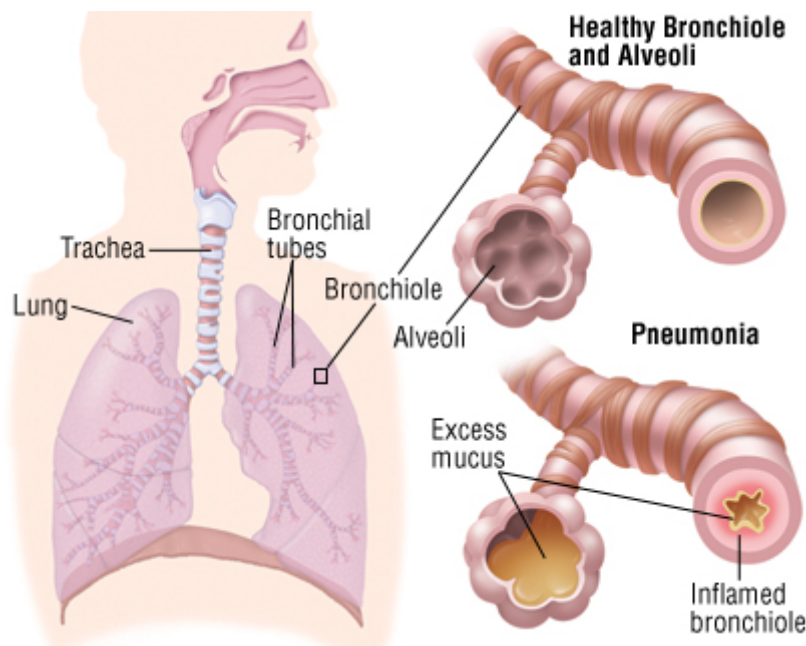


What is Pneumonia ?

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.

