

# dementia-svm-project

October 15, 2023

```
[1]: import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

```
[2]: df=pd.read_excel(r"C:\Users\prera\OneDrive\Desktop\Imarticus\ML\datasets\dementia_dataset.xlsx")
```

```
[3]: df
```

```
[3]:
```

	Subject ID	MRI ID	Group	Visit	MR Delay	M/F	Hand	Age	\
0	OAS2_0001	OAS2_0001_MR1	Nondemented	1.0	0.0	M	R	87.0	
1	OAS2_0001	OAS2_0001_MR2	Nondemented	2.0	457.0	M	R	88.0	
2	OAS2_0002	OAS2_0002_MR1	Demented	1.0	0.0	M	R	75.0	
3	OAS2_0002	OAS2_0002_MR2	Demented	2.0	560.0	M	R	76.0	
4	OAS2_0002	OAS2_0002_MR3	Demented	3.0	1895.0	M	R	80.0	
..	...	...	...	...	...	...	...	...	
368	OAS2_0185	OAS2_0185_MR2	Demented	2.0	842.0	M	R	82.0	
369	OAS2_0185	OAS2_0185_MR3	Demented	3.0	2297.0	NaN	R	86.0	
370	OAS2_0186	OAS2_0186_MR1	Nondemented	1.0	0.0	F	R	61.0	
371	OAS2_0186	OAS2_0186_MR2	Nondemented	NaN	763.0	F	R	63.0	
372	OAS2_0186	OAS2_0186_MR3	Nondemented	3.0	1608.0	F	R	NaN	

	EDUC	SES	MMSE	CDR	eTIV	nWBV	ASF
0	14.0	2.0	27.0	0.0	1987.0	0.696	0.883
1	14.0	2.0	30.0	0.0	2004.0	0.681	0.876
2	12.0	NaN	23.0	0.5	1678.0	0.736	1.046
3	12.0	NaN	28.0	0.5	1738.0	0.713	1.010
4	12.0	NaN	22.0	0.5	1698.0	0.701	1.034
..	...	...	...	...	...	...	...
368	16.0	1.0	NaN	0.5	1693.0	0.694	1.037
369	NaN	1.0	26.0	0.5	1688.0	0.675	NaN
370	13.0	2.0	30.0	0.0	1319.0	0.801	1.331
371	13.0	2.0	NaN	0.0	NaN	0.796	1.323
372	13.0	2.0	30.0	0.0	1333.0	0.801	1.317

[373 rows x 15 columns]

```
[4]: df1=df.copy(deep=True)
      df2=df.copy(deep=True)
      df3=df.copy(deep=True)
```

```
[5]: df.shape
```

```
[5]: (373, 15)
```

```
[6]: df.head(10)
```

```
[6]:   Subject ID      MRI ID      Group  Visit  MR Delay  M/F Hand  Age  \
0  OAS2_0001  OAS2_0001_MR1  Nondemented    1.0      0.0    M    R  87.0
1  OAS2_0001  OAS2_0001_MR2  Nondemented    2.0    457.0    M    R  88.0
2  OAS2_0002  OAS2_0002_MR1    Demented    1.0      0.0    M    R  75.0
3  OAS2_0002  OAS2_0002_MR2    Demented    2.0    560.0    M    R  76.0
4  OAS2_0002  OAS2_0002_MR3    Demented    3.0   1895.0    M    R  80.0
5  OAS2_0004  OAS2_0004_MR1  Nondemented    1.0      0.0   NaN    R  88.0
6  OAS2_0004  OAS2_0004_MR2  Nondemented    2.0    538.0    F   NaN  90.0
7  OAS2_0005  OAS2_0005_MR1  Nondemented    1.0      0.0    M    R  80.0
8  OAS2_0005  OAS2_0005_MR2  Nondemented    2.0   1010.0    M    R  83.0
9  OAS2_0005  OAS2_0005_MR3  Nondemented    3.0   1603.0   NaN    R  85.0
```

	EDUC	SES	MMSE	CDR	eTIV	nWBV	ASF
0	14.0	2.0	27.0	0.0	1987.0	0.696	0.883
1	14.0	2.0	30.0	0.0	2004.0	0.681	0.876
2	12.0	NaN	23.0	0.5	1678.0	0.736	1.046
3	12.0	NaN	28.0	0.5	1738.0	0.713	1.010
4	12.0	NaN	22.0	0.5	1698.0	0.701	1.034
5	18.0	3.0	28.0	0.0	1215.0	0.710	1.444
6	18.0	3.0	27.0	0.0	1200.0	0.718	1.462
7	12.0	4.0	28.0	0.0	1689.0	0.712	1.039
8	12.0	4.0	29.0	0.5	1701.0	0.711	1.032
9	12.0	4.0	30.0	0.0	1699.0	0.705	1.033

```
[7]: df.tail(10)
```

```
[7]:   Subject ID      MRI ID      Group  Visit  MR Delay  M/F Hand  Age  \
363  OAS2_0183  OAS2_0183_MR3  Nondemented    3.0    732.0    F    R  68.0
364  OAS2_0183  OAS2_0183_MR4  Nondemented    4.0   2107.0    F    R  72.0
365  OAS2_0184  OAS2_0184_MR1    Demented    1.0      0.0    F    R  72.0
366  OAS2_0184  OAS2_0184_MR2    Demented    2.0    553.0    F   NaN  73.0
367  OAS2_0185  OAS2_0185_MR1    Demented    1.0      0.0    M    R  80.0
368  OAS2_0185  OAS2_0185_MR2    Demented    2.0    842.0    M    R  82.0
369  OAS2_0185  OAS2_0185_MR3    Demented    3.0   2297.0   NaN    R  86.0
370  OAS2_0186  OAS2_0186_MR1  Nondemented    1.0      0.0    F    R  61.0
```

371	OAS2_0186	OAS2_0186_MR2	Nondemented	NaN	763.0	F	R	63.0
372	OAS2_0186	OAS2_0186_MR3	Nondemented	3.0	1608.0	F	R	NaN

	EDUC	SES	MMSE	CDR	eTIV	nWBV	ASF
363	13.0	2.0	30.0	0.0	1506.0	0.740	NaN
364	13.0	2.0	30.0	0.0	1510.0	0.723	1.162
365	16.0	3.0	24.0	0.5	1354.0	0.733	1.296
366	16.0	3.0	21.0	1.0	NaN	0.708	1.299
367	16.0	1.0	28.0	NaN	1704.0	0.711	1.030
368	16.0	1.0	NaN	0.5	1693.0	0.694	1.037
369	NaN	1.0	26.0	0.5	1688.0	0.675	NaN
370	13.0	2.0	30.0	0.0	1319.0	0.801	1.331
371	13.0	2.0	NaN	0.0	NaN	0.796	1.323
372	13.0	2.0	30.0	0.0	1333.0	0.801	1.317

```
[8]: df.duplicated()
```

```
[8]: 0      False
      1      False
      2      False
      3      False
      4      False
      ...
      368    False
      369    False
      370    False
      371    False
      372    False
      Length: 373, dtype: bool
```

```
[9]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 373 entries, 0 to 372
Data columns (total 15 columns):
#   Column          Non-Null Count  Dtype
---  -
0   Subject ID      373 non-null    object
1   MRI ID          373 non-null    object
2   Group           373 non-null    object
3   Visit           344 non-null    float64
4   MR Delay        366 non-null    float64
5   M/F             345 non-null    object
6   Hand            343 non-null    object
7   Age             355 non-null    float64
8   EDUC            349 non-null    float64
9   SES             337 non-null    float64
```

```

10  MMSE      352 non-null    float64
11  CDR       359 non-null    float64
12  eTIV      340 non-null    float64
13  nWBV      342 non-null    float64
14  ASF       338 non-null    float64
dtypes: float64(10), object(5)
memory usage: 43.8+ KB

```

```
[10]: df.describe(include='all')
```

```
[10]:
```

	Subject ID	MRI ID	Group	Visit	MR Delay	M/F \
count	373	373	373	344.000000	366.000000	345
unique	150	373	3	NaN	NaN	2
top	OAS2_0070	OAS2_0001_MR1	Nondemented	NaN	NaN	F
freq	5	1	190	NaN	NaN	198
mean	NaN	NaN	NaN	1.877907	591.237705	NaN
std	NaN	NaN	NaN	0.933460	634.431780	NaN
min	NaN	NaN	NaN	1.000000	0.000000	NaN
25%	NaN	NaN	NaN	1.000000	0.000000	NaN
50%	NaN	NaN	NaN	2.000000	539.000000	NaN
75%	NaN	NaN	NaN	2.000000	871.250000	NaN
max	NaN	NaN	NaN	5.000000	2639.000000	NaN

	Hand	Age	EDUC	SES	MMSE	CDR \
count	343	355.000000	349.000000	337.000000	352.000000	359.000000
unique	1	NaN	NaN	NaN	NaN	NaN
top	R	NaN	NaN	NaN	NaN	NaN
freq	343	NaN	NaN	NaN	NaN	NaN
mean	NaN	77.011268	14.521490	2.468843	27.369318	0.289694
std	NaN	7.692163	2.897229	1.136414	3.689513	0.376962
min	NaN	60.000000	6.000000	1.000000	4.000000	0.000000
25%	NaN	71.000000	12.000000	2.000000	27.000000	0.000000
50%	NaN	77.000000	14.000000	2.000000	29.000000	0.000000
75%	NaN	82.000000	16.000000	3.000000	30.000000	0.500000
max	NaN	98.000000	23.000000	5.000000	30.000000	2.000000

	eTIV	nWBV	ASF
count	340.000000	342.000000	338.000000
unique	NaN	NaN	NaN
top	NaN	NaN	NaN
freq	NaN	NaN	NaN
mean	1489.447059	0.729456	1.194393
std	174.925303	0.037290	0.134498
min	1123.000000	0.644000	0.876000
25%	1359.750000	0.700000	1.104000
50%	1475.000000	0.729000	1.195500
75%	1597.500000	0.756000	1.291000

```
max      2004.000000    0.837000    1.587000
```

```
[11]: df.nunique()
```

```
[11]: Subject ID      150
MRI ID           373
Group             3
Visit             5
MR Delay         197
M/F               2
Hand              1
Age              39
EDUC             12
SES              5
MMSE             18
CDR               4
eTIV             269
nWBV             132
ASF              246
dtype: int64
```

```
[12]: df.isnull().sum()
```

```
[12]: Subject ID      0
MRI ID             0
Group              0
Visit             29
MR Delay           7
M/F               28
Hand              30
Age              18
EDUC             24
SES              36
MMSE             21
CDR              14
eTIV             33
nWBV             31
ASF              35
dtype: int64
```

```
[13]: (df.isnull().sum()/len(df))*100
```

```
[13]: Subject ID      0.000000
MRI ID           0.000000
Group            0.000000
Visit           7.774799
MR Delay        1.876676
```

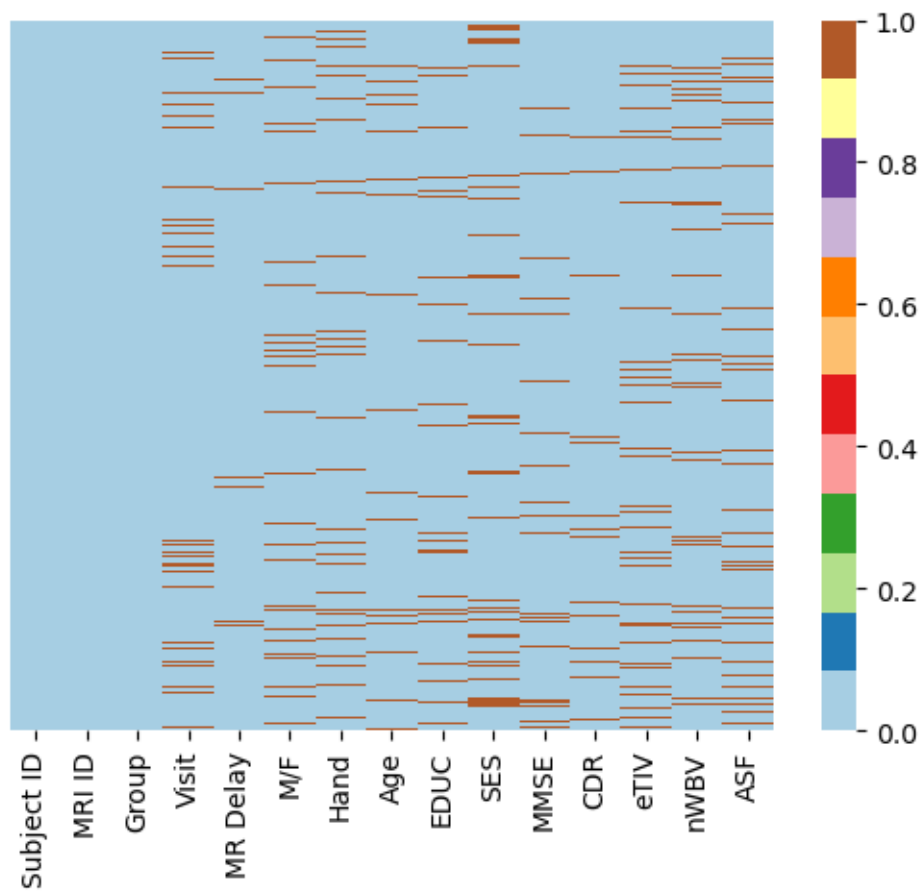
```

