Alzheimer_classification_with_Demographics_Data_NestedNonnestedCV

November 10, 2021

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

from numpy import mean

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

from sklearn.model_selection import GridSearchCV, cross_val_score, KFold

%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
```

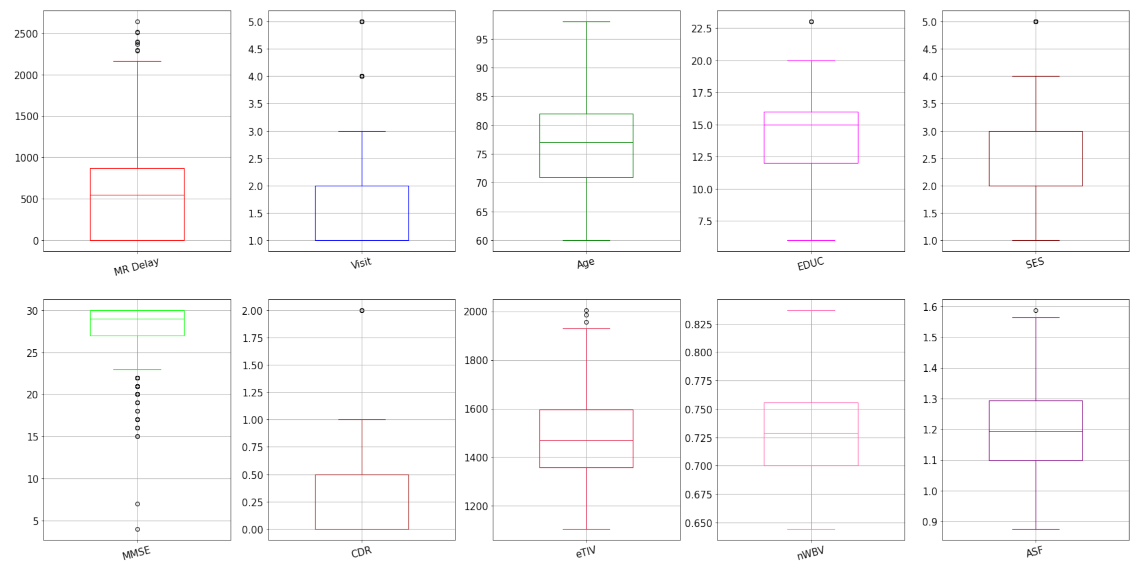
[3]:
```
Subject ID     object
MRI ID         object
Group          object
Visit           int64
MR Delay        int64
M/F            object
Hand           object
Age             int64
EDUC            int64
SES           float64
MMSE          float64
CDR           float64
eTIV          float64
nWBV 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

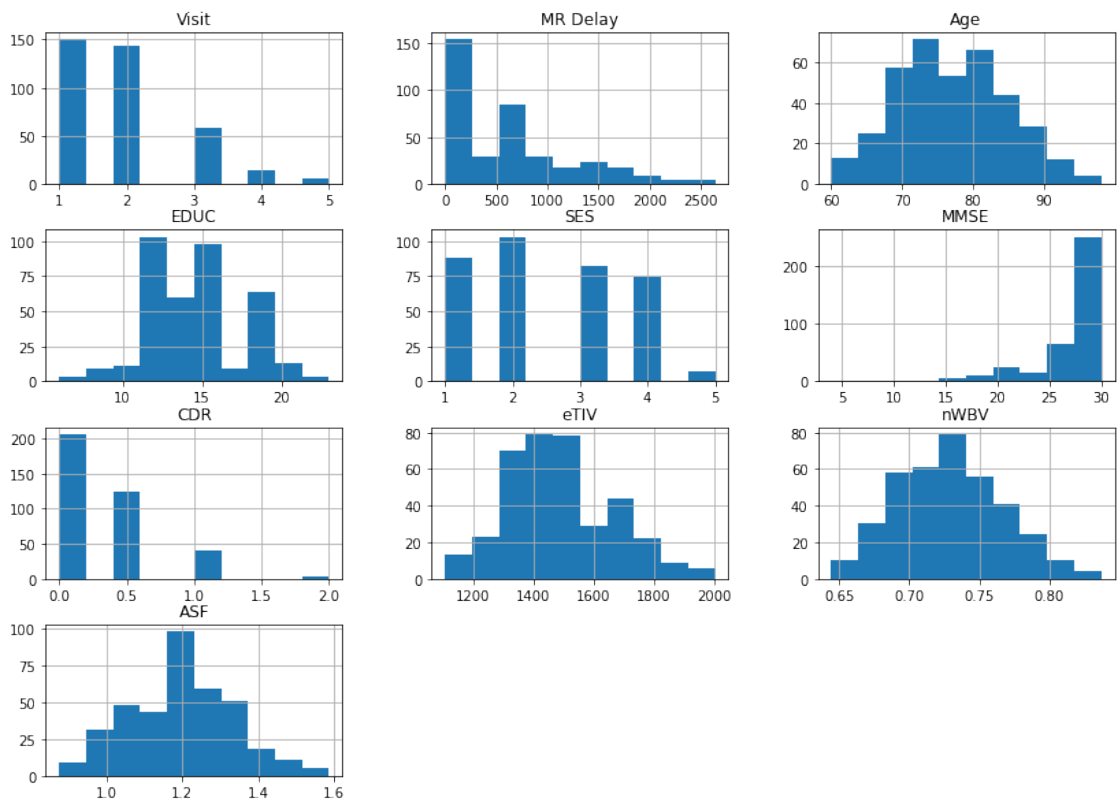
[5]:
```
fig,axs = plt.subplots(2,5,figsize =(30,15))
boxplot_mrdelay = data_frame.boxplot(column=['MR Delay'], rot=15, widths=.
↪5,fontsize=15,color = 'red',ax=axs[0,0])
boxplot_visit =data_frame.boxplot(column=['Visit'], rot=15, fontsize=15,widths=.
↪5,color = 'blue',ax=axs[0,1])
boxplot_Age =data_frame.boxplot(column=['Age'], rot=15, fontsize=15,widths=.
↪5,color = 'green',ax=axs[0,2])
boxplot_EDUC = data_frame.boxplot(column=['EDUC'], rot=15, fontsize=15,widths=.
↪5,color = 'magenta',ax=axs[0,3])
boxplot_SES = data_frame.boxplot(column=['SES'], rot=15, fontsize=15,widths=.
↪5,color = 'maroon',ax=axs[0,4])
boxplot_MMSE = data_frame.boxplot(column=['MMSE'], rot=15, fontsize=15,widths=.
↪5,color = 'lime',ax=axs[1,0])
boxplot_CDR = data_frame.boxplot(column=['CDR'], rot=15, fontsize=15,widths=.
↪5,color = 'brown',ax=axs[1,1])
boxplot_eTIV = data_frame.boxplot(column=['eTIV'], rot=15, fontsize=15,widths=.
↪5,color = 'crimson',ax=axs[1,2])
boxplot_nWBV = data_frame.boxplot(column=['nWBV'], rot=15, fontsize=15,widths=.
↪5,color = 'hotpink',ax=axs[1,3])
boxplot_ASF = data_frame.boxplot(column=['ASF'], rot=15, fontsize=15,widths=.
↪5,color = 'purple',ax=axs[1,4])


plt.show()
```



Histogram

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

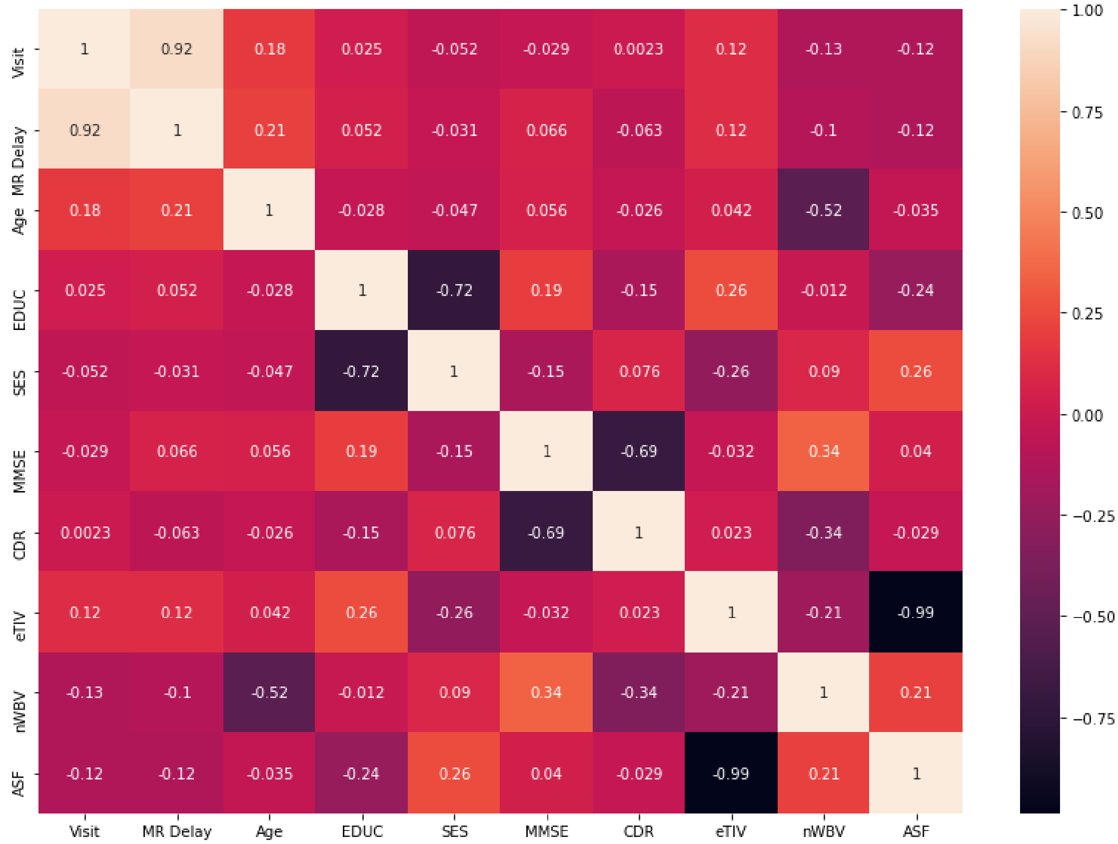
```
[6]: array([[<AxesSubplot:title={'center':'Visit'}>,
            <AxesSubplot:title={'center':'MR Delay'}>,
            <AxesSubplot:title={'center':'Age'}>],
           [<AxesSubplot:title={'center':'EDUC'}>,
            <AxesSubplot:title={'center':'SES'}>,
            <AxesSubplot:title={'center':'MMSE'}>],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



Correlation Heatmap

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

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

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

[7]: <AxesSubplot:>



Dealing the missing values

[8]:
```
missing_data = data_frame.isnull()
missing_data.head()
```

[8]:
```
  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

[9]:
```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    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

[10]:
```
# check the details value of SES
data_frame['SES'].value_counts()
```

[10]:
```
2.0    103
1.0     88
3.0     82
4.0     74
5.0      7
Name: SES, dtype: int64
```

[11]:
```
#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()
```

[11]:
```
2.0
```

[12]:
```
#replace null with most common values
data_frame['SES'].fillna(2.0, inplace=True)
```

[13]:
```
#check the details value of MMSE
data_frame['MMSE'].value_counts()
```

[13]:
```
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
```

[14]:
```
#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()
```

[14]:
```
30.0
```

[15]:
```
#replace null with most common values
data_frame['MMSE'].fillna(30,inplace=True)
```

[16]:
```
missing_data = data_frame.isnull()
missing_data.head()
```

[16]:
```
   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
```

[17]:
```
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
```

[18]:
```
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

[19]:
```
data_frame['Subject ID'].value_counts()
```

[19]:
```
OAS2_0073    5
OAS2_0070    5
OAS2_0127    5
OAS2_0048    5
OAS2_0036    4
            ..
```

```
OAS2_0008    2
OAS2_0108    2
OAS2_0029    2
OAS2_0113    2
OAS2_0096    2
Name: Subject ID, Length: 150, dtype: int64
```

