Project : Automatic classification of skin lesions (melanoma detection)

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I - Database

```
import numpy as np
import imageio as im
import matplotlib.pyplot as plt
import os, glob
import cv2
import skimage

DB_pic = []
DB_seg = []
DB_sup = []
path = r"C:\Users\kbekh\Desktop\machine learning\project 2\
PROJECT_Data"
os.chdir(path)
for file in glob.glob("*.jpg"):
    DB_pic += [im.imread(file)]

for file in glob.glob("*.png"):
    if file[15] == 'g' : #g de segmentation : on range dans DB_seg,
sinon DB_sup
        DB_seg += [im.imread(file)]
    else :
        DB_sup += [im.imread(file)]
```

For the set of properties used, we follow the steps indicated in :

[2] : K. Korotkov and R. Garcia. Computerized analysis of pigmented skin lesions: A review. Artificial Intelligence in Medicine, 56(2):69 – 90, 2012 [7] : Tenenhaus A, Nkengne A, Horn JF, Serruys C, Giron A, Fertil B. Detection of melanoma from dermoscopic images of naevi acquired under uncontrolled conditions. Skin Res Technol. 2010 Feb;16(1):85-97. doi: 10.1111/j.1600-0846.2009.00385.x. PMID: 20384887. (use of the abcd rule) Use of the ABCDE method : Asymetry, Border Irregularity, Color Variegation (non Uniformity of the color on the said mark), diameter.

The first three are usable :

- Asymetry is computed on the segmented image : for that, we count the total number of pixels not superimposed with another pixel when the image is rotated 180° from its main axis

- The segmented image is also used to define both the perimeter and the area : it allows to determine the irregularity of the stain : we consider the stain as a circle and we compute R_circle/R_perimeter, with R_circle = sqrt(area * pi) and R_perimeter = perimeter/2 * pi
- For this part, we use the variance and mean of the values of colors of the original images, using a mask obtained through the segmented image We then add intensity descriptors with mean and variance. For textural description we use the wavelet method that yielded the best result for texture classification in a previous work.

More on the Properties

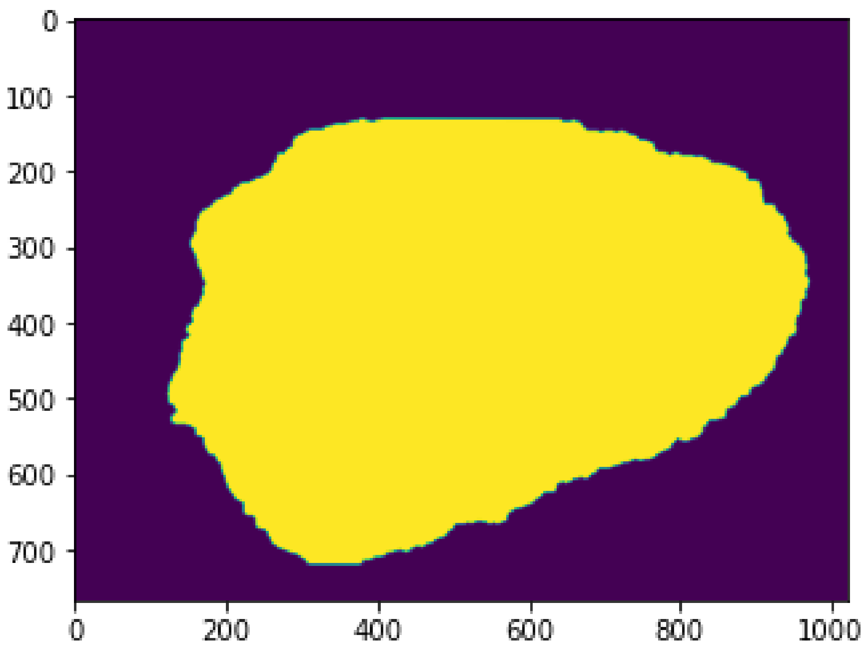
```
I = DB_seg[0]
```

Asymetry :

Using center :

Correct Result

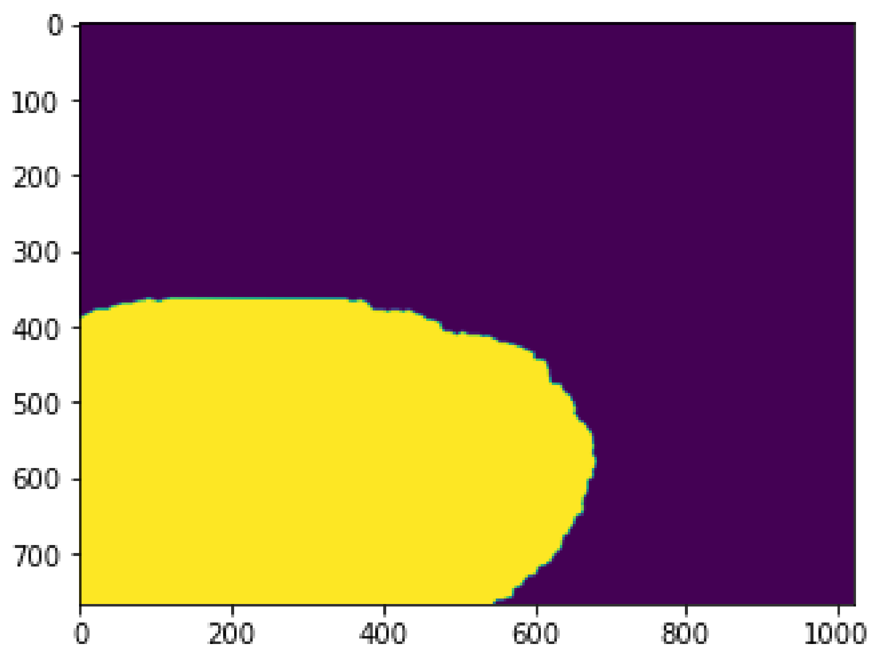
```
moments = cv2.moments(I)
orientation = 1/2*np.arctan2(2*moments['mu11'],moments['mu20']-
moments['mu02'])
center = (I.shape[1]//2, I.shape[0]//2)
rotation_matrix = cv2.getRotationMatrix2D(center, orientation + 180,
1.0)
rotated_I = cv2.warpAffine(I, rotation_matrix, (I.shape[1],
I.shape[0]))
plt.imshow(rotated_I)
plt.show()
```



Using centroid :

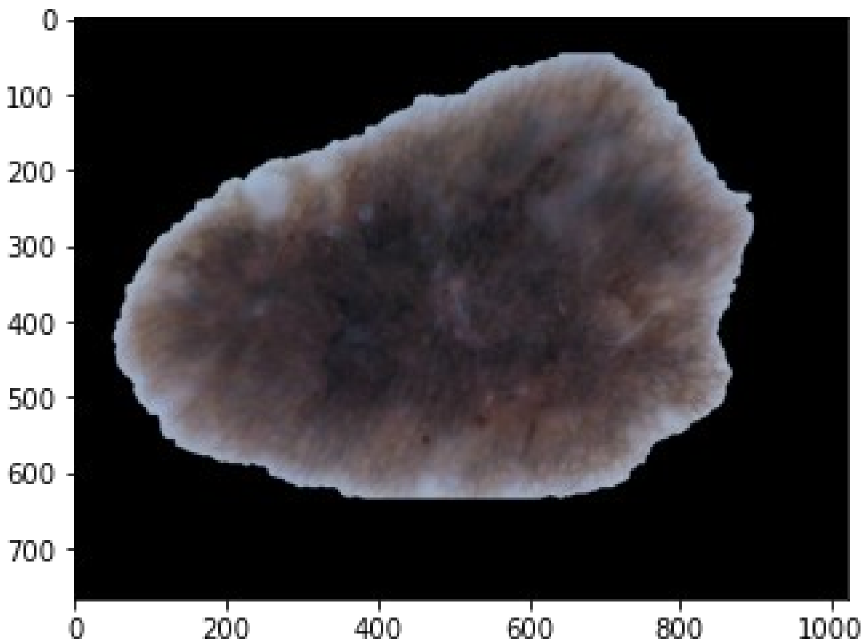
Result not usable

```
region = skimage.measure.label(I)
props = skimage.measure.regionprops(region)

moments = cv2.moments(I)
orientation = 1/2*np.arctan2(2*moments['mu11'],moments['mu20']-
moments['mu02'])
center = props[0].centroid
rotation_matrix = cv2.getRotationMatrix2D(center, orientation + 180,
1.0)
rotated_I = cv2.warpAffine(I, rotation_matrix, (I.shape[1],
I.shape[0]))
plt.imshow(rotated_I)
plt.show()
```



Colors :

```
J = DB_pic[0]
np.max(I)
L = np.where(I==255)
Z = np.zeros(np.shape(J))
Z[L] = J[L]
plt.imshow(Z.astype(int))
I=DB_seg[0]
```



Textures :

We have previously realized a work on texture descriptors and characterization in order to classify textures, and we found out the best method to do so was the granulometry method (the method used were : granulometry, wavelet transform, LBP and tamura's model; the methods are classified in order of precision).

