X-ray image classification based on Pneumonia Positive or Negative (Clean/Unbalanced data)

```
import tensorflow as tf
import numpy as np
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from google.colab import drive
drive.mount('/content/drive')
     Mounted at /content/drive
# Loading training dataset
training_dir="/content/drive/My Drive/problem2/Training"
training generator=ImageDataGenerator(rescale=1/255,featurewise center=False,
        rotation range = 30,
        zoom range = 0.2,
        width shift range=0.1,
        height shift range=0.1,
        horizontal flip = False,
        vertical flip=False)
train generator=training generator.flow from directory(training dir,target size=(200,200),batch size=4,class mode='binary')
     Found 400 images belonging to 2 classes.
# Loading validation dataset
validation_dir="/content/drive/My Drive/problem2/Validation"
validation generator=ImageDataGenerator(rescale=1/255)
val generator=validation generator.flow from directory(validation dir,target size=(200,200),batch size=4,class mode='binary'
     Found 16 images belonging to 2 classes.
# Loading test dataset
test_dir="/content/drive/My Drive/problem2/Testing"
test generator=ImageDataGenerator(rescale=1/255)
```

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test generator=test generator.tiow trom directory(test dir,target Size=(200,200),batch Size=16,Class mode= binary )
     Found 60 images belonging to 2 classes.
# Training the model
model=tf.keras.Sequential([
   tf.keras.layers.Conv2D(32,(3,3),input_shape=(200,200,3),activation='relu'),
   tf.keras.layers.MaxPooling2D(2,2),
   tf.keras.layers.Conv2D(64,(3,3),activation='relu'),
   tf.keras.layers.MaxPooling2D(2,2),
   tf.keras.layers.Dropout(0.2),
   tf.keras.layers.Conv2D(128,(3,3),activation='relu'),
   tf.keras.layers.MaxPooling2D(2,2),
   tf.keras.layers.Dropout(0.2),
   tf.keras.layers.Conv2D(256,(3,3),activation='relu'),
   tf.keras.layers.MaxPooling2D(2,2),
    tf.keras.layers.Flatten(),
   tf.keras.layers.Dropout(0.2),
   tf.keras.layers.Dense(256,activation='relu'),
   tf.keras.layers.Dense(1,activation='sigmoid')
])
# Minimize the loss usign optimizers
model.compile(optimizer=tf.keras.optimizers.Adam(lr=0.001),loss='binary crossentropy',metrics=['acc'])
model.summary()
    Model: "sequential"
                                 Output Shape
     Layer (type)
                                                          Param #
     ______
     conv2d (Conv2D)
                                 (None, 198, 198, 32)
                                                          896
     max pooling2d (MaxPooling2D) (None, 99, 99, 32)
                                                          0
```

conv2d_1 (Conv2D)	(None,	97, 97,	64)	18496	
<pre>max_pooling2d_1 (MaxPooling2</pre>	(None,	48, 48,	64)	0	
dropout (Dropout)	(None,	48, 48,	64)	0	
conv2d_2 (Conv2D)	(None,	46, 46,	128)	73856	
max_pooling2d_2 (MaxPooling2	(None,	23, 23,	128)	0	
dropout_1 (Dropout)	(None,	23, 23,	128)	0	
conv2d_3 (Conv2D)	(None,	21, 21,	256)	295168	
max_pooling2d_3 (MaxPooling2	(None,	10, 10,	256)	0	
flatten (Flatten)	(None,	25600)		0	
dropout_2 (Dropout)	(None,	25600)		0	
dense (Dense)	(None,	256)		6553856	
dense_1 (Dense)	(None,	1)		257	
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Total params: 6,942,529 Trainable params: 6,942,529 Non-trainable params: 0

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Epoch 5/		70	э тотшэ/эсср	1033.	0.5505	acc.	0.00/3	var_1033.	0.5100	va1_acc.
	[=========]	- 48	s 484ms/step	- loss:	0.4788	- acc:	0.7950 -	val loss:	0.6176 -	val acc:
Epoch 6/								_		_
100/100	[=========]	- 48	s 479ms/step	- loss:	0.3606	- acc:	0.8150 -	val_loss:	0.5512 -	val_acc:
Epoch 7/	30									
100/100	[========]	- 49	s 490ms/step	- loss:	0.3583	- acc:	0.8350 -	val_loss:	0.4569 -	val_acc:
Epoch 8/										
	[=======]	- 49	s 491ms/step	- loss:	0.3457	- acc:	0.8400 -	val_loss:	0.4835 -	val_acc:
Epoch 9/										
	[=======]	- 49	s 488ms/step	- loss:	0.5854	- acc:	0.8600 -	val_loss:	1.3036 -	val_acc:
Epoch 10										
	[==========]	- 48	s 480ms/step	- loss:	0.5035	- acc:	0.7975 -	val_loss:	0.5920 -	val_acc:
Epoch 11		40	- 477m - / - t - u	1	0 4110		0 0075		0 (22)	
Epoch 12	[=========]	- 48	s 4//ms/step	- 1055:	0.4118	- acc:	0.80/5 -	vai_ioss:	0.6336 -	vai_acc:
	/ 50 [=========]	_ /10	c 191mc/c+on	1055	0 3580	- 200:	0 8350	val loss:	0 6477 -	val acc:
Epoch 13	-	- 40	5 401m3/3tep	- 1055.	0.550	- acc.	0.0330 -	va1_1033.	0.04// -	vai_acc.
	,	- 48	s 480ms/ster	- loss:	0.3795	- acc.	0.8400 -	val loss:	0.6371 -	val acc:
Epoch 14	-	-10	3 400m3/3ccp	1033.	0.3733	acc.	0.0100	vu1_1033.	0.0371	var_acc.
	,	- 49	s 488ms/ster	- loss:	0.3253	- acc:	0.8500 -	val loss:	0.5674 -	val acc:
Epoch 15	-		,							
	[=========]	- 49	s 494ms/step	- loss:	0.3139	- acc:	0.8725 -	val_loss:	0.6613 -	val_acc:
Epoch 16			·					_		_
100/100	[=========]	- 47	s 474ms/step	- loss:	0.3283	- acc:	0.8600 -	val_loss:	0.7091 -	val_acc:
Epoch 17										
	[=========]	- 48	s 475ms/step	- loss:	0.3220	- acc:	0.8400 -	val_loss:	0.6331 -	val_acc:
Epoch 18										
	[=========]	- 48	s 476ms/step	- loss:	0.3215	- acc:	0.8550 -	val_loss:	0.5974 -	val_acc:
Epoch 19		40	477 / 1	,	0 2202		0.0605		0 6300	,
	[=========]	- 48	s 4//ms/step	- 1055:	0.3292	- acc:	0.8625 -	var_ross:	0.6389 -	vai_acc:
Epoch 20	/ 30 [=========]	40	c 197mc/c+on	1000	0 2010	266.	0 0575	val locci	0 6750	val acc:
Epoch 21	-	- 49	5 40/1113/3CEP	- 1055.	0.3019	- acc.	0.03/3 -	va1_1033.	0.0738 -	vai_acc.
	, 50 [=========]	- 48	s 484ms/ster	- loss:	0.3103	- acc.	0.8700 -	val loss:	0.6284 -	val acc:
Epoch 22	-		3 10 ms, 3 ccp	1033.	0.5205		0.0700		0.020.	var_acc.
•	[=========]	- 50	s 497ms/step	- loss:	0.2936	- acc:	0.8700 -	val loss:	0.6036 -	val acc:
Epoch 23	-		,,							
	[========]	- 47	s 474ms/step	- loss:	0.2674	- acc:	0.8725 -	val_loss:	0.5718 -	val_acc:
Epoch 24	/30							_		
100/100	[========]	- 48	s 476ms/step	- loss:	0.3026	- acc:	0.8800 -	val_loss:	0.5466 -	val_acc:
Epoch 25										
100/100	[========]	- 47	s 475ms/step	- loss:	0.2841	- acc:	0.8850 -	<pre>val_loss:</pre>	0.5577 -	val_acc:
F 26	/20									

