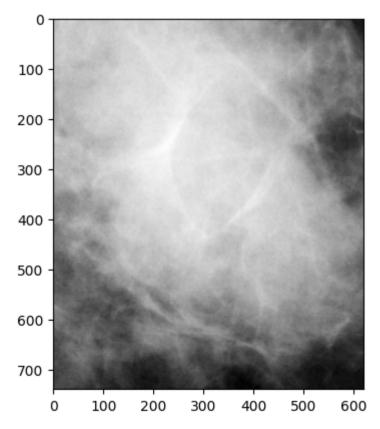
```
In [ ]: import numpy as np
        import matplotlib.pyplot as plt
        import os
        import cv2
        import tensorflow as tf
        import time
        import glob
        import random
        from PIL import Image
        from tensorflow.keras.preprocessing.image import ImageDataGenerator
        from tensorflow.keras.applications.resnet50 import preprocess_input
        from tensorflow.keras.applications.resnet50 import ResNet50
        from tensorflow.keras.models import Sequential
        from tensorflow.keras.layers import Dense, Flatten, GlobalAveragePooling2D,Dropout
        from tensorflow.keras.callbacks import TensorBoard
        from tensorflow.keras.optimizers import Adam
        from keras.preprocessing import image
        import time
        import pandas as pd
        from tensorflow.keras.optimizers import Adam
        NAME = "Tcc_cnn_64_{{}}".format(int(time.time()))
In [ ]: print(tf.config.list_physical_devices('GPU'))
        print("Num GPUs Available: ", len(tf.config.list_physical_devices('GPU')))
        if tf.test.gpu_device_name():
            print('Default GPU Device: {}'.format(tf.test.gpu_device_name()))
        else:
            print("Please install GPU version of TF")
        print(tf.test.is_built_with_cuda())
       [PhysicalDevice(name='/physical_device:GPU:0', device_type='GPU')]
       Num GPUs Available: 1
       Default GPU Device: /device:GPU:0
       True
```

Carregando arquivos

```
In [ ]: all_traning_paths = glob.glob('DATASETS/Training-Mass/*/*.jpg')
        all_val_paths = glob.glob('DATASETS/Validation-Mass/*/*.jpg')
In [ ]: img_path=random.choice(all_traning_paths)
        cropped_img = Image.open(img_path)
        gray = cropped_img.convert('L')
        median =cv2.blur(np.array(gray), (3, 3))
        print(img_path)
        plt.imshow(median, cmap='gray')
```

DATASETS/Training-Mass\WITH CANCER\1-236.jpg Out[]: <matplotlib.image.AxesImage at 0x23c24ed4b50>



Criando datagens

```
In [ ]: datagen_resnet = ImageDataGenerator(preprocessing_function=preprocess_input)
        train_gen = datagen_resnet.flow_from_directory('DATASETS/Training-Mass/',
                                    target_size=(224,224),
                                    class_mode="categorical",
                                    batch_size=16
        validation_gen = datagen_resnet.flow_from_directory('DATASETS/Validation-Mass/',
                                    target_size=(224,224),
                                    class_mode="categorical",
                                    batch_size=16
        test_gen = datagen_resnet.flow_from_directory('DATASETS/Testing-Mass/',
                                    target_size=(224,224),
                                    class_mode="categorical",
                                    batch_size=16,
       Found 945 images belonging to 2 classes.
       Found 146 images belonging to 2 classes.
       Found 464 images belonging to 2 classes.
In [ ]: base_model=ResNet50(include_top=False,
                            input_shape=(224,224,3)
        for layer in base_model.layers: # 'Passo para eu não retreinar as camadas do RESNET
            layer.trainable=False
            tensorBoard = TensorBoard(log_dir='logs/{}'.format(NAME))
        Modelo inicial
In [ ]: modelo = Sequential([ base_model,
                             GlobalAveragePooling2D(),
                             Dense(128, activation='relu'),
                             Dropout(0.2),
```

```
Dense(2, activation='Softmax')
])
modelo.summary() ## me
```