M/F          7.506702
Hand         8.042895
Age          4.825737
EDUC         6.434316
SES          9.651475
MMSE         5.630027
CDR          3.753351
eTIV         8.847185
nWBV         8.310992
ASF          9.383378
dtype: float64

```

```
[14]: sns.heatmap(df.isnull(),yticklabels=False,cmap='Paired')
```

```
[14]: <Axes: >
```



```
[15]: df.drop(['Subject ID','MRI ID'],axis=1,inplace=True)
```

```
[16]: df.columns
```

```
[16]: Index(['Group', 'Visit', 'MR Delay', 'M/F', 'Hand', 'Age', 'EDUC', 'SES',  
         'MMSE', 'CDR', 'eTIV', 'nWBV', 'ASF'],  
        dtype='object')
```

```
[17]: df['Visit'].bfill(axis=0,inplace=True)  
df['MR Delay'].fillna(df['MR Delay'].median(),inplace=True)  
df['M/F'].ffill(axis=0,inplace=True)  
df['Hand'].bfill(axis=0,inplace=True)  
df['Age'].fillna(df['Age'].median(),inplace=True)  
df['EDUC'].ffill(axis=0,inplace=True)  
df['SES'].ffill(axis=0,inplace=True)  
df['MMSE'].fillna(df['MMSE'].median(),inplace=True)  
df['CDR'].ffill(axis=0,inplace=True)  
df['eTIV'].fillna(df['eTIV'].median(),inplace=True)  
df['nWBV'].fillna(df['nWBV'].median(),inplace=True)  
df['ASF'].fillna(df['ASF'].median(),inplace=True)
```

```
[18]: df.isnull().sum()
```

```
[18]: Group      0  
Visit      0  
MR Delay    0  
M/F        0  
Hand       0  
Age        0  
EDUC       0  
SES        0  
MMSE       0  
CDR        0  
eTIV       0  
nWBV       0  
ASF        0  
dtype: int64
```

```
[19]: df['M/F'].value_counts()
```

```
[19]: F      214  
M      159  
Name: M/F, dtype: int64
```

```
[20]: df['Hand'].value_counts()
```

```
[20]: R      373  
Name: Hand, dtype: int64
```

```
[21]: df['SES'].value_counts()
```

```
[21]: 2.0    108
      1.0    94
      3.0    83
      4.0    81
      5.0     7
      Name: SES, dtype: int64
```

```
[22]: df['EDUC'].value_counts()
```

```
[22]: 12.0    104
      16.0    80
      18.0    64
      14.0    32
      13.0    26
      15.0    18
      20.0    13
      11.0    12
      8.0     10
      17.0     8
      6.0     3
      23.0     3
      Name: EDUC, dtype: int64
```

```
[23]: cat_data=df.select_dtypes(include=object)
      num_data=df.select_dtypes(exclude=object)
```

```
[24]: cat_data
```

```
[24]:      Group M/F Hand
0    Nondemented  M    R
1    Nondemented  M    R
2      Demented  M    R
3      Demented  M    R
4      Demented  M    R
..          ...  ..  ...
368    Demented  M    R
369    Demented  M    R
370  Nondemented  F    R
371  Nondemented  F    R
372  Nondemented  F    R
```

[373 rows x 3 columns]

```
[25]: num_data
```

```
[25]:      Visit  MR Delay  Age  EDUC  SES  MMSE  CDR  eTIV  nWBV  ASF
0      1.0        0.0  87.0  14.0  2.0  27.0  0.0  1987.0  0.696  0.8830
```



```

1      2.0      457.0  88.0  14.0  2.0  30.0  0.0  2004.0  0.681  0.8760
2      1.0        0.0  75.0  12.0  2.0  23.0  0.5  1678.0  0.736  1.0460
3      2.0      560.0  76.0  12.0  2.0  28.0  0.5  1738.0  0.713  1.0100
4      3.0     1895.0  80.0  12.0  2.0  22.0  0.5  1698.0  0.701  1.0340
..      ...      ...  ...  ...  ...  ...  ...  ...  ...  ...
368    2.0      842.0  82.0  16.0  1.0  29.0  0.5  1693.0  0.694  1.0370
369    3.0     2297.0  86.0  16.0  1.0  26.0  0.5  1688.0  0.675  1.1955
370    1.0        0.0  61.0  13.0  2.0  30.0  0.0  1319.0  0.801  1.3310
371    3.0      763.0  63.0  13.0  2.0  29.0  0.0  1475.0  0.796  1.3230
372    3.0     1608.0  77.0  13.0  2.0  30.0  0.0  1333.0  0.801  1.3170

```

[373 rows x 10 columns]

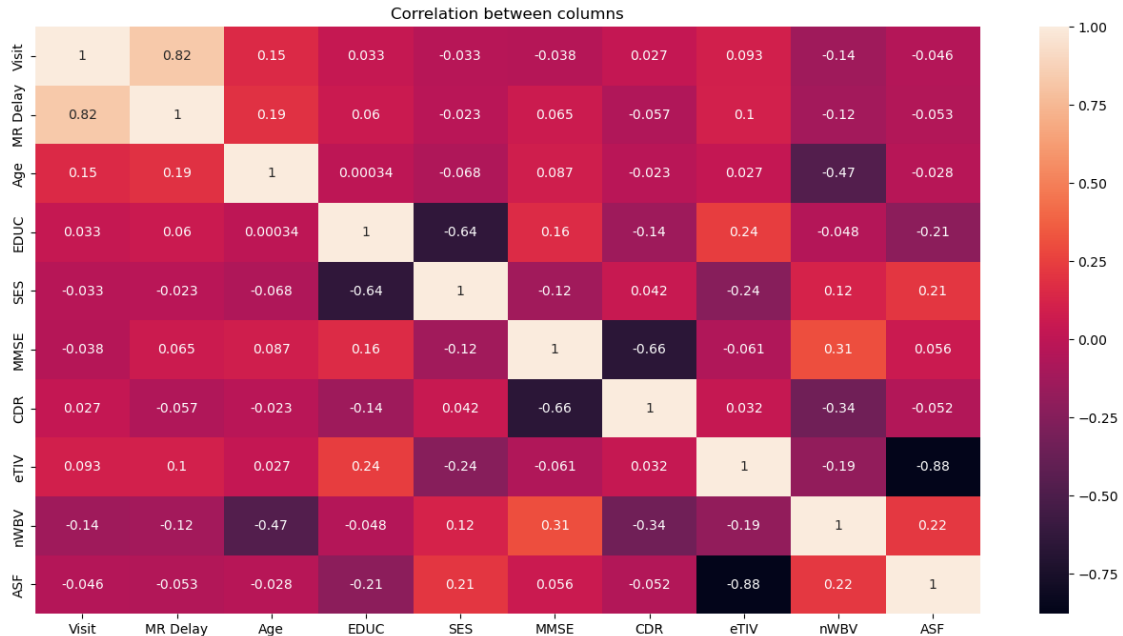
```

[26]: plt.figure(figsize=(16,8))
      sns.heatmap(df.corr(),annot=True)
      plt.title('Correlation between columns')
      plt.show()

```

C:\Users\prera\AppData\Local\Temp\ipykernel\_9388\1066296358.py:2: FutureWarning: The default value of numeric\_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric\_only to silence this warning.

```
sns.heatmap(df.corr(),annot=True)
```

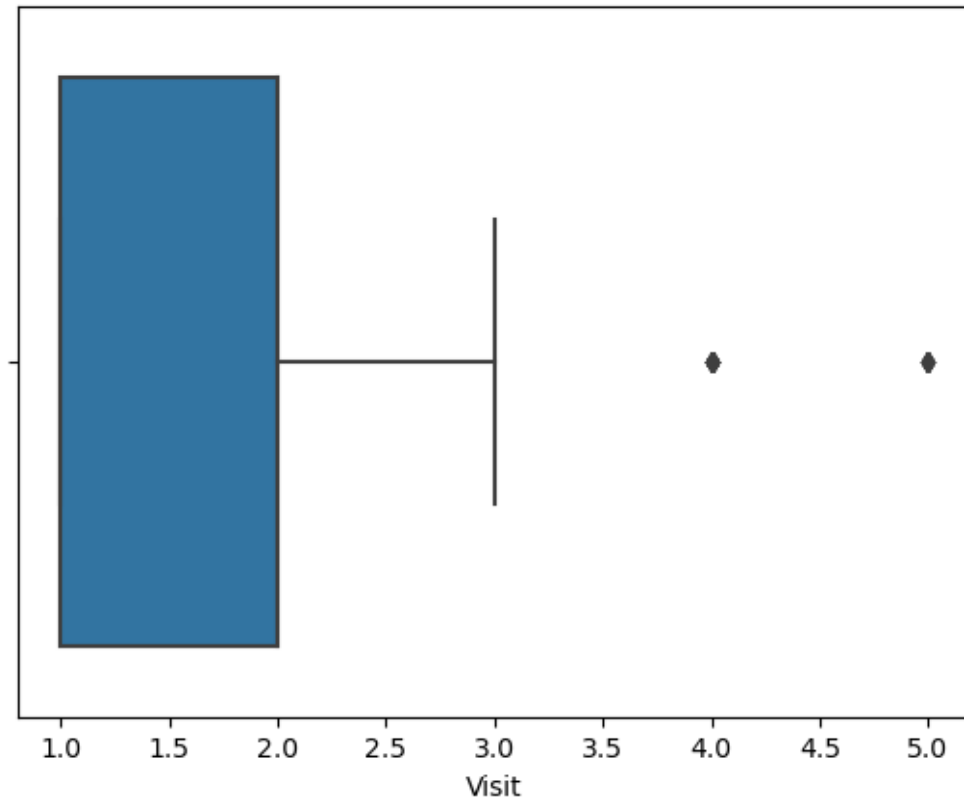


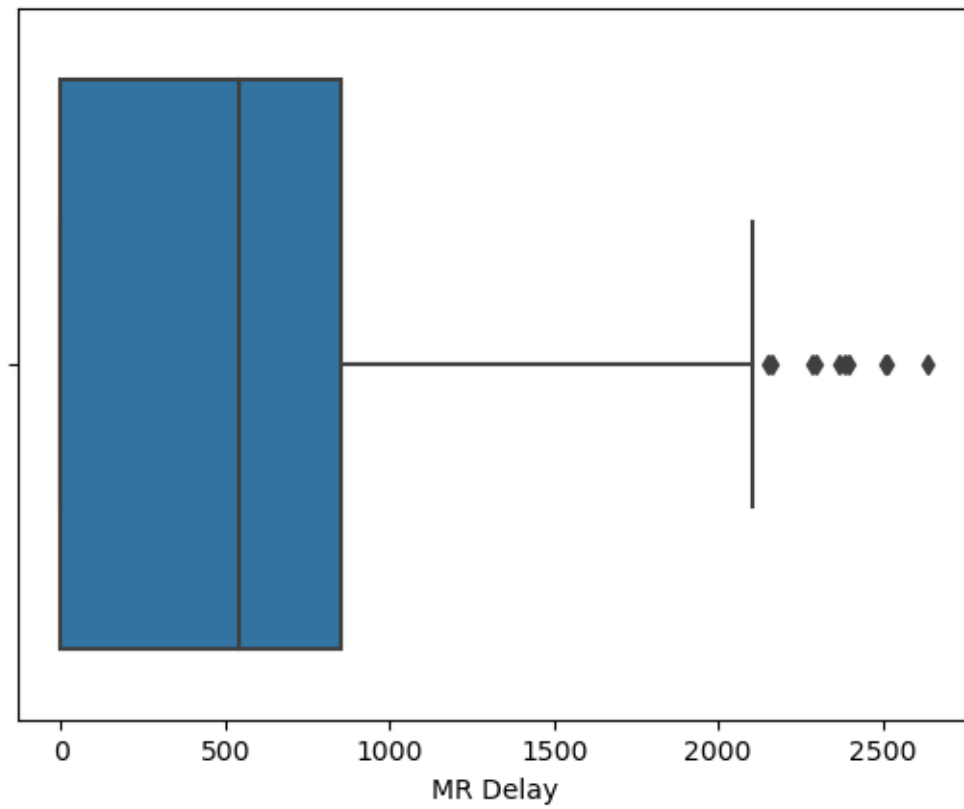
```

