G7Proj

March 14, 2024

1 A Comparative Analysis of Heart Failure Prediction Models: K-Nearest Neighbors, Logistic Regression, and Naive Bayes

[304]:
```
#importing the dependencies
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score
```

[305]:
```
#loading the DataSet
df = pd.read_csv('heart.csv')
```

[306]:
```
df.head()
```

[306]:

	Age	Sex	ChestPainType	RestingBP	Cholesterol	FastingBS	RestingECG	MaxHR	\
0	40	M	ATA	140	289	0	Normal	172	
1	49	F	NAP	160	180	0	Normal	156	
2	37	M	ATA	130	283	0	ST	98	
3	48	F	ASY	138	214	0	Normal	108	
4	54	M	NAP	150	195	0	Normal	122	

	ExerciseAngina	Oldpeak	ST_Slope	HeartDisease
0	N	0.0	Up	0
1	N	1.0	Flat	1
2	N	0.0	Up	0
3	Y	1.5	Flat	1
4	N	0.0	Up	0

[307]:
```
df.isnull().sum()
```

[307]:
```
Age              0
Sex              0
ChestPainType    0
RestingBP        0
Cholesterol      0
```

```
FastingBS         0
RestingECG        0
MaxHR             0
ExerciseAngina    0
Oldpeak           0
ST_Slope          0
HeartDisease      0
dtype: int64
```

[308]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 918 entries, 0 to 917
Data columns (total 12 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Age             918 non-null    int64
 1   Sex             918 non-null    object
 2   ChestPainType   918 non-null    object
 3   RestingBP       918 non-null    int64
 4   Cholesterol     918 non-null    int64
 5   FastingBS       918 non-null    int64
 6   RestingECG      918 non-null    object
 7   MaxHR           918 non-null    int64
 8   ExerciseAngina  918 non-null    object
 9   Oldpeak         918 non-null    float64
 10  ST_Slope        918 non-null    object
 11  HeartDisease    918 non-null    int64
dtypes: float64(1), int64(6), object(5)
memory usage: 86.2+ KB
```

[309]:
```
df.describe().transpose()
```

[309]:

	count	mean	std	min	25%	50%	75%	max
Age	918.0	53.510893	9.432617	28.0	47.00	54.0	60.0	77.0
RestingBP	918.0	132.396514	18.514154	0.0	120.00	130.0	140.0	200.0
Cholesterol	918.0	198.799564	109.384145	0.0	173.25	223.0	267.0	603.0
FastingBS	918.0	0.233115	0.423046	0.0	0.00	0.0	0.0	1.0
MaxHR	918.0	136.809368	25.460334	60.0	120.00	138.0	156.0	202.0
Oldpeak	918.0	0.887364	1.066570	-2.6	0.00	0.6	1.5	6.2
HeartDisease	918.0	0.553377	0.497414	0.0	0.00	1.0	1.0	1.0

1.1 Performing OneHot-Encoding for Categorical Values

[310]:
```
#unique values of sex
print(df['Sex'].unique())
print('\n',df['Sex'].value_counts())
```

```
['M' 'F']

 Sex
M    725
F    193
Name: count, dtype: int64
```

[311]:
```
#unique values of ChestPainType
print(df['ChestPainType'].unique())
print('\n',df['ChestPainType'].value_counts())
```

```
['ATA' 'NAP' 'ASY' 'TA']

 ChestPainType
ASY    496
NAP    203
ATA    173
TA      46
Name: count, dtype: int64
```

[312]:
```
#unique values of FastingBS
print(df['FastingBS'].unique())
print('\n',df['FastingBS'].value_counts())
```

```
[0 1]

 FastingBS
0    704
1    214
Name: count, dtype: int64
```

[313]:
```
#unique values of RestingECG
print(df['RestingECG'].unique())
print('\n',df['RestingECG'].value_counts())
```

```
['Normal' 'ST' 'LVH']

 RestingECG
Normal    552
LVH       188
ST        178
Name: count, dtype: int64
```

[314]:
```
#unique values of ExerciseAngina
print(df['ExerciseAngina'].unique())
print('\n',df['ExerciseAngina'].value_counts())
```

```
['N' 'Y']

 ExerciseAngina
N    547
Y    371
Name: count, dtype: int64
```

[315]:
```
#unique values of ST_Slope
print(df['ST_Slope'].unique())
print('\n',df['ST_Slope'].value_counts())
```

```
['Up' 'Flat' 'Down']

 ST_Slope
Flat    460
Up      395
Down     63
Name: count, dtype: int64
```

[316]:
```
df
```

[316]:

	Age	Sex	ChestPainType	RestingBP	Cholesterol	FastingBS	RestingECG	MaxHR	ExerciseAngina	Oldpeak	ST_Slope	HeartDisease
0	40	M	ATA	140	289	0	Normal	172	N	0.0	Up	0
1	49	F	NAP	160	180	0	Normal	156	N	1.0	Flat	1
2	37	M	ATA	130	283	0	ST	98	N	0.0	Up	0
3	48	F	ASY	138	214	0	Normal	108	Y	1.5	Flat	1
4	54	M	NAP	150	195	0	Normal	122	N	0.0	Up	0
..	…	..	…	…	…	…	…	…	…	…	…	…
913	45	M	TA	110	264	0	Normal	132	N	1.2	Flat	1
914	68	M	ASY	144	193	1	Normal	141	N	3.4	Flat	1
915	57	M	ASY	130	131	0	Normal					
916	57	F	ATA	130	236	0	LVH					
917	38	M	NAP	138	175	0	Normal					

```
915    115              Y      1.2     Flat             1
916    174              N      0.0     Flat             1
917    173              N      0.0       Up             0