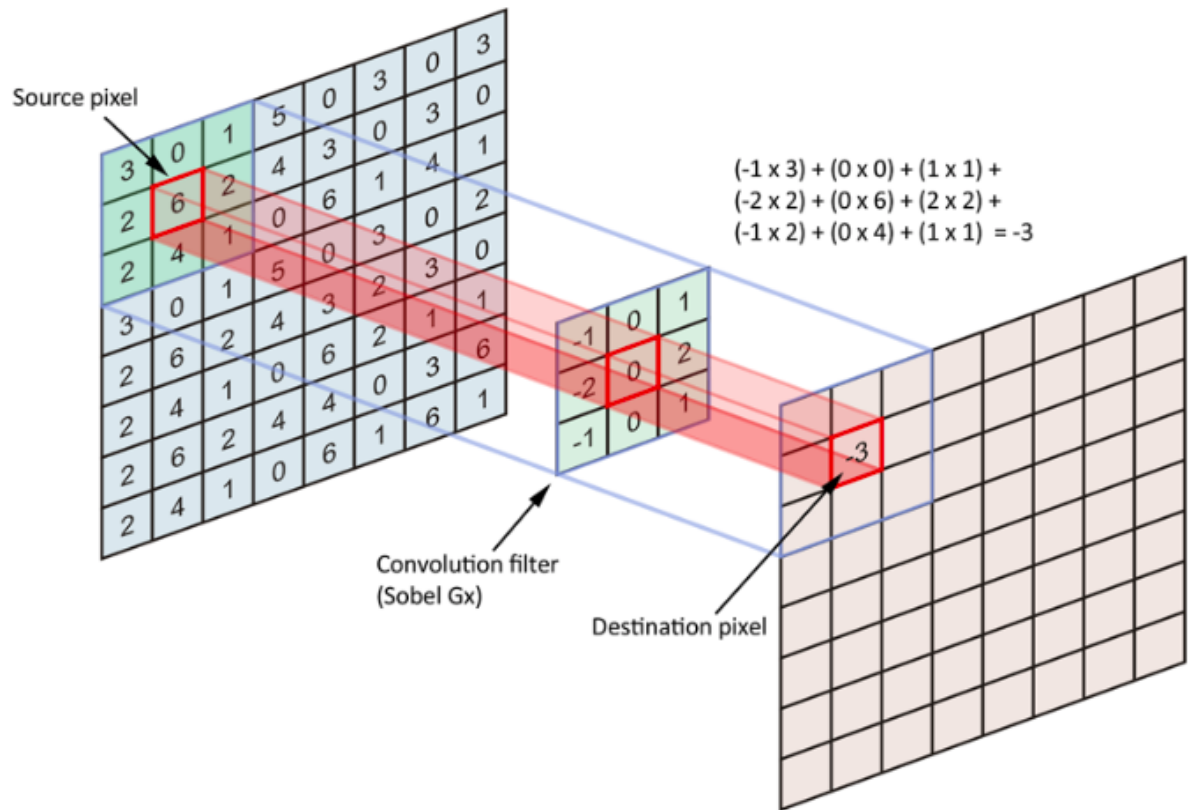


Pneumonia Detection with Convolutional Neural Networks

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:

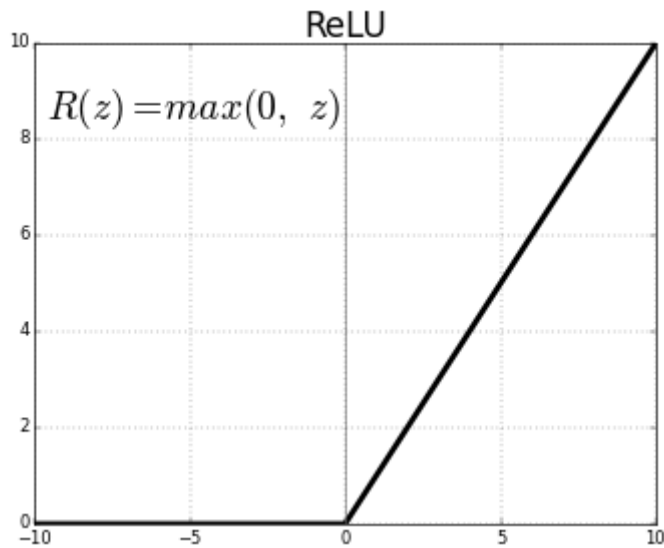
- Filter an image for a particular feature (convolution)
- Detect that feature within the filtered image (using the ReLU activation)
- Condense the image to enhance the features (maximum pooling)

The convolution process is illustrated below

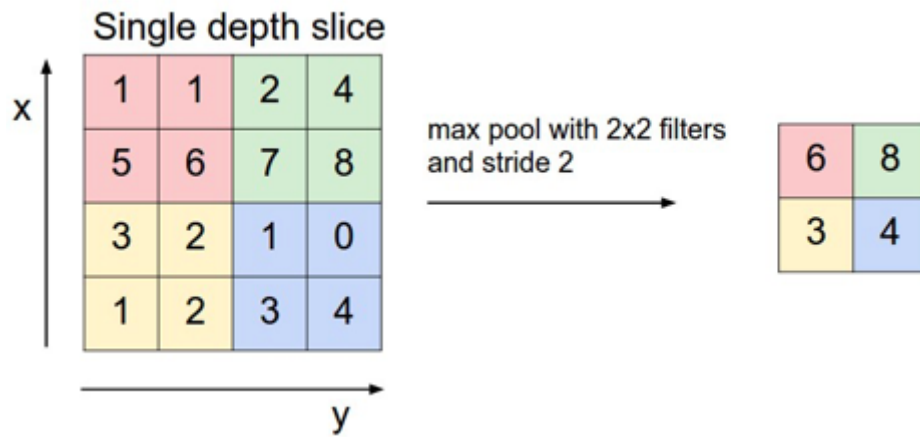


Using convolution filters with different dimensions or values results in different features extracted