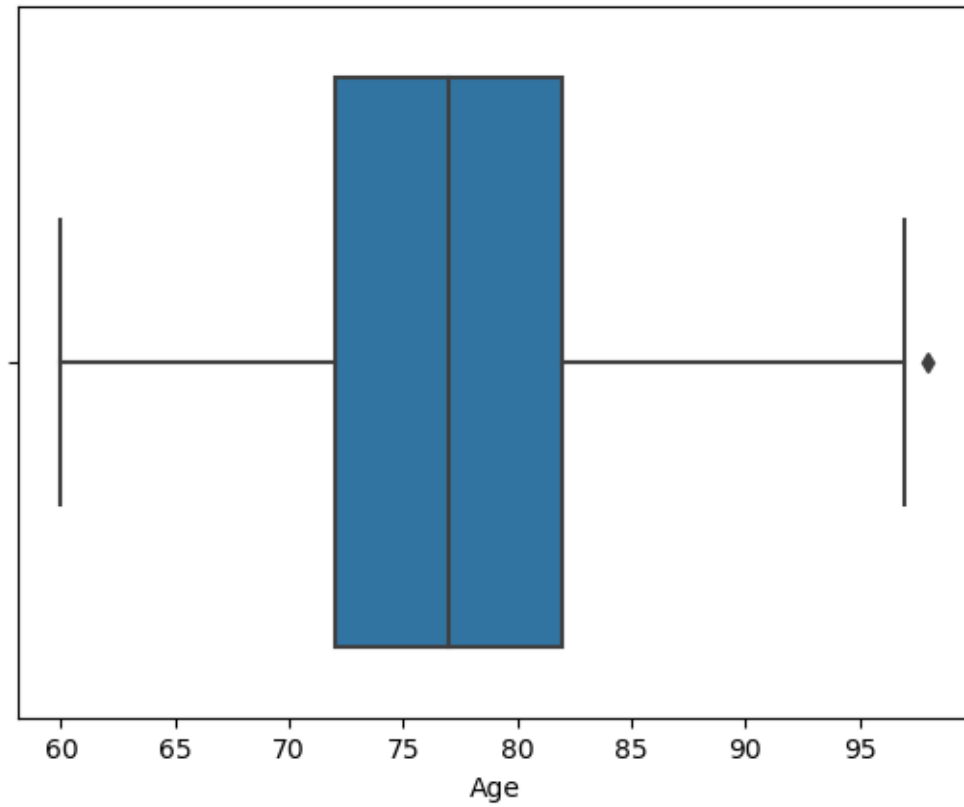
[27]: for i in num_data:
      sns.boxplot(x=df[i])