[918 rows x 12 columns]
```

[317]:
```
# df['Sex']=df['Sex'].map({'M':0,'F':1})
encoded_df=pd.get_dummies(df,columns=['Sex', 'ChestPainType', 'FastingBS',
 ↪'RestingECG', 'ExerciseAngina', 'ST_Slope']).astype(int)
encoded_df
```

[317]:
```
      Age  RestingBP  Cholesterol  MaxHR  Oldpeak  HeartDisease  Sex_F  Sex_M  \
0      40        140          289    172        0             0      0      1
1      49        160          180    156        1             1      1      0
2      37        130          283     98        0             0      0      1
3      48        138          214    108        1             1      1      0
4      54        150          195    122        0             0      0      1
..    …         …            …      …        …             …      …      …
913    45        110          264    132        1             1      0      1
914    68        144          193    141        3             1      0      1
915    57        130          131    115        1             1      0      1
916    57        130          236    174        0             1      1      0
917    38        138          175    173        0             0      0      1

      ChestPainType_ASY  ChestPainType_ATA  …  FastingBS_0  FastingBS_1  \
0                     0                  1  …            1            0
1                     0                  0  …            1            0
2                     0                  1  …            1            0
3                     1                  0  …            1            0
4                     0                  0  …            1            0
..                  …                  …  …            …            …
913                   0                  0  …            1            0
914                   1                  0  …            0            1
915                   1                  0  …            1            0
916                   0                  1  …            1            0
917                   0                  0  …            1            0

      RestingECG_LVH  RestingECG_Normal  RestingECG_ST  ExerciseAngina_N  \
0                  0                  1              0                 1
1                  0                  1              0                 1
2                  0                  0              1                 1
3                  0                  1              0                 0
4                  0                  1              0                 1
..               …                  …              …                 …
913                0                  1              0                 1
914                0                  1              0                 1
915                0                  1              0                 0
```

```
916               1                  0              0                  1
917               0                  1              0                  1

     ExerciseAngina_Y  ST_Slope_Down  ST_Slope_Flat  ST_Slope_Up
0                   0              0              0            1
1                   0              0              1            0
2                   0              0              0            1
3                   1              0              1            0
4                   0              0              0            1
..                ...            ...            ...          ...
913                 0              0              1            0
914                 0              0              1            0
915                 1              0              1            0
916                 0              0              1            0
917                 0              0              0            1

[918 rows x 22 columns]
```

[318]:
```
encoded_df.columns
```

[318]:
```
Index(['Age', 'RestingBP', 'Cholesterol', 'MaxHR', 'Oldpeak', 'HeartDisease',
       'Sex_F', 'Sex_M', 'ChestPainType_ASY', 'ChestPainType_ATA',
       'ChestPainType_NAP', 'ChestPainType_TA', 'FastingBS_0', 'FastingBS_1',
       'RestingECG_LVH', 'RestingECG_Normal', 'RestingECG_ST',
       'ExerciseAngina_N', 'ExerciseAngina_Y', 'ST_Slope_Down',
       'ST_Slope_Flat', 'ST_Slope_Up'],
      dtype='object')
```

[ ]:
```

```

1.2 Logistic Regression

[319]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn import preprocessing
```

[320]:
```
X = encoded_df.drop(columns=['HeartDisease'])
y = encoded_df['HeartDisease']
```

[321]:
```
X
```

[321]:
```
     Age  RestingBP  Cholesterol  MaxHR  Oldpeak  Sex_F  Sex_M  \
0     40        140          289    172        0      0      1
1     49        160          180    156        1      1      0
2     37        130          283     98        0      0      1
3     48        138          214    108        1      1      0
4     54        150          195    122        0      0      1
```

```
..   …         …           …    …      …    …    …
913   45        110          264    132        1      0      1
914   68        144          193    141        3      0      1
915   57        130          131    115        1      0      1
916   57        130          236    174        0      1      0
917   38        138          175    173        0      0      1

     ChestPainType_ASY  ChestPainType_ATA  ChestPainType_NAP  …  \
0                    0                  1                  0  …
1                    0                  0                  1  …
2                    0                  1                  0  …
3                    1                  0                  0  …
4                    0                  0                  1  …
..                 …                  …                  …  …
913                  0                  0                  0  …
914                  1                  0                  0  …
915                  1                  0                  0  …
916                  0                  1                  0  …
917                  0                  0                  1  …

     FastingBS_0  FastingBS_1  RestingECG_LVH  RestingECG_Normal  \
0              1            0               0                  1
1              1            0               0                  1
2              1            0               0                  0
3              1            0               0                  1
4              1            0               0                  1
..           …            …               …                  …
913            1            0               0                  1
914            0            1               0                  1
915            1            0               0                  1
916            1            0               1                  0
917            1            0               0                  1

     RestingECG_ST  ExerciseAngina_N  ExerciseAngina_Y  ST_Slope_Down  \
0                0                 1                 0              0
1                0                 1                 0              0
2                1                 1                 0              0
3                0                 0                 1              0
4                0                 1                 0              0
..             …                 …                 …              …
913              0                 1                 0              0
914              0                 1                 0              0
915              0                 0                 1              0
916              0                 1                 0              0
917              0                 1                 0              0

     ST_Slope_Flat  ST_Slope_Up
```

```
0                0            1
1                1            0
2                0            1
3                1            0
4                0            1
..             …            …
913              1            0
914              1            0
915              1            0
916              1            0
917              0            1

[918 rows x 21 columns]
```

[322]:
```
y
```

[322]:
```
0      0
1      1
2      0
3      1
4      0
      ..
913    1
914    1
915    1
916    1
917    0
Name: HeartDisease, Length: 918, dtype: int64
```

1.2.1 Normalizing the values and Scalling

[323]:
```
X = preprocessing.StandardScaler().fit(X).transform(X.astype(float))
X[:5]
```