[20]:
```
# check the total number of subject
data_frame['Subject ID'].nunique()
```

[20]:
```
150
```

[21]:
```
data_frame['Group'].value_counts()
```

[21]:
```
Nondemented    190
Demented       146
Converted       37
Name: Group, dtype: int64
```

Check for male and female

[22]:
```
data_frame.groupby(['M/F','Group'])['Subject ID'].nunique()
```

[22]:
```
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

[23]:
```
data_frame_sub =data_frame.groupby(['M/F','Group'])
```

[24]:
```
data_frame_sub= data_frame_sub.agg({'Subject ID':'nunique'})
```

[25]:
```
data_frame_sub.head()
```

[25]:
```
                 Subject ID
M/F Group
F   Converted            10
    Demented             28
    Nondemented          50
M   Converted             4
    Demented             36
```

[26]:
```
# Change M to 1 and F to 0
data_frame['M/F'] = data_frame['M/F'].replace(['F','M'], [0,1])
```

[27]:
```
# 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
```

[28]:
```
# Group :Replace Converted to Demented
data_frame['Group'] = data_frame['Group'].replace(['Converted'], ['Demented'])
```

[29]:
```
data_frame.head()
```

[29]:
```
  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
```

[30]:
```
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

[31]:
```python
data_frame_new = data_frame.groupby(['M/F','Group'])
```

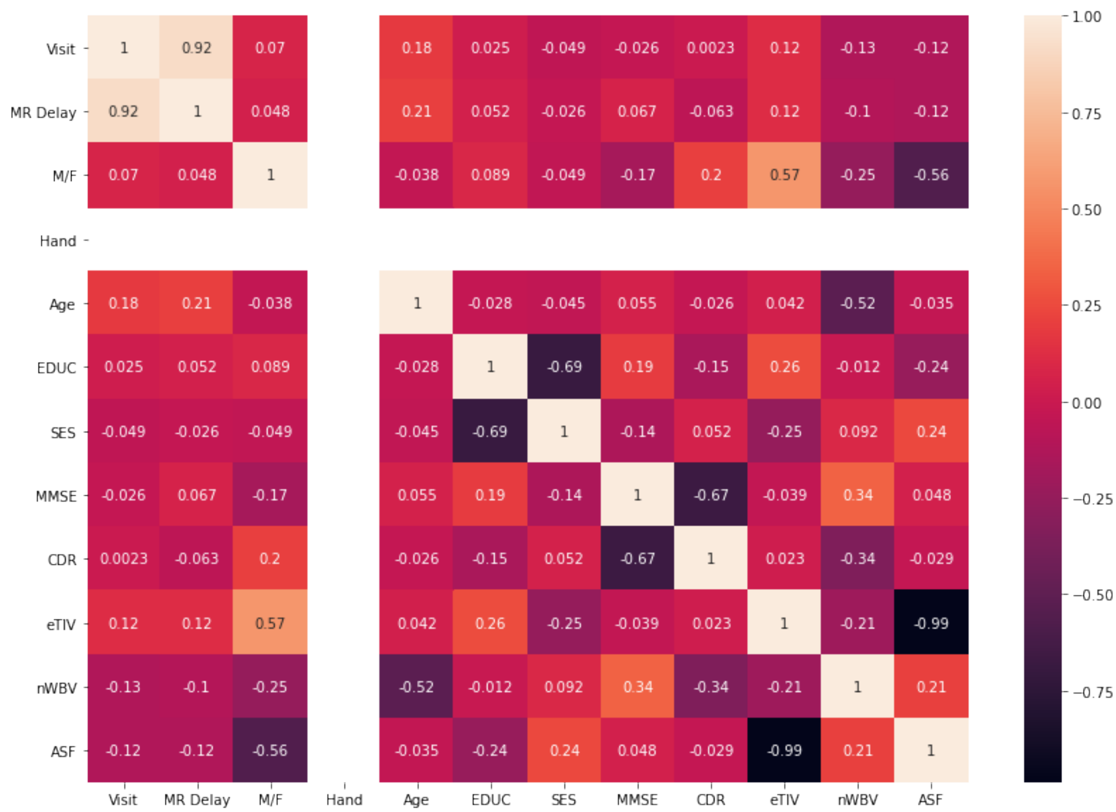
[32]:
```python
data_frame_new = data_frame_new.agg({'Subject ID':'nunique'})
```

[33]:
```python
data_frame_new.head()
```

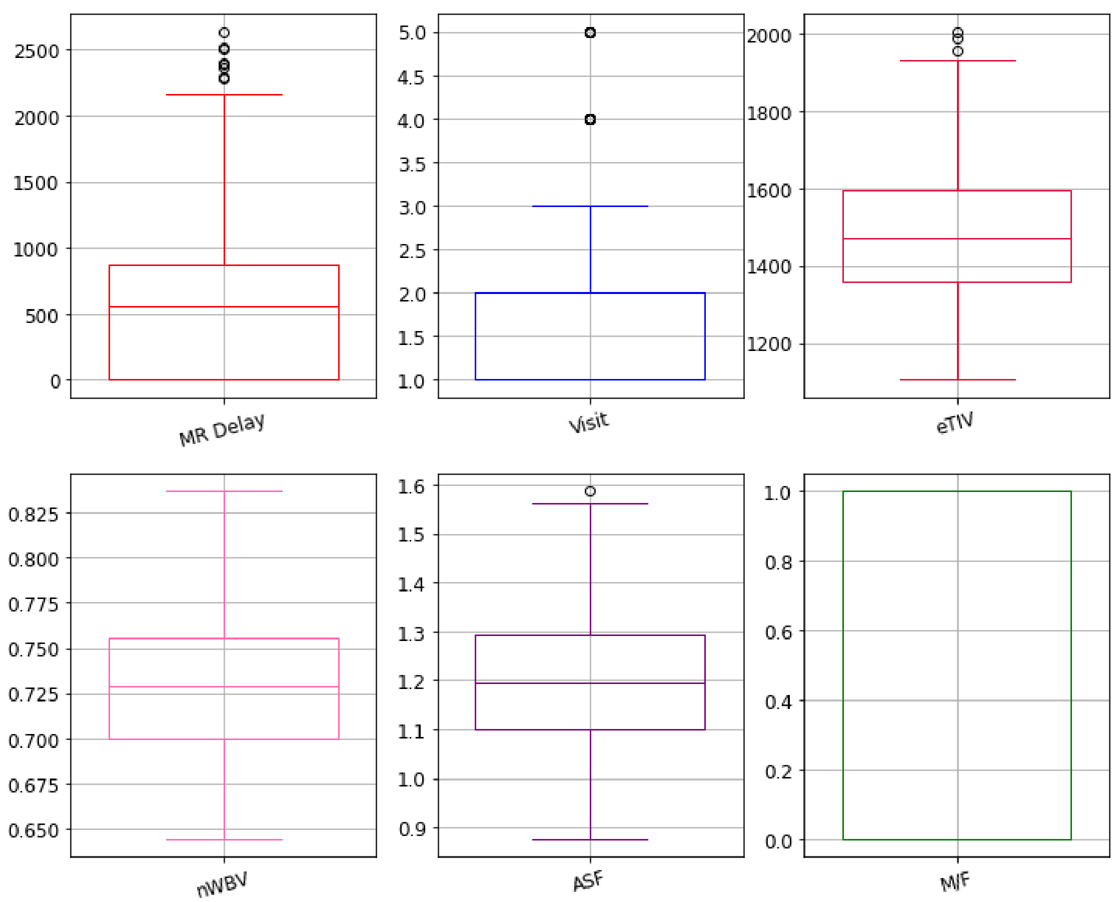
[33]:
```
                Subject ID
M/F Group
0   Demented            38
    Nondemented         50
1   Demented            40
    Nondemented         22
```

[34]:
```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)
```

[34]:
```
<AxesSubplot:>
```



[35]:
```
fig,axs = plt.subplots(2,3,figsize =(12,10))
boplot_mrdelay = data_frame.boxplot(column=['MR Delay'], rot=15, widths=.
 ↪75,fontsize=12,color = 'red',ax=axs[0,0])
boxplot_visit =data_frame.boxplot(column=['Visit'], rot=15, fontsize=12,widths=.
 ↪75,color = 'blue',ax=axs[0,1])
boxplot_eTIV = data_frame.boxplot(column=['eTIV'], rot=15, fontsize=12,widths=.
 ↪75,color = 'crimson',ax=axs[0,2])
boxplot_nWBV = data_frame.boxplot(column=['nWBV'], rot=15, fontsize=12,widths=.
 ↪75,color = 'hotpink',ax=axs[1,0])
boxplot_ASF = data_frame.boxplot(column=['ASF'], rot=15, fontsize=12,widths=.
 ↪75,color = 'purple',ax=axs[1,1])
boxplot_MF = data_frame.boxplot(column=['M/F'], rot=15, fontsize=12,widths=.
 ↪75,color = 'green',ax=axs[1,2])

plt.show()
```



Target value, response variable or dependent variable

[36]:
```
y_data = data_frame['Group']
```

[37]:
```
y_data[0:5]
```

[37]:
```
0    Nondemented
1    Nondemented
2       Demented
3       Demented
4       Demented
Name: Group, dtype: object
```

[38]:
```
# Independent variable or regressor as X
# drop unrelated values
X_data = data_frame.drop(['Subject ID','MRI ID','Group'], axis=1)
X_data.head()
```

[38]:
```
   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

[39]:
```
# 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

[40]:
```
X_data= preprocessing.StandardScaler().fit(X_data).transform(X_data)
X_data[0:5]
```

[40]:
```
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)

[41]:
```
# import SVM library

from sklearn import svm
```

[42]:
```
svm_clf = svm.SVC(C=1, kernel='linear').fit(X_train, y_train)
```

[43]:
```
yhat_svm = svm_clf.predict(X_test)
```

[44]:
```
SVM_accuracy_score = accuracy_score(y_test,yhat_svm)*100
print("SVM_accuracy_score:", SVM_accuracy_score)
```

```
SVM_accuracy_score: 92.74193548387096
```

[45]:
```
# Number of random trials
NUM_TRIALS = 10

# Arrays to store scores
svm_nested_scores = np.zeros(NUM_TRIALS)
svm_non_nested_scores = np.zeros(NUM_TRIALS)

# Set up possible values of parameters to optimize over
p_grid = {"C": [1, 10, 100], "gamma": [0.01, 0.1]}
```

[46]:
```
# Loop for each trial
for i in range(NUM_TRIALS):
```

```
    inner_cv = KFold(n_splits=10, shuffle=True, random_state=i)
    outer_cv = KFold(n_splits=10, shuffle=True, random_state=i)

    # Non_nested parameter search and scoring
    nonnes_svm_clf = GridSearchCV(estimator=svm_clf, param_grid=p_grid,␣
↪cv=outer_cv)
    nonnes_svm_clf.fit(X_data, y_data)
    svm_non_nested_scores[i] = nonnes_svm_clf.best_score_



    # Nested CV with parameter optimization
    Nes_svm_clf = GridSearchCV(estimator=svm_clf, param_grid=p_grid,␣
↪cv=inner_cv)

    svm_nested_score = cross_val_score(svm_clf, X=X_data, y=y_data, cv=outer_cv)

    svm_nested_score[i] = svm_nested_score.mean()
```

[142]:
```
svm_non_nested_score_mean = svm_non_nested_scores.mean()
svm_non_nested_score_mean
```

[142]: 0.9463157894736842

[135]:
```
svm_nested_score_mean = svm_nested_score.mean()
svm_nested_score_mean
```

[135]: 0.94649359886202

[49]:
```
SVM_nested_vs_non_nested_score =  svm_nested_score - svm_non_nested_scores


print(
    "Average difference of nested and nonnested {:6f} with std. dev. of {:6f}.".
↪format(
        SVM_nested_vs_non_nested_score.mean(), SVM_nested_vs_non_nested_score.
↪std()
    )
)
```

