Al for Medical Diagnosis

Computer Vision (CV) has a lot of applications in medical diagnosis:

- Dermatology
- Ophthakmology
- · Histopathology.

X-rays images are critical for the detection of lung cancer, pneumenia ... In this notebook you will learn:

- Data pre-processing
- Preprocess images properly for the train, validation and test sets.
- Set-up a pre-trained neural network to make disease predictions on chest X-rays.

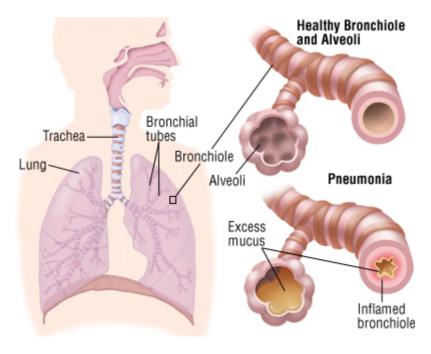
In this notebook you will work with chest X-ray images taken from the public ChestX-ray8 dataset.

What is Pneumonia?

From Mayo Clinic's Article on pneumonia

Pneumonia is an infection that inflames the air sacs in one or both lungs. The air sacs may fill with fluid or pus (purulent material), causing cough with phlegm or pus, fever, chills, and difficulty breathing. A variety of organisms, including bacteria, viruses and fungi, can cause pneumonia.

Pneumonia can range in seriousness from mild to life-threatening. It is most serious for infants and young children, people older than age 65, and people with health problems or weakened immune systems.



Computer Vision

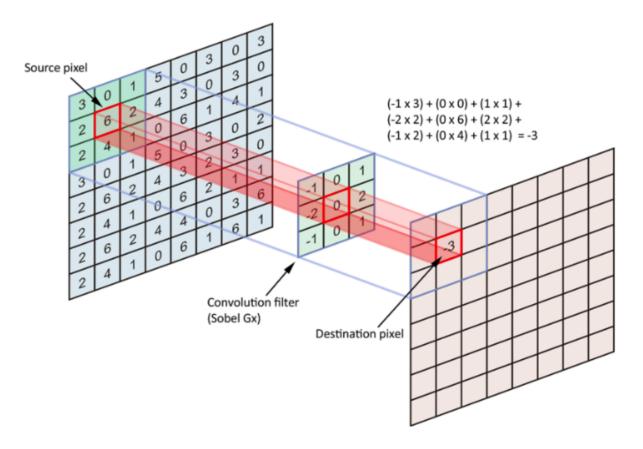
Computer vision is an interdisciplinary scientific field that deals with how computers can gain a high-level understanding from digital images or videos. From the perspective of engineering, it seeks to understand and automate tasks that the human visual system can do. We can use Computer Vision to determine whether a person is affected by pneumonia or not.

Pneumonia Detection with Convolutional Neural Networks

Computer Vision can be realized using Convolutional neural networks (CNN) They are neural networks making features extraction over an image before classifying it. The feature extraction performed consists of three basic operations:

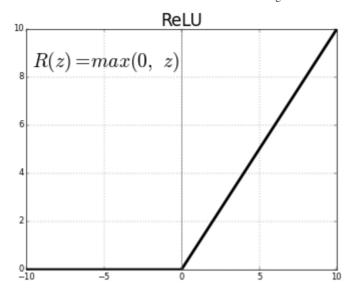
- Filter an image for a particular feature (convolution)
- Detect that feature within the filtered image (using the ReLU activation)
- Condense the image to enhance the features (maximum pooling)

The convolution process is illustrated below

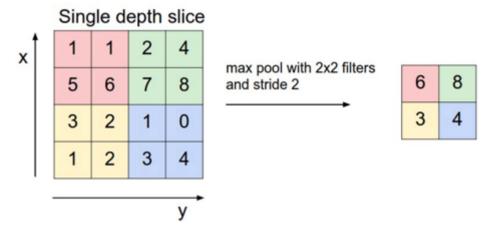


Using convolution filters with different dimensions or values results in differents features extracted

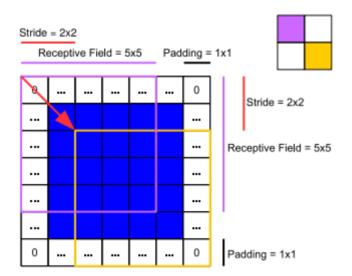
Features are then detected using the reLu activation on each destination pixel.



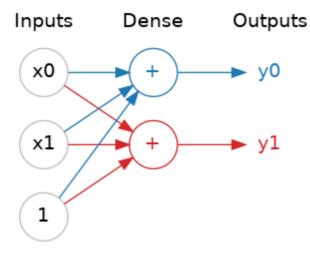
Features are the enhanced with MaxPool layers



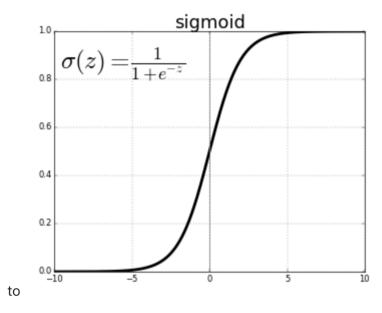
The stride parameters determines the distance between each filters. The padding one determines if we ignore the borderline pixels or not (adding zeros helps the neural network to get information on the border)



The outputs are then concatened in Dense layers



By using a sigmoid activation, the neural network determines which class the image belongs



Import Packages and Functions

We'll make use of the following packages:

- numpy and pandas is what we'll use to manipulate our data
- matplotlib.pyplot and seaborn will be used to produce plots for visualization
- util will provide the locally defined utility functions that have been provided for this assignment We will also use several modules from the keras framework for building deep learning models.

Run the next cell to import all the necessary packages.

```
import os
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import tensorflow as tf
from tensorflow import keras

os.listdir("./chest_xray")
```

```
Out[1]: ['.DS_Store', 'test', 'chest_xray', '__MACOSX', 'train', 'val']

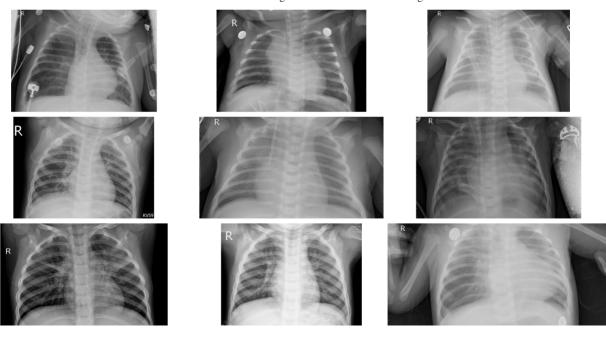
In [2]: len(os.listdir("./chest_xray/train/PNEUMONIA"))

Out[2]: 3875
```

The dataset is divided into three sets: 1) Train set 2) Validation set and 3) Test set.

Data Visualization

```
In [3]:
        train dir = "./chest xray/train"
        test_dir = "./chest_xray/test"
        val_dir = "./chest_xray/val"
        print("Train set:\n========")
        num pneumonia = len(os.listdir(os.path.join(train dir, 'PNEUMONIA')))
        num normal = len(os.listdir(os.path.join(train dir, 'NORMAL')))
        print(f"PNEUMONIA={num pneumonia}")
        print(f"NORMAL={num normal}")
        print("Test set:\n==========")
        print(f"PNEUMONIA={len(os.listdir(os.path.join(test dir, 'PNEUMONIA')))}")
        print(f"NORMAL={len(os.listdir(os.path.join(test dir, 'NORMAL')))}")
        print("Validation set:\n========")
        print(f"PNEUMONIA={len(os.listdir(os.path.join(val dir, 'PNEUMONIA')))}")
        print(f"NORMAL={len(os.listdir(os.path.join(val dir, 'NORMAL')))}")
        pneumonia = os.listdir("./chest xray/train/PNEUMONIA")
        pneumonia dir = "./chest xray/train/PNEUMONIA"
        plt.figure(figsize=(20, 10))
        for i in range(9):
           plt.subplot(3, 3, i + 1)
            img = plt.imread(os.path.join(pneumonia dir, pneumonia[i]))
           plt.imshow(img, cmap='gray')
           plt.axis('off')
        plt.tight layout()
```

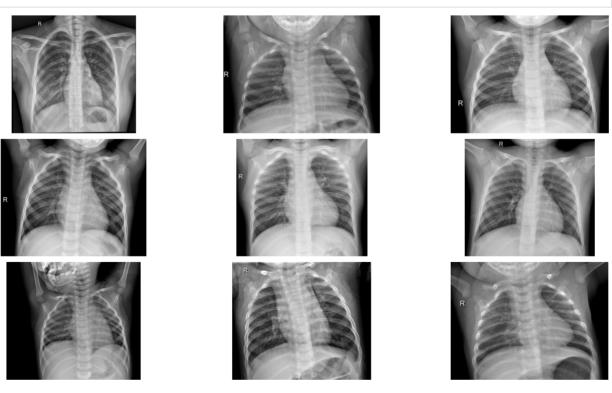


```
In [4]:
    normal = os.listdir("./chest_xray/train/NORMAL")
    normal_dir = "./chest_xray/train/NORMAL"

    plt.figure(figsize=(20, 10))

    for i in range(9):
        plt.subplot(3, 3, i + 1)
        img = plt.imread(os.path.join(normal_dir, normal[i]))
        plt.imshow(img, cmap='gray')
        plt.axis('off')

    plt.tight_layout()
```



```
normal_img = os.listdir("./chest_xray/train/NORMAL")[0]
normal_dir = "./chest_xray/train/NORMAL"
sample_img = plt.imread(os.path.join(normal_dir, normal_img))
plt.imshow(sample_img, cmap='gray')
plt.colorbar()
```

```
plt.title('Raw Chest X Ray Image')

print(f"The dimensions of the image are {sample_img.shape[0]} pixels width an 
print(f"The maximum pixel value is {sample_img.max():.4f} and the minimum is 
print(f"The mean value of the pixels is {sample_img.mean():.4f} and the stand.
```

The dimensions of the image are 2234 pixels width and 2359 pixels height, one single color channel.

The maximum pixel value is 255.0000 and the minimum is 0.0000

The mean value of the pixels is 124.3910 and the standard deviation is 56.3308

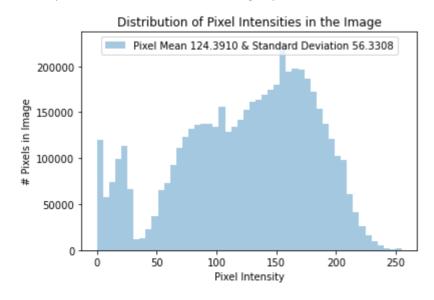


Ivestigate pixel value distribution

/Users/wangshicong/opt/anaconda3/lib/python3.8/site-packages/seaborn/distribut ions.py:2557: FutureWarning: `distplot` is a deprecated function and will be r emoved in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level f unction for histograms).

warnings.warn(msg, FutureWarning)

Out[6]: Text(0, 0.5, '# Pixels in Image')



2. Image Preprocessing

Before training, we'll first modify your images to be better suited for training a convolutional neural network. For this task we'll use the Keras ImageDataGenerator function to perform data preprocessing and data augmentation.

This class also provides support for basic data augmentation such as random horizontal flipping of images. We also use the generator to transform the values in each batch so that their mean is 0 and their standard deviation is 1 (this will faciliate model training by standardizing the input distribution). The generator also converts our single channel X-ray images (gray-scale) to a three-channel format by repeating the values in the image across all channels (we will want this because the pre-trained model that we'll use requires three-channel inputs).

```
In [7]:
    from keras.preprocessing.image import ImageDataGenerator
    image_generator = ImageDataGenerator(
        rotation_range=20,
        width_shift_range=0.1,
        shear_range=0.1,
        zoom_range=0.1,
        samplewise_center=True,
        samplewise_std_normalization=True
)
```

Build a separate generator for valid and test sets

Now we need to build a new generator for validation and testing data.

Why can't use the same generator as for the training data?

Look back at the generator we wrote for the training data.

It normalizes each image per batch, meaning that it uses batch statistics. We should not do this with the test and validation data, since in a real life scenario we don't process incoming images a batch at a time (we process one image at a time). Knowing the average per batch of test data would effectively give our model an advantage (The model should not have any information about the test data). What we need to do is to normalize incomming test data using the statistics computed from the training set.

Found 5216 images belonging to 2 classes. Found 16 images belonging to 2 classes. Found 624 images belonging to 2 classes.

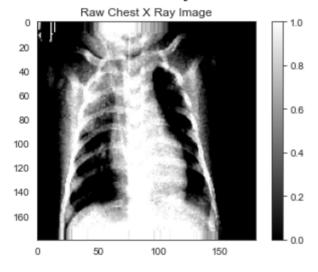
```
In [9]:
    sns.set_style('white')
    generated_image, label = train.__getitem__(0)
    plt.imshow(generated_image[0], cmap='gray')
    plt.colorbar()
    plt.title('Raw Chest X Ray Image')

    print(f"The dimensions of the image are {generated_image.shape[1]} pixels wide print(f"The maximum pixel value is {generated_image.max():.4f} and the minimum print(f"The mean value of the pixels is {generated_image.mean():.4f} and the second contents.
```

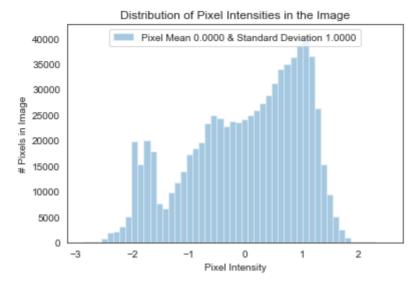
Clipping input data to the valid range for imshow with RGB data ([0..1] for fl oats or [0..255] for integers).

The dimensions of the image are 180 pixels width and 180 pixels height, one single color channel.