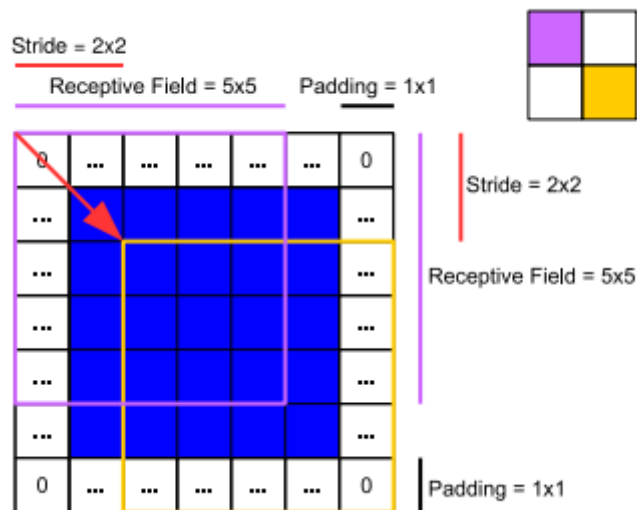
Features are then detected using the ReLU activation on each destination pixel.



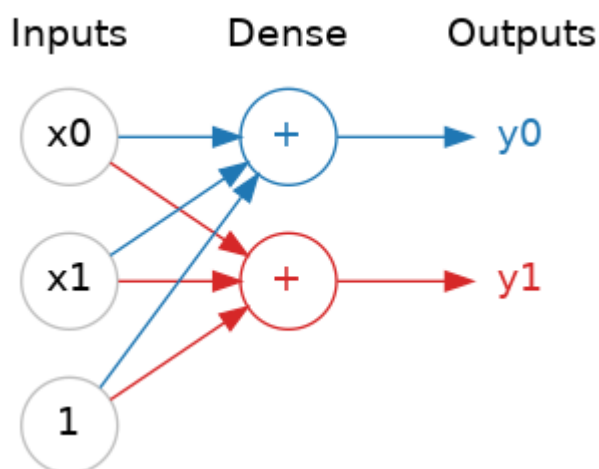
Features are enhanced with MaxPool layers



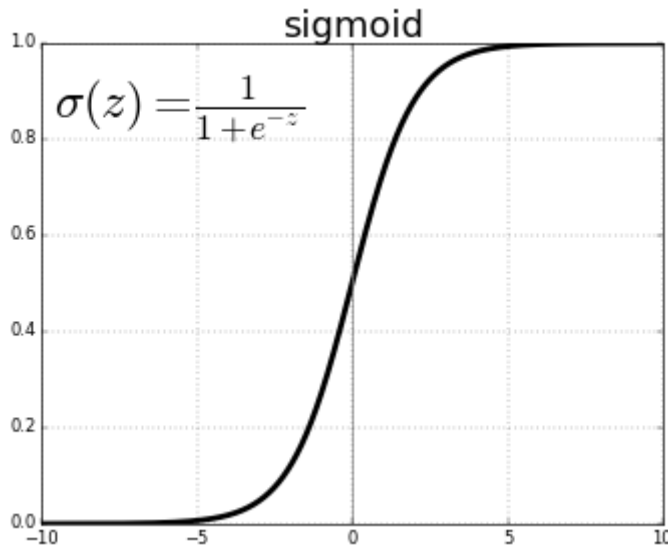
The stride parameters determines the distance between each filters. The padding one determines if we ignore the borderline pixels or not (adding zeros helps the neural network to get information on the border)



The outputs are then concatenated in Dense layers



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



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.

```
In [1]: 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]: ['chest_xray', 'test', 'train', 'val', '__MACOSX']
```

```
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()

```

Train set:

=====

PNEUMONIA=3875

NORMAL=1341

Test set:

=====

PNEUMONIA=390

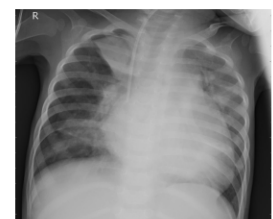
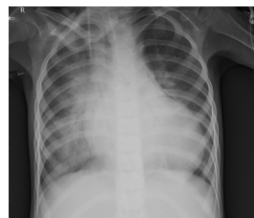
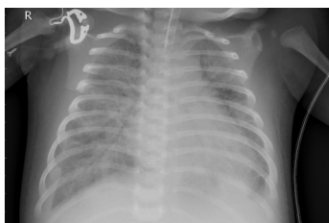
NORMAL=234

Validation set:

=====

PNEUMONIA=8

NORMAL=8

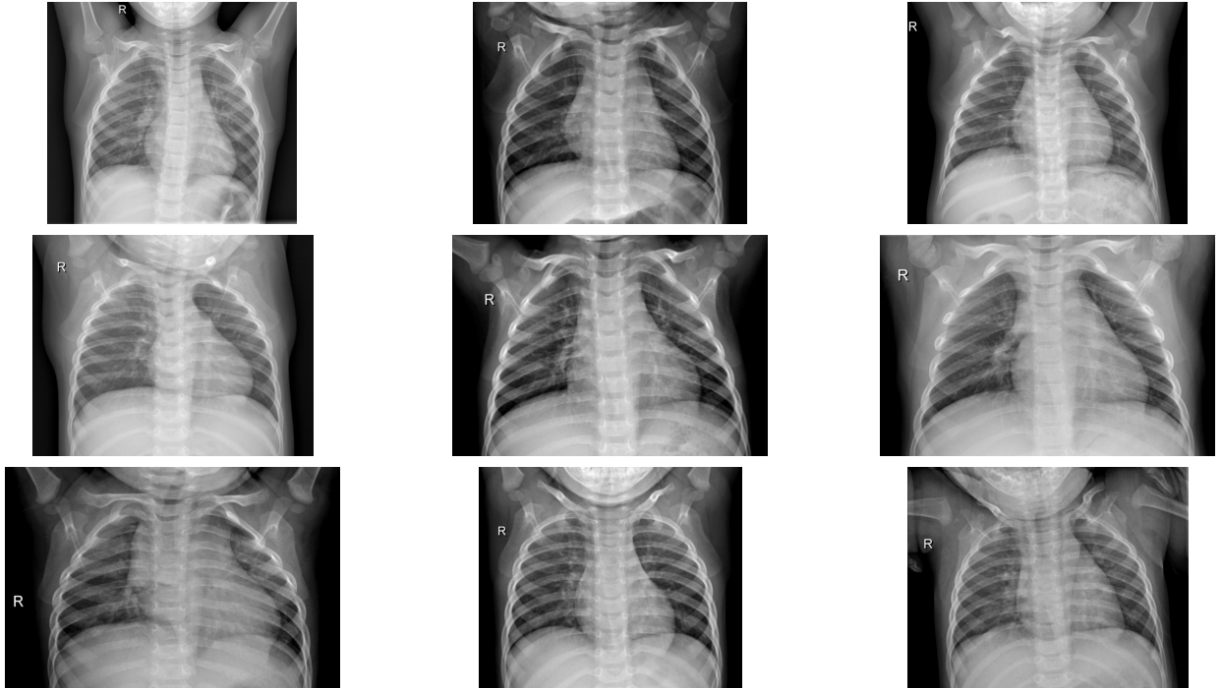


```
In [4]: normal = os.listdir("chest_xray/train/NORMAL")
normal_dir = "chest_xray/train/NORMAL"

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()
```



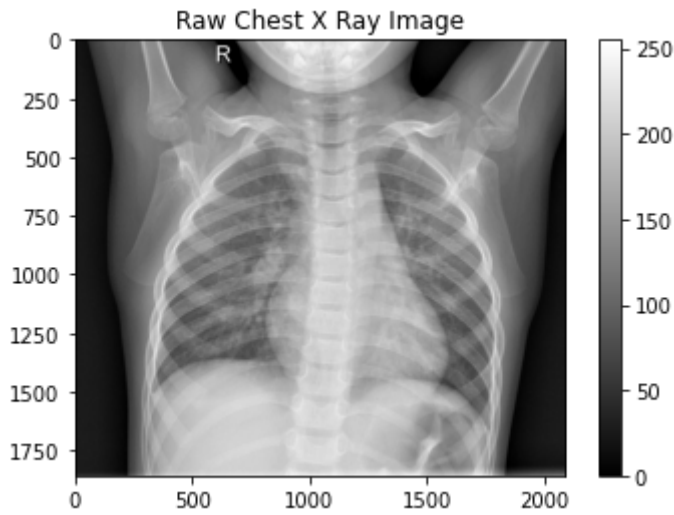
```
In [5]: normal_img = os.listdir("chest_xray/train/NORMAL")[0]
normal_dir = "chest_xray/train/NORMAL"
sample_img = plt.imread(os.path.join(normal_dir, normal_img))
plt.imshow(sample_img, cmap='gray')
plt.colorbar()
plt.title('Raw Chest X Ray Image')

print(f"The dimensions of the image are {sample_img.shape[0]} pixels width and {sample_img.shape[1]} pixels height")
print(f"The maximum pixel value is {sample_img.max():.4f} and the minimum is {sample_img.min():.4f}")
print(f"The mean value of the pixels is {sample_img.mean():.4f} and the standard deviation is {sample_img.std():.4f}")
```

