Alzheimer_Prediction_with_Demographics_Data____

November 4, 2021

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sn
from sklearn import preprocessing
from sklearn.metrics import log_loss
from sklearn.metrics import confusion_matrix
import sklearn.metrics as metrics
from sklearn.metrics import plot_confusion_matrix
from sklearn.metrics import classification_report
%matplotlib inline
```

Load The data files Display data frame head

[2]:
```
data_frame = pd.read_excel('C:/Users/amran/Downloads/
↪oasis_longitudinal_demographics.xlsx')

data_frame.head()
```

[2]:
```
  Subject ID         MRI ID        Group  Visit  MR Delay M/F Hand  Age  EDUC  \
0  OAS2_0001  OAS2_0001_MR1  Nondemented      1         0   M    R   87    14
1  OAS2_0001  OAS2_0001_MR2  Nondemented      2       457   M    R   88    14
2  OAS2_0002  OAS2_0002_MR1     Demented      1         0   M    R   75    12
3  OAS2_0002  OAS2_0002_MR2     Demented      2       560   M    R   76    12
4  OAS2_0002  OAS2_0002_MR3     Demented      3      1895   M    R   80    12

   SES  MMSE  CDR         eTIV      nWBV       ASF
0  2.0  27.0  0.0  1986.550000  0.696106  0.883440
1  2.0  30.0  0.0  2004.479526  0.681062  0.875539
2  NaN  23.0  0.5  1678.290000  0.736336  1.045710
3  NaN  28.0  0.5  1737.620000  0.713402  1.010000
4  NaN  22.0  0.5  1697.911134  0.701236  1.033623
```

Data pre-processing and selection Lets first look at columns data types

[3]:
```
data_frame.dtypes
```

[3]:
```
Subject ID     object
MRI ID         object
Group          object
Visit           int64
MR Delay        int64
M/F            object
Hand           object
Age             int64
EDUC            int64
SES           float64
MMSE          float64
CDR           float64
eTIV          float64
nWBV          float64
ASF           float64
dtype: object
```

[4]:
```
data_frame.info()
```

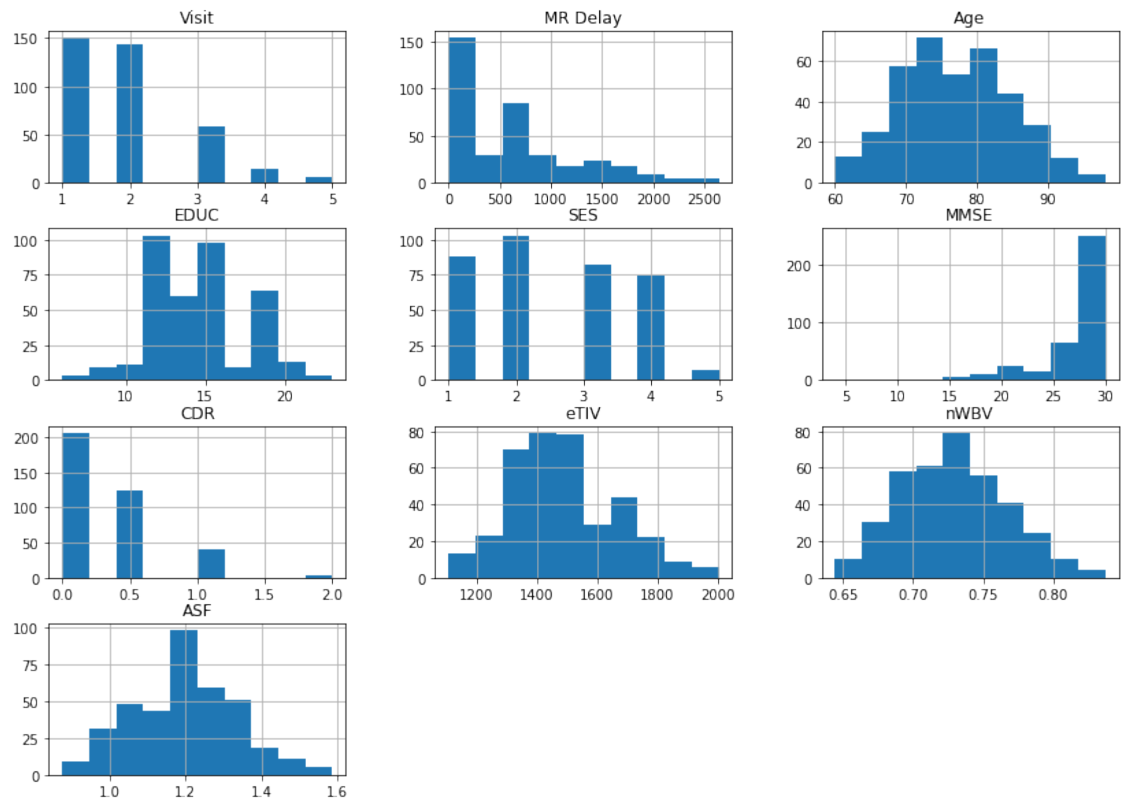
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 373 entries, 0 to 372
Data columns (total 15 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Subject ID  373 non-null    object
 1   MRI ID      373 non-null    object
 2   Group       373 non-null    object
 3   Visit       373 non-null    int64
 4   MR Delay    373 non-null    int64
 5   M/F         373 non-null    object
 6   Hand        373 non-null    object
 7   Age         373 non-null    int64
 8   EDUC        373 non-null    int64
 9   SES         354 non-null    float64
 10  MMSE        371 non-null    float64
 11  CDR         373 non-null    float64
 12  eTIV        373 non-null    float64
 13  nWBV        373 non-null    float64
 14  ASF         373 non-null    float64
dtypes: float64(6), int64(4), object(5)
memory usage: 43.8+ KB
```

Histogram

[5]:
```
data_frame.hist(figsize =(14,10))
```

[5]:
```
array([[<AxesSubplot:title={'center':'Visit'}>,
        <AxesSubplot:title={'center':'MR Delay'}>,
```

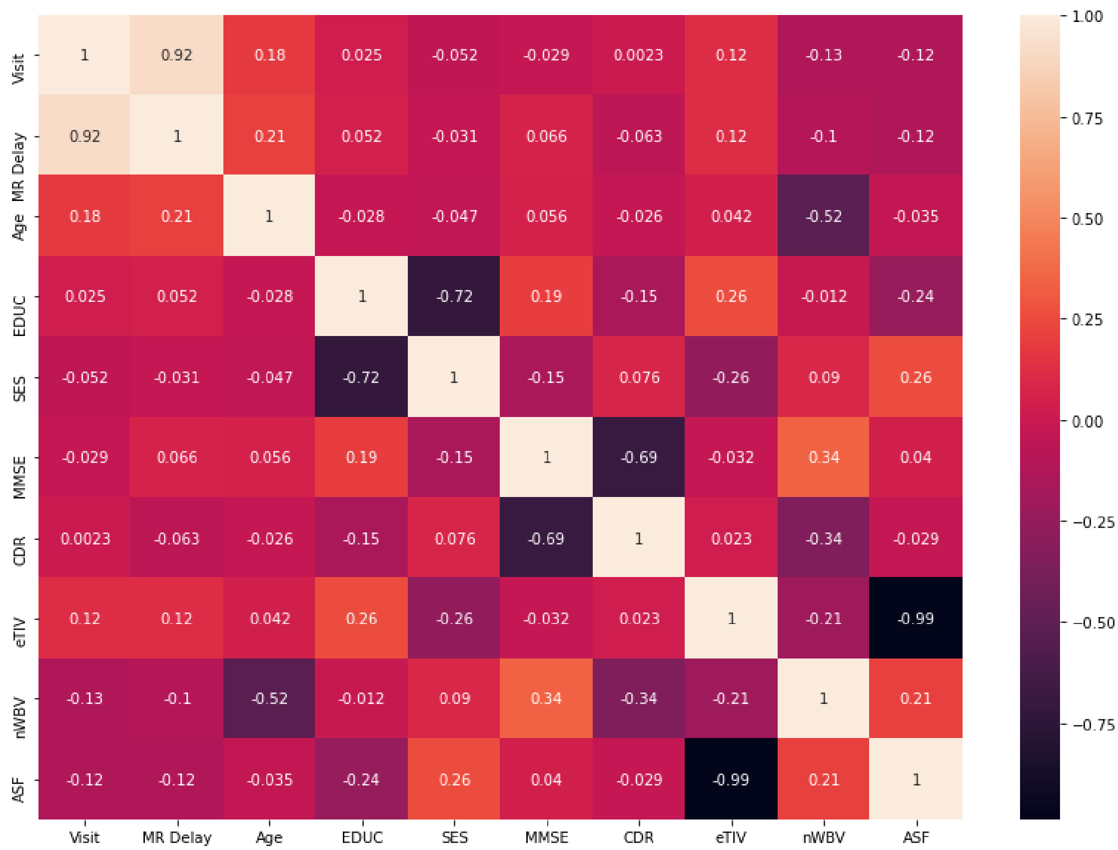
```
 <AxesSubplot:title={'center':'Age'}>],
[<AxesSubplot:title={'center':'EDUC'}>,
 <AxesSubplot:title={'center':'SES'}>,
 <AxesSubplot:title={'center':'MMSE'}>],
[<AxesSubplot:title={'center':'CDR'}>,
 <AxesSubplot:title={'center':'eTIV'}>,
 <AxesSubplot:title={'center':'nWBV'}>],
[<AxesSubplot:title={'center':'ASF'}>, <AxesSubplot:>,
 <AxesSubplot:>]], dtype=object)
```