The maximum pixel value is 2.5148 and the minimum is -2.8703 The mean value of the pixels is 0.0000 and the standard deviation is 1.0000



Out[10]: Text(0, 0.5, '# Pixels in Image')



Building a CNN model

Impact of imbalance data on loss function

Loss Function:

$$\mathcal{L}_{cross-entropy}(x_i) = -(y_i \log(f(x_i)) + (1-y_i) \log(1-f(x_i))),$$

We can rewrite the the overall average cross-entropy loss over the entire training set $\, D \,$ of size $\, N \,$ as follows:

$$\mathcal{L}_{cross-entropy}(\mathcal{D}) = -rac{1}{N}ig(\sum_{ ext{positive examples}} \log(f(x_i)) + \sum_{ ext{negative examples}} \log(1-f(x_i))ig).$$

When we have an imbalance data, using a normal loss function will result a model that bias toward the dominating class. One solution is to use a weighted loss function. Using weighted loss function will balance the contribution in the loss function.

$$\mathcal{L}^w_{cross-entropy}(x) = -(w_p y \log(f(x)) + w_n (1-y) \log(1-f(x))).$$

```
In [11]: # Class weights

weight_for_0 = num_pneumonia / (num_normal + num_pneumonia)
weight_for_1 = num_normal / (num_normal + num_pneumonia)

class_weight = {0: weight_for_0, 1: weight_for_1}

print(f"Weight for class 0: {weight_for_0:.2f}")
print(f"Weight for class 1: {weight_for_1:.2f}")

Weight for class 0: 0.74
Weight for class 1: 0.26

In [12]: from keras.models import Sequential
from keras.layers import Dense, Conv2D, MaxPool2D, Dropout, Flatten, BatchNorn
model = Sequential()
```

```
model.add(Conv2D(filters=32, kernel_size=(3, 3), input_shape=(180, 180, 3), a
model.add(BatchNormalization())
model.add(Conv2D(filters=32, kernel size=(3, 3), input shape=(180, 180, 3), a
model.add(BatchNormalization())
model.add(MaxPool2D(pool size=(2, 2)))
model.add(Conv2D(filters=64, kernel size=(3, 3), activation='relu'))
model.add(BatchNormalization())
model.add(Conv2D(filters=64, kernel size=(3, 3), activation='relu'))
model.add(BatchNormalization())
model.add(MaxPool2D(pool size=(2, 2)))
model.add(Conv2D(filters=128, kernel size=(3, 3), activation='relu'))
model.add(BatchNormalization())
model.add(Conv2D(filters=128, kernel size=(3, 3), activation='relu'))
model.add(BatchNormalization())
model.add(MaxPool2D(pool size=(2, 2)))
model.add(Flatten())
model.add(Dense(128, activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(1, activation='sigmoid'))
model.compile(loss='binary_crossentropy',
              optimizer='adam',
              metrics=['accuracy'])
```

In [13]:

model.summary()

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 178, 178, 32)	========= 896
batch_normalization (BatchNo	(None, 178, 178, 32)	128
conv2d_1 (Conv2D)	(None, 176, 176, 32)	9248
batch_normalization_1 (Batch	(None, 176, 176, 32)	128
max_pooling2d (MaxPooling2D)	(None, 88, 88, 32)	0
conv2d_2 (Conv2D)	(None, 86, 86, 64)	18496
batch_normalization_2 (Batch	(None, 86, 86, 64)	256
conv2d_3 (Conv2D)	(None, 84, 84, 64)	36928
batch_normalization_3 (Batch	(None, 84, 84, 64)	256
max_pooling2d_1 (MaxPooling2	(None, 42, 42, 64)	0
conv2d_4 (Conv2D)	(None, 40, 40, 128)	73856
batch_normalization_4 (Batch	(None, 40, 40, 128)	512
conv2d_5 (Conv2D)	(None, 38, 38, 128)	147584
batch_normalization_5 (Batch	(None, 38, 38, 128)	512
max_pooling2d_2 (MaxPooling2	(None, 19, 19, 128)	0
flatten (Flatten)	(None, 46208)	0

```
dense (Dense) (None, 128) 5914752

dropout (Dropout) (None, 128) 0

dense_1 (Dense) (None, 1) 129

Total params: 6,203,681
Trainable params: 6,202,785
Non-trainable params: 896
```

```
In [14]:
    r = model.fit(
          train,
          epochs=10,
          validation_data=validation,
          class_weight=class_weight,
          steps_per_epoch=100,
          validation_steps=25,
)
```

```
Epoch 1/10
0.8037WARNING:tensorflow:Your input ran out of data; interrupting training. Ma
ke sure that your dataset or generator can generate at least `steps per epoch
* epochs` batches (in this case, 25 batches). You may need to use the repeat()
function when building your dataset.
100/100 [============ ] - 53s 518ms/step - loss: 1.3081 - acc
uracy: 0.8037 - val loss: 58.2382 - val accuracy: 0.5000
Epoch 2/10
100/100 [============== ] - 50s 503ms/step - loss: 0.5672 - acc
uracy: 0.8525
Epoch 3/10
100/100 [=============== ] - 50s 500ms/step - loss: 0.2279 - acc
uracy: 0.8650
Epoch 4/10
100/100 [=============== ] - 50s 499ms/step - loss: 0.1383 - acc
uracy: 0.8788
Epoch 5/10
100/100 [==============] - 50s 498ms/step - loss: 0.0726 - acc
uracy: 0.9187
Epoch 6/10
100/100 [============= ] - 50s 497ms/step - loss: 0.0771 - acc
uracy: 0.9300
Epoch 7/10
100/100 [============= ] - 50s 498ms/step - loss: 0.0860 - acc
uracy: 0.9262
Epoch 8/10
100/100 [============= ] - 50s 496ms/step - loss: 0.0951 - acc
uracy: 0.9175
Epoch 9/10
100/100 [============= ] - 50s 498ms/step - loss: 0.0803 - acc
uracy: 0.9388
Epoch 10/10
100/100 [============= ] - 50s 498ms/step - loss: 0.0799 - acc
uracy: 0.9262
```

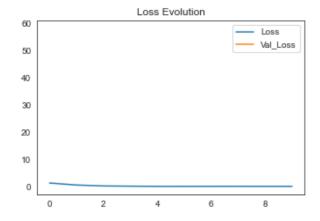
```
In [15]: plt.figure(figsize=(12, 8))

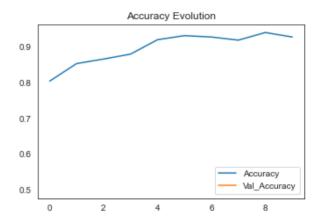
plt.subplot(2, 2, 1)
plt.plot(r.history['loss'], label='Loss')
plt.plot(r.history['val_loss'], label='Val_Loss')
plt.legend()
plt.title('Loss Evolution')

plt.subplot(2, 2, 2)
```

```
plt.plot(r.history['accuracy'], label='Accuracy')
plt.plot(r.history['val accuracy'], label='Val Accuracy')
plt.legend()
plt.title('Accuracy Evolution')
```

```
Out[15]: Text(0.5, 1.0, 'Accuracy Evolution')
```





624.000000

```
In [16]:
         evaluation = model.evaluate(test)
         print(f"Test Accuracy: {evaluation[1] * 100:.2f}%")
         evaluation = model.evaluate(train)
         print(f"Train Accuracy: {evaluation[1] * 100:.2f}%")
        624/624 [============= ] - 17s 26ms/step - loss: 0.9774 - accu
```

racy: 0.7933 Test Accuracy: 79.33% 652/652 [==============] - 128s 196ms/step - loss: 0.1926 - ac curacy: 0.9411 Train Accuracy: 94.11%

In [17]: from sklearn.metrics import confusion matrix, classification report pred = model.predict(test) print(confusion matrix(test.classes, pred > 0.5)) pd.DataFrame(classification report(test.classes, pred > 0.5, output dict=True

> [[110 124] 4 38611

0 1 accuracy macro avg weighted avg Out[17]: precision 0.964912 0.756863 0.794872 0.860888 0.834881 recall 0.470085 0.989744 0.794872 0.729915 0.794872 0.632184 0.773180 f1-score 0.857778 0.794872 0.744981

support 234.000000 390.000000 0.794872 624.000000

```
In [18]:
          print(confusion matrix(test.classes, pred > 0.7))
          pd.DataFrame(classification report(test.classes, pred > 0.7, output dict=True
```

[[134 100] 8 382]]

0 accuracy macro avg weighted avg Out[18]: precision 0.943662 0.792531 0.826923 0.868097 0.849205

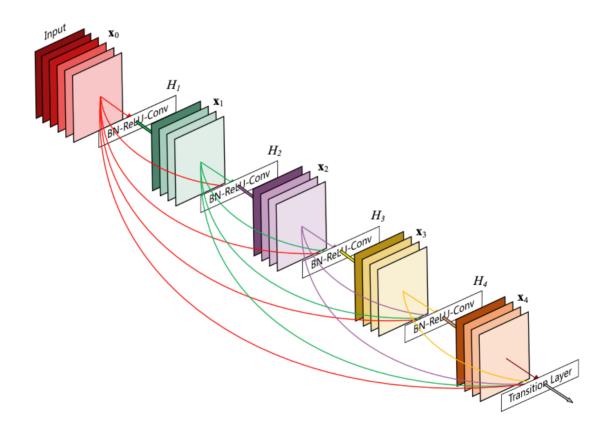
	0	1	accuracy	macro avg	weighted avg
recall	0.572650	0.979487	0.826923	0.776068	0.826923
f1-score	0.712766	0.876147	0.826923	0.794456	0.814879
support	234.000000	390.000000	0.826923	624.000000	624.000000

Transfer Learning

DenseNet

Densenet is a convolutional network where each layer is connected to all other layers that are deeper in the network:

- The first layer is connected to the 2nd, 3rd, 4th etc.
- The second layer is conected to the 3rd, 4th, 5th etc.



for more information about the DenseNet Architecture visit this website : https://keras.io/api/applications/densenet/

```
from keras.applications.densenet import DenseNet121
from keras.layers import Dense, GlobalAveragePooling2D
from keras.models import Model
from keras import backend as K

base_model = DenseNet121(input_shape=(180, 180, 3), include_top=False, weight:
base_model.summary()
```

Layer (type)	Output	_		Param #	
<pre>====================================</pre>		, 180, 1			
zero_padding2d (ZeroPadding2D)	(None,	186, 18	6, 3)	0	input_1[0][0]
conv1/conv (Conv2D) d[0][0]	(None,	90, 90,	64)	9408	zero_padding2
conv1/bn (BatchNormalization) [0]	(None,	90, 90,	64)	256	conv1/conv[0]
conv1/relu (Activation) [0]	(None,	90, 90,	64)	0	conv1/bn[0]
zero_padding2d_1 (ZeroPadding2D [0]	(None,	92, 92,	64)	0	conv1/relu[0]
pool1 (MaxPooling2D) d_1[0][0]	(None,	45, 45,	64)	0	zero_padding2
conv2_block1_0_bn (BatchNormali	(None,	45, 45,	64)	256	pool1[0][0]
conv2_block1_0_relu (Activation 0_bn[0][0]	(None,	45, 45,	64)	0	conv2_block1_
conv2_block1_1_conv (Conv2D) 0_relu[0][0]	(None,	45, 45,	128)	8192	conv2_block1_
conv2_block1_1_bn (BatchNormali1_conv[0][0]	(None,	45, 45,	128)	512	conv2_block1_
<pre>conv2_block1_1_relu (Activation 1_bn[0][0]</pre>	(None,	45, 45,	128)	0	conv2_block1_
<pre>conv2_block1_2_conv (Conv2D) 1_relu[0][0]</pre>	(None,	45, 45,	32)	36864	conv2_block1_
<pre>conv2_block1_concat (Concatenat 2_conv[0][0]</pre>	(None,	45, 45,	96)	0	pool1[0][0] conv2_block1_
<pre>conv2_block2_0_bn (BatchNormali concat[0][0]</pre>	(None,	45, 45,	96)	384	conv2_block1_
conv2_block2_0_relu (Activation	(None,	45, 45,	96)	0	conv2_block2_

0_bn[0][0]

conv2_block2_1_conv (Conv2D) 0_relu[0][0]	(None,	45,	45,	128)	12288	conv2_block2_
conv2_block2_1_bn (BatchNormali 1_conv[0][0]	(None,	45,	45,	128)	512	conv2_block2_
<pre>conv2_block2_1_relu (Activation 1_bn[0][0]</pre>	(None,	45,	45,	128)	0	conv2_block2_
conv2_block2_2_conv (Conv2D) 1_relu[0][0]	(None,	45,	45,	32)	36864	conv2_block2_
conv2_block2_concat (Concatenat concat[0][0]	(None,	45,	45,	128)	0	conv2_block1_
2_conv[0][0]						
<pre>conv2_block3_0_bn (BatchNormali concat[0][0]</pre>	(None,	45,	45,	128)	512	conv2_block2_
conv2_block3_0_relu (Activation 0_bn[0][0]	(None,	45,	45,	128)	0	conv2_block3_
conv2_block3_1_conv (Conv2D) 0_relu[0][0]	(None,	45,	45,	128)	16384	conv2_block3_
conv2_block3_1_bn (BatchNormali 1_conv[0][0]	(None,	45,	45,	128)	512	conv2_block3_
conv2_block3_1_relu (Activation 1_bn[0][0]	(None,	45,	45,	128)	0	conv2_block3_
conv2_block3_2_conv (Conv2D) 1_relu[0][0]	(None,	45,	45,	32)	36864	conv2_block3_
<pre>conv2_block3_concat (Concatenat concat[0][0]</pre>	(None,	45,	45,	160)	0	conv2_block2_
2_conv[0][0]						2011 1 D TOCK 2
<pre>conv2_block4_0_bn (BatchNormali concat[0][0]</pre>	(None,	45,	45,	160)	640	conv2_block3_
<pre>conv2_block4_0_relu (Activation 0_bn[0][0]</pre>	(None,	45,	45,	160)	0	conv2_block4_
conv2_block4_1_conv (Conv2D) 0_relu[0][0]	(None,	45,	45,	128)	20480	conv2_block4_
conv2_block4_1_bn (BatchNormali 1_conv[0][0]	(None,	45,	45,	128)	512	conv2_block4_

<pre>conv2_block4_1_relu (Activation 1_bn[0][0]</pre>	(None,	45,	45,	128)	0	conv2_block4_
conv2_block4_2_conv (Conv2D) 1_relu[0][0]	(None,	45,	45,	32)	36864	conv2_block4_
conv2_block4_concat (Concatenat concat[0][0]	(None,	45,	45,	192)	0	conv2_block3_
2_conv[0][0]						
conv2_block5_0_bn (BatchNormali concat[0][0]	(None,	45,	45,	192)	768	conv2_block4_
conv2_block5_0_relu (Activation 0_bn[0][0]	(None,	45,	45,	192)	0	conv2_block5_
conv2_block5_1_conv (Conv2D) 0_relu[0][0]	(None,	45,	45,	128)	24576	conv2_block5_
conv2_block5_1_bn (BatchNormali 1_conv[0][0]	(None,	45,	45,	128)	512	conv2_block5_
<pre>conv2_block5_1_relu (Activation 1_bn[0][0]</pre>	(None,	45,	45,	128)	0	conv2_block5_
conv2_block5_2_conv (Conv2D) 1_relu[0][0]	(None,	45,	45,	32)	36864	conv2_block5_
conv2_block5_concat (Concatenat concat[0][0]	(None,	45,	45,	224)	0	conv2_block4_
2_conv[0][0]						
<pre>conv2_block6_0_bn (BatchNormali concat[0][0]</pre>	(None,	45,	45,	224)	896	conv2_block5_
conv2_block6_0_relu (Activation 0_bn[0][0]	(None,	45,	45,	224)	0	conv2_block6_
conv2_block6_1_conv (Conv2D) 0_relu[0][0]	(None,	45,	45,	128)	28672	conv2_block6_
<pre>conv2_block6_1_bn (BatchNormali 1_conv[0][0]</pre>	(None,	45,	45,	128)	512	conv2_block6_
conv2_block6_1_relu (Activation 1_bn[0][0]	(None,	45,	45,	128)	0	conv2_block6_
conv2_block6_2_conv (Conv2D) 1_relu[0][0]	(None,	45,	45,	32)	36864	conv2_block6_

<pre>conv2_block6_concat (Concatenat concat[0][0] 2_conv[0][0]</pre>	(None,	45,	45,	256)	0	conv2_block5_ conv2_block6_
pool2_bn (BatchNormalization) concat[0][0]	(None,	45,	45,	256)	1024	conv2_block6_
pool2_relu (Activation) [0]	(None,	45,	45,	256)	0	pool2_bn[0]
pool2_conv (Conv2D) [0]	(None,	45,	45,	128)	32768	pool2_relu[0]
pool2_pool (AveragePooling2D) [0]	(None,	22,	22,	128)	0	pool2_conv[0]
conv3_block1_0_bn (BatchNormali [0]	(None,	22,	22,	128)	512	pool2_pool[0]
conv3_block1_0_relu (Activation 0_bn[0][0]	(None,	22,	22,	128)	0	conv3_block1_
conv3_block1_1_conv (Conv2D) 0_relu[0][0]	(None,	22,	22,	128)	16384	conv3_block1_
conv3_block1_1_bn (BatchNormali 1_conv[0][0]	(None,	22,	22,	128)	512	conv3_block1_
conv3_block1_1_relu (Activation 1_bn[0][0]	(None,	22,	22,	128)	0	conv3_block1_
conv3_block1_2_conv (Conv2D) 1_relu[0][0]	(None,	22,	22,	32)	36864	conv3_block1_
conv3_block1_concat (Concatenat [0] 2_conv[0][0]	(None,	22,	22,	160)	0	pool2_pool[0] conv3_block1_
<pre>conv3_block2_0_bn (BatchNormali concat[0][0]</pre>	(None,	22,	22,	160)	640	conv3_block1_
<pre>conv3_block2_0_relu (Activation 0_bn[0][0]</pre>	(None,	22,	22,	160)	0	conv3_block2_
conv3_block2_1_conv (Conv2D) 0_relu[0][0]	(None,	22,	22,	128)	20480	conv3_block2_
<pre>conv3_block2_1_bn (BatchNormali 1_conv[0][0]</pre>	(None,	22,	22,	128)	512	conv3_block2_