The dimensions of the image are 1858 pixels width and 2090 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 128.9075 and the standard deviation is 62.3010



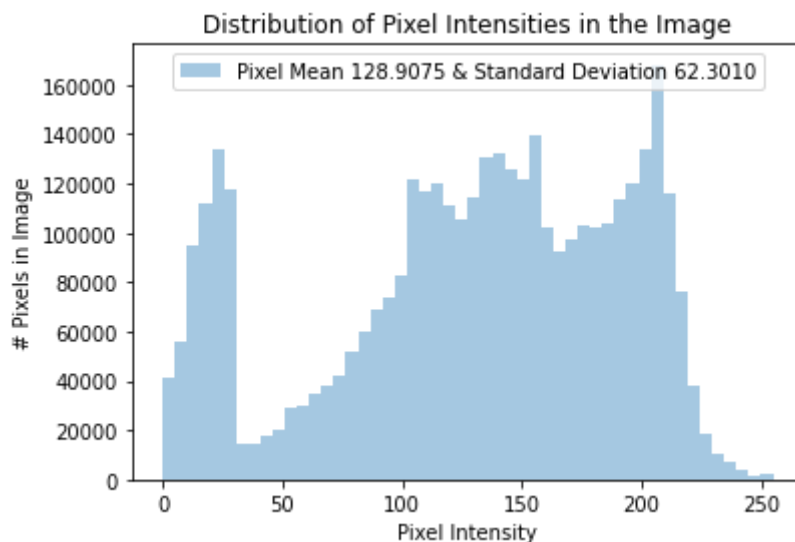
Investigate pixel value distribution

```
In [6]: sns.distplot(sample_img.ravel(),
                    label=f"Pixel Mean {np.mean(sample_img):.4f} & Standard Deviation {np.st
plt.legend(loc='upper center')
plt.title('Distribution of Pixel Intensities in the Image')
plt.xlabel('Pixel Intensity')
plt.ylabel('# Pixels in Image')
```

C:\Users\MCHOME\.conda\envs\pbl\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

warnings.warn(msg, FutureWarning)

```
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 facilitate 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 incoming test data using the statistics computed from the training set.

```
In [8]: train = image_generator.flow_from_directory(train_dir,
                                                    batch_size=8,
                                                    shuffle=True,
                                                    class_mode='binary',
                                                    target_size=(180, 180))

validation = image_generator.flow_from_directory(val_dir,
                                                  batch_size=1,
                                                  shuffle=False,
                                                  class_mode='binary',
                                                  target_size=(180, 180))

test = image_generator.flow_from_directory(test_dir,
                                           batch_size=1,
                                           shuffle=False,
                                           class_mode='binary',
                                           target_size=(180, 180))
```

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')

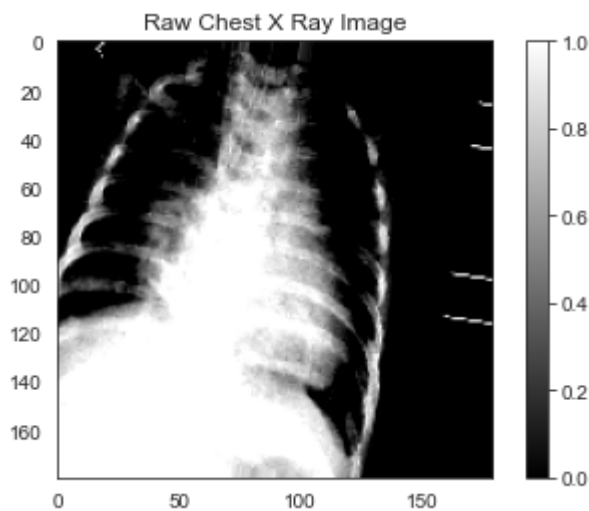
print(f"The dimensions of the image are {generated_image.shape[1]} pixels width and
print(f"The maximum pixel value is {generated_image.max():.4f} and the minimum is {g
print(f"The mean value of the pixels is {generated_image.mean():.4f} and the standar
```