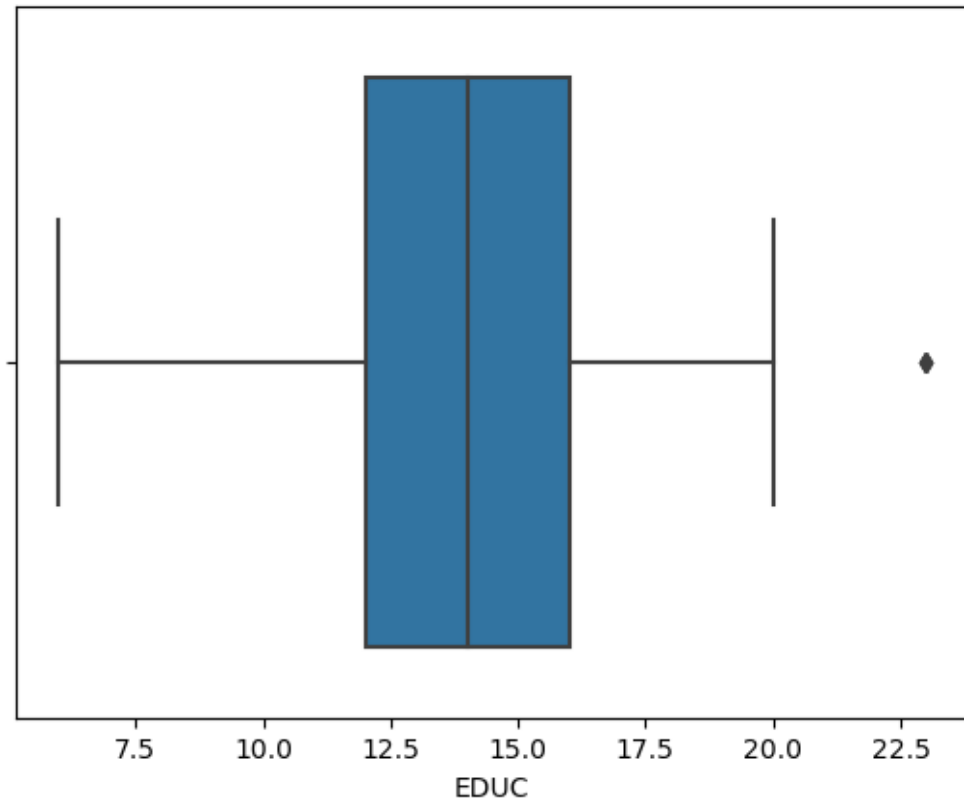
```

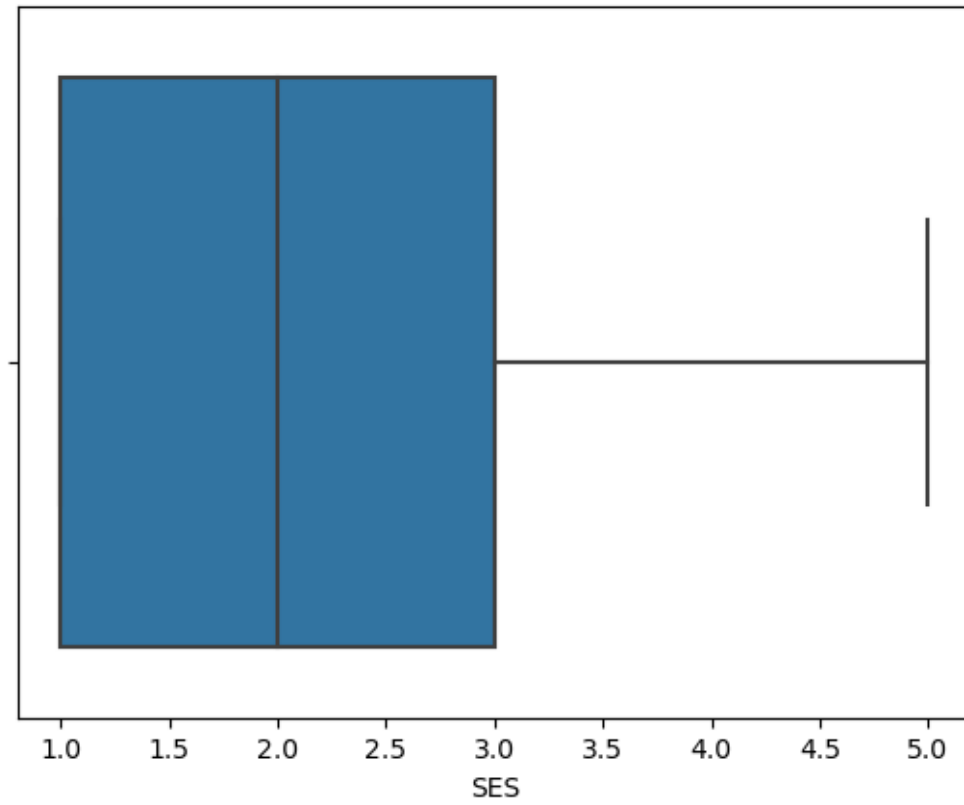
```
plt.show()
```

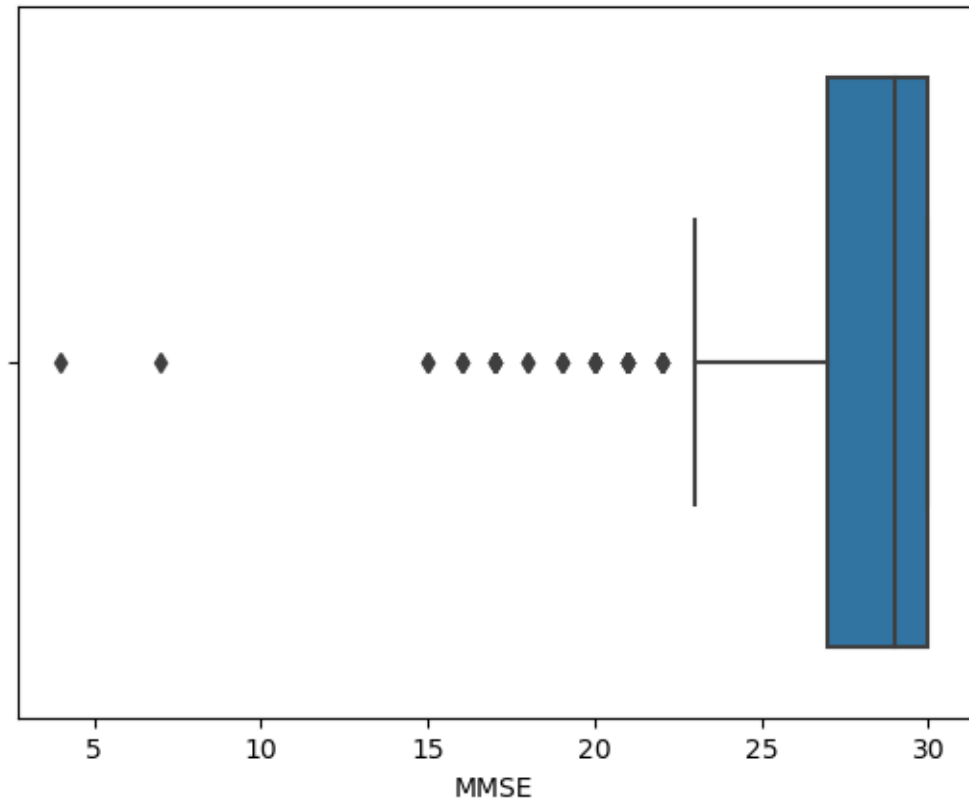


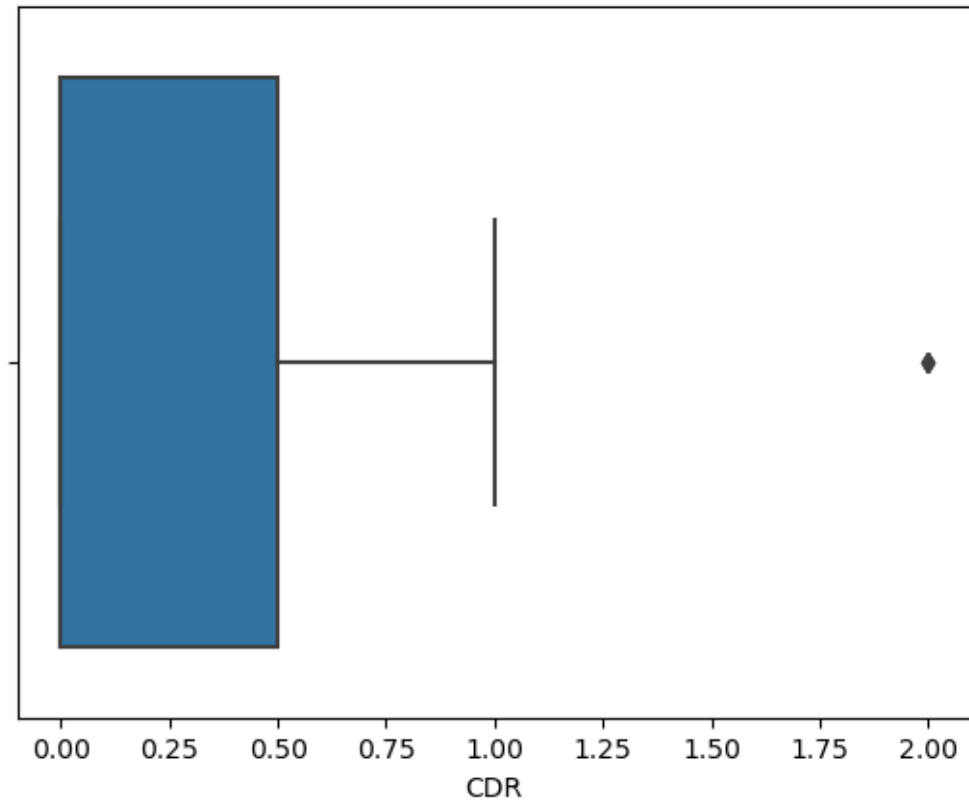




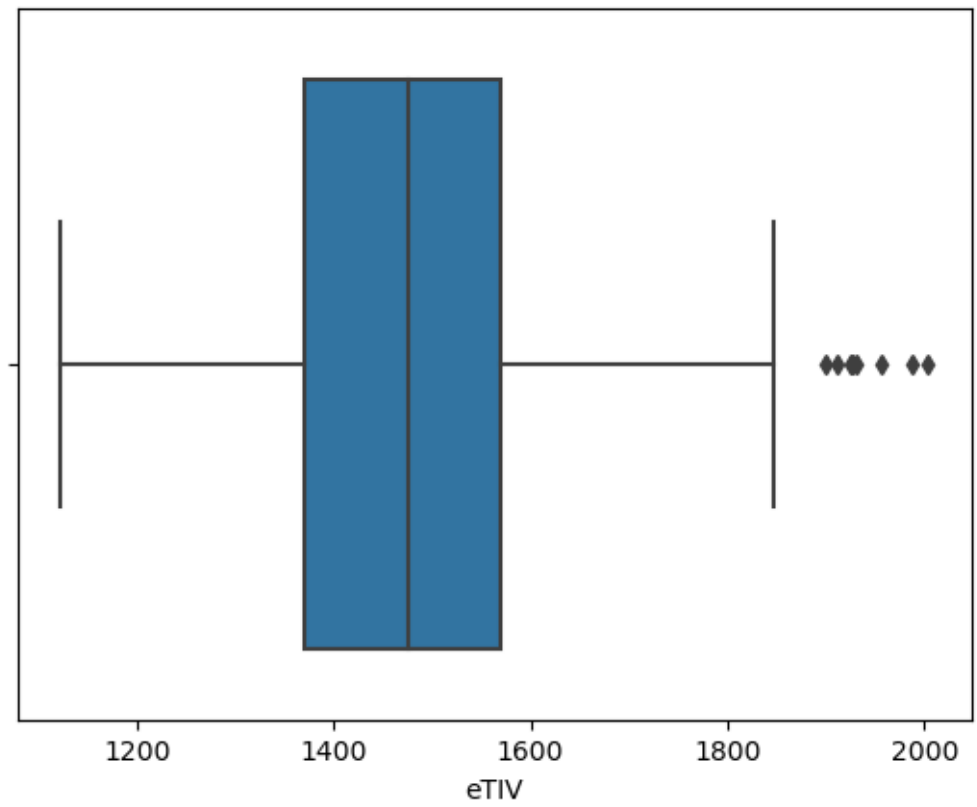


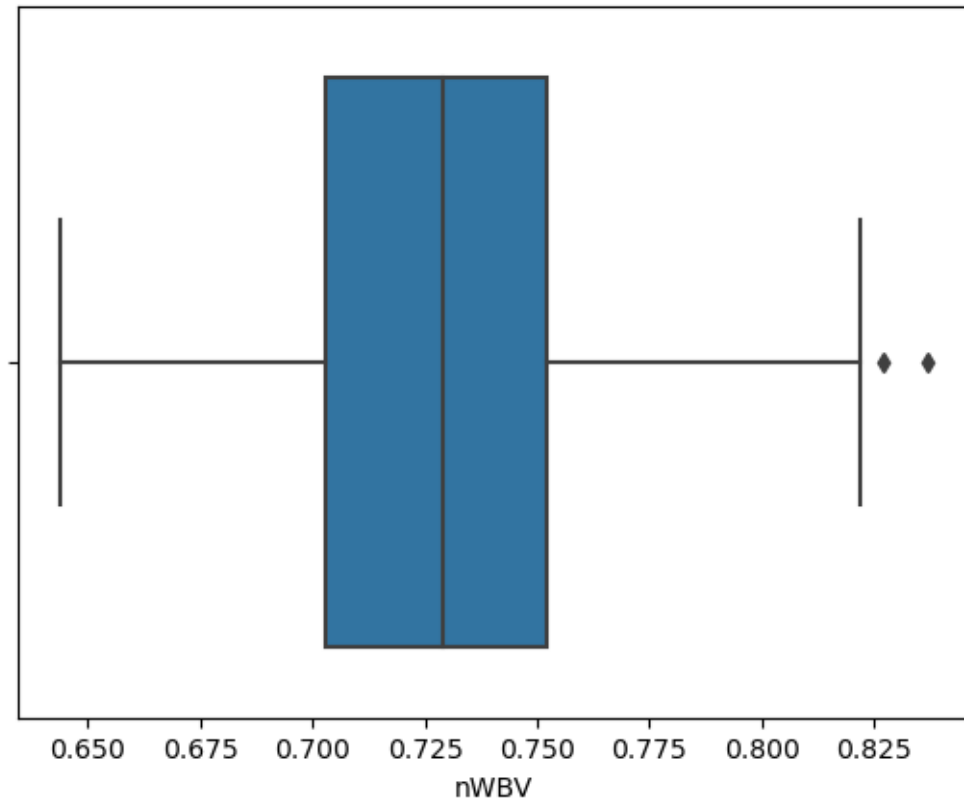


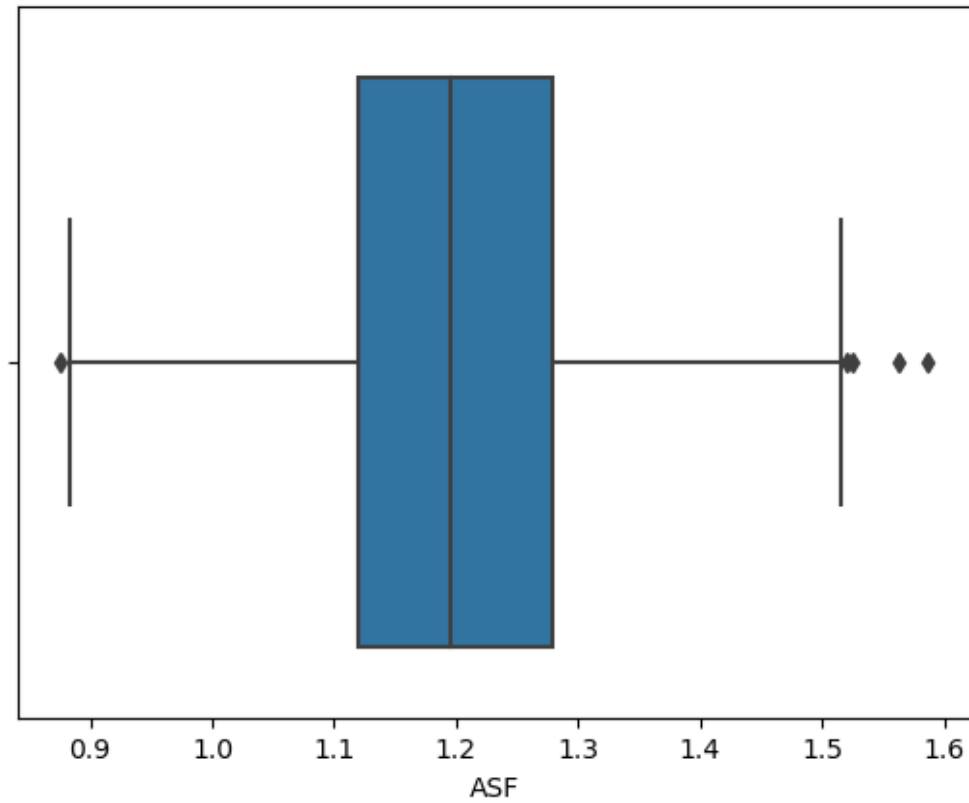






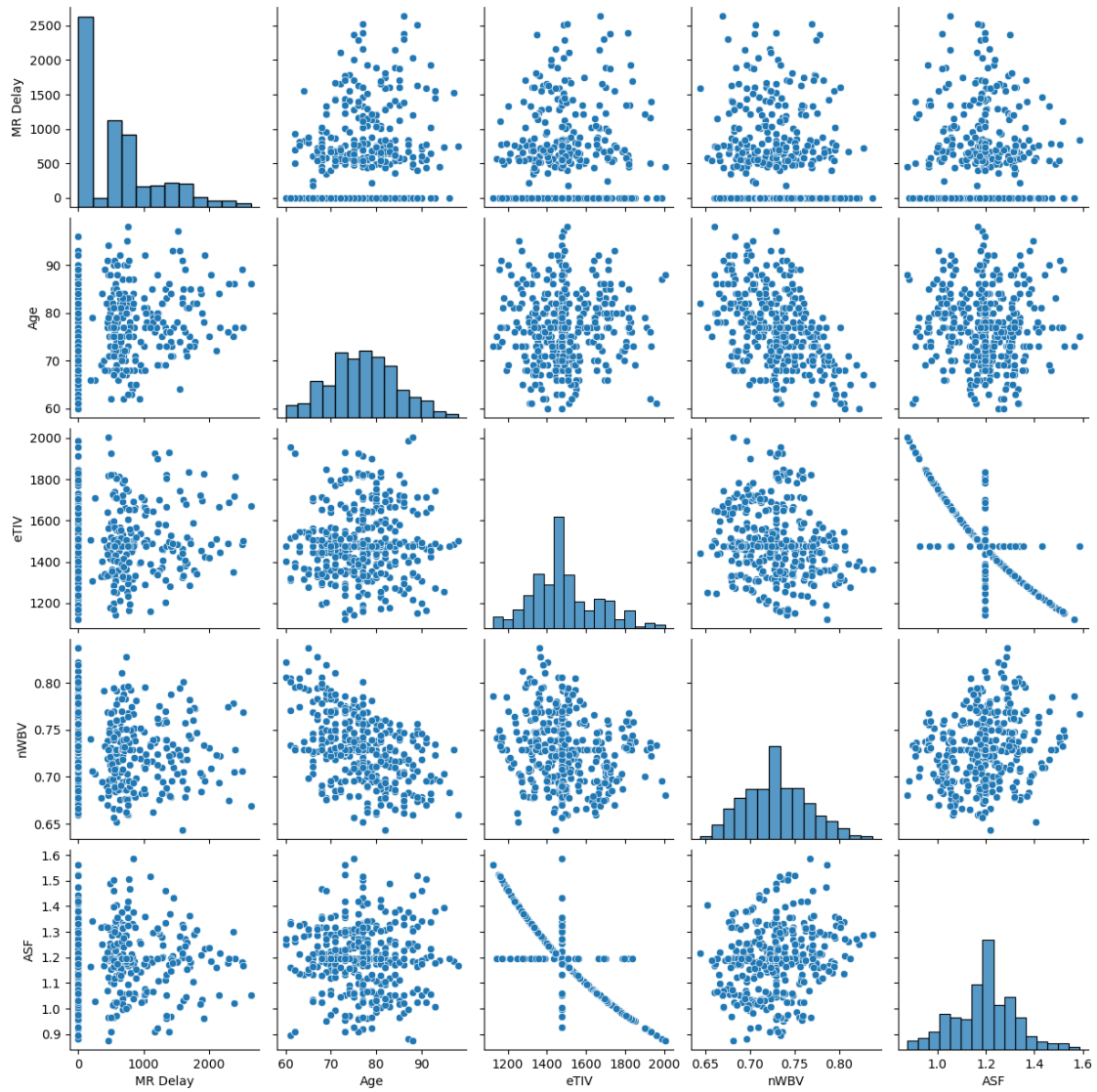






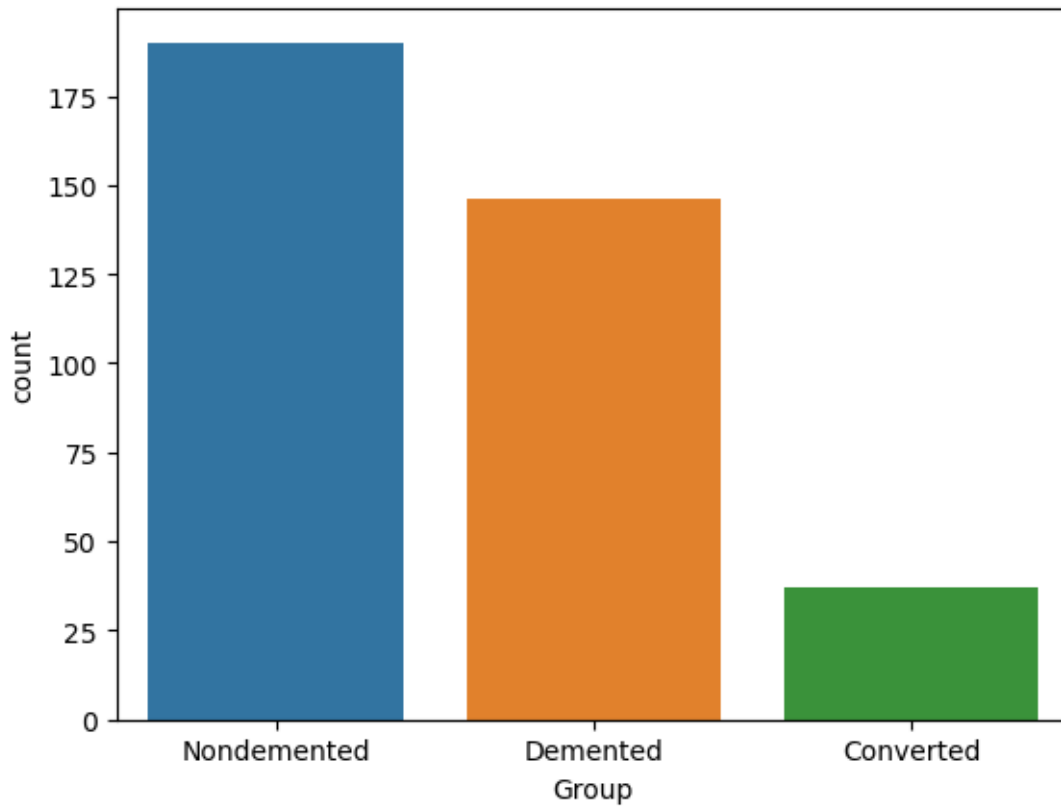
```
[28]: pair_columns=['MR Delay', 'Age', 'eTIV', 'nWBV', 'ASF']  
sns.pairplot(df[pair_columns])
```