Model: "sequential"

```
Layer (type)
                        Output Shape
                                              Param #
______
resnet50 (Functional)
                        (None, 7, 7, 2048)
                                              23587712
global_average_pooling2d (G (None, 2048)
lobalAveragePooling2D)
dense (Dense)
                        (None, 128)
                                              262272
dropout (Dropout)
                        (None, 128)
                        (None, 2)
dense_1 (Dense)
                                               258
Total params: 23,850,242
Trainable params: 262,530
Non-trainable params: 23,587,712
```

```
In [ ]: modelo.compile(optimizer=Adam(learning_rate=1e-4),
                       loss='categorical_crossentropy',
                       metrics=['accuracy']
        history = modelo.fit(train_gen,
                   validation_data=validation_gen,
                   epochs=10,
                   batch_size=16,
                   callbacks=[tensorBoard]
```

```
Epoch 1/10
890
Epoch 2/10
Epoch 3/10
Epoch 4/10
  60/60 [====
Epoch 5/10
12
Epoch 6/10
81
Epoch 7/10
Epoch 8/10
   =========] - 3s 44ms/step - loss: 0.4906 - accuracy: 0.7619 - val_loss: 0.5917 - val_accuracy: 0.67
60/60 [====
Epoch 9/10
Epoch 10/10
```

In []: pd.DataFrame(history.history)

Out[]: loss accuracy val_loss val_accuracy

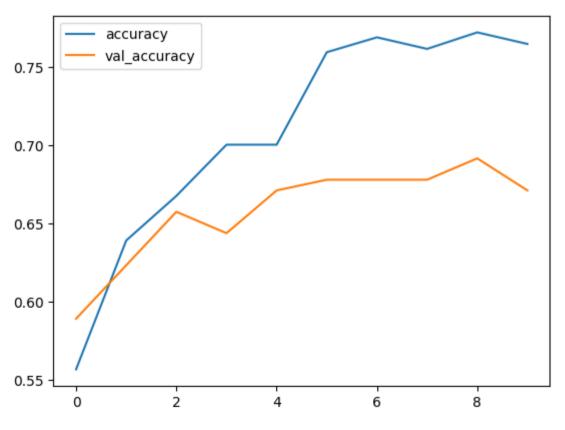
0	0.753492	0.556614	0.685075	0.589041
1	0.644023	0.639153	0.675698	0.623288
2	0.604379	0.667725	0.640057	0.657534
3	0.562373	0.700529	0.640370	0.643836
4	0.558892	0.700529	0.615067	0.671233
5	0.514859	0.759788	0.611495	0.678082
6	0.505593	0.769312	0.610784	0.678082
7	0.490554	0.761905	0.591738	0.678082
8	0.468376	0.772487	0.593174	0.691781
9	0.470836	0.765079	0.591003	0.671233

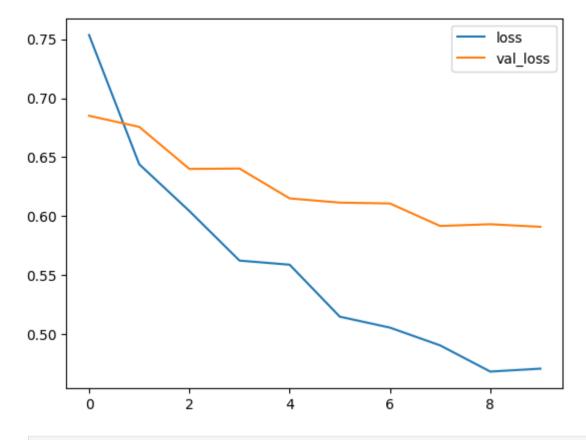
```
In [ ]: df = pd.DataFrame(history.history)

df[['accuracy', 'val_accuracy']].plot()

df[['loss', 'val_loss']].plot()
```

Out[]: <Axes: >





In []:

Modelo 2 Aumentando as camadas

Model: "sequential_1"

```
Output Shape
                                                        Param #
Layer (type)
resnet50 (Functional)
                             (None, 7, 7, 2048)
                                                        23587712
 global_average_pooling2d_1
                              (None, 2048)
 (GlobalAveragePooling2D)
dense_2 (Dense)
                             (None, 128)
                                                        262272
dropout_1 (Dropout)
                             (None, 128)
 dense_3 (Dense)
                             (None, 2)
                                                        258
Total params: 23,850,242
Trainable params: 262,530
```