Clipping input data to the valid range for imshow with RGB data ([0..1] for floats 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 2.4701 and the minimum is -3.2370

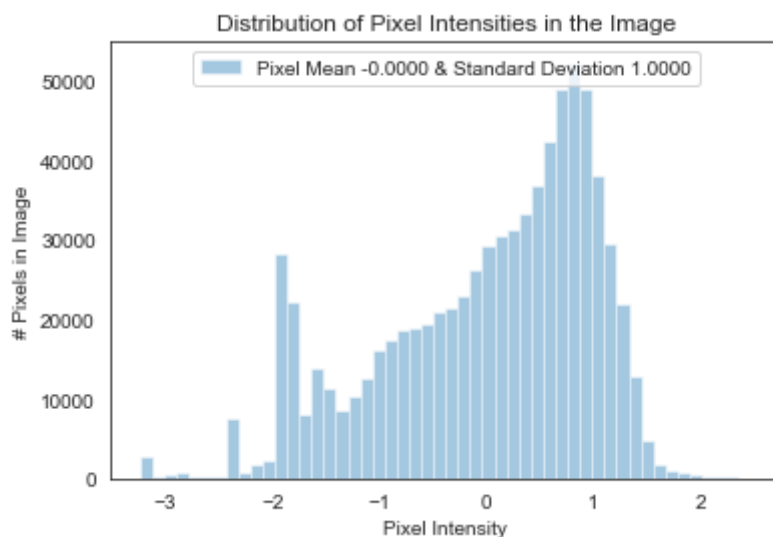
The mean value of the pixels is -0.0000 and the standard deviation is 1.0000



In [10]:

```
sns.distplot(generated_image.ravel(),
              label=f"Pixel Mean {np.mean(generated_image):.4f} & Standard Deviation {
plt.legend(loc='upper center')
plt.title('Distribution of Pixel Intensities in the Image')
plt.xlabel('Pixel Intensity')
plt.ylabel('# Pixels in Image')
```

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 \mathcal{D} of size N as follows:

$$\mathcal{L}_{cross-entropy}(\mathcal{D}) = -\frac{1}{N} \left(\sum_{\text{positive examples}} \log(f(x_i)) + \sum_{\text{negative examples}} \log(1 - f(x_i)) \right).$$

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.

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

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, BatchNormalizat

model = Sequential()

model.add(Conv2D(filters=32, kernel_size=(3, 3), input_shape=(180, 180, 3), activation='relu'))
model.add(BatchNormalization())
model.add(Conv2D(filters=32, kernel_size=(3, 3), input_shape=(180, 180, 3), activation='relu'))
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 (Batch Normalization)	(None, 178, 178, 32)	128
conv2d_1 (Conv2D)	(None, 176, 176, 32)	9248
batch_normalization_1 (Batch Normalization)	(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 Normalization)	(None, 86, 86, 64)	256
conv2d_3 (Conv2D)	(None, 84, 84, 64)	36928
batch_normalization_3 (Batch Normalization)	(None, 84, 84, 64)	256
max_pooling2d_1 (MaxPooling2D)	(None, 42, 42, 64)	0
conv2d_4 (Conv2D)	(None, 40, 40, 128)	73856
batch_normalization_4 (Batch Normalization)	(None, 40, 40, 128)	512
conv2d_5 (Conv2D)	(None, 38, 38, 128)	147584
batch_normalization_5 (Batch Normalization)	(None, 38, 38, 128)	512
max_pooling2d_2 (MaxPooling2D)	(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