<pre>conv3_block2_1_relu (Activation 1_bn[0][0]</pre>	(None,	22,	22,	128)	0	conv3_block2_
conv3_block2_2_conv (Conv2D) 1_relu[0][0]	(None,	22,	22,	32)	36864	conv3_block2_
conv3_block2_concat (Concatenat concat[0][0]	(None,	22,	22,	192)	0	conv3_block1_ conv3_block2_
2_conv[0][0]						
<pre>conv3_block3_0_bn (BatchNormali concat[0][0]</pre>	(None,	22,	22,	192)	768	conv3_block2_
<pre>conv3_block3_0_relu (Activation 0_bn[0][0]</pre>	(None,	22,	22,	192)	0	conv3_block3_
conv3_block3_1_conv (Conv2D) 0_relu[0][0]	(None,	22,	22,	128)	24576	conv3_block3_
conv3_block3_1_bn (BatchNormali 1_conv[0][0]	(None,	22,	22,	128)	512	conv3_block3_
conv3_block3_1_relu (Activation 1_bn[0][0]	(None,	22,	22,	128)	0	conv3_block3_
conv3_block3_2_conv (Conv2D) 1_relu[0][0]	(None,	22,	22,	32)	36864	conv3_block3_
<pre>conv3_block3_concat (Concatenat concat[0][0]</pre>	(None,	22,	22,	224)	0	conv3_block2_
2_conv[0][0]						conv3_block3_
<pre>conv3_block4_0_bn (BatchNormali concat[0][0]</pre>	(None,	22,	22,	224)	896	conv3_block3_
<pre>conv3_block4_0_relu (Activation 0_bn[0][0]</pre>	(None,	22,	22,	224)	0	conv3_block4_
conv3_block4_1_conv (Conv2D) 0_relu[0][0]	(None,	22,	22,	128)	28672	conv3_block4_
conv3_block4_1_bn (BatchNormali 1_conv[0][0]	(None,	22,	22,	128)	512	conv3_block4_
conv3_block4_1_relu (Activation 1_bn[0][0]	(None,	22,	22,	128)	0	conv3_block4_
conv3_block4_2_conv (Conv2D) 1_relu[0][0]	(None,	22,	22,	32)	36864	conv3_block4_
conv3_block4_concat (Concatenat	(None,	22,	22,	256)	0	conv3_block3_

med	iicai-diagnos	ıs-wıtn-	cnn-tra	nster-tearn	iing	
concat[0][0] 2_conv[0][0]						conv3_block4_
2_00\[0][0]						
<pre>conv3_block5_0_bn (BatchNormali concat[0][0]</pre>	(None,	22,	22,	256)	1024	conv3_block4_
<pre>conv3_block5_0_relu (Activation 0_bn[0][0]</pre>	(None,	22,	22,	256)	0	conv3_block5_
conv3_block5_1_conv (Conv2D) 0_relu[0][0]	(None,	22,	22,	128)	32768	conv3_block5_
conv3_block5_1_bn (BatchNormali 1_conv[0][0]	(None,	22,	22,	128)	512	conv3_block5_
conv3_block5_1_relu (Activation 1_bn[0][0]	(None,	22,	22,	128)	0	conv3_block5_
conv3_block5_2_conv (Conv2D) 1_relu[0][0]	(None,	22,	22,	32)	36864	conv3_block5_
conv3_block5_concat (Concatenat concat[0][0]	(None,	22,	22,	288)	0	conv3_block4_
2_conv[0][0]						conv3_block5_
conv3_block6_0_bn (BatchNormali concat[0][0]	(None,	22,	22,	288)	1152	conv3_block5_
conv3_block6_0_relu (Activation 0_bn[0][0]	(None,	22,	22,	288)	0	conv3_block6_
conv3_block6_1_conv (Conv2D) 0_relu[0][0]	(None,	22,	22,	128)	36864	conv3_block6_
conv3_block6_1_bn (BatchNormali 1_conv[0][0]	(None,	22,	22,	128)	512	conv3_block6_
conv3_block6_1_relu (Activation 1_bn[0][0]	(None,	22,	22,	128)	0	conv3_block6_
conv3_block6_2_conv (Conv2D) 1_relu[0][0]	(None,	22,	22,	32)	36864	conv3_block6_
conv3_block6_concat (Concatenat concat[0][0]	(None,	22,	22,	320)	0	conv3_block5_
2_conv[0][0]						
<pre>conv3_block7_0_bn (BatchNormali concat[0][0]</pre>	(None,	22,	22,	320)	1280	conv3_block6_

<pre>conv3_block7_0_relu (Activation 0_bn[0][0]</pre>	(None,	22,	22,	320)	0	conv3_block7_
conv3_block7_1_conv (Conv2D) 0_relu[0][0]	(None,	22,	22,	128)	40960	conv3_block7_
<pre>conv3_block7_1_bn (BatchNormali 1_conv[0][0]</pre>	(None,	22,	22,	128)	512	conv3_block7_
<pre>conv3_block7_1_relu (Activation 1_bn[0][0]</pre>	(None,	22,	22,	128)	0	conv3_block7_
conv3_block7_2_conv (Conv2D) 1_relu[0][0]	(None,	22,	22,	32)	36864	conv3_block7_
<pre>conv3_block7_concat (Concatenat concat[0][0] 2_conv[0][0]</pre>	(None,	22,	22,	352)	0	conv3_block6_ conv3_block7_
	427			250	1400	
<pre>conv3_block8_0_bn (BatchNormali concat[0][0]</pre>	(None,	22,	22,	352)	1408	conv3_block7_
conv3_block8_0_relu (Activation 0_bn[0][0]	(None,	22,	22,	352)	0	conv3_block8_
conv3_block8_1_conv (Conv2D) 0_relu[0][0]	(None,	22,	22,	128)	45056	conv3_block8_
conv3_block8_1_bn (BatchNormali 1_conv[0][0]	(None,	22,	22,	128)	512	conv3_block8_
conv3_block8_1_relu (Activation 1_bn[0][0]	(None,	22,	22,	128)	0	conv3_block8_
conv3_block8_2_conv (Conv2D) 1_relu[0][0]	(None,	22,	22,	32)	36864	conv3_block8_
<pre>conv3_block8_concat (Concatenat concat[0][0]</pre>	(None,	22,	22,	384)	0	conv3_block7_
2_conv[0][0]						conv3_block8_
conv3_block9_0_bn (BatchNormali concat[0][0]	(None,	22,	22,	384)	1536	conv3_block8_
conv3_block9_0_relu (Activation 0_bn[0][0]	(None,	22,	22,	384)	0	conv3_block9_
conv3_block9_1_conv (Conv2D) 0_relu[0][0]	(None,	22,	22,	128)	49152	conv3_block9_
conv3_block9_1_bn (BatchNormali	(None,	22,	22,	128)	512	conv3_block9_

1_conv[0][0]

conv3_block9_1_relu (Activation 1_bn[0][0]	(None,	22,	22,	128)	0	conv3_block9_
<pre>conv3_block9_2_conv (Conv2D) 1_relu[0][0]</pre>	(None,	22,	22,	32)	36864	conv3_block9_
conv3_block9_concat (Concatenat concat[0][0]	(None,	22,	22,	416)	0	conv3_block8_
2_conv[0][0]						conv3_block9_
conv3_block10_0_bn (BatchNormal concat[0][0]	(None,	22,	22,	416)	1664	conv3_block9_
conv3_block10_0_relu (Activatio _0_bn[0][0]	(None,	22,	22,	416)	0	conv3_block10
conv3_block10_1_conv (Conv2D) _0_relu[0][0]	(None,	22,	22,	128)	53248	conv3_block10
conv3_block10_1_bn (BatchNormal _1_conv[0][0]	(None,	22,	22,	128)	512	conv3_block10
conv3_block10_1_relu (Activatio _1_bn[0][0]	(None,	22,	22,	128)	0	conv3_block10
conv3_block10_2_conv (Conv2D) _1_relu[0][0]	(None,	22,	22,	32)	36864	conv3_block10
conv3_block10_concat (Concatena concat[0][0]	(None,	22,	22,	448)	0	conv3_block9_
_2_conv[0][0]						conv3_block10
conv3_block11_0_bn (BatchNormal _concat[0][0]	(None,	22,	22,	448)	1792	conv3_block10
<pre>conv3_block11_0_relu (Activatio _0_bn[0][0]</pre>	(None,	22,	22,	448)	0	conv3_block11
conv3_block11_1_conv (Conv2D) _0_relu[0][0]	(None,	22,	22,	128)	57344	conv3_block11
conv3_block11_1_bn (BatchNormal _1_conv[0][0]	(None,	22,	22,	128)	512	conv3_block11
conv3_block11_1_relu (Activatio _1_bn[0][0]	(None,	22,	22,	128)	0	conv3_block11
conv3_block11_2_conv (Conv2D) _1_relu[0][0]	(None,	22,	22,	32)	36864	conv3_block11

conv3_block11_concat (Concatena	(None,	22,	22,	480)	0	conv3_block10
_concat[0][0]						conv3_block11
_2_conv[0][0]						_
conv3_block12_0_bn (BatchNormal	(None,	22,	22,	480)	1920	conv3_block11
_concat[0][0]						
conv3_block12_0_relu (Activatio	(None,	22,	22,	480)	0	conv3_block12
_0_bn[0][0]						
2 11 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2	(27	0.0	0.0	100	61440	2 1 1 1 10
conv3_block12_1_conv (Conv2D) _0_relu[0][0]	(None,	22,	22,	128)	61440	conv3_block12
conv3 block12 1 bn (BatchNormal	(None.	22.	22.	128)	512	conv3 block12
_1_conv[0][0]	(2,0120)	,	,	,	012	
conv3_block12_1_relu (Activatio	(None,	22,	22,	128)	0	conv3_block12
_1_bn[0][0]						_
conv3_block12_2_conv (Conv2D)	(None,	22,	22,	32)	36864	conv3_block12
_1_relu[0][0]						
						
conv3_block12_concat (Concatena	(None,	22,	22,	512)	0	conv3_block11
_concat[0][0]						conv3_block12
_2_conv[0][0]						_
pool3_bn (BatchNormalization)	(None,	22,	22,	512)	2048	conv3_block12
_concat[0][0]						
<pre>pool3_relu (Activation) [0]</pre>	(None,	22,	22,	512)	0	pool3_bn[0]
pool3_conv (Conv2D)	(None,	22	22	256)	131072	pool3 relu[0]
[0]	(None,	22,	22,	230)	131072	boo12_reru[0]
pool3 pool (AveragePooling2D)	(None,	11,	11,	256)	0	pool3_conv[0]
[0]	(,	,	,	/		
conv4_block1_0_bn (BatchNormali	(None,	11,	11,	256)	1024	pool3_pool[0]
[0]						
conv4_block1_0_relu (Activation	(None,	11,	11,	256)	0	conv4_block1_
0_bn[0][0]						
417-15	(27		1.1	100:	20762	
<pre>conv4_block1_1_conv (Conv2D) 0_relu[0][0]</pre>	(None,	11,	11,	128)	32768	conv4_block1_
conv4_block1_1_bn (BatchNormali	(None	11	11	1281	512	conv4_block1_
1_conv[0][0]	(2,0110)	,	,	120)	J.2	2011 1 2 2 0 0 1 1

conv4_block1_1_relu (Activation 1_bn[0][0]	(None,	11,	11,	128)	0	conv4_block1_
conv4_block1_2_conv (Conv2D) 1_relu[0][0]	(None,	11,	11,	32)	36864	conv4_block1_
<pre>conv4_block1_concat (Concatenat [0]</pre>	(None,	11,	11,	288)	0	<pre>pool3_pool[0] conv4 block1</pre>
2_conv[0][0]						
conv4_block2_0_bn (BatchNormali concat[0][0]	(None,	11,	11,	288)	1152	conv4_block1_
conv4_block2_0_relu (Activation 0_bn[0][0]	(None,	11,	11,	288)	0	conv4_block2_
conv4_block2_1_conv (Conv2D) 0_relu[0][0]	(None,	11,	11,	128)	36864	conv4_block2_
conv4_block2_1_bn (BatchNormali 1_conv[0][0]	(None,	11,	11,	128)	512	conv4_block2_
conv4_block2_1_relu (Activation 1_bn[0][0]	(None,	11,	11,	128)	0	conv4_block2_
conv4_block2_2_conv (Conv2D) 1_relu[0][0]	(None,	11,	11,	32)	36864	conv4_block2_
conv4_block2_concat (Concatenat concat[0][0]	(None,	11,	11,	320)	0	conv4_block1_
2_conv[0][0]						conv4_block2_
<pre>conv4_block3_0_bn (BatchNormali concat[0][0]</pre>	(None,	11,	11,	320)	1280	conv4_block2_
<pre>conv4_block3_0_relu (Activation 0_bn[0][0]</pre>	(None,	11,	11,	320)	0	conv4_block3_
conv4_block3_1_conv (Conv2D) 0_relu[0][0]	(None,	11,	11,	128)	40960	conv4_block3_
conv4_block3_1_bn (BatchNormali 1_conv[0][0]	(None,	11,	11,	128)	512	conv4_block3_
conv4_block3_1_relu (Activation 1_bn[0][0]	(None,	11,	11,	128)	0	conv4_block3_
conv4_block3_2_conv (Conv2D) 1_relu[0][0]	(None,	11,	11,	32)	36864	conv4_block3_

conv4_block3_concat (Concatenat concat[0][0]	(None,				0	conv4_block2_
2_conv[0][0]						conv4_block3_
conv4_block4_0_bn (BatchNormali concat[0][0]	(None,	11,	11,	352)	1408	conv4_block3_
conv4_block4_0_relu (Activation 0_bn[0][0]	(None,	11,	11,	352)	0	conv4_block4_
conv4_block4_1_conv (Conv2D) 0_relu[0][0]	(None,	11,	11,	128)	45056	conv4_block4_
conv4_block4_1_bn (BatchNormali 1_conv[0][0]	(None,	11,	11,	128)	512	conv4_block4_
<pre>conv4_block4_1_relu (Activation 1_bn[0][0]</pre>	(None,	11,	11,	128)	0	conv4_block4_
conv4_block4_2_conv (Conv2D) 1_relu[0][0]	(None,	11,	11,	32)	36864	conv4_block4_
conv4_block4_concat (Concatenat concat[0][0]	(None,	11,	11,	384)	0	conv4_block4_
2_conv[0][0]						
<pre>conv4_block5_0_bn (BatchNormali concat[0][0]</pre>	(None,	11,	11,	384)	1536	conv4_block4_
conv4_block5_0_relu (Activation 0_bn[0][0]	(None,	11,	11,	384)	0	conv4_block5_
conv4_block5_1_conv (Conv2D) 0_relu[0][0]	(None,	11,	11,	128)	49152	conv4_block5_
conv4_block5_1_bn (BatchNormali1_conv[0][0]	(None,	11,	11,	128)	512	conv4_block5_
<pre>conv4_block5_1_relu (Activation 1_bn[0][0]</pre>	(None,	11,	11,	128)	0	conv4_block5_
conv4_block5_2_conv (Conv2D) 1_relu[0][0]	(None,	11,	11,	32)	36864	conv4_block5_
conv4_block5_concat (Concatenat concat[0][0]	(None,	11,	11,	416)	0	conv4_block4_
2_conv[0][0]						conv4_block5_
conv4_block6_0_bn (BatchNormali concat[0][0]	(None,	11,	11,	416)	1664	conv4_block5_