```
[28]: <seaborn.axisgrid.PairGrid at 0x28285953610>
```



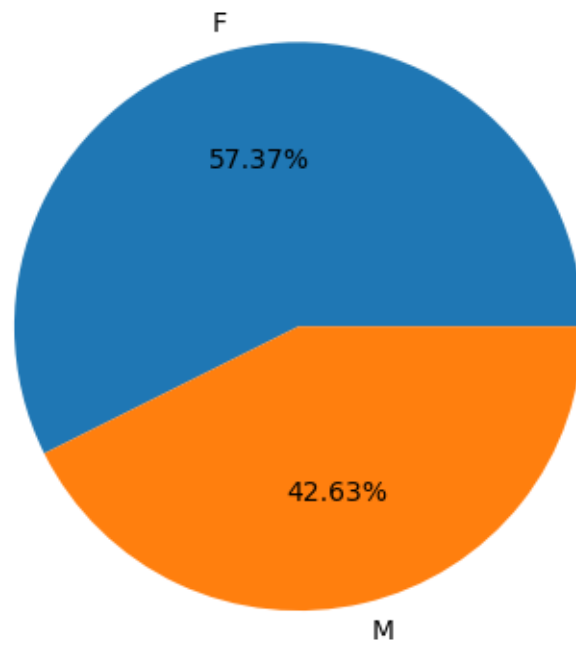
```
[29]: sns.countplot(x='Group',data=df)
```

```
[29]: <Axes: xlabel='Group', ylabel='count'>
```



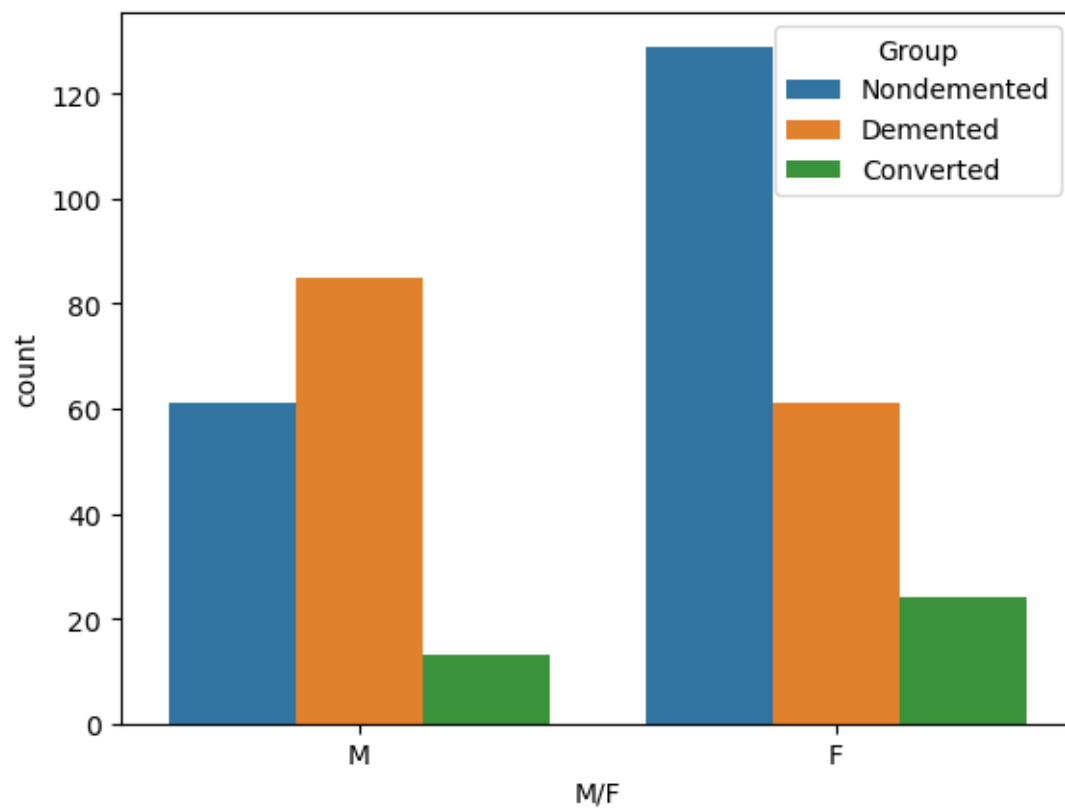
```
[30]: a=df.groupby('M/F')['M/F'].count()
      plt.pie(a,labels=a.index,autopct='%.2f%%')
```

```
[30]: ([<matplotlib.patches.Wedge at 0x28288353710>,
        <matplotlib.patches.Wedge at 0x28288364b10>],
        [Text(-0.25250867084593326, 1.0706256914289047, 'F'),
         Text(0.2525086708459333, -1.0706256914289047, 'M')],
        [Text(-0.13773200227959995, 0.5839776498703116, '57.37%'),
         Text(0.13773200227959997, -0.5839776498703116, '42.63%')])
```



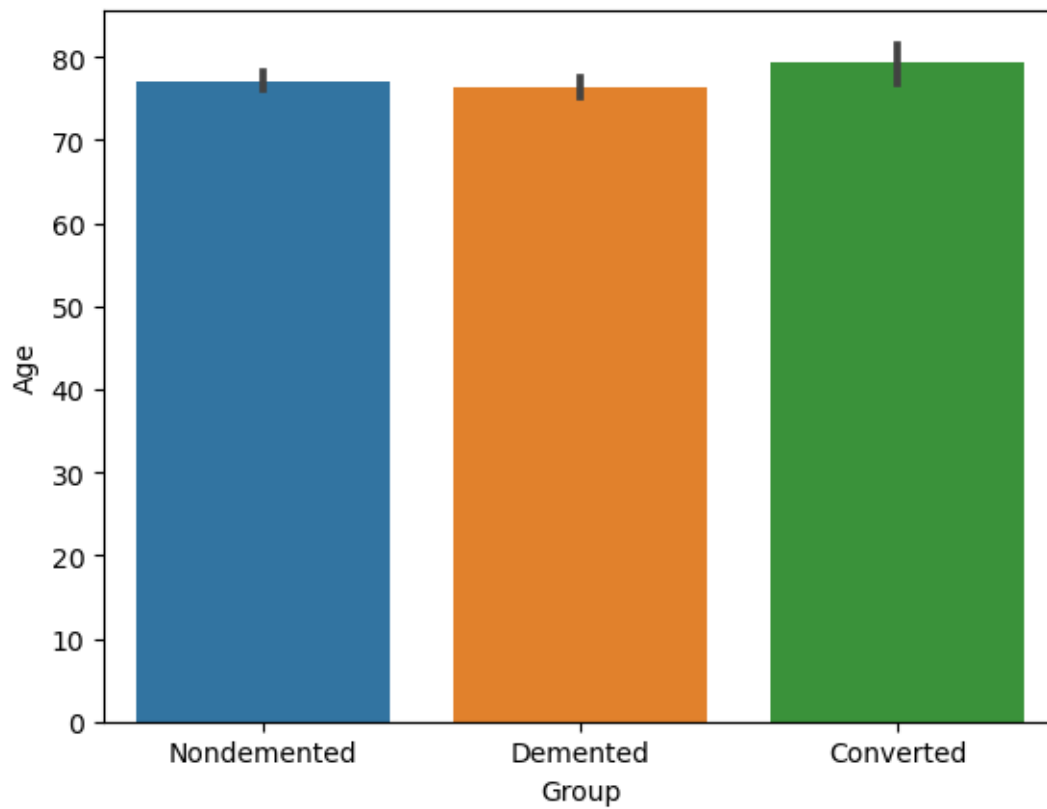
```
[31]: sns.countplot(x='M/F',hue='Group',data=df)
```

```
[31]: <Axes: xlabel='M/F', ylabel='count'>
```



```
[32]: sns.barplot(x='Group',y='Age',data=df)
```

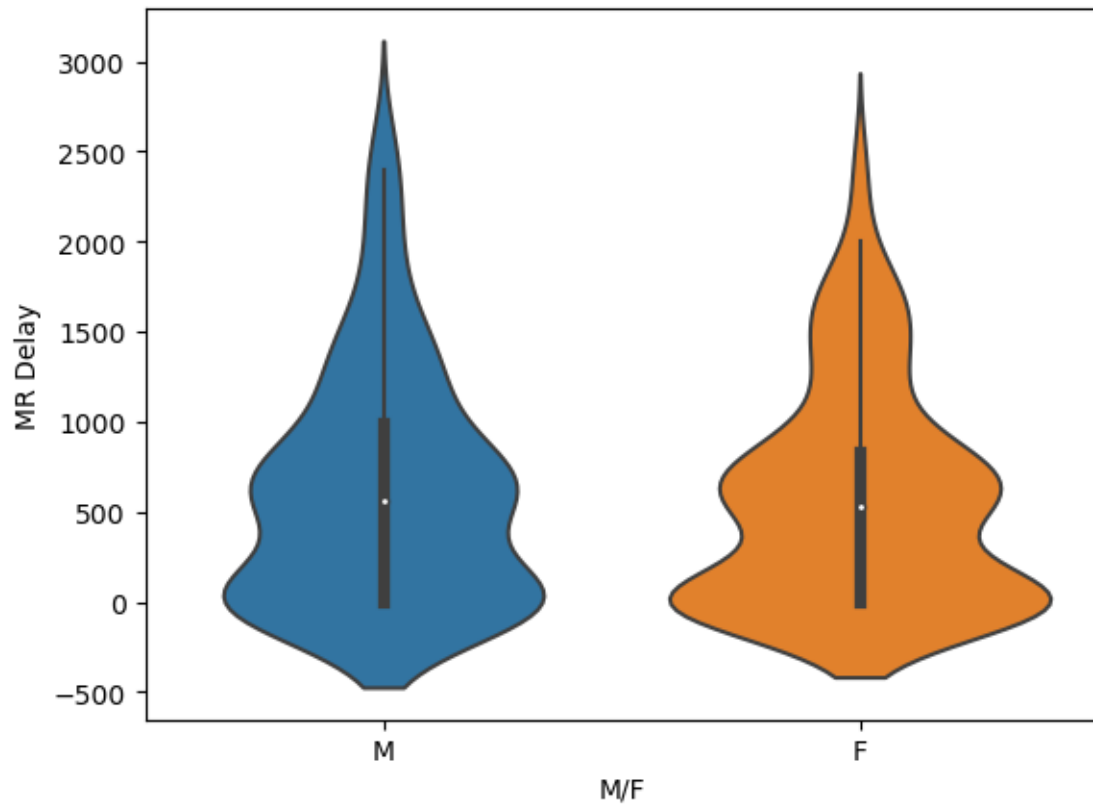
```
[32]: <Axes: xlabel='Group', ylabel='Age'>
```