[323]:
```
array([[-1.4331398 ,  0.41090889,  0.82507026,  1.38292822, -0.72759199,
        -0.51595242,  0.51595242, -1.08413811,  2.07517671, -0.53283777,
        -0.22967867,  0.55134134, -0.55134134, -0.50747832,  0.81427482,
        -0.49044933,  0.8235563 , -0.8235563 , -0.27144836, -1.00218103,
         1.15067399],
       [-0.47848359,  1.49175234, -0.17196105,  0.75415714,  0.28289129,
         1.93816322, -1.93816322, -1.08413811, -0.48188667,  1.87674385,
        -0.22967867,  0.55134134, -0.55134134, -0.50747832,  0.81427482,
        -0.49044933,  0.8235563 , -0.8235563 , -0.27144836,  0.99782372,
        -0.86905588],
       [-1.75135854, -0.12951283,  0.7701878 , -1.52513802, -0.72759199,
        -0.51595242,  0.51595242, -1.08413811,  2.07517671, -0.53283777,
        -0.22967867,  0.55134134, -0.55134134, -0.50747832, -1.22808661,
```

```
        2.03894663,  0.8235563 , -0.8235563 , -0.27144836, -1.00218103,
        1.15067399],
       [-0.5845565 ,  0.30282455,  0.13903954, -1.13215609,  0.28289129,
        1.93816322, -1.93816322,  0.9223917 , -0.48188667, -0.53283777,
       -0.22967867,  0.55134134, -0.55134134, -0.50747832,  0.81427482,
       -0.49044933, -1.21424608,  1.21424608, -0.27144836,  0.99782372,
       -0.86905588],
       [ 0.05188098,  0.95133062, -0.0347549 , -0.5819814 , -0.72759199,
       -0.51595242,  0.51595242, -1.08413811, -0.48188667,  1.87674385,
       -0.22967867,  0.55134134, -0.55134134, -0.50747832,  0.81427482,
       -0.49044933,  0.8235563 , -0.8235563 , -0.27144836, -1.00218103,
        1.15067399]])
```

[324]:
```
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size = 0.
↪2,random_state=42)
```

[325]:
```
X_train.shape
```

[325]: (734, 21)

[326]:
```
y_train.shape
```

[326]: (734,)

[327]:
```
X_test.shape
```

[327]: (184, 21)

[328]:
```
y_test.shape
```

[328]: (184,)

1.2.2 model training

[329]:
```
from sklearn.linear_model import LogisticRegression
Classifier = LogisticRegression(C=1000.0,random_state=0)
```

[330]:
```
Classifier.fit(X_train,y_train)
```

[330]: LogisticRegression(C=1000.0, random_state=0)

1.2.3 model eval

[331]:
```
from sklearn.metrics import accuracy_score
pred = Classifier.predict(X_test)

#accuracy
```

```
accuracy = accuracy_score(y_test,pred)
print("Accuracy: ",accuracy)
```

```
Accuracy:  0.8532608695652174
```

1.2.4 HyperParamps Tuning

[332]:
```
from sklearn.model_selection import RepeatedStratifiedKFold,GridSearchCV
```

[333]:
```
log_reg = LogisticRegression()

# Define the parameter grid
solvers = ['newton-cg', 'lbfgs', 'liblinear']
penalty = ['l2']
c_values = [100, 10, 1.0, 0.1, 0.01]
max_iter_values = [100, 1000, 2500, 5000]
grid = dict(solver=solvers, penalty=penalty, C=c_values,␣
 ↪max_iter=max_iter_values)

# Define the cross-validation strategy
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)
```

[334]:
```
clf = GridSearchCV(log_reg, param_grid=grid, n_jobs=-1, cv=cv,␣
 ↪scoring='accuracy', error_score=0)
```

[335]:
```
best_clf = clf.fit(X,y)
```

[336]:
```
best_clf.best_estimator_
```

[336]:
```
LogisticRegression(C=0.01, solver='newton-cg')
```

[337]:
```
print (f'Accuracy after tuning : {best_clf.score(X,y):.3f}')
```

```
Accuracy after tuning : 0.871
```

1.2.5 Cross Validation

[338]:
```
from sklearn.model_selection import cross_val_score

cvScore = cross_val_score(log_reg,X_train,y_train,cv=5)
print("Cross-Validation Scores:", cvScore)
print("Mean CV Score:", cvScore.mean())
```