Non-trainable params: 23,587,712

```
Epoch 1/15
33
Epoch 2/15
Epoch 3/15
Epoch 4/15
60/60 [==
     ==================] - 3s 42ms/step - loss: 0.5691 - accuracy: 0.6952 - val_loss: 0.6365 - val_accuracy: 0.59
Epoch 5/15
       =========] - 3s 43ms/step - loss: 0.5244 - accuracy: 0.7418 - val_loss: 0.6501 - val_accuracy: 0.58
60/60 [===
Epoch 6/15
07
Epoch 7/15
60/60 [======
      =============] - 3s 44ms/step - loss: 0.5159 - accuracy: 0.7302 - val_loss: 0.6465 - val_accuracy: 0.60
Epoch 8/15
60/60 [===:
     ==================] - 3s 44ms/step - loss: 0.4857 - accuracy: 0.7481 - val_loss: 0.6324 - val_accuracy: 0.60
Epoch 9/15
60/60 [====
   Epoch 10/15
70
Epoch 11/15
33
Epoch 12/15
Epoch 13/15
60/60 [======
     Epoch 14/15
Epoch 15/15
75
```

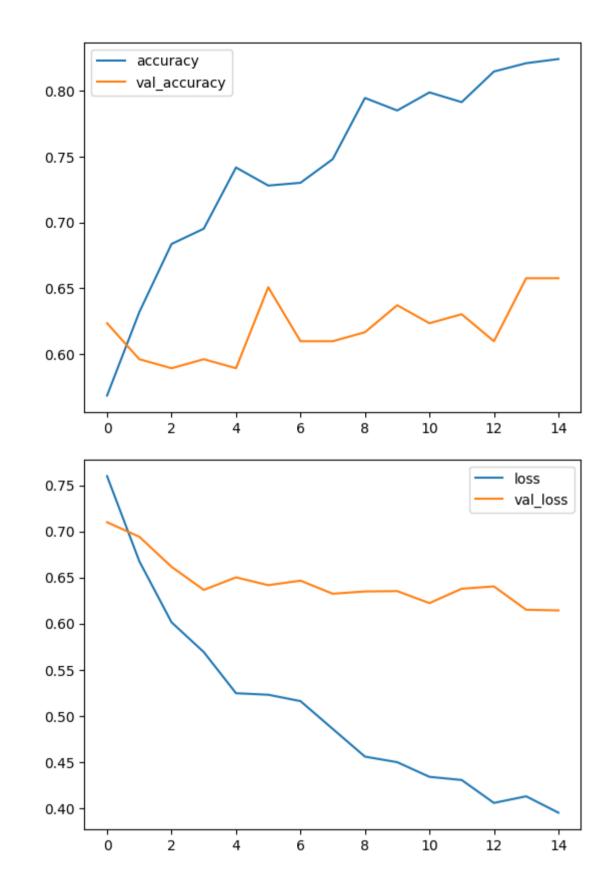
In []: pd.DataFrame(history.history)

Out[]: loss accuracy val_loss val_accuracy

```
0 0.759903 0.568254 0.709909
                                   0.623288
 1 0.667656 0.631746 0.694188
                                   0.595890
 2 0.601387 0.683598 0.661586
                                   0.589041
 3 0.569085 0.695238 0.636529
                                   0.595890
 4 0.524445 0.741799 0.650144
                                   0.589041
 5 0.522804 0.728042 0.641632
                                   0.650685
 6 0.515900 0.730159 0.646549
                                    0.609589
 7 0.485738 0.748148 0.632361
                                    0.609589
 8 0.455683 0.794709 0.634818
                                   0.616438
 9 0.449658 0.785185 0.635210
                                    0.636986
10 0.433755 0.798942 0.622208
                                    0.623288
11 0.430352 0.791534 0.637779
                                    0.630137
                                    0.609589
12 0.405475 0.814815 0.640306
13 0.412644 0.821164 0.615006
                                   0.657534
14 0.394876 0.824339 0.614274
                                   0.657534
```

```
In [ ]: df = pd.DataFrame(history.history)

df[['accuracy', 'val_accuracy']].plot()
df[['loss', 'val_loss']].plot()
```



Modelo 3 ADICIONANDO MAIS UMA CADMADA DENSE E UMA DE DROPOUT

Output Shape

Param #

Layer (type)

