insurance-claim-fraud-detection-2

April 2, 2024

[1]:
```
import pandas as pd

#Data Loading

datapath = "insurance_claims.csv"

data = pd.read_csv(datapath)

original_data = data.copy()

data.head()
```

[1]:
```
   months_as_customer  age  policy_number policy_bind_date policy_state  \
0                 328   48         521585       2014-10-17           OH
1                 228   42         342868       2006-06-27           IN
2                 134   29         687698       2000-09-06           OH
3                 256   41         227811       1990-05-25           IL
4                 228   44         367455       2014-06-06           IL

  policy_csl  policy_deductable  policy_annual_premium  umbrella_limit  \
0    250/500               1000                1406.91               0
1    250/500               2000                1197.22         5000000
2    100/300               2000                1413.14         5000000
3    250/500               2000                1415.74         6000000
4   500/1000               1000                1583.91         6000000

   insured_zip  … police_report_available total_claim_amount injury_claim  \
0       466132  …                     YES              71610         6510
1       468176  …                       ?               5070          780
2       430632  …                      NO              34650         7700
3       608117  …                      NO              63400         6340
4       610706  …                      NO               6500         1300

  property_claim vehicle_claim  auto_make  auto_model auto_year  \
0          13020         52080       Saab         92x      2004
1            780          3510   Mercedes        E400      2007
2           3850         23100      Dodge         RAM      2007
```

```
3            6340         50720  Chevrolet       Tahoe      2014
4             650          4550     Accura         RSX      2009

  fraud_reported _c39
0              Y  NaN
1              Y  NaN
2              N  NaN
3              Y  NaN
4              N  NaN

[5 rows x 40 columns]
```

[2]:
```
#Data Exploration

data.columns
```

[2]:
```
Index(['months_as_customer', 'age', 'policy_number', 'policy_bind_date',
       'policy_state', 'policy_csl', 'policy_deductable',
       'policy_annual_premium', 'umbrella_limit', 'insured_zip', 'insured_sex',
       'insured_education_level', 'insured_occupation', 'insured_hobbies',
       'insured_relationship', 'capital-gains', 'capital-loss',
       'incident_date', 'incident_type', 'collision_type', 'incident_severity',
       'authorities_contacted', 'incident_state', 'incident_city',
       'incident_location', 'incident_hour_of_the_day',
       'number_of_vehicles_involved', 'property_damage', 'bodily_injuries',
       'witnesses', 'police_report_available', 'total_claim_amount',
       'injury_claim', 'property_claim', 'vehicle_claim', 'auto_make',
       'auto_model', 'auto_year', 'fraud_reported', '_c39'],
      dtype='object')
```

[3]:
```
data.shape
```

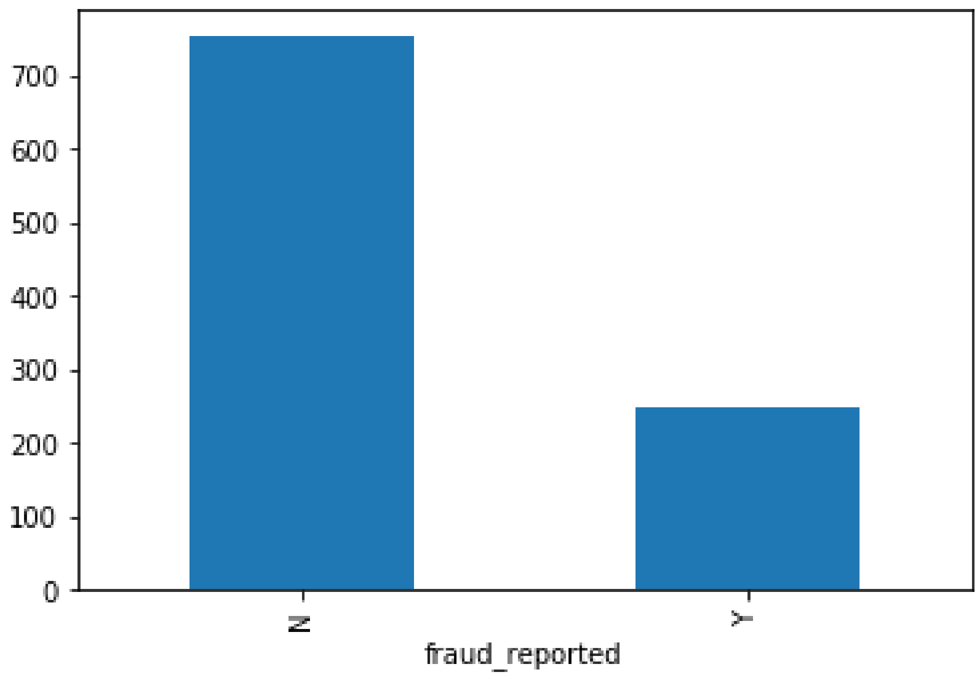
[3]:
```
(1000, 40)
```

[4]:
```
#check missing or null or any values
print("Null Values: " + str(data.isnull().any().sum()))
```

```
Null Values: 1
```

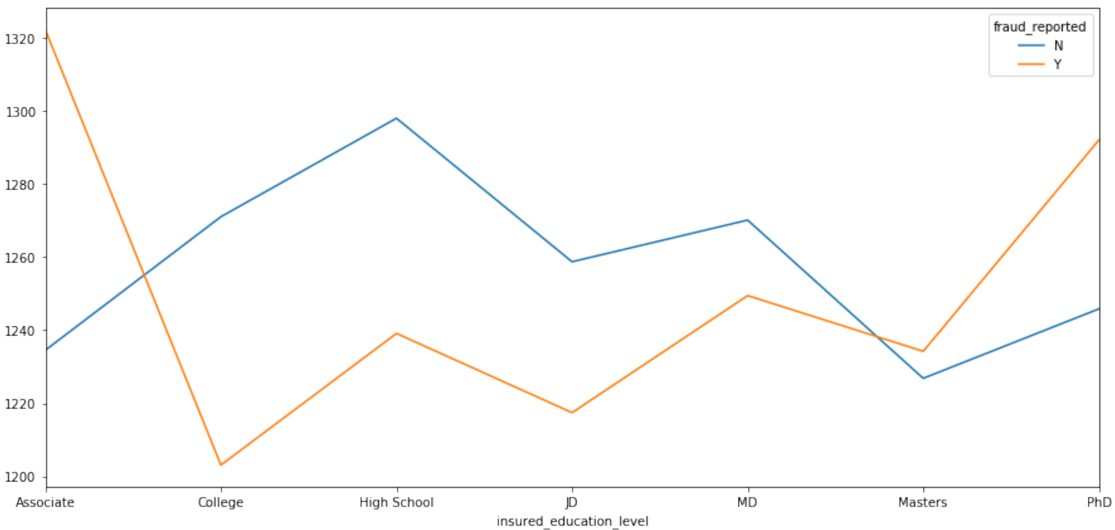
[5]:
```
#Fraud Reported Stats
df_count_fraud = data.groupby(['fraud_reported']).count()
df_fraud = df_count_fraud['policy_number']
df_fraud.plot.bar(x='Fraud Reported', y='Count')
```