Correlation Heatmap

[6]:
```python
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize = (14,10))

sns.heatmap(data_frame[data_frame.columns].corr(), annot=True)
```

[6]: `<AxesSubplot:>`



Dealing the missing values

[7]:
```
missing_data = data_frame.isnull()
missing_data.head()
```

[7]:
```
  Subject ID  MRI ID  Group  Visit  MR Delay    M/F   Hand    Age   EDUC  \
0      False   False  False  False     False  False  False  False  False
1      False   False  False  False     False  False  False  False  False
2      False   False  False  False     False  False  False  False  False
3      False   False  False  False     False  False  False  False  False
4      False   False  False  False     False  False  False  False  False

     SES   MMSE    CDR   eTIV   nWBV    ASF
0  False  False  False  False  False  False
1  False  False  False  False  False  False
2   True  False  False  False  False  False
3   True  False  False  False  False  False
4   True  False  False  False  False  False
```

Count missing values in each column

[8]:
```
for column in missing_data.columns.values.tolist():
    print(column)
    print(missing_data[column].value_counts())
    print(" ")
```

```
Subject ID
False    373
Name: Subject ID, dtype: int64

MRI ID
False    373
Name: MRI ID, dtype: int64

Group
False    373
Name: Group, dtype: int64

Visit
False    373
Name: Visit, dtype: int64

MR Delay
False    373
Name: MR Delay, dtype: int64

M/F
False    373
Name: M/F, dtype: int64

Hand
False    373
Name: Hand, dtype: int64

Age
False    373
Name: Age, dtype: int64

EDUC
False    373
Name: EDUC, dtype: int64

SES
False    354
True      19
Name: SES, dtype: int64

MMSE
False    371
```

```
True       2
Name: MMSE, dtype: int64

CDR
False    373
Name: CDR, dtype: int64

eTIV
False    373
Name: eTIV, dtype: int64

nWBV
False    373
Name: nWBV, dtype: int64

ASF
False    373
Name: ASF, dtype: int64
```

SES have 19 missing value and MMSE have 2 missing Value replace missing values

[9]:
```
# check the details value of SES
data_frame['SES'].value_counts()
```

[9]:
```
2.0    103
1.0     88
3.0     82
4.0     74
5.0      7
Name: SES, dtype: int64
```

[10]:
```
#Here 2 is most common values. use the ".idxmax()" method to calculate for us␣
↪the most common type automatically:

data_frame['SES'].value_counts().idxmax()
```

[10]:
```
2.0
```

[11]:
```
#replace null with most common values
data_frame['SES'].fillna(2.0, inplace=True)
```

[12]:
```
#check the details value of MMSE
data_frame['MMSE'].value_counts()
```

[12]:
```
30.0    114
29.0     91
28.0     45
```

```
27.0     32
26.0     20
25.0     12
23.0     11
21.0     11
20.0      7
22.0      7
17.0      5
24.0      4
16.0      3
19.0      3
18.0      2
15.0      2
7.0       1
4.0       1
Name: MMSE, dtype: int64
```

[13]:
```
#30 is the most common value. We can also use the ".idxmax()" method to␣
↪calculate for us the most common type automatically:
data_frame['MMSE'].value_counts().idxmax()
```

[13]:
```
30.0
```

[14]:
```
#replace null with most common values
data_frame['MMSE'].fillna(30,inplace=True)
```

[15]:
```
missing_data = data_frame.isnull()
missing_data.head()
```

[15]:
```
   Subject ID  MRI ID  Group  Visit  MR Delay    M/F   Hand    Age   EDUC  \
0       False   False  False  False     False  False  False  False  False
1       False   False  False  False     False  False  False  False  False
2       False   False  False  False     False  False  False  False  False
3       False   False  False  False     False  False  False  False  False
4       False   False  False  False     False  False  False  False  False

     SES   MMSE    CDR   eTIV   nWBV    ASF
0  False  False  False  False  False  False
1  False  False  False  False  False  False
2  False  False  False  False  False  False
3  False  False  False  False  False  False
4  False  False  False  False  False  False
```

[16]:
```
missing_data.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    bool
 1   MRI ID      373 non-null    bool
 2   Group       373 non-null    bool
 3   Visit       373 non-null    bool
 4   MR Delay    373 non-null    bool
 5   M/F         373 non-null    bool
 6   Hand        373 non-null    bool
 7   Age         373 non-null    bool
 8   EDUC        373 non-null    bool
 9   SES         373 non-null    bool
 10  MMSE        373 non-null    bool
 11  CDR         373 non-null    bool
 12  eTIV        373 non-null    bool
 13  nWBV        373 non-null    bool
 14  ASF         373 non-null    bool
dtypes: bool(15)
memory usage: 5.6 KB
```

[17]:
```python
for column in missing_data.columns.values.tolist():
    print(column)
    print(missing_data[column].value_counts())
    print(" ")
```

```
Subject ID
False    373
Name: Subject ID, dtype: int64

MRI ID
False    373
Name: MRI ID, dtype: int64

Group
False    373
Name: Group, dtype: int64

Visit
False    373
Name: Visit, dtype: int64

MR Delay
False    373
Name: MR Delay, dtype: int64

M/F
False    373
Name: M/F, dtype: int64
```

```
Hand
False    373
Name: Hand, dtype: int64

Age
False    373
Name: Age, dtype: int64

EDUC
False    373
Name: EDUC, dtype: int64

SES
False    373
Name: SES, dtype: int64

MMSE
False    373
Name: MMSE, dtype: int64

CDR
False    373
Name: CDR, dtype: int64

eTIV
False    373
Name: eTIV, dtype: int64

nWBV
False    373
Name: nWBV, dtype: int64

ASF
False    373
Name: ASF, dtype: int64
```

Let's see how many of each class is in our data set

[18]:
```
data_frame['Subject ID'].value_counts()
```

[18]:
```
OAS2_0073    5
OAS2_0048    5
OAS2_0127    5
OAS2_0070    5
OAS2_0037    4
            ..
```

```
OAS2_0128    2
OAS2_0120    2
OAS2_0112    2
OAS2_0086    2
OAS2_0063    2
Name: Subject ID, Length: 150, dtype: int64
```

[19]:
```
# check the total number of subject
data_frame['Subject ID'].nunique()
```

[19]:
```
150
```

[20]:
```
data_frame['Group'].value_counts()
```

[20]:
```
Nondemented    190
Demented       146
Converted       37
Name: Group, dtype: int64
```

Check for male and female

[21]:
```
data_frame.groupby(['M/F','Group'])['Subject ID'].nunique()
```

[21]:
```
M/F  Group
F    Converted      10
     Demented       28
     Nondemented    50
M    Converted       4
     Demented       36
     Nondemented    22
Name: Subject ID, dtype: int64
```

Group by Male female and Subject ID

[22]:
```
data_frame_sub =data_frame.groupby(['M/F','Group'])
```

[23]:
```
data_frame_sub= data_frame_sub.agg({'Subject ID':'nunique'})
```

[24]:
```
data_frame_sub.head()
```

[24]:
```
                 Subject ID
M/F Group
F   Converted            10
    Demented             28
    Nondemented          50
M   Converted             4
    Demented             36
```

[25]:
```python
# Change M to 1 and F to 0
data_frame['M/F'] = data_frame['M/F'].replace(['F','M'], [0,1])
```

[26]:
```python
# Hand cloumn value to numaric data R to 1 and L to 0
data_frame['Hand'] = data_frame['Hand'].replace(['L','R'], [0,1]) # Hand column
```

[27]:
```python
# Group :Replace Converted to Demented
data_frame['Group'] = data_frame['Group'].replace(['Converted'], ['Demented'])
```

[28]:
```python
data_frame.head()
```

[28]:
```
  Subject ID         MRI ID        Group  Visit  MR Delay  M/F  Hand  Age  \
0  OAS2_0001  OAS2_0001_MR1  Nondemented      1         0    1     1   87
1  OAS2_0001  OAS2_0001_MR2  Nondemented      2       457    1     1   88
2  OAS2_0002  OAS2_0002_MR1     Demented      1         0    1     1   75
3  OAS2_0002  OAS2_0002_MR2     Demented      2       560    1     1   76
4  OAS2_0002  OAS2_0002_MR3     Demented      3      1895    1     1   80

   EDUC  SES  MMSE  CDR         eTIV      nWBV       ASF
0    14  2.0  27.0  0.0  1986.550000  0.696106  0.883440
1    14  2.0  30.0  0.0  2004.479526  0.681062  0.875539
2    12  2.0  23.0  0.5  1678.290000  0.736336  1.045710
3    12  2.0  28.0  0.5  1737.620000  0.713402  1.010000
4    12  2.0  22.0  0.5  1697.911134  0.701236  1.033623
```