```
[33]: sns.violinplot(x='M/F',y='MR Delay',data=df)
```

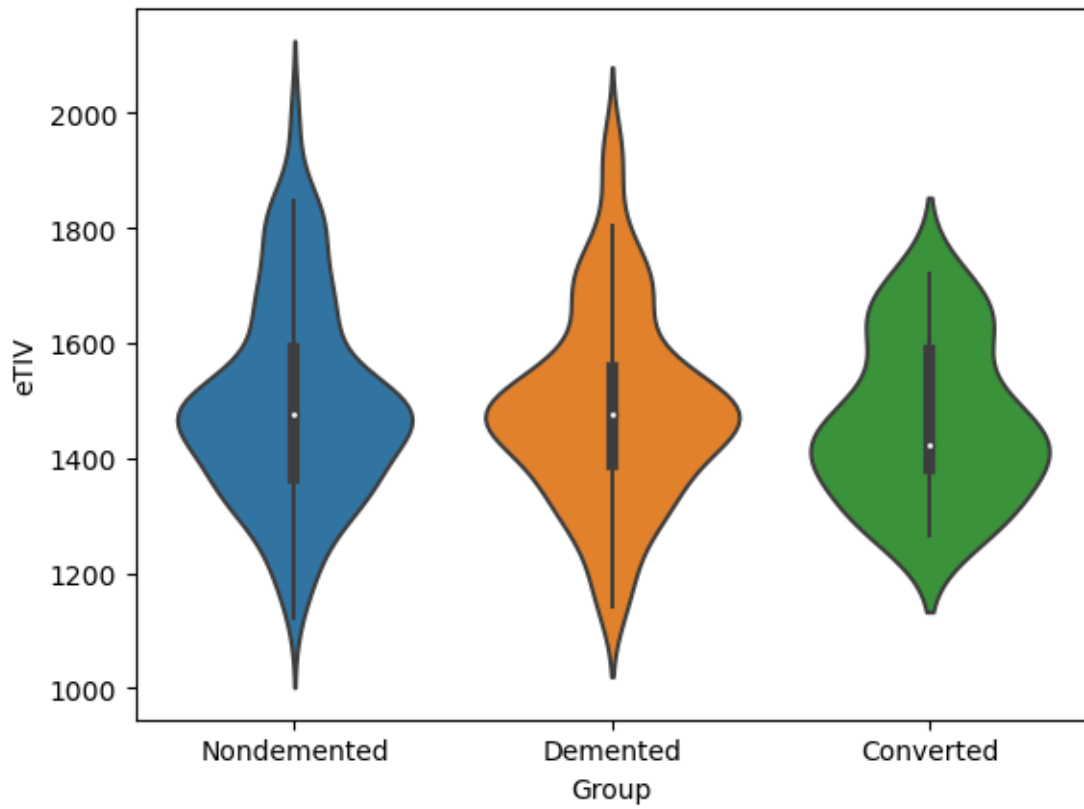
```
[33]: <Axes: xlabel='M/F', ylabel='MR Delay'>
```





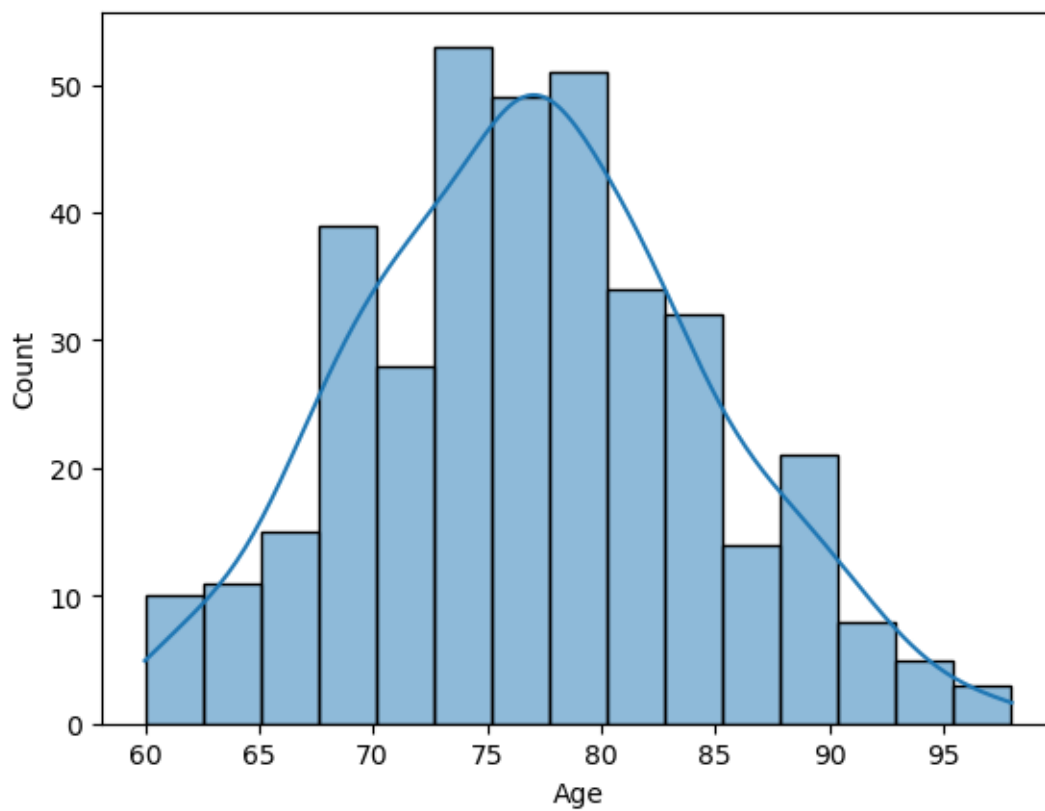
```
[34]: sns.violinplot(x='Group',y='eTIV',data=df)
```

```
[34]: <Axes: xlabel='Group', ylabel='eTIV'>
```



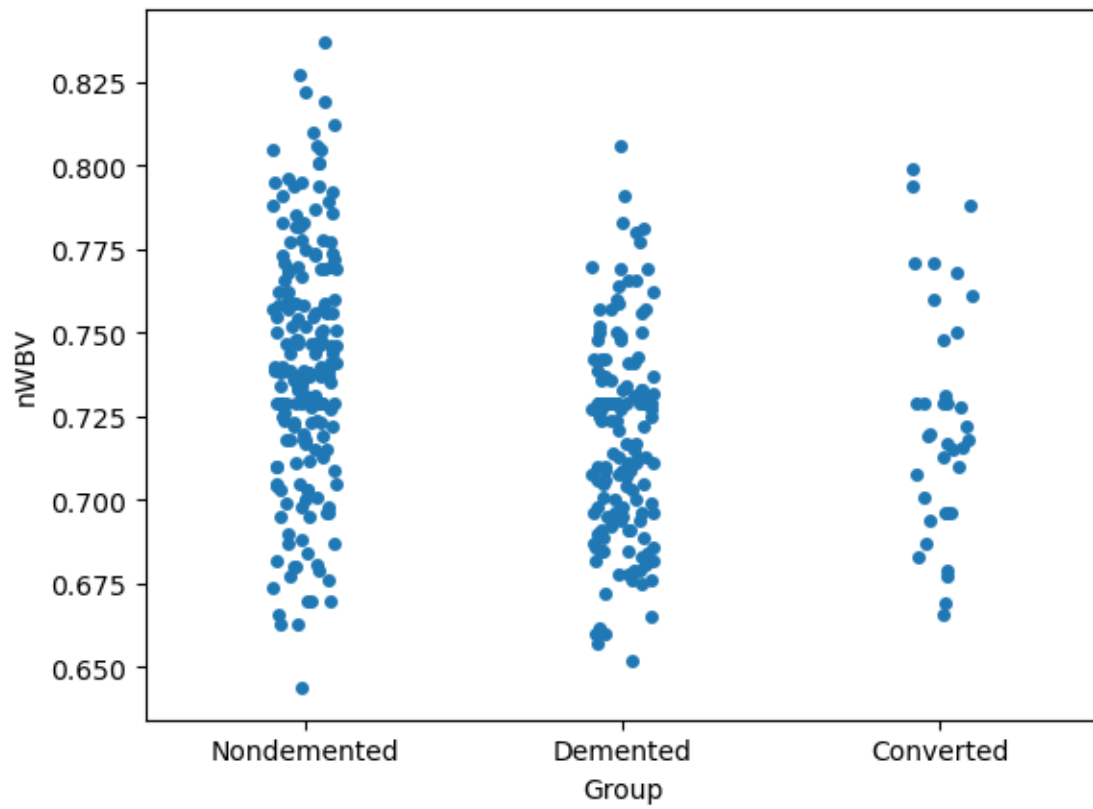
```
[35]: sns.histplot(x='Age',data=df,bins=15,kde=True)
```

```
[35]: <Axes: xlabel='Age', ylabel='Count'>
```



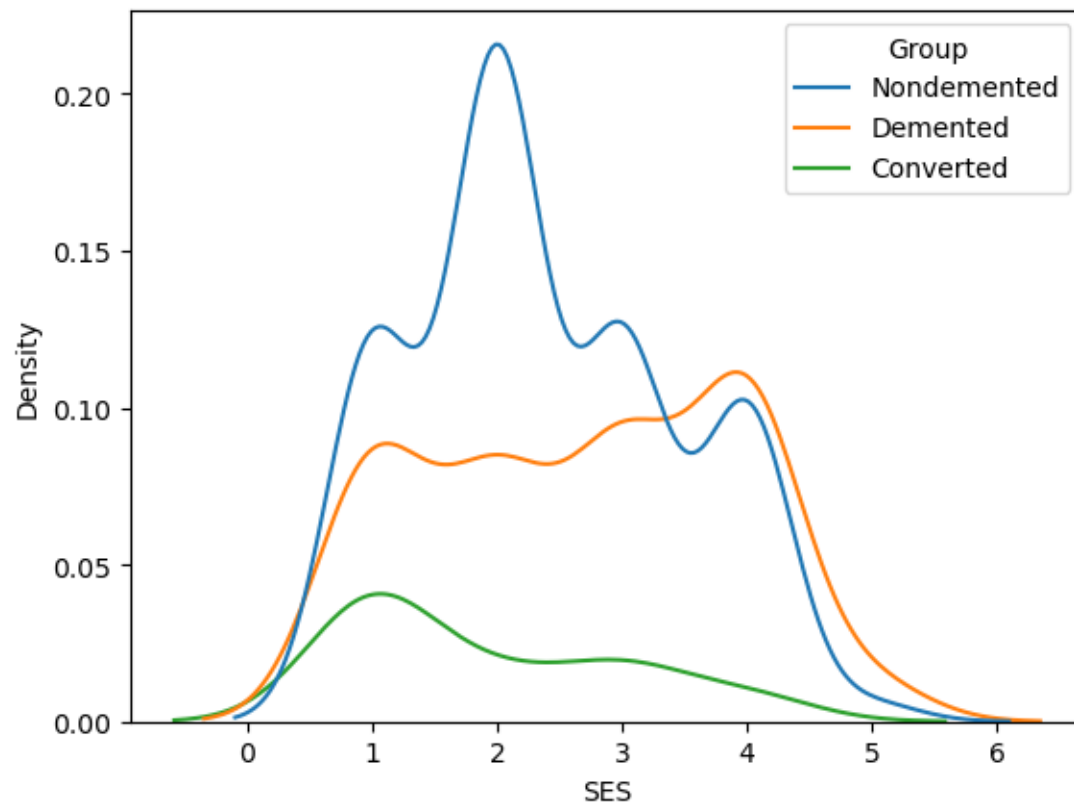
```
[36]: sns.stripplot(x='Group',y='nWBV',data=df)
```

```
[36]: <Axes: xlabel='Group', ylabel='nWBV'>
```



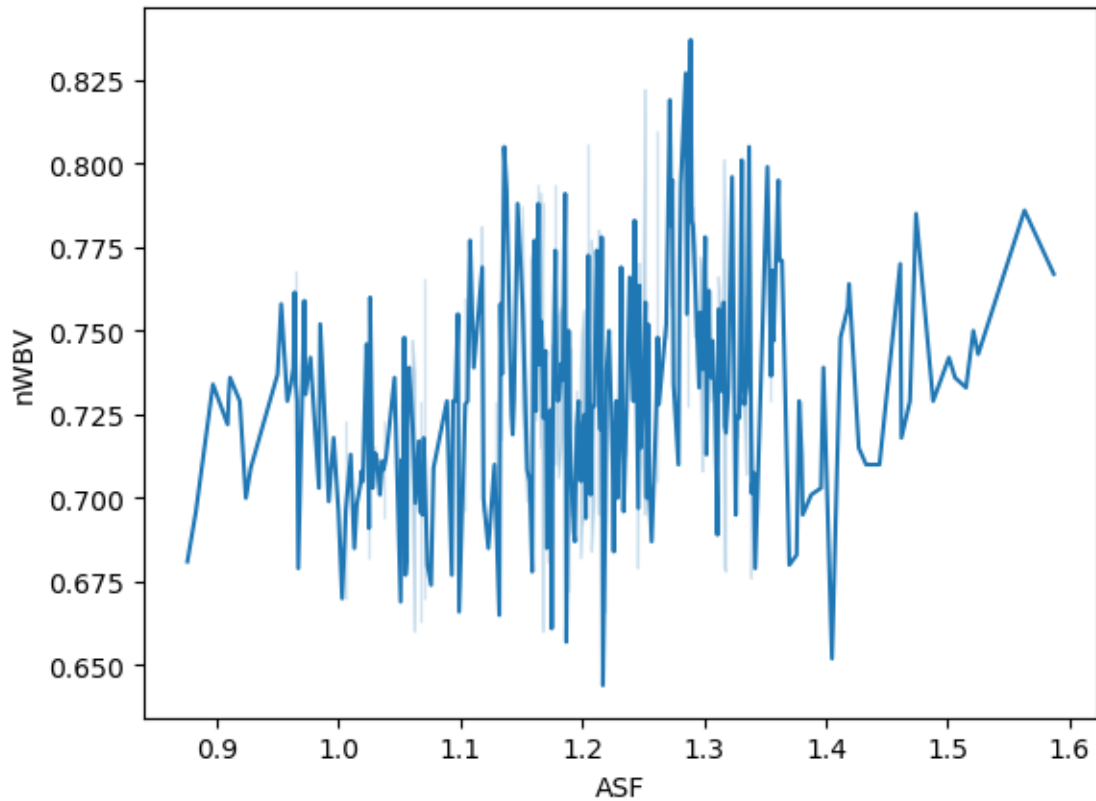
```
[37]: sns.kdeplot(x='SES',hue='Group',data=df)
```