[5]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x20c39b2cbe0>
```



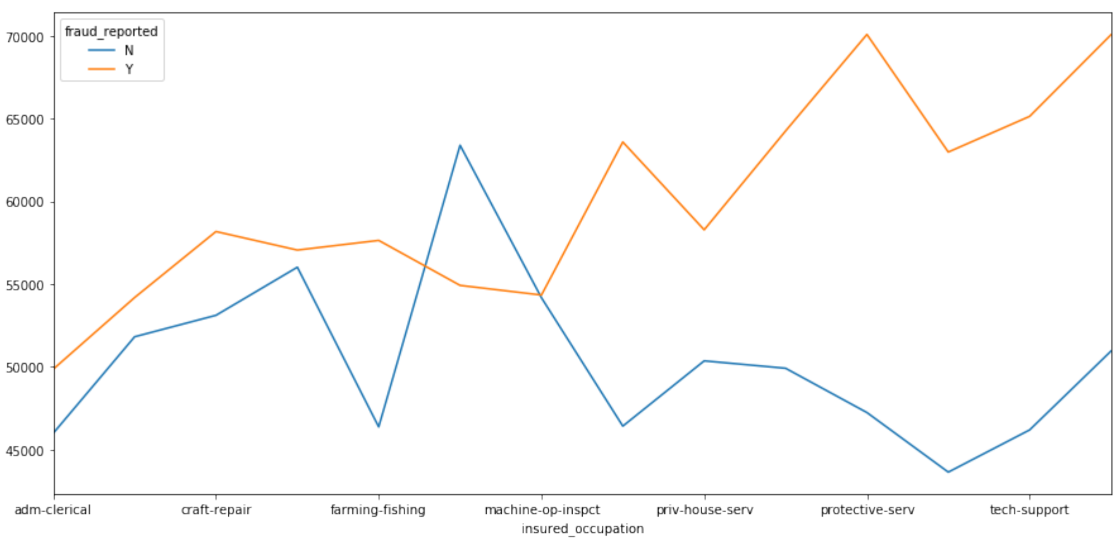
[6]:
```
#Annual premium of education level policy_annual_premium
import matplotlib.pyplot as plt

# plot data
fig, ax = plt.subplots(figsize=(15,7))
df_avg_prem = data.groupby(['insured_education_level', 'fraud_reported']).
↪mean()['policy_annual_premium']
df_avg_prem.unstack().plot(ax=ax)
```

[6]: <matplotlib.axes._subplots.AxesSubplot at 0x20c39c31a90>



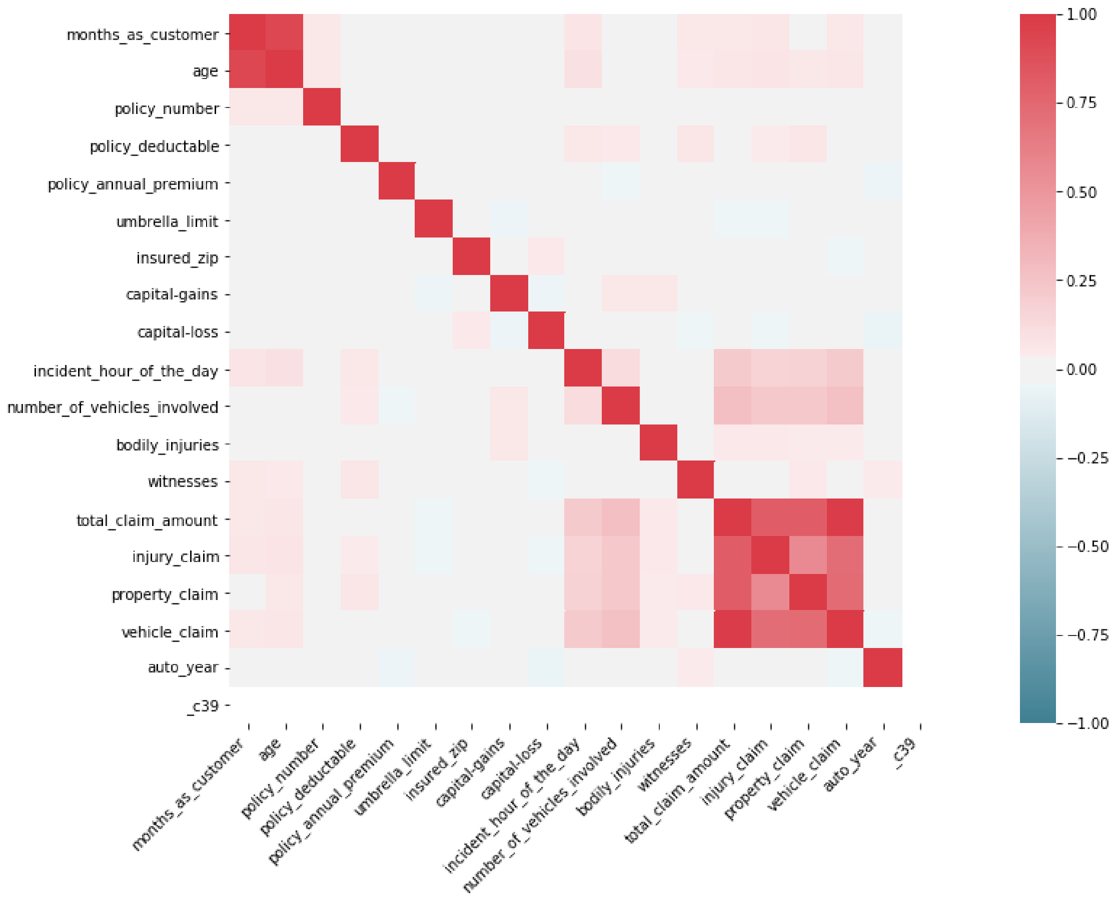
[7]:
```
fig, ax = plt.subplots(figsize=(15,7))
data.groupby(['insured_occupation', 'fraud_reported']).
    ↪mean()['total_claim_amount'].unstack().plot(ax=ax)
```

[7]: <matplotlib.axes._subplots.AxesSubplot at 0x20c39cad278>



[8]:
```
import numpy as np
import seaborn as sns

plt.figure(figsize=(20, 9))
```

```
corr = data.corr()
ax = sns.heatmap(
    corr,
    vmin=-1, vmax=1, center=0,
    cmap=sns.diverging_palette(220, 10, as_cmap=True),
    square=True
)
ax.set_xticklabels(
    ax.get_xticklabels(),
    rotation=45,
    horizontalalignment='right'
);
```



[9]:
```
#Remove Less Correlated Columns
deleteCols = ["policy_number", "policy_bind_date", "insured_zip",␣
 ↪"incident_location", "incident_date", "_c39"]
data = data.drop(deleteCols, axis=1)
data
```

```
[9]:      months_as_customer  age policy_state policy_csl  policy_deductable  \
     0                   328   48           OH    250/500               1000
     1                   228   42           IN    250/500               2000
     2                   134   29           OH    100/300               2000
     3                   256   41           IL    250/500               2000
     4                   228   44           IL   500/1000               1000
     ..                  …  …          …        …               …
     995                   3   38           OH   500/1000               1000
     996                 285   41           IL    100/300               1000
     997                 130   34           OH    250/500                500
     998                 458   62           IL   500/1000               2000
     999                 456   60           OH    250/500               1000

          policy_annual_premium  umbrella_limit insured_sex  \
     0                  1406.91               0        MALE
     1                  1197.22         5000000        MALE
     2                  1413.14         5000000      FEMALE
     3                  1415.74         6000000      FEMALE
     4                  1583.91         6000000        MALE
     ..                   …             …         …
     995                1310.80               0      FEMALE
     996                1436.79               0      FEMALE
     997                1383.49         3000000      FEMALE
     998                1356.92         5000000        MALE
     999                 766.19               0      FEMALE

         insured_education_level insured_occupation  … witnesses  \
     0                        MD       craft-repair  …         2
     1                        MD  machine-op-inspct  …         0
     2                       PhD              sales  …         3
     3                       PhD       armed-forces  …         2
     4                 Associate              sales  …         1
     ..                      …               …  …       …
     995                 Masters       craft-repair  …         1
     996                     PhD     prof-specialty  …         3
     997                 Masters       armed-forces  …         3
     998               Associate  handlers-cleaners  …         1
     999               Associate              sales  …         3

         police_report_available  total_claim_amount  injury_claim property_claim  \
     0                       YES               71610          6510          13020
     1                         ?                5070           780            780
     2                        NO               34650          7700           3850
     3                        NO               63400          6340           6340
     4                        NO                6500          1300            650
     ..                      …                 …           …            …
     995                       ?               87200         17440           8720
```

```
996                      ?             108480          18080          18080
997                    YES              67500           7500           7500
998                    YES              46980           5220           5220
999                      ?               5060            460            920

    vehicle_claim   auto_make auto_model auto_year fraud_reported
0           52080        Saab        92x      2004              Y
1            3510    Mercedes       E400      2007              Y
2           23100       Dodge        RAM      2007              N
3           50720   Chevrolet      Tahoe      2014              Y
4            4550      Accura        RSX      2009              N
..            …           …          …       …             …
995         61040       Honda     Accord      2006              N
996         72320  Volkswagen     Passat      2015              N
997         52500      Suburu    Impreza      1996              N
998         36540        Audi         A5      1998              N
999          3680    Mercedes       E400      2007              N