<pre>conv4_block6_0_relu (Activation 0_bn[0][0]</pre>	(None,	11,	11,	416)	0	conv4_block6_
conv4_block6_1_conv (Conv2D) 0_relu[0][0]	(None,	11,	11,	128)	53248	conv4_block6_
<pre>conv4_block6_1_bn (BatchNormali 1_conv[0][0]</pre>	(None,	11,	11,	128)	512	conv4_block6_
conv4_block6_1_relu (Activation 1_bn[0][0]	(None,	11,	11,	128)	0	conv4_block6_
conv4_block6_2_conv (Conv2D) 1_relu[0][0]	(None,	11,	11,	32)	36864	conv4_block6_
<pre>conv4_block6_concat (Concatenat concat[0][0]</pre>	(None,	11,	11,	448)	0	conv4_block5_
2_conv[0][0]						
<pre>conv4_block7_0_bn (BatchNormali concat[0][0]</pre>	(None,	11,	11,	448)	1792	conv4_block6_
<pre>conv4_block7_0_relu (Activation 0_bn[0][0]</pre>	(None,	11,	11,	448)	0	conv4_block7_
conv4_block7_1_conv (Conv2D) 0_relu[0][0]	(None,	11,	11,	128)	57344	conv4_block7_
conv4_block7_1_bn (BatchNormali 1_conv[0][0]	(None,	11,	11,	128)	512	conv4_block7_
conv4_block7_1_relu (Activation 1_bn[0][0]	(None,	11,	11,	128)	0	conv4_block7_
conv4_block7_2_conv (Conv2D) 1_relu[0][0]	(None,	11,	11,	32)	36864	conv4_block7_
conv4_block7_concat (Concatenat concat[0][0]	(None,	11,	11,	480)	0	conv4_block6_
2_conv[0][0]						conv4_block7_
<pre>conv4_block8_0_bn (BatchNormali concat[0][0]</pre>	(None,	11,	11,	480)	1920	conv4_block7_
<pre>conv4_block8_0_relu (Activation 0_bn[0][0]</pre>	(None,	11,	11,	480)	0	conv4_block8_
<pre>conv4_block8_1_conv (Conv2D) 0_relu[0][0]</pre>	(None,	11,	11,	128)	61440	conv4_block8_

<pre>conv4_block8_1_bn (BatchNormali 1_conv[0][0]</pre>	(None,	11,	11,	128)	512	conv4_block8_
conv4_block8_1_relu (Activation 1_bn[0][0]	(None,	11,	11,	128)	0	conv4_block8_
conv4_block8_2_conv (Conv2D) 1_relu[0][0]	(None,	11,	11,	32)	36864	conv4_block8_
<pre>conv4_block8_concat (Concatenat concat[0][0] 2_conv[0][0]</pre>	(None,	11,	11,	512)	0	conv4_block7_ conv4_block8_
conv4_block9_0_bn (BatchNormali concat[0][0]	(None,	11,	11,	512)	2048	conv4_block8_
conv4_block9_0_relu (Activation 0_bn[0][0]	(None,	11,	11,	512)	0	conv4_block9_
conv4_block9_1_conv (Conv2D) 0_relu[0][0]	(None,	11,	11,	128)	65536	conv4_block9_
conv4_block9_1_bn (BatchNormali 1_conv[0][0]	(None,	11,	11,	128)	512	conv4_block9_
conv4_block9_1_relu (Activation 1_bn[0][0]	(None,	11,	11,	128)	0	conv4_block9_
conv4_block9_2_conv (Conv2D) 1_relu[0][0]	(None,	11,	11,	32)	36864	conv4_block9_
<pre>conv4_block9_concat (Concatenat concat[0][0] 2_conv[0][0]</pre>	(None,	11,	11,	544)	0	conv4_block8_
conv4_block10_0_bn (BatchNormal concat[0][0]	(None,	11,	11,	544)	2176	conv4_block9_
conv4_block10_0_relu (Activatio _0_bn[0][0]	(None,	11,	11,	544)	0	conv4_block10
conv4_block10_1_conv (Conv2D) _0_relu[0][0]	(None,	11,	11,	128)	69632	conv4_block10
conv4_block10_1_bn (BatchNormal _1_conv[0][0]	(None,	11,	11,	128)	512	conv4_block10
conv4_block10_1_relu (Activatio _1_bn[0][0]	(None,	11,	11,	128)	0	conv4_block10
conv4_block10_2_conv (Conv2D)	(None,	11,	11,	32)	36864	conv4_block10

_1_relu[0][0]

<pre>conv4_block10_concat (Concatena concat[0][0]</pre>	(None,	11,	11,	576)	0	conv4_block9_
_2_conv[0][0]						conv4_block10
conv4_block11_0_bn (BatchNormal _concat[0][0]	(None,	11,	11,	576)	2304	conv4_block10
conv4_block11_0_relu (Activatio _0_bn[0][0]	(None,	11,	11,	576)	0	conv4_block11
conv4_block11_1_conv (Conv2D) _0_relu[0][0]	(None,	11,	11,	128)	73728	conv4_block11
conv4_block11_1_bn (BatchNormal _1_conv[0][0]	(None,	11,	11,	128)	512	conv4_block11
conv4_block11_1_relu (Activatio _1_bn[0][0]	(None,	11,	11,	128)	0	conv4_block11
conv4_block11_2_conv (Conv2D) _1_relu[0][0]	(None,	11,	11,	32)	36864	conv4_block11
conv4_block11_concat (Concatena _concat[0][0]	(None,	11,	11,	608)	0	conv4_block10
_2_conv[0][0]						conv4_block11
conv4_block12_0_bn (BatchNormal _concat[0][0]	(None,	11,	11,	608)	2432	conv4_block11
conv4_block12_0_relu (Activatio _0_bn[0][0]	(None,	11,	11,	608)	0	conv4_block12
conv4_block12_1_conv (Conv2D) _0_relu[0][0]	(None,	11,	11,	128)	77824	conv4_block12
conv4_block12_1_bn (BatchNormal _1_conv[0][0]	(None,	11,	11,	128)	512	conv4_block12
conv4_block12_1_relu (Activatio _1_bn[0][0]	(None,	11,	11,	128)	0	conv4_block12
conv4_block12_2_conv (Conv2D) _1_relu[0][0]	(None,	11,	11,	32)	36864	conv4_block12
conv4_block12_concat (Concatena _concat[0][0]	(None,	11,	11,	640)	0	conv4_block11
_2_conv[0][0]						

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conv4_block13 _concat[0][0]	_0_bn (1	BatchNormal	(None,	11,	11,	640)	2560	conv4_block12
conv4_block13 _0_bn[0][0]	_0_relu	(Activatio	(None,	11,	11,	640)	0	conv4_block13
conv4_block13 _0_relu[0][0]	_1_conv	(Conv2D)	(None,	11,	11,	128)	81920	conv4_block13
conv4_block13 _1_conv[0][0]	_1_bn (1	BatchNormal	(None,	11,	11,	128)	512	conv4_block13
conv4_block13 _1_bn[0][0]	_1_relu	(Activatio	(None,	11,	11,	128)	0	conv4_block13
conv4_block13 _1_relu[0][0]	_2_conv	(Conv2D)	(None,	11,	11,	32)	36864	conv4_block13
conv4_block13	_concat	(Concatena	(None,	11,	11,	672)	0	conv4_block12
_concat[0][0] _2_conv[0][0]								conv4_block13
conv4_block14 _concat[0][0]	_0_bn (1	BatchNormal	(None,	11,	11,	672)	2688	conv4_block13
conv4_block14 _0_bn[0][0]	_0_relu	(Activatio	(None,	11,	11,	672)	0	conv4_block14
conv4_block14 _0_relu[0][0]	_1_conv	(Conv2D)	(None,	11,	11,	128)	86016	conv4_block14
conv4_block14 _1_conv[0][0]	_1_bn (1	BatchNormal	(None,	11,	11,	128)	512	conv4_block14
conv4_block14 _1_bn[0][0]	_1_relu	(Activatio	(None,	11,	11,	128)	0	conv4_block14
conv4_block14 _1_relu[0][0]	_2_conv	(Conv2D)	(None,	11,	11,	32)	36864	conv4_block14
conv4_block14 _concat[0][0]	_concat	(Concatena	(None,	11,	11,	704)	0	conv4_block13
_2_conv[0][0]								conv4_block14
conv4_block15 _concat[0][0]	_0_bn (1	BatchNormal	(None,	11,	11,	704)	2816	conv4_block14
conv4_block15 _0_bn[0][0]	_0_relu	(Activatio	(None,	11,	11,	704)	0	conv4_block15
conv4_block15	_1_conv	(Conv2D)	(None,	11,	11,	128)	90112	conv4_block15

_0_relu[0][0]

conv4_block15_1_bn (Bat_1_conv[0][0]	tchNormal	(None,	11,	11,	128)	512	conv4_block15
conv4_block15_1_relu (A	Activatio	(None,	11,	11,	128)	0	conv4_block15
conv4_block15_2_conv (0_1_relu[0][0]	Conv2D)	(None,	11,	11,	32)	36864	conv4_block15
conv4_block15_concat (0_concat[0][0]	Concatena	(None,	11,	11,	736)	0	conv4_block14
_2_conv[0][0]							
conv4_block16_0_bn (Bateconcat[0][0]	tchNormal	(None,	11,	11,	736)	2944	conv4_block15
conv4_block16_0_relu (i	Activatio	(None,	11,	11,	736)	0	conv4_block16
conv4_block16_1_conv (0_0_relu[0][0]	Conv2D)	(None,	11,	11,	128)	94208	conv4_block16
conv4_block16_1_bn (Bat_1_conv[0][0]	tchNormal	(None,	11,	11,	128)	512	conv4_block16
conv4_block16_1_relu (i_1_bn[0][0]	Activatio	(None,	11,	11,	128)	0	conv4_block16
conv4_block16_2_conv ((_1_relu[0][0]	Conv2D)	(None,	11,	11,	32)	36864	conv4_block16
conv4_block16_concat ((Concatena	(None,	11,	11,	768)	0	conv4_block15
_concat[0][0] _2_conv[0][0]							conv4_block16
conv4_block17_0_bn (Bat_concat[0][0]	tchNormal	(None,	11,	11,	768)	3072	conv4_block16
conv4_block17_0_relu (i_0_bn[0][0]	Activatio	(None,	11,	11,	768)	0	conv4_block17
conv4_block17_1_conv (0_0_relu[0][0]	Conv2D)	(None,	11,	11,	128)	98304	conv4_block17
conv4_block17_1_bn (Bat_1_conv[0][0]	tchNormal	(None,	11,	11,	128)	512	conv4_block17
conv4_block17_1_relu (A_1_bn[0][0]	Activatio	(None,	11,	11,	128)	0	conv4_block17

conv4_block17_2_conv _1_relu[0][0]	(Conv2D)	(None,	11,	11,	32)	36864	conv4_block17
conv4_block17_concat _concat[0][0]	(Concatena	(None,	11,	11,	800)	0	conv4_block16
_2_conv[0][0]							
conv4_block18_0_bn (E_concat[0][0]	BatchNormal	(None,	11,	11,	800)	3200	conv4_block17
conv4_block18_0_relu _0_bn[0][0]	(Activatio	(None,	11,	11,	800)	0	conv4_block18
conv4_block18_1_conv _0_relu[0][0]	(Conv2D)	(None,	11,	11,	128)	102400	conv4_block18
conv4_block18_1_bn (E _1_conv[0][0]	3atchNormal	(None,	11,	11,	128)	512	conv4_block18
conv4_block18_1_relu _1_bn[0][0]	(Activatio	(None,	11,	11,	128)	0	conv4_block18
conv4_block18_2_conv _1_relu[0][0]	(Conv2D)	(None,	11,	11,	32)	36864	conv4_block18
conv4_block18_concat _concat[0][0]	(Concatena	(None,	11,	11,	832)	0	conv4_block17
_2_conv[0][0]							conv4_block18
conv4_block19_0_bn (E_concat[0][0]	3atchNormal	(None,	11,	11,	832)	3328	conv4_block18
conv4_block19_0_relu _0_bn[0][0]	(Activatio	(None,	11,	11,	832)	0	conv4_block19
conv4_block19_1_conv _0_relu[0][0]	(Conv2D)	(None,	11,	11,	128)	106496	conv4_block19
conv4_block19_1_bn (E _1_conv[0][0]	3atchNormal	(None,	11,	11,	128)	512	conv4_block19
conv4_block19_1_relu _1_bn[0][0]	(Activatio	(None,	11,	11,	128)	0	conv4_block19
conv4_block19_2_conv _1_relu[0][0]	(Conv2D)	(None,	11,	11,	32)	36864	conv4_block19
conv4_block19_concat _concat[0][0]	(Concatena	(None,	11,	11,	864)	0	conv4_block18