[29]:
```python
data_frame.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       373 non-null    int64
 4   MR Delay    373 non-null    int64
 5   M/F         373 non-null    int64
 6   Hand        373 non-null    int64
 7   Age         373 non-null    int64
 8   EDUC        373 non-null    int64
 9   SES         373 non-null    float64
 10  MMSE        373 non-null    float64
 11  CDR         373 non-null    float64
 12  eTIV        373 non-null    float64
 13  nWBV        373 non-null    float64
 14  ASF         373 non-null    float64
dtypes: float64(6), int64(6), object(3)
```

memory usage: 43.8+ KB

New dataframe for male female group with Unique Subject ID

[30]:
```
data_frame_new = data_frame.groupby(['M/F','Group'])
```

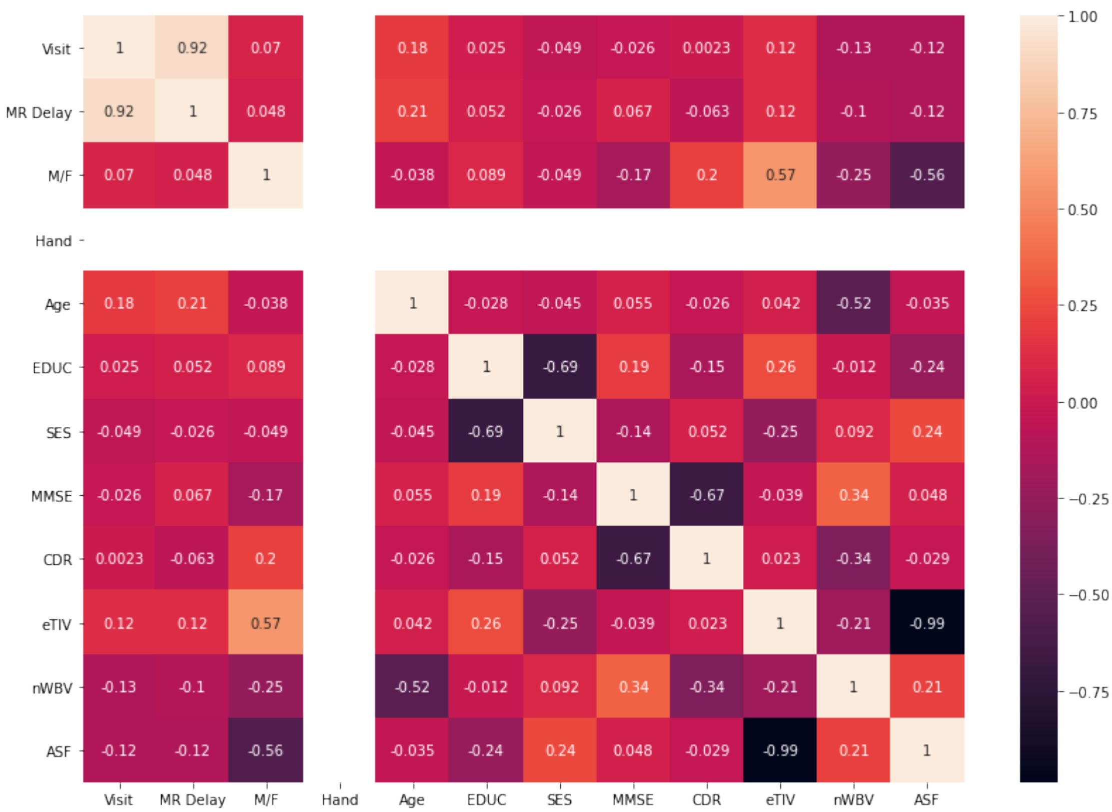
[31]:
```
data_frame_new = data_frame_new.agg({'Subject ID':'nunique'})
```

[32]:
```
data_frame_new.head()
```

[32]:
```
                  Subject ID
M/F Group
0   Demented              38
    Nondemented           50
1   Demented              40
    Nondemented           22
```

[33]:
```
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize = (14,10))

sns.heatmap(data_frame[data_frame.columns].corr(), annot=True)
```

[33]: <AxesSubplot:>



Target value, response variable or dependent variable

[34]:
```
y_data = data_frame['Group']
```

[35]:
```
y_data[0:5]
```

[35]:
```
0    Nondemented
1    Nondemented
2       Demented
3       Demented
4       Demented
Name: Group, dtype: object
```

[36]:
```
# Independent variable or regressor as X
# drop unrelated values
X_data = data_frame.drop(['Subject ID','MRI ID','Group'], axis=1)
X_data.head()
```

[36]:
```
   Visit  MR Delay  M/F  Hand  Age  EDUC  SES  MMSE  CDR         eTIV  \
0      1         0    1     1   87    14  2.0  27.0  0.0  1986.550000
1      2       457    1     1   88    14  2.0  30.0  0.0  2004.479526
2      1         0    1     1   75    12  2.0  23.0  0.5  1678.290000
3      2       560    1     1   76    12  2.0  28.0  0.5  1737.620000
4      3      1895    1     1   80    12  2.0  22.0  0.5  1697.911134

       nWBV       ASF
0  0.696106  0.883440
1  0.681062  0.875539
2  0.736336  1.045710
3  0.713402  1.010000
4  0.701236  1.033623
```

0.0.1 Train and Test Split

[37]:
```
# import train_test_split library
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve, auc

X_train,X_test, y_train, y_test = train_test_split(X_data, y_data, test_size =␣
↪0.33)
print ('Train set:', X_train.shape,  y_train.shape)
print ('Test set:', X_test.shape,  y_test.shape)
```

```
Train set: (249, 12) (249,)
Test set: (124, 12) (124,)
```

Normalize Data Data Standardization give data zero mean and unit variance

[38]:
```python
X_data= preprocessing.StandardScaler().fit(X_data).transform(X_data)
X_data[0:5]
```

[38]:
```
array([[-0.95706686, -0.93771494,  1.15379808,  0.        ,  1.30873772,
        -0.20813199, -0.3944662 , -0.09706416, -0.77765291,  2.83359462,
        -0.90181966, -2.26232493],
       [ 0.12799678, -0.21761337,  1.15379808,  0.        ,  1.43978716,
        -0.20813199, -0.3944662 ,  0.71958842, -0.77765291,  2.93552502,
        -1.30741435, -2.31961167],
       [-0.95706686, -0.93771494,  1.15379808,  0.        , -0.26385558,
        -0.90439416, -0.3944662 , -1.18593426,  0.55905002,  1.08111854,
         0.18280374, -1.08577527],
       [ 0.12799678, -0.05531476,  1.15379808,  0.        , -0.13280614,
        -0.90439416, -0.3944662 ,  0.17515337,  0.55905002,  1.41841305,
        -0.43550978, -1.34469305],
       [ 1.21306043,  2.04826424,  1.15379808,  0.        ,  0.39139163,
        -0.90439416, -0.3944662 , -1.45815179,  0.55905002,  1.19266583,
        -0.76351198, -1.17341289]])
```

0.0.2 Support Vector Machine (SVM)

[39]:
```python
# import SVM library

from sklearn import svm
```

[40]:
```python
svm_clf = svm.SVC(C=1, kernel='linear').fit(X_train, y_train)
```

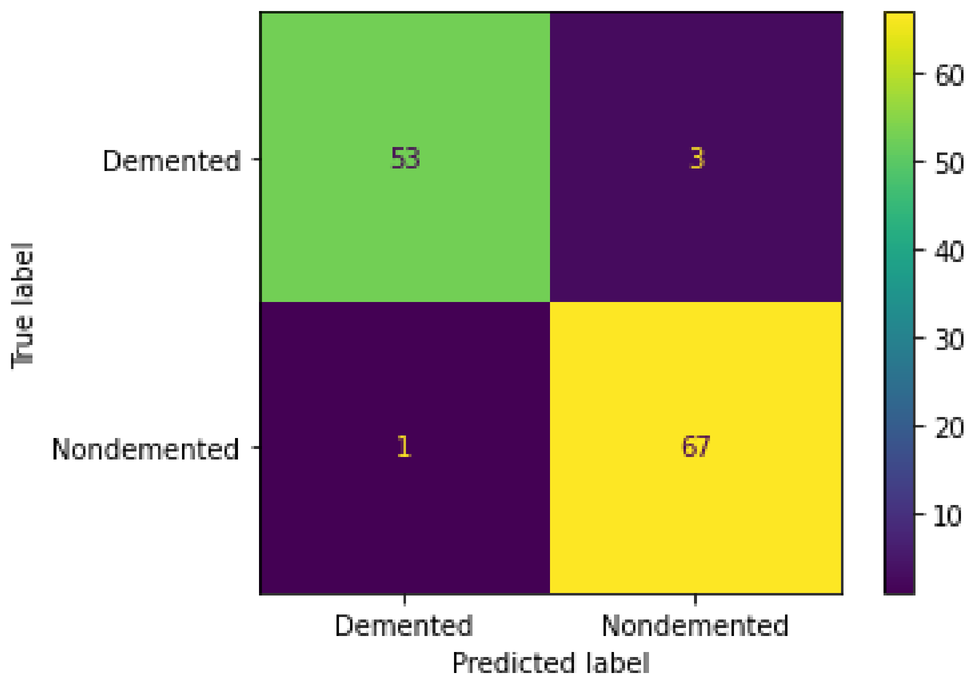
[41]:
```python
yhat_svm = svm_clf.predict(X_test)
```