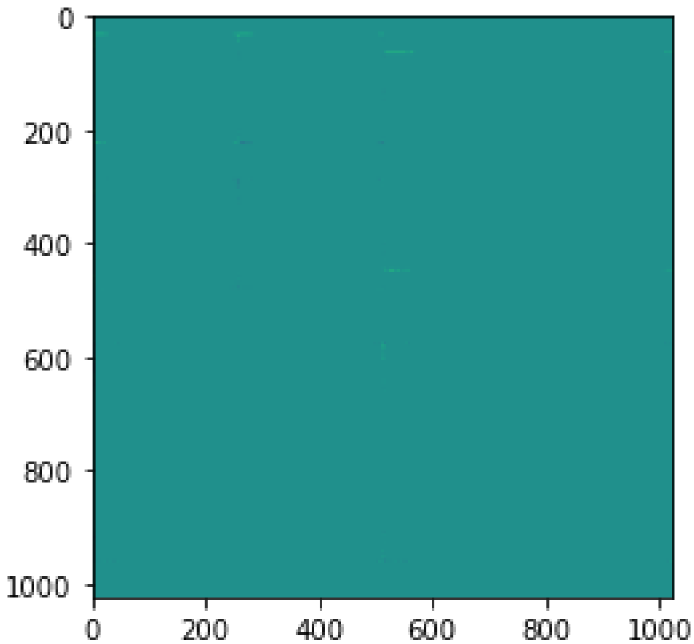
The problem here is that the computational cost of the granular method implemented was far superior to the wavelet transform method, hence the use of wavelet transform here.

```
def Energy(I):
    return np.sum(I**2)

def make_image_square(image):
    new_image = np.copy(image)/np.max(image) #we will normalize the original image in order to keep the wavelet transform relevant
    #if we do not, the upper left part would be much more important than the rest in the later process of texture
    height, width = image.shape[:2]
    maxi = max(height, width)
    if maxi <4092 :
        max_dimension = 4092
    if maxi < 2048 :
        max_dimension = 2048
    if maxi <1024 :
        max_dimension = 1024
    if maxi <512 :
        max_dimension = 512
    if  maxi <256 :
        max_dimension = 256
```

```
    #for consistency (size of the images are not fix in this database)
    square_image = np.zeros((max_dimension, max_dimension,
*image.shape[2:]), dtype=image.dtype)
    x_position = (max_dimension - width)//2
    y_position = (max_dimension - height)//2
    square_image[y_position:y_position + height, x_position:x_position
+ width, ...] = new_image
    return square_image


def wavelet_transform(Images, wt = 'db1'):
    import pywt
    #Transform will take the modifies images, prop will take their
properties
    Transform = []
    prop = []
    #For each image we transform using our wavelet
    for i in range(len(Images)):
        E = [] #will store the energy
        J, (J0, J1, J2) = pywt.dwt2(Images[i], wt)
        K, (K0, K1, K2) = pywt.dwt2(J, wt)

        #This part stack the matrix in order to reform an image
        K00 = np.column_stack((K/(np.max(K)+1),K0/(np.max(K0)+1)))
        K12= np.column_stack((K1/(np.max(K1)+1),K2/(np.max(K2)+1)))
        K_f = np.concatenate((K00,K12))
        J00 = np.column_stack((K_f,J0/(np.max(J0)+1)))
        J12 = np.column_stack((J1/(np.max(J1)+1),J2/(np.max(J2)+1)))
        J_f = np.concatenate((J00,J12))
        #+1 on the max to avoid dividing by 0

        #We calculate the energy of each part of the image [16]
        E = [Energy(J0),Energy(J1), Energy(J2), Energy(K), Energy(K0),
Energy(K1), Energy(K2)]

        #Then we store the values
        Transform.append(J_f)
        prop.append(E)
    return Transform, prop

J = DB_pic[2]
J_gray = cv2.cvtColor(J, cv2.COLOR_BGR2GRAY)
Transform, prop = wavelet_transform([make_image_square(J_gray)])
plt.imshow(Transform[0])
prop
```

```
[[86.50000000000003,
  85.50000000000003,
  12.500000000000004,
  76.12500000000003,
```

```
   38.375000000000014,
   40.125000000000014,
   4.875000000000002]]
```



Implementation

```
def properties(i): #i est le numéro de l'image
    I=DB_seg[i]
    properties = []
    region = skimage.measure.label(I)
    props = skimage.measure.regionprops(region)
    area = props[0].area

    #Asymetry
    moments = cv2.moments(I)
    orientation = 1/2*np.arctan2(2*moments['mu11'],moments['mu20']-
moments['mu02']) #to find the main orientation of the image

    center = (I.shape[1]//2, I.shape[0]//2) #center of rotation of the
image (center of the image, weird result using props[0].centroid)
    rotation_matrix = cv2.getRotationMatrix2D(center, orientation +
180, 1.0)
    rotated_I = cv2.warpAffine(I, rotation_matrix, (I.shape[1],
I.shape[0]))
    J = I - rotated_I
    J[J < 0]=1
    properties += [np.mean(J)*(I.shape[0]*I.shape[1])/(255*(area*2-
1))]  #number of pixel that do not
    #superimpose divided by the area of two stain (max asymetry, if
```

```
only one pixel superimpose)
    #(divided by 255 because the pixels are set at 255 for the mean,
not 1)

    #Irregularity
    perimeter = props[0].perimeter
    properties += [np.sqrt(area*np.pi)/(perimeter/(2*np.pi))]

    #Colors
    J = DB_pic[i]
    np.max(I)
    L = np.where(I==255)
    Z = np.zeros(np.shape(J))
    Z[L] = J[L]
    properties += [np.var(Z), np.mean(Z)]

    #Properties of the superpixel image
    K = DB_pic[i]
    properties += [np.var(K), np.mean(K)]

    #Textural properties of the original pic and the superpixel pic.
    J = DB_pic[i]
    J_gray = cv2.cvtColor(J, cv2.COLOR_BGR2GRAY)
    Transform, energies =
wavelet_transform([make_image_square(J_gray)])
    properties += energies[0]
    J = DB_sup[i]
    J_gray = cv2.cvtColor(J, cv2.COLOR_BGR2GRAY)
    Transform, energies =
wavelet_transform([make_image_square(J_gray)])
    properties += energies[0]

    return properties
properties(1)
```

```
[0.1448074344042849,
 2.40830780951896,
 275.0270672253223,
 3.933459544093396,
 1024.83167015554,
 164.69376753576893,
 215.00000000000009,
 62.000000000000014,
 16.000000000000007,
 126.12500000000004,
 103.12500000000004,
 27.125000000000001,
 4.625000000000002,
 125.25000000000003,
 121.25000000000004,
```

```
 52.250000000000014,
 6427.937500000003,
 182.18750000000009,
 162.93750000000009,
 39.18750000000002]
```

In this part we treat every image, which can be calcul intensive. On my computer, it took 3min23 to achieve

```
data = []
for i in range(len(DB_pic)):
    data +=[properties(i)]

array_data = np.array(data)
for i in range(array_data.shape[1]):
    array_data[:,i] = array_data[:,i]/np.max(array_data[:,i])
np.max(array_data)

1.0
```

Learning of for the Data

First, from the paper quoted before, we apply the learning of four models (SVM, Neural Networks, Bayesian model and Logistic regression) to the dataset of properties for the images we have. Here we import Y for the first time : the problem that has risen from the given database, after thorough inspection, are that there was missing photos (our last picture is labeled 518, while 200 different pictures are in the database), and there were missing labels in the excel. With the use of condition, by getting the idea of each pictures, we managed to import Y properly, as shown below.

```
import pandas as pd

#Creation of X
X = array_data

#Creation of Y
path = r"C:\Users\kbekh\Desktop\machine learning\project 2"
df = pd.read_csv(path+ "\ISIC-
2017_Data_GroundTruth_Classification.csv")
Truth = np.array(df["melanoma"])

#We load the indices of the images we have :
path = r"C:\Users\kbekh\Desktop\machine learning\project 2\
PROJECT_Data"
os.chdir(path)
indices = []
for file in glob.glob("*.jpg"):
    indices +=[file[9:12]]
Y=[]
```

```
for i in indices :
    condition = (df["image_id"] == "ISIC_0000" + i)
    Y += [(df[condition]["melanoma"])]
Y = np.array(Y).astype(int)[:,0]
Y

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

Now, we can split our dataset in 4 parts : part for the learning (X train, Y train) and parts to test. We add a random part (random state) and use 70% of the data set to train.

```
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
test_size = 0.3
(X_train, X_test, Y_train, Y_test) = train_test_split(X, Y,
test_size=test_size, random_state=1111)
```

We define below the functions to produce the four different models.

```
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
import tensorflow as tf
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
#Bayesian Classifier method

def train_bayesian_classifier(X_train, Y_train):
    classifier = GaussianNB()
    classifier.fit(X_train, Y_train)
    return classifier
```

```
#SVM Classifier method

def train_svm_classifier(X_train, Y_train):
    classifier = SVC(kernel="linear", C=1.0, probability=True)
    classifier.fit(X_train, Y_train)
    return classifier

#Neural Network

def train_nn_classifier(X_train, Y_train): #neural network
    model = tf.keras.Sequential([
        tf.keras.layers.Dense(64, activation='relu',
input_shape=(X_train.shape[1],)),
        tf.keras.layers.Dense(1, activation='sigmoid')
    ])
    model.compile(optimizer="adam", loss="binary_crossentropy")
    model.fit(X_train, Y_train, epochs=100, verbose=False)
    return model

#Logistic regression

def train_logistic_regression(X_train, Y_train):
    X_train_split, X_test_split, Y_train_split, Y_test_split =
train_test_split(X_train, Y_train, test_size=0.2, random_state=42)
    logistic_regression_model = LogisticRegression()
    logistic_regression_model.fit(X_train_split, Y_train_split)
    return logistic_regression_model
```

Then we apply the dataset to the different models.