In [

	:=============		
resnet50 (Functional)	(None, 7, 7, 2048)	23587712	
<pre>global_average_pooling2d_2 (GlobalAveragePooling2D)</pre>	(None, 2048)	0	
dense_4 (Dense)	(None, 128)	262272	
dropout_2 (Dropout)	(None, 128)	0	
dense_5 (Dense)	(None, 64)	8256	
dropout_3 (Dropout)	(None, 64)	0	
dense_6 (Dense)	(None, 2)	130	
Total params: 23,858,370 Trainable params: 270,658 Non-trainable params: 23,587		:=====================================	
<pre>modelo3.compile(optimizer=/</pre>	orical_crossentropy', ccuracy'] in_gen, =validation_gen,		
/ Faceb 1/15			
-	======] - 5s 54ms/step	o - loss: 0.7300 - accuracy: 0.5608 - val_loss: 0.6764 - val_accura	acy: 0.56
85 Epoch 2/15] 2- 42m-/-h-m		0 50
90	=======] - 3s 43ms/step	o - loss: 0.6484 - accuracy: 0.6254 - val_loss: 0.6762 - val_accura	acy: 0.58
_	======] - 3s 43ms/step	o - loss: 0.6380 - accuracy: 0.6508 - val_loss: 0.6578 - val_accura	эсу: 0.62
33 Epoch 4/15] 25 42ms/ston	o - loss: 0.6046 - accuracy: 0.6783 - val_loss: 0.6514 - val_accura	
75 Epoch 5/15	:======] - 35 43Ш5/5Сер	7 - 1055. 0.0040 - accuracy. 0.0705 - Val_1055. 0.0514 - Val_accura	acy. 0.03
•	=======] - 3s 43ms/step	o - loss: 0.5811 - accuracy: 0.6804 - val_loss: 0.6437 - val_accura	эсу: 0.66
Epoch 6/15	:=======] - 3s 43ms/sten	o - loss: 0.5639 - accuracy: 0.7090 - val_loss: 0.6384 - val_accura	acv: 0.62
33 Epoch 7/15] 33 .33,3 сер	, 10331 013035	
·	======] - 3s 44ms/step	o - loss: 0.5478 - accuracy: 0.7344 - val_loss: 0.6268 - val_accura	acy: 0.67
Epoch 8/15	:=======] - 3s 45ms/step	o - loss: 0.5150 - accuracy: 0.7439 - val_loss: 0.6172 - val_accura	acv: 0.68
49 Epoch 9/15	,,		,
•	=======] - 3s 45ms/step	o - loss: 0.5116 - accuracy: 0.7280 - val_loss: 0.6204 - val_accura	acy: 0.67
Epoch 10/15	:=======] - 3s 45ms/step	o - loss: 0.5142 - accuracy: 0.7397 - val_loss: 0.6311 - val_accura	acv: 0.6
07 Epoch 11/15	,,,		,.
•	======] - 3s 45ms/step	o - loss: 0.4959 - accuracy: 0.7492 - val_loss: 0.6150 - val_accura	acy: 0.66
Epoch 12/15		o - loss: 0.4790 - accuracy: 0.7661 - val_loss: 0.6538 - val_accura	acv: 0 60
96		7 - 1033. 0.4790 - accuracy. 0.7001 - Val_1033. 0.0936 - Val_accura	1cy. 0.06
	======] - 3s 45ms/step	o - loss: 0.4509 - accuracy: 0.7778 - val_loss: 0.6170 - val_accura	acy: 0.66
44 Epoch 14/15 60/60 [====================================	:=======] - 3c 16mc/ctan	o - loss: 0.4525 - accuracy: 0.7915 - val_loss: 0.6138 - val_accura	acv: 0 66
44 Epoch 15/15	ј 55 чошој эсер	wat_accura	-,. 0.00
•	=======] - 3s 46ms/step	o - loss: 0.4497 - accuracy: 0.7788 - val_loss: 0.6489 - val_accura	acy: 0.61
64			

```
Out[ ]:
                loss accuracy val_loss val_accuracy
                                           0.568493
          0 0.730000 0.560847 0.676440
          1 0.648435 0.625397 0.676223
                                           0.589041
          2 0.638014 0.650794 0.657828
                                           0.623288
                                           0.657534
          3 0.604642 0.678307 0.651429
          4 0.581074 0.680423 0.643710
                                           0.664384
          5 0.563901 0.708995 0.638448
                                           0.623288
          6 0.547844 0.734392 0.626763
                                           0.671233
          7 0.515010 0.743915 0.617181
                                           0.684932
          8 0.511602 0.728042 0.620384
                                           0.671233
          9 0.514208 0.739683 0.631126
                                           0.650685
         10 0.495924 0.749206 0.615044
                                           0.664384
        11 0.478982 0.766138 0.653758
                                           0.609589
         12 0.450874 0.777778 0.616974
                                           0.664384
         13 0.452535 0.791534 0.613810
                                           0.664384
         14 0.449691 0.778836 0.648917
                                           0.616438
In [ ]: df = pd.DataFrame(history3.history)
        df[['accuracy', 'val_accuracy']].plot()
        df[['loss', 'val_loss']].plot()
Out[]: <Axes: >
        0.80
                    accuracy
                    val_accuracy
        0.75
        0.70
        0.65
        0.60
        0.55
                        2
                                  4
                                           6
                                                    8
                                                            10
                                                                     12
                                                                               14
                                                                         loss
                                                                         val_loss
        0.70
       0.65
       0.60
       0.55
       0.50
        0.45
```