```
Average difference of nested and nonnested 0.000178 with std. dev. of 0.023795.
```

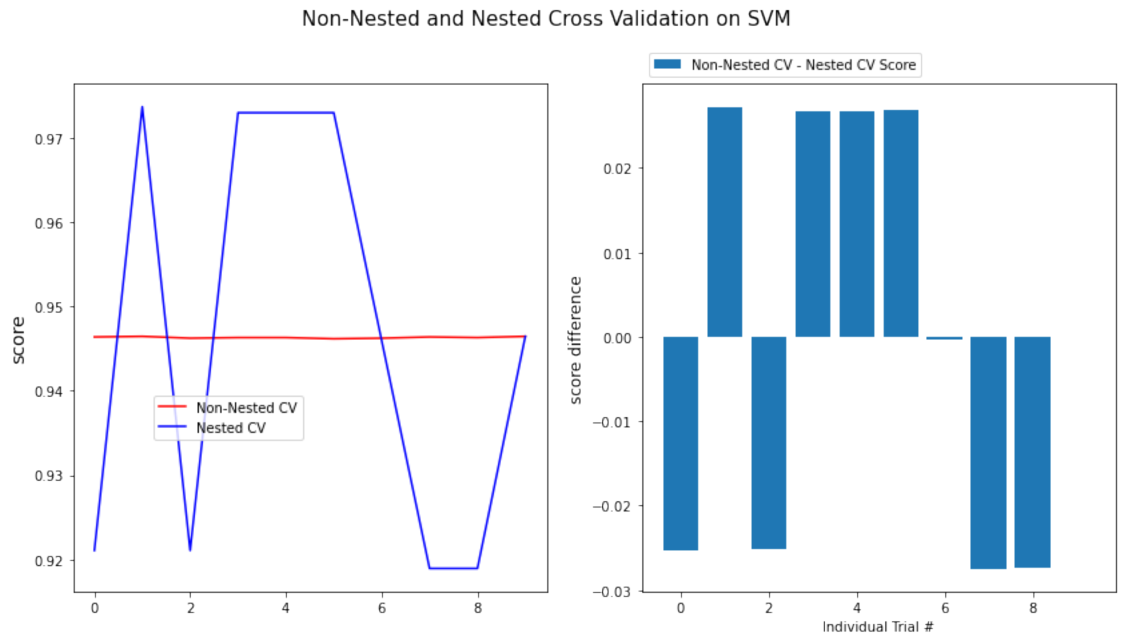
[50]:
```
print('SVM Nested Accuracy: %.3f' % (mean(svm_nested_score)*100))
```

```
SVM Nested Accuracy: 94.649
```

[51]:
```
print('SVM Nonnested Accuracy: %.3f ' % (mean(svm_non_nested_scores)*100))
```

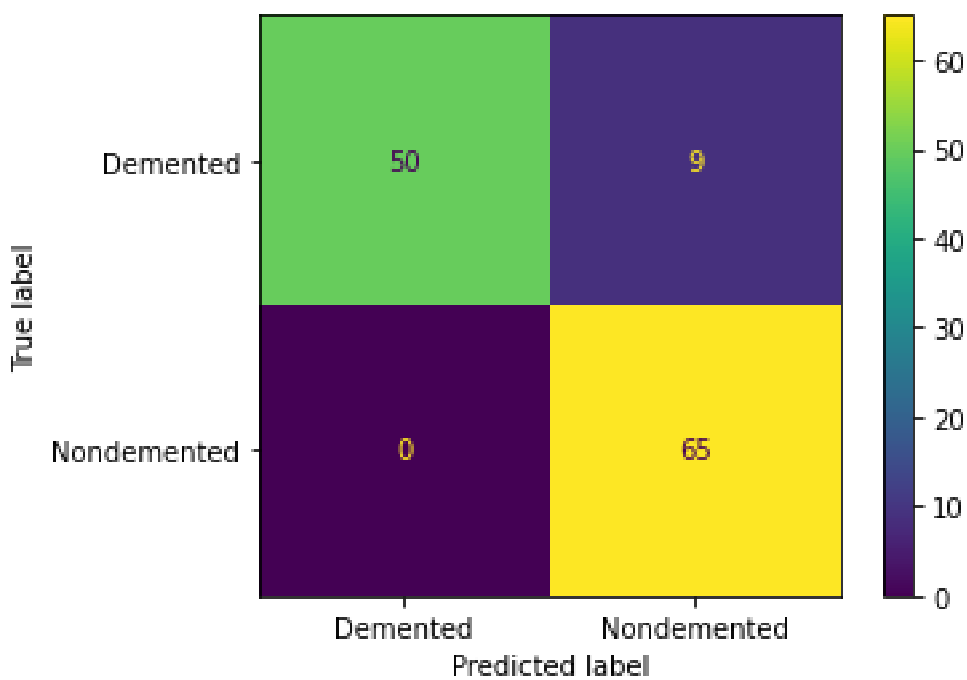
```
SVM Nonnested Accuracy: 94.632
```

[52]:
```
# Plot scores for nested and non-nested CV
plt.figure(figsize=(14, 7))

plt.subplot(1,2,1)
(non_nested_line,) = plt.plot(svm_non_nested_scores, color="r")
(nested_line,) = plt.plot(svm_nested_score, color="b")
plt.ylabel("score", fontsize="14")
plt.legend(
    [non_nested_line, nested_line],
    ["Non-Nested CV", "Nested CV"],
    bbox_to_anchor=(0, 0.4, 0.5, 0),
)

plt.title( "Non-Nested and Nested Cross Validation on SVM", x=1.0, y=1.1,␣
↪fontsize="15" )


# Plot bar chart of the difference.
plt.subplot(1,2,2)
difference_plot = plt.bar(range(NUM_TRIALS), SVM_nested_vs_non_nested_score)
plt.xlabel("Individual Trial #")
plt.legend(
    [difference_plot],
    ["Non-Nested CV - Nested CV Score"],
    bbox_to_anchor=(0, 1, 0.8, 0),
)
plt.ylabel("score difference", fontsize="12")

plt.show()
```



SVM Confusion matrix

[53]:
```
#confusion_matrix(y_test,yhat_svm)
from sklearn.metrics import confusion_matrix
plot_confusion_matrix(svm_clf, X_test, y_test)
plt.show()
```



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

```
[54]: Predicted    Demented  Nondemented  All
      True
      Demented           50            9   59
      Nondemented         0           65   65
      All                50           74  124
```

SVM Classification Report

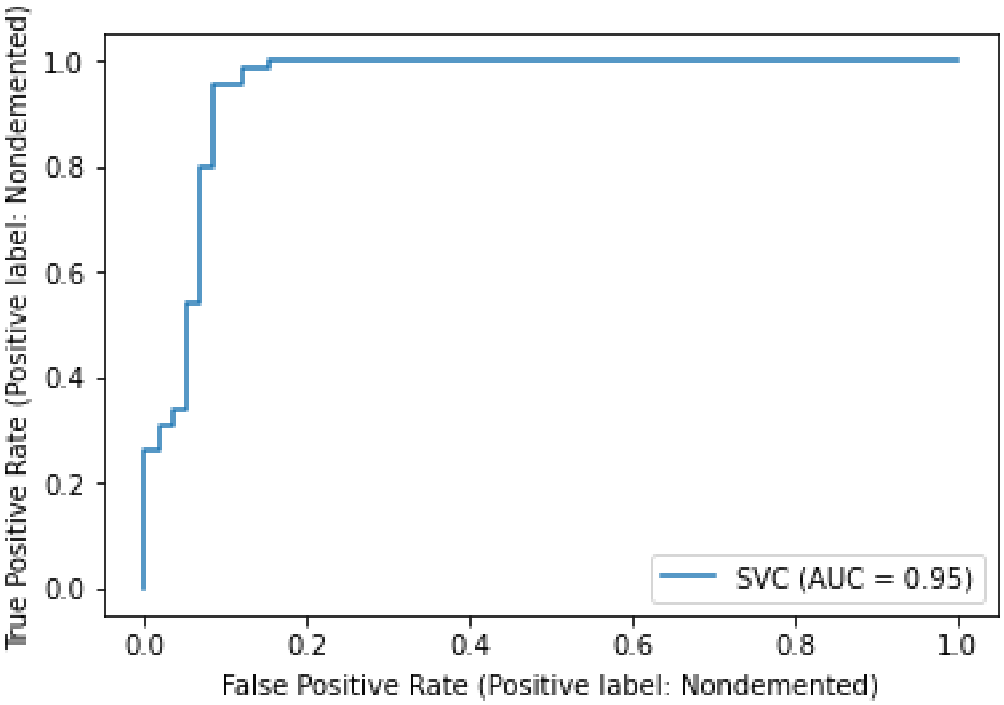
```
[55]: #print(classification_report(y_test,yhat_svm))

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
 [[50  9]
 [ 0 65]]

classification report
               precision    recall  f1-score   support

    Demented       1.00      0.85      0.92        59
 Nondemented       0.88      1.00      0.94        65

    accuracy                           0.93       124
   macro avg       0.94      0.92      0.93       124
weighted avg       0.94      0.93      0.93       124

Accuracy:  92.74193548387096
```

```
[56]: 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: 0.951238591916558
```

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



0.0.3 Logistic Regression

[58]:
```
#import Library LogisticRegression
from sklearn.linear_model import LogisticRegression
```

[59]:
```
#Train

lr_clf = LogisticRegression(C=1, solver='liblinear').fit(X_train,y_train)
lr_clf
```

[59]:
```
LogisticRegression(C=1, solver='liblinear')
```

[60]:
```
yhat_lr = lr_clf.predict(X_test)

lr_yhat_prob = lr_clf.predict_proba(X_test)
```

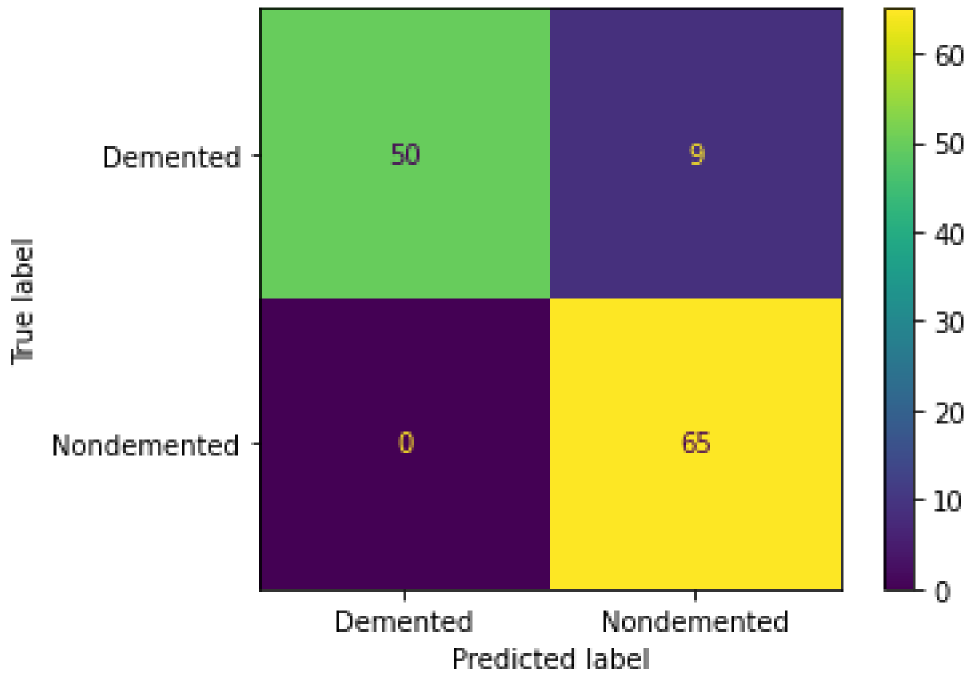
[61]:
```
LR_accuracy_score = accuracy_score(y_test,yhat_lr)*100
print("LR_accuracy_score :",LR_accuracy_score )
```