```
bayesian_model = train_bayesian_classifier(X_train, Y_train)
SVM_model = train_svm_classifier(X_train, Y_train)
logistic_model = train_logistic_regression(X_train, Y_train)
neural_model = train_nn_classifier(X_train, Y_train)

bayesian_predict = bayesian_model.predict(X_test)
logistic_predict = logistic_model.predict(X_test)
SVM_predict = SVM_model.predict(X_test)
Neural_predict = np.round(neural_model.predict(X_test)).astype(int)
[:,0]

2/2 [==============================] - 0s 2ms/step
```

And define a function to produce data to evaluate the models. We use accuracy, F_score, recall, a ROC curve, and the AUC (area under the ROC curve), aswell as a confusion matrix.

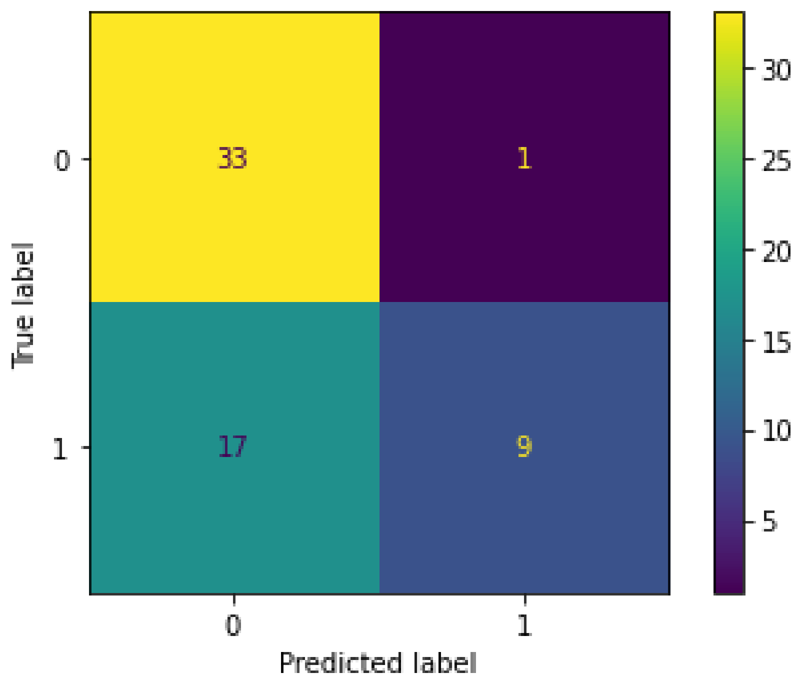
```
def precision(Y_test, model):
      from sklearn.metrics import roc_curve, auc
      import matplotlib.pyplot as plt
```

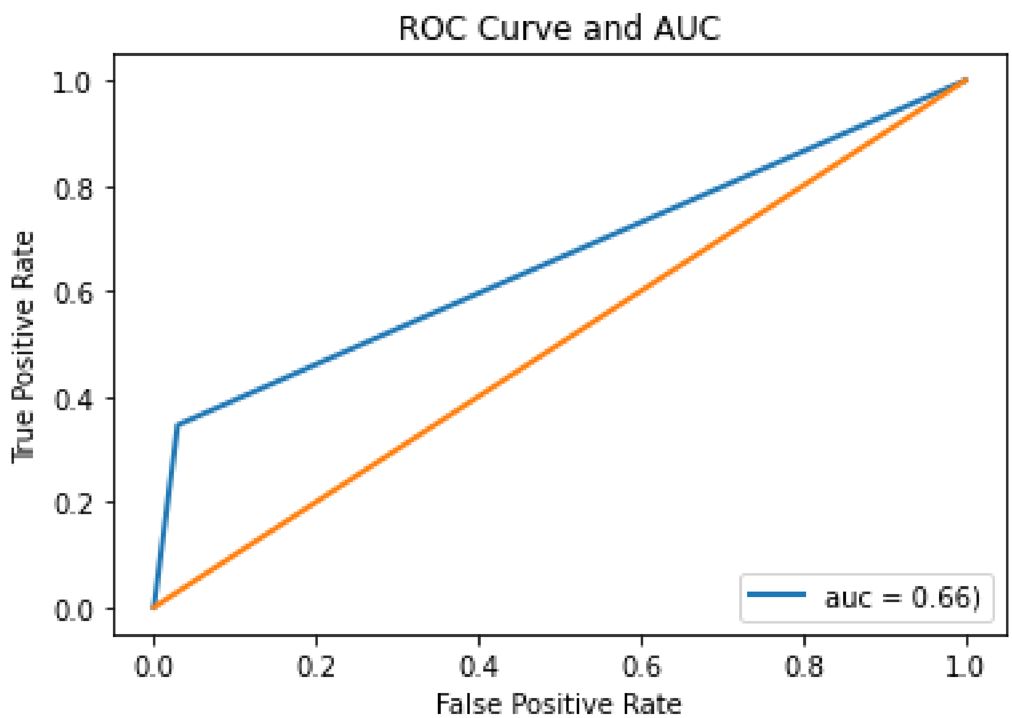
```
      # Show confusion matrix
      Y_test = np.array([Y_test.astype(bool)])
      Y_hat = model.astype(bool)
      confm = confusion_matrix(Y_test.T, Y_hat.T)
      print(confm)
      disp = ConfusionMatrixDisplay(confusion_matrix=confm)
      disp.plot()

      #confusion matrix

      tp = confm[0,0]
      tn = confm[1,1]
      fn = confm[1,0]
      fp = confm[0,1]
      tot = tp + tn + fn + fp
      accuracy = (tp + tn )/ (tot)
      precision = tp/(tp+fp)
      recall = tp/(tp+fn)

      f_score = 2*((precision*recall)/(precision+recall))
      fpr, tpr, _= roc_curve(Y_test.astype(int).ravel(), (Y_hat >
0.5).astype(int).ravel())
      roc_auc = auc(fpr, tpr)

      plt.figure()
      plt.plot(fpr, tpr, lw=2, label='auc = {:.2f})'.format(roc_auc))
      plt.plot([0, 1], [0, 1], lw=2)
      plt.xlabel('False Positive Rate')
      plt.ylabel('True Positive Rate')
      plt.title('ROC Curve and AUC')
      plt.legend(loc='lower right')
      plt.show()
      return "accuracy :", accuracy, "recall", recall, "f_score",
f_score
```

Test 1 :

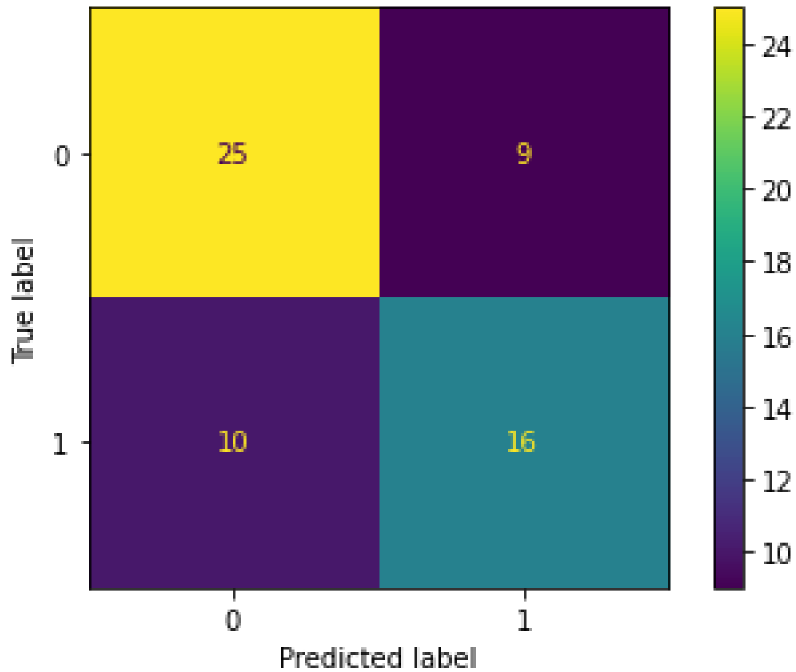
properties : Asymetry, Border Irregularity, Color Variegation, Superpixels variation, Textural Information with Wavelet

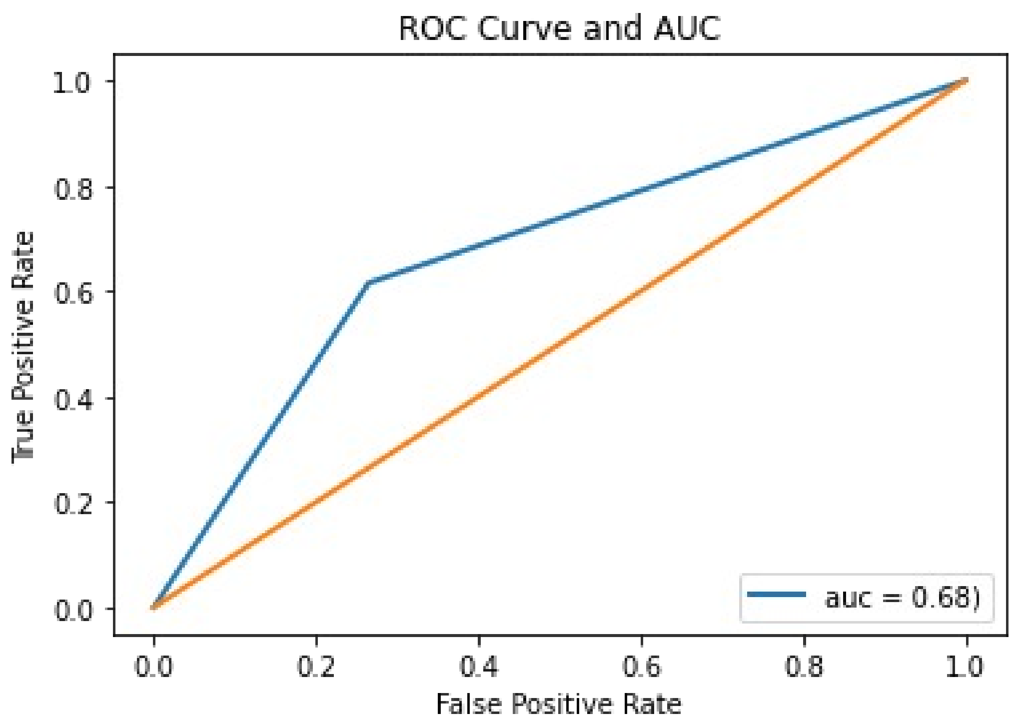
```
precision(Y_test, bayesian_predict)

[[33  1]
 [17  9]]
```





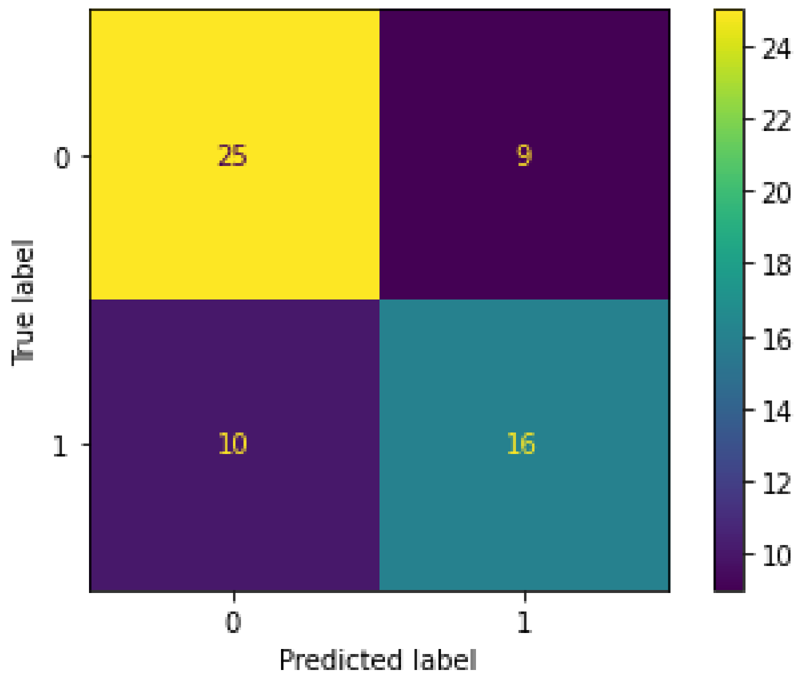

```
('accuracy :', 0.7, 'recall', 0.66, 'f_score', 0.7857142857142857)

precision(Y_test, SVM_predict)

[[25  9]
 [10 16]]
```

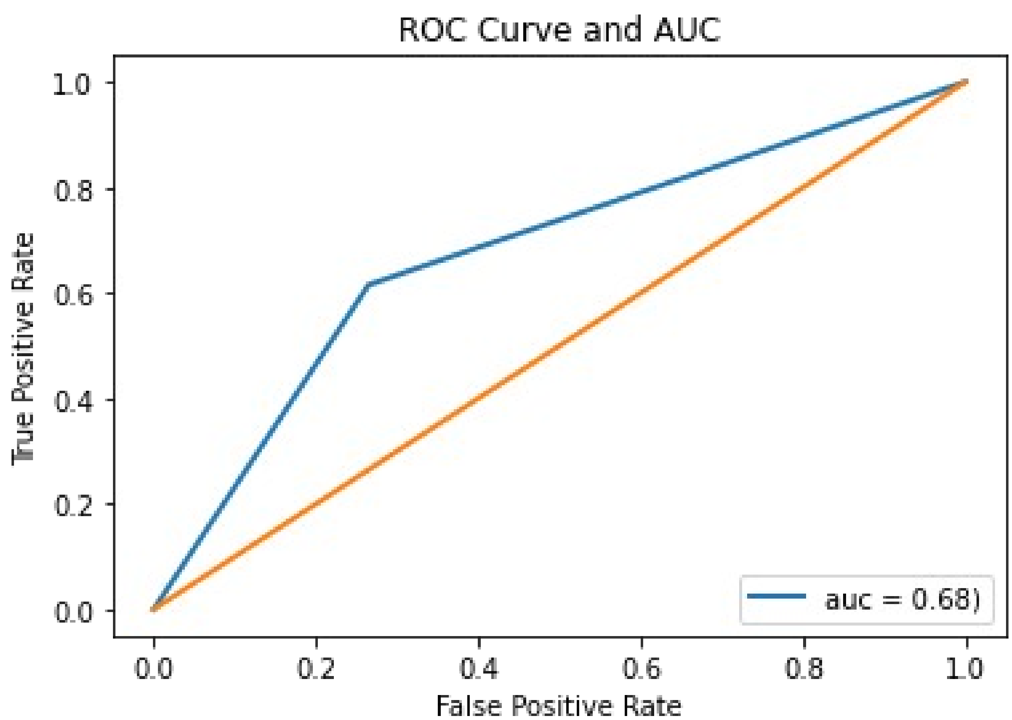




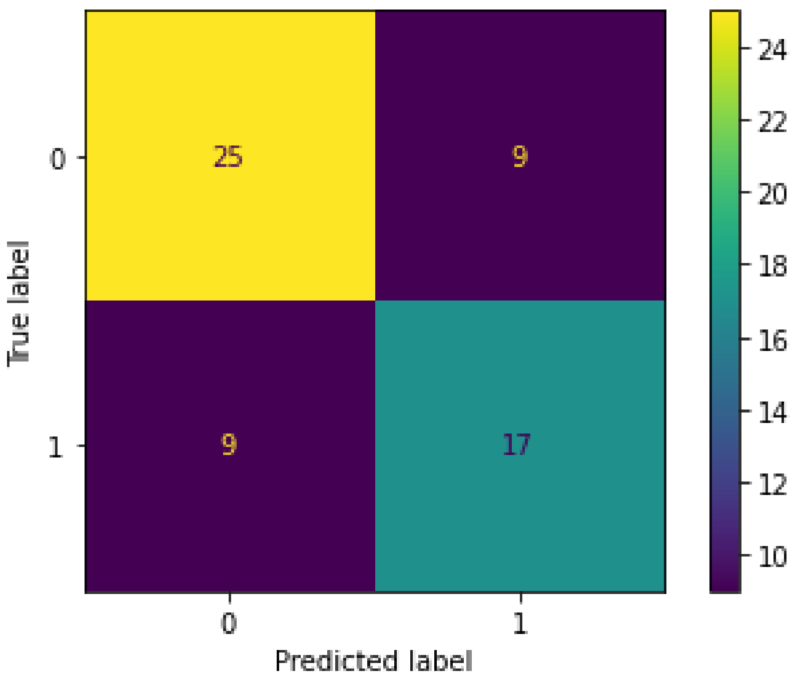

```
('accuracy :',
 0.6833333333333333,
 'recall',
 0.7142857142857143,
 'f_score',
 0.7246376811594202)
```

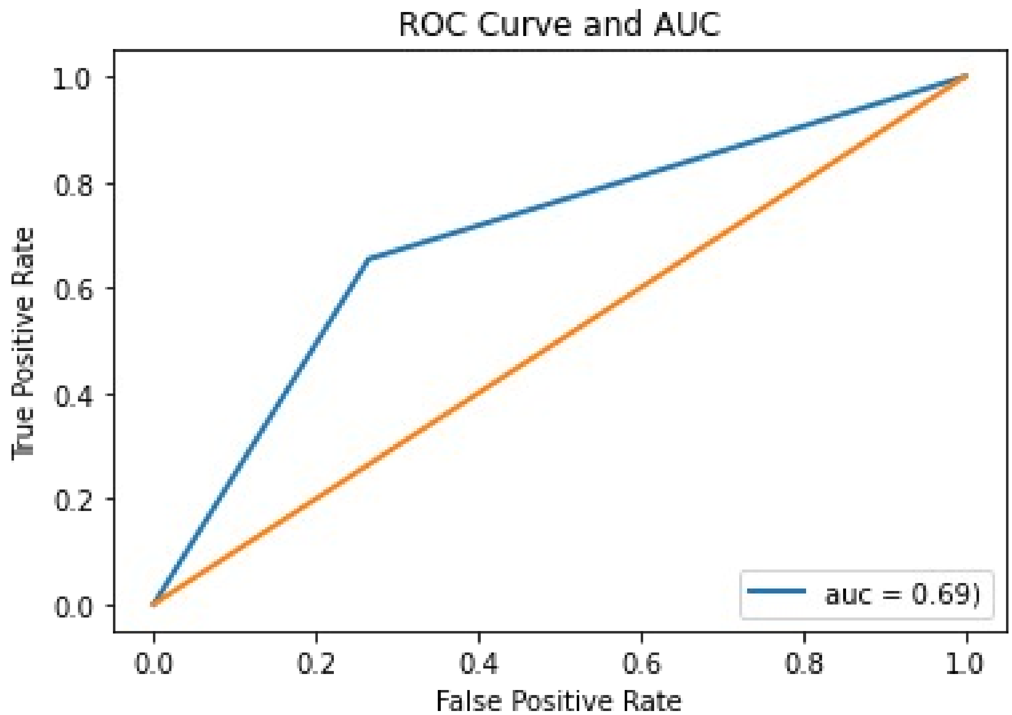
```
precision(Y_test, logistic_predict)

[[25  9]
 [10 16]]
```





```
('accuracy :',
 0.6833333333333333,
 'recall',
 0.7142857142857143,
 'f_score',
 0.7246376811594202)

precision(Y_test, Neural_predict)

[[25  9]
 [ 9 17]]
```






```
('accuracy :', 0.7, 'recall', 0.7352941176470589, 'f_score',
0.735294117647059)
```

Another test, changing the properties takn into account

Test 2

Asymetry, Border Irregularity, Color Variegation, Superpixels variation (whitout textural information)

```
def properties_second(i): #i is the index of the image
    I=DB_seg[i]
    properties = []
    region = skimage.measure.label(I)
    props = skimage.measure.regionprops(region)
    area = props[0].area

    #Asymetry
    moments = cv2.moments(I)
    orientation = 1/2*np.arctan2(2*moments['mu11'],moments['mu20']-
moments['mu02']) #to find the main orientation of the image

    center = (I.shape[1]//2, I.shape[0]//2) #center of rotation of the
image (center of the image, weird result using props[0].centroid)
    rotation_matrix = cv2.getRotationMatrix2D(center, orientation +
180, 1.0)
```

```
    rotated_I = cv2.warpAffine(I, rotation_matrix, (I.shape[1],
I.shape[0]))
    J = I - rotated_I
    J[J < 0]=1
    properties += [np.mean(J)*(I.shape[0]*I.shape[1])/(255*(area*2-
1))]  #number of pixel that do not
    #superimpose divided by the area of two stain (max asymetry, if
only one pixel superimpose)
    #(divided by 255 because the pixels are set at 255 for the mean,
not 1)

    #Irregularity
    perimeter = props[0].perimeter
    properties += [np.sqrt(area*np.pi)/(perimeter/(2*np.pi))]

    #Colors
    J = DB_pic[i]
    np.max(I)
    L = np.where(I==255)
    Z = np.zeros(np.shape(J))
    Z[L] = J[L]
    properties += [np.var(Z), np.mean(Z)]

    #Properties of the superpixel image
    K = DB_pic[i]
    properties += [np.var(K), np.mean(K)]
    return properties
```

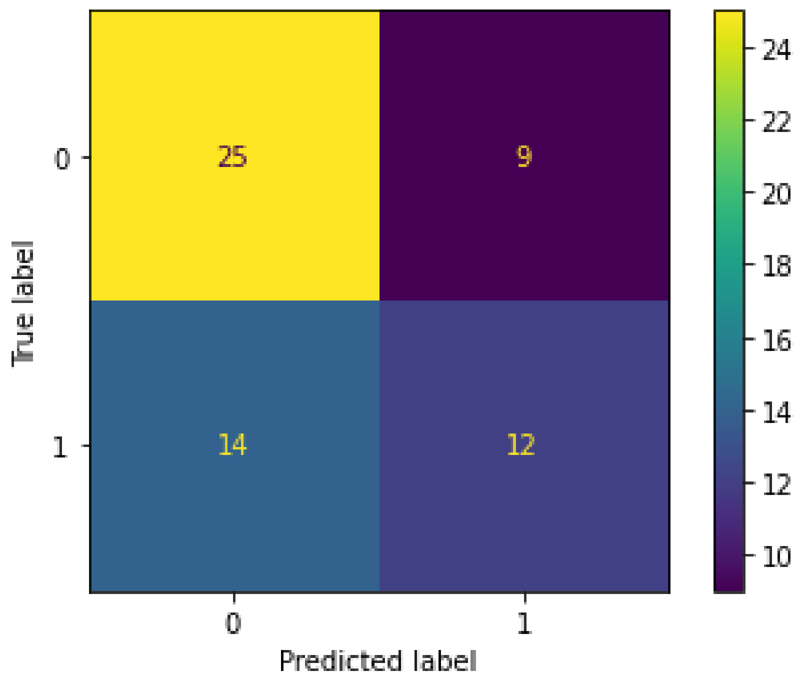
Here we took off the texture informations.

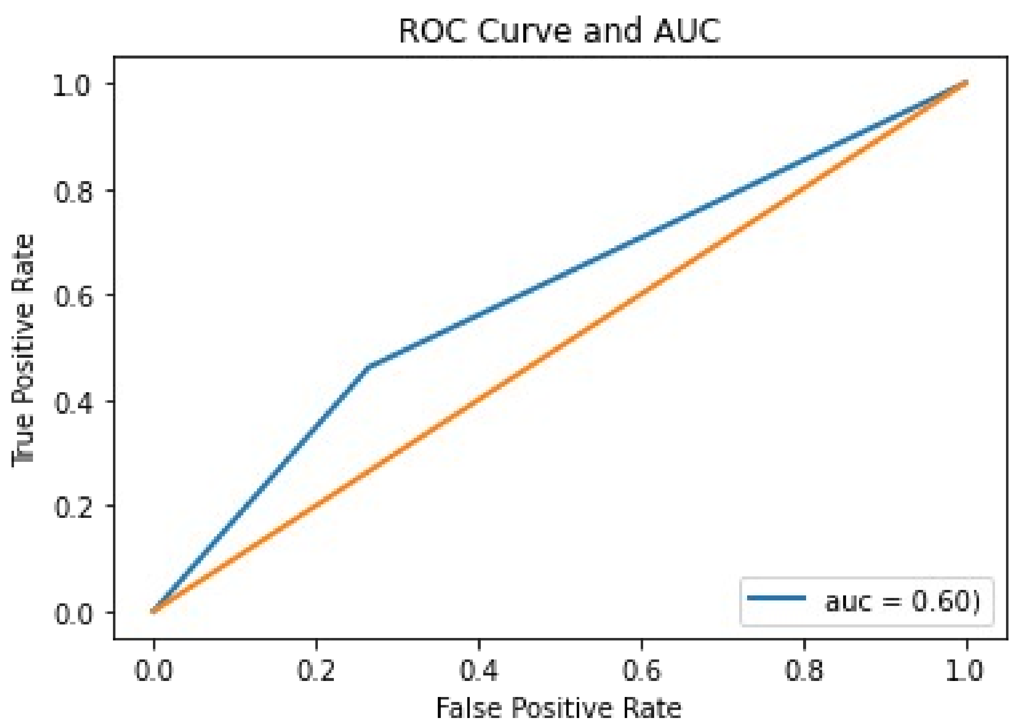
```
data = []
for i in range(len(DB_pic)):
    data +=[properties_second(i)]
test_size = 0.3
X = np.array(data)
(X_train, X_test, Y_train, Y_test) = train_test_split(X, Y,
test_size=test_size, random_state=1111)

bayesian_model = train_bayesian_classifier(X_train, Y_train)
SVM_model = train_svm_classifier(X_train, Y_train)
logistic_model = train_logistic_regression(X_train, Y_train)
neural_model = train_nn_classifier(X_train, Y_train)
Neural_predict = np.round(neural_model.predict(X_test)).astype(int)
[:,0]
```

```
2/2 [==============================] - 0s 0s/step
```

```
precision(Y_test, Neural_predict)
```

```
[[25  9]
 [14 12]]
```






```
('accuracy :',
 0.6166666666666667,
```

```
 'recall',
 0.6410256410256411,
 'f_score',
 0.6849315068493151)
```

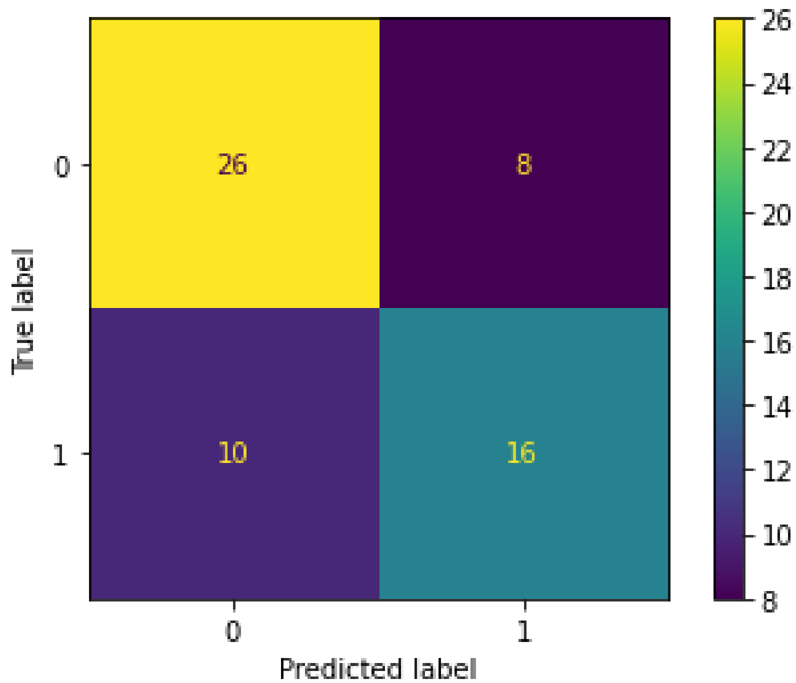
Test 3

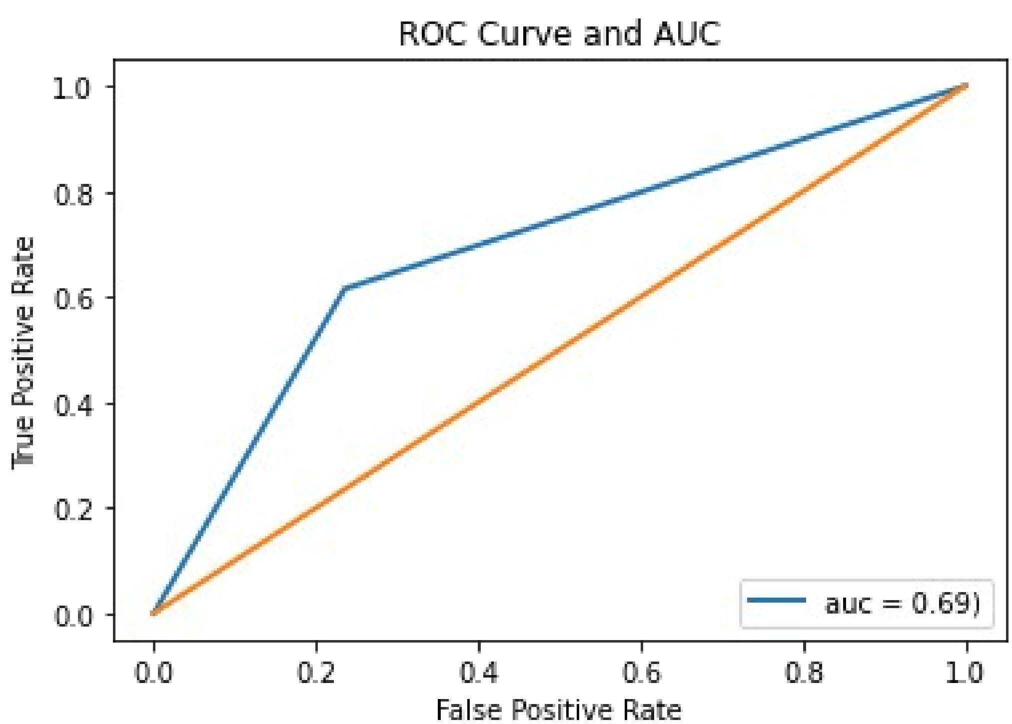
Properties : Asymetry, Border Irregularity, Color Variegation, Superpixels variation, Textural Information with LBP

```
def properties_third(i):
    from skimage import feature
    I=DB_seg[i]
    properties = []
    region = skimage.measure.label(I)
    props = skimage.measure.regionprops(region)
    area = props[0].area

    #Asymetry
    moments = cv2.moments(I)
    orientation = 1/2*np.arctan2(2*moments['mu11'],moments['mu20']-
moments['mu02']) #to find the main orientation of the image

    center = (I.shape[1]//2, I.shape[0]//2) #center of rotation of the
image (center of the image, weird result using props[0].centroid)
    rotation_matrix = cv2.getRotationMatrix2D(center, orientation +
180, 1.0)
    rotated_I = cv2.warpAffine(I, rotation_matrix, (I.shape[1],
I.shape[0]))
    J = I - rotated_I
    J[J < 0]=1
    properties += [np.mean(J)*(I.shape[0]*I.shape[1])/(255*(area*2-
1))]  #number of pixel that do not
    #superimpose divided by the area of two stain (max asymetry, if
only one pixel superimpose)
    #(divided by 255 because the pixels are set at 255 for the mean,
not 1)

    #Irregularity
    perimeter = props[0].perimeter
    properties += [(4*area*np.pi)/(perimeter**2)] #changed

    #Colors
    J = DB_pic[i]
    np.max(I)
    L = np.where(I==255)
    Z = np.zeros(np.shape(J))
    Z[L] = J[L]
    properties += [np.var(Z), np.mean(Z)]
```

```
    #Properties of the superpixel image
    K = DB_pic[i]
    properties += [np.var(K), np.mean(K)]

    #Textural descriptor ##This method is a courtesy of Gaetan Allaire
    J_gray =cv2.cvtColor(J, cv2.COLOR_BGR2GRAY)
    K_gray =cv2.cvtColor(K, cv2.COLOR_BGR2GRAY)
    # Extract texture features using Local Binary Patterns (LBP) on
superpixel image
    lbp_superpixel = feature.local_binary_pattern(K_gray, P=8, R=1,
method="uniform")
    hist_lbp_superpixel, _ = np.histogram(lbp_superpixel.ravel(),
bins=np.arange(0, 10), range=(0, 9))
    lbp_superpixel = feature.local_binary_pattern(J_gray, P=8, R=1,
method="uniform")
    hist_lbp_picture, _ = np.histogram(lbp_superpixel.ravel(),
bins=np.arange(0, 10), range=(0, 9))
    properties += list(hist_lbp_superpixel)
    properties += list(hist_lbp_picture)
    return properties

data = []
for i in range(len(DB_pic)):
    data +=[properties_third(i)]
array_data = np.array(data)
for i in range(array_data.shape[1]):
    array_data[:,i] = array_data[:,i]/np.max(array_data[:,i])
np.max(array_data)
test_size = 0.3
X = array_data
(X_train, X_test, Y_train, Y_test) = train_test_split(X, Y,
test_size=test_size, random_state=1111)

bayesian_model = train_bayesian_classifier(X_train, Y_train)
SVM_model = train_svm_classifier(X_train, Y_train)
logistic_model = train_logistic_regression(X_train, Y_train)
neural_model = train_nn_classifier(X_train, Y_train)
Neural_predict = np.round(neural_model.predict(X_test)).astype(int)
[:,0]
precision(Y_test, Neural_predict)
```

```
2/2 [==============================] - 0s 0s/step
[[26  8]
 [10 16]]
```






```
('accuracy :',
 0.7,
 'recall',
 0.7222222222222222,
```

```
 'f_score',
 0.7428571428571428)
```

Test 4 : More shape descriptors

Asymetry, Border Irregularity, Color Variegation, Superpixels variation, Textural Information with Wavelet + various shape descriptors

```
def properties_fourth(i): #i est le numéro de l'image
    I=DB_seg[i]
    properties = []
    region = skimage.measure.label(I)
    props = skimage.measure.regionprops(region)
    area = props[0].area

    #Asymetry
    moments = cv2.moments(I)
    orientation = 1/2*np.arctan2(2*moments['mu11'],moments['mu20']-
moments['mu02']) #to find the main orientation of the image

    center = (I.shape[1]//2, I.shape[0]//2) #center of rotation of the
image (center of the image, weird result using props[0].centroid)
    rotation_matrix = cv2.getRotationMatrix2D(center, orientation +
180, 1.0)
    rotated_I = cv2.warpAffine(I, rotation_matrix, (I.shape[1],
I.shape[0]))
    J = I - rotated_I
    J[J < 0]=1
    properties += [np.mean(J)*(I.shape[0]*I.shape[1])/(255*(area*2-
1))]  #number of pixel that do not
    #superimpose divided by the area of two stain (max asymetry, if
only one pixel superimpose)
    #(divided by 255 because the pixels are set at 255 for the mean,
not 1)

    #Irregularity
    perimeter = props[0].perimeter
    properties += [np.sqrt(area*np.pi)/(perimeter/(2*np.pi))]

    #Colors
    J = DB_pic[i]
    np.max(I)
    L = np.where(I==255)
    Z = np.zeros(np.shape(J))
    Z[L] = J[L]
    properties += [np.var(Z), np.mean(Z)]

    #Properties of the superpixel image
    K = DB_pic[i]
```

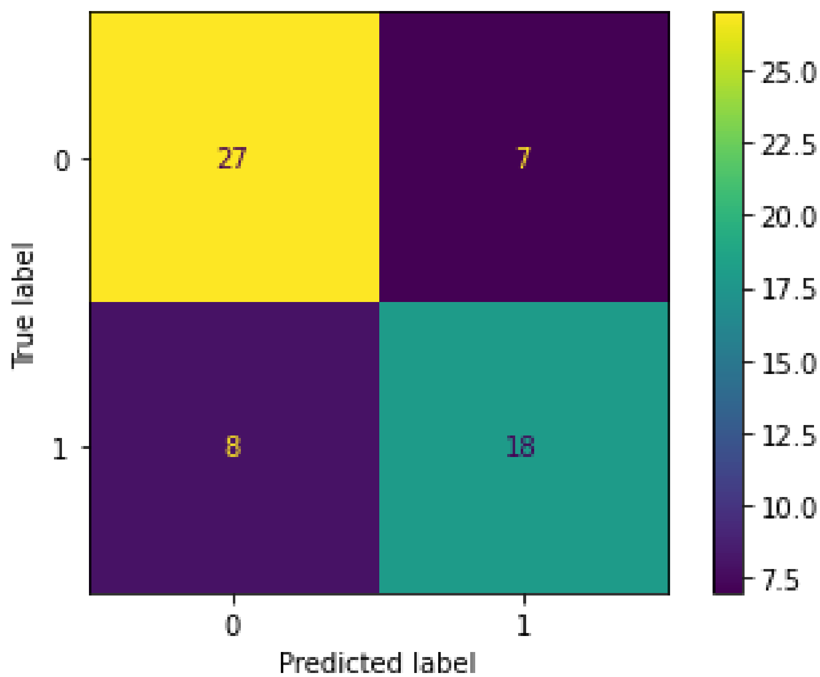
```
    properties += [np.var(K), np.mean(K)]

    #Textural properties of the original pic and the superpixel pic.
    J = DB_pic[i]
    J_gray = cv2.cvtColor(J, cv2.COLOR_BGR2GRAY)
    Transform, energies = 
wavelet_transform([make_image_square(J_gray)])
    properties += energies[0]
    J = DB_sup[i]
    J_gray = cv2.cvtColor(J, cv2.COLOR_BGR2GRAY)
    Transform, energies = 
wavelet_transform([make_image_square(J_gray)])
    properties += energies[0]
    properties+=props[0].eccentricity
    properties+=props[0].perimeter
    properties+=props[0].extent
    properties+=props[0].axis_minor_length
    properties+=props[0].axis_major_length
    properties+=props[0].equivalent_diameter_area
    properties+=props[0].solidity
    return properties
properties(1)
```

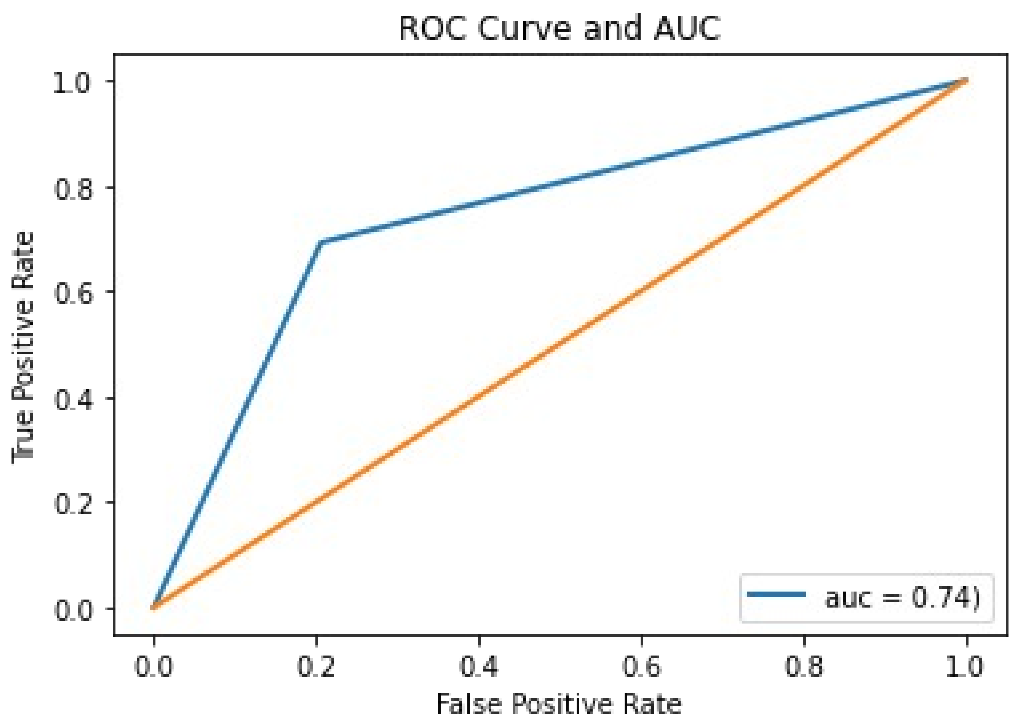
```
[0.1448074344042849,
 2.40830780951896,
 275.0270672253223,
 3.933459544093396,
 1024.83167015554,
 164.69376753576893,
 215.00000000000009,
 62.000000000000014,
 16.000000000000007,
 126.12500000000004,
 103.12500000000004,
 27.125000000000001,
 4.625000000000002,
 125.25000000000003,
 121.25000000000004,
 52.250000000000014,
 6427.937500000003,
 182.18750000000009,
 162.93750000000009,
 39.18750000000002]
```

```
data = []
for i in range(len(DB_pic)):
    data +=[properties_third(i)]
array_data = np.array(data)
for i in range(array_data.shape[1]):
    array_data[:,i] = array_data[:,i]/np.max(array_data[:,i])
```

```python
np.max(array_data)
test_size = 0.3
X = array_data
(X_train, X_test, Y_train, Y_test) = train_test_split(X, Y,
test_size=test_size, random_state=1111)

bayesian_model = train_bayesian_classifier(X_train, Y_train)
SVM_model = train_svm_classifier(X_train, Y_train)
logistic_model = train_logistic_regression(X_train, Y_train)
neural_model = train_nn_classifier(X_train, Y_train)
Neural_predict = np.round(neural_model.predict(X_test)).astype(int)
[:,0]
precision(Y_test, Neural_predict)
```

```
WARNING:tensorflow:5 out of the last 9 calls to <function
Model.make_predict_function.<locals>.predict_function at
0x000001F3B7DA2040> triggered tf.function retracing. Tracing is
expensive and the excessive number of tracings could be due to (1)
creating @tf.function repeatedly in a loop, (2) passing tensors with
different shapes, (3) passing Python objects instead of tensors. For
(1), please define your @tf.function outside of the loop. For (2),
@tf.function has reduce_retracing=True option that can avoid
unnecessary retracing. For (3), please refer to
https://www.tensorflow.org/guide/function#controlling_retracing and
https://www.tensorflow.org/api_docs/python/tf/function for  more
details.
2/2 [==============================] - 0s 0s/step
[[27  7]
 [ 8 18]]
```






```
('accuracy :',
 0.75,
 'recall',
 0.7714285714285715,
 'f_score',
 0.782608695652174)
```

Conclusion

For the Neural network model, the matrix to compare results :

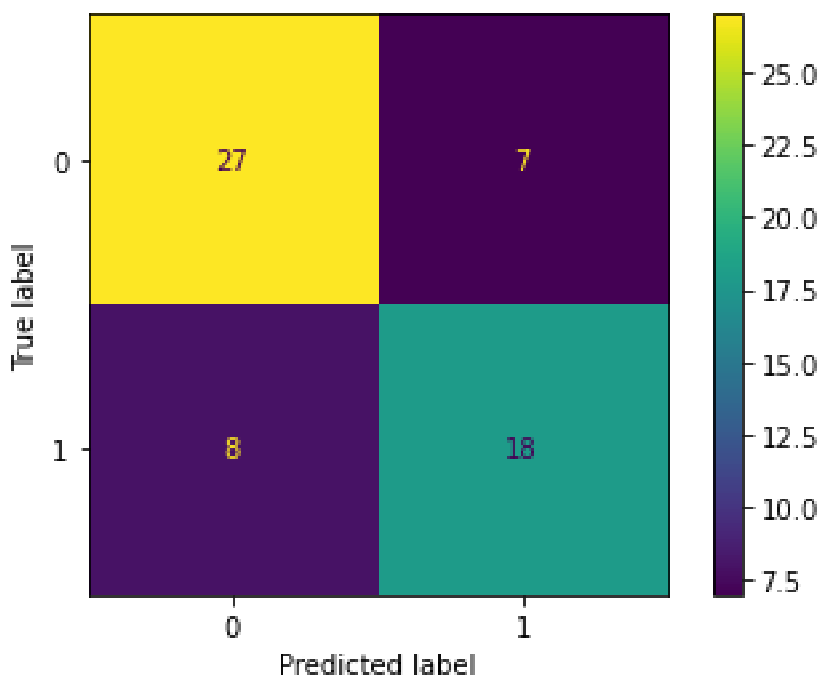
```
L = np.array([["Accuracy",0.7,0.62,0.7,0.75],
["Recall",0.74,0.64,0.72,0.77], ["Fscore",0.74,0.68,0.74,0.78]])
dfL = pd.DataFrame(L, columns=["Metric", "Test 1", "Test 2", "Test 3",
"Test 4"])
dfL
```

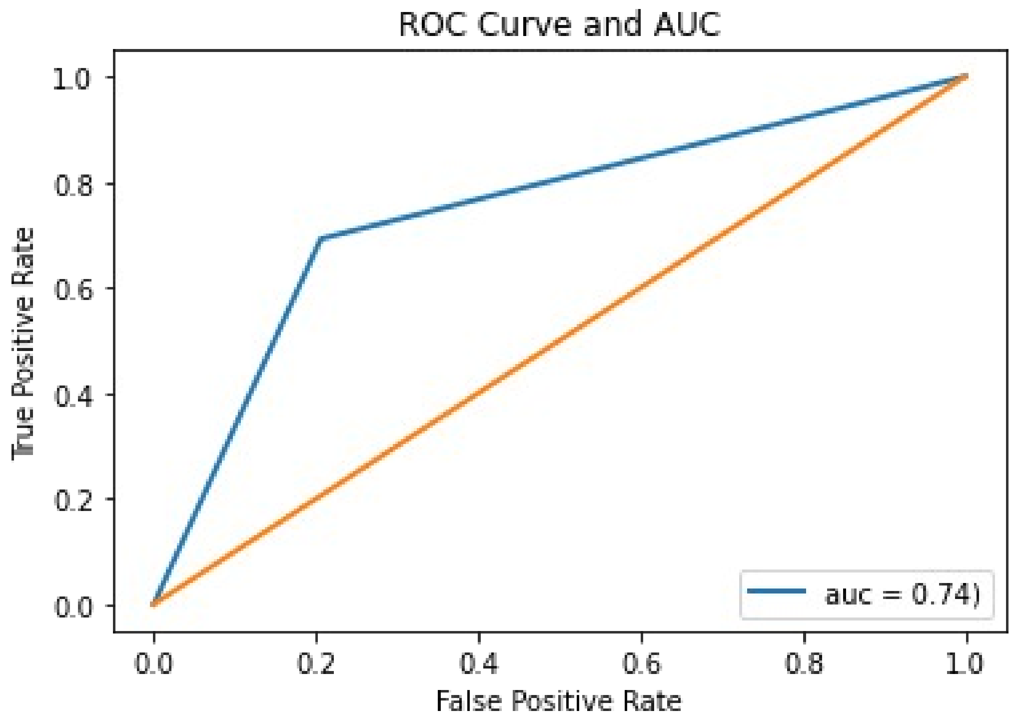
```
     Metric Test 1 Test 2 Test 3 Test 4
0  Accuracy    0.7   0.62    0.7   0.75
1    Recall   0.74   0.64   0.72   0.77
2    Fscore   0.74   0.68   0.74   0.78
```

The test 4 with shapes descriptors, wavelet transform, and ABC method yield the best results, which is confirmed by the area under the ROC curve of the test 4, auc = 0.74

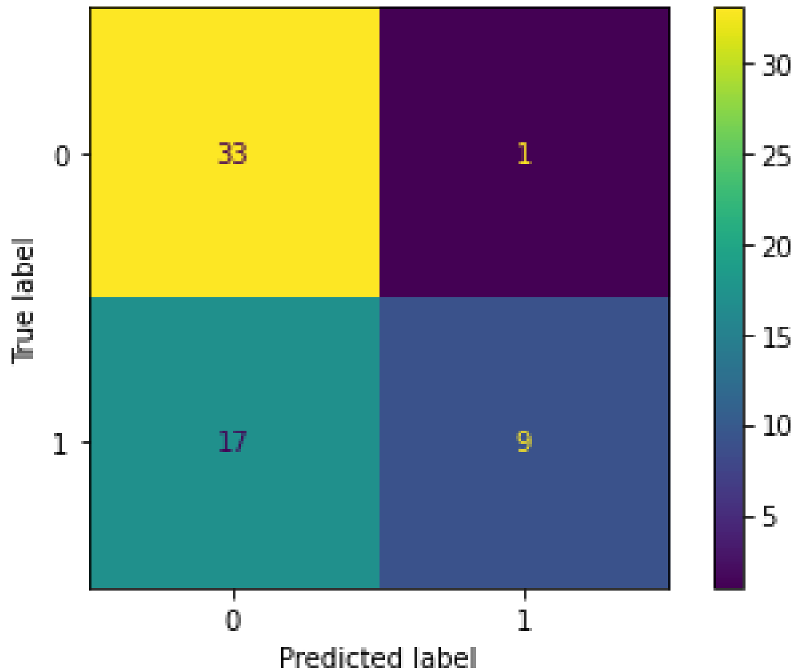
```
precision(Y_test, Neural_predict)
```

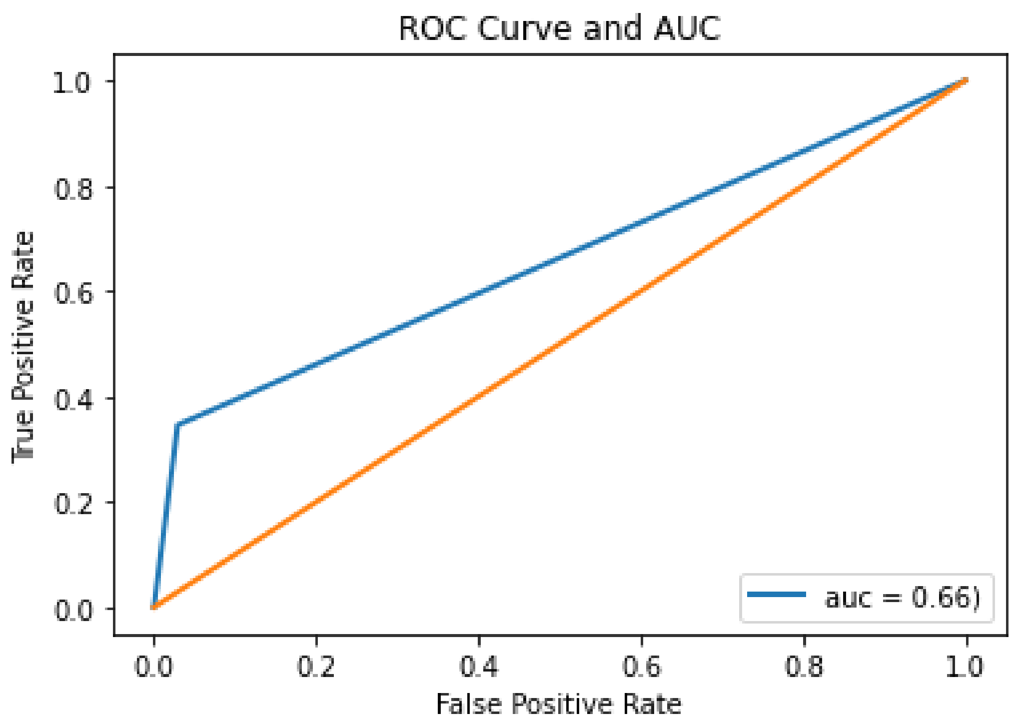
```
[[27  7]
 [ 8 18]]
```



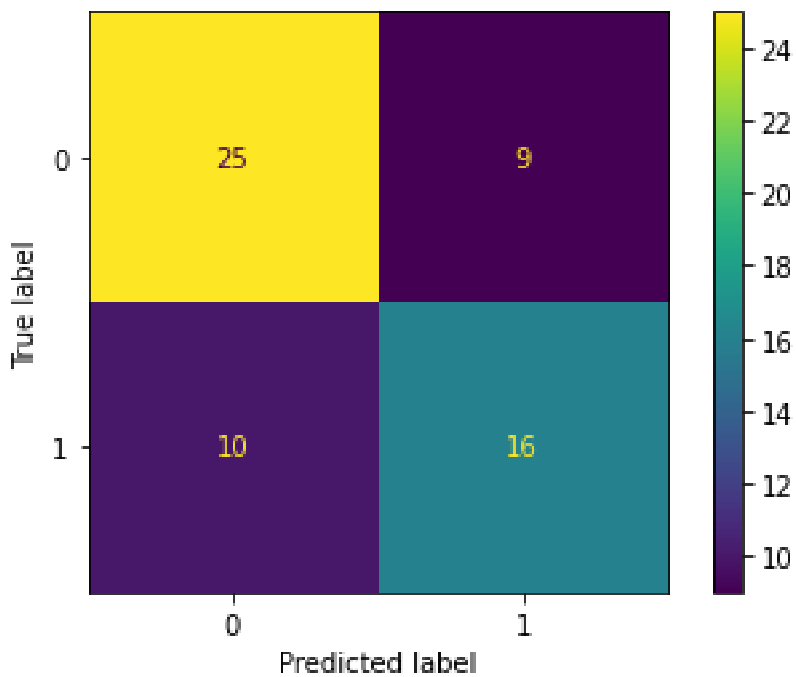


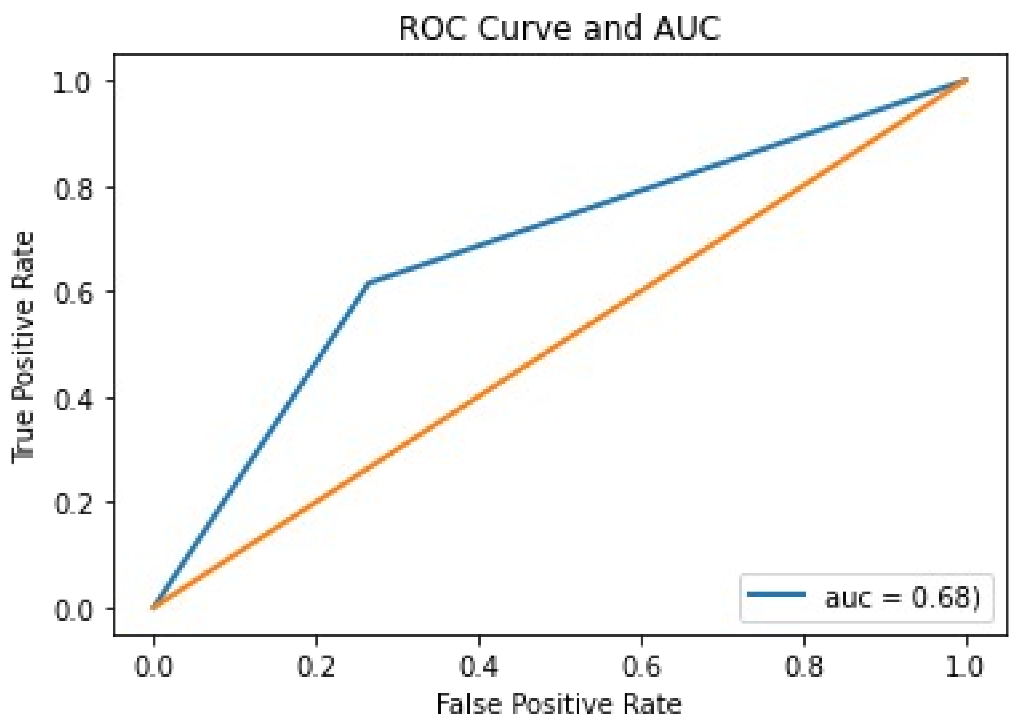

```
('accuracy :',
 0.75,
 'recall',
 0.7714285714285715,
 'f_score',
 0.782608695652174)

precision(Y_test, bayesian_predict)

[[33  1]
 [17  9]]
```





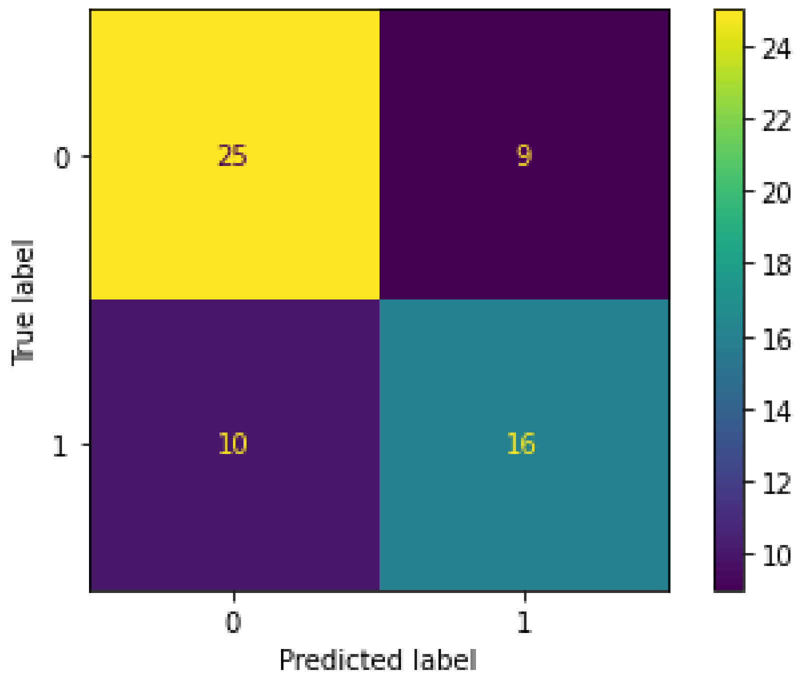

```
('accuracy :', 0.7, 'recall', 0.66, 'f_score', 0.7857142857142857)

precision(Y_test, SVM_predict)

[[25  9]
 [10 16]]
```

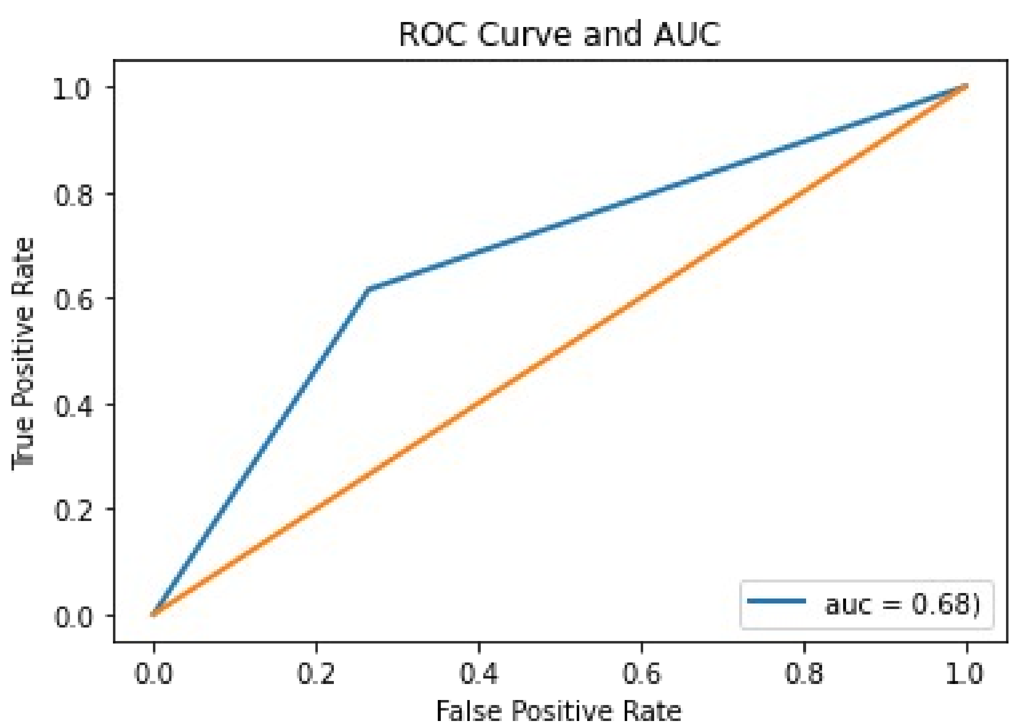





```
('accuracy :',
 0.6833333333333333,
 'recall',
 0.7142857142857143,
 'f_score',
 0.7246376811594202)
```

```
precision(Y_test, logistic_predict)

[[25  9]
 [10 16]]
```





```
('accuracy :',
 0.6833333333333333,
 'recall',
 0.7142857142857143,
 'f_score',
 0.7246376811594202)
```

```
L = np.array([["Accuracy",0.75,0.7,0.68,0.68],
["Recall",0.77,0.66,0.71,0.71], ["Fscore",0.78,0.79,0.72,0.72],
["AUC",0.74,0.66,0.68,0.68]])
dfL = pd.DataFrame(L, columns=["Metric", "Neural Network", "SVM" ,
"Bayesian Model", "Logistic Regression"])
dfL
```

	Metric	Neural Network	SVM	Bayesian Model	Logistic Regression
0	Accuracy	0.75	0.7	0.68	0.68
1	Recall	0.77	0.66	0.71	0.71
2	Fscore	0.78	0.79	0.72	0.72
3	AUC	0.74	0.66	0.68	0.68

Neural Network is the best model to predict the nature of the stain.