```
# Plotting histographic graph for Training and Validation Accuracy
%matplotlib inline
import matplotlib.pyplot as plt
acc = history.history['acc']
val_acc = history.history['val_acc']
loss = history.history['loss']
val_loss = history.history['val_loss']

epochs = range(len(acc))

plt.plot(epochs, acc, 'r', label='Training accuracy')
plt.plot(epochs, val_acc, 'b', label='Validation accuracy')
plt.title('Training and validation accuracy')
plt.legend(loc=0)
plt.figure()
```

```
<Figure size 432x288 with 0 Axes>
               Training and validation accuracy
     va 1
# Finding Loss and Accuracy of the model
print("Loss of the model is - " , model.evaluate(test generator)[0]*100 , "%")
print("Accuracy of the model is - " , model.evaluate(test generator)[1]*100 , "%")
    Loss of the model is - 116.21673107147217 %
    Accuracy of the model is - 55.000001192092896 %
                  17
     054
predicted_classes=model.predict_classes(test_generator)
         0
               5
                    10
                          15
                                 20
                                      25
                                             30
# Confusion matrix in order to number of correct and wrond prediction
from sklearn.metrics import classification report, confusion matrix
print(confusion matrix(test generator.classes,predicted classes))
    [[ 6 24]
     [ 1 29]]
# Finding precision, recall, f1-score
print(classification report(test generator.classes,predicted classes))
                precision
                            recall f1-score
                                            support
              0
                     0.29
                              0.07
                                      0.11
                                                 30
              1
                     0.47
                              0.83
                                      0.60
                                                 30
                                      0.45
                                                 60
        accuracy
       macro avg
                     0.38
                              0.45
                                      0.36
                                                 60
    weighted avg
                     0.38
                              0.45
                                      0.36
                                                 60
```