```
LR_accuracy_score : 92.74193548387096
```

LR Confusion matrix

[62]:
```
#confusion_matrix(y_test,yhat_lr)
```

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



[63]:
```
# Confusion matrix using crosstab method of pandas.
LR_pd = pd.crosstab(y_test, yhat_lr, rownames=['True'], colnames=['Predicted'],␣
↪margins=True)
LR_pd
```

[63]:
```
Predicted    Demented  Nondemented  All
True
Demented           50            9   59
Nondemented         0           65   65
All                50           74  124
```

LR Classification Report

[64]:
```
#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)
```

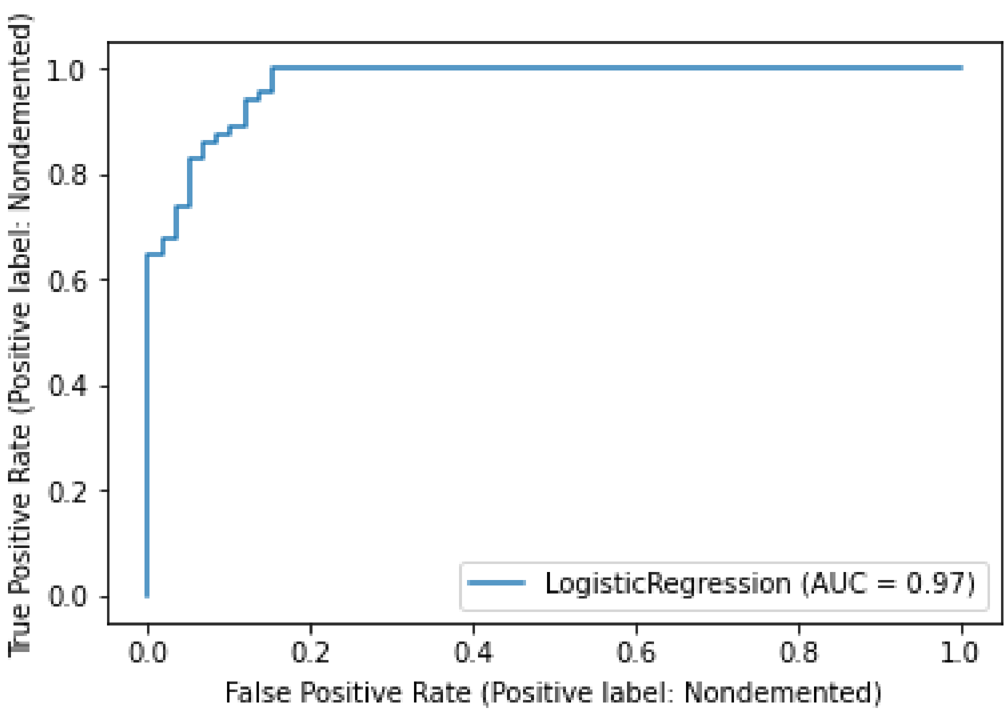
```
confusion matrix
 [[50  9]
 [ 0 65]]
```

```
classification report
              precision    recall  f1-score   support

    Demented       1.00      0.85      0.92        59
 Nondemented       0.88      1.00      0.94        65

    accuracy                           0.93       124
   macro avg       0.94      0.92      0.93       124
weighted avg       0.94      0.93      0.93       124

Accuracy:  92.74193548387096
```

[65]:
```
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 : 0.9731421121251629
```

[66]:
```
metrics.plot_roc_curve(lr_clf, X_test, y_test)
plt.show()
```



[67]:
```
NUM_TRIALS = 10
```

```
lr_nested_scores = np.zeros(NUM_TRIALS)
lr_non_nested_scores = np.zeros(NUM_TRIALS)

p_grid = {"C": [1, 10, 100]}

# Loop for each trial
for i in range(NUM_TRIALS):



    inner_cv = KFold(n_splits=10, shuffle=True, random_state=i)
    outer_cv = KFold(n_splits=10, shuffle=True, random_state=i)

    nonnes_lr_clf = GridSearchCV(estimator=lr_clf, param_grid=p_grid,␣
 ↪cv=outer_cv)
    nonnes_lr_clf.fit(X_data, y_data)
    lr_non_nested_scores[i] = nonnes_lr_clf.best_score_



    # Nested CV with parameter optimization
    Nes_lrclf = GridSearchCV(estimator=lr_clf, param_grid=p_grid, cv=inner_cv)

    lr_nested_score = cross_val_score(lr_clf, X=X_data, y=y_data, cv=outer_cv)
    lr_nested_score[i] = lr_nested_score.mean()
```

[68]:

```
LR_nested_vs_non_nested_score =  lr_nested_score - lr_non_nested_scores



print(
    "Average difference of nested and nonnested {:6f} with std. dev. of {:6f}.".
 ↪format(
        LR_nested_vs_non_nested_score.mean(), LR_nested_vs_non_nested_score.
 ↪std()
    )
)
```

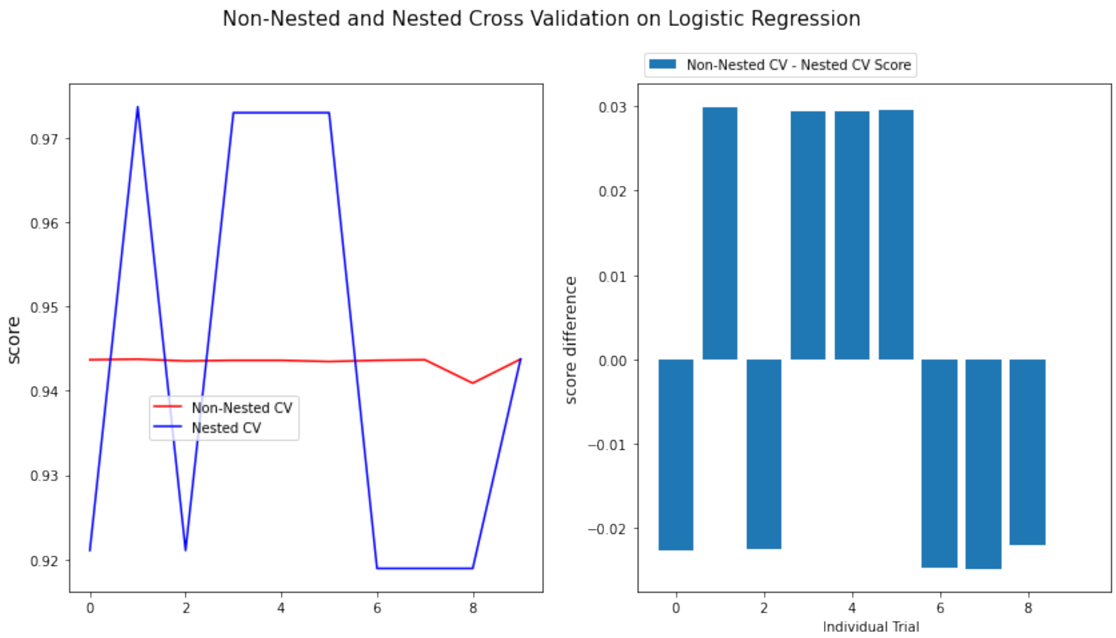
```
Average difference of nested and nonnested 0.000171 with std. dev. of 0.024929.
```

[69]:

```
print('LR Nested Accuracy: %.3f' % (mean(lr_nested_score)*100))



print('LR Nonnested Accuracy: %.3f ' % (mean(lr_non_nested_scores)*100))
```

```
LR Nested Accuracy: 94.352
LR Nonnested Accuracy: 94.335
```

[70]:
```python
# Plot scores for nested and non-nested CV
plt.figure(figsize=(14, 7))

plt.subplot(1,2,1)
(non_nested_line,) = plt.plot(lr_non_nested_scores, color="r")
(nested_line,) = plt.plot(lr_nested_score, color="b")
plt.ylabel("score", fontsize="14")
plt.legend(
    [non_nested_line, nested_line],
    ["Non-Nested CV", "Nested CV"],
    bbox_to_anchor=(0, 0.4, 0.5, 0),
)

plt.title( "Non-Nested and Nested Cross Validation on Logistic Regression", x=1.
↪0, y=1.1, fontsize="15" )


# Plot bar chart of the difference.
plt.subplot(1,2,2)
difference_plot = plt.bar(range(NUM_TRIALS), LR_nested_vs_non_nested_score)
plt.xlabel("Individual Trial ")
plt.legend(
    [difference_plot],
    ["Non-Nested CV - Nested CV Score"],
    bbox_to_anchor=(0, 1, 0.8, 0),
)
plt.ylabel("score difference", fontsize="12")

plt.show()
```



[127]:
```
lr_nested_score_mean = lr_nested_score.mean()
lr_nested_score_mean
```

[127]: 0.943520625889047

[136]:
```
lr_non_nested_score_mean = lr_non_nested_scores.mean()
lr_non_nested_score_mean
```

[136]: 0.9433499288762446

0.0.4 Random Forest Classifier

[71]:
```
from sklearn.ensemble import RandomForestClassifier

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

[72]:
```
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)
```

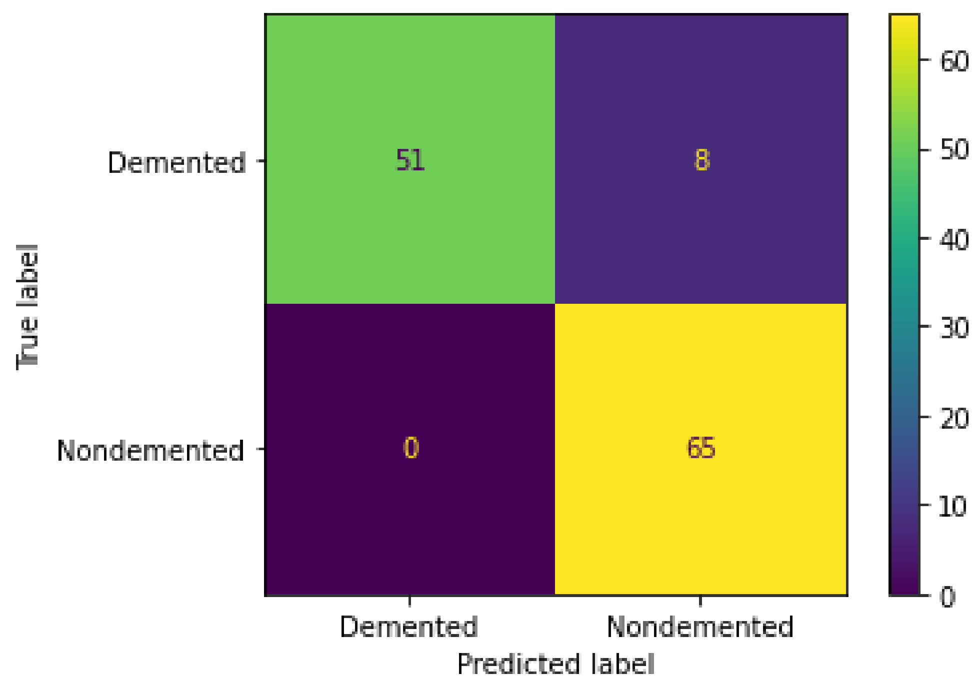
```
confusion matrix
 [[51  8]
```

```
 [ 0 65]]

classification report
              precision    recall  f1-score   support

    Demented       1.00      0.86      0.93        59
 Nondemented       0.89      1.00      0.94        65

    accuracy                           0.94       124
   macro avg       0.95      0.93      0.93       124
weighted avg       0.94      0.94      0.94       124

Accuracy:  93.54838709677419
```

[73]:
```
RF_accuracy_score = accuracy_score(y_test,rf_pred)*100
print("RF_accuracy_score :",RF_accuracy_score )
```

```
RF_accuracy_score : 93.54838709677419
```

[74]:
```
plot_confusion_matrix(rf_clf, X_test, y_test)
plt.show()
```



[75]:
```
# Confusion matrix using crosstab method of pandas.
RF_pd = pd.crosstab(y_test, rf_pred, rownames=['True'], colnames=['Predicted'],␣
 ↪margins=True)
```

```
RF_pd
```