[42]:
```python
SVM_accuracy_score = accuracy_score(y_test,yhat_svm)*100
print("SVM_accuracy_score:", SVM_accuracy_score)
```

```
SVM_accuracy_score: 96.7741935483871
```

SVM Confusion matrix

[43]:
```python
#confusion_matrix(y_test,yhat_svm)
from sklearn.metrics import confusion_matrix
plot_confusion_matrix(svm_clf, X_test, y_test)
plt.show()
```



[44]:
```
# Confusion matrix using crosstab method of pandas.
svm_pd = pd.crosstab(y_test, yhat_svm, rownames=['True'],␣
↪colnames=['Predicted'], margins=True)
svm_pd
```

[44]:
```
Predicted    Demented  Nondemented  All
True
Demented           53            3   56
Nondemented         1           67   68
All                54           70  124
```

SVM Classification Report

[45]:
```
#print(classification_report(y_test,yhat_svm))

print("confusion matrix\n",confusion_matrix(y_test,yhat_svm))
print("\nclassification report\n",classification_report(y_test,yhat_svm))
print("Accuracy: ",accuracy_score(y_test, yhat_svm)*100)
```

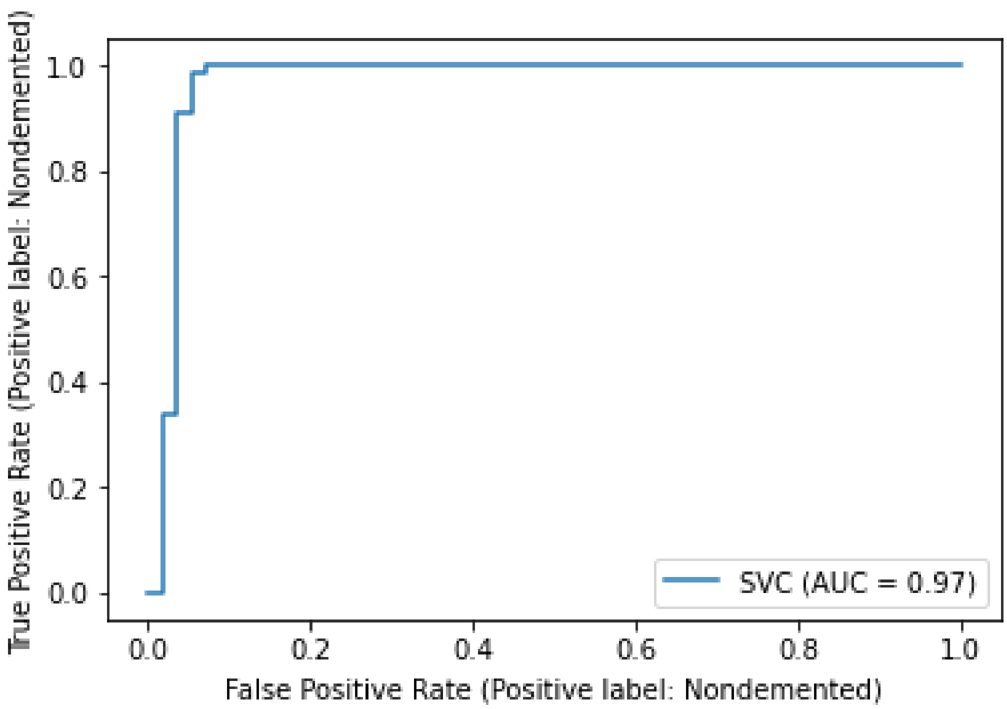
```
confusion matrix
 [[53  3]
 [ 1 67]]

classification report
               precision    recall  f1-score   support
```

```
   Demented       0.98      0.95      0.96        56
Nondemented       0.96      0.99      0.97        68

   accuracy                           0.97       124
  macro avg       0.97      0.97      0.97       124
weighted avg      0.97      0.97      0.97       124

Accuracy:  96.7741935483871
```

[46]:
```
SVM_roc_auc_score = roc_auc_score(y_test, svm_clf.decision_function(X_test),␣
 ↪average=None)
print("SVM_roc_auc_score:", SVM_roc_auc_score)
```

```
SVM_roc_auc_score: 0.9684873949579832
```

[47]:
```
metrics.plot_roc_curve(svm_clf, X_test, y_test)
plt.show()
```



0.0.3 Logistic Regression

[48]:
```
#import Library LogisticRegression
from sklearn.linear_model import LogisticRegression
```

[49]:
```
#Train
lr_clf = LogisticRegression(C=1, solver='liblinear').fit(X_train,y_train)
lr_clf
```

[49]: LogisticRegression(C=1, solver='liblinear')

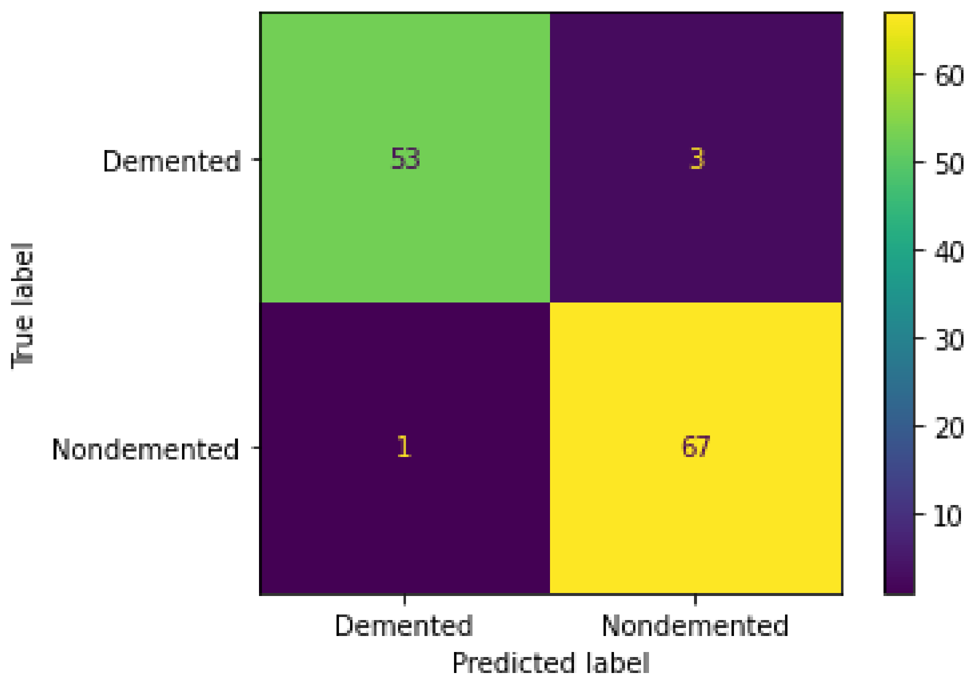
[50]:
```
yhat_lr = lr_clf.predict(X_test)

lr_yhat_prob = lr_clf.predict_proba(X_test)
```

[51]:
```
LR_accuracy_score = accuracy_score(y_test,yhat_lr)*100
print("LR_accuracy_score :",LR_accuracy_score )
```

```
LR_accuracy_score : 96.7741935483871
```

LR Confusion matrix

[52]:
```
#confusion_matrix(y_test,yhat_lr)

plot_confusion_matrix(lr_clf, X_test, y_test)
plt.show()
```



[53]:
```
# Confusion matrix using crosstab method of pandas.
LR_pd = pd.crosstab(y_test, yhat_lr, rownames=['True'], colnames=['Predicted'],␣
↪margins=True)
LR_pd
```

[53]:
```
Predicted    Demented  Nondemented  All
True
Demented           53            3   56
Nondemented         1           67   68
All                54           70  124
```