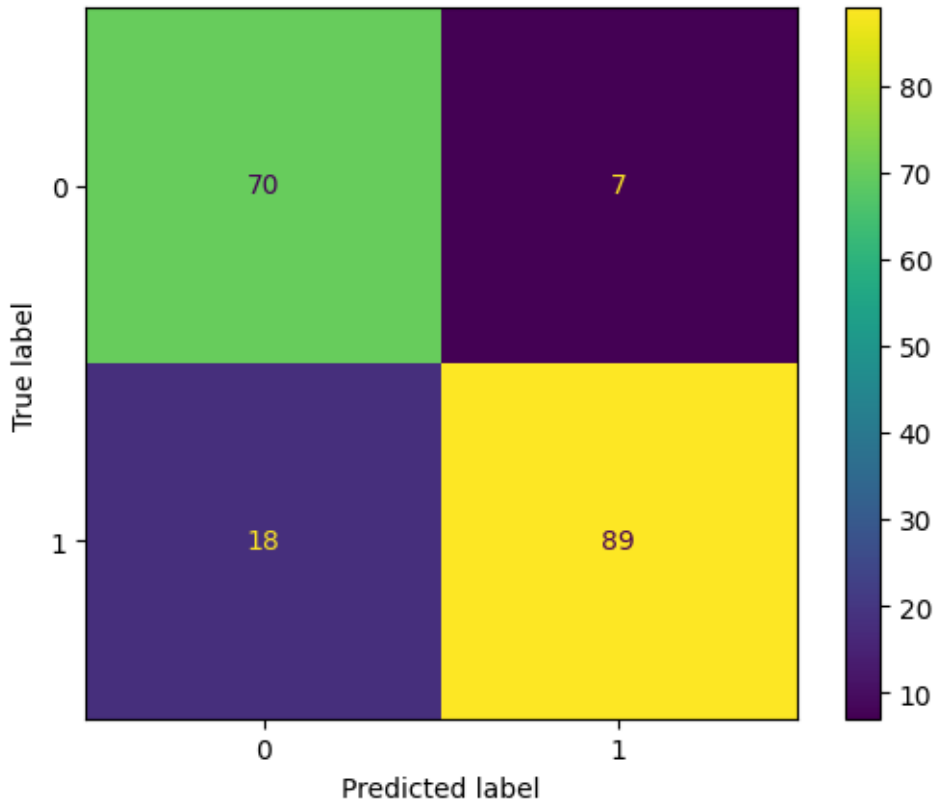
```
Cross-Validation Scores: [0.87755102 0.88435374 0.85714286 0.82993197 0.8630137
]
Mean CV Score: 0.8623986580933745
```

1.2.6 confusion Matrix

[339]:
```
from sklearn.metrics import ConfusionMatrixDisplay, confusion_matrix
```

[340]:
```
classes = np.unique(np.concatenate((y_test, y_pred)))

cm = confusion_matrix(y_test, y_pred, labels=classes)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=classes)
disp.plot()
```

[340]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at
0x7f9b50973190>
```



1.2.7 ROC Curve

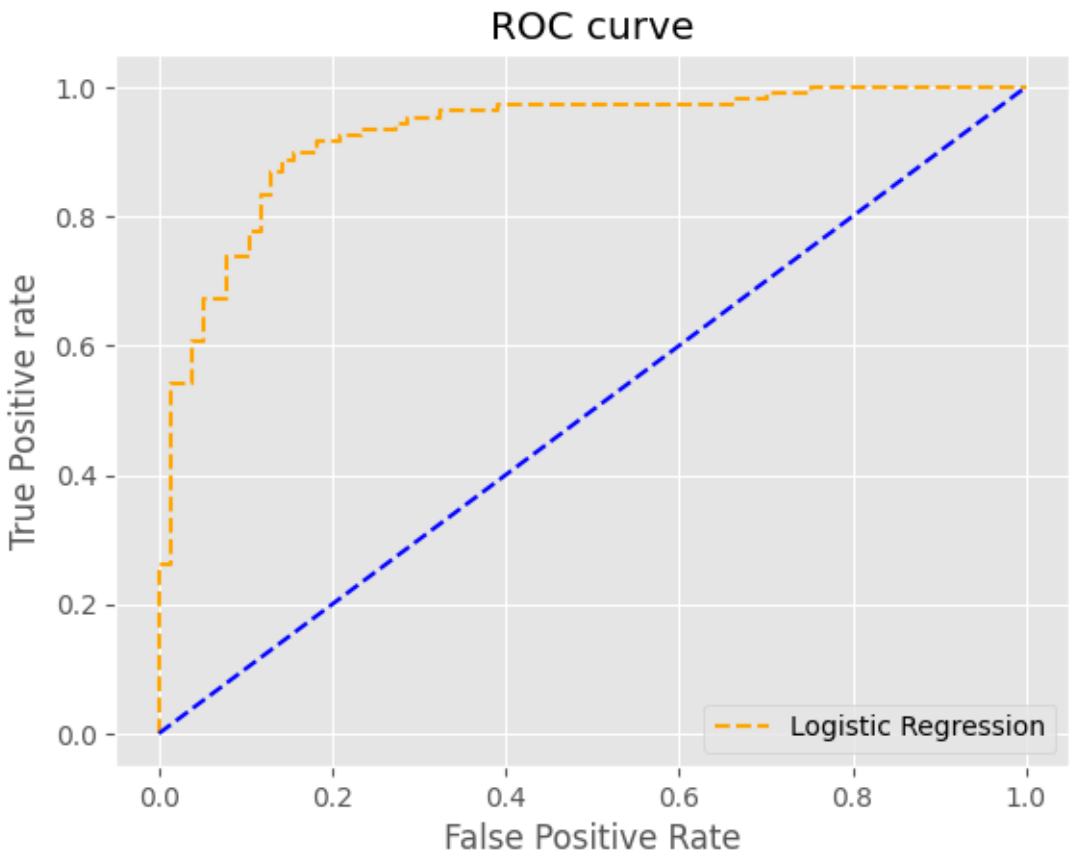
[351]:
```
# predict probabilities
pred_prob1 = Classifier.predict_proba(X_test)
```

[352]:
```
# roc curve for models
fpr1, tpr1, thresh1 = roc_curve(y_test, pred_prob1[:,1], pos_label=1)
```

[354]:
```
# roc curve for tpr = fpr
random_probs = [0 for i in range(len(y_test))]
p_fpr, p_tpr, _ = roc_curve(y_test, random_probs, pos_label=1)
```

[355]:
```
# auc scores
auc_score1 = roc_auc_score(y_test, pred_prob1[:,1])
```

[359]:
```
plt.style.use('ggplot')