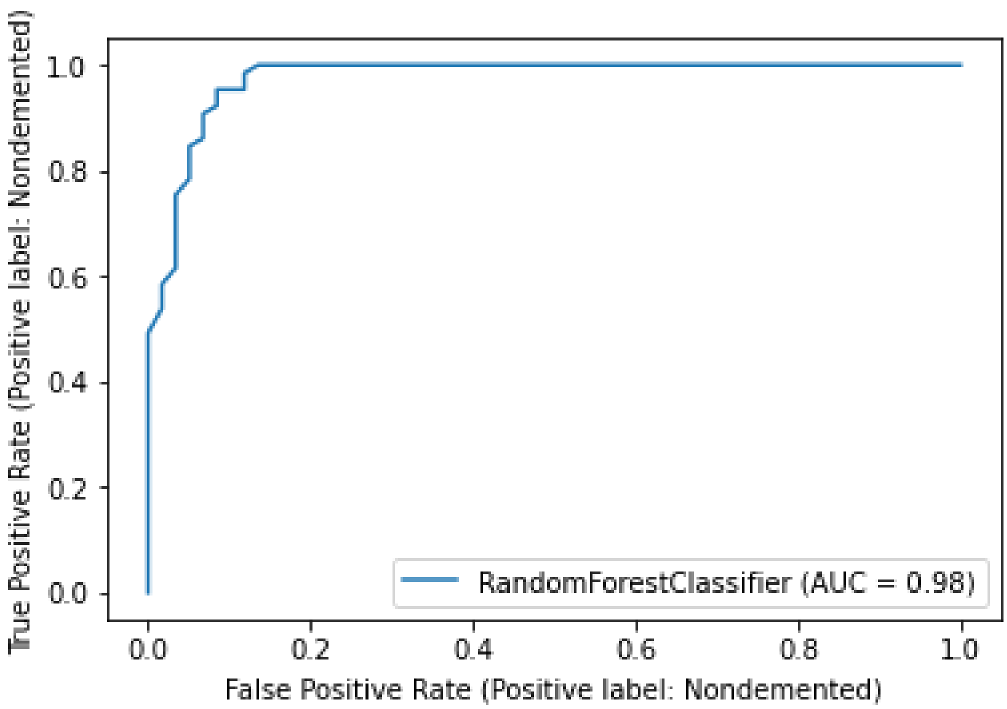
[75]:

Predicted	Demented	Nondemented	All
True			
Demented	51	8	59
Nondemented	0	65	65
All	51	73	124

[76]:
```
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 : 0.9754889178617991
```

[77]:
```
metrics.plot_roc_curve(rf_clf, X_test, y_test)

plt.show()
```



[78]:
```
NUM_TRIALS = 10


rf_nested_scores = np.zeros(NUM_TRIALS)
rf_non_nested_scores = np.zeros(NUM_TRIALS)
```

```
p_grid = {
    'n_estimators': [200, 300],
    'max_features': ['auto', 'sqrt', 'log2'],
    'max_depth' : [3,5,10],
    'min_samples_split': [2, 5, 10],
    'criterion' :['gini', 'entropy']
}


# Loop for each trial
for i in range(NUM_TRIALS):


    inner_cv = KFold(n_splits=10, shuffle=True, random_state=i)
    outer_cv = KFold(n_splits=10, shuffle=True, random_state=i)


    nonnes_rf_clf = GridSearchCV(estimator=rf_clf, param_grid=p_grid,␣
 ↪cv=outer_cv)
    nonnes_rf_clf.fit(X_data, y_data)
    rf_non_nested_scores[i] = nonnes_rf_clf.best_score_



    # Nested CV with parameter optimization
    Nes_rfclf = GridSearchCV(estimator=rf_clf, param_grid=p_grid, cv=inner_cv)

    rf_nested_score = cross_val_score(rf_clf, X=X_data, y=y_data, cv=outer_cv)
    rf_nested_score[i] = rf_nested_score.mean()
```

[ ]:

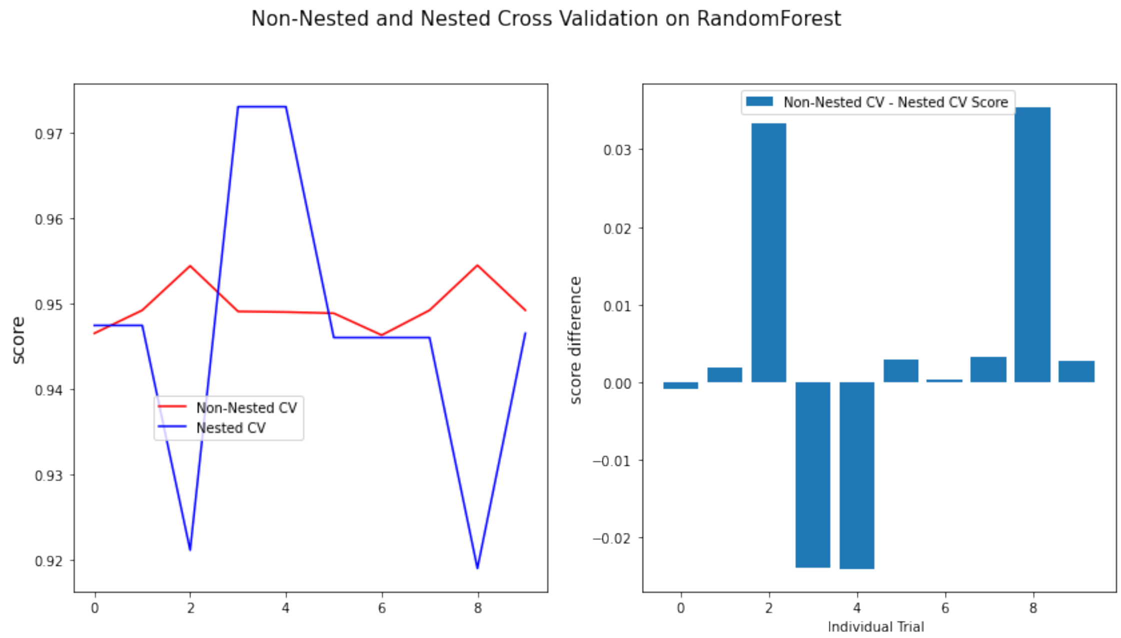
```
[79]: RF_nested_vs_non_nested_score = rf_non_nested_scores- rf_nested_score



print(
    "Average difference of nested and nonnested {:6f} with std. dev. of {:6f}.".
 ↪format(
        RF_nested_vs_non_nested_score.mean(), RF_nested_vs_non_nested_score.
 ↪std()
    )
)
```

```
Average difference of nested and nonnested 0.003065 with std. dev. of 0.018590.
```

[80]:
```
print('RF Nested Accuracy: %.3f' % (mean(rf_nested_score)*100))


print('RF Nonnested Accuracy: %.3f ' % (mean(rf_non_nested_scores)*100))
```

```
RF Nested Accuracy: 94.649
RF Nonnested Accuracy: 94.956
```

[81]:
```
plt.figure(figsize=(14, 7))

plt.subplot(1,2,1)
(non_nested_line,) = plt.plot(rf_non_nested_scores, color="r")
(nested_line,) = plt.plot(rf_nested_score, color="b")
plt.ylabel("score", fontsize="14")
plt.legend(
    [non_nested_line, nested_line],
    ["Non-Nested CV", "Nested CV"],
    bbox_to_anchor=(0, 0.4, 0.5, 0),
)

plt.title( "Non-Nested and Nested Cross Validation on RandomForest", x=1.0, y=1.
 ↪1, fontsize="15" )


# Plot bar chart of the difference.
plt.subplot(1,2,2)
difference_plot = plt.bar(range(NUM_TRIALS), RF_nested_vs_non_nested_score)
plt.xlabel("Individual Trial ")
plt.legend(
    [difference_plot],
    ["Non-Nested CV - Nested CV Score"],
    bbox_to_anchor=(0, 1, 0.8, 0),
)
plt.ylabel("score difference", fontsize="12")

plt.show()
```




```
[128]: rf_nested_score_mean = rf_nested_score.mean()
       rf_nested_score_mean
```

```
[128]: 0.9464935988620198
```

```
[137]: rf_non_nested_score_mean = rf_non_nested_scores.mean()
       rf_non_nested_score_mean
```

```
[137]: 0.9495590327169274
```

0.0.5 Naive Bayes

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

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

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

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

      gnb_yhat_prob = gnb_clf.predict_proba(X_test)
```

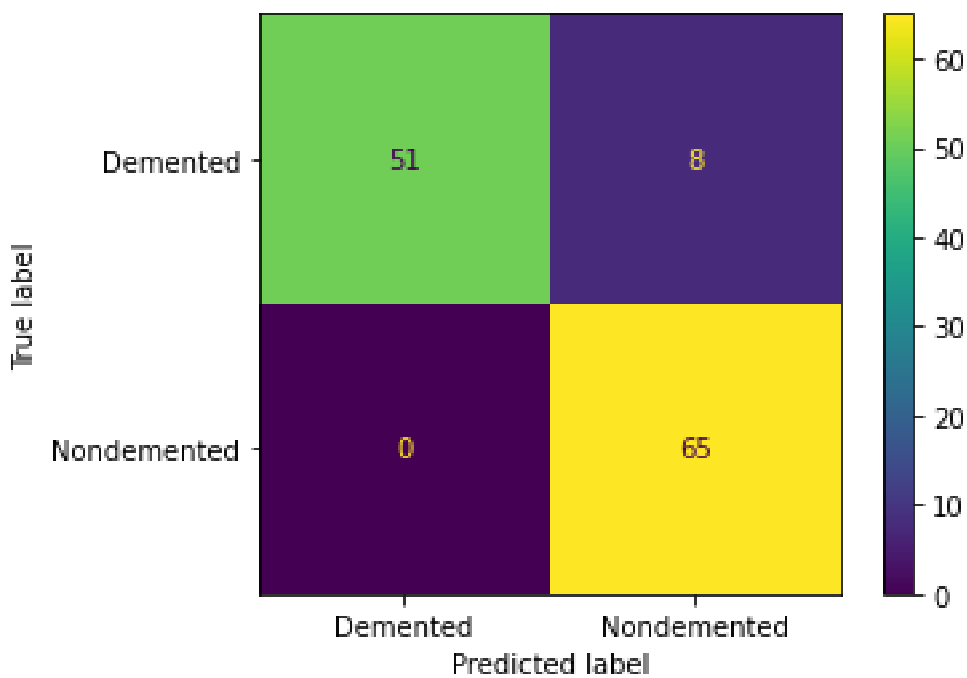
```
[86]: gnb_Accuracy_score = metrics.accuracy_score(y_test, y_pred_gnb)*100
      gnb_Accuracy_score
```

```
[86]: 93.54838709677419
```

[87]:
```
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
 [[51  8]
 [ 0 65]]

classification report
               precision    recall  f1-score   support

    Demented       1.00      0.86      0.93        59
 Nondemented       0.89      1.00      0.94        65

    accuracy                           0.94       124
   macro avg       0.95      0.93      0.93       124
weighted avg       0.94      0.94      0.94       124

Accuracy:  93.54838709677419
```

[88]:
```
plot_confusion_matrix(gnb_clf, X_test, y_test)
plt.show()
```



[89]:
```
# Confusion matrix using crosstab method of pandas.
```

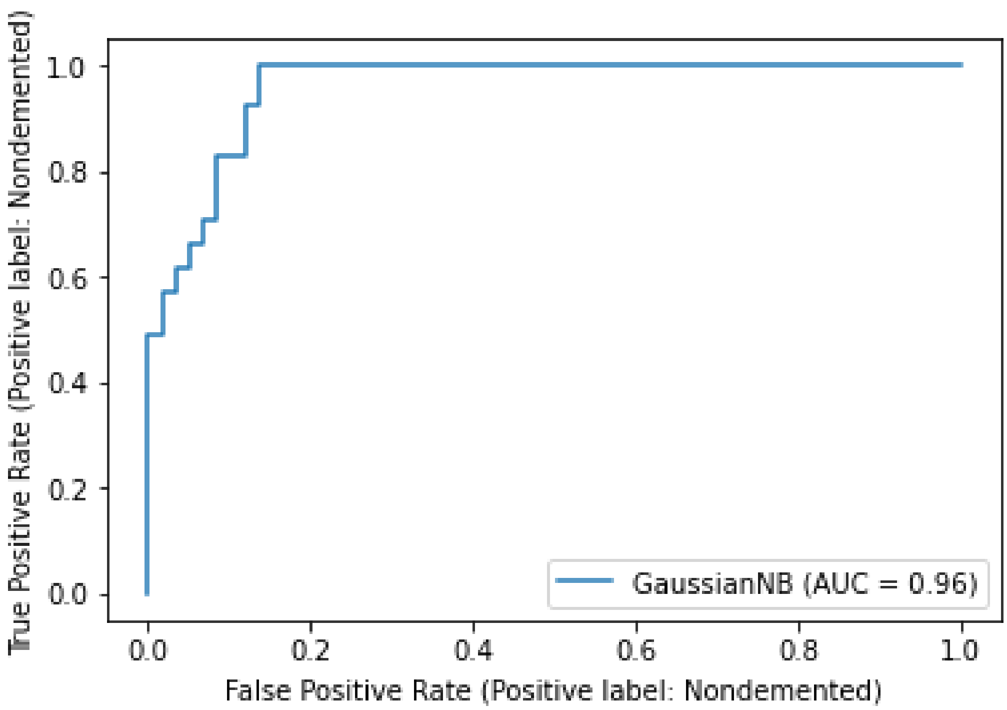
```
GNV_pd = pd.crosstab(y_test, y_pred_gnb, rownames=['True'],␣
↪colnames=['Predicted'], margins=True)
GNV_pd
```

[89]:

Predicted	Demented	Nondemented	All
True			
Demented	51	8	59
Nondemented	0	65	65
All	51	73	124

[90]:

```
metrics.plot_roc_curve(gnb_clf, X_test, y_test)

plt.show()
```



[91]:

```
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 : 0.9598435462842243
```

[92]:

```
gnb_clf.get_params().keys()
```

[92]:

```
dict_keys(['priors', 'var_smoothing'])
```

[93]:
```
NUM_TRIALS = 10

gnb_nested_scores = np.zeros(NUM_TRIALS)
gnb_non_nested_scores = np.zeros(NUM_TRIALS)

p_grid =  { }

#"priors" : "None",  "var_smoothing" : 1e-9

# Loop for each trial
for i in range(NUM_TRIALS):

    # Choose cross-validation techniques for the inner and outer loops,
    # independently of the dataset.
    # E.g "GroupKFold", "LeaveOneOut", "LeaveOneGroupOut", etc.

    inner_cv = KFold(n_splits=10, shuffle=True, random_state=i)
    outer_cv = KFold(n_splits=10, shuffle=True, random_state=i)


     # Non_nested parameter search and scoring
    nonnes_gnb_clf = GridSearchCV(estimator=gnb_clf, param_grid=p_grid,␣
 ↪cv=outer_cv)
    nonnes_gnb_clf.fit(X_data, y_data)
    gnb_non_nested_scores[i] = nonnes_gnb_clf.best_score_



    # Nested CV with parameter optimization
    Nes_gnbclf = GridSearchCV(estimator=gnb_clf, param_grid=p_grid, cv=inner_cv)

    gnb_nested_score = cross_val_score(gnb_clf, X=X_data, y=y_data, cv=outer_cv)
    gnb_nested_score[i] = gnb_nested_score.mean()
```

[129]:
```
gnb_nested_score_mean = gnb_nested_score.mean()
gnb_nested_score_mean
```

[129]: 0.9464153627311523

[138]:
```
gnb_non_nested_score_mean = gnb_non_nested_scores.mean()
gnb_non_nested_score_mean
```

[138]: 0.9449573257467995

[95]:
```
GNB_nested_vs_non_nested_score =  gnb_nested_score - gnb_non_nested_scores
```

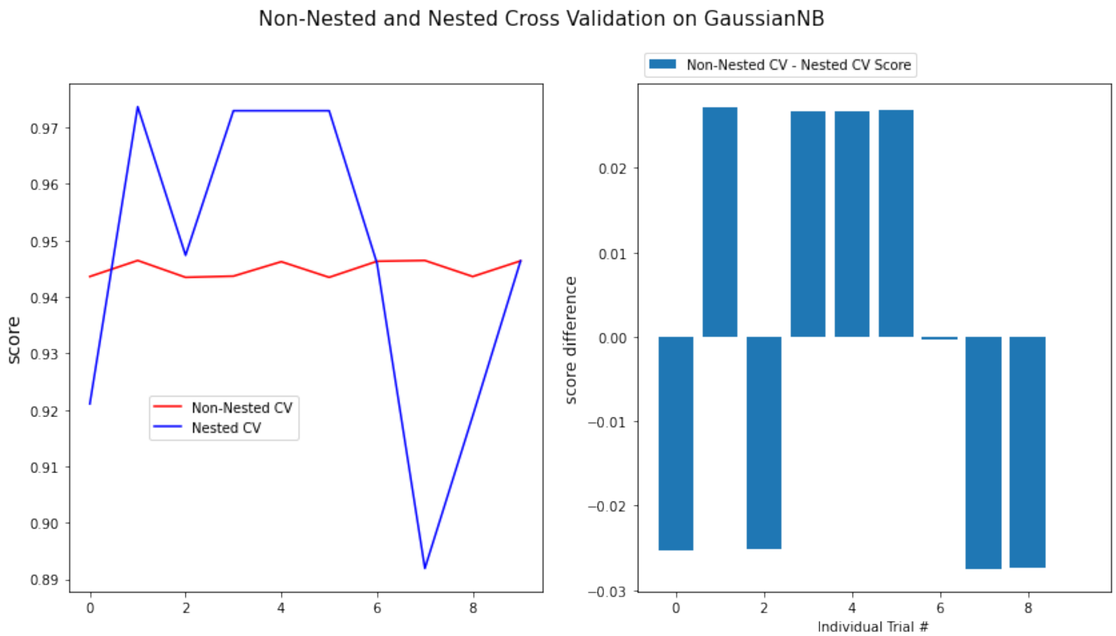
```
print(
    "Average difference of nested and nonnested {:6f} with std. dev. of {:6f}.".
 ↪format(
        GNB_nested_vs_non_nested_score.mean(), GNB_nested_vs_non_nested_score.
 ↪std()
    )
)
```

```
Average difference of nested and nonnested 0.001458 with std. dev. of 0.026971.
```

[96]:
```
print('GNB Nested Accuracy: %.3f' % (mean(gnb_nested_score)*100))


print('GNB Nonnested Accuracy: %.3f ' % (mean(gnb_non_nested_scores)*100))
```

```
GNB Nested Accuracy: 94.642
GNB Nonnested Accuracy: 94.496
```

[97]:
```
# Plot scores for nested and non-nested CV
plt.figure(figsize=(14, 7))

plt.subplot(1,2,1)
(non_nested_line,) = plt.plot(gnb_non_nested_scores, color="r")
(nested_line,) = plt.plot(gnb_nested_score, color="b")
plt.ylabel("score", fontsize="14")
plt.legend(
    [non_nested_line, nested_line],
    ["Non-Nested CV", "Nested CV"],
    bbox_to_anchor=(0, 0.4, 0.5, 0),
)

plt.title( "Non-Nested and Nested Cross Validation on GaussianNB", x=1.0, y=1.
 ↪1, fontsize="15" )


# Plot bar chart of the difference.
plt.subplot(1,2,2)
difference_plot = plt.bar(range(NUM_TRIALS), SVM_nested_vs_non_nested_score)
plt.xlabel("Individual Trial #")
plt.legend(
    [difference_plot],
    ["Non-Nested CV - Nested CV Score"],
    bbox_to_anchor=(0, 1, 0.8, 0),
)
plt.ylabel("score difference", fontsize="12")

plt.show()
```




```
[ ]:
```

0.0.6 Ada Boosting

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

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

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

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

#yhat_ada
```

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

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

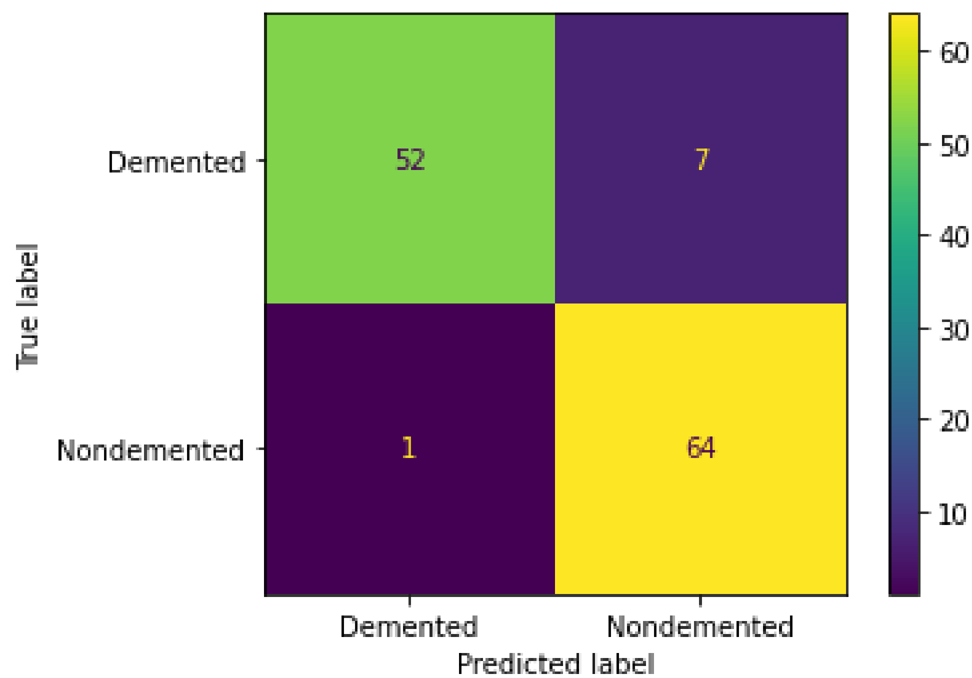
```
ada_accuracy_score : 93.54838709677419
```

```
[102]: 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
 [[52  7]
 [ 1 64]]

classification report
               precision    recall  f1-score   support

    Demented       0.98      0.88      0.93        59
 Nondemented       0.90      0.98      0.94        65

    accuracy                           0.94       124
   macro avg       0.94      0.93      0.93       124
weighted avg       0.94      0.94      0.94       124

Accuracy:  93.54838709677419
```

[103]:
```
plot_confusion_matrix(ada_clf, X_test, y_test)
plt.show()
```

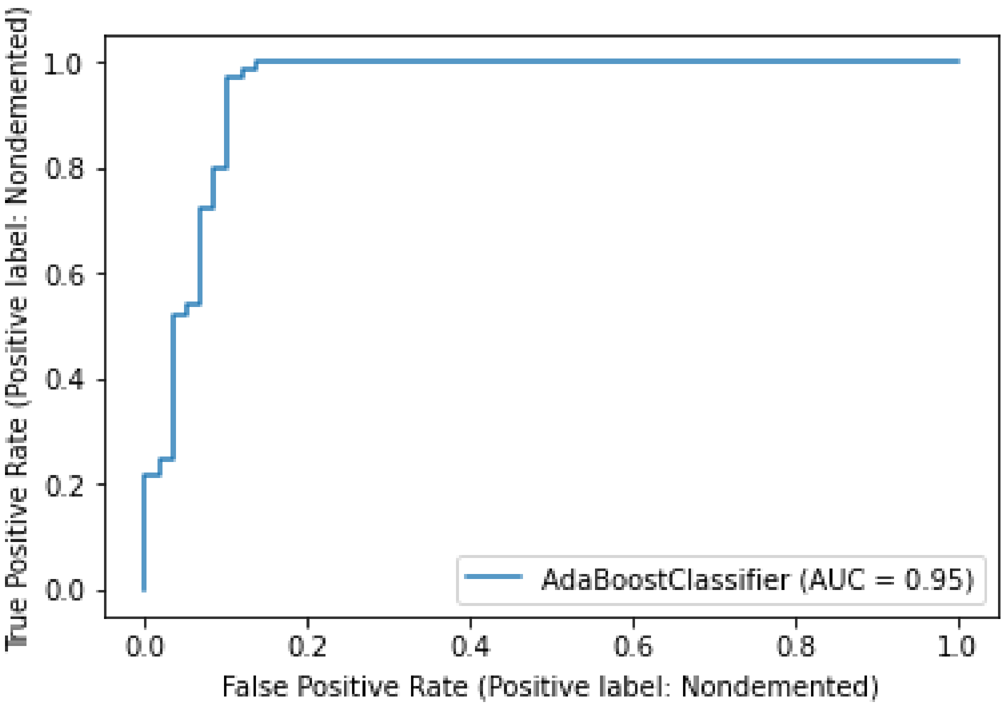


[104]:
```
# Confusion matrix using crosstab method of pandas.
ada_pd = pd.crosstab(y_test, yhat_ada, rownames=['True'],␣
↪colnames=['Predicted'], margins=True)
```

```
ada_pd
```