LR Classification Report

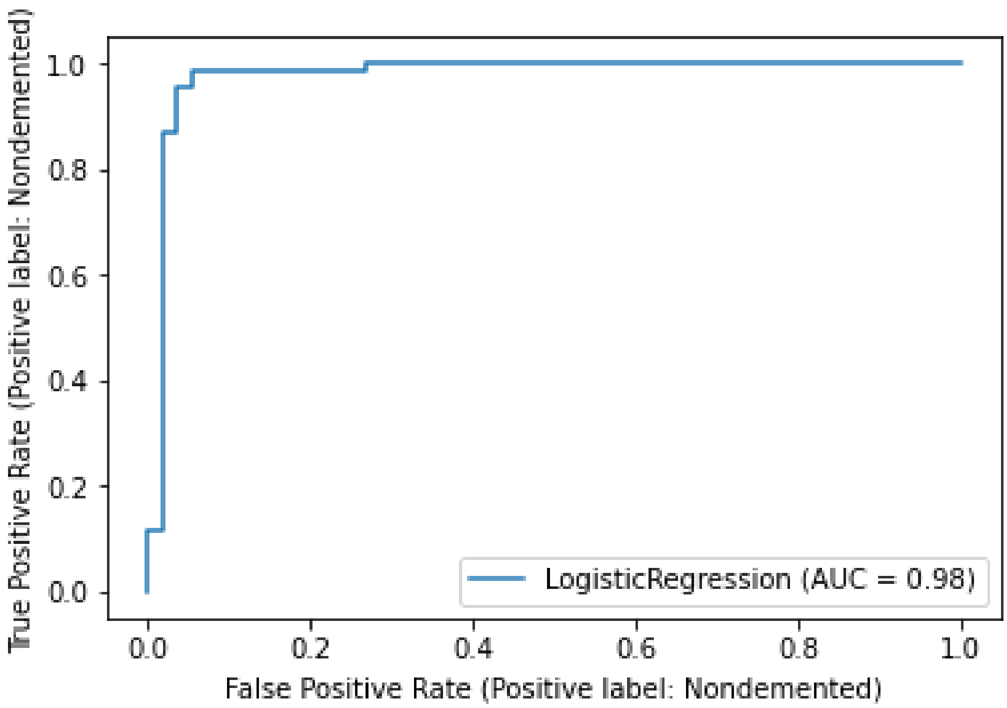
[54]:
```python
#print(classification_report(y_test,yhat_lr))

print("confusion matrix\n",confusion_matrix(y_test,yhat_lr))
print("\nclassification report\n",classification_report(y_test,yhat_lr))
print("Accuracy: ",accuracy_score(y_test, yhat_lr)*100)
```

```
confusion matrix
 [[53  3]
 [ 1 67]]

classification report
               precision    recall  f1-score   support

    Demented       0.98      0.95      0.96        56
 Nondemented       0.96      0.99      0.97        68

    accuracy                           0.97       124
   macro avg       0.97      0.97      0.97       124
weighted avg       0.97      0.97      0.97       124

Accuracy:  96.7741935483871
```

[55]:
```python
LR_roc_auc_score= roc_auc_score(y_test, lr_clf.decision_function(X_test),␣
 ↪average=None)
print("LR_roc_auc_score :",LR_roc_auc_score )
```

```
LR_roc_auc_score : 0.9779411764705883
```

[56]:
```python
 metrics.plot_roc_curve(lr_clf, X_test, y_test)
 plt.show()
```



0.0.4 Random Forest Classifier

[57]:
```
from sklearn.ensemble import RandomForestClassifier

rf_clf = RandomForestClassifier( random_state=0).fit(X_train, y_train)
rf_pred = rf_clf.predict(X_test)
rf_yhat_prob = rf_clf.predict_proba(X_test)
```

[58]:
```
from sklearn.metrics import classification_report, confusion_matrix,␣
↪accuracy_score


print("confusion matrix\n",confusion_matrix(y_test,rf_pred))
print("\nclassification report\n",classification_report(y_test,rf_pred))
print("Accuracy: ",accuracy_score(y_test, rf_pred)*100)
```

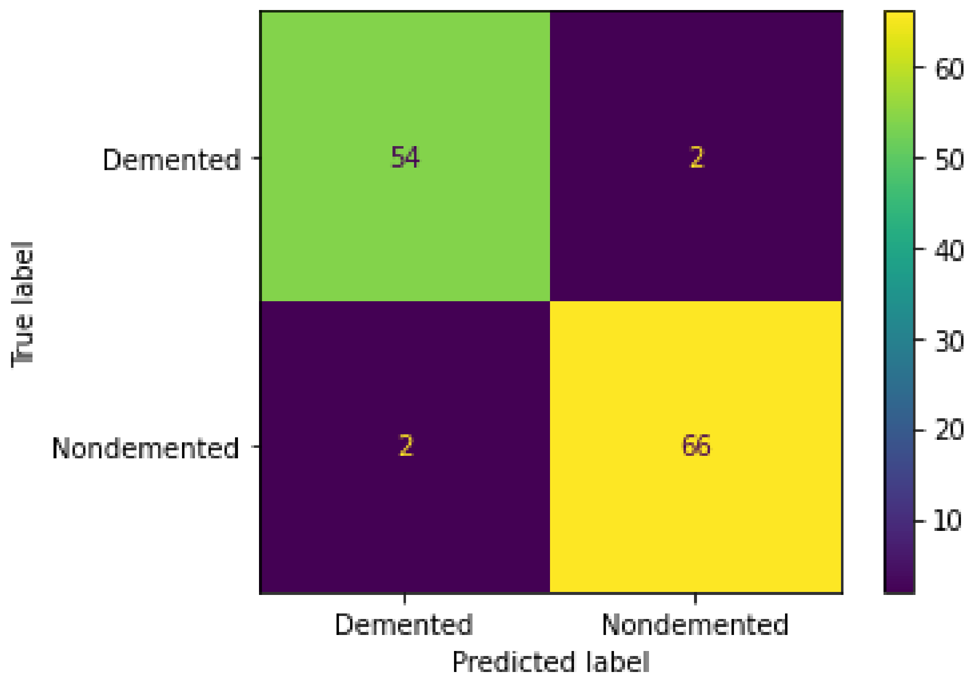
```
confusion matrix
 [[54  2]
 [ 2 66]]

classification report
               precision    recall  f1-score   support

    Demented       0.96      0.96      0.96        56
```

```
 Nondemented       0.97      0.97      0.97        68

    accuracy                           0.97       124
   macro avg       0.97      0.97      0.97       124
weighted avg       0.97      0.97      0.97       124

Accuracy:  96.7741935483871
```

[59]:
```
RF_accuracy_score = accuracy_score(y_test,rf_pred)*100
print("RF_accuracy_score :",RF_accuracy_score )
```

```
RF_accuracy_score : 96.7741935483871
```

[60]:
```
plot_confusion_matrix(rf_clf, X_test, y_test)
plt.show()
```



[61]:
```
# Confusion matrix using crosstab method of pandas.
RF_pd = pd.crosstab(y_test, rf_pred, rownames=['True'], colnames=['Predicted'],␣
 ↪margins=True)
RF_pd
```

[61]:

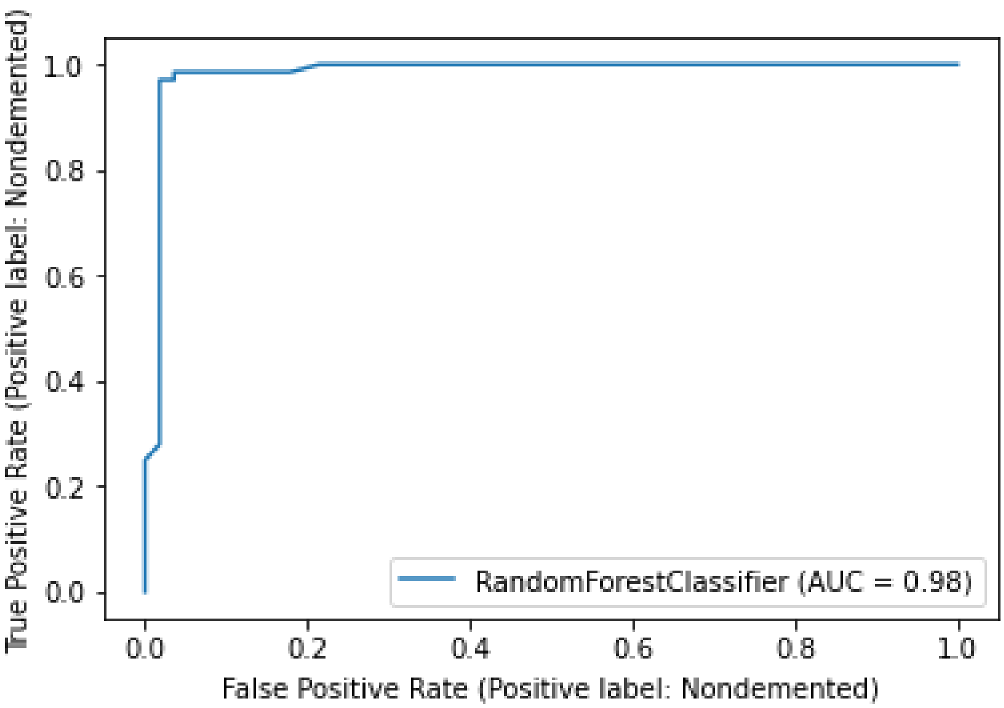
Predicted	Demented	Nondemented	All
True			
Demented	54	2	56
Nondemented	2	66	68

```
All                   56             68   124
```