_2_conv[0][0]

conv4_block20_0_bn (BatchNorma: _concat[0][0]	l (None,	11,	11,	864)	3456	conv4_block19
conv4_block20_0_relu (Activation_0_bn[0][0]	o (None,	11,	11,	864)	0	conv4_block20
conv4_block20_1_conv (Conv2D) _0_relu[0][0]	(None,	11,	11,	128)	110592	conv4_block20
conv4_block20_1_bn (BatchNorma: _1_conv[0][0]	l (None,	11,	11,	128)	512	conv4_block20
conv4_block20_1_relu (Activation_1_bn[0][0]	o (None,	11,	11,	128)	0	conv4_block20
conv4_block20_2_conv (Conv2D) _1_relu[0][0]	(None,	11,	11,	32)	36864	conv4_block20
conv4_block20_concat (Concatenation concat[0][0]	a (None,	11,	11,	896)	0	conv4_block19
_2_conv[0][0]						
conv4_block21_0_bn (BatchNormal_concat[0][0]	l (None,	11,	11,	896)	3584	conv4_block20
conv4_block21_0_relu (Activation_0_bn[0][0]	o (None,	11,	11,	896)	0	conv4_block21
conv4_block21_1_conv (Conv2D) _0_relu[0][0]	(None,	11,	11,	128)	114688	conv4_block21
conv4_block21_1_bn (BatchNorma: _1_conv[0][0]	l (None,	11,	11,	128)	512	conv4_block21
conv4_block21_1_relu (Activation_1_bn[0][0]	o (None,	11,	11,	128)	0	conv4_block21
conv4_block21_2_conv (Conv2D) _1_relu[0][0]	(None,	11,	11,	32)	36864	conv4_block21
conv4_block21_concat (Concatenation concat[0][0]	a (None,	11,	11,	928)	0	conv4_block20
_2_conv[0][0]						2011 1_D10CK21
conv4_block22_0_bn (BatchNorma: _concat[0][0]	l (None,	11,	11,	928)	3712	conv4_block21
<pre>conv4_block22_0_relu (Activation _0_bn[0][0]</pre>	o (None,	11,	11,	928)	0	conv4_block22

conv4_block22_1_conv _0_relu[0][0]	(Conv2D)	(None,	11,	11,	128)	118784	conv4_block22
conv4_block22_1_bn (Ba_1_conv[0][0]	atchNormal	(None,	11,	11,	128)	512	conv4_block22
conv4_block22_1_relu _1_bn[0][0]	(Activatio	(None,	11,	11,	128)	0	conv4_block22
conv4_block22_2_conv _1_relu[0][0]	(Conv2D)	(None,	11,	11,	32)	36864	conv4_block22
conv4_block22_concat _concat[0][0]	(Concatena	(None,	11,	11,	960)	0	conv4_block21
_2_conv[0][0]							conv4_block22
conv4_block23_0_bn (Ba_concat[0][0]	atchNormal	(None,	11,	11,	960)	3840	conv4_block22
conv4_block23_0_relu _0_bn[0][0]	(Activatio	(None,	11,	11,	960)	0	conv4_block23
conv4_block23_1_conv _0_relu[0][0]	(Conv2D)	(None,	11,	11,	128)	122880	conv4_block23
conv4_block23_1_bn (Ba_1_conv[0][0]	atchNormal	(None,	11,	11,	128)	512	conv4_block23
conv4_block23_1_relu _1_bn[0][0]	(Activatio	(None,	11,	11,	128)	0	conv4_block23
conv4_block23_2_conv _1_relu[0][0]	(Conv2D)	(None,	11,	11,	32)	36864	conv4_block23
conv4_block23_concat _concat[0][0]	(Concatena	(None,	11,	11,	992)	0	conv4_block22
_2_conv[0][0]							conv4_block23
conv4_block24_0_bn (Ba_concat[0][0]	atchNormal	(None,	11,	11,	992)	3968	conv4_block23
conv4_block24_0_relu _0_bn[0][0]	(Activatio	(None,	11,	11,	992)	0	conv4_block24
conv4_block24_1_conv _0_relu[0][0]	(Conv2D)	(None,	11,	11,	128)	126976	conv4_block24
conv4_block24_1_bn (Ba_1_conv[0][0]	atchNormal	(None,	11,	11,	128)	512	conv4_block24

<pre>conv4_block24_1_relu (Activatio _1_bn[0][0]</pre>	(None,	11, 11, 128)	0	conv4_block24
conv4_block24_2_conv (Conv2D) _1_relu[0][0]	(None,	11, 11, 32)	36864	conv4_block24
conv4_block24_concat (Concatena _concat[0][0]	(None,	11, 11, 1024)	0	conv4_block23
_2_conv[0][0]				
<pre>pool4_bn (BatchNormalization) _concat[0][0]</pre>	(None,	11, 11, 1024)	4096	conv4_block24
pool4_relu (Activation) [0]	(None,	11, 11, 1024)	0	pool4_bn[0]
pool4_conv (Conv2D) [0]	(None,	11, 11, 512)	524288	pool4_relu[0]
pool4_pool (AveragePooling2D) [0]	(None,	5, 5, 512)	0	pool4_conv[0]
conv5_block1_0_bn (BatchNormali [0]	(None,	5, 5, 512)	2048	pool4_pool[0]
<pre>conv5_block1_0_relu (Activation 0_bn[0][0]</pre>	(None,	5, 5, 512)	0	conv5_block1_
conv5_block1_1_conv (Conv2D) 0_relu[0][0]	(None,	5, 5, 128)	65536	conv5_block1_
conv5_block1_1_bn (BatchNormali 1_conv[0][0]	(None,	5, 5, 128)	512	conv5_block1_
conv5_block1_1_relu (Activation 1_bn[0][0]	(None,	5, 5, 128)	0	conv5_block1_
conv5_block1_2_conv (Conv2D) 1_relu[0][0]	(None,	5, 5, 32)	36864	conv5_block1_
conv5_block1_concat (Concatenat [0]	(None,	5, 5, 544)	0	pool4_pool[0]
2_conv[0][0]				conv5_block1_
<pre>conv5_block2_0_bn (BatchNormali concat[0][0]</pre>	(None,	5, 5, 544)	2176	conv5_block1_
<pre>conv5_block2_0_relu (Activation 0_bn[0][0]</pre>	(None,	5, 5, 544)	0	conv5_block2_

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<pre>conv5_block2_1_conv (Conv2D) 0_relu[0][0]</pre>	(None,	5,	5,	128)	69632	conv5_block2_
<pre>conv5_block2_1_bn (BatchNormali 1_conv[0][0]</pre>	(None,	5,	5,	128)	512	conv5_block2_
<pre>conv5_block2_1_relu (Activation 1_bn[0][0]</pre>	(None,	5,	5,	128)	0	conv5_block2_
conv5_block2_2_conv (Conv2D) 1_relu[0][0]	(None,	5,	5,	32)	36864	conv5_block2_
<pre>conv5_block2_concat (Concatenat concat[0][0]</pre>	(None,	5,	5,	576)	0	conv5_block1_
2_conv[0][0]						conv5_block2_
<pre>conv5_block3_0_bn (BatchNormali concat[0][0]</pre>	(None,	5,	5,	576)	2304	conv5_block2_
<pre>conv5_block3_0_relu (Activation 0_bn[0][0]</pre>	(None,	5,	5,	576)	0	conv5_block3_
conv5_block3_1_conv (Conv2D) 0_relu[0][0]	(None,	5,	5,	128)	73728	conv5_block3_
conv5_block3_1_bn (BatchNormali1_conv[0][0]	(None,	5,	5,	128)	512	conv5_block3_
<pre>conv5_block3_1_relu (Activation 1_bn[0][0]</pre>	(None,	5,	5,	128)	0	conv5_block3_
conv5_block3_2_conv (Conv2D) 1_relu[0][0]	(None,	5,	5,	32)	36864	conv5_block3_
<pre>conv5_block3_concat (Concatenat concat[0][0]</pre>	(None,	5,	5,	608)	0	conv5_block2_
2_conv[0][0]						conv5_block3_
<pre>conv5_block4_0_bn (BatchNormali concat[0][0]</pre>	(None,	5,	5,	608)	2432	conv5_block3_
<pre>conv5_block4_0_relu (Activation 0_bn[0][0]</pre>	(None,	5,	5,	608)	0	conv5_block4_
conv5_block4_1_conv (Conv2D) 0_relu[0][0]	(None,	5,	5,	128)	77824	conv5_block4_
conv5_block4_1_bn (BatchNormali1_conv[0][0]	(None,	5,	5,	128)	512	conv5_block4_
conv5_block4_1_relu (Activation	(None,	5,	5,	128)	0	conv5_block4_

1_bn[0][0]

conv5_block4_2_conv (Conv2D) 1_relu[0][0]	(None,	5,	5,	32)	36864	conv5_block4_
conv5_block4_concat (Concatenat concat[0][0]	(None,	5,	5,	640)	0	conv5_block3_
2_conv[0][0]						conv5_block4_
<pre>conv5_block5_0_bn (BatchNormali concat[0][0]</pre>	(None,	5,	5,	640)	2560	conv5_block4_
conv5_block5_0_relu (Activation 0_bn[0][0]	(None,	5,	5,	640)	0	conv5_block5_
conv5_block5_1_conv (Conv2D) 0_relu[0][0]	(None,	5,	5,	128)	81920	conv5_block5_
<pre>conv5_block5_1_bn (BatchNormali 1_conv[0][0]</pre>	(None,	5,	5,	128)	512	conv5_block5_
conv5_block5_1_relu (Activation 1_bn[0][0]	(None,	5,	5,	128)	0	conv5_block5_
conv5_block5_2_conv (Conv2D) 1_relu[0][0]	(None,	5,	5,	32)	36864	conv5_block5_
conv5_block5_concat (Concatenat	(None,	5,	5,	672)	0	conv5_block4_
concat[0][0] 2_conv[0][0]						conv5_block5_
<pre>conv5_block6_0_bn (BatchNormali concat[0][0]</pre>	(None,	5,	5,	672)	2688	conv5_block5_
conv5_block6_0_relu (Activation 0_bn[0][0]	(None,	5,	5,	672)	0	conv5_block6_
conv5_block6_1_conv (Conv2D) 0_relu[0][0]	(None,	5,	5,	128)	86016	conv5_block6_
conv5_block6_1_bn (BatchNormali 1_conv[0][0]	(None,	5,	5,	128)	512	conv5_block6_
conv5_block6_1_relu (Activation 1_bn[0][0]	(None,	5,	5,	128)	0	conv5_block6_
conv5_block6_2_conv (Conv2D) 1_relu[0][0]	(None,	5,	5,	32)	36864	conv5_block6_
<pre>conv5_block6_concat (Concatenat concat[0][0]</pre>	(None,	5,	5,	704)	0	conv5_block5_

2_conv[0][0]						conv5_block6_
<pre>conv5_block7_0_bn (BatchNormali concat[0][0]</pre>	(None,	5,	5,	704)	2816	conv5_block6_
<pre>conv5_block7_0_relu (Activation 0_bn[0][0]</pre>	(None,	5,	5,	704)	0	conv5_block7_
conv5_block7_1_conv (Conv2D) 0_relu[0][0]	(None,	5,	5,	128)	90112	conv5_block7_
conv5_block7_1_bn (BatchNormali 1_conv[0][0]	(None,	5,	5,	128)	512	conv5_block7_
conv5_block7_1_relu (Activation 1_bn[0][0]	(None,	5,	5,	128)	0	conv5_block7_
conv5_block7_2_conv (Conv2D) 1_relu[0][0]	(None,	5,	5,	32)	36864	conv5_block7_
conv5_block7_concat (Concatenat concat[0][0]	(None,	5,	5,	736)	0	conv5_block6_
2_conv[0][0]						conv5_block7_
conv5_block8_0_bn (BatchNormali concat[0][0]	(None,	5,	5,	736)	2944	conv5_block7_
conv5_block8_0_relu (Activation 0_bn[0][0]	(None,	5,	5,	736)	0	conv5_block8_
conv5_block8_1_conv (Conv2D) 0_relu[0][0]	(None,	5,	5,	128)	94208	conv5_block8_
conv5_block8_1_bn (BatchNormali 1_conv[0][0]	(None,	5,	5,	128)	512	conv5_block8_
conv5_block8_1_relu (Activation 1_bn[0][0]	(None,	5,	5,	128)	0	conv5_block8_
conv5_block8_2_conv (Conv2D) 1_relu[0][0]	(None,	5,	5,	32)	36864	conv5_block8_
conv5_block8_concat (Concatenat concat[0][0]	(None,	5,	5,	768)	0	conv5_block7_
2_conv[0][0]						conv5_block8_
conv5_block9_0_bn (BatchNormali concat[0][0]	(None,	5,	5,	768)	3072	conv5_block8_
conv5_block9_0_relu (Activation	(None,	5,	5,	768)	0	conv5_block9_

0_bn[0][0]

conv5_block9_1_conv (Conv2D) 0_relu[0][0]	(None,	5,	5,	128)	98304	conv5_block9_
conv5_block9_1_bn (BatchNormali 1_conv[0][0]	(None,	5,	5,	128)	512	conv5_block9_
conv5_block9_1_relu (Activation 1_bn[0][0]	(None,	5,	5,	128)	0	conv5_block9_
conv5_block9_2_conv (Conv2D) 1_relu[0][0]	(None,	5,	5,	32)	36864	conv5_block9_
<pre>conv5_block9_concat (Concatenat concat[0][0] 2_conv[0][0]</pre>	(None,	5,	5,	800)	0	conv5_block8_
<pre>conv5_block10_0_bn (BatchNormal concat[0][0]</pre>	(None,	5,	5,	800)	3200	conv5_block9_
<pre>conv5_block10_0_relu (Activatio _0_bn[0][0]</pre>	(None,	5,	5,	800)	0	conv5_block10
conv5_block10_1_conv (Conv2D) _0_relu[0][0]	(None,	5,	5,	128)	102400	conv5_block10
conv5_block10_1_bn (BatchNormal _1_conv[0][0]	(None,	5,	5,	128)	512	conv5_block10
conv5_block10_1_relu (Activatio _1_bn[0][0]	(None,	5,	5,	128)	0	conv5_block10
conv5_block10_2_conv (Conv2D) _1_relu[0][0]	(None,	5,	5,	32)	36864	conv5_block10
<pre>conv5_block10_concat (Concatena concat[0][0] _2_conv[0][0]</pre>	(None,	5,	5,	832)	0	conv5_block9_ conv5_block10
<pre>conv5_block11_0_bn (BatchNormal _concat[0][0]</pre>	(None,	5,	5,	832)	3328	conv5_block10
<pre>conv5_block11_0_relu (Activatio _0_bn[0][0]</pre>	(None,	5,	5,	832)	0	conv5_block11
conv5_block11_1_conv (Conv2D) _0_relu[0][0]	(None,	5,	5,	128)	106496	conv5_block11
conv5_block11_1_bn (BatchNormal _1_conv[0][0]	(None,	5,	5,	128)	512	conv5_block11

conv5_block11_1_relu _1_bn[0][0]	(Activatio	(None,	5,	5,	128)	0	conv5_block11
<pre>conv5_block11_2_conv _1_relu[0][0]</pre>	(Conv2D)	(None,	5,	5,	32)	36864	conv5_block11
conv5_block11_concat _concat[0][0]	(Concatena	(None,	5,	5,	864)	0	conv5_block10
_2_conv[0][0]							conv3_block11
conv5_block12_0_bn (F	BatchNormal	(None,	5,	5,	864)	3456	conv5_block11
conv5_block12_0_relu _0_bn[0][0]	(Activatio	(None,	5,	5,	864)	0	conv5_block12
conv5_block12_1_conv _0_relu[0][0]	(Conv2D)	(None,	5,	5,	128)	110592	conv5_block12
conv5_block12_1_bn (F_1_conv[0][0]	BatchNormal	(None,	5,	5,	128)	512	conv5_block12
conv5_block12_1_relu _1_bn[0][0]	(Activatio	(None,	5,	5,	128)	0	conv5_block12
conv5_block12_2_conv _1_relu[0][0]	(Conv2D)	(None,	5,	5,	32)	36864	conv5_block12
conv5_block12_concat _concat[0][0]	(Concatena	(None,	5,	5,	896)	0	conv5_block11
_2_conv[0][0]							conv5_block12
conv5_block13_0_bn (F	BatchNormal	(None,	5,	5,	896)	3584	conv5_block12
conv5_block13_0_relu _0_bn[0][0]	(Activatio	(None,	5,	5,	896)	0	conv5_block13
conv5_block13_1_conv _0_relu[0][0]	(Conv2D)	(None,	5,	5,	128)	114688	conv5_block13
conv5_block13_1_bn (F	BatchNormal	(None,	5,	5,	128)	512	conv5_block13
conv5_block13_1_relu _1_bn[0][0]	(Activatio	(None,	5,	5,	128)	0	conv5_block13
conv5_block13_2_conv _1_relu[0][0]	(Conv2D)	(None,	5,	5,	32)	36864	conv5_block13