# plot roc curves
plt.plot(fpr1, tpr1, linestyle='--', color='orange', label='Logistic␣
 ↪Regression')
# plt.plot(fpr2, tpr2, linestyle='--', color='green', label='KNN')
plt.plot(p_fpr, p_tpr, linestyle='--', color='blue')
# title
plt.title('ROC curve')
# x label
plt.xlabel('False Positive Rate')
# y label
plt.ylabel('True Positive rate')

plt.legend(loc='best')
plt.savefig('ROC.png', dpi=300)
plt.show()
```



1.2.8 AUC Score

[360]:
```
# auc scores
auc_score1 = roc_auc_score(y_test, pred_prob1[:,1])
```

[361]:
```
print(auc_score1)
```

```
0.926690132297609
```

1.3 KNN

[362]:
```
from sklearn.neighbors import KNeighborsClassifier
```

[363]:
```
k = 5
KNN = KNeighborsClassifier(n_neighbors=k)
```

[364]:
```
KNN.fit(X_train,y_train)
yhat = KNN.predict(X_test)
```

[365]:
```
print('Accuracy Score: ',accuracy_score(y_test,yhat))
```

```
Accuracy Score:  0.8532608695652174
```

1.3.1 Model Eval

[366]:
```
from sklearn.metrics import classification_report
```

[367]:
```
print(classification_report(y_test,yhat))
```

```
              precision    recall  f1-score   support

           0       0.80      0.87      0.83        77
           1       0.90      0.84      0.87       107

    accuracy                           0.85       184
   macro avg       0.85      0.86      0.85       184
weighted avg       0.86      0.85      0.85       184
```

1.3.2 Hyper Paramps Tunning

[368]:
```
#List Hyperparameters that we want to tune.
leaf_size = list(range(1,50))
n_neighbors = list(range(1,30))
p=[1,2]
```

[369]:
```
#Convert to dictionary
hyperparameters = dict(leaf_size=leaf_size, n_neighbors=n_neighbors, p=p)
```

[370]:
```
#Create new KNN object
knn_2 = KNeighborsClassifier()
```

[371]:
```
#Use GridSearch
clf = GridSearchCV(knn_2, hyperparameters, cv=10)
```

[372]:
```
#Fit the model
best_model = clf.fit(X,y)
```

[373]:
```
#Print The value of best Hyperparameters
print('Best leaf_size:', best_model.best_estimator_.get_params()['leaf_size'])
print('Best p:', best_model.best_estimator_.get_params()['p'])
print('Best n_neighbors:', best_model.best_estimator_.
 ↪get_params()['n_neighbors'])
```

```
Best leaf_size: 1
Best p: 1
Best n_neighbors: 27
```

[374]:
```
k3 = KNeighborsClassifier(leaf_size=1,p=1,n_neighbors=27)
```

[375]:
```
k3.fit(X_train,y_train)
```

[375]:
```
KNeighborsClassifier(leaf_size=1, n_neighbors=27, p=1)
```

[376]:
```
predictions = k3.predict(X_test)

# Evaluate the model performance
accuracy = k3.score(X_test, y_test)
```

[377]:
```
accuracy
```

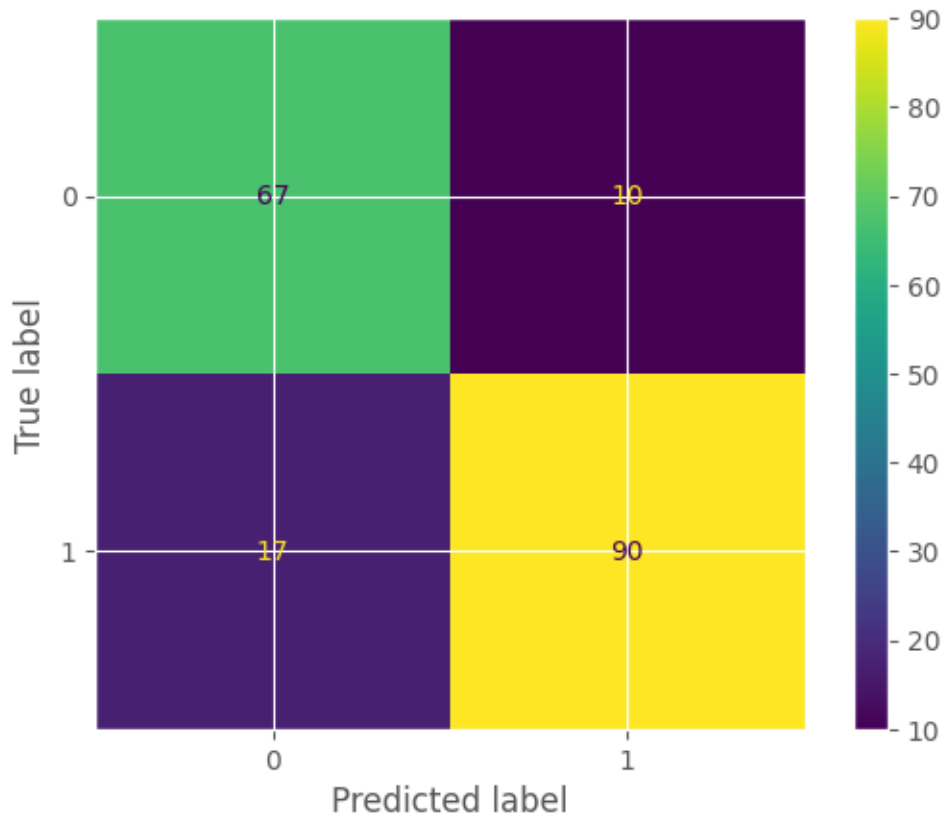
[377]:
```
0.875
```

1.3.3 Plotting

[378]:
```
cm = confusion_matrix(y_test,yhat,labels = KNN.classes_)
```

[380]:
```
disp = ConfusionMatrixDisplay(confusion_matrix=cm,display_labels=KNN.classes_)
disp.plot()
```

[380]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at
0x7f9b57d31630>
```



