2 42]]
```

In [1280]:

```
ab=metrics.confusion_matrix(y_test,y_pred)
ab_m = pd.DataFrame(ab, index = [i for i in ["1","0"]],columns = [i for i in ["Predict 1","Predict 0"]])
plt.figure(figsize = (7,5))
sns.heatmap(ab_m, annot=True)
```

Out[1280]:

```
&lt;matplotlib.axes._subplots.AxesSubplot at 0x202f19d5408&gt;
```



In [1281]:

```
print("Classification Report")
print(metrics.classification_report(y_test,y_pred, labels=[1, 0]))
```

```
Classification Report
              precision    recall  f1-score   support

           1       0.88      0.95      0.91        44
           0       0.82      0.60      0.69        15

    accuracy                           0.86        59
   macro avg       0.85      0.78      0.80        59
weighted avg       0.86      0.86      0.86        59
```

Bagging Classifier

In [1282]:

```
bag = BaggingClassifier(n_estimators=100, max_samples= .7, bootstrap=True, oob_score=True, random_state=22)
bag= bag.fit(x_train, y_train)
```

In [1283]:

```
predBAG =bag.predict(x_test)
```

```
accBAG = accuracy_score(y_test, predBAG)
print(accBAG)
```

```
0.8813559322033898
```

In [1284]:

```
print("Confusion Matrix:\n",confusion_matrix(y_test,predBAG))
```

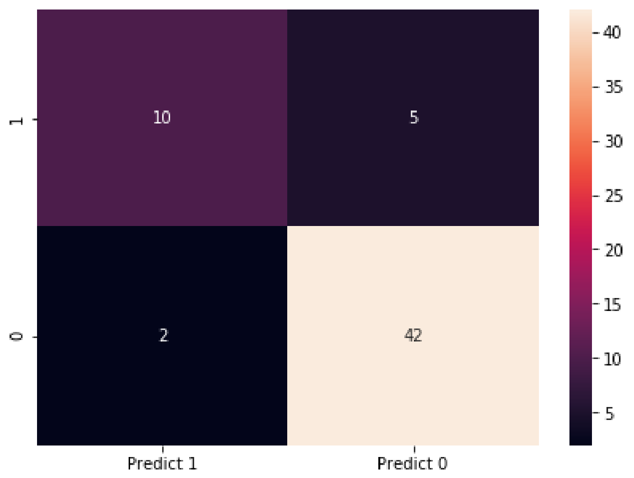
```
Confusion Matrix:
 [[10  5]
 [ 2 42]]
```

In [1285]:

```
bag=metrics.confusion_matrix(y_test,predBAG)
bag_m = pd.DataFrame(bag, index = [i for i in ["1","0"]],columns = [i for i in ["Predict
1","Predict 0"]])
plt.figure(figsize = (7,5))
sns.heatmap(bag_m, annot=True)
```

Out[1285]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x202f1834c48>
```



In [1286]:

```
print("Classification Report")
print(metrics.classification_report(y_test,predBAG, labels=[1, 0]))
```

```
Classification Report
              precision    recall  f1-score   support

           1       0.89      0.95      0.92        44
           0       0.83      0.67      0.74        15

    accuracy                           0.88        59
   macro avg       0.86      0.81      0.83        59
weighted avg       0.88      0.88      0.88        59
```

GradientBoost Classifier

In [1287]:

```
grad = GradientBoostingClassifier(n_estimators = 100, learning_rate = 0.1, random_state=42)
grad = grad.fit(x_train, y_train)
```

In [1288]:

```
predgrad =grad.predict(x_test)
accgrad = accuracy_score(y_test, predgrad)
print(accgrad)
```

```
0.8983050847457628
```

In [1289]:

```
print("Confusion Matrix:\n",confusion_matrix(y_test,predgrad))
```

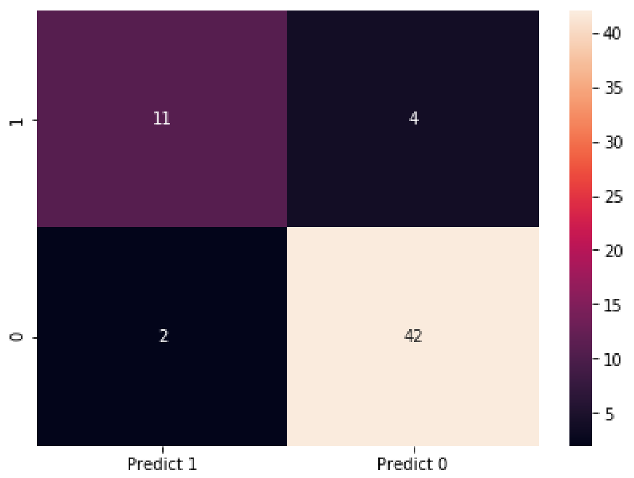
```
Confusion Matrix:
 [[11  4]
 [ 2 42]]
```

In [1290]:

```
grad=metrics.confusion_matrix(y_test,predgrad)
grad_m = pd.DataFrame(grad, index = [i for i in ["1","0"]],columns = [i for i in ["Predict
1","Predict 0"]])
plt.figure(figsize = (7,5))
sns.heatmap(grad_m, annot=True)
```

Out[1290]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x202f223b508>
```



In [1291]:

```
print("Classification Report")
print(metrics.classification_report(y_test,predgrad, labels=[1, 0]))
```

```
Classification Report
              precision    recall  f1-score   support

           1       0.91      0.95      0.93        44
           0       0.85      0.73      0.79        15

    accuracy                           0.90        59
   macro avg       0.88      0.84      0.86        59
weighted avg       0.90      0.90      0.90        59
```

7.meta-classifier

Stacking classifier

In [1292]:

```python
clf1 = KNeighborsClassifier(n_neighbors=1)
clf2 = RandomForestClassifier(random_state=1)
clf3 =SVC(C= .1, kernel='linear', gamma= 1)
lr = LogisticRegression()
sclf = StackingClassifier(classifiers=[clf1, clf2, clf3], meta_classifier=lr)
print('3-fold cross validation:\n')
for clf, label in zip([clf1, clf2, clf3, sclf],
                      ['KNN',
                       'Random Forest',
                       'Naive Bayes',
                       'StackingClassifier']):

    scores = model_selection.cross_val_score(clf, X, Y,
                                              cv=3, scoring='accuracy')
    print("Accuracy: %0.2f (+/- %0.2f) [%s]"
          % (scores.mean(), scores.std(), label))
```

```
3-fold cross validation:

Accuracy: 0.80 (+/- 0.03) [KNN]
Accuracy: 0.80 (+/- 0.03) [Random Forest]
Accuracy: 0.84 (+/- 0.06) [Naive Bayes]
Accuracy: 0.83 (+/- 0.04) [StackingClassifier]
```

9. Picking the best model

> From the above models following are the accuracy
>
> - Logistic Regression 78%
> - KNN classifier 91%
> - Support vector classifier 88%
> - Decision Tree 86%
> - Random Forest 90%
> - Ada boosting classifier 86%
> - Bagging Classifier 88%
> - Gradient boosting Classifier 90%
> - Meta-classifier(Stacking classifier) 87%. The meta classifier used was logistic regression.

> From the above models, we get that
>
> - The best model is the KNN classifier. It has an accuracy of 92%.\ The recall also is 92 which is good.\ Thus for the above reason, we select the KNN classifier is selected.

In [ ]:

```python

```