```
[37]: <Axes: xlabel='SES', ylabel='Density'>
```



```
[38]: sns.lineplot(x='ASF',y='nWBV',data=df)
```

```
[38]: <Axes: xlabel='ASF', ylabel='nWBV'>
```



```
[39]: df.replace({'Group':{'Demented':1,'Nondemented':0,'Converted':2}},inplace=True)
df.replace({'M/F':{'M':1,'F':0}},inplace=True)
df.replace({'Hand':{'R':1}},inplace=True)
```

```
[40]: from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, classification_report, \
    ↪confusion_matrix, roc_curve, auc
```

```
[41]: numerical_cols=['Visit','MR_
    ↪Delay','Age','EDUC','SES','MMSE','CDR','eTIV','nWBV','ASF','M/F','Hand']
scaler=StandardScaler()
scaled_cols=pd.DataFrame(scaler.
    ↪fit_transform(df[numerical_cols]),columns=scaler.
    ↪get_feature_names_out(numerical_cols))
```

```
[42]: scaled_cols
```

```
[42]:      Visit  MR Delay      Age      EDUC      SES      MMSE      CDR \
0   -0.935945 -0.940452  1.333025 -0.193431 -0.404523 -0.128136 -0.773771
```

```

1    0.144883 -0.212318  1.466471 -0.193431 -0.404523  0.705490 -0.773771
2   -0.935945 -0.940452 -0.268322 -0.883862 -0.404523 -1.239637  0.562417
3    0.144883 -0.048209 -0.134877 -0.883862 -0.404523  0.149740  0.562417
4    1.225711  2.078836  0.398906 -0.883862 -0.404523 -1.517512  0.562417
..    ...      ...      ...      ...      ...      ...
368  0.144883  0.401099  0.665797  0.496999 -1.281775  0.427615  0.562417
369  1.225711  2.719339  1.199579  0.496999 -1.281775 -0.406011  0.562417
370 -0.935945 -0.940452 -2.136561 -0.538646 -0.404523  0.705490 -0.773771
371  1.225711  0.275229 -1.869670 -0.538646 -0.404523  0.427615 -0.773771
372  1.225711  1.621561 -0.001431 -0.538646 -0.404523  0.705490 -0.773771

```

```

      eTIV      nWBV      ASF      M/F      Hand
0    2.990364 -0.937282 -2.436553  1.160134  0.0
1    3.092275 -1.357988 -2.491307  1.160134  0.0
2    1.137989  0.184599 -1.161556  1.160134  0.0
3    1.497673 -0.460483 -1.443150  1.160134  0.0
4    1.257883 -0.797047 -1.255421  1.160134  0.0
..    ...      ...      ...      ...
368  1.227910 -0.993377 -1.231954  1.160134  0.0
369  1.197936 -1.526270  0.007843  1.160134  0.0
370 -1.014124  2.007657  1.067733 -0.861969  0.0
371 -0.078944  1.867422  1.005156 -0.861969  0.0
372 -0.930198  2.007657  0.958224 -0.861969  0.0

```

[373 rows x 12 columns]

```
[43]: x=scaled_cols
      y=df['Group']
```

```
[44]: x.dtypes
```

```
[44]: Visit      float64
MR Delay      float64
Age           float64
EDUC          float64
SES           float64
MMSE          float64
CDR           float64
eTIV          float64
nWBV          float64
ASF           float64
M/F           float64
Hand          float64
dtype: object
```

# 1 SVM

```
[45]: x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,random_state=5)
```

```
[46]: svc = SVC(kernel='linear')
      svc.fit(x_train,y_train)
```

```
[46]: SVC(kernel='linear')
```

```
[47]: y_pred=svc.predict(x_test)
```

```
[48]: acc=accuracy_score(y_test,y_pred)
      acc
```

```
[48]: 0.8933333333333333
```

```
[49]: print (classification_report(y_test,y_pred))
```

	precision	recall	f1-score	support
0	0.95	1.00	0.98	41
1	0.87	0.93	0.90	28
2	0.00	0.00	0.00	6
accuracy			0.89	75
macro avg	0.61	0.64	0.62	75
weighted avg	0.84	0.89	0.87	75

```
[50]: cm= confusion_matrix(y_test,y_pred)
      print(cm)
```

```
[[41  0  0]
 [ 0 26  2]
 [ 2  4  0]]
```

```
[51]: from sklearn.preprocessing import label_binarize
      from sklearn.multiclass import OneVsRestClassifier
```

```
[52]: yb=label_binarize(y, classes=[0,1,2])
```

```
[53]: nc = yb.shape[1]
```

```
[54]: classifier = OneVsRestClassifier(SVC(kernel='linear',probability=True,random_state=42))
```

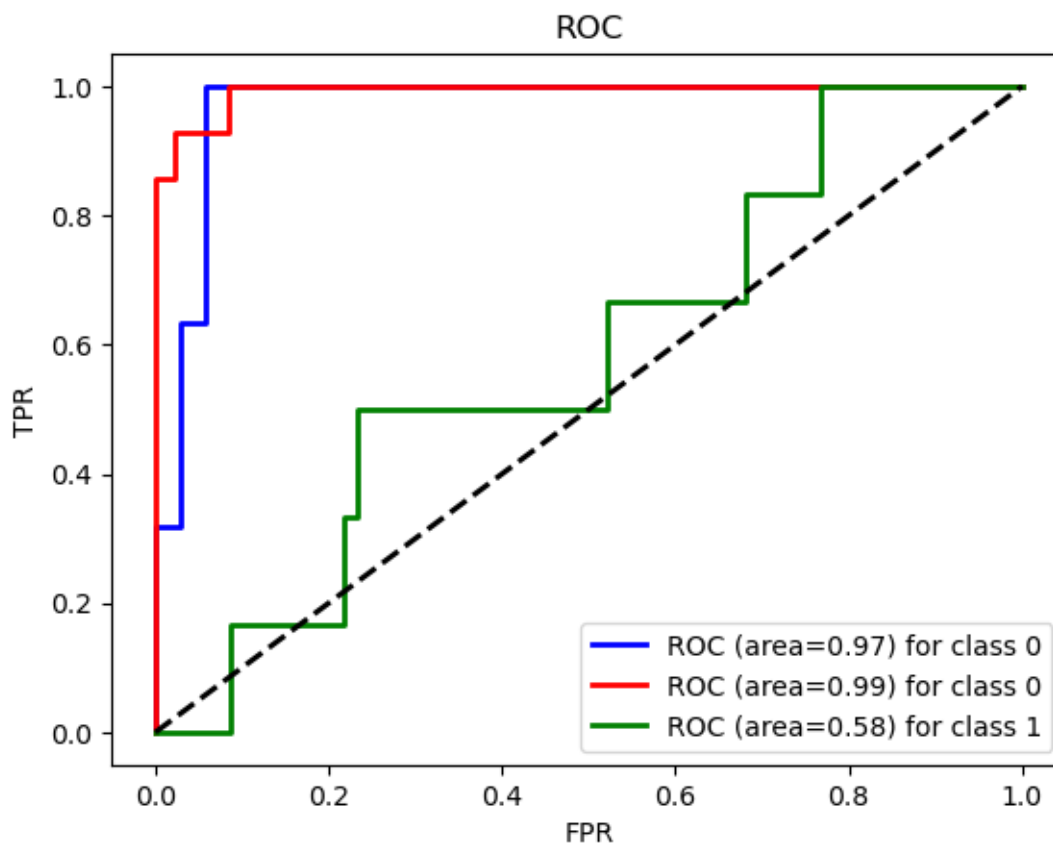
```
[55]: y_score=classifier.fit(x_train,y_train).decision_function(x_test)
```



```
[56]: fpr=dict()
      tpr=dict()
      roc_auc=dict()

      for i in range(nc):
          fpr[i],tpr[i],_=roc_curve(y_test == i, y_score[:,i])
          roc_auc[i]=auc(fpr[i],tpr[i])
```

```
[57]: plt.figure()
      color=['blue','red','green']
      for i, color in zip(range(nc),color):
          plt.plot(fpr[i],tpr[i],color=color, lw=2, label='ROC (area={:.2f}) for_
          ↪class {}'.format(roc_auc[i],df['Group'][i]))
      plt.plot([0,1],[0,1], 'k--',lw=2)
      plt.xlabel('FPR')
      plt.ylabel('TPR')
      plt.title('ROC')
      plt.legend(loc='lower right')
      plt.show()
```



```
[58]: from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
      from scipy.stats import uniform
```

```
[59]: param_grid={'C':[0.1,1,10,100,1000],
                  'gamma':[1,0.1,0.01,0.001,0.0001],
                  'kernel':['linear','rbf','poly','sigmoid']}
```

```
[60]: svc=SVC()
      grid=GridSearchCV(svc,param_grid,cv=5)
      grid.fit(x_train,y_train)
```

```
[60]: GridSearchCV(cv=5, estimator=SVC(),
                  param_grid={'C': [0.1, 1, 10, 100, 1000],
                              'gamma': [1, 0.1, 0.01, 0.001, 0.0001],
                              'kernel': ['linear', 'rbf', 'poly', 'sigmoid']})
```

```
[125]: best_param=grid.best_params_
        best_model=grid.best_estimator_
        y_pred_1=best_model.predict(x_test)
```

C:\Users\prera\anaconda3\Lib\site-packages\sklearn\base.py:439: UserWarning: X does not have valid feature names, but SVC was fitted with feature names  
warnings.warn(

```
[126]: print (classification_report(y_test,y_pred_1))
```

	precision	recall	f1-score	support
0	0.00	0.00	0.00	47
1	0.85	0.85	0.85	40
2	0.09	0.71	0.16	7
accuracy			0.41	94
macro avg	0.31	0.52	0.34	94
weighted avg	0.37	0.41	0.37	94

C:\Users\prera\anaconda3\Lib\site-packages\sklearn\metrics\\_classification.py:1344: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero\_division` parameter to control this behavior.

\_warn\_prf(average, modifier, msg\_start, len(result))

C:\Users\prera\anaconda3\Lib\site-packages\sklearn\metrics\\_classification.py:1344: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero\_division` parameter to control this behavior.

\_warn\_prf(average, modifier, msg\_start, len(result))

C:\Users\prera\anaconda3\Lib\site-

```
packages\sklearn\metrics\_classification.py:1344: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
    _warn_prf(average, modifier, msg_start, len(result))
```

```
[127]: cm= confusion_matrix(y_test,y_pred_1)
        print(cm)
```

```
[[ 0  4 43]
 [ 0 34  6]
 [ 0  2  5]]
```

```
[64]: param_dist={'C':uniform(loc=0,scale=10),
                 'kernel':['linear','rbf','poly','sigmoid']}
```

```
[65]: n_iter_search=20
        random_search = RandomizedSearchCV(svc, param_distributions=param_dist,
        ↪n_iter=n_iter_search, cv=5, n_jobs=-1, random_state=42)
        random_search.fit(x_train,y_train)
```

```
[65]: RandomizedSearchCV(cv=5, estimator=SVC(), n_iter=20, n_jobs=-1,
                        param_distributions={'C':
<scipy.stats._distn_infrastructure.rv_continuous_frozen object at
0x000002828A679C50>,
                                           'kernel': ['linear', 'rbf', 'poly',
                                           'sigmoid']}],
                        random_state=42)
```

```
[128]: best_param = random_search.best_params_
        best_model = random_search.best_estimator_
        y_pred_2=best_model.predict(x_test)
```