<pre>conv5_block13_concat (Concatena _concat[0][0]</pre>	(None,	5,	5,	928)	0	conv5_block12
_2_conv[0][0]						
conv5_block14_0_bn (BatchNormal _concat[0][0]	(None,	5,	5,	928)	3712	conv5_block13
<pre>conv5_block14_0_relu (Activatio _0_bn[0][0]</pre>	(None,	5,	5,	928)	0	conv5_block14
conv5_block14_1_conv (Conv2D) _0_relu[0][0]	(None,	5,	5,	128)	118784	conv5_block14
conv5_block14_1_bn (BatchNormal _1_conv[0][0]	(None,	5,	5,	128)	512	conv5_block14
conv5_block14_1_relu (Activatio _1_bn[0][0]	(None,	5,	5,	128)	0	conv5_block14
conv5_block14_2_conv (Conv2D) _1_relu[0][0]	(None,	5,	5,	32)	36864	conv5_block14
conv5_block14_concat (Concatena _concat[0][0]	(None,	5,	5,	960)	0	conv5_block13
_2_conv[0][0]						conv5_block14
conv5_block15_0_bn (BatchNormal _concat[0][0]	(None,	5,	5,	960)	3840	conv5_block14
<pre>conv5_block15_0_relu (Activatio _0_bn[0][0]</pre>	(None,	5,	5,	960)	0	conv5_block15
conv5_block15_1_conv (Conv2D) _0_relu[0][0]	(None,	5,	5,	128)	122880	conv5_block15
conv5_block15_1_bn (BatchNormal _1_conv[0][0]	(None,	5,	5,	128)	512	conv5_block15
conv5_block15_1_relu (Activatio _1_bn[0][0]	(None,	5,	5,	128)	0	conv5_block15
conv5_block15_2_conv (Conv2D) _1_relu[0][0]	(None,	5,	5,	32)	36864	conv5_block15
conv5_block15_concat (Concatena _concat[0][0]	(None,	5,	5,	992)	0	conv5_block14
_2_conv[0][0]						conv5_block15
<pre>conv5_block16_0_bn (BatchNormal _concat[0][0]</pre>	(None,	5,	5,	992)	3968	conv5_block15

```
conv5 block16 0 relu (Activatio (None, 5, 5, 992)
                                                            0
                                                                       conv5 block16
         0 bn[0][0]
         conv5_block16_1_conv (Conv2D)
                                                            126976
                                        (None, 5, 5, 128)
                                                                       conv5 block16
         0 relu[0][0]
         conv5 block16 1 bn (BatchNormal (None, 5, 5, 128)
                                                            512
                                                                       conv5 block16
         1 conv[0][0]
         conv5 block16 1 relu (Activatio (None, 5, 5, 128)
                                                            Λ
                                                                       conv5 block16
         1 bn[0][0]
                                                            36864
         conv5 block16 2 conv (Conv2D)
                                        (None, 5, 5, 32)
                                                                       conv5 block16
         1 relu[0][0]
         conv5 block16 concat (Concatena (None, 5, 5, 1024)
                                                                       conv5 block15
         _concat[0][0]
                                                                       conv5 block16
         _2_conv[0][0]
         bn (BatchNormalization)
                                        (None, 5, 5, 1024)
                                                            4096
                                                                       conv5 block16
         _concat[0][0]
         relu (Activation)
                                        (None, 5, 5, 1024)
                                                                       bn[0][0]
         avg pool (GlobalAveragePooling2 (None, 1024)
                                                            0
                                                                       relu[0][0]
         ______
         Total params: 7,037,504
         Trainable params: 6,953,856
         Non-trainable params: 83,648
In [20]:
         layers = base model.layers
         print(f"The model has {len(layers)} layers")
         The model has 428 layers
In [21]:
         print(f"The input shape {base model.input}")
         print(f"The output shape {base model.output}")
         The input shape KerasTensor(type spec=TensorSpec(shape=(None, 180, 180, 3), dt
         ype=tf.float32, name='input 1'), name='input 1', description="created by layer
         'input 1'")
         The output shape KerasTensor(type_spec=TensorSpec(shape=(None, 1024), dtype=t
         f.float32, name=None), name='avg_pool/Mean:0', description="created by layer
         'avg_pool'")
In [22]:
         #model = Sequential()
         base model = DenseNet121(include top=False, weights='imagenet')
         x = base model.output
         x = GlobalAveragePooling2D()(x)
         predictions = Dense(1, activation="sigmoid")(x)
```

```
Epoch 1/10
0.8062WARNING:tensorflow:Your input ran out of data; interrupting training. Ma
ke sure that your dataset or generator can generate at least `steps_per_epoch
* epochs` batches (in this case, 25 batches). You may need to use the repeat()
function when building your dataset.
100/100 [============ ] - 151s 1s/step - loss: 0.1880 - accur
acy: 0.8062 - val loss: 7.6849 - val accuracy: 0.5000
Epoch 2/10
100/100 [============ ] - 141s 1s/step - loss: 0.1025 - accur
acy: 0.8725
Epoch 3/10
100/100 [============= ] - 142s 1s/step - loss: 0.0920 - accur
acy: 0.9013
Epoch 4/10
100/100 [==============] - 141s 1s/step - loss: 0.0928 - accur
acy: 0.9075
Epoch 5/10
100/100 [============== ] - 141s 1s/step - loss: 0.0602 - accur
acy: 0.9312
Epoch 6/10
100/100 [==============] - 141s 1s/step - loss: 0.1165 - accur
acy: 0.8825
Epoch 7/10
100/100 [==============] - 146s ls/step - loss: 0.0896 - accur
acy: 0.9025
Epoch 8/10
100/100 [==============] - 145s 1s/step - loss: 0.0859 - accur
acy: 0.9038
Epoch 9/10
100/100 [============= ] - 141s 1s/step - loss: 0.0844 - accur
acy: 0.9025
Epoch 10/10
100/100 [============= ] - 142s ls/step - loss: 0.0769 - accur
acy: 0.9250
```

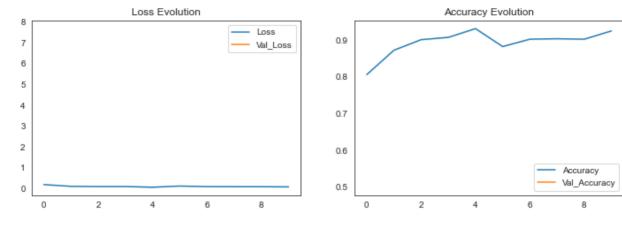
```
In [24]:
    plt.figure(figsize=(12, 8))

    plt.subplot(2, 2, 1)
    plt.plot(r.history['loss'], label='Loss')
    plt.plot(r.history['val_loss'], label='Val_Loss')
    plt.legend()
    plt.title('Loss Evolution')

    plt.subplot(2, 2, 2)
    plt.plot(r.history['accuracy'], label='Accuracy')
```

```
plt.plot(r.history['val_accuracy'], label='Val_Accuracy')
plt.legend()
plt.title('Accuracy Evolution')
```

```
Out[24]: Text(0.5, 1.0, 'Accuracy Evolution')
```



Evaluation

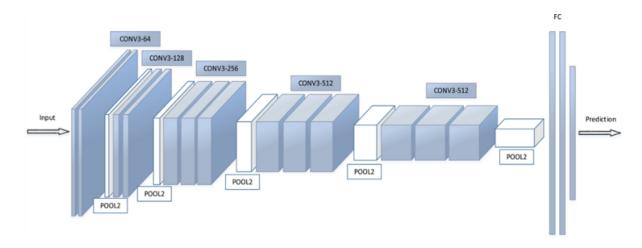
Train Accuracy: 91.32%

```
In [26]:
           predicted vals = model.predict(test, steps=len(test))
In [27]:
           print(confusion_matrix(test.classes, predicted_vals > 0.5))
           pd.DataFrame(classification_report(test.classes, predicted_vals > 0.5, output
          [[140 94]
           [ 25 365]]
                            0
                                        1 accuracy
                                                      macro avg
                                                                weighted avg
Out[27]:
          precision
                      0.848485
                                  0.795207 0.809295
                                                       0.821846
                                                                    0.815186
             recall
                      0.598291
                                  0.935897 0.809295
                                                       0.767094
                                                                    0.809295
           f1-score
                      0.701754
                                  0.859835 0.809295
                                                       0.780795
                                                                    0.800555
                                                                 624.000000
           support 234.000000 390.000000 0.809295 624.000000
```

VGG16

Presented in 2014, VGG16 has a very simple and classical architecture, with blocks of 2 or 3 convolutional layers followed by a pooling layer, plus a final dense network composed of 2

hidden layers (of 4096 nodes each) and one output layer (of 1000 nodes). Only 3x3 filters are used.



from keras.models import Sequential
 from keras.layers import GlobalAveragePooling2D
 from keras.applications.vgg16 import VGG16

vgg16_base_model = VGG16(input_shape=(180,180,3),include_top=False,weights='include_top=False,weight

In [30]:

vgg16_base_model.summary()

Model: "vgg16"

Layer (type)	Output Shape	Param #
input_3 (InputLayer)	[(None, 180, 180, 3)]	0
block1_conv1 (Conv2D)	(None, 180, 180, 64)	1792
block1_conv2 (Conv2D)	(None, 180, 180, 64)	36928
block1_pool (MaxPooling2D)	(None, 90, 90, 64)	0
block2_conv1 (Conv2D)	(None, 90, 90, 128)	73856
block2_conv2 (Conv2D)	(None, 90, 90, 128)	147584
block2_pool (MaxPooling2D)	(None, 45, 45, 128)	0
block3_conv1 (Conv2D)	(None, 45, 45, 256)	295168
block3_conv2 (Conv2D)	(None, 45, 45, 256)	590080
block3_conv3 (Conv2D)	(None, 45, 45, 256)	590080
block3_pool (MaxPooling2D)	(None, 22, 22, 256)	0
block4_conv1 (Conv2D)	(None, 22, 22, 512)	1180160
block4_conv2 (Conv2D)	(None, 22, 22, 512)	2359808

```
block4 conv3 (Conv2D)
                                    (None, 22, 22, 512)
                                                            2359808
                                    (None, 11, 11, 512)
        block4 pool (MaxPooling2D)
                                    (None, 11, 11, 512)
        block5 conv1 (Conv2D)
                                                            2359808
        block5 conv2 (Conv2D)
                                    (None, 11, 11, 512)
                                                            2359808
        block5 conv3 (Conv2D)
                                    (None, 11, 11, 512)
                                                            2359808
        block5 pool (MaxPooling2D)
                                   (None, 5, 5, 512)
         _____
        Total params: 14,714,688
        Trainable params: 14,714,688
        Non-trainable params: 0
In [31]:
             vgg16 model = tf.keras.Sequential([
                vgg16 base model,
                GlobalAveragePooling2D(),
                Dense(512, activation="relu"),
                BatchNormalization(),
                Dropout(0.6),
                Dense(128, activation="relu"),
                BatchNormalization(),
                Dropout(0.4),
                Dense(64, activation="relu"),
                BatchNormalization(),
                Dropout(0.3),
                Dense(1,activation="sigmoid")
             ])
In [32]:
             opt = tf.keras.optimizers.Adam(learning rate=0.001)
             METRICS = [
                 'accuracy',
                tf.keras.metrics.Precision(name='precision'),
                tf.keras.metrics.Recall(name='recall')
             vgg16 model.compile(optimizer=opt,loss='binary crossentropy',metrics=METR
In [33]:
         r = vgg16 model.fit(train,
                  epochs=10,
                  validation data=validation,
                  class weight=class weight,
                  steps per epoch=100,
                  validation steps=25)
        Epoch 1/10
        0.5512 - precision: 0.8158 - recall: 0.5175WARNING:tensorflow:Your input ran o
        ut of data; interrupting training. Make sure that your dataset or generator ca
        n generate at least `steps per epoch * epochs` batches (in this case, 25 batch
        es). You may need to use the repeat() function when building your dataset.
        100/100 [============= ] - 224s 2s/step - loss: 0.3160 - accur
        acy: 0.5512 - precision: 0.8158 - recall: 0.5175 - val_loss: 3.2663 - val accu
        racy: 0.5000 - val_precision: 0.0000e+00 - val_recall: 0.0000e+00
        Epoch 2/10
        100/100 [================ ] - 217s 2s/step - loss: 0.2063 - accur
        acy: 0.7200 - precision: 0.9103 - recall: 0.6881
```

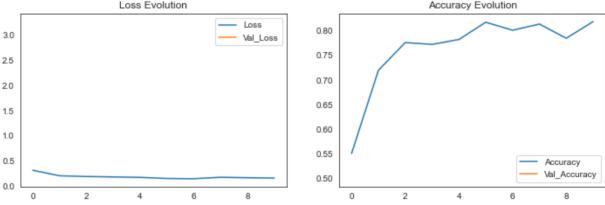
100/100 [===============] - 222s 2s/step - loss: 0.1919 - accur

acy: 0.7763 - precision: 0.9468 - recall: 0.7429

Epoch 3/10

Epoch 4/10

```
11/23/21, 8:40 PM
                                      medical-diagnosis-with-cnn-transfer-learning
           100/100 [=============== ] - 226s 2s/step - loss: 0.1828 - accur
           acy: 0.7725 - precision: 0.9291 - recall: 0.7574
           Epoch 5/10
           100/100 [============== ] - 229s 2s/step - loss: 0.1748 - accur
           acy: 0.7825 - precision: 0.9293 - recall: 0.7615
           Epoch 6/10
           100/100 [============= ] - 235s 2s/step - loss: 0.1521 - accur
           acy: 0.8175 - precision: 0.9512 - recall: 0.8010
           Epoch 7/10
           100/100 [============= ] - 236s 2s/step - loss: 0.1475 - accur
           acy: 0.8012 - precision: 0.9526 - recall: 0.7726
           Epoch 8/10
           100/100 [============ ] - 242s 2s/step - loss: 0.1765 - accur
           acy: 0.8138 - precision: 0.9278 - recall: 0.8147
           Epoch 9/10
           acy: 0.7850 - precision: 0.9340 - recall: 0.7639
           Epoch 10/10
           100/100 [============== ] - 229s 2s/step - loss: 0.1605 - accur
           acy: 0.8188 - precision: 0.9380 - recall: 0.8107
  In [34]:
            plt.figure(figsize=(12, 8))
            plt.subplot(2, 2, 1)
            plt.plot(r.history['loss'], label='Loss')
            plt.plot(r.history['val_loss'], label='Val_Loss')
            plt.legend()
            plt.title('Loss Evolution')
            plt.subplot(2, 2, 2)
            plt.plot(r.history['accuracy'], label='Accuracy')
            plt.plot(r.history['val accuracy'], label='Val Accuracy')
            plt.legend()
            plt.title('Accuracy Evolution')
  Out[34]: Text(0.5, 1.0, 'Accuracy Evolution')
                         Loss Evolution
                                                             Accuracy Evolution
```



```
In [35]:
        evaluation =vgg16 model.evaluate(test)
        print(f"Test Accuracy: {evaluation[1] * 100:.2f}%")
        evaluation = vgg16 model.evaluate(train)
        print(f"Train Accuracy: {evaluation[1] * 100:.2f}%")
       624/624 [========================] - 61s 98ms/step - loss: 0.5405 - accu
       racy: 0.7228 - precision: 0.7020 - recall: 0.9667
       Test Accuracy: 72.28%
       curacy: 0.8892 - precision: 0.9077 - recall: 0.9471
       Train Accuracy: 88.92%
```

ResNet

See the full explanation and schemes in the Research Paper on Deep Residual Learning (https://arxiv.org/pdf/1512.03385.pdf)