[62]:
```
RF_roc_auc_score= roc_auc_score(y_test, rf_clf.predict_proba(X_test)[:,1],␣
↪average=None)
print("RF roc_auc score :",RF_roc_auc_score )
```

```
RF roc_auc score : 0.9839810924369747
```

[63]:
```
metrics.plot_roc_curve(rf_clf, X_test, y_test)

plt.show()
```



0.0.5 Naive Bayes

[64]:
```
from sklearn.naive_bayes import GaussianNB
```

[65]:
```
gnb_clf = GaussianNB()
```

[66]:
```
y_pred_gnb = gnb_clf.fit(X_train, y_train).predict(X_test)
```

[67]:
```
#yhat_gnb = gnb.predict(X_test)

gnb_yhat_prob = gnb_clf.predict_proba(X_test)
```

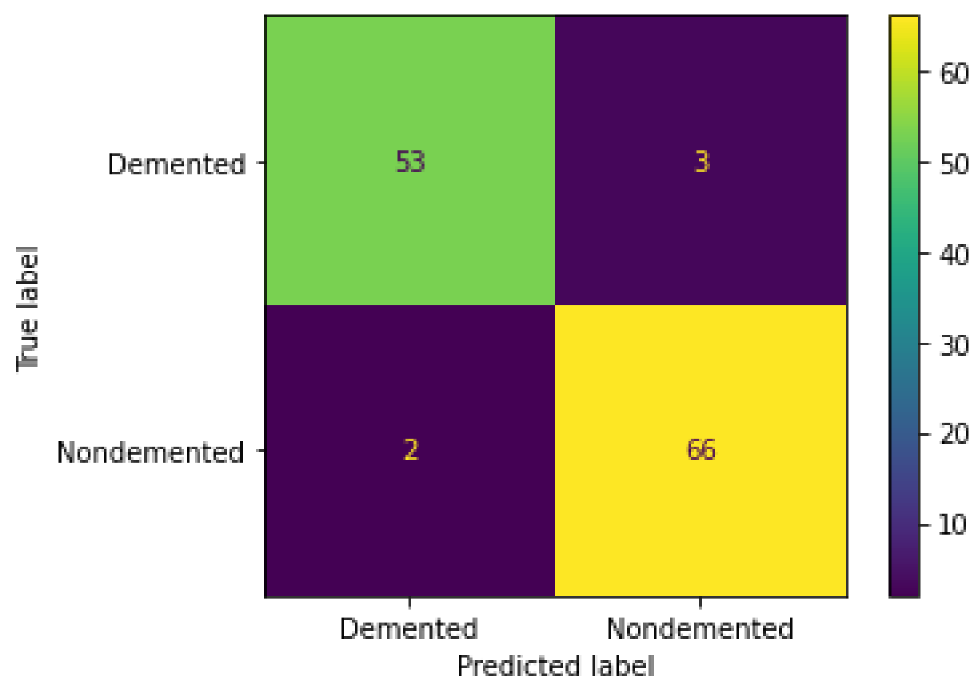
[68]:
```
gnb_Accuracy_score = metrics.accuracy_score(y_test, y_pred_gnb)*100
gnb_Accuracy_score
```

[68]: 95.96774193548387

[69]:
```
print("confusion matrix\n",confusion_matrix(y_test,y_pred_gnb))
print("\nclassification report\n",classification_report(y_test,y_pred_gnb))
print("Accuracy: ",accuracy_score(y_test, y_pred_gnb)*100)
```

```
confusion matrix
 [[53  3]
 [ 2 66]]

classification report
               precision    recall  f1-score   support

    Demented       0.96      0.95      0.95        56
 Nondemented       0.96      0.97      0.96        68

    accuracy                           0.96       124
   macro avg       0.96      0.96      0.96       124
weighted avg       0.96      0.96      0.96       124

Accuracy:  95.96774193548387
```

[70]:
```
plot_confusion_matrix(gnb_clf, X_test, y_test)
plt.show()
```

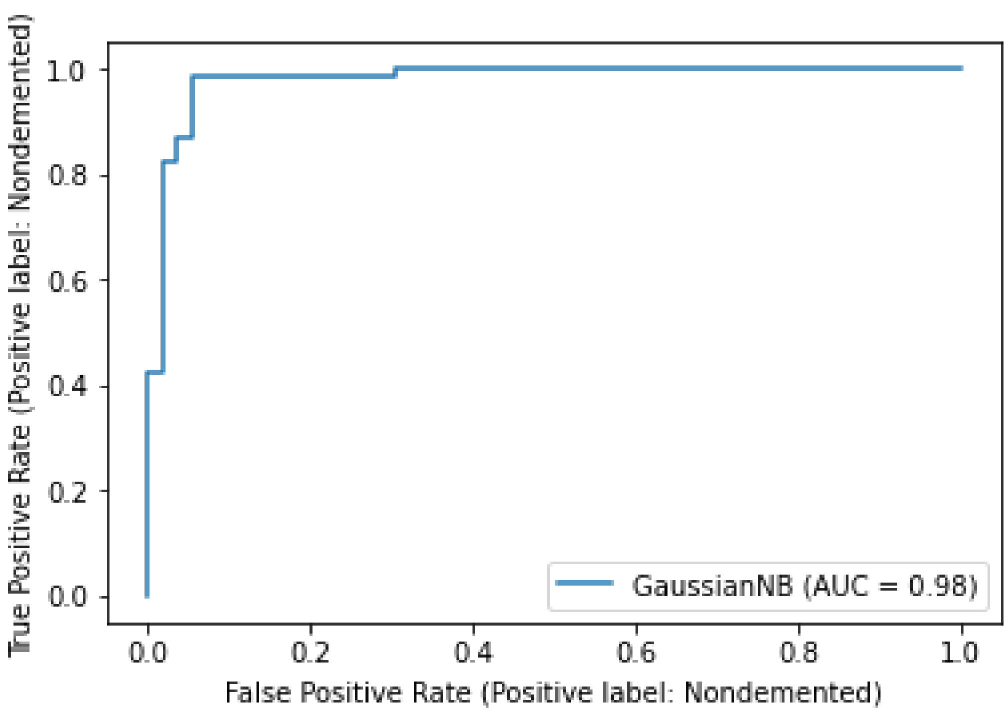


[71]:
```
# Confusion matrix using crosstab method of pandas.
GNV_pd = pd.crosstab(y_test, y_pred_gnb, rownames=['True'],␣
↪colnames=['Predicted'], margins=True)
GNV_pd
```

[71]:

Predicted	Demented	Nondemented	All
True			
Demented	53	3	56
Nondemented	2	66	68
All	55	69	124

[72]:
```
metrics.plot_roc_curve(gnb_clf, X_test, y_test)

plt.show()
```



[73]:
```
gnb_roc_auc_score= roc_auc_score(y_test, gnb_clf.predict_proba(X_test)[:,1],␣
↪average=None)
print("GNB roc_auc score :",gnb_roc_auc_score )
```

```
GNB roc_auc score : 0.9805672268907563
```

0.0.6 Ada Boosting

[74]:
```
from sklearn.ensemble import AdaBoostClassifier

ada_clf = AdaBoostClassifier(n_estimators=100, random_state=42)
ada_clf.fit(X_train, y_train)
```