10

8

6

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14

Adicionando ao modelo 3 mais uma dense e de dropout

```
In [ ]: modelo4 = Sequential([ base_model,
                             GlobalAveragePooling2D(),
                             Dense(128, activation='relu'),
                             Dropout(0.4),
                             Dense(64, activation='relu'),
                             Dropout(0.2),
                             Dense(32, activation='relu'),
                             Dropout(0.2),
                             Dense(2, activation='Softmax')
        ])
        modelo4.summary()
       Model: "sequential_3"
        Layer (type)
                                    Output Shape
                                                              Param #
        resnet50 (Functional)
                                    (None, 7, 7, 2048)
                                                               23587712
        global_average_pooling2d_3
                                     (None, 2048)
        (GlobalAveragePooling2D)
        dense_7 (Dense)
                                    (None, 128)
                                                               262272
        dropout_4 (Dropout)
                                    (None, 128)
        dense_8 (Dense)
                                    (None, 64)
                                                               8256
        dropout_5 (Dropout)
                                    (None, 64)
        dense_9 (Dense)
                                    (None, 32)
                                                               2080
        dropout_6 (Dropout)
                                    (None, 32)
                                    (None, 2)
        dense_10 (Dense)
                                                               66
       Total params: 23,860,386
       Trainable params: 272,674
       Non-trainable params: 23,587,712
In [ ]: modelo4.compile(optimizer=Adam(learning_rate=1e-4),
                       loss='categorical_crossentropy',
                       metrics=['accuracy']
        history3 = modelo4.fit(train_gen,
                   validation_data=validation_gen,
```

epochs=15,
batch_size=16,

callbacks=[tensorBoard]

```
Epoch 1/15
Epoch 2/15
Epoch 3/15
Epoch 4/15
60/60 [==
   Epoch 5/15
    :==========] - 3s 43ms/step - loss: 0.6719 - accuracy: 0.6000 - val_loss: 0.6692 - val_accuracy: 0.55
60/60 [===
Epoch 6/15
96
Epoch 7/15
Epoch 8/15
60/60 [====
  Epoch 9/15
Epoch 10/15
33
Epoch 11/15
Epoch 12/15
Epoch 13/15
60/60 [======
   ==================] - 3s 46ms/step - loss: 0.5871 - accuracy: 0.6741 - val_loss: 0.6276 - val_accuracy: 0.65
Epoch 14/15
Epoch 15/15
75
```

