Lung Cancer Recognition Using CT-Scan with NCA-XG Boosting & KNN

GitHub Link: https://github.com/AishaFar/Lung-Cancer-Recognition-Using-CT-Scan-with-NCA-XG-Boosting-KNN

Name: Ayesha Farhana
CRN: 12644
ID: 700735341

Code Results Screenshots:

1. Importing all the required libraries

Importing all the required libraries

In [25]:
```
import itertools
import pickle
import random
import matplotlib
import math
import copy
import cv2
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
from imutils import paths
from sklearn.neighbors import NeighborhoodComponentsAnalysis, KNeighborsClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler
from xgboost import XGBClassifier

from sklearn.metrics import confusion_matrix, classification_report, accuracy_score, plot_precision_recall_curve, plot_confus
from sklearn.model_selection import train_test_split
from collections import Counter
```

Here, Import Itertools , pickle, random, Matplotlib, math, copy, cv2, pandas as pd, matplotlib.pyplot as plt, numpy as np, imutils import paths, NeighnorhoodCompnentAnalysis,KNeighborsClassifier,AdaBoostClassifier, make_pipeline, StandardScaler, XGBClassifier, Confui=sion_matrix, Classification_Report, accuracy_score, plot_precision_recall_curve, plot_confusion_matrix, train_test_split, Counter

```
rtools
kle
dom
plotlib
h
y

das as pd
plotlib.pyplot as plt
py as np
ls import paths
rn.neighbors import NeighborhoodComponentsAnalysis, KNeighborsClassifier
rn.ensemble import AdaBoostClassifier
rn.pipeline import make_pipeline
rn.preprocessing import StandardScaler
st import XGBClassifier

rn.metrics import confusion_matrix, classification_report, accuracy_score, plot_precision_recall_curve, plot_confusion_matrix
rn.model_selection import train_test_split
ctions import Counter
```

2.Reading dataset path and loading images

Reading dataset path and loading images

In [26]:

```
print("Loading images...")
data = []
labels = []

imagePaths = sorted(list(paths.list_images("data/training")))
random.seed(42)
random.shuffle(imagePaths)

for imagePath in imagePaths:
    image = cv2.imread(imagePath, 0)
    image = cv2.resize(image, (40, 40))
    image = np.reshape(image, 1600)
    data.append(image)

    label = imagePath[-7:-4]
    if label == "pos":
        label = 1
    else:
        label = 0
    labels.append(label)

data = np.array(data, dtype="float") / 255.0
labels = np.array(labels)
```

```
Loading images...
```

3.Displaying array sample

Displaying array sample

In [27]:

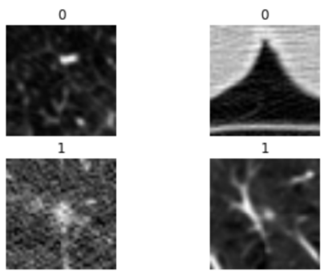
```
# displaying image array
print(data[:4])

# displaying labels
print(labels[:4])
```

```
[[0.01176471 0.07058824 0.09411765 ... 0.11372549 0.10196078 0.11764706]
 [0.68627451 0.68235294 0.74509804 ... 0.11372549 0.12156863 0.09803922]
 [0.16862745 0.20392157 0.29019608 ... 0.19215686 0.06666667 0.20784314]
 [0.22745098 0.24313725 0.28235294 ... 0.19607843 0.14117647 0.11764706]]
[0 0 1 1]
```

4. Displaying Training Image

Displaying training image

In [28]:
```
for i, images in enumerate(imagePaths[:4]):
    img = cv2.imread(images)
    img = cv2.resize(img, (100, 100))
    plt.subplot(2, 2, i + 1)
    plt.title(labels[i])
    plt.imshow(img)
    plt.grid(False)
    plt.axis('off')
plt.show()
```



5. Splitting dataset into train-test

Splitting dataset into train-test

In [29]:
```
trainX, testX, trainY, testY = train_test_split(data, labels, test_size=0.25, random_state=3)
```

In [30]:
```
trainX.shape, testX.shape
```

Out[30]:
```
((2206, 1600), (736, 1600))
```

6. NCA-XGBoosting

NCA-XGBoosting

In [31]:
```
dim = len(trainX[0])
n_classes = len(np.unique(trainY))
```

In [32]:
```
nca = make_pipeline(
    StandardScaler(),
    NeighborhoodComponentsAnalysis(n_components=2, random_state=3),
)
```

In [33]:
```
xgb = XGBClassifier(n_estimators=3)
```

In [34]:
```
nca.fit(trainX, trainY)
```

Out[34]:
```
Pipeline(memory=None,
         steps=[('standardscaler',
                 StandardScaler(copy=True, with_mean=True, with_std=True)),
                ('neighborhoodcomponentsanalysis',
                 NeighborhoodComponentsAnalysis(callback=None, init='auto',
                                                max_iter=50, n_components=2,
                                                random_state=3, tol=1e-05,
                                                verbose=0, warm_start=False))],
         verbose=False)
```

In [35]:
```
xgb.fit(nca.transform(trainX), trainY)
```

Out[35]:
```
XGBClassifier(base_score=0.5, booster=None, colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
              importance_type='gain', interaction_constraints=None,
              learning_rate=0.300000012, max_delta_step=0, max_depth=6,
              min_child_weight=1, missing=nan, monotone_constraints=None,
              n_estimators=3, n_jobs=0, num_parallel_tree=1,
              objective='binary:logistic', random_state=0, reg_alpha=0,
              reg_lambda=1, scale_pos_weight=1, subsample=1, tree_method=None,
              validate_parameters=False, verbosity=None)
```

In [36]:
```
print("Accuracy score -->" ,accuracy_score(xgb.predict(nca.transform(testX)), testY))
```

```
Accuracy score --> 0.7459239130434783
```