[1000 rows x 34 columns]
```

[10]:
```python
#Handle Categorical Data
data.dtypes
```

[10]:
```
months_as_customer              int64
age                             int64
policy_state                   object
policy_csl                     object
policy_deductable               int64
policy_annual_premium         float64
umbrella_limit                  int64
insured_sex                    object
insured_education_level        object
insured_occupation             object
insured_hobbies                object
insured_relationship           object
capital-gains                   int64
capital-loss                    int64
incident_type                  object
collision_type                 object
incident_severity              object
authorities_contacted          object
incident_state                 object
incident_city                  object
incident_hour_of_the_day        int64
number_of_vehicles_involved     int64
property_damage                object
bodily_injuries                 int64
```

```
witnesses                        int64
police_report_available         object
total_claim_amount               int64
injury_claim                     int64
property_claim                   int64
vehicle_claim                    int64
auto_make                       object
auto_model                      object
auto_year                        int64
fraud_reported                  object
dtype: object
```

[11]:
```
#One-hot encoding all categorical columns except output column(i.e.␣
↪fraud_reported)
list_hot_encoded = []
for column in data.columns:
    if(data[column].dtypes==object and column != 'fraud_reported'):
        data = pd.concat([data, pd.get_dummies(data[column], prefix=column)],␣
↪axis=1)
        list_hot_encoded.append(column)
#Drop hot-encoded columns
data = data.drop(list_hot_encoded, axis=1)

#Binary encoder for output column
data['fraud_reported'] = data['fraud_reported'].map( {'Y':1, 'N':0})

data
```

[11]:
```
     months_as_customer  age  policy_deductable  policy_annual_premium  \
0                   328   48               1000                1406.91
1                   228   42               2000                1197.22
2                   134   29               2000                1413.14
3                   256   41               2000                1415.74
4                   228   44               1000                1583.91
..                  …    …                 …                     …
995                   3   38               1000                1310.80
996                 285   41               1000                1436.79
997                 130   34                500                1383.49
998                 458   62               2000                1356.92
999                 456   60               1000                 766.19

     umbrella_limit  capital-gains  capital-loss  incident_hour_of_the_day  \
0                 0          53300             0                         5
1           5000000              0             0                         8
2           5000000          35100             0                         7
3           6000000          48900        -62400                         5
4           6000000          66000        -46000                        20
```

```
..          …         …         …                 …
995         0         0         0                20
996         0     70900         0                23
997   3000000     35100         0                 4
998   5000000         0         0                 2
999         0         0         0                 6

     number_of_vehicles_involved  bodily_injuries  …  auto_model_Pathfinder  \
0                              1                1  …                      0
1                              1                0  …                      0
2                              3                2  …                      0
3                              1                1  …                      0
4                              1                0  …                      0
..                           …              …  …                    …
995                            1                0  …                      0
996                            1                2  …                      0
997                            3                2  …                      0
998                            1                0  …                      0
999                            1                0  …                      0

     auto_model_RAM  auto_model_RSX  auto_model_Silverado  auto_model_TL  \
0                 0               0                     0              0
1                 0               0                     0              0
2                 1               0                     0              0
3                 0               0                     0              0
4                 0               1                     0              0
..              …             …                   …            …
995               0               0                     0              0
996               0               0                     0              0
997               0               0                     0              0
998               0               0                     0              0
999               0               0                     0              0

     auto_model_Tahoe  auto_model_Ultima  auto_model_Wrangler  auto_model_X5  \
0                   0                  0                    0              0
1                   0                  0                    0              0
2                   0                  0                    0              0
3                   1                  0                    0              0
4                   0                  0                    0              0
..                …                …                  …            …
995                 0                  0                    0              0
996                 0                  0                    0              0
997                 0                  0                    0              0
998                 0                  0                    0              0
999                 0                  0                    0              0

     auto_model_X6
```

```
0                  0
1                  0
2                  0
3                  0
4                  0
..               …
995                0
996                0
997                0
998                0
999                0

[1000 rows x 162 columns]
```

[12]:
```
#Model Training
from sklearn.metrics import confusion_matrix
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.model_selection import train_test_split

y = data['fraud_reported']
X = data.drop(['fraud_reported'], axis=1)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.15,␣
  ↪random_state=42)
```

[13]:
```
from sklearn import neighbors

#K-Nearest Neighbors
print("KNN Score :")
KNNClassifier = neighbors.KNeighborsClassifier(n_neighbors=12,␣
  ↪weights='distance')
KNNClassifier.fit(X=X_train,y=y_train)
KNNClassifier.score(X_test,y_test)
```

```
KNN Score :
```

[13]:
```
0.7333333333333333
```

[14]:
```
KNN_y_predicted = KNNClassifier.predict(X_test)
class_names = np.unique(np.array(y_test))
confusion_matrix(y_test, KNN_y_predicted)
```

[14]:
```
array([[108,   5],
       [ 35,   2]], dtype=int64)
```

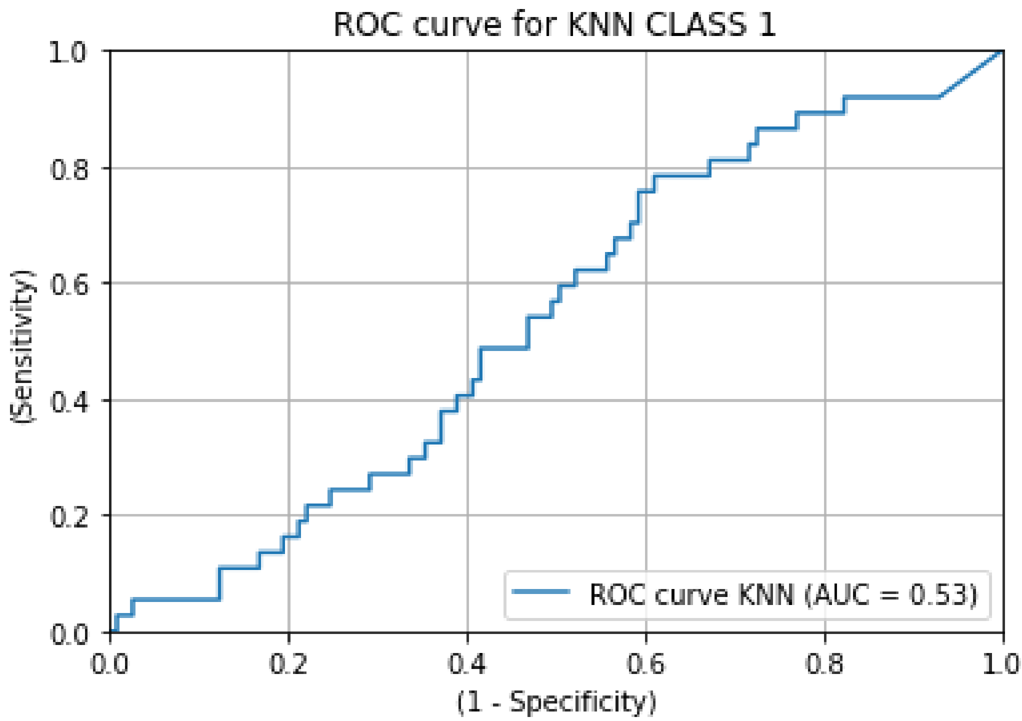
[15]:

```
from sklearn.metrics import classification_report
from sklearn.model_selection import cross_val_score

print(classification_report(y_test, KNN_y_predicted))

scores = cross_val_score(KNNClassifier, X, y, cv=10, scoring='accuracy')
knn_accuracy = scores.mean()
print('Cross-Validated Accuracy: %0.2f' % knn_accuracy)
```

```
              precision    recall  f1-score   support

           0       0.76      0.96      0.84       113
           1       0.29      0.05      0.09        37

    accuracy                           0.73       150
   macro avg       0.52      0.50      0.47       150
weighted avg       0.64      0.73      0.66       150

