In [1]:
```
import os
import pandas as pd
import glob
import shutil
import matplotlib.pyplot as plt
import tensorflow as tf
from tensorflow.keras.preprocessing import image_dataset_from_directory
from tensorflow.keras.preprocessing.image import ImageDataGenerator
import seaborn as sns
import numpy as np
from tensorflow.keras.layers import Input, Conv2D, Dense, Flatten, Dropout, BatchNormalization, MaxPooling2D,GlobalAveragePooling2
from tensorflow.keras.models import Model, Sequential
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.applications.resnet50 import ResNet50
from tensorflow.keras.callbacks import EarlyStopping,ModelCheckpoint
from tensorflow.keras.applications.densenet import DenseNet169
import cv2
from sklearn.metrics import multilabel_confusion_matrix
import tqdm
from sklearn.metrics import classification_report
from sklearn.metrics import precision_recall_curve, roc_curve
```

In [2]:
```
def generate_dataset_from_directory(folder_path, size = 224,batch_size = 32):

    '''fetch all out test data from directory
    folder path is a list of n directories for n class classification '''

    image_generator = ImageDataGenerator(
        samplewise_center=True, #Set each sample mean to 0.
        samplewise_std_normalization= True, # Divide each input by its standard deviation]
        #rescale=1./255,
        validation_split = 0.3
    )

    #create training and testing datasets
    train_data = image_generator.flow_from_directory(directory =
        folder_path,
        class_mode="categorical",
        color_mode="grayscale",
        target_size = (size, size),
        batch_size  = batch_size,
```

```
        shuffle=True,
        seed=123,
        subset="training"
    )

    #create training and testing datasets
    val_data = image_generator.flow_from_directory(directory =
        folder_path,
        class_mode="categorical",
        color_mode="grayscale",
        target_size = (size, size),
        batch_size  = batch_size,
        shuffle=True,
        seed=123,
        subset="validation"
    )
    return train_data, val_data

def get_filepath_from_generator(gen):
    if gen.batch_index <=0:
        raise ValueError('Use iterator to move to batch_index > 0')
    idx_l = (gen.batch_index - 1) * gen.batch_size
    idx_r = idx_l + gen.batch_size if idx_l >= 0 else None
    indices = gen.index_array[idx_l:idx_r]
    filenames = [gen.filenames[i] for i in indices]
    return indices, filenames
```

In [3]:

```
folder_path = 'Chest_X-rays'
train_data, val_data = generate_dataset_from_directory(
    folder_path, size = 128,batch_size = 32)
```

```
Found 14818 images belonging to 4 classes.
Found 6347 images belonging to 4 classes.
```

In [4]:

```
class_names = train_data.class_indices
print(class_names)
```

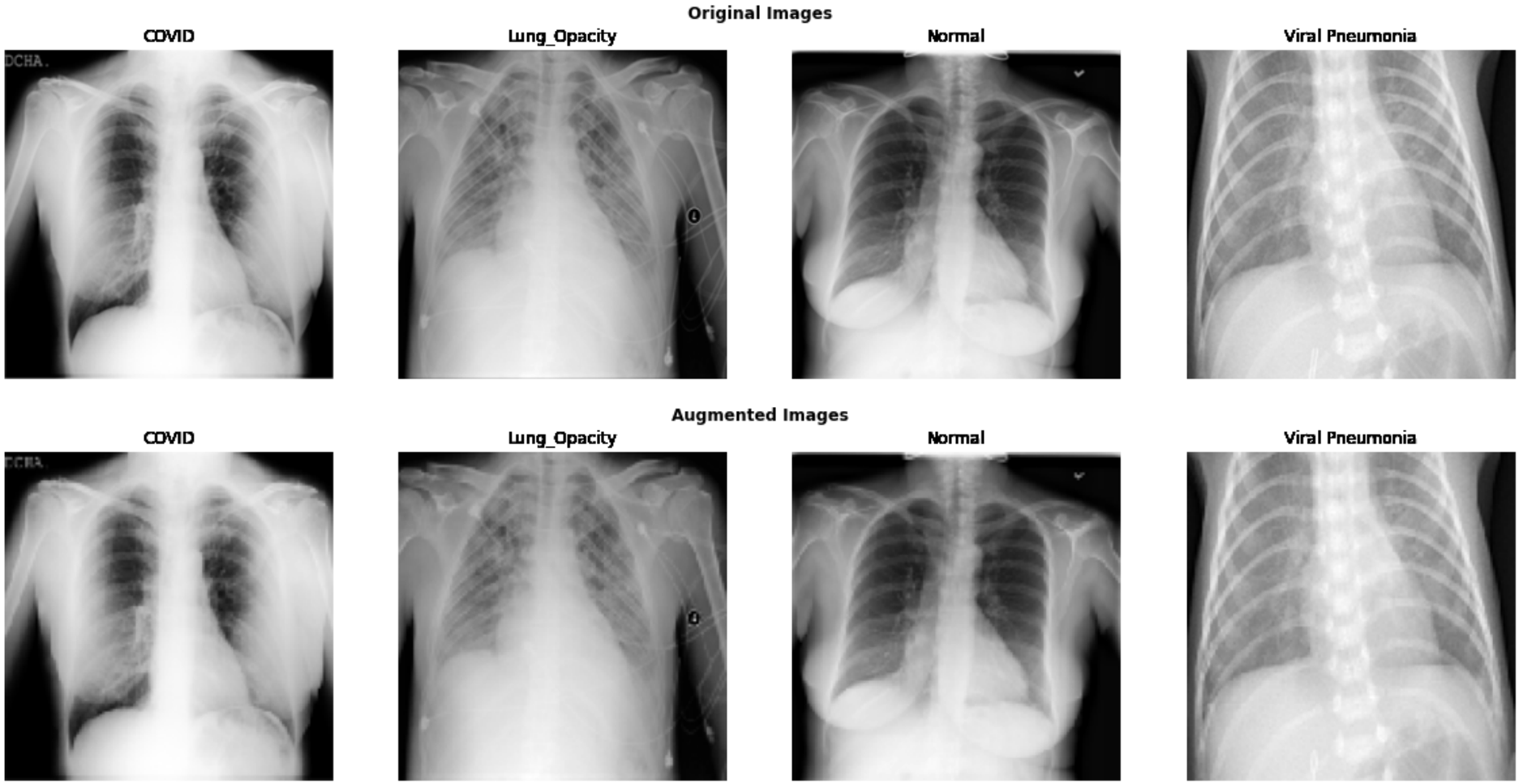
```
{'COVID': 0, 'Lung_Opacity': 1, 'Normal': 2, 'Viral Pneumonia': 3}
```

In [5]:
```
classes = list(class_names.keys())
print(classes)
```

```
['COVID', 'Lung_Opacity', 'Normal', 'Viral Pneumonia']
```

In [6]:
```
images,labels = next(train_data)
indices,image_path = get_filepath_from_generator(train_data)
labels = np.argmax(labels, axis=1)
class_dict = train_data.class_indices
class_dict_inv = dict((v, k) for k, v in class_dict.items())
y_names = [class_dict_inv[key] for key in labels]
```

In [7]:
```
#Lets visualize the augmented images
fig, big_axes = plt.subplots( figsize=(20, 10) , nrows=2, ncols=1, sharey=True)
titles = ['Original Images','Augmented Images']
for title, big_ax in zip(titles, big_axes):
    big_ax.set_title(f'{title}\n', fontweight='semibold')
    big_ax.set_frame_on = False
    big_ax.axis('off')
for image in images:
    j  = 0
    for i in range(4):
        ax = fig.add_subplot(2, 4, i+1)
        ax1 = fig.add_subplot(2,4,i+1+4)
        for k in range(len(labels)):
            if labels[k] == j:
                og = cv2.imread(folder_path+image_path[k],0)
                ax.imshow(og,cmap = 'gray')
                ax.set_title(classes[i])
                ax.axis("off")
                ax1.imshow(images[k],cmap = 'gray')
                ax1.set_title(classes[i])
                ax1.axis("off")
                break
        j = j+1
plt.show()
```

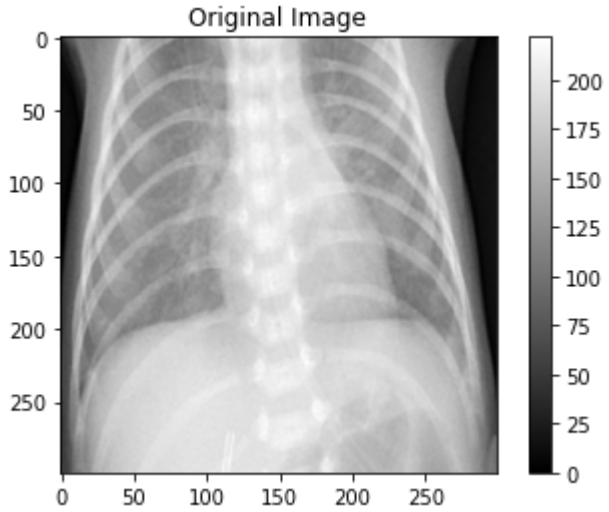


In [8]:

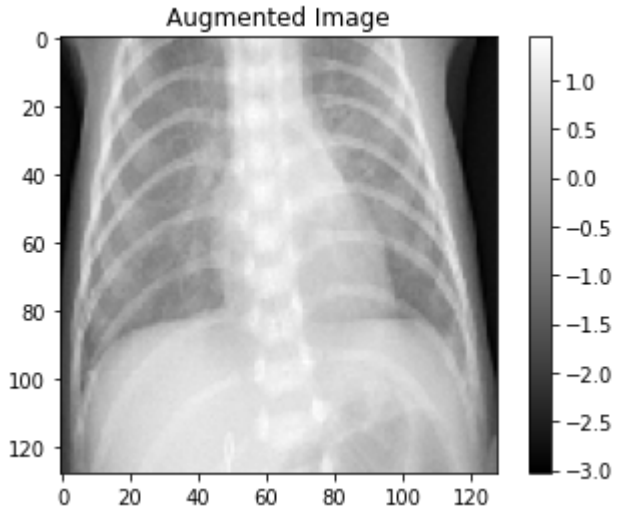
```
# Investigating single original image
def plot_single_image(raw_image,title):
    plt.imshow(raw_image, cmap='gray')
    plt.colorbar()
    plt.title(title)
    print(f"The dimensions of the image are {raw_image.shape[0]} pixels width and {raw_image.shape[1]} pixels height, one single c
    print(f"The maximum pixel value is {raw_image.max():.4f} and the minimum is {raw_image.min():.4f}")
    print(f"The mean value of the pixels is {raw_image.mean():.4f} and the standard deviation is {raw_image.std():.4f}")
    plt.show()
```

In [9]:
```
plt.figure(1)
image = cv2.imread(folder_path+image_path[k],0)
plot_single_image(image,'Original Image')
plt.figure(2)
plot_single_image(images[k],'Augmented Image')
```

```
The dimensions of the image are 299 pixels width and 299 pixels height, one single color channel
The maximum pixel value is 222.0000 and the minimum is 0.0000
The mean value of the pixels is 149.5784 and the standard deviation is 49.4926
```




```
The dimensions of the image are 128 pixels width and 128 pixels height, one single color channel
The maximum pixel value is 1.4452 and the minimum is -3.0251
The mean value of the pixels is 0.0000 and the standard deviation is 1.0000
```

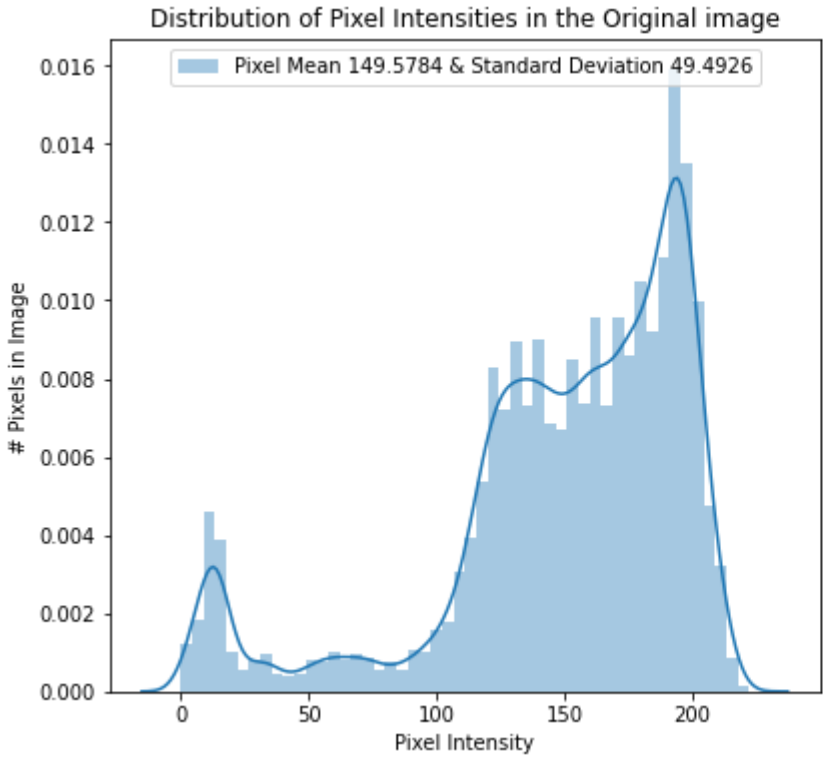


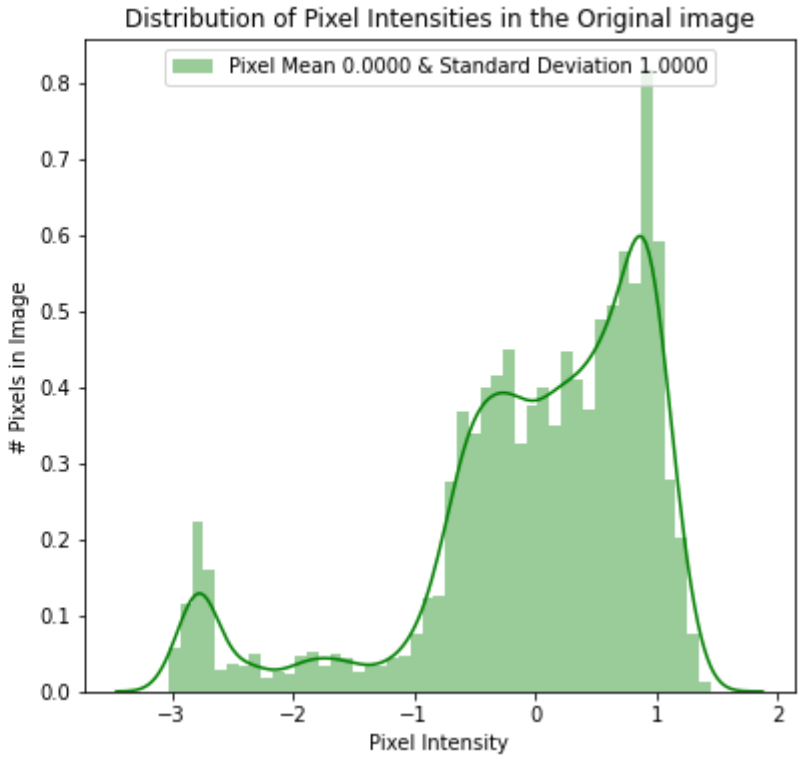
In [10]:

```
# Plot a histogram of the distribution of the pixels
sns.despine(left=True)
fig,(ax1,ax2) = plt.subplots(1,2,figsize =(14,6))
sns.distplot(image.ravel(),
             label=f'Pixel Mean {np.mean(image):.4f} & Standard Deviation {np.std(image):.4f}', kde=True, ax = ax1)
ax1.legend(loc='upper center')
ax1.set_title('Distribution of Pixel Intensities in the Original image')
ax1.set_xlabel('Pixel Intensity')
ax1.set_ylabel('# Pixels in Image')

sns.distplot(images[k].ravel(),
             label=f'Pixel Mean {np.mean(images[k]):.4f} & Standard Deviation {np.std(images[k]):.4f}', kde=True,color = 'green',a
ax2.legend(loc='upper center')
ax2.set_title('Distribution of Pixel Intensities in the Original image')
ax2.set_xlabel('Pixel Intensity')
ax2.set_ylabel('# Pixels in Image')

plt.show()
```

```
/opt/conda/lib/python3.7/site-packages/seaborn/distributions.py:2557: FutureWarning: `distplot` is a deprecated function and will b
e removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or
`histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
/opt/conda/lib/python3.7/site-packages/seaborn/distributions.py:2557: FutureWarning: `distplot` is a deprecated function and will b
e removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or
```

```
`histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
<Figure size 432x288 with 0 Axes>
```



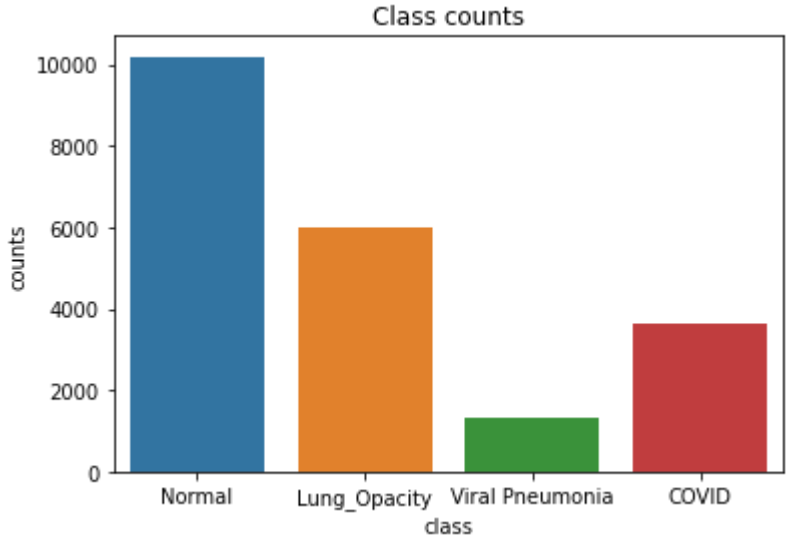


In [11]:
```
all_items,dirs,files = next(os.walk(folder_path))
```

In [12]:
```
image_in_classes = []
for i in range(len(dirs)):
    no_of_images =len(os.listdir(os.path.join(folder_path,dirs[i])))
    image_in_classes.append(no_of_images)
df_data = {'class': dirs,'counts': image_in_classes}
classes_df = pd.DataFrame(df_data)
```

In [13]:
```
n_classes = len(dirs)
```

In [14]:
```
sns.barplot(x = 'class', y = 'counts',data = classes_df)
plt.title('Class counts')
plt.show()
```



Convolutional Neural Networks

In [15]:
```
def plotLearningCurve(history,epochs):
  epochRange = range(1,epochs+1)
  fig, ax = plt.subplots(1,2,figsize=(20,10))
  ax[0].plot(epochRange,history.history['accuracy'],'b',label = 'Training Accuracy')
  ax[0].plot(epochRange,history.history['val_accuracy'],'r',label = 'Validation Accuracy')
  ax[0].set_title('Training and Validation accuracy')
  ax[0].set_xlabel('Epoch', fontsize = 20)
  ax[0].set_ylabel('Accuracy', fontsize = 20)
  ax[0].legend()
  ax[0].grid(color='gray', linestyle='--')
  ax[1].plot(epochRange,history.history['loss'],'b',label = 'Training Loss')
  ax[1].plot(epochRange,history.history['val_loss'],'r',label = 'Validation Loss')
  ax[1].set_title('Training and Validation loss')
  ax[1].set_xlabel('Epoch', fontsize = 20)
  ax[1].set_ylabel('Loss', fontsize = 20)
  ax[1].legend()
  ax[1].grid(color='gray', linestyle='--')
```

```
  plt.show()
```

In [16]:

```
def cnn_model(train_data,test_data, epochs,size):
#Building the model using Keras functional API
    print("----Building the model----")
    i = Input(shape=(size,size,1)) #defining input
    x = BatchNormalization()(i)
    x = Conv2D(32,3, activation= 'relu')(i) #adding convolution layers
    x = MaxPooling2D()(x)
    x = Dropout(0.2)(x)
    x = Conv2D(64, 3, activation='relu')(x)
    x = MaxPooling2D()(x)
    x = Dropout(0.2)(x)
    x = Conv2D(128, 3, activation='relu')(x)
    x = MaxPooling2D()(x)
    x = Dropout(0.2)(x)
    x = Flatten()(x)
    x = Dense(256, activation='relu')(x)
    x = Dropout(0.1)(x)
    x = Dense(4, activation= 'softmax')(x)

    model = Model(i,x)
    model.summary()
#Training the Convolutional Neural Network
    print("----Training the network----")
    model.compile(optimizer= Adam(0.0001),
              loss='categorical_crossentropy',
              metrics=['accuracy'])

    early_stop = EarlyStopping(monitor='val_loss',
                               mode='min',
                               patience = 5 ,
                               restore_best_weights=True)
    #model_checkpoint
    mc = ModelCheckpoint('cnn_model.h5', monitor='val_loss', mode='min', verbose=1, save_best_only=True)
    r = model.fit(train_data,
                  validation_data = val_data,
                  epochs = epochs,
                  verbose = 2,
                  batch_size = 32,
```

```
                    callbacks = [early_stop,mc])
    print("Train score:", model.evaluate(train_data))
    print("Test score:", model.evaluate(val_data))
    n_epochs = len(r.history['loss'])

    return r,model,n_epochs
```

In [17]:

```
epochs = 20
r,model,n_epochs = cnn_model(train_data, val_data,epochs,128)
```

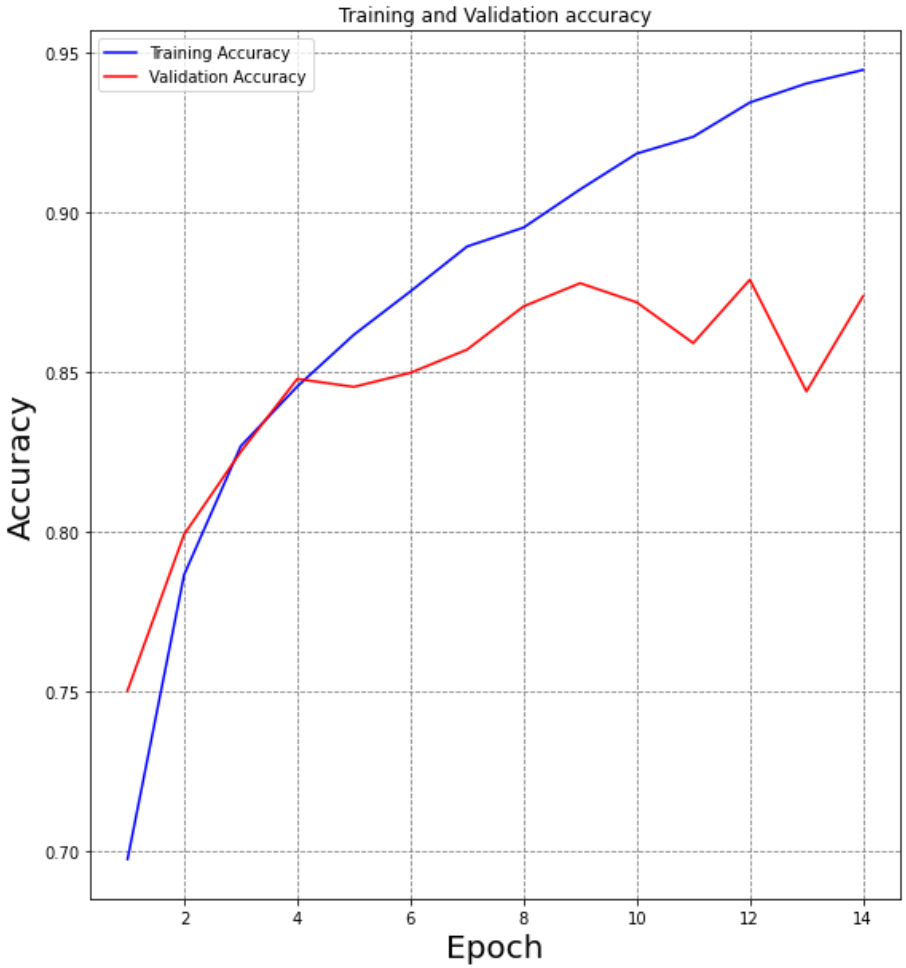
```
----Building the model----
Model: "model"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 128, 128, 1)]     0
_________________________________________________________________
conv2d (Conv2D)              (None, 126, 126, 32)      320
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 63, 63, 32)        0
_________________________________________________________________
dropout (Dropout)            (None, 63, 63, 32)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 61, 61, 64)        18496
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 30, 30, 64)        0
_________________________________________________________________
dropout_1 (Dropout)          (None, 30, 30, 64)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 28, 28, 128)       73856
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 14, 14, 128)       0
_________________________________________________________________
dropout_2 (Dropout)          (None, 14, 14, 128)       0
_________________________________________________________________
flatten (Flatten)            (None, 25088)             0
_________________________________________________________________
dense (Dense)                (None, 256)               6422784
_________________________________________________________________
dropout_3 (Dropout)          (None, 256)               0
_________________________________________________________________
dense_1 (Dense)              (None, 4)                 1028
```

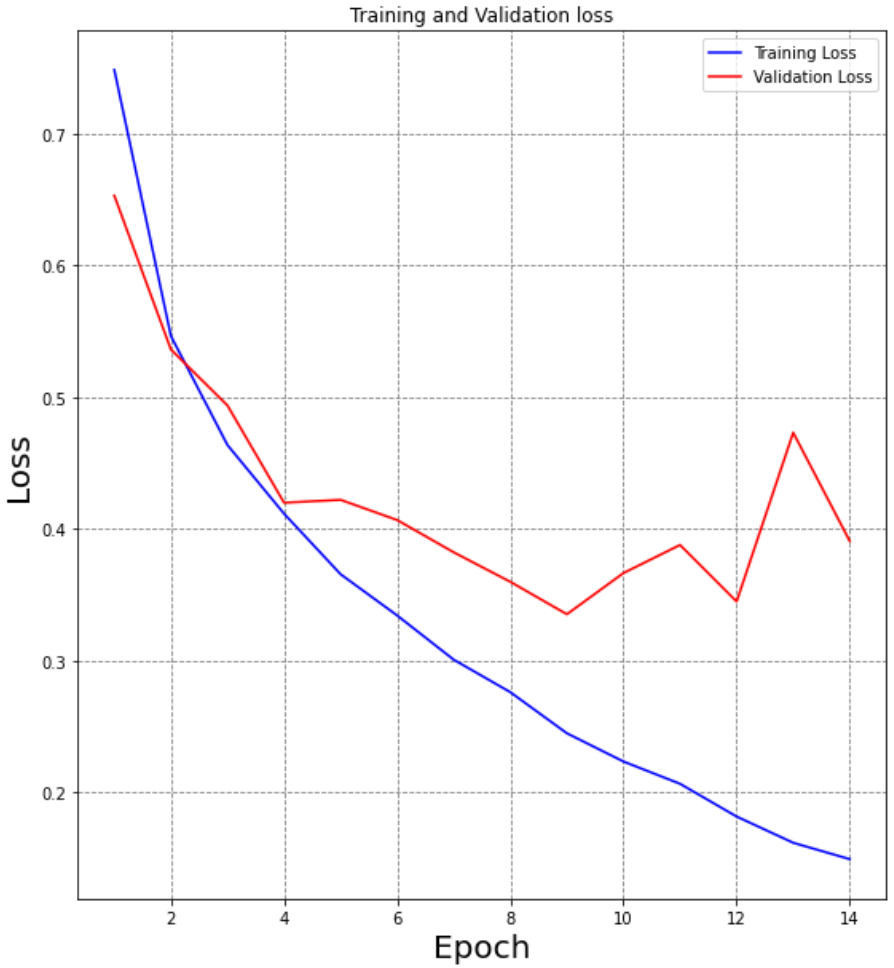
```
=================================================================
Total params: 6,516,484
Trainable params: 6,516,484
Non-trainable params: 0

_________________________________________________________________
----Training the network----
Epoch 1/20
464/464 - 184s - loss: 0.7486 - accuracy: 0.6973 - val_loss: 0.6531 - val_accuracy: 0.7501

Epoch 00001: val_loss improved from inf to 0.65313, saving model to cnn_model.h5
Epoch 2/20
464/464 - 49s - loss: 0.5465 - accuracy: 0.7863 - val_loss: 0.5363 - val_accuracy: 0.7990

Epoch 00002: val_loss improved from 0.65313 to 0.53631, saving model to cnn_model.h5
Epoch 3/20
464/464 - 48s - loss: 0.4637 - accuracy: 0.8266 - val_loss: 0.4937 - val_accuracy: 0.8248

Epoch 00003: val_loss improved from 0.53631 to 0.49372, saving model to cnn_model.h5
Epoch 4/20
464/464 - 49s - loss: 0.4116 - accuracy: 0.8453 - val_loss: 0.4199 - val_accuracy: 0.8476

Epoch 00004: val_loss improved from 0.49372 to 0.41990, saving model to cnn_model.h5
Epoch 5/20
464/464 - 48s - loss: 0.3656 - accuracy: 0.8615 - val_loss: 0.4221 - val_accuracy: 0.8451

Epoch 00005: val_loss did not improve from 0.41990
Epoch 6/20
464/464 - 48s - loss: 0.3342 - accuracy: 0.8750 - val_loss: 0.4067 - val_accuracy: 0.8495

Epoch 00006: val_loss improved from 0.41990 to 0.40671, saving model to cnn_model.h5
Epoch 7/20
464/464 - 48s - loss: 0.3006 - accuracy: 0.8891 - val_loss: 0.3822 - val_accuracy: 0.8568

Epoch 00007: val_loss improved from 0.40671 to 0.38219, saving model to cnn_model.h5
Epoch 8/20
464/464 - 49s - loss: 0.2760 - accuracy: 0.8950 - val_loss: 0.3598 - val_accuracy: 0.8703

Epoch 00008: val_loss improved from 0.38219 to 0.35979, saving model to cnn_model.h5
Epoch 9/20
464/464 - 48s - loss: 0.2448 - accuracy: 0.9069 - val_loss: 0.3352 - val_accuracy: 0.8776

Epoch 00009: val_loss improved from 0.35979 to 0.33516, saving model to cnn_model.h5
Epoch 10/20
464/464 - 48s - loss: 0.2233 - accuracy: 0.9181 - val_loss: 0.3665 - val_accuracy: 0.8716
```

```
Epoch 00010: val_loss did not improve from 0.33516
Epoch 11/20
464/464 - 48s - loss: 0.2064 - accuracy: 0.9234 - val_loss: 0.3878 - val_accuracy: 0.8588

Epoch 00011: val_loss did not improve from 0.33516
Epoch 12/20
464/464 - 48s - loss: 0.1815 - accuracy: 0.9341 - val_loss: 0.3448 - val_accuracy: 0.8787

Epoch 00012: val_loss did not improve from 0.33516
Epoch 13/20
464/464 - 48s - loss: 0.1616 - accuracy: 0.9401 - val_loss: 0.4731 - val_accuracy: 0.8437

Epoch 00013: val_loss did not improve from 0.33516
Epoch 14/20
464/464 - 49s - loss: 0.1492 - accuracy: 0.9443 - val_loss: 0.3907 - val_accuracy: 0.8735

Epoch 00014: val_loss did not improve from 0.33516
464/464 [==============================] - 35s 75ms/step - loss: 0.2077 - accuracy: 0.9311
Train score: [0.20766136050224304, 0.9310973286628723]
199/199 [==============================] - 15s 74ms/step - loss: 0.3352 - accuracy: 0.8776
Test score: [0.33516475558280945, 0.8775799870491028]
```

In [18]:

```
plotLearningCurve(r,n_epochs)
```





In [19]:

```
# printing model accuracy for train and test data
test_evaluation = model.evaluate(val_data)
print(f"Test Accuracy using CNN: {test_evaluation[1] * 100:.2f}%")

train_evaluation = model.evaluate(train_data)
print(f"Train Accuracy using CNN: {train_evaluation[1] * 100:.2f}%")
```

```
199/199 [==============================] - 15s 76ms/step - loss: 0.3352 - accuracy: 0.8776
Test Accuracy using CNN: 87.76%
464/464 [==============================] - 35s 75ms/step - loss: 0.2077 - accuracy: 0.9311
Train Accuracy using CNN: 93.11%
```

In [20]:
```
def extract_from_generator(data):
    data.reset()
    X, y = next(data)
    for i in tqdm.tqdm(range(int(data.n/data.batch_size)-1)):
        img, label = next(data)
        X = np.append(X, img, axis=0 )
        y = np.append(y, label, axis=0)
    return X,y
```

In [21]:
```
X_train,y_train = extract_from_generator(train_data)
print('X_train:',X_train.shape,'y_train:',y_train.shape)
```

```
100%|██████████| 462/462 [01:57<00:00,  3.95it/s]
X_train: (14816, 128, 128, 1) y_train: (14816, 4)
```

In [22]:
```
X_test,y_test = extract_from_generator(val_data)
print('X_test:',X_test.shape,'y_test:',y_test.shape)
```

```
100%|██████████| 197/197 [00:29<00:00,  6.68it/s]
X_test: (6336, 128, 128, 1) y_test: (6336, 4)
```

In [23]:
```
y_pred  = np.round(model.predict(X_test))
```

In [24]:
```
y_test_c = np.argmax(y_test,axis = 1)
y_pred_c = np.argmax(y_pred,axis = 1)
```

In [25]:
```
print(classification_report(y_test,y_pred))
```

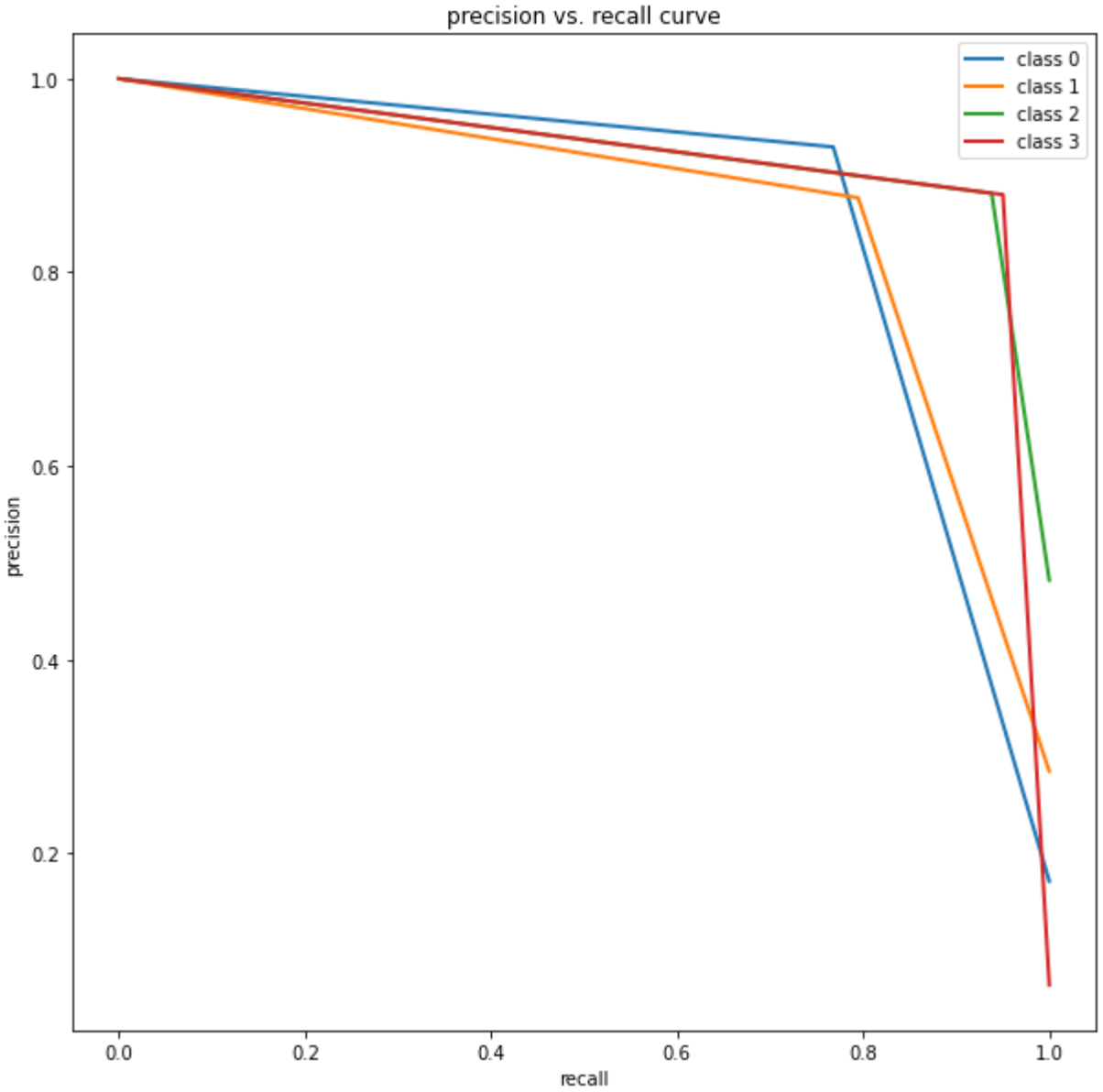
```
              precision    recall  f1-score   support

           0       0.93      0.77      0.84      1081
           1       0.88      0.79      0.83      1801
           2       0.88      0.94      0.91      3052
           3       0.88      0.95      0.91       402
```

```
   micro avg       0.89      0.87      0.88      6336
   macro avg       0.89      0.86      0.87      6336
weighted avg       0.89      0.87      0.88      6336
 samples avg       0.87      0.87      0.87      6336
```

```
/opt/conda/lib/python3.7/site-packages/sklearn/metrics/_classification.py:1221: UndefinedMetricWarning: Precision and F-score are i
ll-defined and being set to 0.0 in samples with no predicted labels. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

In [26]:

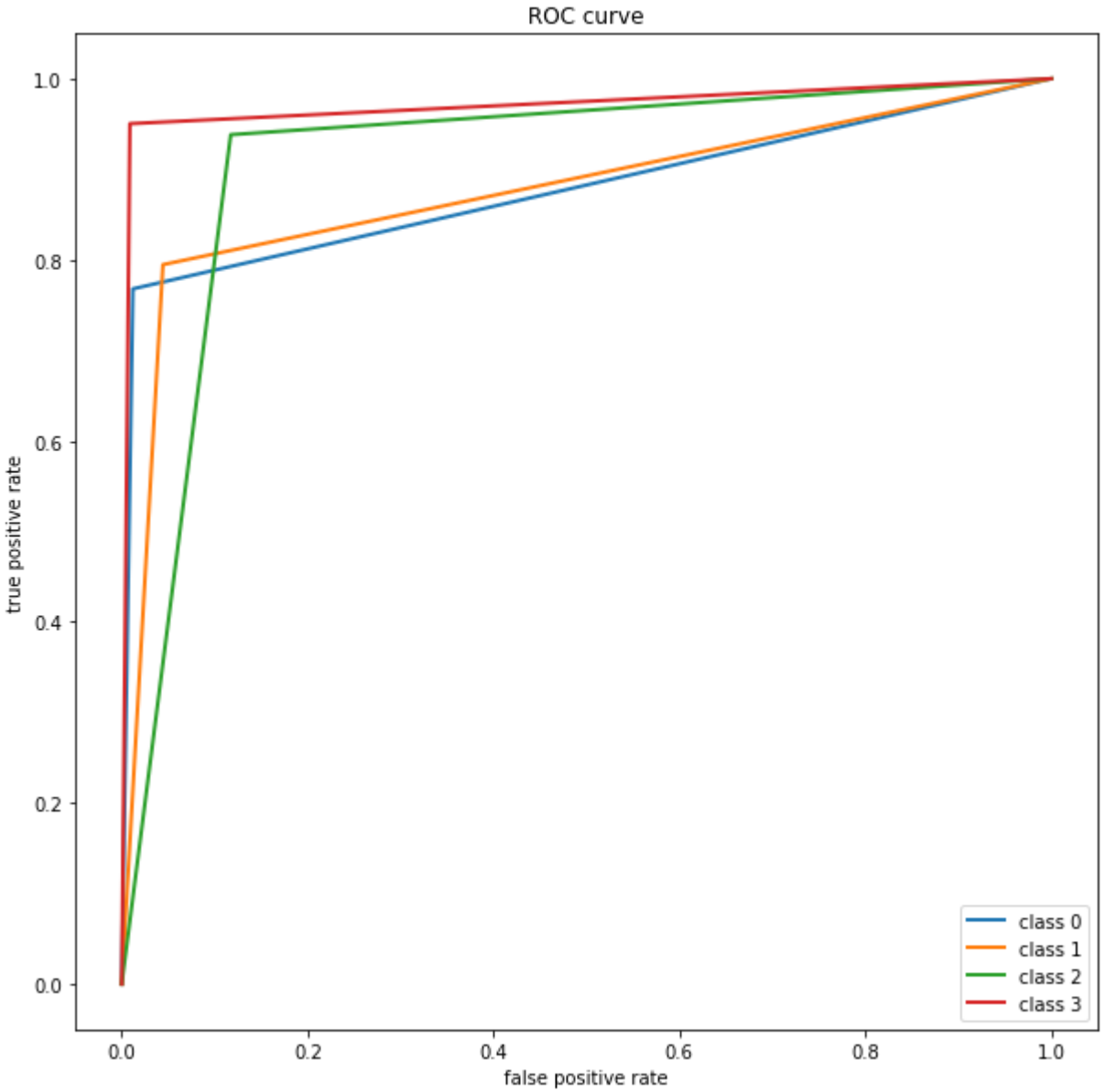
```
plt.figure(figsize = (10,10))
precision = dict()
recall = dict()
for i in range(n_classes):
    precision[i], recall[i], _ = precision_recall_curve(y_test[:, i],
                                                        y_pred[:, i])
    plt.plot(recall[i], precision[i], lw=2, label='class {}'.format(i))

plt.xlabel("recall")
plt.ylabel("precision")
plt.legend(loc="best")
plt.title("precision vs. recall curve")
plt.show()
```



In [27]:

```
plt.figure(figsize = (10,10))
fpr = dict()
tpr = dict()

for i in range(n_classes):
```

```
    fpr[i], tpr[i], _ = roc_curve(y_test[:, i],
                                  y_pred[:, i])
    plt.plot(fpr[i], tpr[i], lw=2, label='class {}'.format(i))

plt.xlabel("false positive rate")
plt.ylabel("true positive rate")
plt.legend(loc="best")
plt.title("ROC curve")
plt.show()
```



Using Resnet50

In [28]:
```
def resnet_model(train_data,test_data, epochs,size):
#Building the model using Keras functional API
```

```
    print("----Building the model----")

    base_model = ResNet50(input_shape= (size,size,1), weights = None, include_top=False)
#     base_model.trainable=False #freezing the layer


    x=base_model.output
    x=GlobalAveragePooling2D()(x)
    x = Dense(128, activation='relu')(x)
    x = Dense(64, activation='relu')(x)
    out=Dense(4,activation='softmax')(x)

    model=Model(inputs=base_model.input,outputs=out)
    # model.summary()
#Training the Convolutional Neural Network
    print("----Training the network----")
    model.compile(optimizer= Adam(0.0001),
              loss='categorical_crossentropy',
              metrics=['accuracy'])

    early_stop = EarlyStopping(monitor='val_loss',
                               mode='min',
                               patience = 5 ,
                               restore_best_weights=True)
    #model_checkpoint
    mc = ModelCheckpoint('resnet_model.h5', monitor='val_loss', mode='min', verbose=1, save_best_only=True)
    r = model.fit(train_data,
                  validation_data = val_data,
                  epochs = epochs,
                  verbose = 2,
                  batch_size = 32,
                  callbacks = [early_stop,mc])
    print("Train score:", model.evaluate(train_data))
    print("Test score:", model.evaluate(val_data))
    n_epochs = len(r.history['loss'])

    return r,model,n_epochs
```

In [29]:

```
epochs = 20
r,model,n_epochs = resnet_model(train_data, val_data,epochs,128)
```

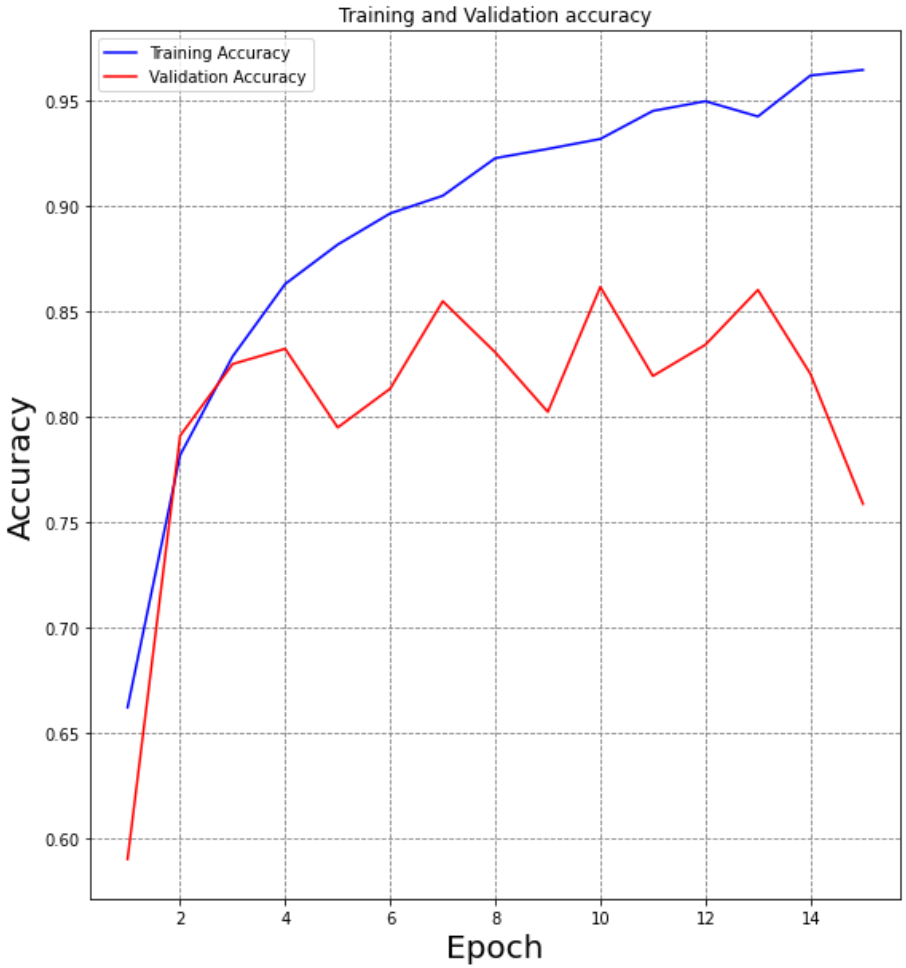
```
----Building the model----
----Training the network----
```

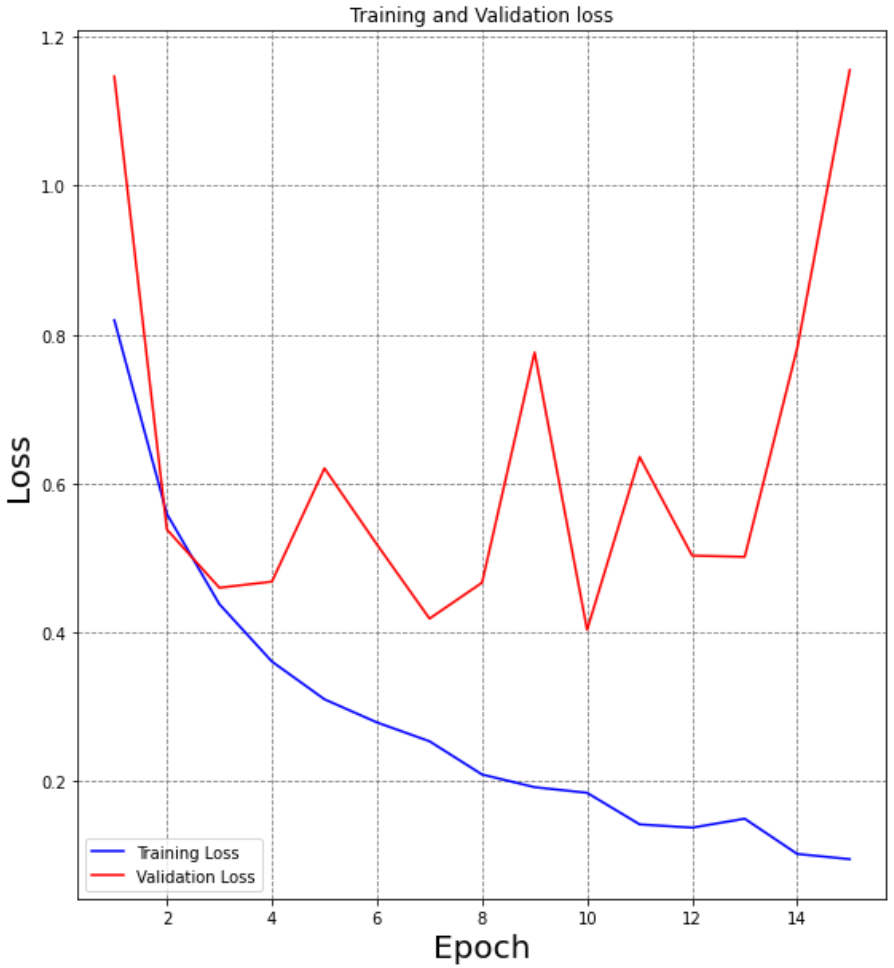
```
Epoch 1/20
464/464 - 65s - loss: 0.8195 - accuracy: 0.6623 - val_loss: 1.1468 - val_accuracy: 0.5904

Epoch 00001: val_loss improved from inf to 1.14677, saving model to resnet_model.h5
Epoch 2/20
464/464 - 58s - loss: 0.5592 - accuracy: 0.7819 - val_loss: 0.5384 - val_accuracy: 0.7911

Epoch 00002: val_loss improved from 1.14677 to 0.53835, saving model to resnet_model.h5
Epoch 3/20
464/464 - 58s - loss: 0.4379 - accuracy: 0.8287 - val_loss: 0.4600 - val_accuracy: 0.8251

Epoch 00003: val_loss improved from 0.53835 to 0.45997, saving model to resnet_model.h5
Epoch 4/20
464/464 - 58s - loss: 0.3608 - accuracy: 0.8631 - val_loss: 0.4682 - val_accuracy: 0.8324

Epoch 00004: val_loss did not improve from 0.45997
Epoch 5/20
464/464 - 58s - loss: 0.3101 - accuracy: 0.8818 - val_loss: 0.6204 - val_accuracy: 0.7950

Epoch 00005: val_loss did not improve from 0.45997
Epoch 6/20
464/464 - 59s - loss: 0.2790 - accuracy: 0.8965 - val_loss: 0.5180 - val_accuracy: 0.8135

Epoch 00006: val_loss did not improve from 0.45997
Epoch 7/20
464/464 - 58s - loss: 0.2538 - accuracy: 0.9049 - val_loss: 0.4185 - val_accuracy: 0.8549

Epoch 00007: val_loss improved from 0.45997 to 0.41853, saving model to resnet_model.h5
Epoch 8/20
464/464 - 58s - loss: 0.2091 - accuracy: 0.9227 - val_loss: 0.4668 - val_accuracy: 0.8306

Epoch 00008: val_loss did not improve from 0.41853
Epoch 9/20
464/464 - 59s - loss: 0.1921 - accuracy: 0.9271 - val_loss: 0.7761 - val_accuracy: 0.8024

Epoch 00009: val_loss did not improve from 0.41853
Epoch 10/20
464/464 - 60s - loss: 0.1845 - accuracy: 0.9318 - val_loss: 0.4034 - val_accuracy: 0.8617

Epoch 00010: val_loss improved from 0.41853 to 0.40343, saving model to resnet_model.h5
Epoch 11/20
464/464 - 60s - loss: 0.1421 - accuracy: 0.9451 - val_loss: 0.6357 - val_accuracy: 0.8194

Epoch 00011: val_loss did not improve from 0.40343
```

```
Epoch 12/20
464/464 - 59s - loss: 0.1377 - accuracy: 0.9497 - val_loss: 0.5031 - val_accuracy: 0.8343

Epoch 00012: val_loss did not improve from 0.40343
Epoch 13/20
464/464 - 59s - loss: 0.1497 - accuracy: 0.9425 - val_loss: 0.5015 - val_accuracy: 0.8602

Epoch 00013: val_loss did not improve from 0.40343
Epoch 14/20
464/464 - 60s - loss: 0.1024 - accuracy: 0.9619 - val_loss: 0.7822 - val_accuracy: 0.8204

Epoch 00014: val_loss did not improve from 0.40343
Epoch 15/20
464/464 - 58s - loss: 0.0954 - accuracy: 0.9646 - val_loss: 1.1557 - val_accuracy: 0.7588

Epoch 00015: val_loss did not improve from 0.40343
464/464 [==============================] - 38s 83ms/step - loss: 0.1220 - accuracy: 0.9554
Train score: [0.12195096909999847, 0.955392062664032]
199/199 [==============================] - 16s 80ms/step - loss: 0.4034 - accuracy: 0.8617
Test score: [0.40343183279037476, 0.8616669178009033]
```

In [30]:

```
plotLearningCurve(r,n_epochs)
```





In [31]:

```
# printing model accuracy for train and test data
test_evaluation = model.evaluate(val_data)
print(f"Test Accuracy using ResNet50: {test_evaluation[1] * 100:.2f}%")

train_evaluation = model.evaluate(train_data)
print(f"Train Accuracy using ResNet50: {train_evaluation[1] * 100:.2f}%")
```

```
199/199 [==============================] - 17s 84ms/step - loss: 0.4034 - accuracy: 0.8617
Test Accuracy using ResNet50: 86.17%
464/464 [==============================] - 39s 83ms/step - loss: 0.1220 - accuracy: 0.9554
Train Accuracy using ResNet50: 95.54%
```

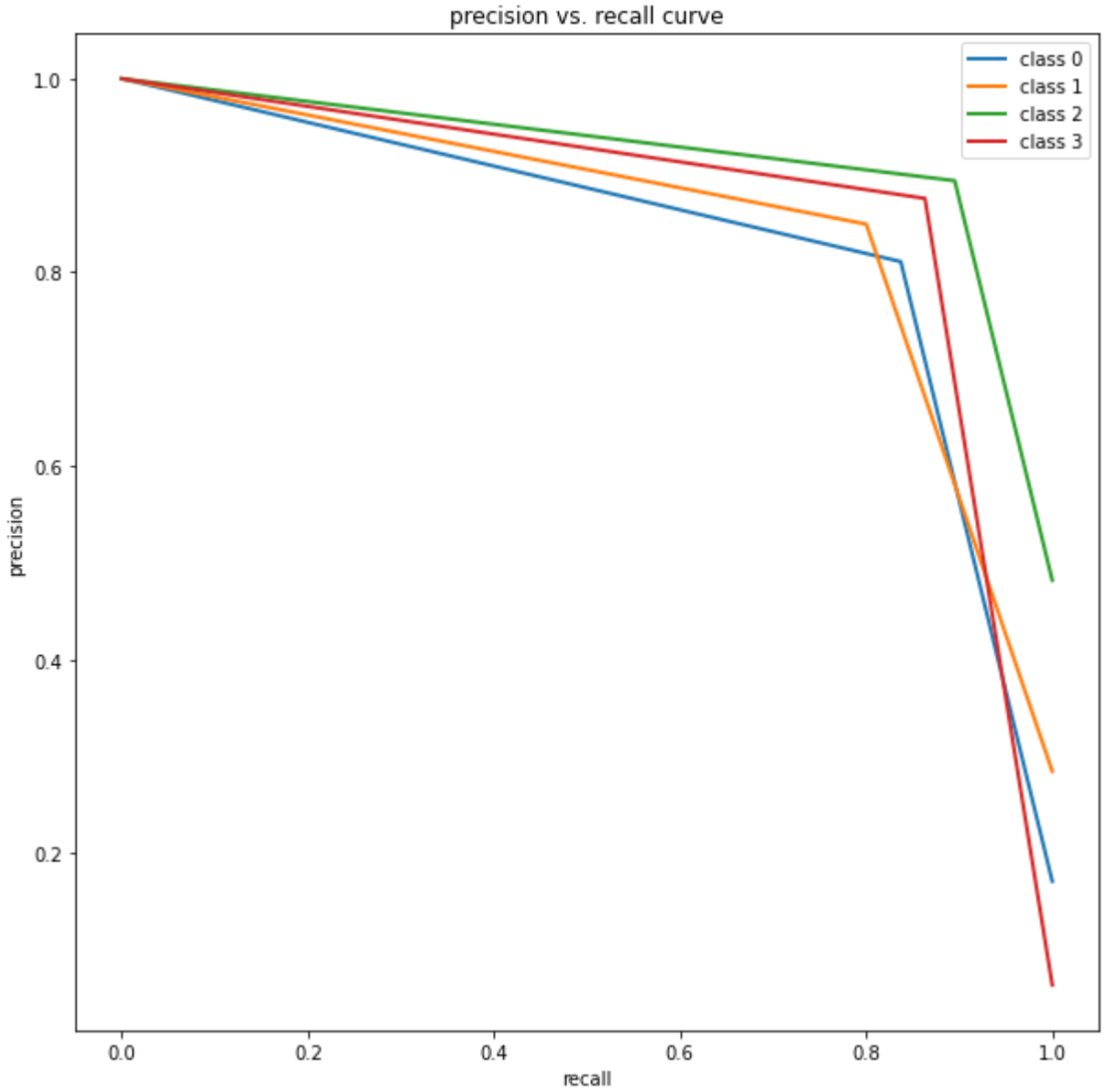
In [32]:
```
y_pred  = np.round(model.predict(X_test))
y_pred_c = np.argmax(y_pred,axis = 1)
```

In [33]:
```
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.81      0.84      0.82      1081
           1       0.85      0.80      0.82      1801
           2       0.89      0.90      0.89      3052
           3       0.88      0.86      0.87       402

   micro avg       0.87      0.86      0.86      6336
   macro avg       0.86      0.85      0.85      6336
weighted avg       0.87      0.86      0.86      6336
 samples avg       0.86      0.86      0.86      6336

```

```
/opt/conda/lib/python3.7/site-packages/sklearn/metrics/_classification.py:1221: UndefinedMetricWarning: Precision and F-score are i
ll-defined and being set to 0.0 in samples with no predicted labels. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

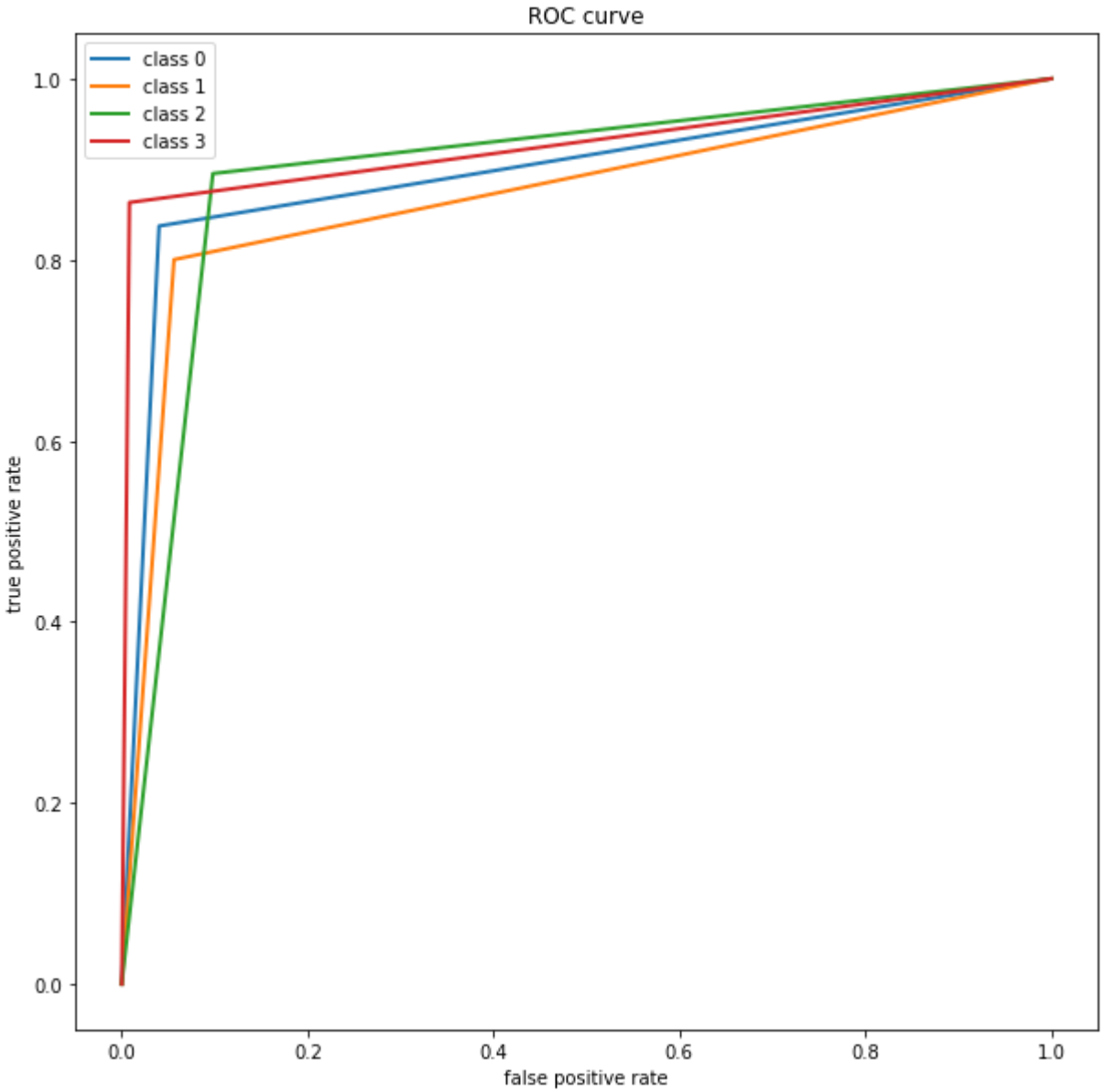
In [34]:
```
plt.figure(figsize = (10,10))
precision = dict()
recall = dict()
for i in range(n_classes):
    precision[i], recall[i], _ = precision_recall_curve(y_test[:, i],
                                                        y_pred[:, i])
    plt.plot(recall[i], precision[i], lw=2, label='class {}'.format(i))

plt.xlabel("recall")
plt.ylabel("precision")
plt.legend(loc="best")
plt.title("precision vs. recall curve")
plt.show()
```



In [35]:

```
plt.figure(figsize = (10,10))
fpr = dict()
tpr = dict()

for i in range(n_classes):
```

```
    fpr[i], tpr[i], _ = roc_curve(y_test[:, i],
                                  y_pred[:, i])
    plt.plot(fpr[i], tpr[i], lw=2, label='class {}'.format(i))

plt.xlabel("false positive rate")
plt.ylabel("true positive rate")
plt.legend(loc="best")
plt.title("ROC curve")
plt.show()
```


ROC curve
class 0
class 1
class 2
class 3
true positive rate
false positive rate
0.0
0.2
0.4
0.6
0.8
1.0