[104]:
```
Predicted     Demented  Nondemented  All
True
Demented            52            7   59
Nondemented          1           64   65
All                 53           71  124
```

[105]:
```
metrics.plot_roc_curve(ada_clf, X_test, y_test)

plt.show()
```



[106]:
```
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 : 0.9491525423728814
```

[107]:
```
NUM_TRIALS = 10


ada_nested_scores = np.zeros(NUM_TRIALS)
ada_non_nested_scores = np.zeros(NUM_TRIALS)
```

```
p_grid={'n_estimators':[100,200,500],'learning_rate':[.001,0.01,.1]}

# Loop for each trial
for i in range(NUM_TRIALS):



    inner_cv = KFold(n_splits=10, shuffle=True, random_state=i)
    outer_cv = KFold(n_splits=10, shuffle=True, random_state=i)

    # Non_nested parameter search and scoring
    nonnes_ada_clf = GridSearchCV(estimator=ada_clf, param_grid=p_grid,␣
 ↪cv=outer_cv)
    nonnes_ada_clf.fit(X_data, y_data)
    ada_non_nested_scores[i] = nonnes_ada_clf.best_score_


    # Nested CV with parameter optimization
    Nes_adaclf = GridSearchCV(estimator=ada_clf, param_grid=p_grid, cv=inner_cv)

    ada_nested_score = cross_val_score(ada_clf, X=X_data, y=y_data, cv=outer_cv)
    ada_nested_score[i] = ada_nested_score.mean()
```

[108]:
```
ADA_nested_vs_non_nested_score = ada_non_nested_scores - ada_nested_score


print(
    "Average difference of nested and nonnested {:6f} with std. dev. of {:6f}.".
 ↪format(
        ADA_nested_vs_non_nested_score.mean(), ADA_nested_vs_non_nested_score.
 ↪std()
    )
)
```

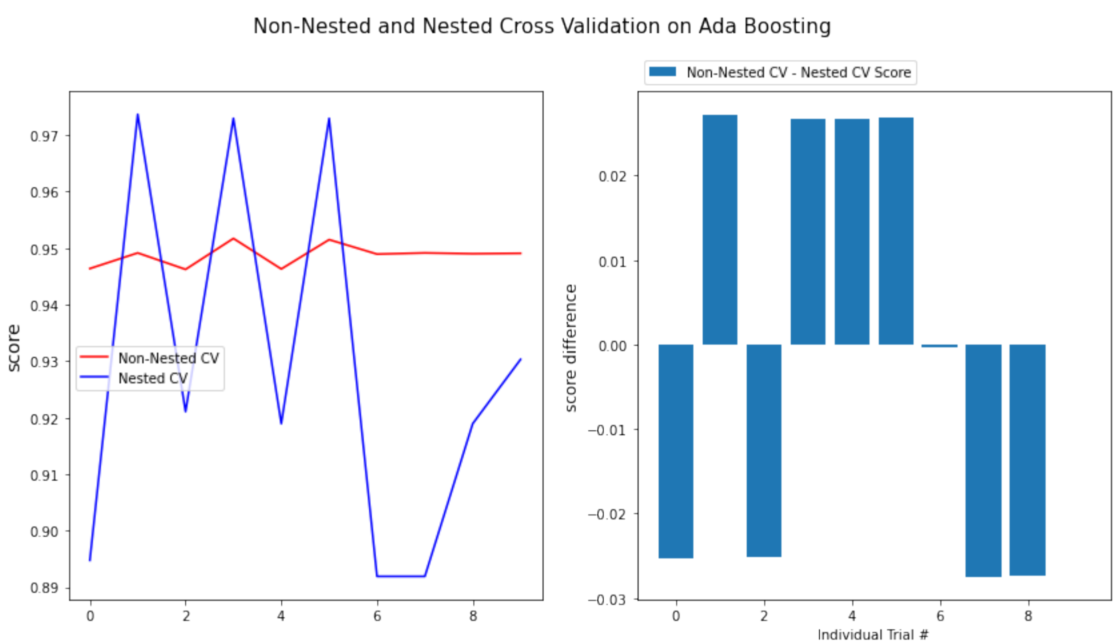
```
Average difference of nested and nonnested 0.020007 with std. dev. of 0.030582.
```

[109]:
```
print('ADA Nested Accuracy: %.3f' % (mean(ada_nested_score)*100))


print('ADA Nonnested Accuracy: %.3f ' % (mean(ada_non_nested_scores)*100))
```

```
ADA Nested Accuracy: 92.873
ADA Nonnested Accuracy: 94.874
```

[146]:
```
# Plot scores for nested and non-nested CV
plt.figure(figsize=(14, 7))
```

```
plt.subplot(1,2,1)
(non_nested_line,) = plt.plot(ada_non_nested_scores, color="r")
(nested_line,) = plt.plot(ada_nested_score, color="b")
plt.ylabel("score", fontsize="14")
plt.legend(
    [non_nested_line, nested_line],
    ["Non-Nested CV", "Nested CV"],
    bbox_to_anchor=(0, 0.4, 0.5, 0),
)

plt.title( "Non-Nested and Nested Cross Validation on Ada Boosting", x=1.0, y=1.1, fontsize="15" )


# Plot bar chart of the difference.
plt.subplot(1,2,2)
difference_plot = plt.bar(range(NUM_TRIALS), SVM_nested_vs_non_nested_score)
plt.xlabel("Individual Trial #")
plt.legend(
    [difference_plot],
    ["Non-Nested CV - Nested CV Score"],
    bbox_to_anchor=(0, 1, 0.8, 0),
)
plt.ylabel("score difference", fontsize="12")

plt.show()
```



[130]:
```
ada_nested_score_mean = ada_nested_score.mean()
ada_nested_score_mean
```

[130]: 0.9287339971550498

[139]:
```
ada_non_nested_score_mean = ada_non_nested_scores.mean()
ada_non_nested_score_mean
```

[139]: 0.9487411095305832

0.0.7 Gradient boosting

[111]:
```
from sklearn.ensemble import GradientBoostingClassifier
```

[112]:
```
Gra_clf = GradientBoostingClassifier(n_estimators=100, learning_rate=1.0,
                                      max_depth=1, random_state=0).fit(X_train,␣
 ↪y_train)
```

[113]:
```
Gra_clf.score(X_test, y_test)
```

[113]: 0.9274193548387096

[114]:
```
yhat_Gra_cl = Gra_clf.predict(X_test)

Gra_yhat_prob = Gra_clf.predict_proba(X_test)
```

[115]:
```
gra_accuracy_score = Gra_clf.score(X_test, y_test)*100
print("gra_accuracy_score :", gra_accuracy_score )
```

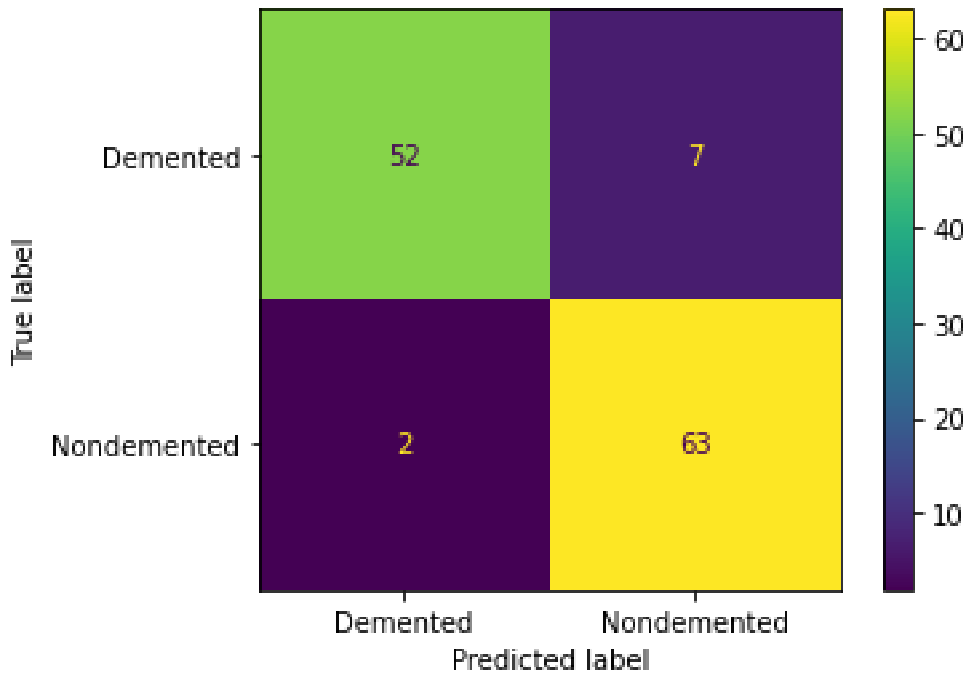
```
gra_accuracy_score : 92.74193548387096
```

[116]:
```
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
 [[52  7]
 [ 2 63]]

classification report
               precision    recall  f1-score   support

    Demented       0.96      0.88      0.92        59
 Nondemented       0.90      0.97      0.93        65

    accuracy                           0.93       124
   macro avg       0.93      0.93      0.93       124
weighted avg       0.93      0.93      0.93       124
```

```
Accuracy:  92.74193548387096
```

[117]:
```python
plot_confusion_matrix(Gra_clf, X_test, y_test)
plt.show()
```

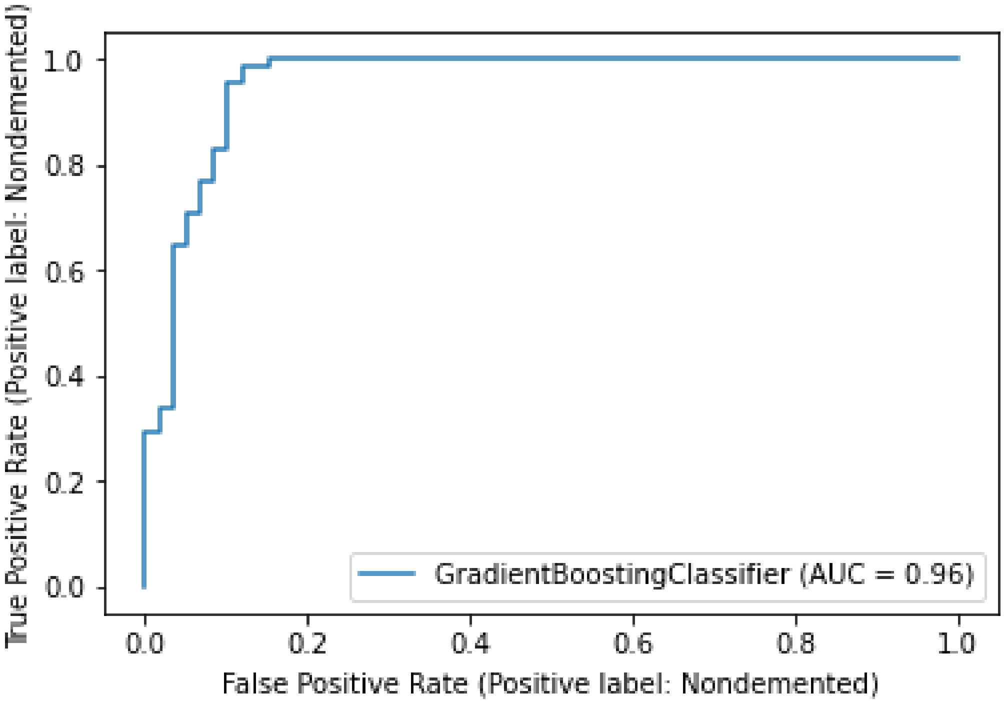


[118]:
```python
# Confusion matrix using crosstab method of pandas.
Gra_pd = pd.crosstab(y_test, yhat_Gra_cl, rownames=['True'],␣
 ↪colnames=['Predicted'], margins=True)
Gra_pd
```