[74]:
```
AdaBoostClassifier(n_estimators=100, random_state=42)
```

[75]:
```
yhat_ada = ada_clf.predict(X_test)

#yhat_ada
```

[76]:
```
ada_yhat_prob = ada_clf.predict_proba(X_test)
#ada_yhat_prob
```

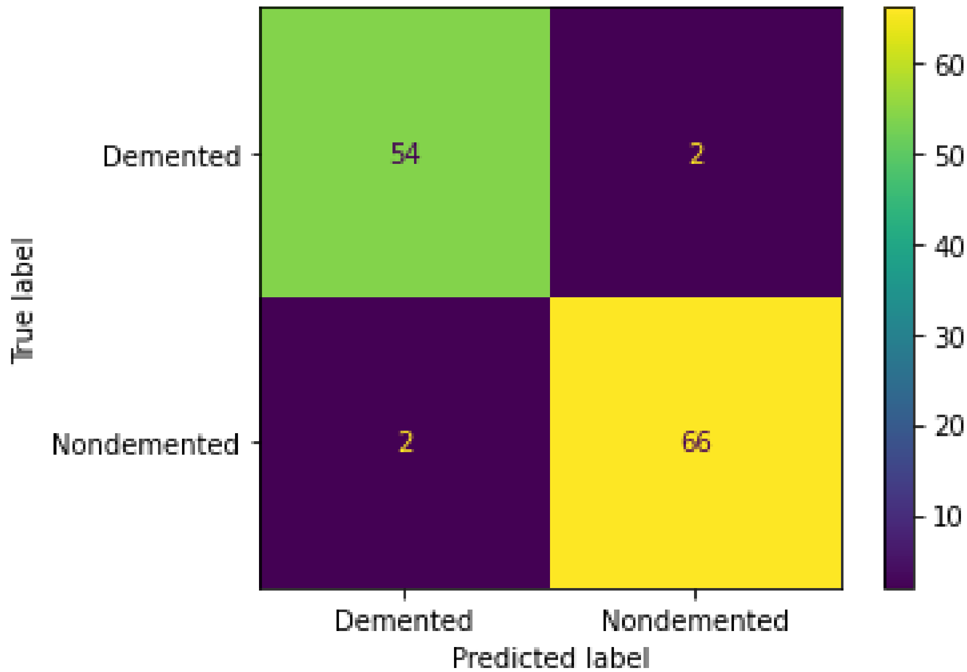
[77]:
```
ada_accuracy_score =accuracy_score(y_test, yhat_ada)*100
print("ada_accuracy_score :", ada_accuracy_score )
```

```
ada_accuracy_score : 96.7741935483871
```

[78]:
```
from sklearn.metrics import classification_report, confusion_matrix,␣
↪accuracy_score

print("confusion matrix\n",confusion_matrix(y_test,yhat_ada))
print("\nclassification report\n",classification_report(y_test,yhat_ada))
print("Accuracy: ",accuracy_score(y_test, yhat_ada)*100)
```

```
confusion matrix
 [[54  2]
 [ 2 66]]

classification report
               precision    recall  f1-score   support

    Demented       0.96      0.96      0.96        56
 Nondemented       0.97      0.97      0.97        68

    accuracy                           0.97       124
   macro avg       0.97      0.97      0.97       124
weighted avg       0.97      0.97      0.97       124

Accuracy:  96.7741935483871
```

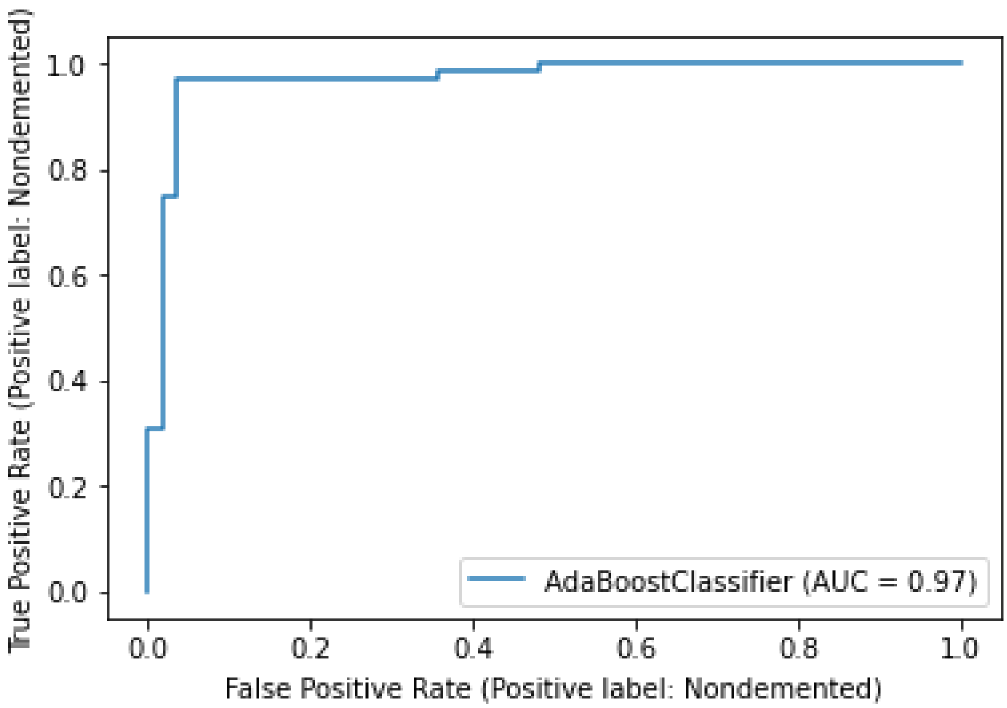
[79]:
```
plot_confusion_matrix(ada_clf, X_test, y_test)
plt.show()
```



[80]:
```
# Confusion matrix using crosstab method of pandas.
ada_pd = pd.crosstab(y_test, yhat_ada, rownames=['True'],
 ↪colnames=['Predicted'], margins=True)
ada_pd
```

[80]:
```
Predicted    Demented  Nondemented  All
True
Demented           54            2   56
Nondemented         2           66   68
All                56           68  124
```

[81]:
```
metrics.plot_roc_curve(ada_clf, X_test, y_test)

plt.show()
```



[82]:
```
ada_roc_auc_score= roc_auc_score(y_test, ada_clf.decision_function(X_test),␣
 ↪average=None)
print("ada_roc_auc_score :",ada_roc_auc_score )
```

```
ada_roc_auc_score : 0.9719012605042017
```

0.0.7 Gradient boosting

[83]:
```
from sklearn.ensemble import GradientBoostingClassifier
```

[84]:
```
Gra_clf = GradientBoostingClassifier(n_estimators=100, learning_rate=1.0,
                                     max_depth=1, random_state=0).fit(X_train,␣
 ↪y_train)
```

[85]:
```
Gra_clf.score(X_test, y_test)
```

[85]: 0.9758064516129032

[86]:
```
yhat_Gra_cl = Gra_clf.predict(X_test)

Gra_yhat_prob = Gra_clf.predict_proba(X_test)
```

[87]:
```
#print(accuracy_score(y_test, yhat_Gra_cl)*100)
#print(accuracy_score(y_test, yhat_Gra_cl))
```

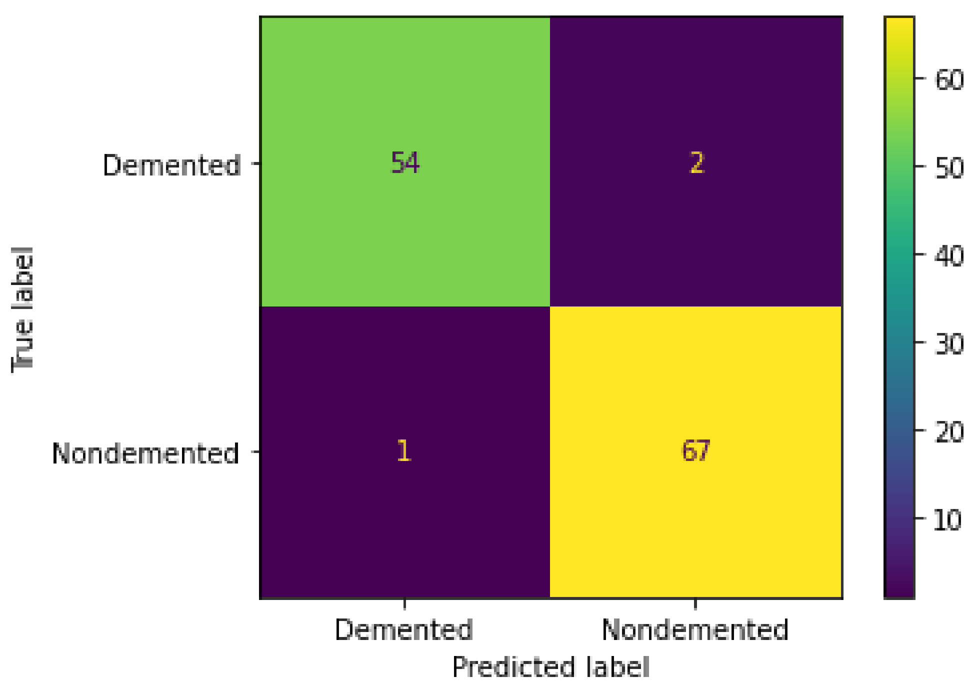
```
gra_accuracy_score = Gra_clf.score(X_test, y_test)*100
print("gra_accuracy_score :", gra_accuracy_score )
```

```
gra_accuracy_score : 97.58064516129032
```

[88]:
```
print("confusion matrix\n",confusion_matrix(y_test,yhat_Gra_cl))
print("\nclassification report\n",classification_report(y_test,yhat_Gra_cl))
print("Accuracy: ",accuracy_score(y_test, yhat_Gra_cl)*100)
```

```
confusion matrix
 [[54  2]
 [ 1 67]]

classification report
               precision    recall  f1-score   support

    Demented       0.98      0.96      0.97        56
 Nondemented       0.97      0.99      0.98        68

    accuracy                           0.98       124
   macro avg       0.98      0.97      0.98       124
weighted avg       0.98      0.98      0.98       124

Accuracy:  97.58064516129032
```