1.3.4 ROC Curve

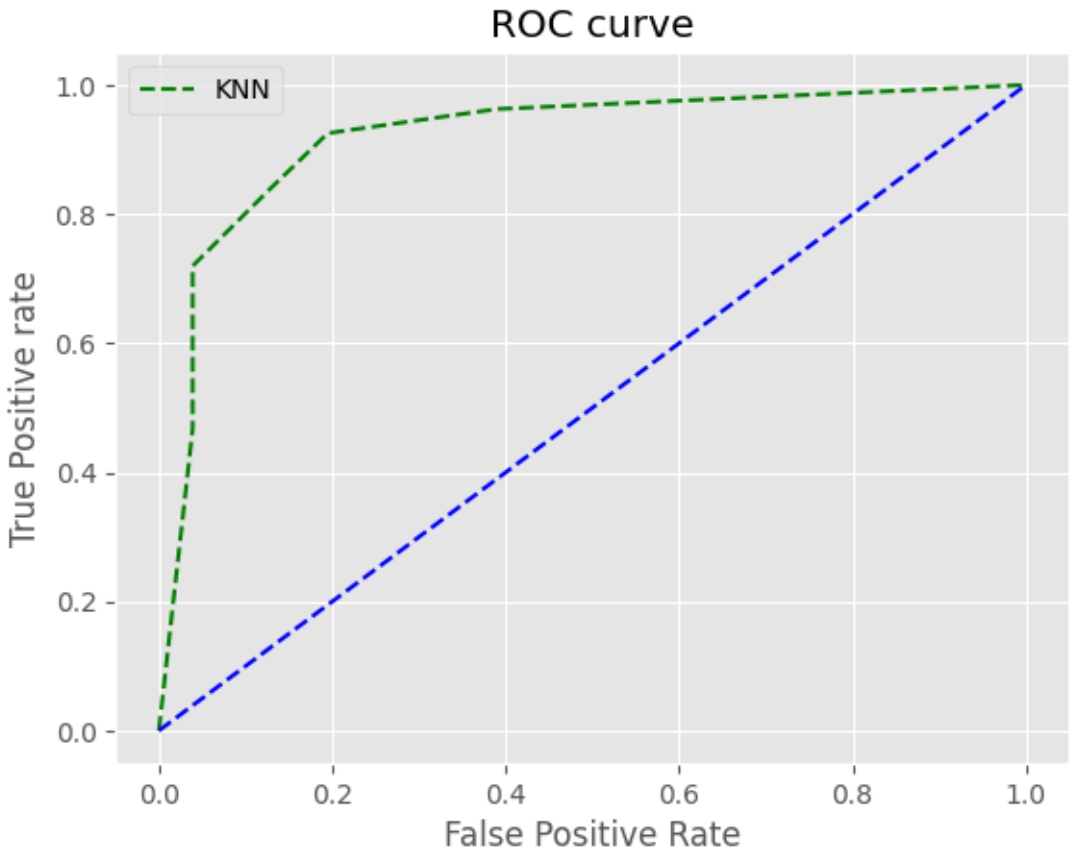
[381]:
```
# predict probabilities
pred_prob2 = KNN.predict_proba(X_test)
```

[382]:
```
fpr2, tpr2, thresh2 = roc_curve(y_test, pred_prob2[:,1], pos_label=1)
```

[383]:
```
# roc curve for tpr = fpr
random_probs = [0 for i in range(len(y_test))]
p_fpr, p_tpr, _ = roc_curve(y_test, random_probs, pos_label=1)
```

[384]:
```
plt.style.use('ggplot')

# plot roc curves
plt.plot(fpr2, tpr2, linestyle='--', color='green', label='KNN')
plt.plot(p_fpr, p_tpr, linestyle='--', color='blue')
# title
plt.title('ROC curve')
# x label
plt.xlabel('False Positive Rate')
```

```
# y label
plt.ylabel('True Positive rate')

plt.legend(loc='best')
plt.savefig('ROC.png', dpi=300)
plt.show()
```



1.3.5 AUC Score

[385]:
```
auc_score2 = roc_auc_score(y_test, pred_prob2[:,1])
auc_score2
```

[385]: 0.9202573127806772

1.4 Naive Bayes

[272]:
```
from sklearn.naive_bayes import GaussianNB
classifier = GaussianNB()
classifier.fit(X_train, y_train)
```

[272]:
```
GaussianNB()
```

[273]:
```
y_pred  =  classifier.predict(X_test)
```

[274]:
```
y_pred
```

[274]:
```
array([0, 1, 1, 1, 0, 1, 1, 0, 1, 1, 0, 0, 0, 0, 1, 1, 0, 1, 1, 0, 1, 1,
       0, 1, 1, 1, 0, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0,
       0, 1, 1, 1, 1, 0, 0, 0, 1, 1, 1, 0, 0, 1, 1, 1, 0, 0, 0, 1, 0, 1,
       1, 1, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 1, 1, 0, 1, 0, 0, 1,
       0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 1, 1, 0, 1, 1, 0, 0, 1, 0, 1, 1, 0,
       1, 1, 0, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1,
       1, 0, 1, 0, 1, 1, 0, 1, 0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0, 1, 1, 0,
       1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 1, 1, 1, 0, 0, 1, 1, 0, 1, 0, 1,
       1, 1, 0, 0, 1, 1, 0, 1])
```