Cross-Validated Accuracy: 0.73
```

[16]:

```
from sklearn.metrics import roc_curve, auc
knn_pred_prob = KNNClassifier.predict_proba(X_test)[:, 1]
fpr, tpr, thresholds = roc_curve(y_test, knn_pred_prob)
roc_auc = auc(fpr, tpr)
lw = 2
plt.plot(fpr, tpr,label='ROC curve KNN (AUC = %0.2f)' % roc_auc)
plt.xlim([0.0, 1])
plt.ylim([0.0, 1])
plt.title('ROC curve for KNN CLASS 1')
plt.xlabel('(1 - Specificity)')
plt.ylabel('(Sensitivity)')
plt.grid(True)
plt.legend(loc="lower right")
plt.show()
```



[17]:

```
from sklearn import tree

#DecisionTree
DTClassifier = tree.DecisionTreeClassifier()
DTClassifier.fit(X_train, y_train)

print("Decision Tree Score :")
DTClassifier.score(X_test,y_test)
```

```
Decision Tree Score :
```

[17]:

```
0.8066666666666666
```

[18]:

```
DT_y_predicted = DTClassifier.predict(X_test)
class_names = np.unique(np.array(y_test))
confusion_matrix(y_test, DT_y_predicted)
```

[18]:

```
array([[96, 17],
       [12, 25]], dtype=int64)
```

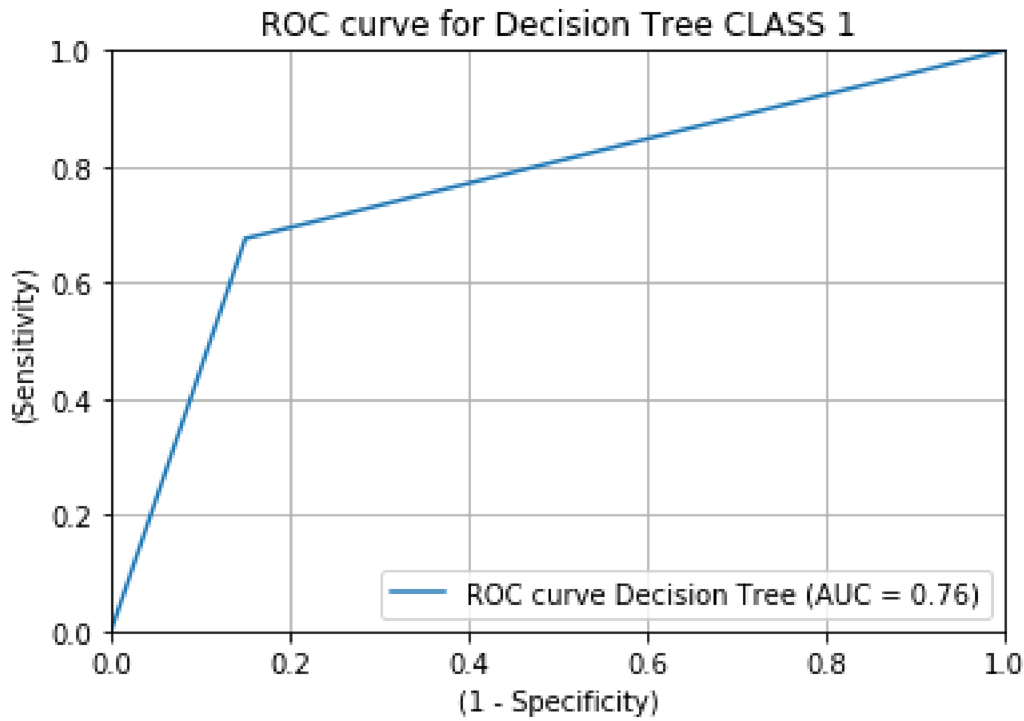
[19]:

```
print(classification_report(y_test, DT_y_predicted))

scores = cross_val_score(DTClassifier, X, y, cv=10, scoring='accuracy')
dt_accuracy = scores.mean()
```

```
print('Cross-Validated Accuracy: %0.2f' % dt_accuracy)
```

```
              precision    recall  f1-score   support

           0       0.89      0.85      0.87       113
           1       0.60      0.68      0.63        37

    accuracy                           0.81       150
   macro avg       0.74      0.76      0.75       150
weighted avg       0.82      0.81      0.81       150

Cross-Validated Accuracy: 0.78
```

[20]:
```
from sklearn.metrics import roc_curve, auc
dt_pred_prob = DTClassifier.predict_proba(X_test)[:, 1]
fpr, tpr, thresholds = roc_curve(y_test, dt_pred_prob)
roc_auc = auc(fpr, tpr)
lw = 2
plt.plot(fpr, tpr,label='ROC curve Decision Tree (AUC = %0.2f)' % roc_auc)
plt.xlim([0.0, 1])
plt.ylim([0.0, 1])
plt.title('ROC curve for Decision Tree CLASS 1')
plt.xlabel('(1 - Specificity)')
plt.ylabel('(Sensitivity)')
plt.grid(True)
plt.legend(loc="lower right")
plt.show()
```



[21]:
```
from sklearn.svm import SVC

#Support Vector Machine
SVMClassifier = SVC(kernel='rbf',probability=True,random_state=42, gamma='auto')
SVMClassifier.fit(X_train, y_train)
print("SVM Score :")
SVMClassifier.score(X_test,y_test)
```

```
SVM Score :
```

[21]:
```
0.7533333333333333
```

[22]:
```
SVM_y_predicted = SVMClassifier.predict(X_test)
class_names = np.unique(np.array(y_test))
confusion_matrix(y_test, SVM_y_predicted)
```

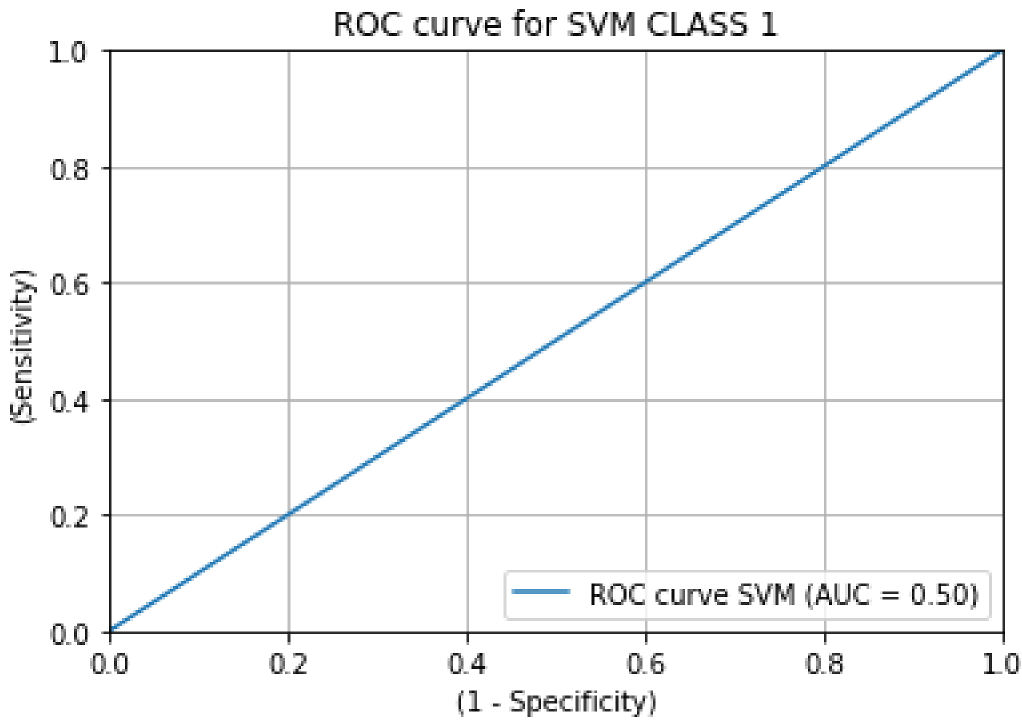
[22]:
```
array([[113,   0],
       [ 37,   0]], dtype=int64)
```

[23]:
```
from sklearn.metrics import classification_report
report = classification_report(y_test, SVM_y_predicted)
print(report)

scores = cross_val_score(SVMClassifier, X, y, cv=10, scoring='accuracy')
```

```
svm_accuracy = scores.mean()
print('Cross-Validated Accuracy: %0.2f' % svm_accuracy)
```