In [43]: from tensorflow.python.keras.applications.resnet import ResNet50 resnet base model = ResNet50(input shape=(180,180,3), include top=False, weigh In [44]: resnet base model.summary() Model: "resnet50" Output Shape Connected to Layer (type) Param # ______ _____ input 2 (InputLayer) [(None, 180, 180, 3) 0 conv1 pad (ZeroPadding2D) (None, 186, 186, 3) input 2[0][0] conv1 conv (Conv2D) (None, 90, 90, 64) 9472 conv1 pad[0] [0] conv1 bn (BatchNormalization) (None, 90, 90, 64) 256 conv1 conv[0] [0] conv1 relu (Activation) (None, 90, 90, 64) conv1 bn[0] [0] pool1 pad (ZeroPadding2D) (None, 92, 92, 64) 0 conv1 relu[0] [0] pool1 pool (MaxPooling2D) (None, 45, 45, 64) 0 pool1 pad[0] [0] conv2 block1_1_conv (Conv2D) (None, 45, 45, 64) 4160 pool1 pool[0] [0] conv2 block1 1 bn (BatchNormali (None, 45, 45, 64) 256 conv2 block1 1 conv[0][0] conv2 block1 1 relu (Activation (None, 45, 45, 64) 0 conv2 block1 1 bn[0][0] conv2_block1_2_conv (Conv2D) (None, 45, 45, 64) 36928 conv2 block1 1 relu[0][0] conv2_block1_2_bn (BatchNormali (None, 45, 45, 64) 256 conv2_block1_ 2_conv[0][0]

conv2_block1_2_relu (Activation (None, 45, 45, 64)

conv2_block1_

0

2_bn[0][0]

<pre>conv2_block1_0_conv (Conv2D) [0]</pre>	(None,	45,	45,	256)	16640	pool1_pool[0]
conv2_block1_3_conv (Conv2D) 2_relu[0][0]	(None,	45,	45,	256)	16640	conv2_block1_
<pre>conv2_block1_0_bn (BatchNormali 0_conv[0][0]</pre>	(None,	45,	45,	256)	1024	conv2_block1_
<pre>conv2_block1_3_bn (BatchNormali 3_conv[0][0]</pre>	(None,	45,	45,	256)	1024	conv2_block1_
conv2_block1_add (Add) 0_bn[0][0] 3_bn[0][0]	(None,	45,	45,	256)	0	conv2_block1_
<pre>conv2_block1_out (Activation) add[0][0]</pre>	(None,	45,	45,	256)	0	conv2_block1_
conv2_block2_1_conv (Conv2D) out[0][0]	(None,	45,	45,	64)	16448	conv2_block1_
<pre>conv2_block2_1_bn (BatchNormali 1_conv[0][0]</pre>	(None,	45,	45,	64)	256	conv2_block2_
<pre>conv2_block2_1_relu (Activation 1_bn[0][0]</pre>	(None,	45,	45,	64)	0	conv2_block2_
conv2_block2_2_conv (Conv2D) 1_relu[0][0]	(None,	45,	45,	64)	36928	conv2_block2_
conv2_block2_2_bn (BatchNormali 2_conv[0][0]	(None,	45,	45,	64)	256	conv2_block2_
<pre>conv2_block2_2_relu (Activation 2_bn[0][0]</pre>	(None,	45,	45,	64)	0	conv2_block2_
conv2_block2_3_conv (Conv2D) 2_relu[0][0]	(None,	45,	45,	256)	16640	conv2_block2_
<pre>conv2_block2_3_bn (BatchNormali 3_conv[0][0]</pre>	(None,	45,	45,	256)	1024	conv2_block2_
conv2_block2_add (Add) out[0][0]	(None,	45,	45,	256)	0	conv2_block1_
3_bn[0][0]						
conv2_block2_out (Activation) add[0][0]	(None,	45,	45,	256)	0	conv2_block2_

conv2_block3_1_conv (Conv2D) out[0][0]	(None,	45,	45,	64)	16448	conv2_block2_
conv2_block3_1_bn (BatchNormali 1_conv[0][0]	(None,	45,	45,	64)	256	conv2_block3_
conv2_block3_1_relu (Activation 1_bn[0][0]	(None,	45,	45,	64)	0	conv2_block3_
conv2_block3_2_conv (Conv2D) 1_relu[0][0]	(None,	45,	45,	64)	36928	conv2_block3_
conv2_block3_2_bn (BatchNormali 2_conv[0][0]	(None,	45,	45,	64)	256	conv2_block3_
conv2_block3_2_relu (Activation 2_bn[0][0]	(None,	45,	45,	64)	0	conv2_block3_
conv2_block3_3_conv (Conv2D) 2_relu[0][0]	(None,	45,	45,	256)	16640	conv2_block3_
conv2_block3_3_bn (BatchNormali 3_conv[0][0]	(None,	45,	45,	256)	1024	conv2_block3_
conv2_block3_add (Add) out[0][0]	(None,	45,	45,	256)	0	conv2_block2_
3_bn[0][0]						conv2_block3_
conv2_block3_out (Activation) add[0][0]	(None,	45,	45,	256)	0	conv2_block3_
conv3_block1_1_conv (Conv2D) out[0][0]	(None,	23,	23,	128)	32896	conv2_block3_
<pre>conv3_block1_1_bn (BatchNormali 1_conv[0][0]</pre>	(None,	23,	23,	128)	512	conv3_block1_
conv3_block1_1_relu (Activation 1_bn[0][0]	(None,	23,	23,	128)	0	conv3_block1_
conv3_block1_2_conv (Conv2D) 1_relu[0][0]	(None,	23,	23,	128)	147584	conv3_block1_
conv3_block1_2_bn (BatchNormali 2_conv[0][0]	(None,	23,	23,	128)	512	conv3_block1_
conv3_block1_2_relu (Activation 2_bn[0][0]	(None,	23,	23,	128)	0	conv3_block1_
conv3_block1_0_conv (Conv2D)	(None,	23,	23,	512)	131584	conv2_block3_

conv3_block1_3_conv (Conv2D) 2_relu[0][0]	(None,	23,	23,	512)	66048	conv3_block1_
<pre>conv3_block1_0_bn (BatchNormali 0_conv[0][0]</pre>	(None,	23,	23,	512)	2048	conv3_block1_
<pre>conv3_block1_3_bn (BatchNormali 3_conv[0][0]</pre>	(None,	23,	23,	512)	2048	conv3_block1_
conv3_block1_add (Add) 0_bn[0][0]	(None,	23,	23,	512)	0	conv3_block1_
3_bn[0][0]						
<pre>conv3_block1_out (Activation) add[0][0]</pre>	(None,	23,	23,	512)	0	conv3_block1_
conv3_block2_1_conv (Conv2D) out[0][0]	(None,	23,	23,	128)	65664	conv3_block1_
conv3_block2_1_bn (BatchNormali 1_conv[0][0]	(None,	23,	23,	128)	512	conv3_block2_
conv3_block2_1_relu (Activation 1_bn[0][0]	(None,	23,	23,	128)	0	conv3_block2_
conv3_block2_2_conv (Conv2D) 1_relu[0][0]	(None,	23,	23,	128)	147584	conv3_block2_
conv3_block2_2_bn (BatchNormali 2_conv[0][0]	(None,	23,	23,	128)	512	conv3_block2_
conv3_block2_2_relu (Activation 2_bn[0][0]	(None,	23,	23,	128)	0	conv3_block2_
conv3_block2_3_conv (Conv2D) 2_relu[0][0]	(None,	23,	23,	512)	66048	conv3_block2_
conv3_block2_3_bn (BatchNormali 3_conv[0][0]	(None,	23,	23,	512)	2048	conv3_block2_
conv3_block2_add (Add) out[0][0]	(None,	23,	23,	512)	0	conv3_block1_
3_bn[0][0]						conv3_block2_
conv3_block2_out (Activation) add[0][0]	(None,	23,	23,	512)	0	conv3_block2_
conv3_block3_1_conv (Conv2D) out[0][0]	(None,	23,	23,	128)	65664	conv3_block2_

<pre>conv3_block3_1_bn (BatchNormali 1_conv[0][0]</pre>	(None,	23,	23,	128)	512	conv3_block3_
conv3_block3_1_relu (Activation 1_bn[0][0]	(None,	23,	23,	128)	0	conv3_block3_
conv3_block3_2_conv (Conv2D) 1_relu[0][0]	(None,	23,	23,	128)	147584	conv3_block3_
conv3_block3_2_bn (BatchNormali 2_conv[0][0]	(None,	23,	23,	128)	512	conv3_block3_
conv3_block3_2_relu (Activation 2_bn[0][0]	(None,	23,	23,	128)	0	conv3_block3_
conv3_block3_3_conv (Conv2D) 2_relu[0][0]	(None,	23,	23,	512)	66048	conv3_block3_
conv3_block3_3_bn (BatchNormali 3_conv[0][0]	(None,	23,	23,	512)	2048	conv3_block3_
conv3_block3_add (Add) out[0][0]	(None,	23,	23,	512)	0	conv3_block2_
3_bn[0][0]						conv3_block3_
<pre>conv3_block3_out (Activation) add[0][0]</pre>	(None,	23,	23,	512)	0	conv3_block3_
conv3_block4_1_conv (Conv2D) out[0][0]	(None,	23,	23,	128)	65664	conv3_block3_
<pre>conv3_block4_1_bn (BatchNormali 1_conv[0][0]</pre>	(None,	23,	23,	128)	512	conv3_block4_
conv3_block4_1_relu (Activation 1_bn[0][0]	(None,	23,	23,	128)	0	conv3_block4_
conv3_block4_2_conv (Conv2D) 1_relu[0][0]	(None,	23,	23,	128)	147584	conv3_block4_
conv3_block4_2_bn (BatchNormali 2_conv[0][0]	(None,	23,	23,	128)	512	conv3_block4_
conv3_block4_2_relu (Activation 2_bn[0][0]	(None,	23,	23,	128)	0	conv3_block4_
conv3_block4_3_conv (Conv2D) 2_relu[0][0]	(None,	23,	23,	512)	66048	conv3_block4_
conv3_block4_3_bn (BatchNormali	(None,	23,	23,	512)	2048	conv3_block4_

3_conv[0][0]

conv3_block4_add (Add) out[0][0]	(None,	23,	23,	512)	0	conv3_block3_
3_bn[0][0]						conv3_block4_
conv3_block4_out (Activation) add[0][0]	(None,	23,	23,	512)	0	conv3_block4_
conv4_block1_1_conv (Conv2D) out[0][0]	(None,	12,	12,	256)	131328	conv3_block4_
conv4_block1_1_bn (BatchNormali 1_conv[0][0]	(None,	12,	12,	256)	1024	conv4_block1_
conv4_block1_1_relu (Activation 1_bn[0][0]	(None,	12,	12,	256)	0	conv4_block1_
conv4_block1_2_conv (Conv2D) 1_relu[0][0]	(None,	12,	12,	256)	590080	conv4_block1_
conv4_block1_2_bn (BatchNormali 2_conv[0][0]	(None,	12,	12,	256)	1024	conv4_block1_
conv4_block1_2_relu (Activation 2_bn[0][0]	(None,	12,	12,	256)	0	conv4_block1_
conv4_block1_0_conv (Conv2D) out[0][0]	(None,	12,	12,	1024)	525312	conv3_block4_
conv4_block1_3_conv (Conv2D) 2_relu[0][0]	(None,	12,	12,	1024)	263168	conv4_block1_
<pre>conv4_block1_0_bn (BatchNormali 0_conv[0][0]</pre>	(None,	12,	12,	1024)	4096	conv4_block1_
conv4_block1_3_bn (BatchNormali 3_conv[0][0]	(None,	12,	12,	1024)	4096	conv4_block1_
conv4_block1_add (Add) 0_bn[0][0]	(None,	12,	12,	1024)	0	conv4_block1_
3_bn[0][0]						conv4_block1_
conv4_block1_out (Activation) add[0][0]	(None,	12,	12,	1024)	0	conv4_block1_
conv4_block2_1_conv (Conv2D) out[0][0]	(None,	12,	12,	256)	262400	conv4_block1_
<pre>conv4_block2_1_bn (BatchNormali 1_conv[0][0]</pre>	(None,	12,	12,	256)	1024	conv4_block2_

<pre>conv4_block2_1_relu (Activation 1_bn[0][0]</pre>	(None,	12,	12,	256)	0	conv4_block2_
conv4_block2_2_conv (Conv2D) 1_relu[0][0]	(None,	12,	12,	256)	590080	conv4_block2_
conv4_block2_2_bn (BatchNormali 2_conv[0][0]	(None,	12,	12,	256)	1024	conv4_block2_
<pre>conv4_block2_2_relu (Activation 2_bn[0][0]</pre>	(None,	12,	12,	256)	0	conv4_block2_
conv4_block2_3_conv (Conv2D) 2_relu[0][0]	(None,	12,	12,	1024)	263168	conv4_block2_
<pre>conv4_block2_3_bn (BatchNormali 3_conv[0][0]</pre>	(None,	12,	12,	1024)	4096	conv4_block2_
conv4_block2_add (Add) out[0][0] 3_bn[0][0]	(None,	12,	12,	1024)	0	conv4_block1_ conv4_block2_
<pre>conv4_block2_out (Activation) add[0][0]</pre>	(None,	12,	12,	1024)	0	conv4_block2_
conv4_block3_1_conv (Conv2D) out[0][0]	(None,	12,	12,	256)	262400	conv4_block2_
<pre>conv4_block3_1_bn (BatchNormali 1_conv[0][0]</pre>	(None,	12,	12,	256)	1024	conv4_block3_
<pre>conv4_block3_1_relu (Activation 1_bn[0][0]</pre>	(None,	12,	12,	256)	0	conv4_block3_
conv4_block3_2_conv (Conv2D) 1_relu[0][0]	(None,	12,	12,	256)	590080	conv4_block3_
conv4_block3_2_bn (BatchNormali 2_conv[0][0]	(None,	12,	12,	256)	1024	conv4_block3_
<pre>conv4_block3_2_relu (Activation 2_bn[0][0]</pre>	(None,	12,	12,	256)	0	conv4_block3_
conv4_block3_3_conv (Conv2D) 2_relu[0][0]	(None,	12,	12,	1024)	263168	conv4_block3_
<pre>conv4_block3_3_bn (BatchNormali 3_conv[0][0]</pre>	(None,	12,	12,	1024)	4096	conv4_block3_
conv4_block3_add (Add)	(None,	12,	12,	1024)	0	conv4_block2_

out[0][0]						
3_bn[0][0]						conv4_block3_
conv4_block3_out (Activation) add[0][0]	(None,	12,	12,	1024)	0	conv4_block3_
conv4_block4_1_conv (Conv2D) out[0][0]	(None,	12,	12,	256)	262400	conv4_block3_
conv4_block4_1_bn (BatchNormali 1_conv[0][0]	(None,	12,	12,	256)	1024	conv4_block4_
conv4_block4_1_relu (Activation 1_bn[0][0]	(None,	12,	12,	256)	0	conv4_block4_
conv4_block4_2_conv (Conv2D) 1_relu[0][0]	(None,	12,	12,	256)	590080	conv4_block4_
<pre>conv4_block4_2_bn (BatchNormali 2_conv[0][0]</pre>	(None,	12,	12,	256)	1024	conv4_block4_
conv4_block4_2_relu (Activation 2_bn[0][0]	(None,	12,	12,	256)	0	conv4_block4_
conv4_block4_3_conv (Conv2D) 2_relu[0][0]	(None,	12,	12,	1024)	263168	conv4_block4_
<pre>conv4_block4_3_bn (BatchNormali 3_conv[0][0]</pre>	(None,	12,	12,	1024)	4096	conv4_block4_
conv4_block4_add (Add) out[0][0]	(None,	12,	12,	1024)	0	conv4_block3_
3_bn[0][0]						conv4_block4_
<pre>conv4_block4_out (Activation) add[0][0]</pre>	(None,	12,	12,	1024)	0	conv4_block4_
conv4_block5_1_conv (Conv2D) out[0][0]	(None,	12,	12,	256)	262400	conv4_block4_
<pre>conv4_block5_1_bn (BatchNormali 1_conv[0][0]</pre>	(None,	12,	12,	256)	1024	conv4_block5_
conv4_block5_1_relu (Activation 1_bn[0][0]	(None,	12,	12,	256)	0	conv4_block5_
conv4_block5_2_conv (Conv2D) 1_relu[0][0]	(None,	12,	12,	256)	590080	conv4_block5_
conv4_block5_2_bn (BatchNormali 2_conv[0][0]	(None,	12,	12,	256)	1024	conv4_block5_