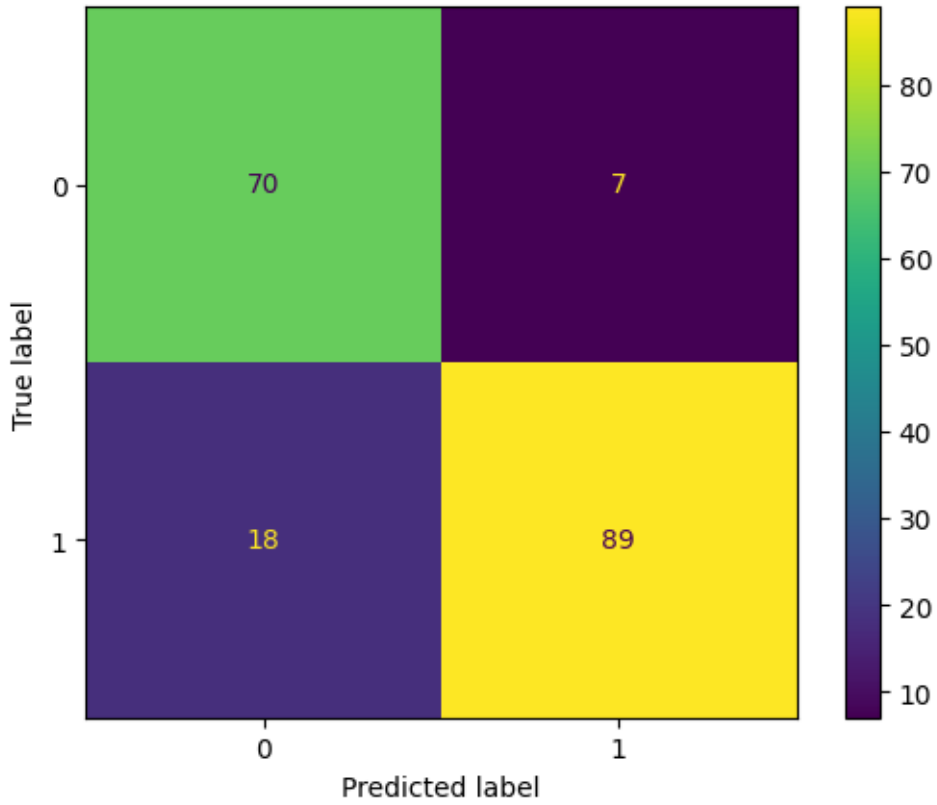
1.4.1 Model Eval

[278]:
```
accuracy = accuracy_score(y_test,y_pred)
print("Accuracy: ",accuracy)
```

```
Accuracy:  0.8641304347826086
```

[283]:
```
cm = confusion_matrix(y_test,y_pred,labels = classifier.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=cm,display_labels=classifier.
 ↪classes_)
disp.plot()
```

[283]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at
0x7f9b508b00a0>
```



1.4.2 Hyper paramps Tunning

[285]:
```
param_grid_nb = {
    'var_smoothing': np.logspace(0,-9, num=100)
}
```

[286]:
```
nbModel_grid = GridSearchCV(estimator=GaussianNB(), param_grid=param_grid_nb,␣
↪verbose=1, cv=10, n_jobs=-1)
nbModel_grid.fit(X_train, y_train)
print(nbModel_grid.best_estimator_)
```

```
Fitting 10 folds for each of 100 candidates, totalling 1000 fits
GaussianNB(var_smoothing=0.12328467394420659)
```

[287]:
```
y_pred = nbModel_grid.predict(X_test)
```

[289]:
```
print(accuracy_score(y_test, y_pred), ": is the accuracy score")
```

```
0.8641304347826086 : is the accuracy score
```

[292]:
```
accuracy
```

[292]: 0.8641304347826086

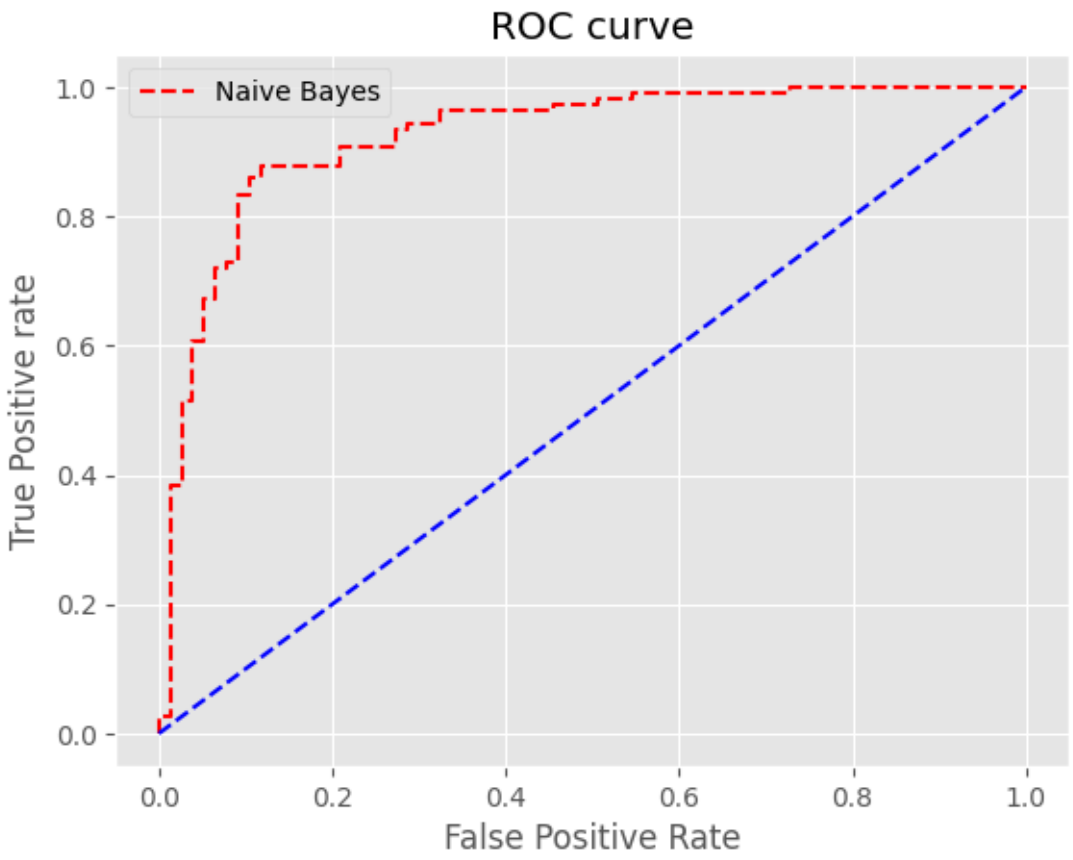
1.5 ROC Curve

[386]:
```
# predict probabilities
pred_prob3 = classifier.predict_proba(X_test)
```

[387]:
```
fpr3, tpr3, thresh3 = roc_curve(y_test, pred_prob3[:,1], pos_label=1)
```

[388]:
```
# roc curve for tpr = fpr
random_probs = [0 for i in range(len(y_test))]
p_fpr, p_tpr, _ = roc_curve(y_test, random_probs, pos_label=1)
```

[391]:
```
plt.style.use('ggplot')