[118]:

Predicted True	Demented	Nondemented	All
Demented	52	7	59
Nondemented	2	63	65
All	54	70	124

[119]:
```python
metrics.plot_roc_curve(Gra_clf, X_test, y_test)

plt.show()
```



[120]:
```
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 : 0.9577574967405476
```

[121]:
```
NUM_TRIALS = 10


gra_nested_scores = np.zeros(NUM_TRIALS)
gra_non_nested_scores = np.zeros(NUM_TRIALS)

p_grid = {
    "loss":["deviance"],
    "learning_rate": [0.01, 0.025, 0.05, 0.075, 0.1, 0.15, 0.2],
    "min_samples_split": np.linspace(0.1, 0.5, 12),
    "min_samples_leaf": np.linspace(0.1, 0.5, 12),
    "max_depth":[3,5,8],
    "max_features":["log2","sqrt"],
    "criterion": ["friedman_mse"],
    "subsample":[0.5, 0.618, 0.8, 0.85, 0.9, 0.95, 1.0],
    "n_estimators":[10]
    }
```

```
for i in range(NUM_TRIALS):



    inner_cv = KFold(n_splits=10, shuffle=True, random_state=i)
    outer_cv = KFold(n_splits=10, shuffle=True, random_state=i)

    # Non_nested parameter search and scoring
    nonnes_gra_clf = GridSearchCV(estimator=Gra_clf, param_grid=p_grid,␣
 ↪cv=outer_cv)
    nonnes_gra_clf.fit(X_data, y_data)
    gra_non_nested_scores[i] = nonnes_gra_clf.best_score_



    # Nested CV with parameter optimization
    Nes_graclf = GridSearchCV(estimator=Gra_clf, param_grid=p_grid, cv=inner_cv)

    gra_nested_scores = cross_val_score(Gra_clf, X=X_data, y=y_data,␣
 ↪cv=outer_cv)
    gra_nested_scores[i] = gra_nested_scores.mean()
```

[122]:
```
GRA_nested_vs_non_nested_score =  gra_nested_scores - gra_non_nested_scores


print(
    "Average difference of nested and nonnested {:6f} with std. dev. of {:6f}.".
 ↪format(
        GRA_nested_vs_non_nested_score.mean(), GRA_nested_vs_non_nested_score.
 ↪std()
    )
)
```

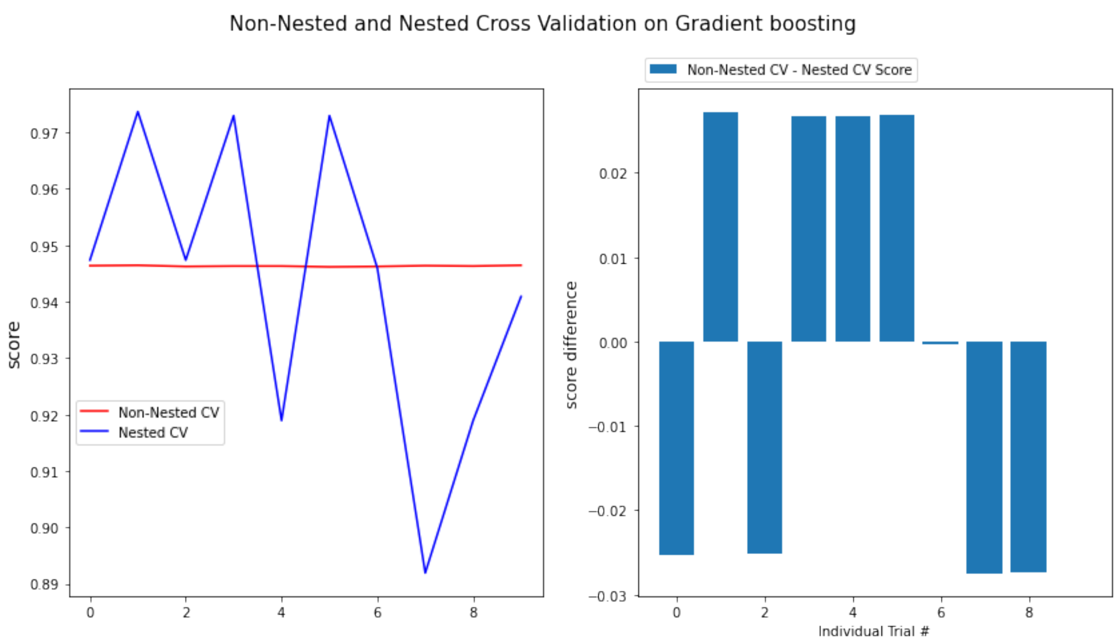
```
Average difference of nested and nonnested -0.003222 with std. dev. of 0.025631.
```

[123]:
```
print('Gradient Nested Accuracy: %.3f' % (mean(gra_nested_scores)*100))


print('Gradient Nonnested Accuracy: %.3f ' % (mean(gra_non_nested_scores)*100))
```

```
Gradient Nested Accuracy: 94.309
Gradient Nonnested Accuracy: 94.632
```

[124]:
```
# Plot scores for nested and non-nested CV
plt.figure(figsize=(14, 7))

plt.subplot(1,2,1)
```

```
(non_nested_line,) = plt.plot(gra_non_nested_scores, color="r")
(nested_line,) = plt.plot(gra_nested_scores, color="b")
plt.ylabel("score", fontsize="14")
plt.legend(
    [non_nested_line, nested_line],
    ["Non-Nested CV", "Nested CV"],
    bbox_to_anchor=(0, 0.4, 0.5, 0),
)

plt.title( "Non-Nested and Nested Cross Validation on Gradient boosting", x=1.
↪0, y=1.1, fontsize="15" )


# Plot bar chart of the difference.
plt.subplot(1,2,2)
difference_plot = plt.bar(range(NUM_TRIALS), SVM_nested_vs_non_nested_score)
plt.xlabel("Individual Trial #")
plt.legend(
    [difference_plot],
    ["Non-Nested CV - Nested CV Score"],
    bbox_to_anchor=(0, 1, 0.8, 0),
)
plt.ylabel("score difference", fontsize="12")

plt.show()
```



```
[131]: gra_nested_score_mean = gra_nested_scores.mean()
gra_nested_score_mean
```

```
[131]: 0.9430938833570414
```

```
[140]: gra_non_nested_score_mean = gra_non_nested_scores.mean()
gra_non_nested_score_mean
```

```
[140]: 0.9463157894736842
```

0.0.8 Results

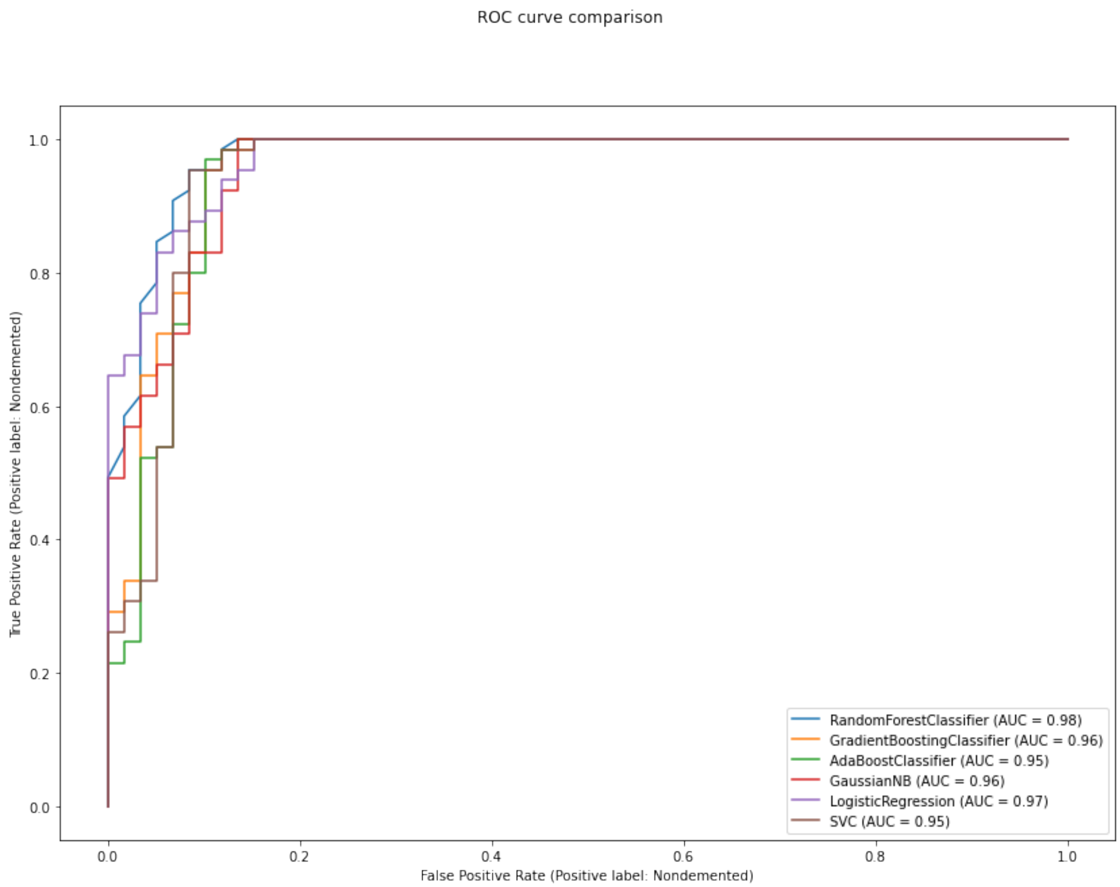
Accuracy score report dataframe

```
[144]: # create a accuracy list
accuracy_score = [␣
 ↪SVM_accuracy_score,LR_accuracy_score,RF_accuracy_score,gnb_Accuracy_score,
                  ada_accuracy_score,gra_accuracy_score]

# 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,gra_roc_auc_score,]


# create a nested-score list
Nested_score = [svm_nested_score_mean,lr_nested_score_mean,rf_nested_score_mean,
              ␣
 ↪gnb_nested_score_mean,ada_nested_score_mean,gra_nested_score_mean]

# create a non_nested-score list
Non_Nested_score =␣
 ↪[svm_non_nested_score_mean,lr_non_nested_score_mean,rf_non_nested_score_mean,
              ␣
 ↪gnb_non_nested_score_mean,ada_non_nested_score_mean,gra_non_nested_score_mean]


# 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.insert(loc=2, column='Nested Score (mean)', value= Nested_score)
df_report.insert(loc=3, column='Non Nested Score (mean)', value=␣
 ↪Non_Nested_score)
df_report.columns.name = 'Algorithm'
```

```
df_report
```

[144]:
```
Algorithm             Accuracy Score  ROC AUC Score  Nested Score (mean)  \
SVM                        92.741935       0.951239             0.946494
Logistic Regression        92.741935       0.973142             0.943521
Random Forest              93.548387       0.975489             0.946494
Naive Bayes                93.548387       0.959844             0.946415
Ada Boosting               93.548387       0.949153             0.928734
Gradient boosting          92.741935       0.957757             0.943094

Algorithm             Non Nested Score (mean)
SVM                                  0.946316
Logistic Regression                  0.943350
Random Forest                        0.949559
Naive Bayes                          0.944957
Ada Boosting                         0.948741
Gradient boosting                    0.946316
```

[126]:
```
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
True Positive Rate (Positive label: Nondemented)
False Positive Rate (Positive label: Nondemented)
0.0
0.2
0.4
0.6
0.8
1.0
RandomForestClassifier (AUC = 0.98)
GradientBoostingClassifier (AUC = 0.96)
AdaBoostClassifier (AUC = 0.95)
GaussianNB (AUC = 0.96)
LogisticRegression (AUC = 0.97)
SVC (AUC = 0.95)