```
C:\ProgramData\Anaconda3\lib\site-
packages\sklearn\metrics\_classification.py:1272: 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))
              precision    recall  f1-score   support

           0       0.75      1.00      0.86       113
           1       0.00      0.00      0.00        37

    accuracy                           0.75       150
   macro avg       0.38      0.50      0.43       150
weighted avg       0.57      0.75      0.65       150

Cross-Validated Accuracy: 0.75
```

[24]:
```
svm_pred_prob = SVMClassifier.predict_proba(X_test)[:, 1]
fpr, tpr, thresholds = roc_curve(y_test, svm_pred_prob)
roc_auc = auc(fpr, tpr)
lw = 2
plt.plot(fpr, tpr,label='ROC curve SVM (AUC = %0.2f)' % roc_auc)
plt.xlim([0.0, 1])
plt.ylim([0.0, 1])
plt.title('ROC curve for SVM CLASS 1')
plt.xlabel('(1 - Specificity)')
plt.ylabel('(Sensitivity)')
plt.grid(True)
plt.legend(loc="lower right")
plt.show()
```



[25]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import cross_val_score

#Random Forest
RFClassifier = RandomForestClassifier()
RFClassifier.fit(X_train, y_train)
print("Random Forest Score :")
RFClassifier.score(X_test,y_test)
```

```
Random Forest Score :
```

[25]:
```
0.7466666666666667
```

[26]:
```
RF_y_predicted = RFClassifier.predict(X_test)
class_names = np.unique(np.array(y_test))
confusion_matrix(y_test, RF_y_predicted)
```

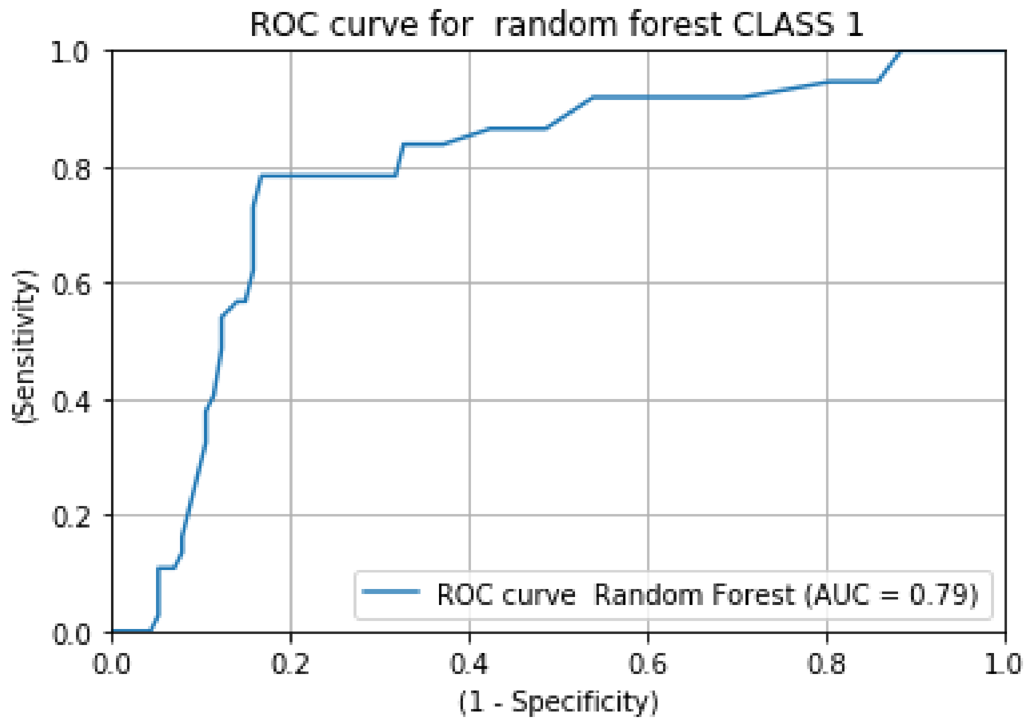
[26]:
```
array([[102,  11],
       [ 27,  10]], dtype=int64)
```

[27]:
```
from sklearn.metrics import classification_report
report = classification_report(y_test, RF_y_predicted)
print(report)
```

```
scores = cross_val_score(RFClassifier, X, y, cv=10, scoring='accuracy')
rf_accuracy = scores.mean()
print('Cross-Validated Accuracy: %0.2f' % rf_accuracy)
```

```
              precision    recall  f1-score   support

           0       0.79      0.90      0.84       113
           1       0.48      0.27      0.34        37

    accuracy                           0.75       150
   macro avg       0.63      0.59      0.59       150
weighted avg       0.71      0.75      0.72       150

Cross-Validated Accuracy: 0.78
```

[28]:
```
from sklearn.metrics import roc_curve, auc
rf_pred_prob = RFClassifier.predict_proba(X_test)[:, 1]
fpr, tpr, thresholds = roc_curve(y_test, rf_pred_prob)
roc_auc = auc(fpr, tpr)
lw = 2
plt.plot(fpr, tpr,label='ROC curve  Random Forest (AUC = %0.2f)' % roc_auc)
plt.xlim([0.0, 1])
plt.ylim([0.0, 1])
plt.title('ROC curve for  random forest CLASS 1')
plt.xlabel('(1 - Specificity)')
plt.ylabel('(Sensitivity)')
plt.grid(True)
plt.legend(loc="lower right")
plt.show()
```



[29]:
```python
from imblearn.ensemble import BalancedRandomForestClassifier
#Balanced Random Forest
BRFClassifier=BalancedRandomForestClassifier()
BRFClassifier.fit(X_train, y_train)
print("Balanced Random Forest Score :")
BRFClassifier.score(X_test,y_test)
```

```
Balanced Random Forest Score :
```

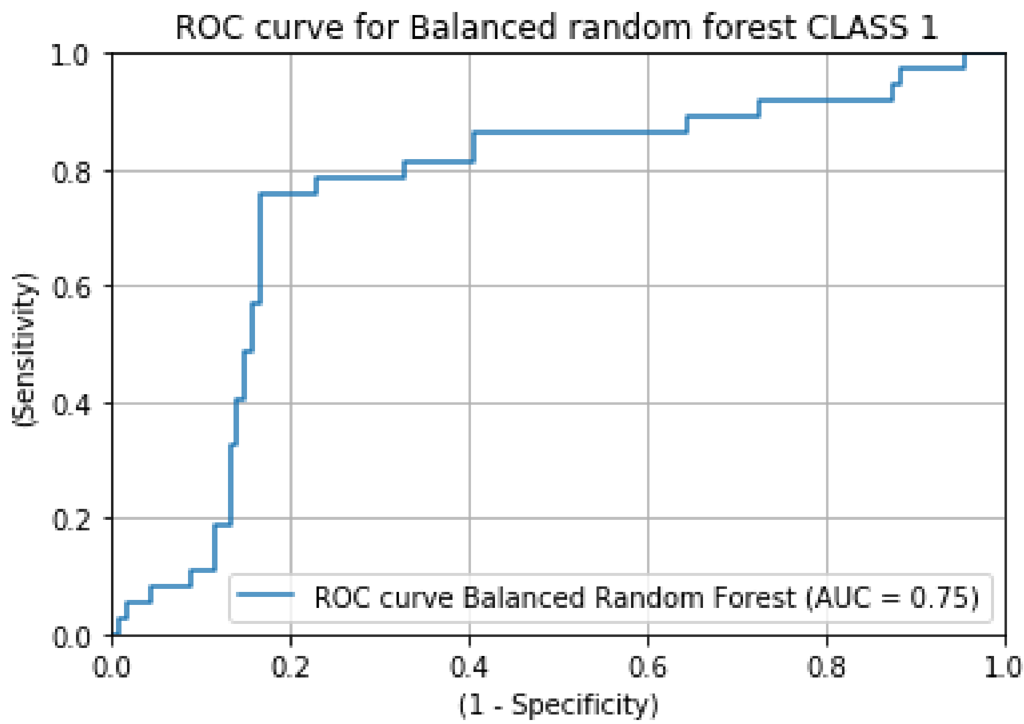
[29]: 0.7866666666666666

[30]:
```python
BRF_y_predicted = BRFClassifier.predict(X_test)
report = classification_report(y_test, BRF_y_predicted)
print(report)

scores = cross_val_score(BRFClassifier, X, y, cv=10, scoring='accuracy')
brf_accuracy = scores.mean()
print('Cross-Validated Accuracy: %0.2f' % brf_accuracy)
```

```
              precision    recall  f1-score   support

           0       0.88      0.83      0.85       113
           1       0.56      0.65      0.60        37
```

```
    accuracy                           0.79       150
   macro avg       0.72      0.74      0.73       150
weighted avg       0.80      0.79      0.79       150

Cross-Validated Accuracy: 0.83
```