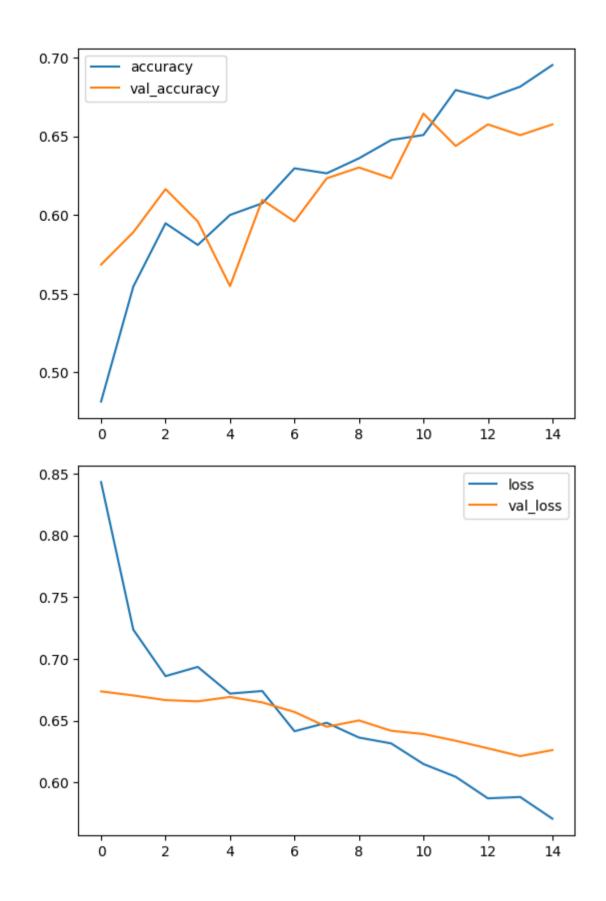
In []: pd.DataFrame(history3.history)

Out[]: loss accuracy val_loss val_accuracy

```
0 0.843121 0.481481 0.673684
                                   0.568493
 1 0.723682 0.554497 0.670413
                                   0.589041
 2 0.686067 0.594709 0.666642
                                   0.616438
 3 0.693518 0.580952 0.665650
                                   0.595890
 4 0.671918 0.600000 0.669199
                                   0.554795
 5 0.673999 0.607407 0.664767
                                   0.609589
                                   0.595890
 6 0.641436 0.629630 0.657030
 7 0.648265 0.626455 0.645025
                                    0.623288
 8 0.636314 0.635979 0.650180
                                   0.630137
 9 0.631558 0.647619 0.641797
                                    0.623288
10 0.614887 0.650794 0.639178
                                    0.664384
11 0.604542 0.679365 0.633729
                                    0.643836
12 0.587087 0.674074 0.627609
                                    0.657534
13 0.588198 0.681481 0.621289
                                   0.650685
14 0.570622 0.695238 0.626174
                                   0.657534
```

```
In [ ]: df = pd.DataFrame(history3.history)

df[['accuracy', 'val_accuracy']].plot()
df[['loss', 'val_loss']].plot()
```