In [37]:
```
print(classification_report(testY, xgb.predict(nca.transform(testX))))
```

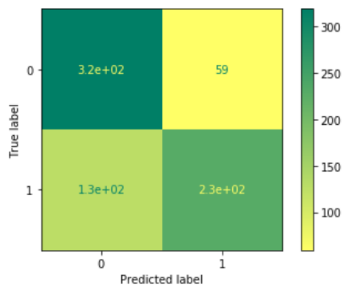
```
              precision    recall  f1-score   support

           0       0.71      0.84      0.77       378
           1       0.80      0.64      0.71       358

    accuracy                           0.75       736
   macro avg       0.75      0.74      0.74       736
weighted avg       0.75      0.75      0.74       736
```

In [38]:
```
confusion_matrix(testY, xgb.predict(nca.transform(testX)))
```

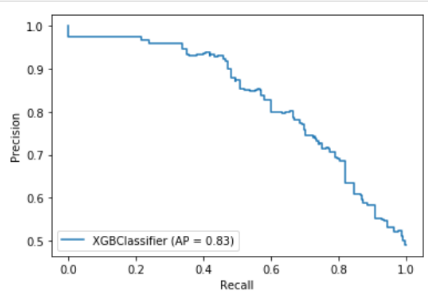
Out[38]:
```
array([[319,  59],
       [128, 230]], dtype=int64)
```

this is the result of the confusion matrix which provides an accuracy of 74.59%

In [39]:
```
plot_confusion_matrix(estimator=xgb, X=nca.transform(testX), y_true=testY, cmap="summer_r")
plt.show()
```



In [40]:
```
plot_precision_recall_curve(estimator=xgb, X=nca.transform(testX), y=testY)
plt.show()
```



KNN Classifier

In [41]:
```
knn = KNeighborsClassifier(n_neighbors=5)
```

In [42]:
```
knn.fit(trainX, trainY)
```

Out[42]:
```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                     metric_params=None, n_jobs=None, n_neighbors=5, p=2,
                     weights='uniform')
```

In [43]:
```
print("Accuracy score -->" ,accuracy_score(knn.predict(testX), testY))
```

```
Accuracy score --> 0.9171195652173914
```

In [44]:
```
print(classification_report(testY, knn.predict(testX)))
```

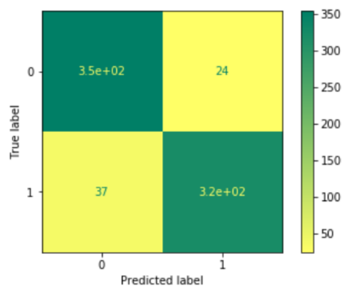
```
              precision    recall  f1-score   support

           0       0.91      0.94      0.92       378
           1       0.93      0.90      0.91       358

    accuracy                           0.92       736
   macro avg       0.92      0.92      0.92       736
weighted avg       0.92      0.92      0.92       736
```

In [45]:
```
confusion_matrix(testY, knn.predict(testX))
```

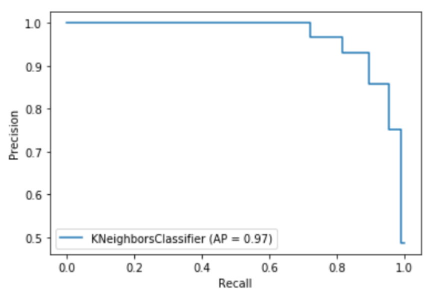
Out[45]:
```
array([[354,  24],
       [ 37, 321]], dtype=int64)
```

this is the result of the confusion matrix which provides an accuracy of 91.71%

In [46]:
```
plot_confusion_matrix(estimator=knn, X=testX, y_true=testY, cmap="summer_r")
plt.show()
```



In [47]:
```
plot_precision_recall_curve(estimator=knn, X=testX, y=testY)
plt.show()
```



The KNN Algorithm performances best among all the 3 algorithm with highest accuracy.

Adaboost Classifier

In [48]:
```
ada = AdaBoostClassifier(n_estimators=50,
                         learning_rate=1.0,
                         algorithm='SAMME.R')
```

In [49]:
```
ada.fit(trainX, trainY)
```

Out[49]:
```
AdaBoostClassifier(algorithm='SAMME.R', base_estimator=None, learning_rate=1.0,
                   n_estimators=50, random_state=None)
```

In [50]:
```
print("Accuracy score -->" ,accuracy_score(ada.predict(testX), testY))
```

```
Accuracy score --> 0.8627717391304348
```

In [51]:
```
print(classification_report(testY, ada.predict(testX)))
```

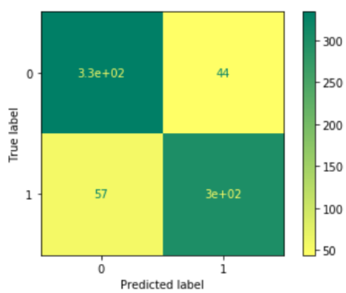
```
              precision    recall  f1-score   support

           0       0.85      0.88      0.87       378
           1       0.87      0.84      0.86       358

    accuracy                           0.86       736
   macro avg       0.86      0.86      0.86       736
weighted avg       0.86      0.86      0.86       736
```

In [52]:
```
confusion_matrix(testY, ada.predict(testX))
```

Out[52]:
```
array([[334,  44],
       [ 57, 301]], dtype=int64)
```

this is the result of the confusion matrix which provides an accuracy of 86.27%

In [53]:
```
plot_confusion_matrix(estimator=ada, X=testX, y_true=testY, cmap="summer_r")
plt.show()
```



In [54]:
```
plot_precision_recall_curve(estimator=ada, X=testX, y=testY)
plt.show()
```