[31]:
```
brf_pred_prob = BRFClassifier.predict_proba(X_test)[:, 1]
fpr, tpr, thresholds = roc_curve(y_test, brf_pred_prob)
roc_auc = auc(fpr, tpr)
lw = 2
plt.plot(fpr, tpr,label='ROC curve Balanced Random Forest (AUC = %0.2f)' %␣
 ↪roc_auc)
plt.xlim([0.0, 1])
plt.ylim([0.0, 1])
plt.title('ROC curve for Balanced random forest CLASS 1')
plt.xlabel('(1 - Specificity)')
plt.ylabel('(Sensitivity)')
plt.grid(True)
plt.legend(loc="lower right")
plt.show()
```



[32]:
```
#LDA model
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis as LDA
lda = LDA()
```

```
lda.fit(X_train, y_train)
print("Linear Discriminant Analysis Score :")
lda.score(X_test,y_test)
```

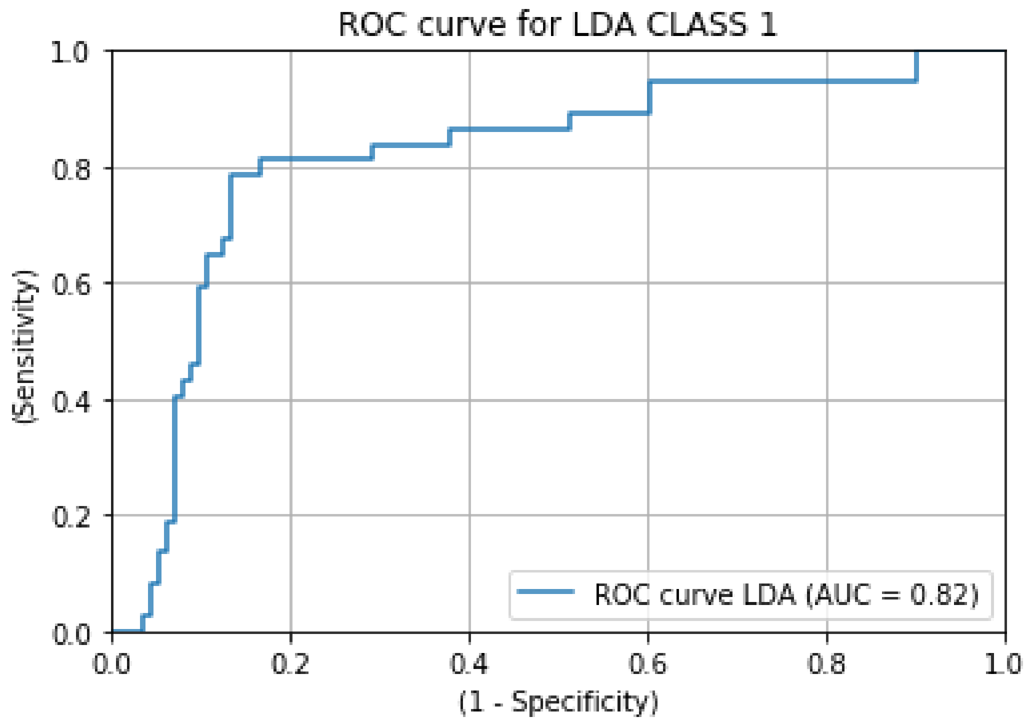
```
Linear Discriminant Analysis Score :
```

[32]:
```
0.8266666666666667
```

[33]:
```
lda_y_predicted = lda.predict(X_test)
report = classification_report(y_test, lda_y_predicted)
print(report)

scores = cross_val_score(lda, X, y, cv=10, scoring='accuracy')
lda_accuracy = scores.mean()
print('Cross-Validated Accuracy: %0.2f' % lda_accuracy)
```

```
              precision    recall  f1-score   support

           0       0.88      0.89      0.89       113
           1       0.66      0.62      0.64        37

    accuracy                           0.83       150
   macro avg       0.77      0.76      0.76       150
weighted avg       0.82      0.83      0.83       150

Cross-Validated Accuracy: 0.84
```

[34]:
```
lda_pred_prob = lda.predict_proba(X_test)[:, 1]
fpr, tpr, thresholds = roc_curve(y_test, lda_pred_prob)
roc_auc = auc(fpr, tpr)
lw = 2
plt.plot(fpr, tpr,label='ROC curve LDA (AUC = %0.2f)' % roc_auc)
plt.xlim([0.0, 1])
plt.ylim([0.0, 1])
plt.title('ROC curve for LDA CLASS 1')
plt.xlabel('(1 - Specificity)')
plt.ylabel('(Sensitivity)')
plt.grid(True)
plt.legend(loc="lower right")
plt.show()
```



[35]:
```
from sklearn.naive_bayes import BernoulliNB
#Naive Bayes Classifier
NBClassifier = BernoulliNB()
NBClassifier.fit(X_train, y_train)
print("Naive Bayes Classifier Score :")
NBClassifier.score(X_test,y_test)
```

```
Naive Bayes Classifier Score :
```

[35]: 0.8

[36]:
```
nb_y_predicted = NBClassifier.predict(X_test)
report = classification_report(y_test, nb_y_predicted)

print(report)

scores = cross_val_score(NBClassifier, X, y, cv=10, scoring='accuracy')
nb_accuracy = scores.mean()
print('Cross-Validated Accuracy: %0.2f' % nb_accuracy)
```

```
              precision    recall  f1-score   support

           0       0.87      0.86      0.87       113
           1       0.59      0.62      0.61        37
```

```
    accuracy                           0.80       150
   macro avg       0.73      0.74      0.74       150
weighted avg       0.80      0.80      0.80       150

Cross-Validated Accuracy: 0.82
```

[37]:
```python
from xgboost import XGBClassifier
#XGBOOST Classifier
model_xgb = XGBClassifier()
model_xgb.fit(X_train, y_train, verbose=False)
print("XGBClassifier Score :")
model_xgb.score(X_test,y_test)
```

```
XGBClassifier Score :
```