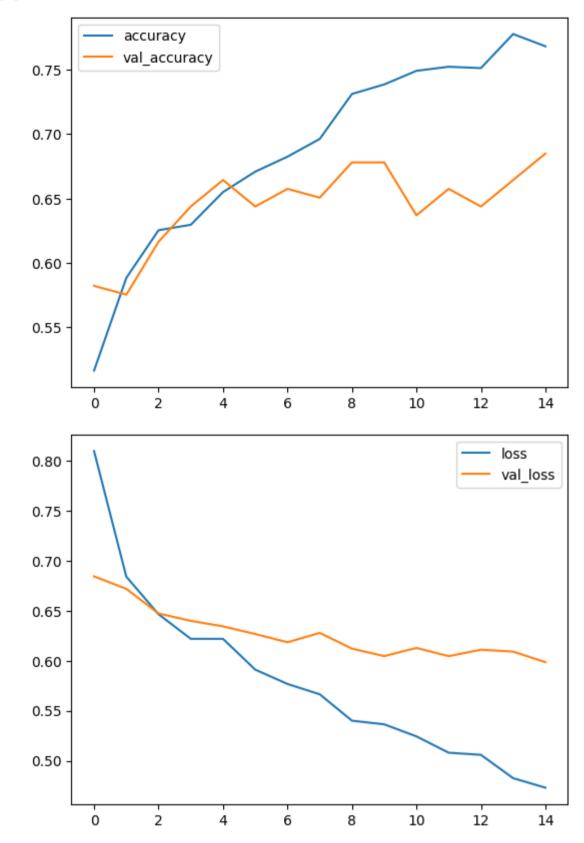


Aumentando o bach size com base no modelo 3

Found 945 images belonging to 2 classes. Found 146 images belonging to 2 classes.

```
Output Shape
   Layer (type)
  ------
   resnet50 (Functional)
             (None, 7, 7, 2048)
                       23587712
   global_average_pooling2d_4
             (None, 2048)
   (GlobalAveragePooling2D)
   dense_11 (Dense)
                       262272
             (None, 128)
   dropout_7 (Dropout)
             (None, 128)
                       0
   dense_12 (Dense)
                       8256
             (None, 64)
   dropout_8 (Dropout)
             (None, 64)
   dense_13 (Dense)
             (None, 2)
                       130
  Total params: 23,858,370
  Trainable params: 270,658
  Non-trainable params: 23,587,712
In [ ]: modelo_op.compile(optimizer=Adam(learning_rate=1e-4),
        loss='categorical_crossentropy',
        metrics=['accuracy']
   history_op = modelo_op.fit(train_gen_32,
       validation_data=validation_gen_32,
       epochs=15,
       batch_size=32,
       callbacks=[tensorBoard]
      )
  Epoch 1/15
  22
  Epoch 2/15
         30/30 [====
  53
  Epoch 3/15
  Epoch 4/15
  38
  Epoch 5/15
  Epoch 6/15
  38
  Epoch 7/15
  75
  Epoch 8/15
  Epoch 9/15
  81
  Epoch 10/15
  30/30 [========================] - 2s 72ms/step - loss: 0.5364 - accuracy: 0.7386 - val_loss: 0.6047 - val_accuracy: 0.67
  Epoch 11/15
  Epoch 12/15
  75
  Epoch 13/15
  Epoch 14/15
  Epoch 15/15
  In [ ]: df = pd.DataFrame(history_op.history)
   df[['accuracy', 'val_accuracy']].plot()
   df[['loss', 'val_loss']].plot()
```

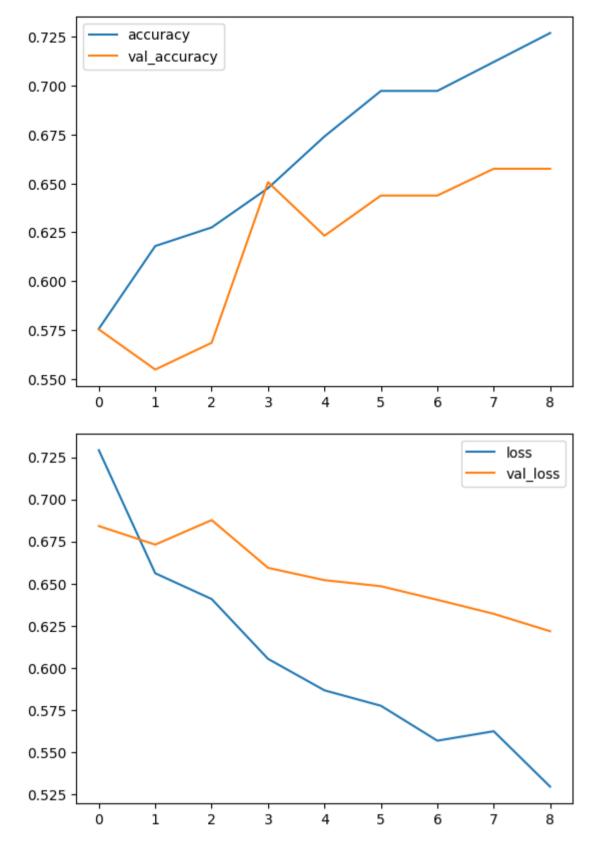
Param #



reduzindo epocas do modelo op de 15 para 9

Out[]: <Axes: >

```
Output Shape
   Layer (type)
                          Param #
   ______
   resnet50 (Functional)
               (None, 7, 7, 2048)
                          23587712
   global_average_pooling2d_5
               (None, 2048)
   (GlobalAveragePooling2D)
   dense_14 (Dense)
               (None, 128)
                          262272
   dropout_9 (Dropout)
               (None, 128)
                          0
   dense_15 (Dense)
                          8256
               (None, 64)
               (None, 64)
   dropout_10 (Dropout)
   dense_16 (Dense)
               (None, 2)
                          130
   Total params: 23,858,370
   Trainable params: 270,658
   Non-trainable params: 23,587,712
In [ ]: modelo_nove.compile(optimizer=Adam(learning_rate=1e-4),
          loss='categorical_crossentropy',
          metrics=['accuracy']
   history_nove = modelo_nove.fit(train_gen_32,
        validation_data=validation_gen_32,
        epochs=9,
        batch_size=32,
        callbacks=[tensorBoard]
       )
   Epoch 1/9
   53
   Epoch 2/9
          Epoch 3/9
   Epoch 4/9
   07
   Epoch 5/9
   Epoch 6/9
   38
   Epoch 7/9
   38
   Epoch 8/9
   75
In [ ]: pd2 = pd.DataFrame(history_nove.history)
   pd2[['accuracy', 'val_accuracy']].plot()
   pd2[['loss', 'val_loss']].plot()
```



```
In [ ]: predictions = modelo4.predict(test_gen, verbose=1)
```