```
C:\Users\prera\anaconda3\Lib\site-packages\sklearn\base.py:439: UserWarning: X
does not have valid feature names, but SVC was fitted with feature names
    warnings.warn(
```

```
[129]: print(classification_report(y_test,y_pred_2))
```

	precision	recall	f1-score	support
0	0.00	0.00	0.00	47
1	0.94	0.82	0.88	40
2	0.12	1.00	0.21	7
accuracy			0.43	94
macro avg	0.35	0.61	0.36	94
weighted avg	0.41	0.43	0.39	94

```
C:\Users\prera\anaconda3\Lib\site-
packages\sklearn\metrics\_classification.py:1344: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
    _warn_prf(average, modifier, msg_start, len(result))
C:\Users\prera\anaconda3\Lib\site-
packages\sklearn\metrics\_classification.py:1344: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
    _warn_prf(average, modifier, msg_start, len(result))
C:\Users\prera\anaconda3\Lib\site-
packages\sklearn\metrics\_classification.py:1344: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
    _warn_prf(average, modifier, msg_start, len(result))
```

```
[130]: cm= confusion_matrix(y_test,y_pred_2)
print(cm)
```

```
[[ 0  2 45]
 [ 0 33  7]
 [ 0  0  7]]
```

## 2 Naive Bayes

```
[69]: from sklearn import model_selection, naive_bayes, svm,
      ↪ metrics, feature_extraction
```

```
[70]: x=scaled_cols
      y=df['Group']
```

```
[71]: x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.
      ↪ 25,random_state=32)
```

```
[72]: from sklearn.preprocessing import MinMaxScaler
      scaler = MinMaxScaler()
      x_train = scaler.fit_transform(x_train)
      x_test = scaler.transform(x_test)
```

```
[73]: bayes = naive_bayes.MultinomialNB()
```

```
[109]: bayes.fit(x_train,y_train)
```

```
[109]: MultinomialNB()
```

```
[110]: y_pred_nb=bayes.predict(x_test)
```

```
[76]: accuracy=metrics.accuracy_score(y_test,y_pred_nb)
accuracy
```

```
[76]: 0.9042553191489362
```

```
[111]: print(metrics.classification_report(y_test, y_pred_nb))
```

	precision	recall	f1-score	support
0	0.90	1.00	0.95	47
1	0.90	0.95	0.93	40
2	0.00	0.00	0.00	7
accuracy			0.90	94
macro avg	0.60	0.65	0.63	94
weighted avg	0.84	0.90	0.87	94

```
C:\Users\prera\anaconda3\Lib\site-
packages\sklearn\metrics\_classification.py:1344: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
```

```
_warn_prf(average, modifier, msg_start, len(result))
```

```
C:\Users\prera\anaconda3\Lib\site-
packages\sklearn\metrics\_classification.py:1344: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
```

```
_warn_prf(average, modifier, msg_start, len(result))
```

```
C:\Users\prera\anaconda3\Lib\site-
packages\sklearn\metrics\_classification.py:1344: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
```

```
_warn_prf(average, modifier, msg_start, len(result))
```

```
[78]: cm=confusion_matrix(y_test,y_pred_nb)
cm
```

```
[78]: array([[47,  0,  0],
          [ 2, 38,  0],
          [ 3,  4,  0]], dtype=int64)
```

```
[79]: yb=label_binarize(y, classes=[0,1,2])
nc = yb.shape[1]
```

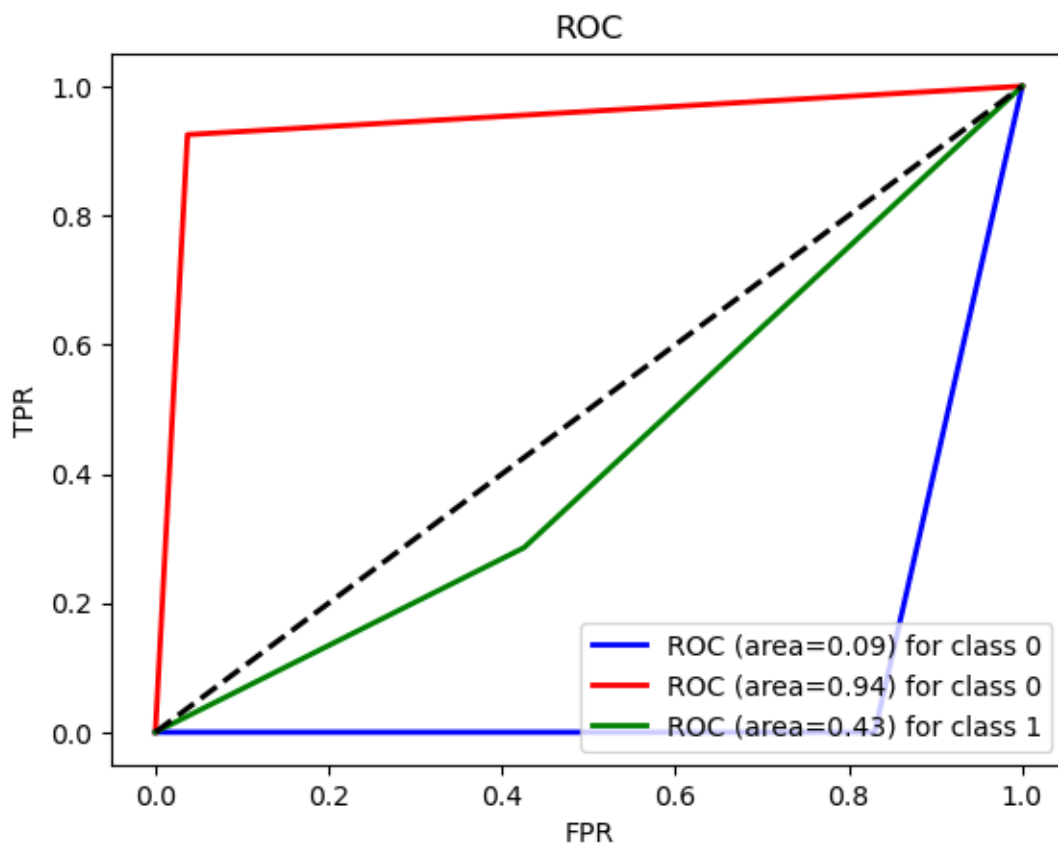
```
[80]: classifier = OneVsRestClassifier(bayes)
```

```
[81]: y_score=classifier.fit(x_train,y_train).predict(x_test)
```

```
[82]: fpr=dict()
      tpr=dict()
      roc_auc=dict()

      for i in range(nc):
          fpr[i],tpr[i],_=roc_curve(y_test == i, y_score)
          roc_auc[i]=auc(fpr[i],tpr[i])
```

```
[83]: plt.figure()
      color=['blue','red','green']
      for i, color in zip(range(nc),color):
          plt.plot(fpr[i],tpr[i],color=color, lw=2, label='ROC (area={:.2f}) for_
          ↪class {}'.format(roc_auc[i],df['Group'][i]))
      plt.plot([0,1],[0,1], 'k--',lw=2)
      plt.xlabel('FPR')
      plt.ylabel('TPR')
      plt.title('ROC')
      plt.legend(loc='lower right')
      plt.show()
```



## 2.1 Grid Search & Randomized Search

```
[84]: param_grid = {  
      'alpha': [0.1, 1, 10, 100],  
      'fit_prior': [True, False]  
      }
```

```
[85]: bayes = naive_bayes.MultinomialNB()  
      grid_search = GridSearchCV(bayes, param_grid, cv=5)  
      grid_search.fit(x_train, y_train)
```

```
[85]: GridSearchCV(cv=5, estimator=MultinomialNB(),  
                  param_grid={'alpha': [0.1, 1, 10, 100],  
                              'fit_prior': [True, False]})
```

```
[112]: best_param = grid_search.best_params_  
      best_nb = naive_bayes.MultinomialNB(alpha = best_param['alpha'], fit_prior =   
      ↪best_param['fit_prior'])  
      best_nb.fit(x_train, y_train)  
      y_pred_1 = best_nb.predict(x_test)
```

```
[87]: print("Best Hyperparameter : ", best_param)
```

Best Hyperparameter : {'alpha': 0.1, 'fit\_prior': True}

```
[113]: acc = accuracy_score(y_test, y_pred_1)  
      acc
```

```
[113]: 0.925531914893617
```

```
[114]: print(classification_report(y_test, y_pred_1))
```

	precision	recall	f1-score	support
0	0.94	1.00	0.97	47
1	0.91	1.00	0.95	40
2	0.00	0.00	0.00	7
accuracy			0.93	94
macro avg	0.62	0.67	0.64	94
weighted avg	0.86	0.93	0.89	94

```
C:\Users\prera\anaconda3\Lib\site-  
packages\sklearn\metrics\_classification.py:1344: UndefinedMetricWarning:  
Precision and F-score are ill-defined and being set to 0.0 in labels with no  
predicted samples. Use `zero_division` parameter to control this behavior.
```

```
_warn_prf(average, modifier, msg_start, len(result))  
C:\Users\prera\anaconda3\Lib\site-
```

```
packages\sklearn\metrics\_classification.py:1344: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
```

```
_warn_prf(average, modifier, msg_start, len(result))
```

```
C:\Users\prera\anaconda3\Lib\site-
```

```
packages\sklearn\metrics\_classification.py:1344: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
```

```
_warn_prf(average, modifier, msg_start, len(result))
```

```
[120]: cm=confusion_matrix(y_test,y_pred_1)
cm
```

```
[120]: array([[47,  0,  0],
             [ 0, 40,  0],
             [ 3,  4,  0]], dtype=int64)
```

```
[91]: #Randomized Search
param_dist = {
    'alpha': uniform(0.1, 2.0), # Example: Uniform distribution for alpha
    'fit_prior':[True,False]
}
```

```
[92]: bayes = naive_bayes.MultinomialNB()
```

```
[93]: x=scaler.fit_transform(x)
```

```
[94]: from sklearn.utils.validation import check_non_negative
check_non_negative(x, "MultinomialNB (input x)")
```

```
[95]: randomized_search = RandomizedSearchCV(bayes, param_distributions=param_dist,
    ↪n_iter=10, scoring='accuracy', cv=5)
randomized_search.fit(x, y) # X is your input data, y is your target labels
```

```
[95]: RandomizedSearchCV(cv=5, estimator=MultinomialNB(),
                        param_distributions={'alpha':
<scipy.stats._distn_infrastructure.rv_continuous_frozen object at
0x0000002828A670910>,
                                           'fit_prior': [True, False]},
                        scoring='accuracy')
```

```
[96]: best_param = randomized_search.best_params_
print("Best Hyperparameter : ", best_param)
```

```
Best Hyperparameter :  {'alpha': 0.7407188763455518, 'fit_prior': True}
```



```
[122]: best_nb = naive_bayes.MultinomialNB(alpha = best_param['alpha'], fit_prior =  
↳best_param['fit_prior'])  
best_nb.fit(x_train, y_train)  
y_pred_2 = best_nb.predict(x_test)
```

```
[123]: acc = accuracy_score(y_test, y_pred_2)  
acc
```

```
[123]: 0.925531914893617
```

```
[124]: print(classification_report(y_test, y_pred_2))
```

	precision	recall	f1-score	support
0	0.94	1.00	0.97	47
1	0.91	1.00	0.95	40
2	0.00	0.00	0.00	7
accuracy			0.93	94
macro avg	0.62	0.67	0.64	94
weighted avg	0.86	0.93	0.89	94

```
C:\Users\prera\anaconda3\Lib\site-  
packages\sklearn\metrics\_classification.py:1344: UndefinedMetricWarning:  
Precision and F-score are ill-defined and being set to 0.0 in labels with no  
predicted samples. Use `zero_division` parameter to control this behavior.
```

```
_warn_prf(average, modifier, msg_start, len(result))
```

```
C:\Users\prera\anaconda3\Lib\site-  
packages\sklearn\metrics\_classification.py:1344: UndefinedMetricWarning:  
Precision and F-score are ill-defined and being set to 0.0 in labels with no  
predicted samples. Use `zero_division` parameter to control this behavior.
```

```
_warn_prf(average, modifier, msg_start, len(result))
```

```
C:\Users\prera\anaconda3\Lib\site-  
packages\sklearn\metrics\_classification.py:1344: UndefinedMetricWarning:  
Precision and F-score are ill-defined and being set to 0.0 in labels with no  
predicted samples. Use `zero_division` parameter to control this behavior.
```

```
_warn_prf(average, modifier, msg_start, len(result))
```

```
[121]: cm=confusion_matrix(y_test,y_pred_2)  
cm
```

```
[121]: array([[47,  0,  0],  
          [ 0, 40,  0],  
          [ 3,  4,  0]], dtype=int64)
```

```
[ ]:
```