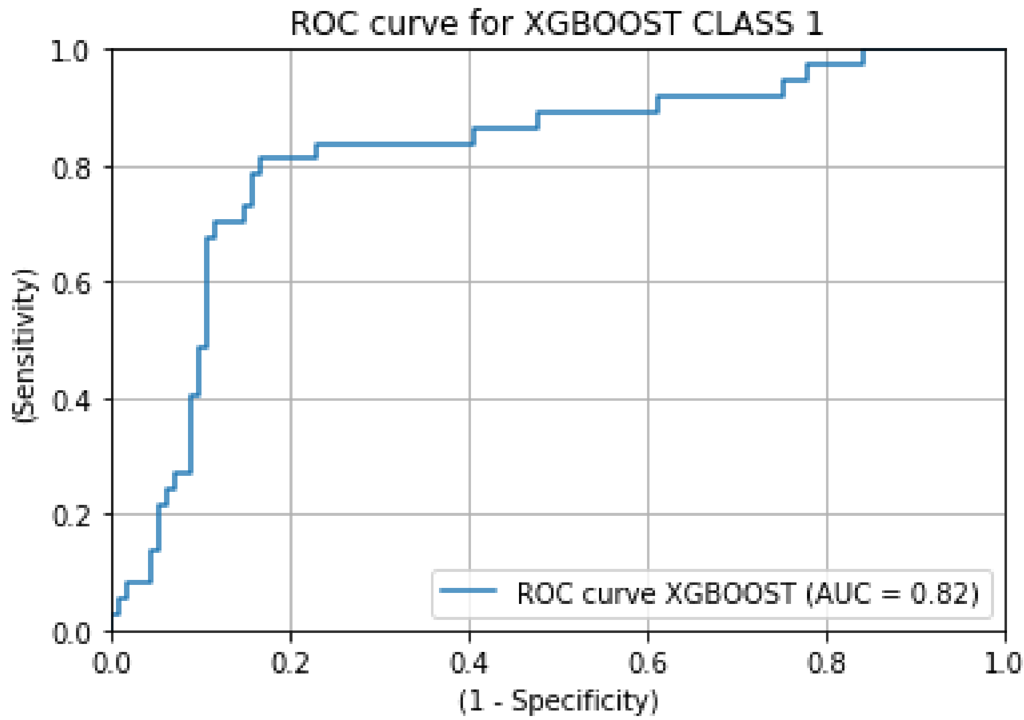
[37]:
```
0.8266666666666667
```

[38]:
```python
xgboost_y_predicted = model_xgb.predict(X_test)
report = classification_report(y_test, xgboost_y_predicted)

print(report)

scores = cross_val_score(model_xgb, X, y, cv=10, scoring='accuracy')
xgb_accuracy = scores.mean()
print('Cross-Validated Accuracy: %0.2f' % xgb_accuracy)
```

```
              precision    recall  f1-score   support

           0       0.88      0.89      0.89       113
           1       0.66      0.62      0.64        37

    accuracy                           0.83       150
   macro avg       0.77      0.76      0.76       150
weighted avg       0.82      0.83      0.83       150

Cross-Validated Accuracy: 0.82
```

[39]:
```python
xgb_pred_prob = model_xgb.predict_proba(X_test)[:, 1]
fpr, tpr, thresholds = roc_curve(y_test, xgb_pred_prob)
roc_auc = auc(fpr, tpr)
lw = 2
plt.plot(fpr, tpr,label='ROC curve XGBOOST (AUC = %0.2f)' % roc_auc)
plt.xlim([0.0, 1])
plt.ylim([0.0, 1])
plt.title('ROC curve for XGBOOST CLASS 1')
plt.xlabel('(1 - Specificity)')
plt.ylabel('(Sensitivity)')
```

```
plt.grid(True)
plt.legend(loc="lower right")
plt.show()
```



[40]:
```
from sklearn.neural_network import MLPClassifier
#Neural Network Classifier
clf_MLP = MLPClassifier(alpha=1e-05, hidden_layer_sizes=(64))
clf_MLP.fit(X_train, y_train)
print("MLPClassifier Score :")
clf_MLP.score(X_test,y_test)
```

```
MLPClassifier Score :

C:\ProgramData\Anaconda3\lib\site-
packages\sklearn\neural_network\_multilayer_perceptron.py:571:
ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) reached and
the optimization hasn't converged yet.
  % self.max_iter, ConvergenceWarning)
```

[40]: 0.74

[41]:
```
mlp_y_predicted = clf_MLP.predict(X_test)
report = classification_report(y_test, mlp_y_predicted)
```

```python
print(report)

scores = cross_val_score(clf_MLP, X, y, cv=10, scoring='accuracy')
mlp_accuracy = scores.mean()
print('Cross-Validated Accuracy: %0.2f' % mlp_accuracy)
```

```
              precision    recall  f1-score   support

           0       0.75      0.98      0.85       113
           1       0.00      0.00      0.00        37

    accuracy                           0.74       150
   macro avg       0.38      0.49      0.43       150
weighted avg       0.56      0.74      0.64       150


C:\ProgramData\Anaconda3\lib\site-
packages\sklearn\neural_network\_multilayer_perceptron.py:571:
ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) reached and
the optimization hasn't converged yet.
  % self.max_iter, ConvergenceWarning)
C:\ProgramData\Anaconda3\lib\site-
packages\sklearn\neural_network\_multilayer_perceptron.py:571:
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C:\ProgramData\Anaconda3\lib\site-
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ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) reached and
the optimization hasn't converged yet.
  % self.max_iter, ConvergenceWarning)
C:\ProgramData\Anaconda3\lib\site-
packages\sklearn\neural_network\_multilayer_perceptron.py:571:
```

```
ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) reached and
the optimization hasn't converged yet.
  % self.max_iter, ConvergenceWarning)
C:\ProgramData\Anaconda3\lib\site-
packages\sklearn\neural_network\_multilayer_perceptron.py:571:
ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) reached and
the optimization hasn't converged yet.
  % self.max_iter, ConvergenceWarning)
C:\ProgramData\Anaconda3\lib\site-
packages\sklearn\neural_network\_multilayer_perceptron.py:571:
ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) reached and
the optimization hasn't converged yet.
  % self.max_iter, ConvergenceWarning)
```

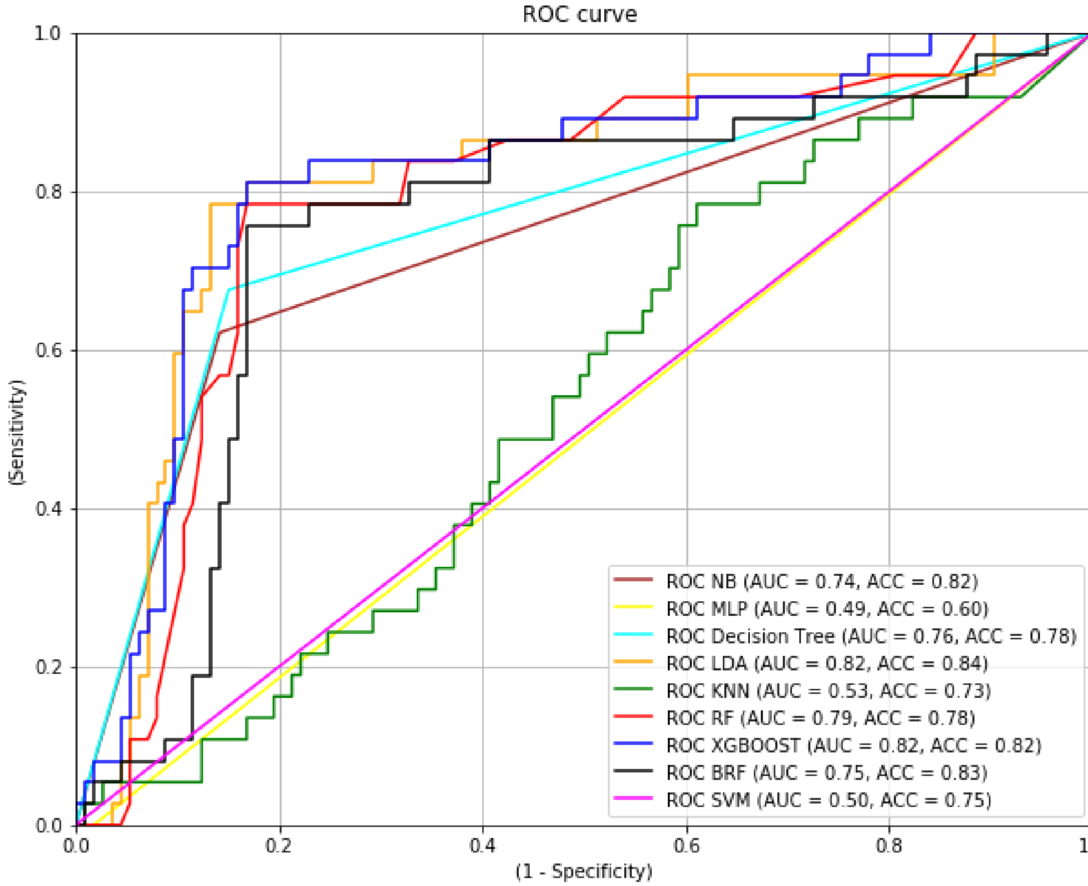
```
Cross-Validated Accuracy: 0.60
```

```
C:\ProgramData\Anaconda3\lib\site-
packages\sklearn\neural_network\_multilayer_perceptron.py:571:
ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) reached and
the optimization hasn't converged yet.
  % self.max_iter, ConvergenceWarning)
```