# plot roc curves
plt.plot(fpr3, tpr3, linestyle='--', color='red', label='Naive Bayes')
plt.plot(p_fpr, p_tpr, linestyle='--', color='blue')
# title
plt.title('ROC curve')
# x label
plt.xlabel('False Positive Rate')
# y label
plt.ylabel('True Positive rate')

plt.legend(loc='best')
plt.savefig('ROC.png', dpi=300)
plt.show()
```



1.5.1 AUC Score

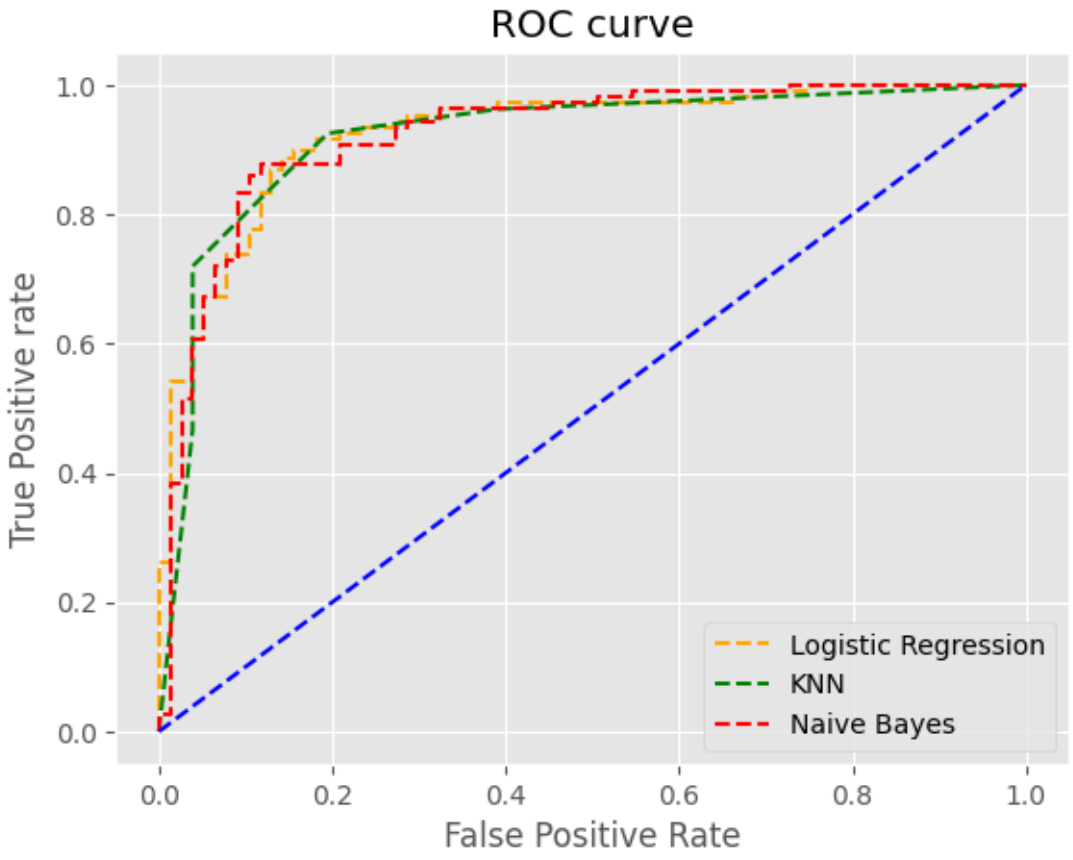
[392]:
```
auc_score3 = roc_auc_score(y_test, pred_prob3[:,1])
auc_score3
```

[392]:
```
0.9236557834688677
```

1.5.2 Combined ROC

[393]:
```
import matplotlib.pyplot as plt

plt.style.use('ggplot')

# plot roc curves for Logistic Regression
plt.plot(fpr1, tpr1, linestyle='--', color='orange', label='Logistic␣
 ↪Regression')
# plot roc curves for KNN
plt.plot(fpr2, tpr2, linestyle='--', color='green', label='KNN')
# plot roc curves for Naive Bayes
```

```
plt.plot(fpr3, tpr3, linestyle='--', color='red', label='Naive Bayes')

# plot the baseline (random) ROC curve
plt.plot(p_fpr, p_tpr, linestyle='--', color='blue')

# title
plt.title('ROC curve')
# x label
plt.xlabel('False Positive Rate')
# y label
plt.ylabel('True Positive rate')

plt.legend(loc='best')
plt.savefig('ROC.png', dpi=300)
plt.show()
```



[ ]: