Notebook_DeepLearning

September 18, 2023

1 Importation des librairies

[1]:
```
import numpy as np
import pandas as pd
from pandas import DataFrame
import time
import glob
import os
import shutil

import pydot
import graphviz
import matplotlib.pyplot as plt
from matplotlib.pyplot import imshow
import seaborn as sns

import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
from tensorflow.keras.layers import Dense, Activation,Dropout,Conv2D,␣
 ↪MaxPooling2D,BatchNormalization
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.metrics import categorical_crossentropy
from tensorflow.keras import regularizers
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.models import Sequential

from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, classification_report
from sklearn.metrics import r2_score, roc_auc_score, f1_score

pd.set_option('display.width', 150)

from keras.utils import to_categorical, plot_model
from keras.preprocessing import image

from keras.applications.vgg16 import VGG16
```

```
from keras.applications.vgg16 import preprocess_input, decode_predictions
```

2 Préparation des données

On va définir les répertoires des fichiers. On a opté pour kaggle compte tenu d'un certain nombre d'avantage qu'il présente. En effet, contrairement à moi googleCollab, on a plus besoin de charger tous les images sur notre drive avant de les importer (Un importation sur drive estimé à 7h de durée). Par ailleurs, les modèles sont extrêments long à tourner sur nos machines.

[2]:
```
covid_dir='../input/covid19-radiography-dataset/COVID-19_Radiography_Dataset/
 ↪COVID-19_Radiography_Dataset/COVID'
lung_opacity_dir='../input/covid19-radiography-dataset/
 ↪COVID-19_Radiography_Dataset/COVID-19_Radiography_Dataset/Lung_Opacity'
normal_dir='../input/covid19-radiography-dataset/COVID-19_Radiography_Dataset/
 ↪COVID-19_Radiography_Dataset/Normal'
pneumonia_dir='../input/covid19-radiography-dataset/
 ↪COVID-19_Radiography_Dataset/COVID-19_Radiography_Dataset/Viral Pneumonia'
```

[3]:
```
dirlist=[covid_dir, lung_opacity_dir, normal_dir, pneumonia_dir]
classes=['covid', 'lung_opacity', 'normal', 'pneumonia']
filepaths=[]
labels=[]
for d,c in zip(dirlist, classes):
    flist=os.listdir(d)
    for f in flist:
        fpath=os.path.join (d,f)
        filepaths.append(fpath)
        labels.append(c)
print ('filepaths: ', len(filepaths), '   labels: ', len(labels))
```

```
filepaths:  21165    labels:  21165
```

[4]:
```
Fseries=pd.Series(filepaths, name='file_paths')
Lseries=pd.Series(labels, name='labels')
df=pd.concat([Fseries,Lseries], axis=1)
df=DataFrame(np.array(df).reshape(21165,2), columns = ['file_paths', 'labels'])
print(df['labels'].value_counts())
```

```
normal          10192
lung_opacity     6012
covid            3616
pneumonia        1345
Name: labels, dtype: int64
```

On peut remarquer un énorme déséquilibre entre les differents facteurs. L'idée étant de nous focaliser sur la détection du covid, on va réduire la taille des modalités **nomal** et **lung_opacity** à la taille de covid.

[6]:
```python
#Compte du nombre d'élément à retirer
normal_count = 10192
lung_opacity_count = 6012
covid_count = 3616
normal_image_max_index = (df.labels.values == 'normal').argmax()
print(normal_image_max_index)
lung_opacity_max_index = (df.labels.values == 'lung_opacity').argmax()
print(lung_opacity_max_index)
```

```
9628
3616
```

[7]:
```python
for i in range(normal_count - covid_count):
    df = df.drop([normal_image_max_index + i])

for n in range(lung_opacity_count - covid_count):
    df = df.drop([lung_opacity_max_index + n])

df['labels'].value_counts()
```

[7]:
```
covid           3616
lung_opacity    3616
normal          3616
pneumonia       1345
Name: labels, dtype: int64
```

Le dernier élément à équilibrer est la **pneumonia**, pour équilibré les données, on a décider d'importer d'autres radiographie de pneumonia, également présente sur kaggle. On a préféré cette solution qui présente à notre avis, plus d'avantage qu'une data augmentation. L'idée étant éventuellement de faire une data augmentation pour voir si cela améliore les résultats de notre modèle

[8]:
```python
filepaths=[]
labels=[]
for file in glob.glob('../input/chest-xray-pneumonia/chest_xray/train/PNEUMONIA/
 ↪*jpeg'):
    filepaths.append(file)
    labels.append('pneumonia')
print ('filepaths: ', len(filepaths), '   labels: ', len(labels))
```

```
filepaths:  3875    labels:  3875
```

[9]:
```python
fseries = pd.Series(filepaths, name='file_name', dtype='str')
lseries = pd.Series(labels, name='label', dtype='str')
extra_df = pd.concat([fseries, lseries], axis=1)
extra_df = DataFrame(np.array(extra_df).reshape(3875,2), columns =␣
 ↪['file_paths', 'labels'])
extra_df.head()
```

```
[9]:                                           file_paths     labels
0  ../input/chest-xray-pneumonia/chest_xray/train…  pneumonia
1  ../input/chest-xray-pneumonia/chest_xray/train…  pneumonia
2  ../input/chest-xray-pneumonia/chest_xray/train…  pneumonia
3  ../input/chest-xray-pneumonia/chest_xray/train…  pneumonia
4  ../input/chest-xray-pneumonia/chest_xray/train…  pneumonia
```

```
[10]: df=pd.concat([df,extra_df], axis=0)
      df=df.reset_index()
```

On va donc réduire les **pneumonie** pour avoir la même taille

```
[11]: # Compte des éléments
      pneumonia_count=5220
      pneumonia_max_index=(df.labels.values == 'pneumonia').argmax()
      print(pneumonia_max_index)
      for i in range(pneumonia_count - covid_count):
          df = df.drop([pneumonia_max_index + i])
```

```
10848
```

```
[12]: print(df['labels'].value_counts())
      df.head()
```

```
covid           3616
lung_opacity    3616
normal          3616
pneumonia       3616
Name: labels, dtype: int64
```

```
[12]:    index                                        file_paths labels
0      0  ../input/covid19-radiography-dataset/COVID-19_…  covid
1      1  ../input/covid19-radiography-dataset/COVID-19_…  covid
2      2  ../input/covid19-radiography-dataset/COVID-19_…  covid
3      3  ../input/covid19-radiography-dataset/COVID-19_…  covid
4      4  ../input/covid19-radiography-dataset/COVID-19_…  covid
```

On peut ainsi observé que notre base de données est bien équilibré

3 Constitution des échantillons…

```
[13]: target_size = (299,299)
      batch_size = 64
```

```
[14]: train_datagen = ImageDataGenerator(rotation_range=20, zoom_range=0.2,␣
       ↪preprocessing_function=tf.keras.applications.inception_resnet_v2.
       ↪preprocess_input, validation_split=0.1)
      test_datagen = ImageDataGenerator(preprocessing_function=tf.keras.applications.
       ↪inception_resnet_v2.preprocess_input)
```

```
[15]: train_df, test_df = train_test_split(df, train_size=0.8, shuffle=True,␣
      ↪random_state=123)
      train_set = train_datagen.flow_from_dataframe(train_df, x_col='file_paths',␣
      ↪y_col='labels', target_size=target_size, batch_size=batch_size,␣
      ↪color_mode='rgb', shuffle=True, class_mode='categorical', subset='training')
      valid_set = train_datagen.flow_from_dataframe(train_df, x_col='file_paths',␣
      ↪y_col='labels', target_size=target_size, batch_size=batch_size,␣
      ↪color_mode='rgb', shuffle=True, class_mode='categorical',␣
      ↪subset='validation')
      test_set = test_datagen.flow_from_dataframe(test_df, x_col='file_paths',␣
      ↪y_col='labels', target_size=target_size, batch_size=batch_size,␣
      ↪color_mode='rgb', shuffle=True, class_mode='categorical')
```

```
Found 10414 validated image filenames belonging to 4 classes.
Found 1157 validated image filenames belonging to 4 classes.
Found 2893 validated image filenames belonging to 4 classes.
```

```
[16]: classes=list(train_set.class_indices.keys())
      print(classes)
```

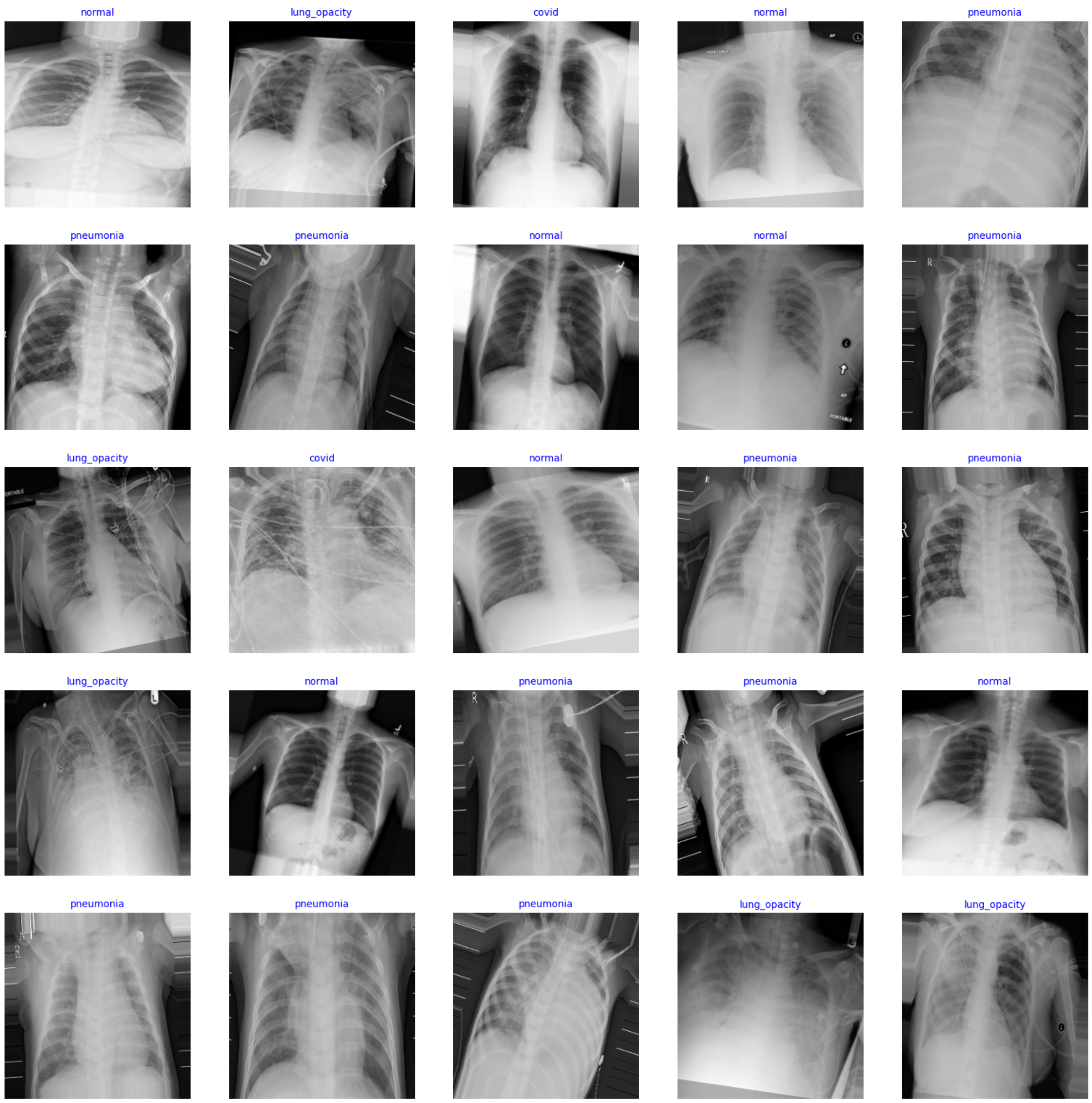
```
['covid', 'lung_opacity', 'normal', 'pneumonia']
```

4 Définition des fonctions

```
[18]: def show_image_samples(gen):
          test_dict=test_set.class_indices
          classes=list(test_dict.keys())
          images,labels=next(gen) # get a sample batch from the generator
          plt.figure(figsize=(20, 20))
          length=len(labels)
          if length<25:   #show maximum of 25 images
              r=length
          else:
              r=25
          for i in range(r):
              plt.subplot(5, 5, i + 1)
              image=(images[i]+1)/2 # scale images between 0 and 1 becaue␣
      ↪pre-processor set them between -1 and +1
              plt.imshow(image)
              index=np.argmax(labels[i])
              class_name=classes[index]
              plt.title(class_name, color='blue', fontsize=10)
              plt.axis('off')
          plt.show()
```

5 Visualation des données

[19]:
```
show_image_samples(train_set)
```



6 Analyse

[20]:
```
input_shape=(299,299,3)
num_classes = len(classes)
```

[21]:
```
def plot_loss(history):
    """
```

```
    Cette fonction trace la progression du training loss et de la validation␣
↪loss
    ainsi que le meilleur epoch sur le même graphique.

    :param history: Objet history renvoyé par la méthode compile() (keras.
↪callbacks.History)
    """
    # Plot du training loss et du validation loss
    plt.plot(history.history['loss'], label='Training loss')
    plt.plot(history.history['val_loss'], label='Validation loss')

    # Plot de l'epoch avec le meilleur validation loss
    best_epoch = np.argmin(history.history['val_loss']) + 1
    plt.scatter(best_epoch, history.history['val_loss'][best_epoch-1],␣
↪marker='o', color='blue', label='Best epoch')

    plt.title('Training and validation loss')
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.legend()
    plt.show()

def plot_accuracy(history):
    """
    Cette fonction trace la progression de l'accuracy d'entraînement et de␣
↪validation ainsi que le meilleur epoch sur le même graphique.

    :param history: Objet history renvoyé par la méthode compile() (keras.
↪callbacks.History)
    """
    # Plot de l'accuracy d'entraînement et de validation
    plt.plot(history.history['accuracy'], label='Training accuracy')
    plt.plot(history.history['val_accuracy'], label='Validation accuracy')

    # Plot de l'epoch avec le meilleur validation accuracy
    best_epoch = np.argmax(history.history['val_accuracy']) + 1
    plt.scatter(best_epoch, history.history['val_accuracy'][best_epoch-1],␣
↪marker='o', color='blue', label='Best epoch')

    plt.title('Training and validation accuracy')
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.legend()
    plt.show()
```

[22]:
```
def affichage_matrix_confusion(y_true, y_predict, classes):
    plt.figure(figsize=(8,4))
    x = confusion_matrix(np.argmax(y_true, axis=1),np.argmax(y_predict, axis=1))
    Confusion_Matrix = pd.DataFrame(x, index=classes, columns=classes)
    sns.set(font_scale=1.5, color_codes=True, palette='deep')
    sns.heatmap(Confusion_Matrix, annot=True, vmin=0, fmt='g', cmap='Blues',␣
 ↪cbar=False)
    plt.xticks(np.arange(4)+.5, classes, rotation= 90)
    plt.yticks(np.arange(4)+.5, classes, rotation=0)
    plt.ylabel("Actual")
    plt.xlabel("Predicted")
    plt.title('Confusion Matrix')
    plt.show()
```

[24]:
```
def afficher_erreur_class(y_true, y_predit, classes):
    x = confusion_matrix(np.argmax(y_true, axis=1),np.argmax(y_predit, axis=1))
    conf_matrix = pd.DataFrame(x, index=classes, columns=classes)
    # Compute the number of true positives
    true_positives = np.diag(conf_matrix)
    # Compute the number of false positives and negatives
    false_positives = np.sum(conf_matrix, axis=0) - true_positives
    false_negatives = np.sum(conf_matrix, axis=1) - true_positives
    # Compute the total number of examples
    total_examples = np.sum(conf_matrix)
    # Compute the error rate by class
    error_rate = (false_positives + false_negatives) / total_examples
    # Create a bar plot of the error rate by class
    plt.figure(figsize=(12, 8))
    sns.barplot(x=classes, y=error_rate)
    plt.title('Error Rate by Class')
    plt.xlabel('Class')
    plt.ylabel('Error Rate')
    plt.xticks(rotation=45, ha='right')
    plt.show()
```

[25]:
```
# Extraire y_true à partir du générateur de données de test
y_true = []
num_batches = len(test_set)
for i in range(num_batches):
    _, batch_y = next(test_set)
    y_true.extend(batch_y)

# Convertir y_true en un tableau numpy de forme (num_samples, num_classes)
y_true = np.array(y_true)
```

[26]:
```
y_true
```

[26]: array([[0., 1., 0., 0.],
        [0., 0., 1., 0.],
        [1., 0., 0., 0.],
        …,
        [0., 1., 0., 0.],
        [0., 1., 0., 0.],
        [0., 0., 1., 0.]], dtype=float32)

6.1 Modèle pré-entrainés : Modèle InceptionResNetV2

[57]:
```
base_model = tf.keras.applications.InceptionResNetV2(include_top=False,␣
↪input_shape=(299,299,3))
```

[ ]:
```
base_model.summary()
```

[59]:
```
model = tf.keras.Sequential([
    base_model,
    tf.keras.layers.GlobalAveragePooling2D(),
    tf.keras.layers.Dense(256, activation='relu'),
    tf.keras.layers.BatchNormalization(), tf.keras.layers.Dropout(0.2),
    tf.keras.layers.Dense(4, activation='softmax')
])
lr=0.001
model.compile(loss='categorical_crossentropy', optimizer=Adam(lr=lr),␣
↪metrics=['accuracy'])
```

[61]:
```
patience = 1
stop_patience = 5
factor = 0.5

callbacks = [
    tf.keras.callbacks.EarlyStopping(patience=stop_patience,␣
↪monitor='val_loss', verbose=1, restore_best_weights=True),
    tf.keras.callbacks.ReduceLROnPlateau(monitor='val_loss', factor=factor,␣
↪patience=patience, verbose=1)
]
```

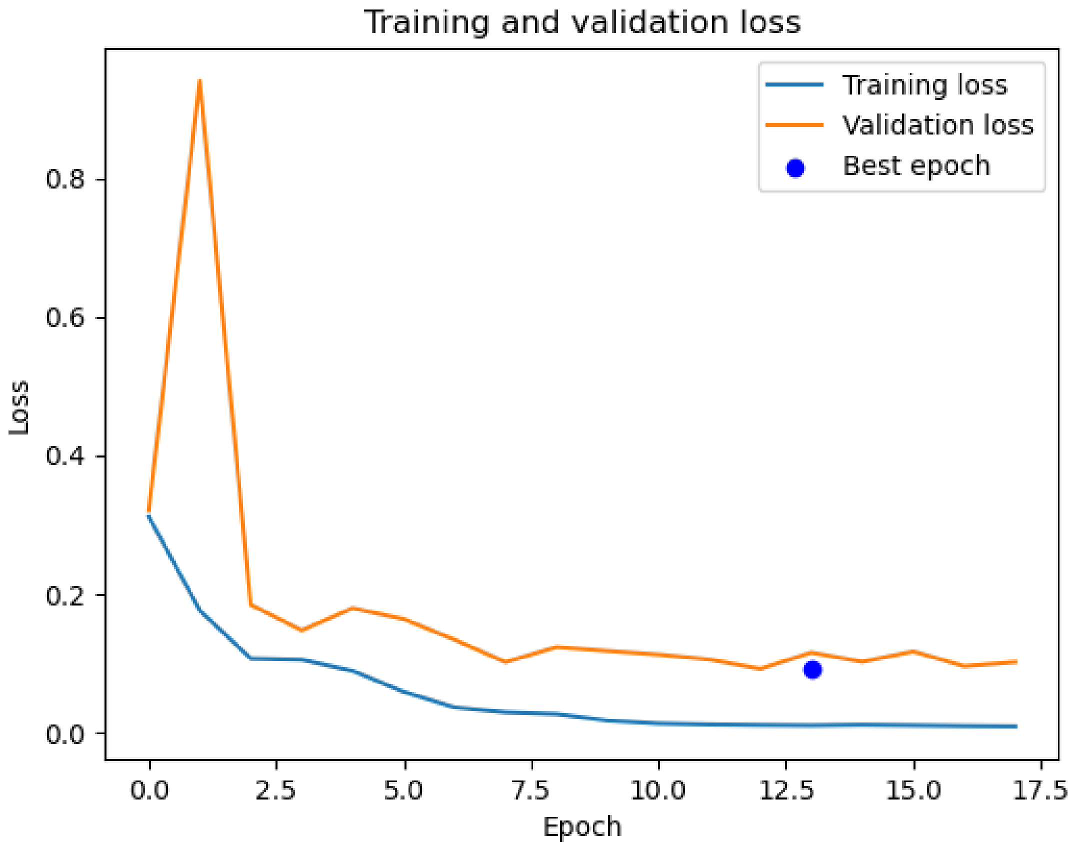
[62]:
```
epochs = 20
history = model.fit(train_set, validation_data=valid_set, epochs=epochs,␣
↪callbacks=callbacks, verbose=1)
```

```
Epoch 1/20
163/163 [==============================] - 494s 2s/step - loss: 0.3111 -
accuracy: 0.8858 - val_loss: 0.3204 - val_accuracy: 0.8911 - lr: 0.0010
Epoch 2/20
163/163 [==============================] - ETA: 0s - loss: 0.1756 - accuracy:
0.9332
Epoch 2: ReduceLROnPlateau reducing learning rate to 0.0005000000237487257.
```

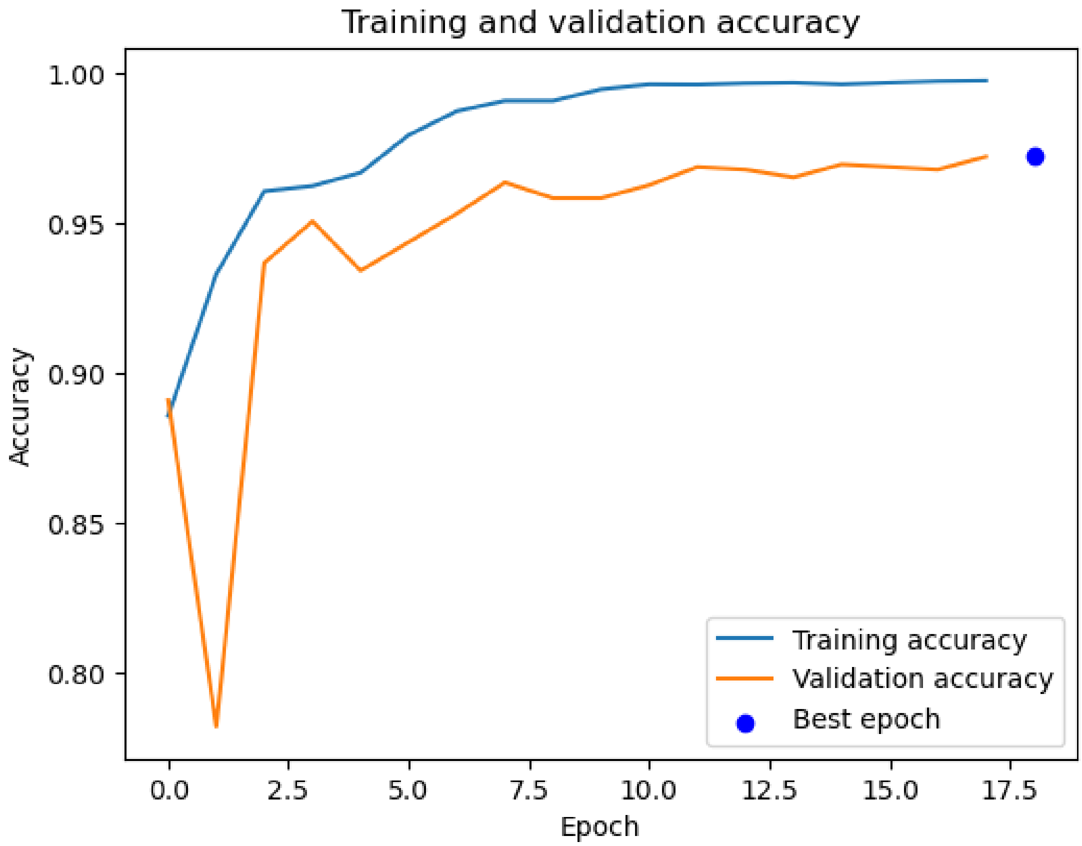
```
163/163 [==============================] - 349s 2s/step - loss: 0.1756 -
accuracy: 0.9332 - val_loss: 0.9404 - val_accuracy: 0.7822 - lr: 0.0010
Epoch 3/20
163/163 [==============================] - 347s 2s/step - loss: 0.1062 -
accuracy: 0.9608 - val_loss: 0.1839 - val_accuracy: 0.9369 - lr: 5.0000e-04
Epoch 4/20
163/163 [==============================] - 342s 2s/step - loss: 0.1046 -
accuracy: 0.9626 - val_loss: 0.1470 - val_accuracy: 0.9507 - lr: 5.0000e-04
Epoch 5/20
163/163 [==============================] - ETA: 0s - loss: 0.0884 - accuracy:
0.9670
Epoch 5: ReduceLROnPlateau reducing learning rate to 0.0002500000118743628.
163/163 [==============================] - 335s 2s/step - loss: 0.0884 -
accuracy: 0.9670 - val_loss: 0.1789 - val_accuracy: 0.9343 - lr: 5.0000e-04
Epoch 6/20
163/163 [==============================] - ETA: 0s - loss: 0.0582 - accuracy:
0.9795
Epoch 6: ReduceLROnPlateau reducing learning rate to 0.0001250000059371814.
163/163 [==============================] - 342s 2s/step - loss: 0.0582 -
accuracy: 0.9795 - val_loss: 0.1633 - val_accuracy: 0.9438 - lr: 2.5000e-04
Epoch 7/20
163/163 [==============================] - 347s 2s/step - loss: 0.0358 -
accuracy: 0.9875 - val_loss: 0.1333 - val_accuracy: 0.9533 - lr: 1.2500e-04
Epoch 8/20
163/163 [==============================] - 361s 2s/step - loss: 0.0286 -
accuracy: 0.9910 - val_loss: 0.1010 - val_accuracy: 0.9637 - lr: 1.2500e-04
Epoch 9/20
163/163 [==============================] - ETA: 0s - loss: 0.0260 - accuracy:
0.9910
Epoch 9: ReduceLROnPlateau reducing learning rate to 6.25000029685907e-05.
163/163 [==============================] - 348s 2s/step - loss: 0.0260 -
accuracy: 0.9910 - val_loss: 0.1228 - val_accuracy: 0.9585 - lr: 1.2500e-04
Epoch 10/20
163/163 [==============================] - ETA: 0s - loss: 0.0166 - accuracy:
0.9948
Epoch 10: ReduceLROnPlateau reducing learning rate to 3.125000148429535e-05.
163/163 [==============================] - 350s 2s/step - loss: 0.0166 -
accuracy: 0.9948 - val_loss: 0.1172 - val_accuracy: 0.9585 - lr: 6.2500e-05
Epoch 11/20
163/163 [==============================] - ETA: 0s - loss: 0.0124 - accuracy:
0.9964
Epoch 11: ReduceLROnPlateau reducing learning rate to 1.5625000742147677e-05.
163/163 [==============================] - 344s 2s/step - loss: 0.0124 -
accuracy: 0.9964 - val_loss: 0.1120 - val_accuracy: 0.9628 - lr: 3.1250e-05
Epoch 12/20
163/163 [==============================] - ETA: 0s - loss: 0.0110 - accuracy:
0.9964
Epoch 12: ReduceLROnPlateau reducing learning rate to 7.812500371073838e-06.
```

```
163/163 [==============================] - 346s 2s/step - loss: 0.0110 -
accuracy: 0.9964 - val_loss: 0.1049 - val_accuracy: 0.9689 - lr: 1.5625e-05
Epoch 13/20
163/163 [==============================] - 337s 2s/step - loss: 0.0102 -
accuracy: 0.9968 - val_loss: 0.0915 - val_accuracy: 0.9680 - lr: 7.8125e-06
Epoch 14/20
163/163 [==============================] - ETA: 0s - loss: 0.0097 - accuracy:
0.9970
Epoch 14: ReduceLROnPlateau reducing learning rate to 3.906250185536919e-06.
163/163 [==============================] - 337s 2s/step - loss: 0.0097 -
accuracy: 0.9970 - val_loss: 0.1148 - val_accuracy: 0.9654 - lr: 7.8125e-06
Epoch 15/20
163/163 [==============================] - ETA: 0s - loss: 0.0105 - accuracy:
0.9964
Epoch 15: ReduceLROnPlateau reducing learning rate to 1.9531250927684596e-06.
163/163 [==============================] - 337s 2s/step - loss: 0.0105 -
accuracy: 0.9964 - val_loss: 0.1016 - val_accuracy: 0.9697 - lr: 3.9063e-06
Epoch 16/20
163/163 [==============================] - ETA: 0s - loss: 0.0098 - accuracy:
0.9970
Epoch 16: ReduceLROnPlateau reducing learning rate to 9.765625463842298e-07.
163/163 [==============================] - 336s 2s/step - loss: 0.0098 -
accuracy: 0.9970 - val_loss: 0.1163 - val_accuracy: 0.9689 - lr: 1.9531e-06
Epoch 17/20
163/163 [==============================] - ETA: 0s - loss: 0.0089 - accuracy:
0.9975
Epoch 17: ReduceLROnPlateau reducing learning rate to 4.882812731921149e-07.
163/163 [==============================] - 336s 2s/step - loss: 0.0089 -
accuracy: 0.9975 - val_loss: 0.0953 - val_accuracy: 0.9680 - lr: 9.7656e-07
Epoch 18/20
163/163 [==============================] - ETA: 0s - loss: 0.0083 - accuracy:
0.9977Restoring model weights from the end of the best epoch: 13.

Epoch 18: ReduceLROnPlateau reducing learning rate to 2.4414063659605745e-07.
163/163 [==============================] - 339s 2s/step - loss: 0.0083 -
accuracy: 0.9977 - val_loss: 0.1011 - val_accuracy: 0.9723 - lr: 4.8828e-07
Epoch 18: early stopping
```

[83]:
```
plot_loss(history)
```



[84]:
```
plot_accuracy(history)
```



Evalutation du modèle

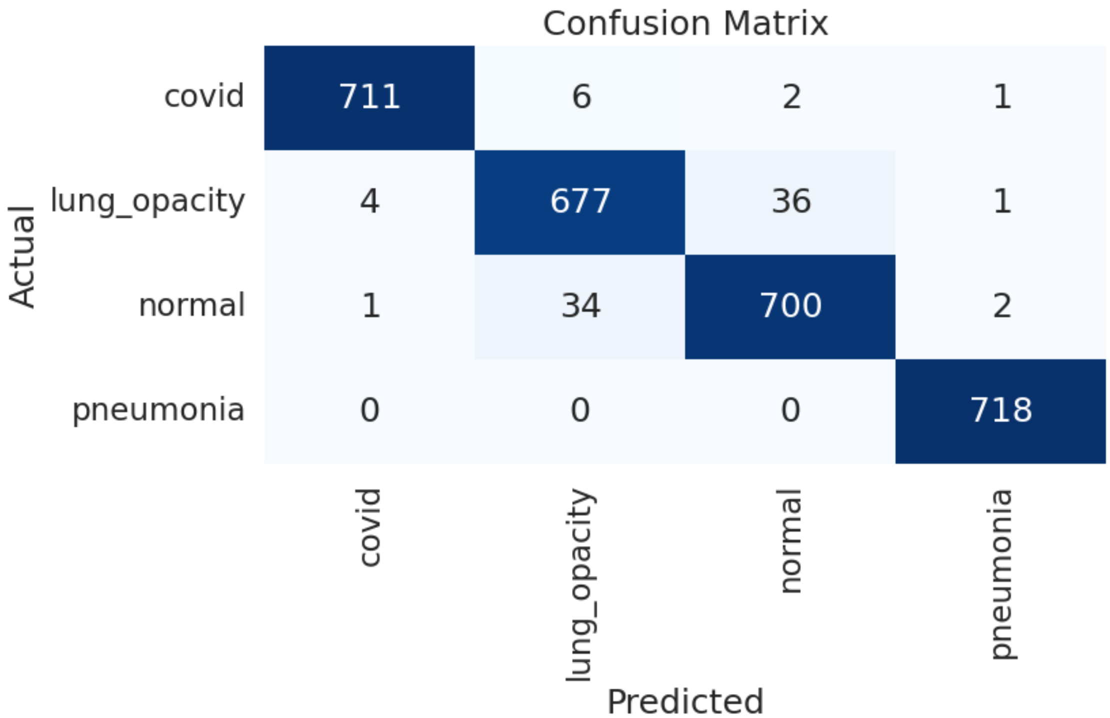
[89]:
```
loss, acc = model.evaluate(test_set)
print("Test loss: %.5f" % loss)
print("Test accuracy: %.2f%%" % (100.0 * acc))
print("Error rate: %.2f%%" % (100.0 * (1-acc)))
```

```
46/46 [==============================] - 22s 478ms/step - loss: 0.1208 -
accuracy: 0.9699
Test loss: 0.12079
Test accuracy: 96.99%
Error rate: 3.01%
```

[101]:
```
prediction_res_net =  model.predict(test_set)
```

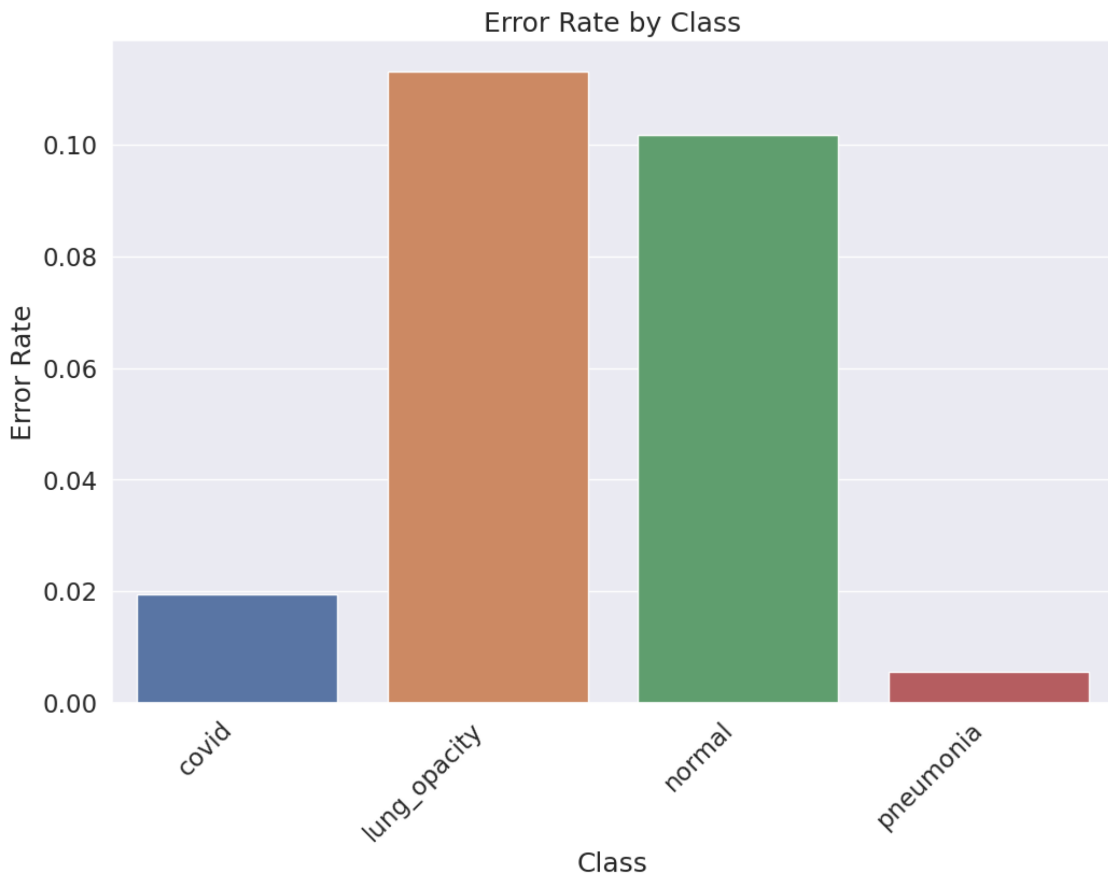
```
46/46 [==============================] - 22s 473ms/step
```

[133]:
```
affichage_matrix_confusion(y_true, prediction_res_net, classes)
```



Erreur par class sur l'échantillon sur le test_set

[145]:
```
afficher_erreur_class(y_true,prediction_res_net,classes = classes)
```



6.2 Modèle pré-entrainés : Modèle VGG16

[27]:
```
from keras.applications.vgg16 import VGG16
from keras.applications.vgg16 import preprocess_input
```

[29]:
```
# Loading VGG16 model
model_vgg16 = VGG16(weights="imagenet", include_top=False,␣
↪input_shape=(299,299,3))
```

[30]:
```
model_vgg16.trainable = False
model_vgg16.summary()
```

```
Model: "vgg16"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_3 (InputLayer)        [(None, 299, 299, 3)]     0

 block1_conv1 (Conv2D)       (None, 299, 299, 64)      1792
```

```
 block1_conv2 (Conv2D)       (None, 299, 299, 64)      36928

 block1_pool (MaxPooling2D)  (None, 149, 149, 64)      0

 block2_conv1 (Conv2D)       (None, 149, 149, 128)     73856

 block2_conv2 (Conv2D)       (None, 149, 149, 128)     147584

 block2_pool (MaxPooling2D)  (None, 74, 74, 128)       0

 block3_conv1 (Conv2D)       (None, 74, 74, 256)       295168

 block3_conv2 (Conv2D)       (None, 74, 74, 256)       590080

 block3_conv3 (Conv2D)       (None, 74, 74, 256)       590080

 block3_pool (MaxPooling2D)  (None, 37, 37, 256)       0

 block4_conv1 (Conv2D)       (None, 37, 37, 512)       1180160

 block4_conv2 (Conv2D)       (None, 37, 37, 512)       2359808

 block4_conv3 (Conv2D)       (None, 37, 37, 512)       2359808

 block4_pool (MaxPooling2D)  (None, 18, 18, 512)       0

 block5_conv1 (Conv2D)       (None, 18, 18, 512)       2359808

 block5_conv2 (Conv2D)       (None, 18, 18, 512)       2359808

 block5_conv3 (Conv2D)       (None, 18, 18, 512)       2359808

 block5_pool (MaxPooling2D)  (None, 9, 9, 512)         0

=================================================================
Total params: 14,714,688
Trainable params: 0
Non-trainable params: 14,714,688
_________________________________________________________________
```

[36]:

```
model_2 = keras.Sequential(
    [
        keras.Input(shape=(299,299,3)),
        model_vgg16,
        layers.Flatten(),
        layers.Dropout(0.5, seed=235),
        layers.Dense(256),
```

```
        layers.BatchNormalization(),
        layers.Dense(128),
        layers.BatchNormalization(),
        layers.Activation("relu"),
        layers.Dense(num_classes, activation="softmax"),
    ]
)

model_2.summary()
```

```
Model: "sequential_3"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 vgg16 (Functional)          (None, 9, 9, 512)         14714688

 flatten_3 (Flatten)         (None, 41472)             0

 dropout_3 (Dropout)         (None, 41472)             0

 dense_9 (Dense)             (None, 256)               10617088

 batch_normalization_6 (Batc  (None, 256)              1024
 hNormalization)

 dense_10 (Dense)            (None, 128)               32896

 batch_normalization_7 (Batc  (None, 128)              512
 hNormalization)

 activation_3 (Activation)   (None, 128)               0

 dense_11 (Dense)            (None, 4)                 516

=================================================================
Total params: 25,366,724
Trainable params: 10,651,268
Non-trainable params: 14,715,456
_________________________________________________________________
```

[37]:
```
from tensorflow.keras.callbacks import EarlyStopping
```

[38]:
```
model_2.compile(loss="categorical_crossentropy", optimizer="adam",␣
 ↪metrics=["accuracy"])
es = EarlyStopping(monitor='val_accuracy', mode='max', patience=10, ␣
 ↪restore_best_weights=True)
```

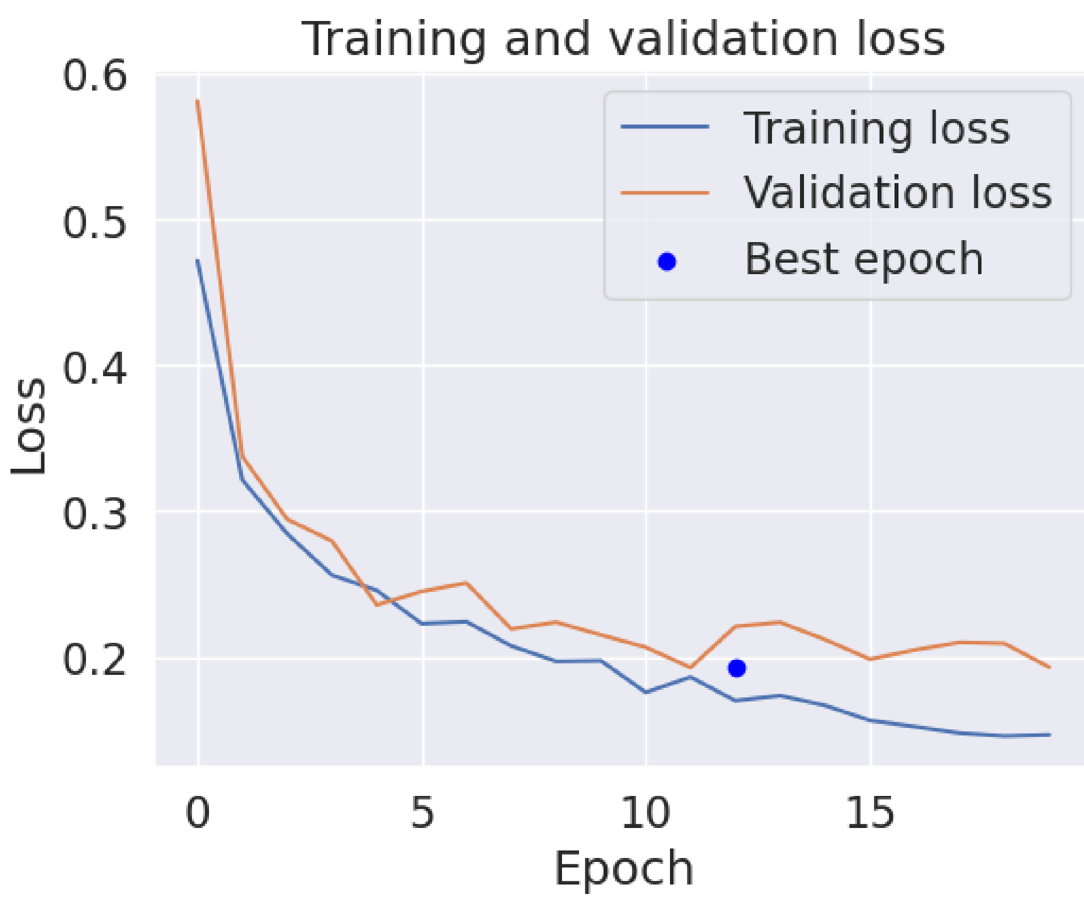
[39]:
```
start_time = time.time()
history_vgg16 = model_2.
  ↪fit(train_set,validation_data=valid_set,batch_size=64,epochs=20,␣
  ↪callbacks=[es])
print("Temps de calcul :", time.time() - start_time)
```

```
Epoch 1/20
163/163 [==============================] - 348s 2s/step - loss: 0.4718 -
accuracy: 0.8133 - val_loss: 0.5810 - val_accuracy: 0.7753
Epoch 2/20
163/163 [==============================] - 283s 2s/step - loss: 0.3215 -
accuracy: 0.8764 - val_loss: 0.3376 - val_accuracy: 0.8669
Epoch 3/20
163/163 [==============================] - 284s 2s/step - loss: 0.2846 -
accuracy: 0.8915 - val_loss: 0.2945 - val_accuracy: 0.8842
Epoch 4/20
163/163 [==============================] - 285s 2s/step - loss: 0.2562 -
accuracy: 0.9057 - val_loss: 0.2796 - val_accuracy: 0.8971
Epoch 5/20
163/163 [==============================] - 284s 2s/step - loss: 0.2458 -
accuracy: 0.9085 - val_loss: 0.2358 - val_accuracy: 0.9092
Epoch 6/20
163/163 [==============================] - 286s 2s/step - loss: 0.2230 -
accuracy: 0.9145 - val_loss: 0.2450 - val_accuracy: 0.9067
Epoch 7/20
163/163 [==============================] - 284s 2s/step - loss: 0.2244 -
accuracy: 0.9171 - val_loss: 0.2508 - val_accuracy: 0.9032
Epoch 8/20
163/163 [==============================] - 285s 2s/step - loss: 0.2077 -
accuracy: 0.9208 - val_loss: 0.2194 - val_accuracy: 0.9231
Epoch 9/20
163/163 [==============================] - 285s 2s/step - loss: 0.1972 -
accuracy: 0.9270 - val_loss: 0.2239 - val_accuracy: 0.9170
Epoch 10/20
163/163 [==============================] - 285s 2s/step - loss: 0.1976 -
accuracy: 0.9236 - val_loss: 0.2153 - val_accuracy: 0.9153
Epoch 11/20
163/163 [==============================] - 285s 2s/step - loss: 0.1759 -
accuracy: 0.9342 - val_loss: 0.2068 - val_accuracy: 0.9162
Epoch 12/20
163/163 [==============================] - 284s 2s/step - loss: 0.1864 -
accuracy: 0.9323 - val_loss: 0.1929 - val_accuracy: 0.9283
Epoch 13/20
163/163 [==============================] - 284s 2s/step - loss: 0.1702 -
accuracy: 0.9365 - val_loss: 0.2210 - val_accuracy: 0.9179
Epoch 14/20
163/163 [==============================] - 281s 2s/step - loss: 0.1737 -
accuracy: 0.9346 - val_loss: 0.2239 - val_accuracy: 0.9170
```

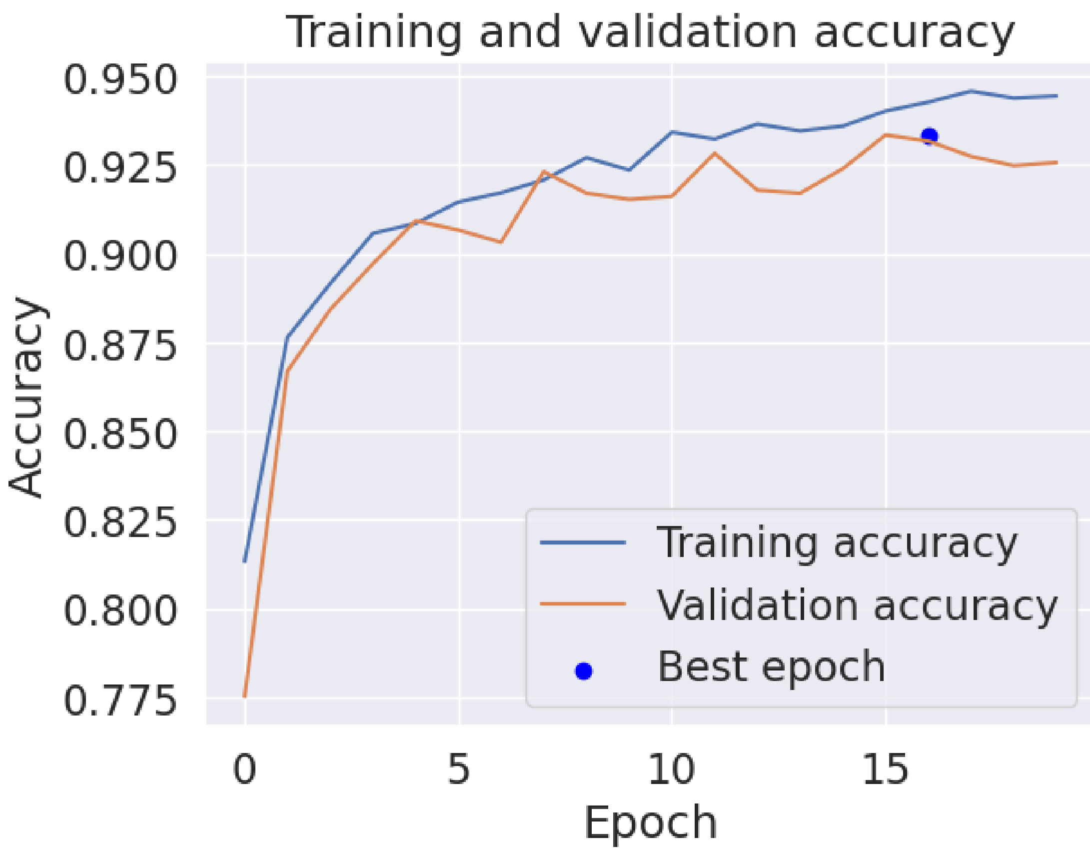
```
Epoch 15/20
163/163 [==============================] - 283s 2s/step - loss: 0.1669 -
accuracy: 0.9360 - val_loss: 0.2121 - val_accuracy: 0.9239
Epoch 16/20
163/163 [==============================] - 281s 2s/step - loss: 0.1567 -
accuracy: 0.9402 - val_loss: 0.1986 - val_accuracy: 0.9334
Epoch 17/20
163/163 [==============================] - 281s 2s/step - loss: 0.1524 -
accuracy: 0.9427 - val_loss: 0.2050 - val_accuracy: 0.9317
Epoch 18/20
163/163 [==============================] - 281s 2s/step - loss: 0.1480 -
accuracy: 0.9457 - val_loss: 0.2102 - val_accuracy: 0.9274
Epoch 19/20
163/163 [==============================] - 280s 2s/step - loss: 0.1460 -
accuracy: 0.9438 - val_loss: 0.2094 - val_accuracy: 0.9248
Epoch 20/20
163/163 [==============================] - 281s 2s/step - loss: 0.1468 -
accuracy: 0.9444 - val_loss: 0.1931 - val_accuracy: 0.9257
Temps de calcul : 5773.619660377502
```

[72]:

```
plot_loss(history_vgg16)
```



```
[73]: plot_accuracy(history_vgg16)
```



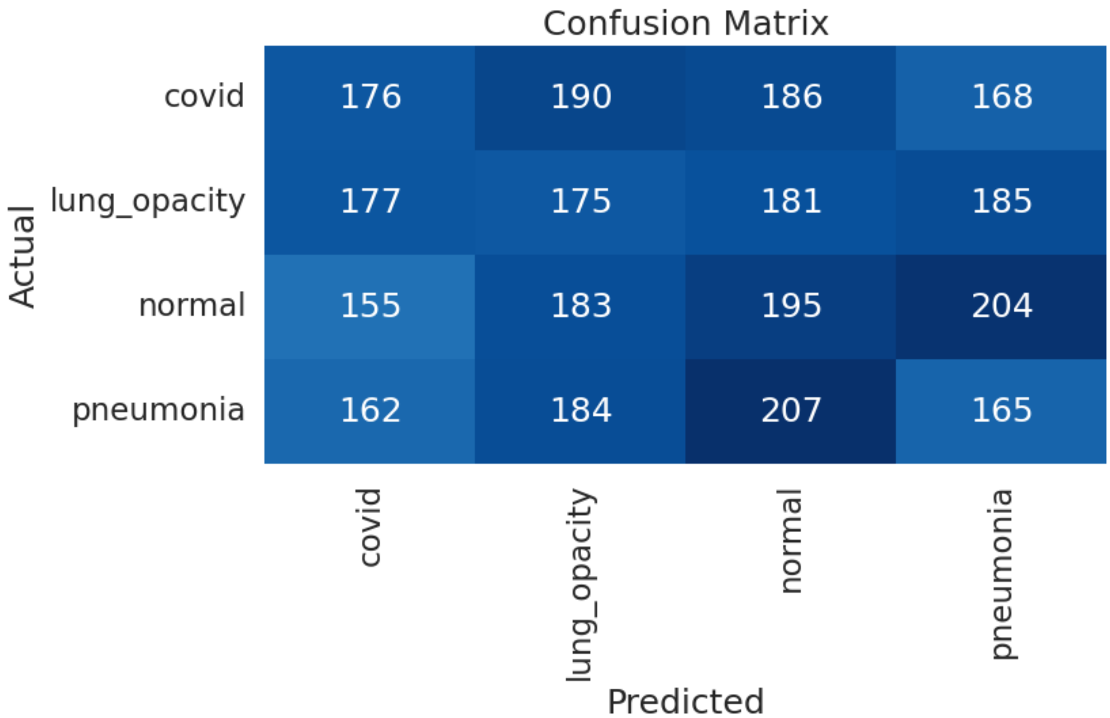

```
[42]: loss_vgg16, acc_vgg16 = model_2.evaluate(test_set)
print("Test loss: %.5f" % loss_vgg16)
print("Test accuracy: %.2f%%" % (100.0 * acc_vgg16))
print("Error rate: %.2f%%" % (100.0 * (1-acc_vgg16)))
```

```
46/46 [==============================] - 32s 702ms/step - loss: 0.1736 -
accuracy: 0.9371
Test loss: 0.17359
Test accuracy: 93.71%
Error rate: 6.29%
```

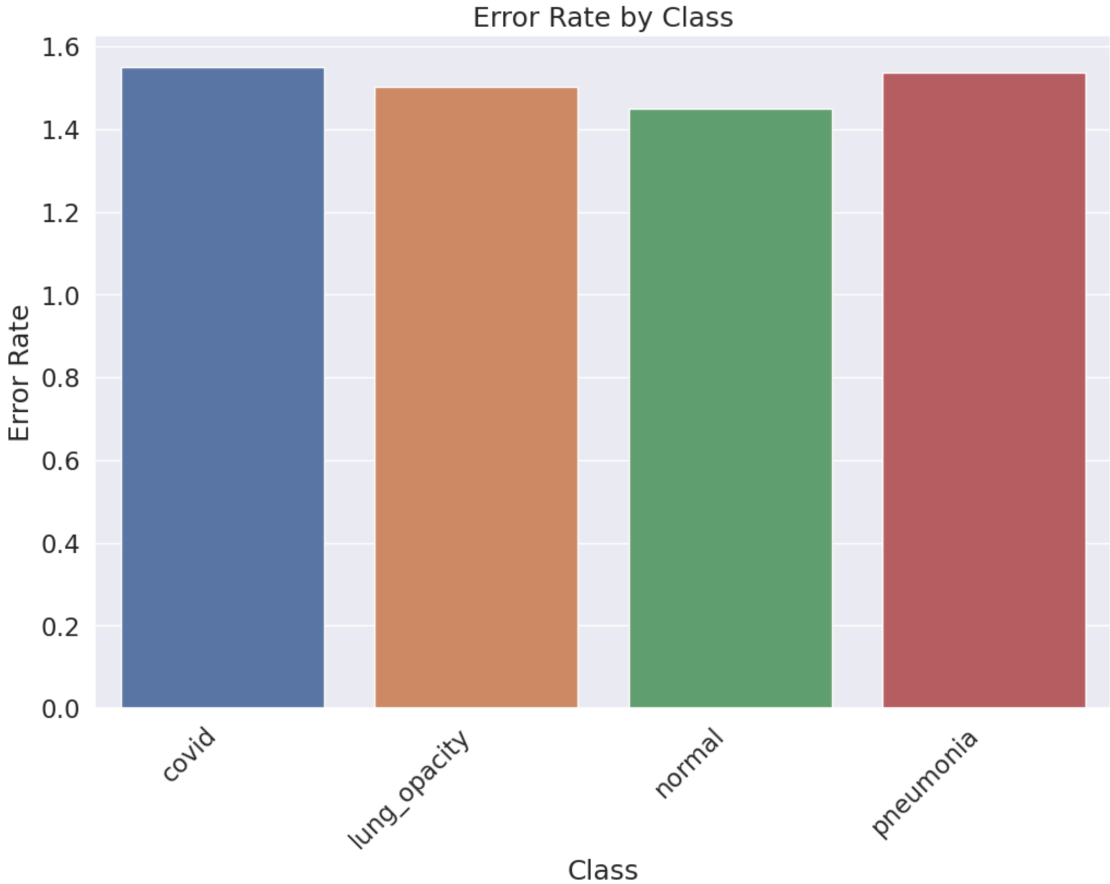
```
[43]: predict_vgg15 =  model_2.predict(test_set)
```

```
46/46 [==============================] - 21s 448ms/step
```

```
[47]: affichage_matrix_confusion(y_true, predict_vgg15, classes)
```



[48]:
```
afficher_erreur_class(y_true,predict_vgg15,classes = classes)
```



6.3 Modèle pré-entrainés : Modèle VGG19

[33]:
```
from tensorflow.keras.applications import VGG19
```

[34]:
```
# Création du modèle
model_vgg19 = VGG19(weights='imagenet', include_top=False,␣
↪input_shape=(299,299,3))
model_vgg19.trainable = False
model_vgg19.summary()
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-
applications/vgg19/vgg19_weights_tf_dim_ordering_tf_kernels_notop.h5
80134624/80134624 [==============================] - 0s 0us/step
Model: "vgg19"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_3 (InputLayer)        [(None, 299, 299, 3)]     0
```

```
 block1_conv1 (Conv2D)       (None, 299, 299, 64)      1792

 block1_conv2 (Conv2D)       (None, 299, 299, 64)      36928

 block1_pool (MaxPooling2D)  (None, 149, 149, 64)      0

 block2_conv1 (Conv2D)       (None, 149, 149, 128)     73856

 block2_conv2 (Conv2D)       (None, 149, 149, 128)     147584

 block2_pool (MaxPooling2D)  (None, 74, 74, 128)       0

 block3_conv1 (Conv2D)       (None, 74, 74, 256)       295168

 block3_conv2 (Conv2D)       (None, 74, 74, 256)       590080

 block3_conv3 (Conv2D)       (None, 74, 74, 256)       590080

 block3_conv4 (Conv2D)       (None, 74, 74, 256)       590080

 block3_pool (MaxPooling2D)  (None, 37, 37, 256)       0

 block4_conv1 (Conv2D)       (None, 37, 37, 512)       1180160

 block4_conv2 (Conv2D)       (None, 37, 37, 512)       2359808

 block4_conv3 (Conv2D)       (None, 37, 37, 512)       2359808

 block4_conv4 (Conv2D)       (None, 37, 37, 512)       2359808

 block4_pool (MaxPooling2D)  (None, 18, 18, 512)       0

 block5_conv1 (Conv2D)       (None, 18, 18, 512)       2359808

 block5_conv2 (Conv2D)       (None, 18, 18, 512)       2359808

 block5_conv3 (Conv2D)       (None, 18, 18, 512)       2359808

 block5_conv4 (Conv2D)       (None, 18, 18, 512)       2359808

 block5_pool (MaxPooling2D)  (None, 9, 9, 512)         0

=================================================================
Total params: 20,024,384
Trainable params: 0
Non-trainable params: 20,024,384
_________________________________________________________________
```

[57]:
```
model_3 = keras.Sequential(
    [
        keras.Input(shape=(299,299,3)),
        model_vgg19,
        layers.Flatten(),
        layers.Dropout(0.5, seed=235),
        layers.Dense(256),
        layers.Activation("relu"),
        layers.Dense(num_classes, activation="softmax"),
    ]
)
```

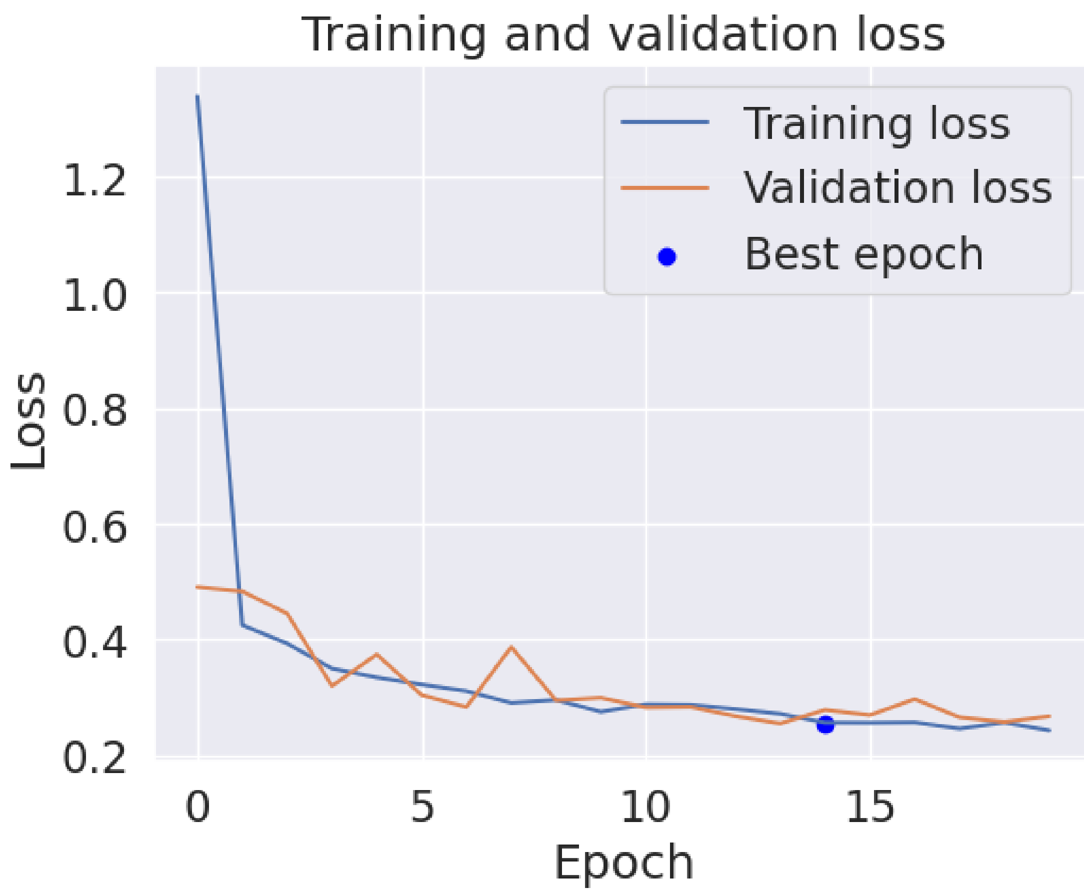
[58]:
```
model_3.compile(loss="categorical_crossentropy", optimizer="adam",␣
 ↪metrics=["accuracy"])
es = EarlyStopping(monitor='val_accuracy', mode='max', patience=10, ␣
 ↪restore_best_weights=True)
```

[59]:
```
start_time = time.time()
history_vgg19 = model_3.
 ↪fit(train_set,validation_data=valid_set,batch_size=64,epochs=20,␣
 ↪callbacks=[es])
print("Temps de calcul :", time.time() - start_time)
```

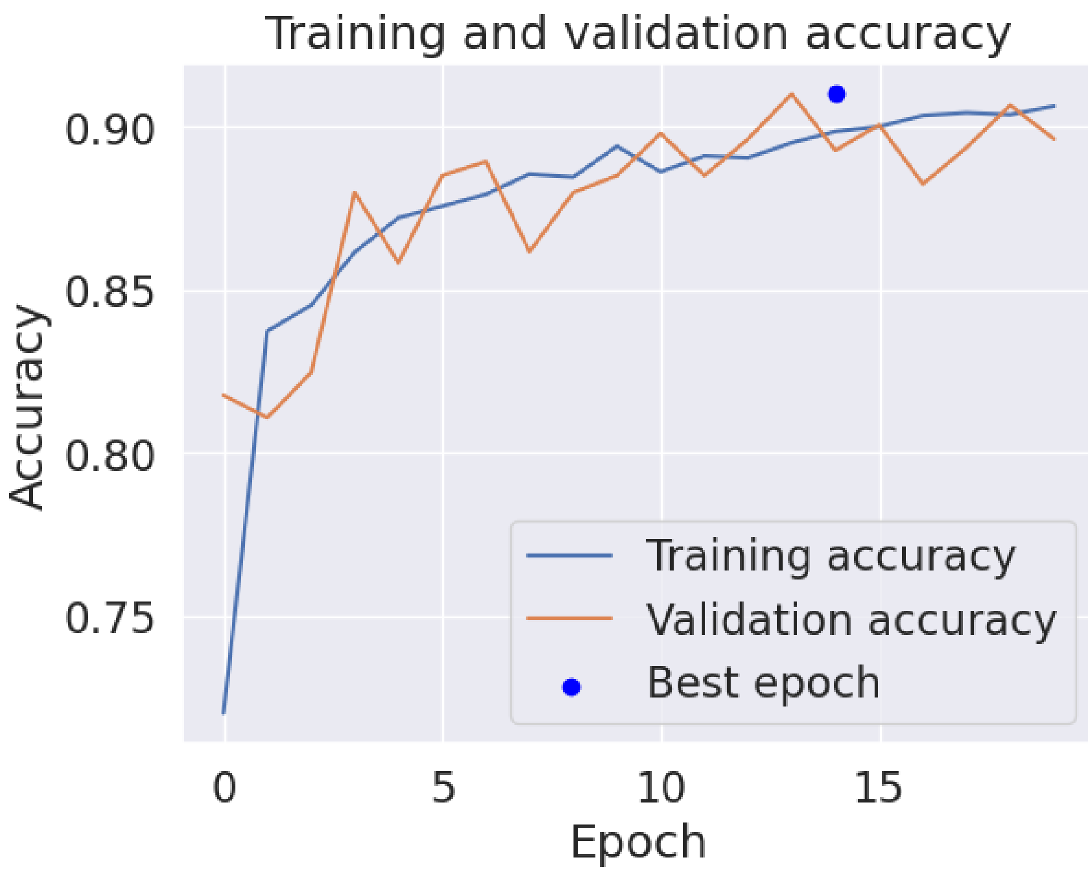
```
Epoch 1/20
163/163 [==============================] - 288s 2s/step - loss: 1.3392 -
accuracy: 0.7201 - val_loss: 0.4910 - val_accuracy: 0.8176
Epoch 2/20
163/163 [==============================] - 281s 2s/step - loss: 0.4253 -
accuracy: 0.8373 - val_loss: 0.4836 - val_accuracy: 0.8107
Epoch 3/20
163/163 [==============================] - 281s 2s/step - loss: 0.3934 -
accuracy: 0.8452 - val_loss: 0.4455 - val_accuracy: 0.8245
Epoch 4/20
163/163 [==============================] - 283s 2s/step - loss: 0.3502 -
accuracy: 0.8615 - val_loss: 0.3200 - val_accuracy: 0.8799
Epoch 5/20
163/163 [==============================] - 281s 2s/step - loss: 0.3348 -
accuracy: 0.8721 - val_loss: 0.3746 - val_accuracy: 0.8583
Epoch 6/20
163/163 [==============================] - 283s 2s/step - loss: 0.3225 -
accuracy: 0.8756 - val_loss: 0.3044 - val_accuracy: 0.8850
Epoch 7/20
163/163 [==============================] - 281s 2s/step - loss: 0.3112 -
accuracy: 0.8793 - val_loss: 0.2836 - val_accuracy: 0.8894
Epoch 8/20
163/163 [==============================] - 283s 2s/step - loss: 0.2907 -
accuracy: 0.8855 - val_loss: 0.3874 - val_accuracy: 0.8617
Epoch 9/20
```

```
163/163 [==============================] - 283s 2s/step - loss: 0.2958 -
accuracy: 0.8846 - val_loss: 0.2951 - val_accuracy: 0.8799
Epoch 10/20
163/163 [==============================] - 281s 2s/step - loss: 0.2755 -
accuracy: 0.8941 - val_loss: 0.2996 - val_accuracy: 0.8850
Epoch 11/20
163/163 [==============================] - 281s 2s/step - loss: 0.2881 -
accuracy: 0.8862 - val_loss: 0.2828 - val_accuracy: 0.8980
Epoch 12/20
163/163 [==============================] - 281s 2s/step - loss: 0.2874 -
accuracy: 0.8911 - val_loss: 0.2838 - val_accuracy: 0.8850
Epoch 13/20
163/163 [==============================] - 280s 2s/step - loss: 0.2802 -
accuracy: 0.8905 - val_loss: 0.2679 - val_accuracy: 0.8963
Epoch 14/20
163/163 [==============================] - 282s 2s/step - loss: 0.2719 -
accuracy: 0.8951 - val_loss: 0.2552 - val_accuracy: 0.9101
Epoch 15/20
163/163 [==============================] - 281s 2s/step - loss: 0.2567 -
accuracy: 0.8986 - val_loss: 0.2787 - val_accuracy: 0.8928
Epoch 16/20
163/163 [==============================] - 281s 2s/step - loss: 0.2565 -
accuracy: 0.9001 - val_loss: 0.2697 - val_accuracy: 0.9006
Epoch 17/20
163/163 [==============================] - 280s 2s/step - loss: 0.2571 -
accuracy: 0.9035 - val_loss: 0.2973 - val_accuracy: 0.8825
Epoch 18/20
163/163 [==============================] - 280s 2s/step - loss: 0.2465 -
accuracy: 0.9044 - val_loss: 0.2659 - val_accuracy: 0.8937
Epoch 19/20
163/163 [==============================] - 281s 2s/step - loss: 0.2568 -
accuracy: 0.9038 - val_loss: 0.2577 - val_accuracy: 0.9067
Epoch 20/20
163/163 [==============================] - 282s 2s/step - loss: 0.2433 -
accuracy: 0.9064 - val_loss: 0.2677 - val_accuracy: 0.8963
Temps de calcul : 5638.388345956802
```

[61]:
```
plot_loss(history_vgg19)
```



[67]:
```
plot_accuracy(history_vgg19)
```



Evaluation du modèle

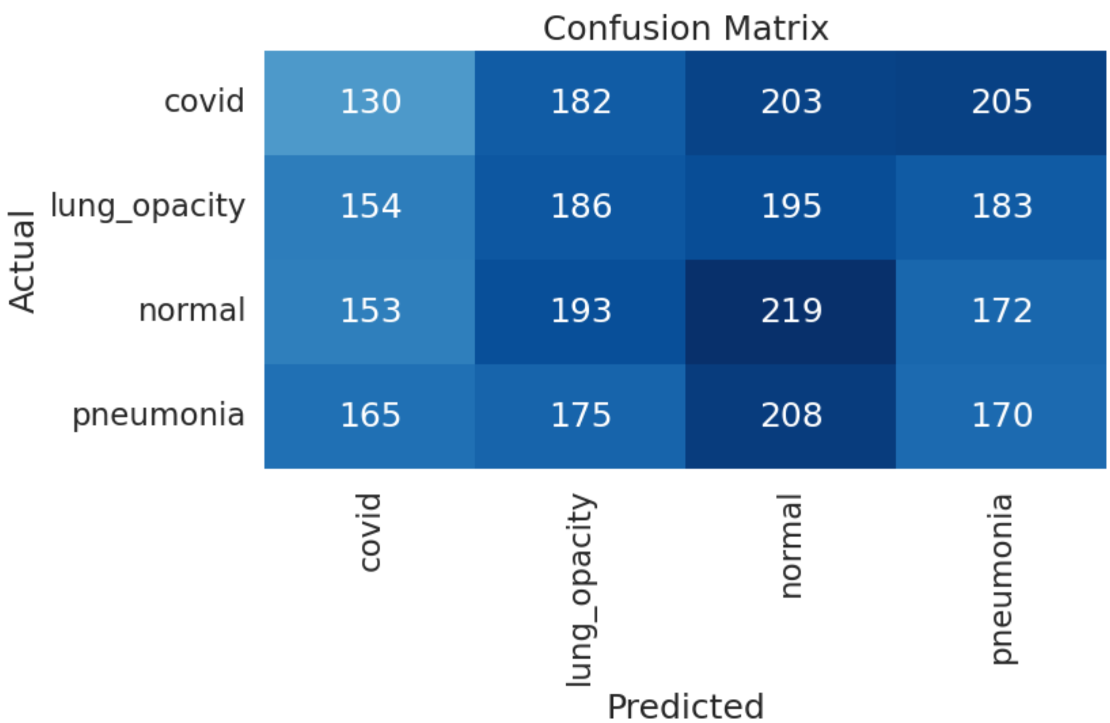
[68]:
```
loss_vgg19, acc_vgg19 = model_3.evaluate(test_set)
print("Test loss: %.5f" % loss_vgg19)
print("Test accuracy: %.2f%%" % (100.0 * acc_vgg19))
print("Error rate: %.2f%%" % (100.0 * (1-acc_vgg19)))
```

```
46/46 [==============================] - 23s 490ms/step - loss: 0.2450 -
accuracy: 0.9101
Test loss: 0.24498
Test accuracy: 91.01%
Error rate: 8.99%
```

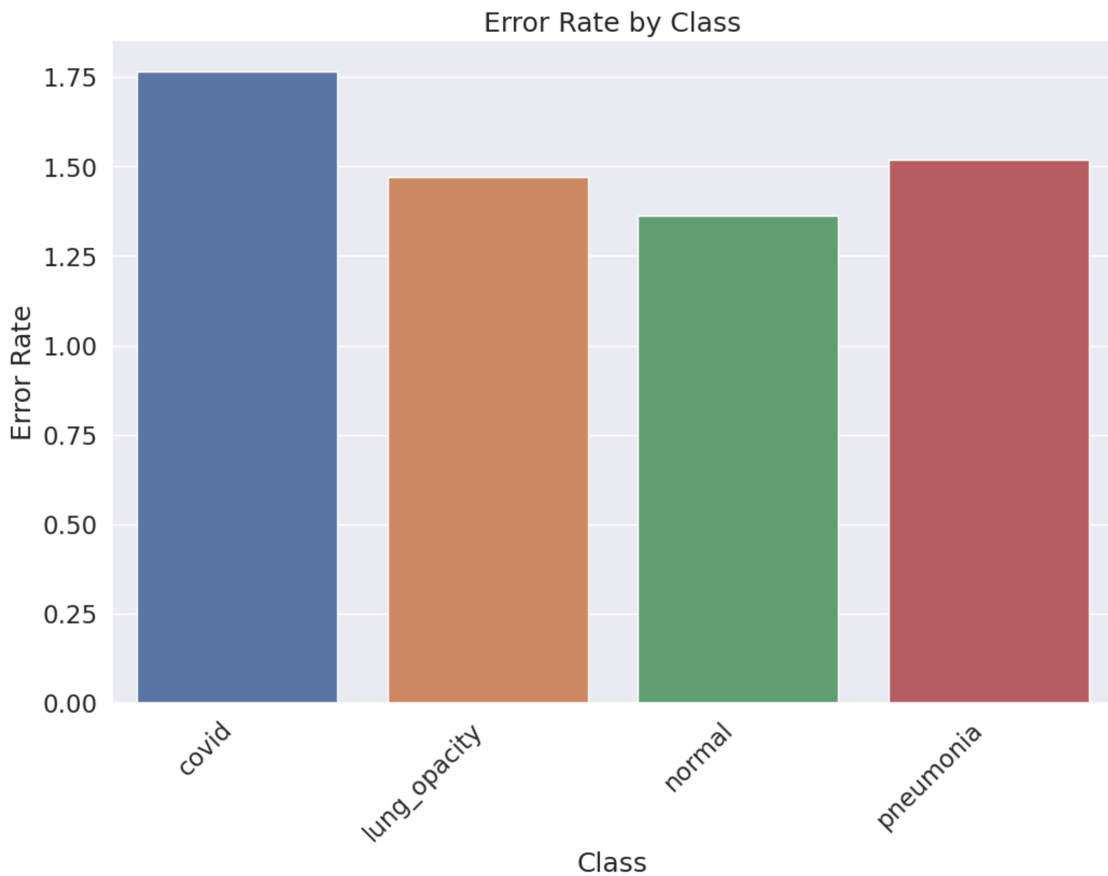
[69]:
```
predict_vgg19 = model_3.predict(test_set)
```

```
46/46 [==============================] - 21s 462ms/step
```

[70]:
```
affichage_matrix_confusion(y_true, predict_vgg19, classes)
```



[71]:
```
afficher_erreur_class(y_true,predict_vgg19,classes = classes)
```



7 Modèle CNN

[81]:
```
model_cnn = keras.Sequential(
    [
        keras.Input(shape=input_shape),
        layers.Conv2D(32, kernel_size=(3, 3), activation="relu"),
        layers.MaxPooling2D(pool_size=(2, 2)),
        layers.Conv2D(64, kernel_size=(3, 3), activation="relu"),
        layers.MaxPooling2D(pool_size=(2, 2)),
        layers.Flatten(),
        layers.Dropout(0.5),
        layers.Dense(num_classes, activation="softmax"),
    ]
)

model_cnn.summary()
```

```
Model: "sequential_7"
_________________________________________________________________
```

```
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 297, 297, 32)      896

 max_pooling2d (MaxPooling2D  (None, 148, 148, 32)     0
 )

 conv2d_1 (Conv2D)           (None, 146, 146, 64)      18496

 max_pooling2d_1 (MaxPooling  (None, 73, 73, 64)       0
 2D)

 flatten_7 (Flatten)         (None, 341056)            0

 dropout_7 (Dropout)         (None, 341056)            0

 dense_18 (Dense)            (None, 4)                 1364228

=================================================================
Total params: 1,383,620
Trainable params: 1,383,620
Non-trainable params: 0
_________________________________________________________________
```

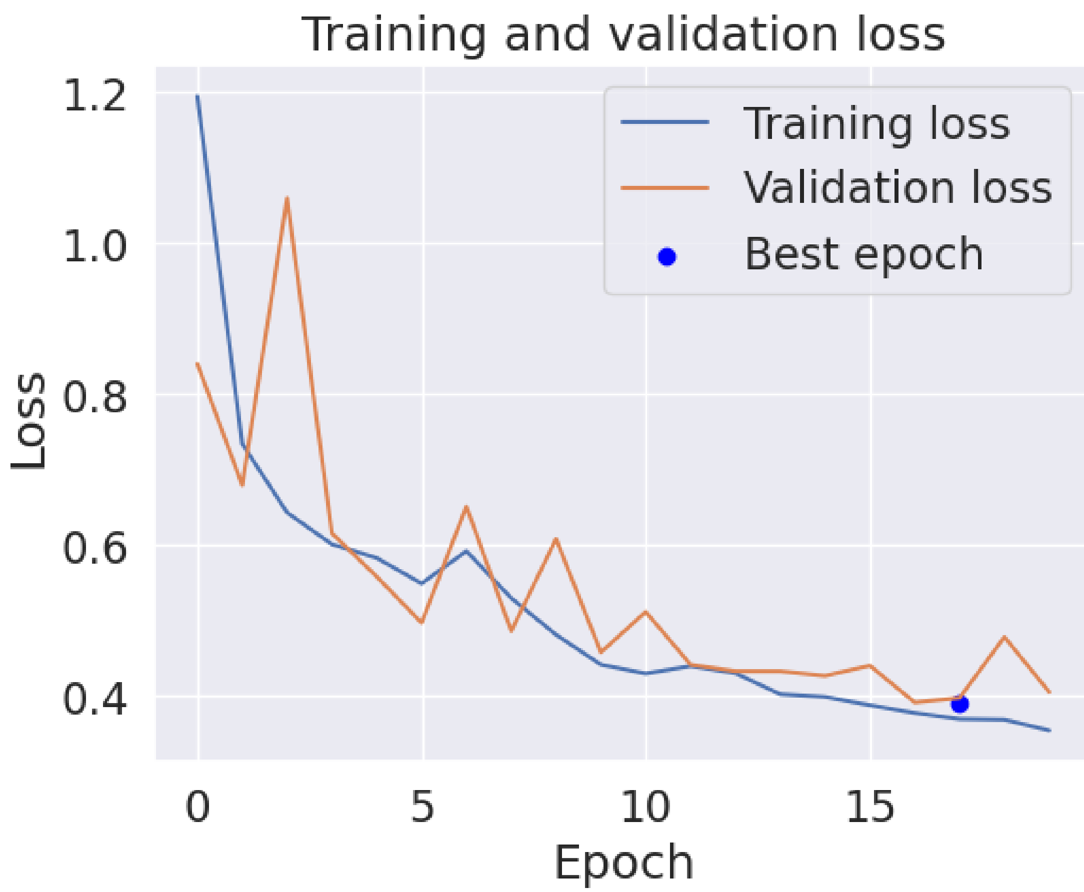
[82]:
```python
model_cnn.compile(loss="categorical_crossentropy", optimizer="rmsprop",␣
 ↪metrics=["accuracy"])
```

[83]:
```python
start_time = time.time()
history_cnn = model_cnn.
 ↪fit(train_set,validation_data=valid_set,batch_size=64,epochs=20)
print("Temps de calcul :", time.time() - start_time)
```

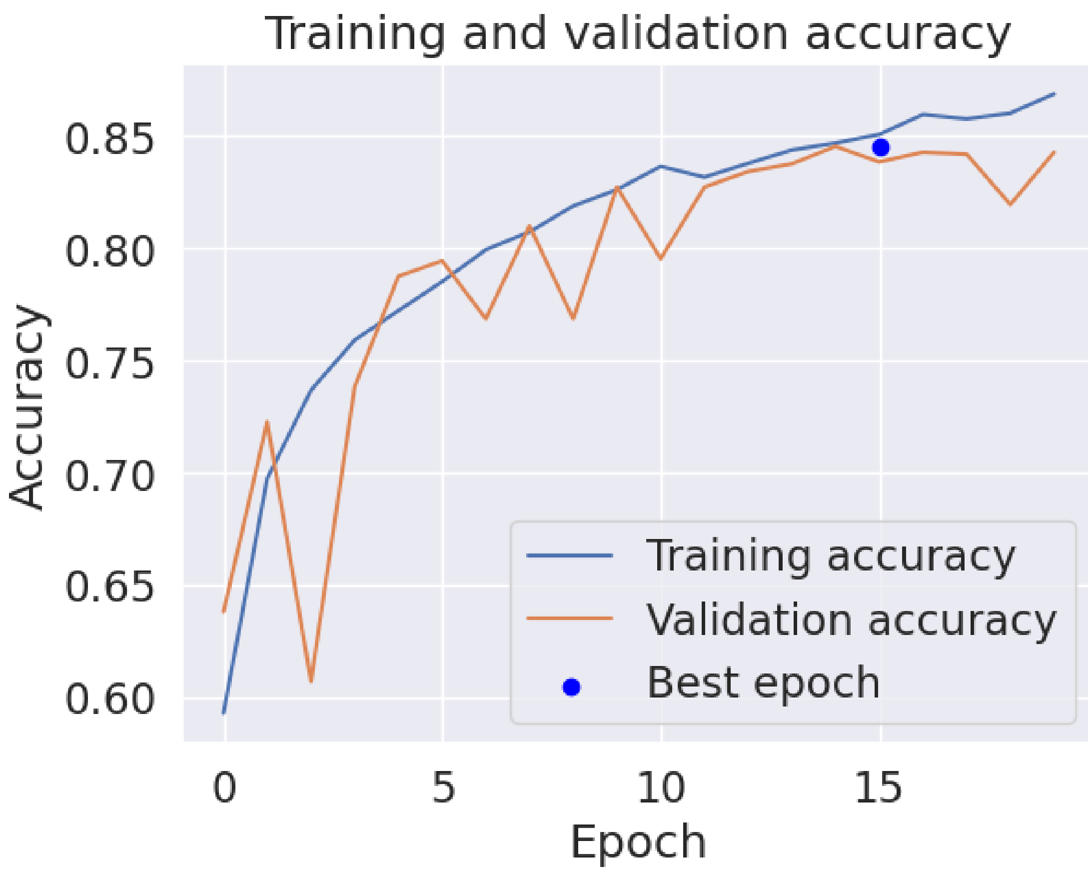
```
Epoch 1/20
163/163 [==============================] - 285s 2s/step - loss: 1.1945 -
accuracy: 0.5928 - val_loss: 0.8404 - val_accuracy: 0.6379
Epoch 2/20
163/163 [==============================] - 272s 2s/step - loss: 0.7345 -
accuracy: 0.6972 - val_loss: 0.6798 - val_accuracy: 0.7226
Epoch 3/20
163/163 [==============================] - 286s 2s/step - loss: 0.6434 -
accuracy: 0.7366 - val_loss: 1.0596 - val_accuracy: 0.6067
Epoch 4/20
163/163 [==============================] - 274s 2s/step - loss: 0.6014 -
accuracy: 0.7590 - val_loss: 0.6160 - val_accuracy: 0.7381
Epoch 5/20
163/163 [==============================] - 269s 2s/step - loss: 0.5833 -
accuracy: 0.7720 - val_loss: 0.5585 - val_accuracy: 0.7874
Epoch 6/20
```

```
163/163 [==============================] - 268s 2s/step - loss: 0.5496 -
accuracy: 0.7850 - val_loss: 0.4975 - val_accuracy: 0.7943
Epoch 7/20
163/163 [==============================] - 268s 2s/step - loss: 0.5924 -
accuracy: 0.7992 - val_loss: 0.6516 - val_accuracy: 0.7684
Epoch 8/20
163/163 [==============================] - 268s 2s/step - loss: 0.5303 -
accuracy: 0.8072 - val_loss: 0.4864 - val_accuracy: 0.8099
Epoch 9/20
163/163 [==============================] - 271s 2s/step - loss: 0.4817 -
accuracy: 0.8187 - val_loss: 0.6085 - val_accuracy: 0.7684
Epoch 10/20
163/163 [==============================] - 268s 2s/step - loss: 0.4421 -
accuracy: 0.8260 - val_loss: 0.4583 - val_accuracy: 0.8271
Epoch 11/20
163/163 [==============================] - 269s 2s/step - loss: 0.4302 -
accuracy: 0.8364 - val_loss: 0.5121 - val_accuracy: 0.7952
Epoch 12/20
163/163 [==============================] - 272s 2s/step - loss: 0.4401 -
accuracy: 0.8316 - val_loss: 0.4421 - val_accuracy: 0.8271
Epoch 13/20
163/163 [==============================] - 273s 2s/step - loss: 0.4308 -
accuracy: 0.8377 - val_loss: 0.4333 - val_accuracy: 0.8341
Epoch 14/20
163/163 [==============================] - 271s 2s/step - loss: 0.4029 -
accuracy: 0.8437 - val_loss: 0.4333 - val_accuracy: 0.8375
Epoch 15/20
163/163 [==============================] - 272s 2s/step - loss: 0.3993 -
accuracy: 0.8467 - val_loss: 0.4273 - val_accuracy: 0.8453
Epoch 16/20
163/163 [==============================] - 272s 2s/step - loss: 0.3884 -
accuracy: 0.8506 - val_loss: 0.4407 - val_accuracy: 0.8384
Epoch 17/20
163/163 [==============================] - 272s 2s/step - loss: 0.3781 -
accuracy: 0.8595 - val_loss: 0.3921 - val_accuracy: 0.8427
Epoch 18/20
163/163 [==============================] - 271s 2s/step - loss: 0.3701 -
accuracy: 0.8576 - val_loss: 0.3980 - val_accuracy: 0.8418
Epoch 19/20
163/163 [==============================] - 273s 2s/step - loss: 0.3692 -
accuracy: 0.8601 - val_loss: 0.4788 - val_accuracy: 0.8194
Epoch 20/20
163/163 [==============================] - 273s 2s/step - loss: 0.3551 -
accuracy: 0.8686 - val_loss: 0.4058 - val_accuracy: 0.8427
Temps de calcul : 5450.080677270889
```

[84]:
```
plot_loss(history_cnn)
```



[85]:
```
plot_accuracy(history_cnn)
```



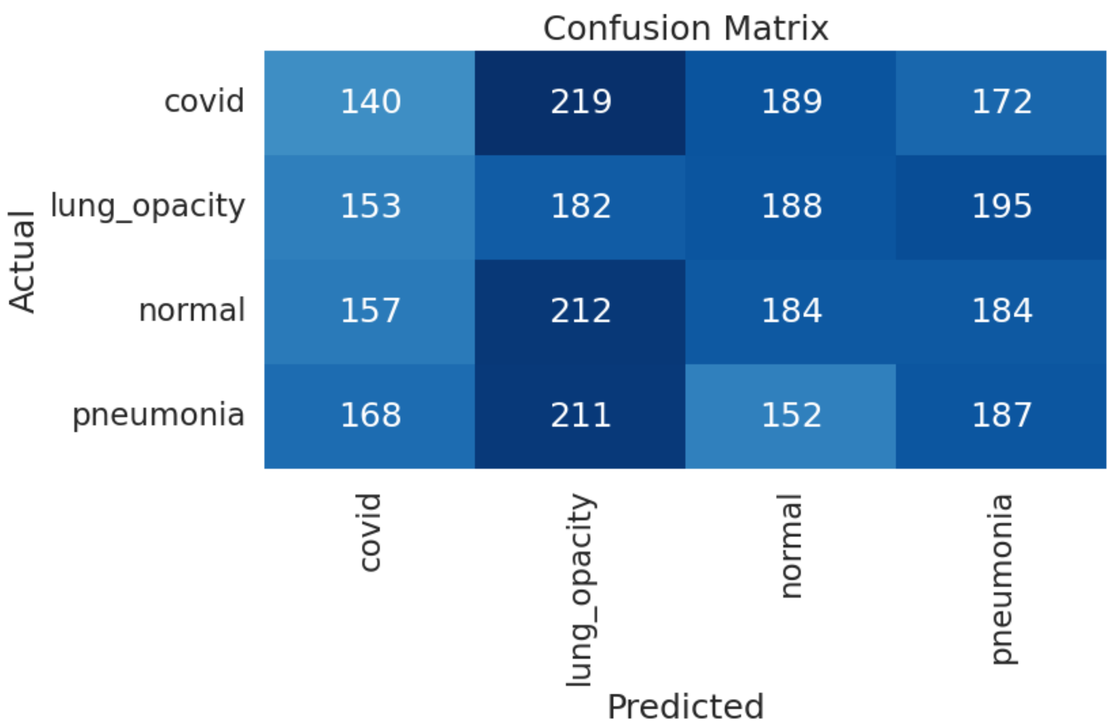
[88]:
```
loss_cnn, acc_cnn = model_cnn.evaluate(test_set)
print("Test loss: %.5f" % loss_cnn)
print("Test accuracy: %.2f%%" % (100.0 * acc_cnn))
print("Error rate: %.2f%%" % (100.0 * (1-acc_cnn)))
```

```
46/46 [==============================] - 22s 470ms/step - loss: 0.3579 -
accuracy: 0.8731
Test loss: 0.35786
Test accuracy: 87.31%
Error rate: 12.69%
```

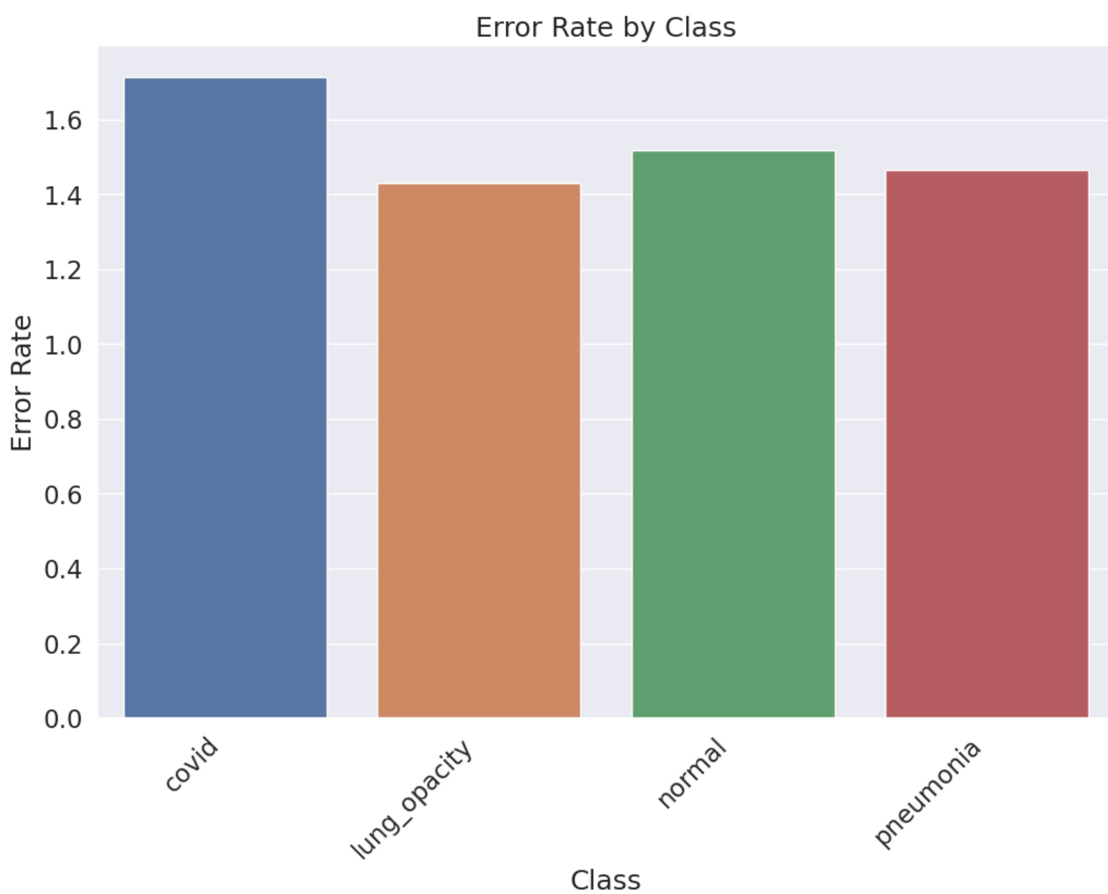
[89]:
```
predict_cnn = model_cnn.predict(test_set)
```

```
46/46 [==============================] - 19s 410ms/step
```

[90]:
```
affichage_matrix_confusion(y_true, predict_cnn, classes)
```



[91]:
```
afficher_erreur_class(y_true,predict_cnn,classes = classes)
```



[92]:
```
model_cnn.save("modelCNN")
```

7.1 Modèle pré-entrainé : Modèle Xception

[26]:
```
from keras.applications.xception import Xception
```

[37]:
```
model_xception = Xception(weights = None, input_shape = (299,299,3), classes =␣
    ↪num_classes)
model_xception.trainable = False
#model_xception.summary()
```

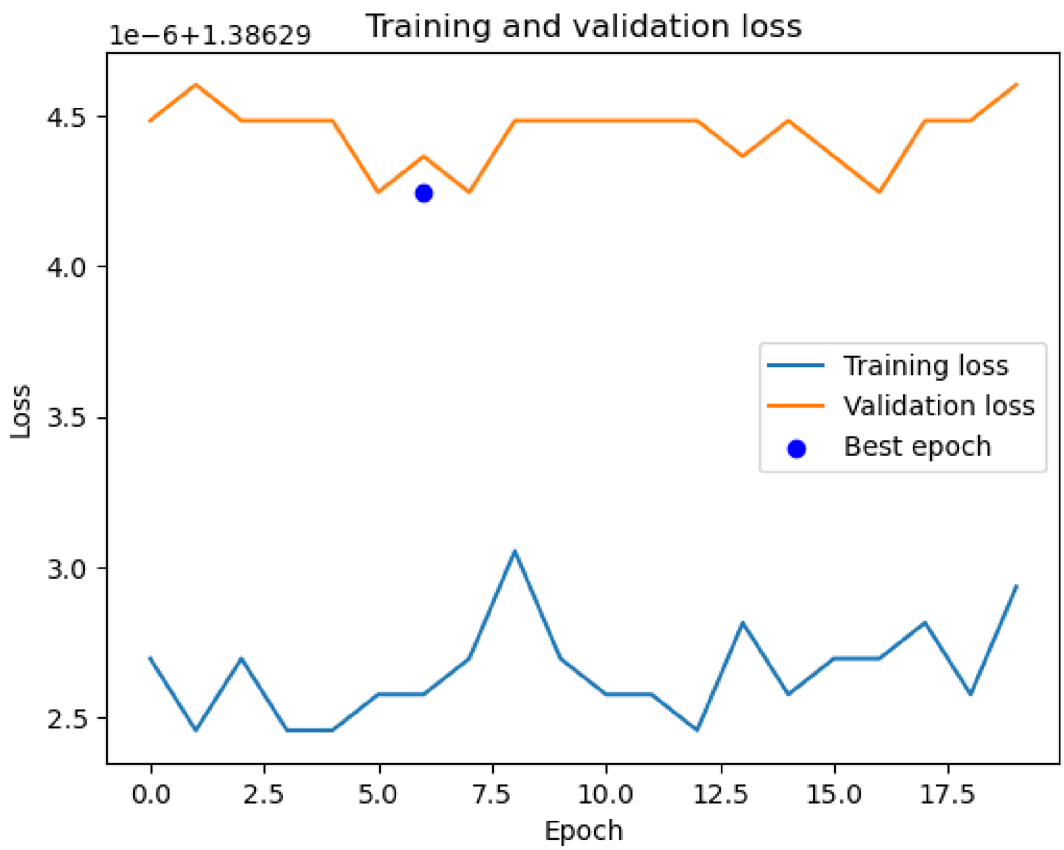
[39]:
```
model_xception.compile(optimizer='adam', loss='categorical_crossentropy',␣
    ↪metrics=['accuracy'])
```

[40]:
```
start_time = time.time()
history_xception = model_xception.
    ↪fit(train_set,validation_data=valid_set,batch_size=64,epochs=20)
print("Temps de calcul :", time.time() - start_time)
```

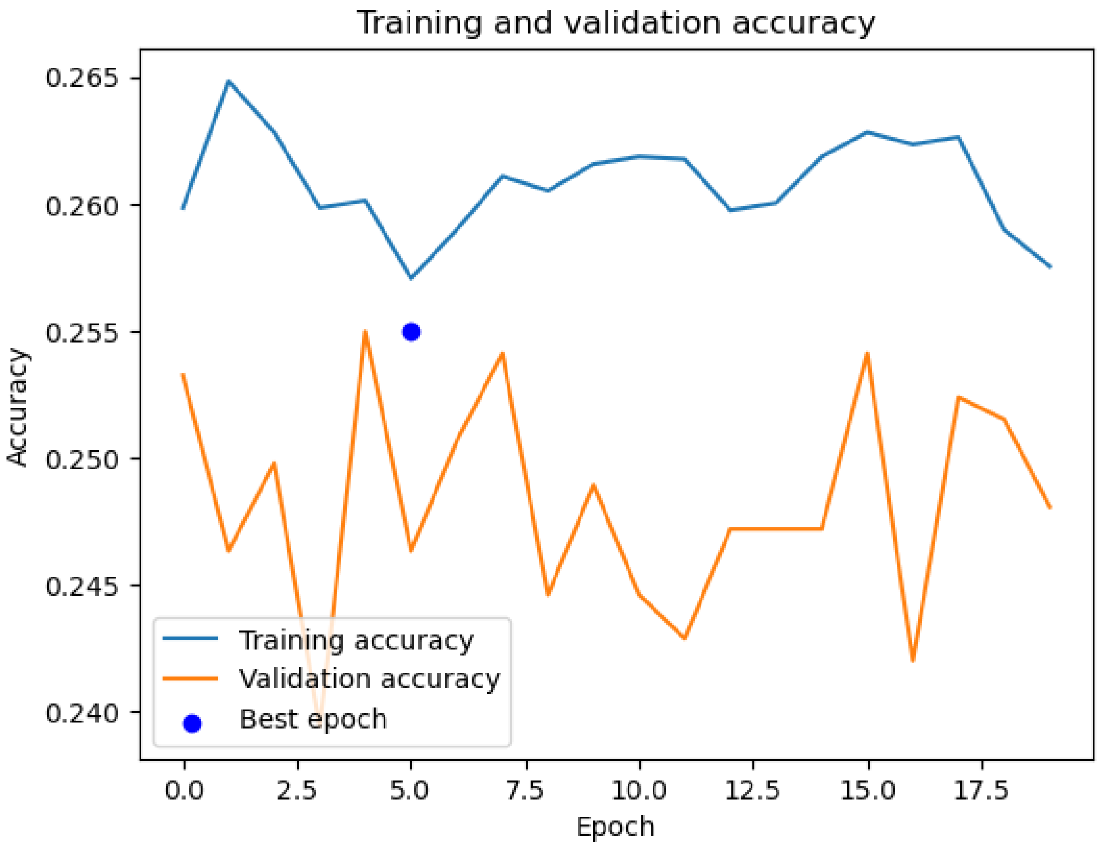
```
Epoch 1/20
163/163 [==============================] - 362s 2s/step - loss: 1.3863 -
accuracy: 0.2598 - val_loss: 1.3863 - val_accuracy: 0.2532
Epoch 2/20
163/163 [==============================] - 274s 2s/step - loss: 1.3863 -
accuracy: 0.2648 - val_loss: 1.3863 - val_accuracy: 0.2463
Epoch 3/20
163/163 [==============================] - 272s 2s/step - loss: 1.3863 -
accuracy: 0.2628 - val_loss: 1.3863 - val_accuracy: 0.2498
Epoch 4/20
163/163 [==============================] - 272s 2s/step - loss: 1.3863 -
accuracy: 0.2598 - val_loss: 1.3863 - val_accuracy: 0.2394
Epoch 5/20
163/163 [==============================] - 273s 2s/step - loss: 1.3863 -
accuracy: 0.2601 - val_loss: 1.3863 - val_accuracy: 0.2550
Epoch 6/20
163/163 [==============================] - 273s 2s/step - loss: 1.3863 -
accuracy: 0.2571 - val_loss: 1.3863 - val_accuracy: 0.2463
Epoch 7/20
163/163 [==============================] - 272s 2s/step - loss: 1.3863 -
accuracy: 0.2590 - val_loss: 1.3863 - val_accuracy: 0.2506
Epoch 8/20
163/163 [==============================] - 274s 2s/step - loss: 1.3863 -
accuracy: 0.2611 - val_loss: 1.3863 - val_accuracy: 0.2541
Epoch 9/20
163/163 [==============================] - 272s 2s/step - loss: 1.3863 -
accuracy: 0.2605 - val_loss: 1.3863 - val_accuracy: 0.2446
Epoch 10/20
163/163 [==============================] - 276s 2s/step - loss: 1.3863 -
accuracy: 0.2616 - val_loss: 1.3863 - val_accuracy: 0.2489
Epoch 11/20
163/163 [==============================] - 274s 2s/step - loss: 1.3863 -
accuracy: 0.2619 - val_loss: 1.3863 - val_accuracy: 0.2446
Epoch 12/20
163/163 [==============================] - 274s 2s/step - loss: 1.3863 -
accuracy: 0.2618 - val_loss: 1.3863 - val_accuracy: 0.2429
Epoch 13/20
163/163 [==============================] - 273s 2s/step - loss: 1.3863 -
accuracy: 0.2597 - val_loss: 1.3863 - val_accuracy: 0.2472
Epoch 14/20
163/163 [==============================] - 274s 2s/step - loss: 1.3863 -
accuracy: 0.2600 - val_loss: 1.3863 - val_accuracy: 0.2472
Epoch 15/20
163/163 [==============================] - 286s 2s/step - loss: 1.3863 -
accuracy: 0.2619 - val_loss: 1.3863 - val_accuracy: 0.2472
Epoch 16/20
163/163 [==============================] - 271s 2s/step - loss: 1.3863 -
accuracy: 0.2628 - val_loss: 1.3863 - val_accuracy: 0.2541
```

```
Epoch 17/20
163/163 [==============================] - 274s 2s/step - loss: 1.3863 -
accuracy: 0.2623 - val_loss: 1.3863 - val_accuracy: 0.2420
Epoch 18/20
163/163 [==============================] - 272s 2s/step - loss: 1.3863 -
accuracy: 0.2626 - val_loss: 1.3863 - val_accuracy: 0.2524
Epoch 19/20
163/163 [==============================] - 272s 2s/step - loss: 1.3863 -
accuracy: 0.2590 - val_loss: 1.3863 - val_accuracy: 0.2515
Epoch 20/20
163/163 [==============================] - 272s 2s/step - loss: 1.3863 -
accuracy: 0.2575 - val_loss: 1.3863 - val_accuracy: 0.2481
Temps de calcul : 5564.813514947891
```

[47]:
```
plot_loss(history_xception)
```



[48]:
```
plot_accuracy(history_xception)
```



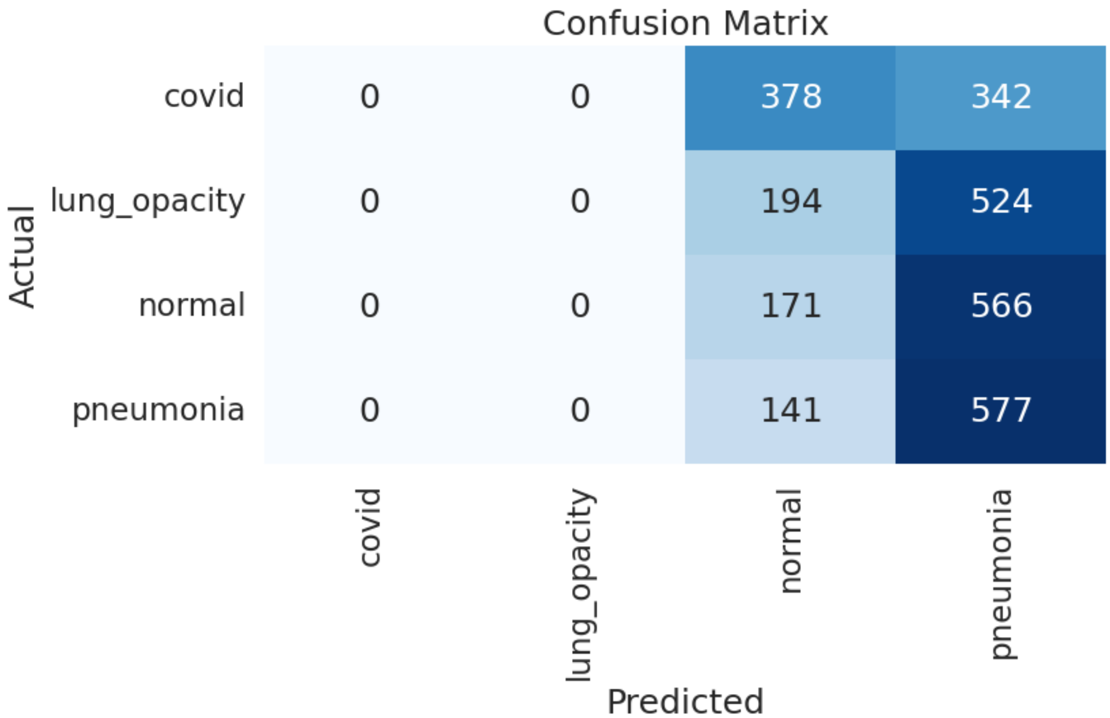
[51]:
```
loss_xception, acc_xception = model_xception.evaluate(test_set)
print("Test loss: %.5f" % loss_xception)
print("Test accuracy: %.2f%%" % (100.0 * acc_xception))
print("Error rate: %.2f%%" % (100.0 * (1-acc_xception)))
```

```
46/46 [==============================] - 21s 448ms/step - loss: 1.3863 -
accuracy: 0.2586
Test loss: 1.38629
Test accuracy: 25.86%
Error rate: 74.14%
```

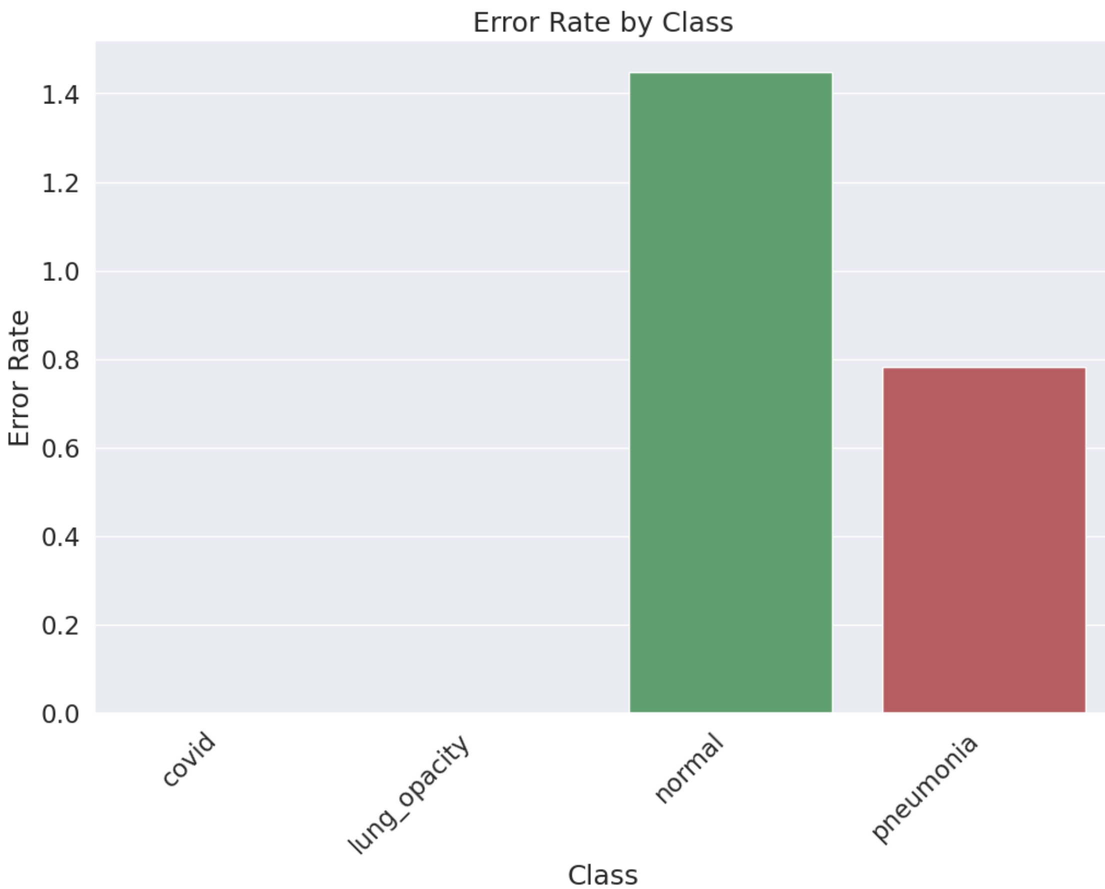
[49]:
```
predict_xception = model_xception.predict(test_set)
```

```
46/46 [==============================] - 22s 456ms/step
```

[50]:
```
affichage_matrix_confusion(y_true, predict_xception, classes)
```




```
[52]: afficher_erreur_class(y_true,predict_xception,classes = classes)
```



7.2 Modèle à couches 4 de convolutions et normalisation Batch : PaquarseCouche4

[42]:
```
from tensorflow.keras.callbacks import EarlyStopping
```

[39]:
```
# exemple cours
# https://keras.io/api/layers/
#from tensorflow.keras.layers import Dense, BatchNormalization
model_paquarse4 = keras.Sequential(
    [
        keras.Input(shape=input_shape),
        layers.Conv2D(32, kernel_size=(3,3), padding="same"),
        layers.BatchNormalization(),
        layers.Activation("relu"),
        layers.Conv2D(32, kernel_size=(3,3), padding="valid"),
        layers.BatchNormalization(),
        layers.Activation("relu"),
        layers.MaxPooling2D(pool_size=(2,2)),
        layers.Dropout(0.2, seed=235),
```

```python
        layers.Conv2D(32, kernel_size=(3,3), padding="same"),
        layers.BatchNormalization(),
        layers.Activation("relu"),
        layers.Conv2D(32, kernel_size=(3,3), padding="valid"),
        layers.BatchNormalization(),
        layers.Activation("relu"),
        layers.MaxPooling2D(pool_size=(2,2)),
        layers.Dropout(0.2, seed=235),
        layers.Flatten(),
        layers.Dropout(0.5, seed=235),
        layers.Dense(512),
        layers.BatchNormalization(),
        layers.Activation("relu"),
        layers.Dense(num_classes, activation="softmax"),
    ]
)
model_paquarse4.summary()
```

```
Model: "sequential_2"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_8 (Conv2D)           (None, 299, 299, 32)      896

 batch_normalization_10 (Bat  (None, 299, 299, 32)     128
 chNormalization)

 activation_10 (Activation)  (None, 299, 299, 32)      0

 conv2d_9 (Conv2D)           (None, 297, 297, 32)      9248

 batch_normalization_11 (Bat  (None, 297, 297, 32)     128
 chNormalization)

 activation_11 (Activation)  (None, 297, 297, 32)      0

 max_pooling2d_4 (MaxPooling  (None, 148, 148, 32)     0
 2D)

 dropout_6 (Dropout)         (None, 148, 148, 32)      0

 conv2d_10 (Conv2D)          (None, 148, 148, 32)      9248

 batch_normalization_12 (Bat  (None, 148, 148, 32)     128
 chNormalization)

 activation_12 (Activation)  (None, 148, 148, 32)      0
```

```
 conv2d_11 (Conv2D)          (None, 146, 146, 32)      9248

 batch_normalization_13 (Bat  (None, 146, 146, 32)     128
 chNormalization)

 activation_13 (Activation)  (None, 146, 146, 32)      0

 max_pooling2d_5 (MaxPooling  (None, 73, 73, 32)       0
 2D)

 dropout_7 (Dropout)         (None, 73, 73, 32)        0

 flatten_2 (Flatten)         (None, 170528)            0

 dropout_8 (Dropout)         (None, 170528)            0

 dense_4 (Dense)             (None, 512)               87310848

 batch_normalization_14 (Bat  (None, 512)              2048
 chNormalization)

 activation_14 (Activation)  (None, 512)               0

 dense_5 (Dense)             (None, 4)                 2052

=================================================================
Total params: 87,344,100
Trainable params: 87,342,820
Non-trainable params: 1,280
_________________________________________________________________
```

[40]:
```python
model_paquarse4.compile(loss="categorical_crossentropy", optimizer="adam",␣
 ↪metrics=["accuracy"])
es = EarlyStopping(monitor='val_accuracy', mode='max', patience=10, ␣
 ↪restore_best_weights=True)
```

[41]:
```python
start_time = time.time()
history_paquarse4 = model_paquarse4.
 ↪fit(train_set,validation_data=valid_set,batch_size=64,epochs=20,␣
 ↪callbacks=[es])
print("Temps de calcul :", time.time() - start_time)
```

```
Epoch 1/20
```

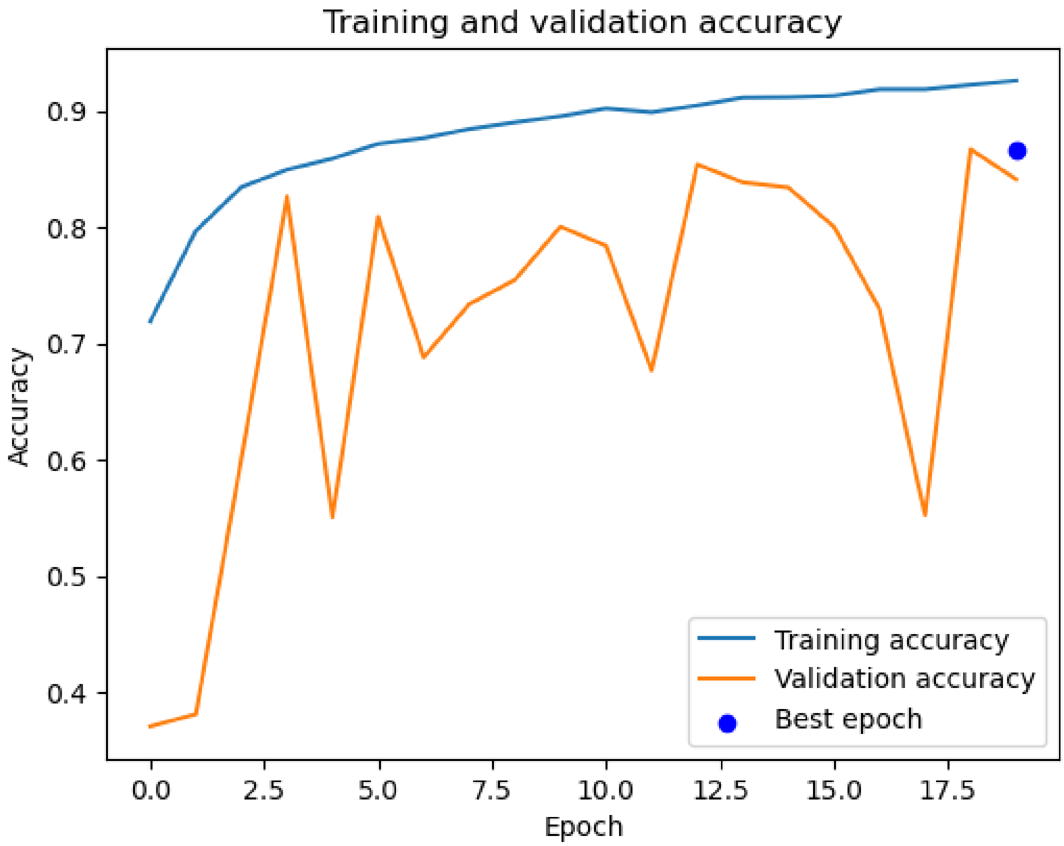
```
2023-04-04 11:45:06.839091: E
tensorflow/core/grappler/optimizers/meta_optimizer.cc:954] layout failed:
INVALID_ARGUMENT: Size of values 0 does not match size of permutation 4 @ fanin
shape insequential_2/dropout_6/dropout/SelectV2-2-TransposeNHWCToNCHW-
```

```
LayoutOptimizer
163/163 [==============================] - 316s 2s/step - loss: 0.7453 -
accuracy: 0.7189 - val_loss: 2.2702 - val_accuracy: 0.3708
Epoch 2/20
163/163 [==============================] - 270s 2s/step - loss: 0.4912 -
accuracy: 0.7967 - val_loss: 2.5771 - val_accuracy: 0.3812
Epoch 3/20
163/163 [==============================] - 269s 2s/step - loss: 0.4226 -
accuracy: 0.8344 - val_loss: 1.0320 - val_accuracy: 0.6007
Epoch 4/20
163/163 [==============================] - 270s 2s/step - loss: 0.3797 -
accuracy: 0.8493 - val_loss: 0.4429 - val_accuracy: 0.8263
Epoch 5/20
163/163 [==============================] - 269s 2s/step - loss: 0.3628 -
accuracy: 0.8589 - val_loss: 2.9461 - val_accuracy: 0.5506
Epoch 6/20
163/163 [==============================] - 269s 2s/step - loss: 0.3326 -
accuracy: 0.8715 - val_loss: 0.4392 - val_accuracy: 0.8090
Epoch 7/20
163/163 [==============================] - 269s 2s/step - loss: 0.3170 -
accuracy: 0.8765 - val_loss: 0.7618 - val_accuracy: 0.6880
Epoch 8/20
163/163 [==============================] - 268s 2s/step - loss: 0.2983 -
accuracy: 0.8843 - val_loss: 0.6233 - val_accuracy: 0.7338
Epoch 9/20
163/163 [==============================] - 270s 2s/step - loss: 0.2824 -
accuracy: 0.8900 - val_loss: 0.6550 - val_accuracy: 0.7545
Epoch 10/20
163/163 [==============================] - 269s 2s/step - loss: 0.2647 -
accuracy: 0.8952 - val_loss: 0.4826 - val_accuracy: 0.8003
Epoch 11/20
163/163 [==============================] - 272s 2s/step - loss: 0.2571 -
accuracy: 0.9020 - val_loss: 0.6086 - val_accuracy: 0.7839
Epoch 12/20
163/163 [==============================] - 271s 2s/step - loss: 0.2608 -
accuracy: 0.8987 - val_loss: 0.9841 - val_accuracy: 0.6768
Epoch 13/20
163/163 [==============================] - 272s 2s/step - loss: 0.2475 -
accuracy: 0.9046 - val_loss: 0.3840 - val_accuracy: 0.8539
Epoch 14/20
163/163 [==============================] - 269s 2s/step - loss: 0.2268 -
accuracy: 0.9113 - val_loss: 0.4231 - val_accuracy: 0.8384
Epoch 15/20
163/163 [==============================] - 271s 2s/step - loss: 0.2328 -
accuracy: 0.9117 - val_loss: 0.4407 - val_accuracy: 0.8341
Epoch 16/20
163/163 [==============================] - 271s 2s/step - loss: 0.2241 -
```

```
accuracy: 0.9129 - val_loss: 0.5114 - val_accuracy: 0.8003
Epoch 17/20
163/163 [==============================] - 271s 2s/step - loss: 0.2135 -
accuracy: 0.9185 - val_loss: 0.7444 - val_accuracy: 0.7295
Epoch 18/20
163/163 [==============================] - 272s 2s/step - loss: 0.2050 -
accuracy: 0.9185 - val_loss: 1.8452 - val_accuracy: 0.5523
Epoch 19/20
163/163 [==============================] - 286s 2s/step - loss: 0.2042 -
accuracy: 0.9222 - val_loss: 0.3410 - val_accuracy: 0.8669
Epoch 20/20
163/163 [==============================] - 271s 2s/step - loss: 0.1919 -
accuracy: 0.9259 - val_loss: 0.3747 - val_accuracy: 0.8410
Temps de calcul : 5464.477719783783
```

[42]:
```
plot_loss(history_paquarse4)
```

[43]:
```
plot_accuracy(history_paquarse4)
```



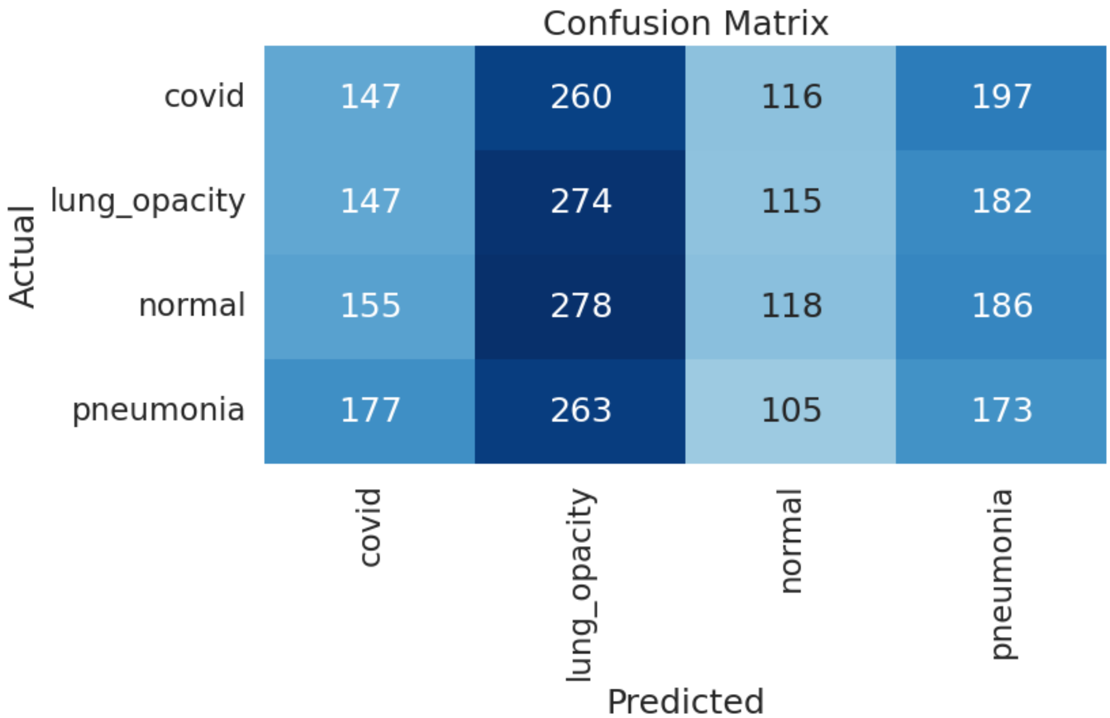
[44]:
```
loss_paquarse4, acc_paquarse4 = model_paquarse4.evaluate(test_set)
print("Test loss: %.5f" % loss_paquarse4)
print("Test accuracy: %.2f%%" % (100.0 * acc_paquarse4))
print("Error rate: %.2f%%" % (100.0 * (1-acc_paquarse4)))
```

```
46/46 [==============================] - 21s 467ms/step - loss: 0.3673 -
accuracy: 0.8483
Test loss: 0.36734
Test accuracy: 84.83%
Error rate: 15.17%
```

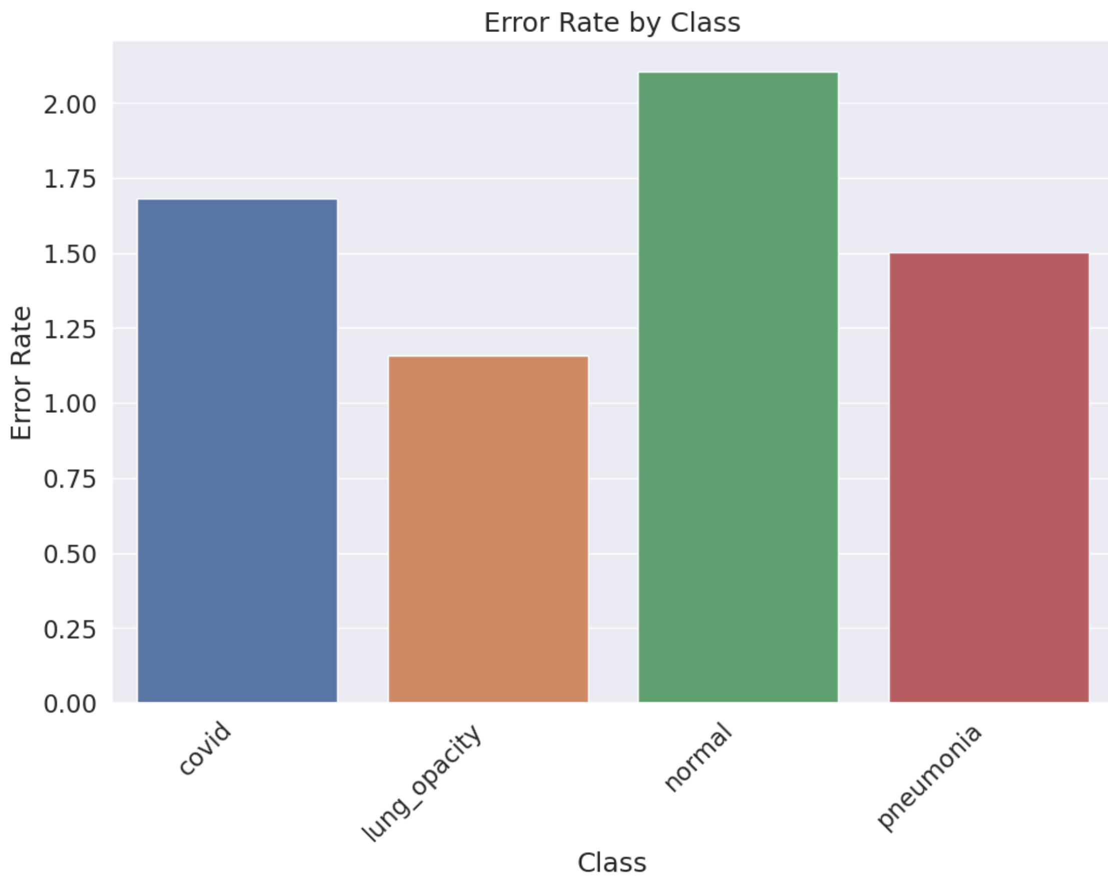
[45]:
```
predict_paquarse4 = model_paquarse4.predict(test_set)
```

```
46/46 [==============================] - 18s 395ms/step
```