<pre>conv4_block5_2_relu (Activation 2_bn[0][0]</pre>	(None,	12,	12,	256)	0	conv4_block5_
conv4_block5_3_conv (Conv2D) 2_relu[0][0]	(None,	12,	12,	1024)	263168	conv4_block5_
conv4_block5_3_bn (BatchNormali 3_conv[0][0]	(None,	12,	12,	1024)	4096	conv4_block5_
conv4_block5_add (Add) out[0][0]	(None,	12,	12,	1024)	0	conv4_block4_
3_bn[0][0]						
conv4_block5_out (Activation) add[0][0]	(None,	12,	12,	1024)	0	conv4_block5_
<pre>conv4_block6_1_conv (Conv2D) out[0][0]</pre>	(None,	12,	12,	256)	262400	conv4_block5_
<pre>conv4_block6_1_bn (BatchNormali 1_conv[0][0]</pre>	(None,	12,	12,	256)	1024	conv4_block6_
<pre>conv4_block6_1_relu (Activation 1_bn[0][0]</pre>	(None,	12,	12,	256)	0	conv4_block6_
<pre>conv4_block6_2_conv (Conv2D) 1_relu[0][0]</pre>	(None,	12,	12,	256)	590080	conv4_block6_
<pre>conv4_block6_2_bn (BatchNormali 2_conv[0][0]</pre>	(None,	12,	12,	256)	1024	conv4_block6_
conv4_block6_2_relu (Activation 2_bn[0][0]	(None,	12,	12,	256)	0	conv4_block6_
conv4_block6_3_conv (Conv2D) 2_relu[0][0]	(None,	12,	12,	1024)	263168	conv4_block6_
conv4_block6_3_bn (BatchNormali 3_conv[0][0]	(None,	12,	12,	1024)	4096	conv4_block6_
conv4_block6_add (Add) out[0][0]	(None,	12,	12,	1024)	0	conv4_block5_
3_bn[0][0]						conv4_block6_
conv4_block6_out (Activation) add[0][0]	(None,	12,	12,	1024)	0	conv4_block6_
conv5_block1_1_conv (Conv2D) out[0][0]	(None,	6, 6	5, 5:	12)	524800	conv4_block6_

<pre>conv5_block1_1_bn (BatchNormali 1_conv[0][0]</pre>	(None,	6,	6,	512)	2048	conv5_block1_
conv5_block1_1_relu (Activation 1_bn[0][0]	(None,	6,	6,	512)	0	conv5_block1_
conv5_block1_2_conv (Conv2D) 1_relu[0][0]	(None,	6,	6,	512)	2359808	conv5_block1_
conv5_block1_2_bn (BatchNormali 2_conv[0][0]	(None,	6,	6,	512)	2048	conv5_block1_
conv5_block1_2_relu (Activation 2_bn[0][0]	(None,	6,	6,	512)	0	conv5_block1_
conv5_block1_0_conv (Conv2D) out[0][0]	(None,	6,	6,	2048)	2099200	conv4_block6_
conv5_block1_3_conv (Conv2D) 2_relu[0][0]	(None,	6,	6,	2048)	1050624	conv5_block1_
<pre>conv5_block1_0_bn (BatchNormali 0_conv[0][0]</pre>	(None,	6,	6,	2048)	8192	conv5_block1_
conv5_block1_3_bn (BatchNormali 3_conv[0][0]	(None,	6,	6,	2048)	8192	conv5_block1_
conv5_block1_add (Add) 0_bn[0][0]	(None,	6,	6,	2048)	0	conv5_block1_
3_bn[0][0]						conv5_block1_
conv5_block1_out (Activation) add[0][0]	(None,	6,	6,	2048)	0	conv5_block1_
conv5_block2_1_conv (Conv2D) out[0][0]	(None,	6,	6,	512)	1049088	conv5_block1_
conv5_block2_1_bn (BatchNormali 1_conv[0][0]	(None,	6,	6,	512)	2048	conv5_block2_
conv5_block2_1_relu (Activation 1_bn[0][0]	(None,	6,	6,	512)	0	conv5_block2_
<pre>conv5_block2_2_conv (Conv2D) 1_relu[0][0]</pre>	(None,	6,	6,	512)	2359808	conv5_block2_
<pre>conv5_block2_2_bn (BatchNormali 2_conv[0][0]</pre>	(None,	6,	6,	512)	2048	conv5_block2_
<pre>conv5_block2_2_relu (Activation 2_bn[0][0]</pre>	(None,	6,	6,	512)	0	conv5_block2_

<pre>conv5_block2_3_conv (Conv2D) 2_relu[0][0]</pre>	(None,	6,	6,	2048)	1050624	conv5_block2_
conv5_block2_3_bn (BatchNormali 3_conv[0][0]	(None,	6,	6,	2048)	8192	conv5_block2_
conv5_block2_add (Add) out[0][0]	(None,	6,	6,	2048)	0	conv5_block1_
3_bn[0][0]						conv5_block2_
conv5_block2_out (Activation) add[0][0]	(None,	6,	6,	2048)	0	conv5_block2_
conv5_block3_1_conv (Conv2D) out[0][0]	(None,	6,	6,	512)	1049088	conv5_block2_
conv5_block3_1_bn (BatchNormali 1_conv[0][0]	(None,	6,	6,	512)	2048	conv5_block3_
<pre>conv5_block3_1_relu (Activation 1_bn[0][0]</pre>	(None,	6,	6,	512)	0	conv5_block3_
conv5_block3_2_conv (Conv2D) 1_relu[0][0]	(None,	6,	6,	512)	2359808	conv5_block3_
conv5_block3_2_bn (BatchNormali 2_conv[0][0]	(None,	6,	6,	512)	2048	conv5_block3_
conv5_block3_2_relu (Activation 2_bn[0][0]	(None,	6,	6,	512)	0	conv5_block3_
conv5_block3_3_conv (Conv2D) 2_relu[0][0]	(None,	6,	6,	2048)	1050624	conv5_block3_
conv5_block3_3_bn (BatchNormali 3_conv[0][0]	(None,	6,	6,	2048)	8192	conv5_block3_
conv5_block3_add (Add) out[0][0]	(None,	6,	6,	2048)	0	conv5_block2_
3_bn[0][0]						conv5_block3_
conv5_block3_out (Activation) add[0][0]	(None,	6,	6,	2048)	0	conv5_block3_
Total params: 23,587,712 Trainable params: 23,534,592 Non-trainable params: 53,120						

Non-trainable params: 53,120

```
resnet base model,
    GlobalAveragePooling2D(),
    Dense(512, activation="relu"),
    BatchNormalization(),
    Dropout(0.6),
    Dense(128, activation="relu"),
    BatchNormalization(),
    Dropout(0.4),
    Dense(64, activation="relu"),
    BatchNormalization(),
    Dropout(0.3),
    Dense(1,activation="sigmoid")
])
opt = tf.keras.optimizers.Adam(learning rate=0.001)
METRICS = [
    'accuracy',
    tf.keras.metrics.Precision(name='precision'),
    tf.keras.metrics.Recall(name='recall')
resnet model.compile(optimizer=opt,loss='binary crossentropy',metrics=MET
```

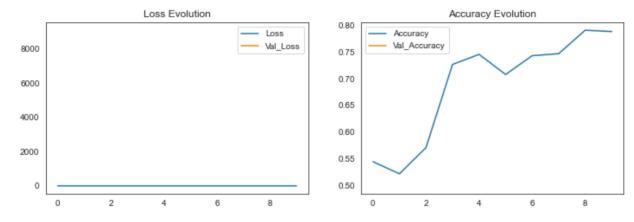
```
Epoch 1/10
0.5450 - precision: 0.7888 - recall: 0.5399WARNING:tensorflow:Your input ran o
ut of data; interrupting training. Make sure that your dataset or generator ca
n generate at least `steps per epoch * epochs` batches (in this case, 25 batch
es). You may need to use the repeat() function when building your dataset.
100/100 [============= ] - 144s ls/step - loss: 0.3237 - accur
acy: 0.5450 - precision: 0.7888 - recall: 0.5399 - val loss: 9098.6367 - val a
ccuracy: 0.5000 - val precision: 0.5000 - val recall: 1.0000
Epoch 2/10
100/100 [============= ] - 133s 1s/step - loss: 0.3136 - accur
acy: 0.5225 - precision: 0.7724 - recall: 0.5255
Epoch 3/10
100/100 [==============] - 126s 1s/step - loss: 0.2928 - accur
acy: 0.5713 - precision: 0.8072 - recall: 0.5395
Epoch 4/10
100/100 [=============] - 129s 1s/step - loss: 0.2005 - accur
acy: 0.7262 - precision: 0.9234 - recall: 0.6964
Epoch 5/10
100/100 [=============] - 134s 1s/step - loss: 0.2195 - accur
acy: 0.7450 - precision: 0.8921 - recall: 0.7436
Epoch 6/10
100/100 [============= ] - 153s 2s/step - loss: 0.2269 - accur
acy: 0.7075 - precision: 0.8671 - recall: 0.7150
Epoch 7/10
100/100 [============= ] - 142s ls/step - loss: 0.2106 - accur
acy: 0.7425 - precision: 0.8834 - recall: 0.7435
Epoch 8/10
100/100 [============ ] - 135s ls/step - loss: 0.1953 - accur
acy: 0.7462 - precision: 0.9110 - recall: 0.7333
Epoch 9/10
100/100 [==============] - 136s ls/step - loss: 0.1814 - accur
acy: 0.7900 - precision: 0.9160 - recall: 0.7947
Epoch 10/10
100/100 [==============] - 132s 1s/step - loss: 0.1778 - accur
acy: 0.7875 - precision: 0.9275 - recall: 0.7805
```

```
plt.figure(figsize=(12, 8))

plt.subplot(2, 2, 1)
plt.plot(r.history['loss'], label='Loss')
plt.plot(r.history['val_loss'], label='Val_Loss')
plt.legend()
plt.title('Loss Evolution')

plt.subplot(2, 2, 2)
plt.plot(r.history['accuracy'], label='Accuracy')
plt.plot(r.history['val_accuracy'], label='Val_Accuracy')
plt.legend()
plt.title('Accuracy Evolution')
```

Out[47]: Text(0.5, 1.0, 'Accuracy Evolution')



InceptionNet

Also known as GoogleNet, this architecture presents sub-networks called inception modules, which allows fast training computing, complex patterns detection, and optimal use of parameters

for more information visit

https://static.googleusercontent.com/media/research.google.com/en//pubs/archive/43022.pdf

```
from keras.applications.inception_v3 import InceptionV3
from tensorflow.keras.applications import imagenet_utils
inception_base_model = InceptionV3(input_shape=(180,180,3),include_top=False,v)
```

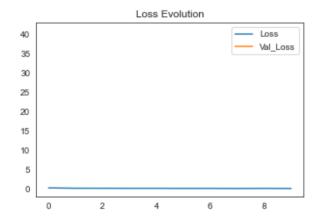
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/inception_v3/inception_v3_weights_tf_dim_ordering_tf_kernels_notop.h5

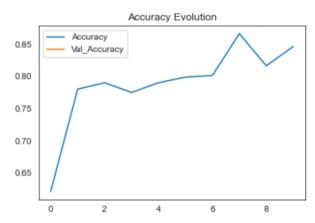
```
In [52]:
             inception model = tf.keras.Sequential([
                 inception base model,
                 GlobalAveragePooling2D(),
                 Dense(512, activation="relu"),
                 BatchNormalization(),
                 Dropout(0.6),
                 Dense(128, activation="relu"),
                 BatchNormalization(),
                 Dropout(0.4),
                 Dense(64,activation="relu"),
                 BatchNormalization(),
                 Dropout(0.3),
                 Dense(1,activation="sigmoid")
             1)
             opt = tf.keras.optimizers.Adam(learning rate=0.001)
             METRICS = [
                 'accuracy',
                 tf.keras.metrics.Precision(name='precision'),
                 tf.keras.metrics.Recall(name='recall')
             inception model.compile(optimizer=opt,loss='binary crossentropy',metrics=
In [53]:
         r = inception model.fit(train,
                  epochs=10,
                   validation data=validation,
                  class weight=class weight,
                   steps per epoch=100,
                   validation steps=25)
```

```
Epoch 1/10
0.6212 - precision: 0.8239 - recall: 0.6062WARNING:tensorflow:Your input ran o
ut of data; interrupting training. Make sure that your dataset or generator ca
n generate at least `steps per epoch * epochs` batches (in this case, 25 batch
es). You may need to use the repeat() function when building your dataset.
100/100 [============ ] - 91s 834ms/step - loss: 0.2935 - acc
uracy: 0.6212 - precision: 0.8239 - recall: 0.6062 - val loss: 40.9358 - val a
ccuracy: 0.6250 - val precision: 0.5714 - val recall: 1.0000
Epoch 2/10
100/100 [============= ] - 81s 813ms/step - loss: 0.1979 - acc
uracy: 0.7800 - precision: 0.9126 - recall: 0.7602
Epoch 3/10
100/100 [===============] - 82s 815ms/step - loss: 0.1927 - acc
uracy: 0.7900 - precision: 0.9293 - recall: 0.7694
Epoch 4/10
100/100 [==============] - 80s 797ms/step - loss: 0.1804 - acc
uracy: 0.7750 - precision: 0.9244 - recall: 0.7534
Epoch 5/10
100/100 [============] - 84s 837ms/step - loss: 0.1836 - acc
uracy: 0.7900 - precision: 0.9208 - recall: 0.7841
Epoch 6/10
100/100 [============= ] - 84s 833ms/step - loss: 0.1624 - acc
uracy: 0.7987 - precision: 0.9481 - recall: 0.7787
Epoch 7/10
100/100 [============ ] - 84s 842ms/step - loss: 0.1728 - acc
uracy: 0.8012 - precision: 0.9193 - recall: 0.8086
Epoch 8/10
100/100 [============ ] - 95s 947ms/step - loss: 0.1419 - acc
uracy: 0.8662 - precision: 0.9542 - recall: 0.8640
Epoch 9/10
100/100 [============= ] - 92s 920ms/step - loss: 0.1731 - acc
```

```
uracy: 0.8163 - precision: 0.9206 - recall: 0.8226
         Epoch 10/10
         100/100 [============ ] - 85s 845ms/step - loss: 0.1457 - acc
         uracy: 0.8462 - precision: 0.9332 - recall: 0.8475
In [54]:
         plt.figure(figsize=(12, 8))
         plt.subplot(2, 2, 1)
         plt.plot(r.history['loss'], label='Loss')
         plt.plot(r.history['val loss'], label='Val Loss')
         plt.legend()
         plt.title('Loss Evolution')
         plt.subplot(2, 2, 2)
         plt.plot(r.history['accuracy'], label='Accuracy')
         plt.plot(r.history['val_accuracy'], label='Val_Accuracy')
         plt.legend()
         plt.title('Accuracy Evolution')
```

Out[54]: Text(0.5, 1.0, 'Accuracy Evolution')





```
evaluation =inception_model.evaluate(test)
print(f"Test Accuracy: {evaluation[1] * 100:.2f}%")

evaluation = inception_model.evaluate(train)
print(f"Train Accuracy: {evaluation[1] * 100:.2f}%")
```