29/29 [======] - 1s 44ms/step

import numpy as np

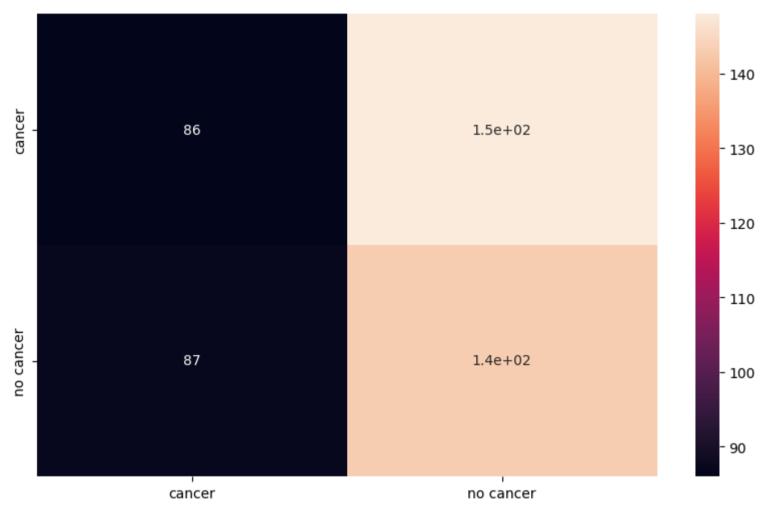
labels = (test_gen.class_indices) res = tf.math.confusion_matrix(labels=test_gen.classes.astype(int), predictions=np.argmax(np.array(predictions).reshape(-1, 2), axis=1))

```
[[ 86 148]
[ 87 143]]
              precision
                            recall f1-score
                                               support
           0
                   0.50
                              0.37
                                        0.42
                                                   234
           1
                   0.49
                              0.62
                                        0.55
                                                   230
   accuracy
                                        0.49
                                                   464
                   0.49
                              0.49
                                        0.49
                                                   464
   macro avg
                   0.49
                                        0.49
                                                   464
weighted avg
                              0.49
```

```
In []: from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
    from sklearn.metrics import confusion_matrix
    import seaborn as sns
    import matplotlib.pyplot as plt
    print(cm)
    index = ['cancer', 'no cancer']
    columns = ['cancer', 'no cancer']
    cm_df = pd.DataFrame(cm,columns,index)
    plt.figure(figsize=(10,6))
    sns.heatmap(cm_df, annot=True)
```

[[86 148] [87 143]]

Out[]: <Axes: >



```
In [ ]: import numpy as np
In [ ]: def predicao(modelo, path):
            image = Image.open(path)
        # Redimensione a imagem
            resized_image = image.resize((224, 224))
            # Certifique-se de que a imagem seja colorida (3 canais)
            if resized_image.mode == 'L':
                # Converta a imagem em escala de cinza em uma imagem RGB (colorida)
                resized_image = resized_image.convert('RGB')
            # Converta a imagem redimensionada em uma matriz NumPy
            np_array = np.array(resized_image)
            img_np = preprocess_input(np_array)
            imp_np2=img_np.reshape(1,224,224,3)
            result = modelo2.predict(imp_np2)
            id_max= result[0].argmax()
            index_to_class = {v: k for k, v in train_gen.class_indices.items()}
            plt.title(f'Resultado: {index_to_class[id_max]}')
            plt.imshow(resized_image)
```

In []: predicao(modelo, 'DATASETS/Validation-Mass/WITH CANCER/2-233.jpg')

NameError

Traceback (most recent call last)

c:\Users\yagok\OneDrive\Área de Trabalho\Resnet50\Breast-Cancer-Detection-AI-System\TCC2_MODELS.ipynb Célula 45 line 1
----> 1 predicao(modelo,'DATASETS/Validation-Mass/WITH CANCER/2-233.jpg')

NameError: name 'modelo' is not defined

end