[46]:
```
affichage_matrix_confusion(y_true, predict_paquarse4, classes)
```



[47]:
```
afficher_erreur_class(y_true,predict_paquarse4,classes = classes)
```



7.3 Modèle à 6 couches de convolutions et normalisation

[29]:
```
from tensorflow.keras.callbacks import EarlyStopping
```

[38]:
```
model6couches = keras.Sequential(
    [
        keras.Input(shape=input_shape),
        layers.Conv2D(32, kernel_size=(3,3), padding="same"),
        layers.BatchNormalization(),
        layers.Activation("relu"),
        layers.Conv2D(32, kernel_size=(3,3), padding="valid"),
        layers.BatchNormalization(),
        layers.Activation("relu"),
        layers.MaxPooling2D(pool_size=(2,2)),
        layers.Dropout(0.2, seed=235),
        layers.Conv2D(32, kernel_size=(3,3), padding="same"),
        layers.BatchNormalization(),
        layers.Activation("relu"),
        layers.Conv2D(32, kernel_size=(3,3), padding="valid"),
```

```
        layers.BatchNormalization(),
        layers.Activation("relu"),
        layers.MaxPooling2D(pool_size=(2,2)),
        layers.Dropout(0.2, seed=235),
        layers.Conv2D(32, kernel_size=(3,3), padding="same"),
        layers.BatchNormalization(),
        layers.Activation("relu"),
        layers.Conv2D(32, kernel_size=(3,3), padding="valid"),
        layers.BatchNormalization(),
        layers.Activation("relu"),
        layers.MaxPooling2D(pool_size=(2,2)),
        layers.Dropout(0.2, seed=235),
        layers.Flatten(),
        layers.Dropout(0.5, seed=235),
        layers.Dense(32),
        layers.BatchNormalization(),
        layers.Activation("relu"),
        layers.Dropout(0.5, seed=235),
        layers.Dense(512),
        layers.BatchNormalization(),
        layers.Activation("relu"),
        layers.Dense(num_classes, activation="softmax"),
    ]
)

model6couches.summary()
```

```
Model: "sequential_3"

_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 conv2d_12 (Conv2D)          (None, 299, 299, 32)      896       
                                                                 
 batch_normalization_18 (Bat  (None, 299, 299, 32)     128       
 chNormalization)                                                
                                                                 
 activation (Activation)     (None, 299, 299, 32)      0         
                                                                 
 conv2d_13 (Conv2D)          (None, 297, 297, 32)      9248      
                                                                 
 batch_normalization_19 (Bat  (None, 297, 297, 32)     128       
 chNormalization)                                                
                                                                 
 activation_1 (Activation)   (None, 297, 297, 32)      0         
                                                                 
 max_pooling2d_6 (MaxPooling  (None, 148, 148, 32)     0         
 2D)                                                             
```

```
dropout (Dropout)           (None, 148, 148, 32)      0

conv2d_14 (Conv2D)          (None, 148, 148, 32)      9248

batch_normalization_20 (Bat  (None, 148, 148, 32)     128
chNormalization)

activation_2 (Activation)   (None, 148, 148, 32)      0

conv2d_15 (Conv2D)          (None, 146, 146, 32)      9248

batch_normalization_21 (Bat  (None, 146, 146, 32)     128
chNormalization)

activation_3 (Activation)   (None, 146, 146, 32)      0

max_pooling2d_7 (MaxPooling  (None, 73, 73, 32)       0
2D)

dropout_1 (Dropout)         (None, 73, 73, 32)        0

conv2d_16 (Conv2D)          (None, 73, 73, 32)        9248

batch_normalization_22 (Bat  (None, 73, 73, 32)       128
chNormalization)

activation_4 (Activation)   (None, 73, 73, 32)        0

conv2d_17 (Conv2D)          (None, 71, 71, 32)        9248

batch_normalization_23 (Bat  (None, 71, 71, 32)       128
chNormalization)

activation_5 (Activation)   (None, 71, 71, 32)        0

max_pooling2d_8 (MaxPooling  (None, 35, 35, 32)       0
2D)

dropout_2 (Dropout)         (None, 35, 35, 32)        0

flatten_3 (Flatten)         (None, 39200)             0

dropout_3 (Dropout)         (None, 39200)             0

dense_9 (Dense)             (None, 32)                1254432

batch_normalization_24 (Bat  (None, 32)               128
chNormalization)
```

```
 activation_6 (Activation)    (None, 32)                0

 dropout_4 (Dropout)          (None, 32)                0

 dense_10 (Dense)             (None, 512)               16896

 batch_normalization_25 (Bat  (None, 512)               2048
 chNormalization)

 activation_7 (Activation)    (None, 512)               0

 dense_11 (Dense)             (None, 4)                 2052

=================================================================
Total params: 1,323,460
Trainable params: 1,321,988
Non-trainable params: 1,472
_________________________________________________________________
```

[40]:

```
model6couches.compile(loss="categorical_crossentropy", optimizer="adam",␣
 ↪metrics=["accuracy"])
es = EarlyStopping(monitor='val_accuracy', mode='max', patience=10, ␣
 ↪restore_best_weights=True)
```

[41]:

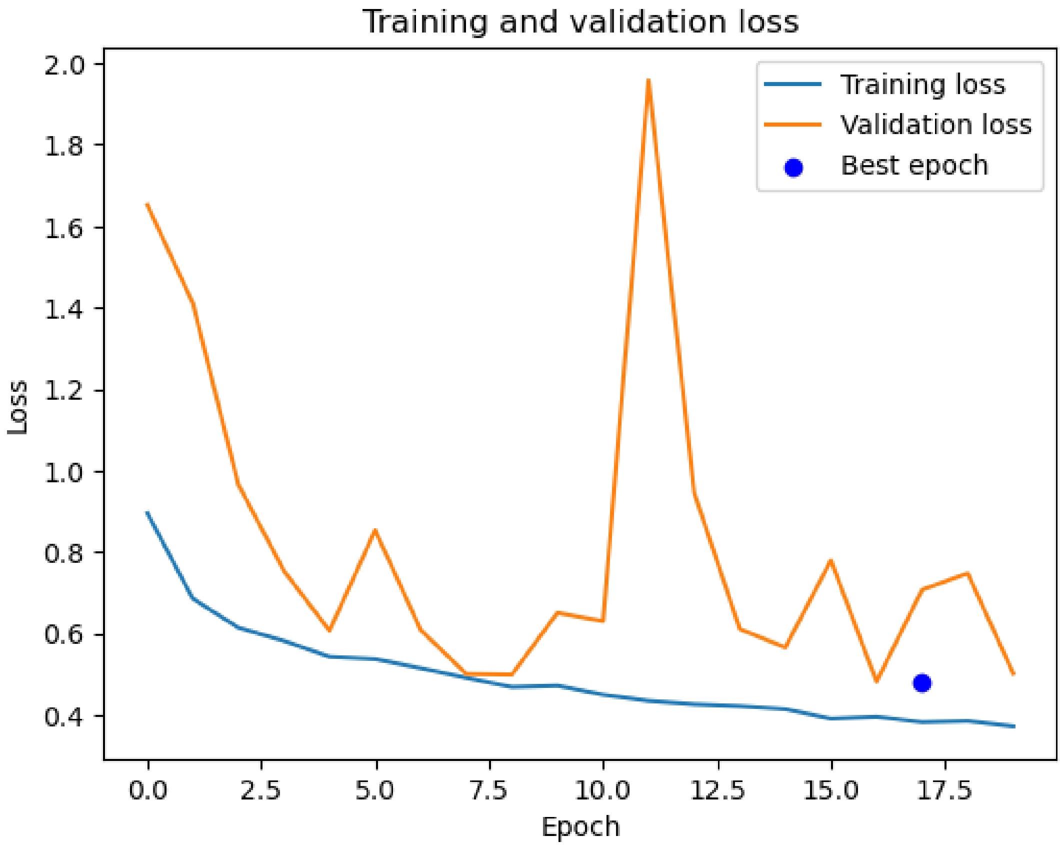
```
start_time = time.time()
history_paquarse5 = model6couches.
 ↪fit(train_set,validation_data=valid_set,batch_size=64,epochs=20,␣
 ↪callbacks=[es])
print("Temps de calcul :", time.time() - start_time)
```

```
Epoch 1/20

2023-04-05 07:43:25.747958: E
tensorflow/core/grappler/optimizers/meta_optimizer.cc:954] layout failed:
INVALID_ARGUMENT: Size of values 0 does not match size of permutation 4 @ fanin
shape insequential_3/dropout/dropout/SelectV2-2-TransposeNHWCToNCHW-
LayoutOptimizer

163/163 [==============================] - 353s 2s/step - loss: 0.8952 -
accuracy: 0.6072 - val_loss: 1.6524 - val_accuracy: 0.2550
Epoch 2/20
163/163 [==============================] - 288s 2s/step - loss: 0.6849 -
accuracy: 0.6982 - val_loss: 1.4111 - val_accuracy: 0.4192
Epoch 3/20
163/163 [==============================] - 284s 2s/step - loss: 0.6136 -
accuracy: 0.7349 - val_loss: 0.9649 - val_accuracy: 0.6266
Epoch 4/20
163/163 [==============================] - 283s 2s/step - loss: 0.5812 -
```

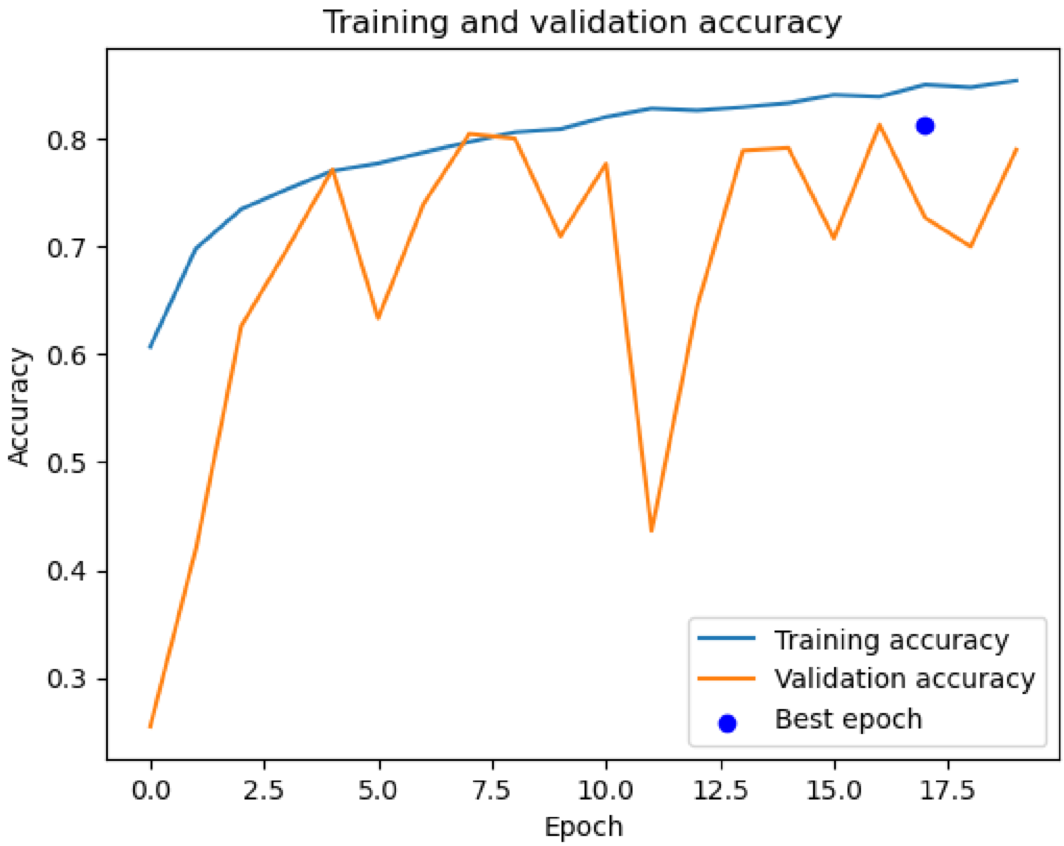
```
accuracy: 0.7533 - val_loss: 0.7531 - val_accuracy: 0.6975
Epoch 5/20
163/163 [==============================] - 285s 2s/step - loss: 0.5423 -
accuracy: 0.7703 - val_loss: 0.6061 - val_accuracy: 0.7718
Epoch 6/20
163/163 [==============================] - 291s 2s/step - loss: 0.5367 -
accuracy: 0.7773 - val_loss: 0.8530 - val_accuracy: 0.6335
Epoch 7/20
163/163 [==============================] - 284s 2s/step - loss: 0.5142 -
accuracy: 0.7875 - val_loss: 0.6079 - val_accuracy: 0.7398
Epoch 8/20
163/163 [==============================] - 281s 2s/step - loss: 0.4906 -
accuracy: 0.7972 - val_loss: 0.5000 - val_accuracy: 0.8047
Epoch 9/20
163/163 [==============================] - 283s 2s/step - loss: 0.4679 -
accuracy: 0.8062 - val_loss: 0.4984 - val_accuracy: 0.8003
Epoch 10/20
163/163 [==============================] - 281s 2s/step - loss: 0.4712 -
accuracy: 0.8092 - val_loss: 0.6501 - val_accuracy: 0.7096
Epoch 11/20
163/163 [==============================] - 283s 2s/step - loss: 0.4489 -
accuracy: 0.8203 - val_loss: 0.6295 - val_accuracy: 0.7770
Epoch 12/20
163/163 [==============================] - 282s 2s/step - loss: 0.4340 -
accuracy: 0.8282 - val_loss: 1.9585 - val_accuracy: 0.4365
Epoch 13/20
163/163 [==============================] - 280s 2s/step - loss: 0.4257 -
accuracy: 0.8264 - val_loss: 0.9453 - val_accuracy: 0.6448
Epoch 14/20
163/163 [==============================] - 281s 2s/step - loss: 0.4210 -
accuracy: 0.8295 - val_loss: 0.6102 - val_accuracy: 0.7891
Epoch 15/20
163/163 [==============================] - 281s 2s/step - loss: 0.4138 -
accuracy: 0.8333 - val_loss: 0.5650 - val_accuracy: 0.7917
Epoch 16/20
163/163 [==============================] - 283s 2s/step - loss: 0.3902 -
accuracy: 0.8409 - val_loss: 0.7790 - val_accuracy: 0.7079
Epoch 17/20
163/163 [==============================] - 281s 2s/step - loss: 0.3949 -
accuracy: 0.8393 - val_loss: 0.4808 - val_accuracy: 0.8133
Epoch 18/20
163/163 [==============================] - 285s 2s/step - loss: 0.3817 -
accuracy: 0.8502 - val_loss: 0.7068 - val_accuracy: 0.7269
Epoch 19/20
163/163 [==============================] - 284s 2s/step - loss: 0.3845 -
accuracy: 0.8478 - val_loss: 0.7472 - val_accuracy: 0.7001
Epoch 20/20
163/163 [==============================] - 282s 2s/step - loss: 0.3714 -
```

```
accuracy: 0.8540 - val_loss: 0.5012 - val_accuracy: 0.7900
Temps de calcul : 5777.9525327682495
```

[43]:
```
plot_loss(history_paquarse5)
```



[44]:
```
plot_accuracy(history_paquarse5)
```



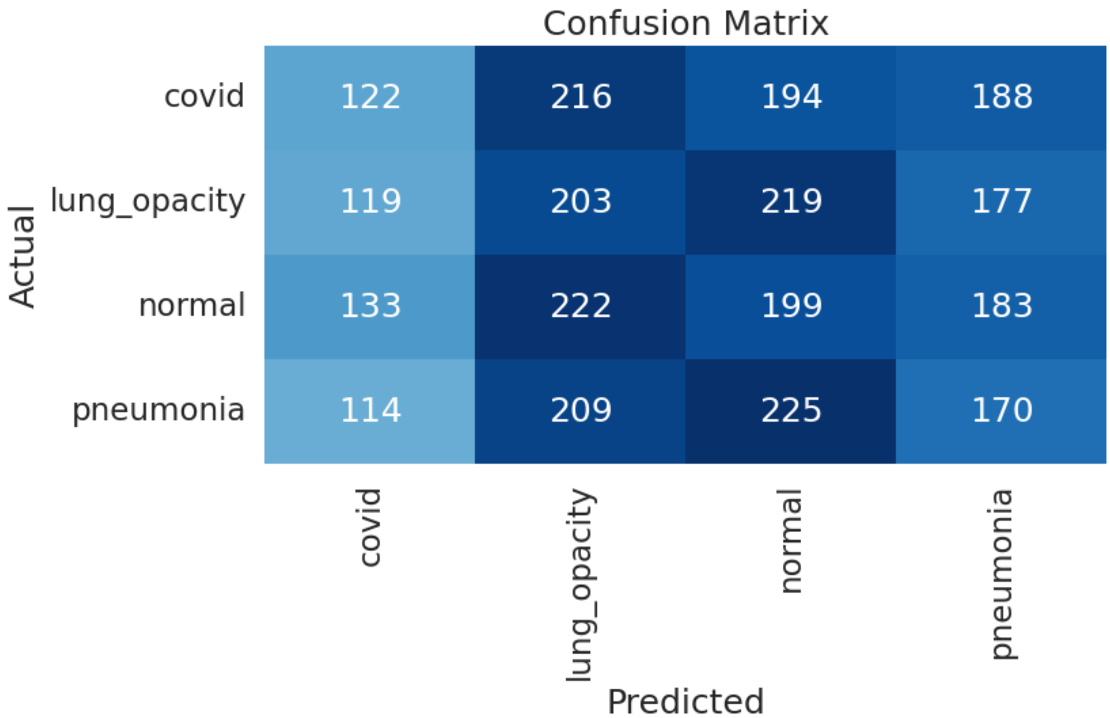
[46]:
```
loss_paquarse6, acc_paquarse6 = model6couches.evaluate(test_set)
print("Test loss: %.5f" % loss_paquarse6)
print("Test accuracy: %.2f%%" % (100.0 * acc_paquarse6))
print("Error rate: %.2f%%" % (100.0 * (1-acc_paquarse6)))
```

```
46/46 [==============================] - 20s 444ms/step - loss: 0.4032 -
accuracy: 0.8438
Test loss: 0.40322
Test accuracy: 84.38%
Error rate: 15.62%
```

[47]:
```
predict_paquarse6 = model6couches.predict(test_set)
```

```
46/46 [==============================] - 20s 422ms/step
```

[48]:
```
affichage_matrix_confusion(y_true, predict_paquarse6, classes)
```



[ ]:
```
afficher_erreur_class(y_true,predict_paquarse6,classes = classes)
```