[89]:
```
plot_confusion_matrix(Gra_clf, X_test, y_test)
plt.show()
```

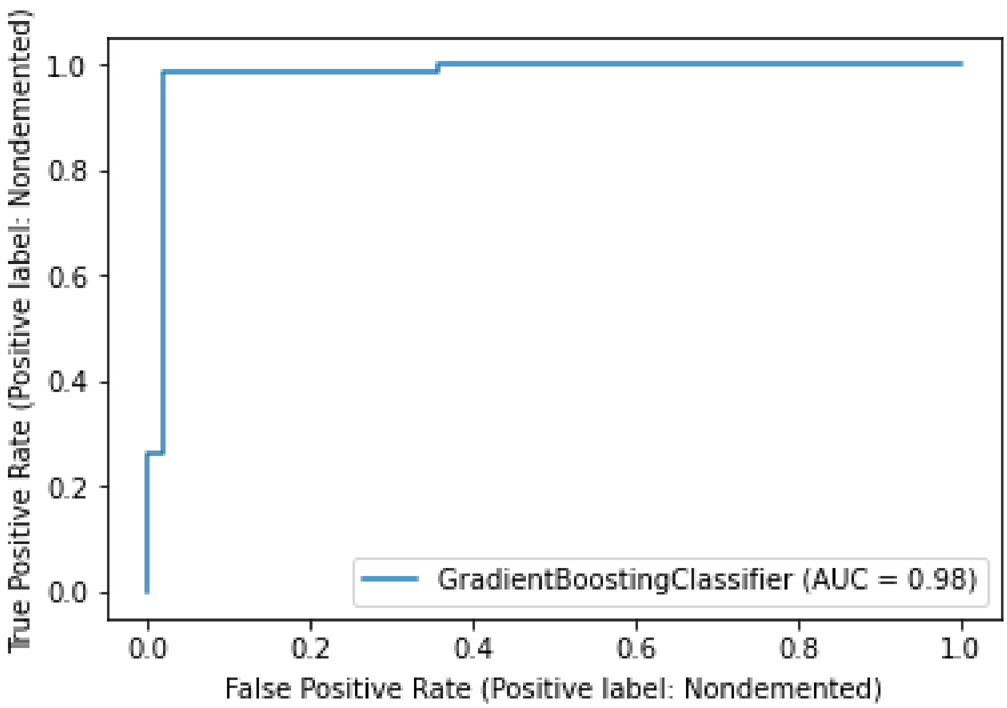


[90]:
```
# Confusion matrix using crosstab method of pandas.
Gra_pd = pd.crosstab(y_test, yhat_Gra_cl, rownames=['True'],␣
↪colnames=['Predicted'], margins=True)
Gra_pd
```

[90]:

Predicted	Demented	Nondemented	All
True			
Demented	54	2	56
Nondemented	1	67	68
All	55	69	124

[91]:
```
metrics.plot_roc_curve(Gra_clf, X_test, y_test)

plt.show()
```



[92]:
```
gra_roc_auc_score= roc_auc_score(y_test, Gra_clf.decision_function(X_test),␣
↪average=None)
print("gra_roc_auc_score :",gra_roc_auc_score )
```

```
gra_roc_auc_score : 0.9818802521008403
```

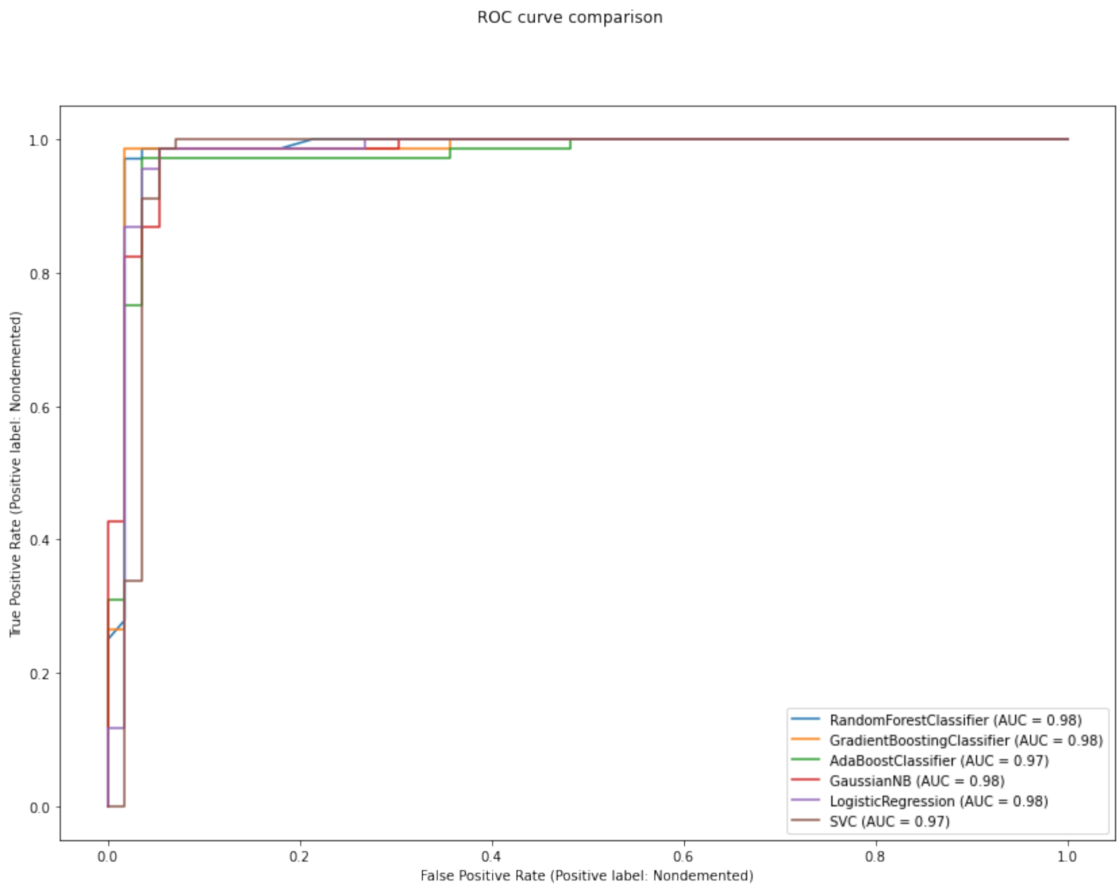
0.0.8 Results

Accuracy score report dataframe

[102]:
```
# create a accuracy list
accuracy_score = [␣
↪SVM_accuracy_score,LR_accuracy_score,RF_accuracy_score,gnb_Accuracy_score,ada_accuracy_scor

# create a AUC-score list
auc_score =␣
↪[SVM_roc_auc_score,LR_roc_auc_score,RF_roc_auc_score,gnb_roc_auc_score,ada_roc_auc_score,gr



# fomulate the report format
df_report = pd.DataFrame(accuracy_score, index=['SVM','Logistic␣
↪Regression','Random Forest','Naive Bayes','Ada Boosting','Gradient␣
↪boosting',])
df_report.columns = ['Accuracy Score']
df_report.insert(loc=1, column='ROC AUC Score', value= auc_score)
df_report.columns.name = 'Algorithm'
df_report
```

[102]:
```
Algorithm            Accuracy Score ROC AUC Score
SVM                       96.774194      0.968487
Logistic Regression       96.774194      0.977941
Random Forest             96.774194      0.983981
Naive Bayes               95.967742      0.980567
Ada Boosting              96.774194      0.971901
Gradient boosting         97.580645       0.98188
EVM                       96.774194            NA
```

[103]:
```
fig = metrics.plot_roc_curve(rf_clf, X_test, y_test)
fig = metrics.plot_roc_curve(Gra_clf, X_test, y_test,ax = fig.ax_ )
fig = metrics.plot_roc_curve(ada_clf, X_test, y_test,ax = fig.ax_ )
fig = metrics.plot_roc_curve(gnb_clf, X_test, y_test,ax = fig.ax_ )
#metrics.plot_roc_curve(rf_regressor, X_test, y_test)
fig = metrics.plot_roc_curve(lr_clf, X_test, y_test,ax = fig.ax_ )
fig = metrics.plot_roc_curve(svm_clf, X_test, y_test,ax = fig.ax_ )


fig.figure_.suptitle("ROC curve comparison")
fig.figure_.set_size_inches(14,10)
plt.show()
```


ROC curve comparison
RandomForestClassifier (AUC = 0.98)
GradientBoostingClassifier (AUC = 0.98)
AdaBoostClassifier (AUC = 0.97)
GaussianNB (AUC = 0.98)
LogisticRegression (AUC = 0.98)
SVC (AUC = 0.97)
True Positive Rate (Positive label: Nondemented)
False Positive Rate (Positive label: Nondemented)