[42]:

```
#Comparing the models
fpr9, tpr9, thresholds9 = roc_curve(y_test, nb_y_predicted)
roc_auc9 = auc(fpr9, tpr9)

fpr8, tpr8, thresholds8 = roc_curve(y_test, mlp_y_predicted)
roc_auc8 = auc(fpr8, tpr8)

fpr7, tpr7, thresholds7 = roc_curve(y_test, DT_y_predicted)
roc_auc7 = auc(fpr7, tpr7)

fpr6, tpr6, thresholds6 = roc_curve(y_test, lda_pred_prob)
roc_auc6 = auc(fpr6, tpr6)

fpr5, tpr5, thresholds5 = roc_curve(y_test, knn_pred_prob)
roc_auc5 = auc(fpr5, tpr5)

fpr4, tpr4, thresholds4 = roc_curve(y_test, rf_pred_prob)
roc_auc4 = auc(fpr4, tpr4)

fpr3, tpr3, thresholds3 = roc_curve(y_test, xgb_pred_prob)
roc_auc3 = auc(fpr3, tpr3)

fpr2, tpr2, thresholds2 = roc_curve(y_test, brf_pred_prob)
roc_auc2 = auc(fpr2, tpr2)

fpr1, tpr1, thresholds1 = roc_curve(y_test,svm_pred_prob)
```

```python
roc_auc1 = auc(fpr1, tpr1)
lw = 2
plt.figure(figsize=(10, 8))
plt.plot(fpr9, tpr9,color='brown',label='ROC NB (AUC = %0.2f, ACC = %0.2f)' % (roc_auc9, nb_accuracy))
plt.plot(fpr8, tpr8,color='yellow',label='ROC MLP (AUC = %0.2f, ACC = %0.2f)' % (roc_auc8, mlp_accuracy))
plt.plot(fpr7, tpr7,color='cyan',label='ROC Decision Tree (AUC = %0.2f, ACC = %0.2f)' % (roc_auc7, dt_accuracy))
plt.plot(fpr6, tpr6,color='orange',label='ROC LDA (AUC = %0.2f, ACC = %0.2f)' % (roc_auc6, lda_accuracy))
plt.plot(fpr5, tpr5,color='green',label='ROC KNN (AUC = %0.2f, ACC = %0.2f)' % (roc_auc5, knn_accuracy))
plt.plot(fpr4, tpr4,color='red',label='ROC RF (AUC = %0.2f, ACC = %0.2f)' % (roc_auc4, rf_accuracy))
plt.plot(fpr3, tpr3,color='blue',label='ROC XGBOOST (AUC = %0.2f, ACC = %0.2f)' % (roc_auc3, xgb_accuracy))
plt.plot(fpr2, tpr2,color='black',label='ROC BRF (AUC = %0.2f, ACC = %0.2f)' % (roc_auc2, brf_accuracy))
plt.plot(fpr1, tpr1,color='magenta',label='ROC SVM (AUC = %0.2f, ACC = %0.2f)' % (roc_auc1, svm_accuracy))
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
plt.title('ROC curve ')
plt.xlabel('(1 - Specificity)')
plt.ylabel('(Sensitivity)')
plt.grid(True)
plt.legend(loc="lower right")
plt.show()

print("The predictive power of each model expressed by ROC curves. For instance, Linear Discriminant Analysis and XGBOOST model has\
       higher probability of accurate prediction of correct class member, and gaining high level of accuracy prediction probability\
       as compared to Random Forest, KNN, Naive Bayes, Neural Network and SVM models.")
```



The predictive power of each model expressed by ROC curves. For instance, Linear Discriminant Analysis and XGBOOST model has higher probability of accurate prediction of correct class member, and gaining high level of accuracy prediction probability as compared to Random Forest, KNN, Naive Bayes, Neural Network and SVM models.

[43]:
```
#XGBOOST model has better ROC Curve and Cross-validated accuracy, plot feature␣
↪importance
def rf_feat_importance(m, df):
    return pd.DataFrame({'feature':df.columns, 'imp':m.feature_importances_}
                       ).sort_values('imp', ascending=False)
def plot_fi(fi):
    return fi.plot('feature', 'imp', 'barh', figsize=(15,7), legend=False)

fi = rf_feat_importance(model_xgb, X_train); fi[:15]
```

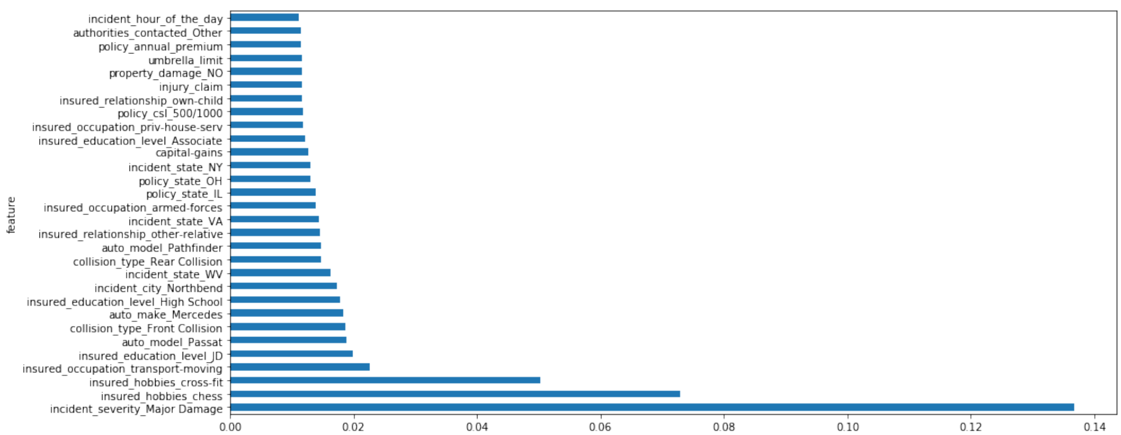
[43]:

	feature	imp
79	incident_severity_Major Damage	0.136822
50	insured_hobbies_chess	0.072968

```
51                 insured_hobbies_cross-fit  0.050191
44    insured_occupation_transport-moving  0.022682
27              insured_education_level_JD  0.019782
150                      auto_model_Passat  0.018868
76           collision_type_Front Collision  0.018670
116                     auto_make_Mercedes  0.018290
26    insured_education_level_High School  0.017856
98                 incident_city_Northbend  0.017273
94                        incident_state_WV  0.016270
77            collision_type_Rear Collision  0.014769
151                  auto_model_Pathfinder  0.014738
67    insured_relationship_other-relative  0.014554
93                        incident_state_VA  0.014317
```

[44]:
```python
plot_fi(fi[:30])
```

[44]: <matplotlib.axes._subplots.AxesSubplot at 0x20c3e1169e8>



[45]:
```python
#As XGBOOST has the best results with an AUC of 0.82, using this model for␣
↪scoring
test_target = y_test.copy()
test_target.reset_index(drop=True, inplace=True)
test_target = test_target.replace({1:'Y', 0:'N'})

predicted_target = model_xgb.predict(X_test)
predicted_target = pd.Series(predicted_target).replace({1:'Y', 0:'N'})
```

[46]:
```python
ranks=pd.DataFrame(data=
                   {
                       'RealClass':test_target,
                       'PredictedClass':predicted_target,
                       'rank':xgb_pred_prob
```

```
                    })
ranks.sort_values(by=['rank'],ascending=False,inplace=True)
ranks.head()
```

[46]:

	RealClass	PredictedClass	rank
7	Y	Y	0.942978
44	N	Y	0.919296
127	Y	Y	0.914629
82	N	Y	0.817602
76	Y	Y	0.808937

[47]:

```
top = ranks.where(ranks['rank']>0.5,).dropna()
top.head()
```

[47]:

	RealClass	PredictedClass	rank
7	Y	Y	0.942978
44	N	Y	0.919296
127	Y	Y	0.914629
82	N	Y	0.817602
76	Y	Y	0.808937