100/100 [=====] - ETA: 0s - loss: 0.5413 - accuracy: 0.7850
 WARNING:tensorflow:Your input ran out of data; interrupting training. Make 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 [=====] - 316s 3s/step - loss: 0.5413 - accuracy:
 0.7850 - val_loss: 8.3759 - val_accuracy: 0.5625

Epoch 2/10

100/100 [=====] - 291s 3s/step - loss: 0.2271 - accuracy:
 0.8687

Epoch 3/10

100/100 [=====] - 289s 3s/step - loss: 0.1325 - accuracy:
 0.8575

Epoch 4/10

100/100 [=====] - 293s 3s/step - loss: 0.1650 - accuracy:
 0.8475

Epoch 5/10

100/100 [=====] - 290s 3s/step - loss: 0.4424 - accuracy:
 0.8562

Epoch 6/10

100/100 [=====] - 292s 3s/step - loss: 0.1272 - accuracy:
 0.8512

Epoch 7/10

100/100 [=====] - 298s 3s/step - loss: 0.1121 - accuracy:
 0.9062

Epoch 8/10

100/100 [=====] - 291s 3s/step - loss: 0.1004 - accuracy:
 0.8850

Epoch 9/10

100/100 [=====] - 298s 3s/step - loss: 0.1313 - accuracy:
 0.8938

Epoch 10/10

100/100 [=====] - 286s 3s/step - loss: 0.0761 - accuracy:
 0.9212

In [15]:

```

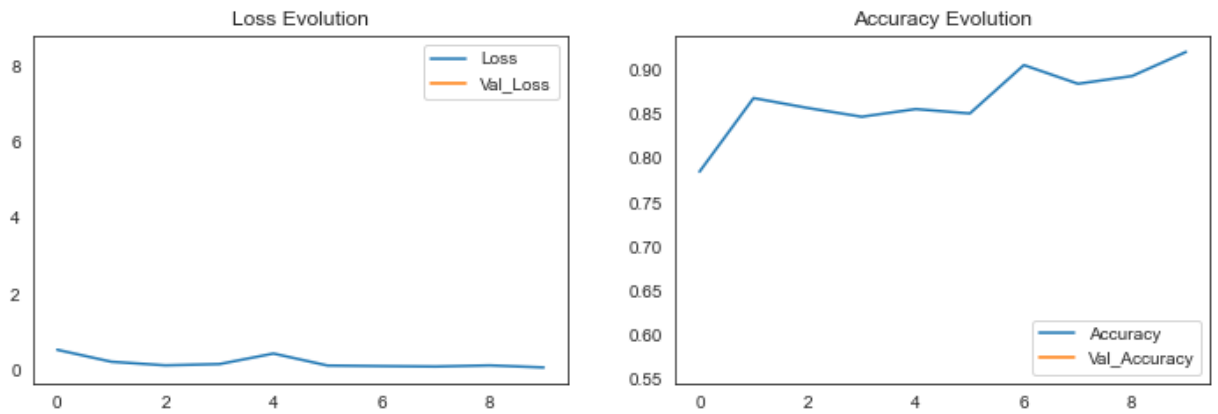
plt.figure(figsize=(12, 8))

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')



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 [=====] - 68s 108ms/step - loss: 0.5916 - accuracy: 0.7997
Test Accuracy: 79.97%
652/652 [=====] - 561s 861ms/step - loss: 0.6874 - accuracy: 0.7795
Train Accuracy: 77.95%
```

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))
```

```
[[209  25]
 [104 286]]
```

Out[17]:

	0	1	accuracy	macro avg	weighted avg
precision	0.667732	0.919614	0.793269	0.793673	0.825158
recall	0.893162	0.733333	0.793269	0.813248	0.793269
f1-score	0.764168	0.815977	0.793269	0.790073	0.796549
support	234.000000	390.000000	0.793269	624.000000	624.000000

In [18]:

```
print(confusion_matrix(test.classes, pred > 0.7))
pd.DataFrame(classification_report(test.classes, pred > 0.7, output_dict=True))
```

```
[[220  14]
 [141 249]]
```

Out[18]:

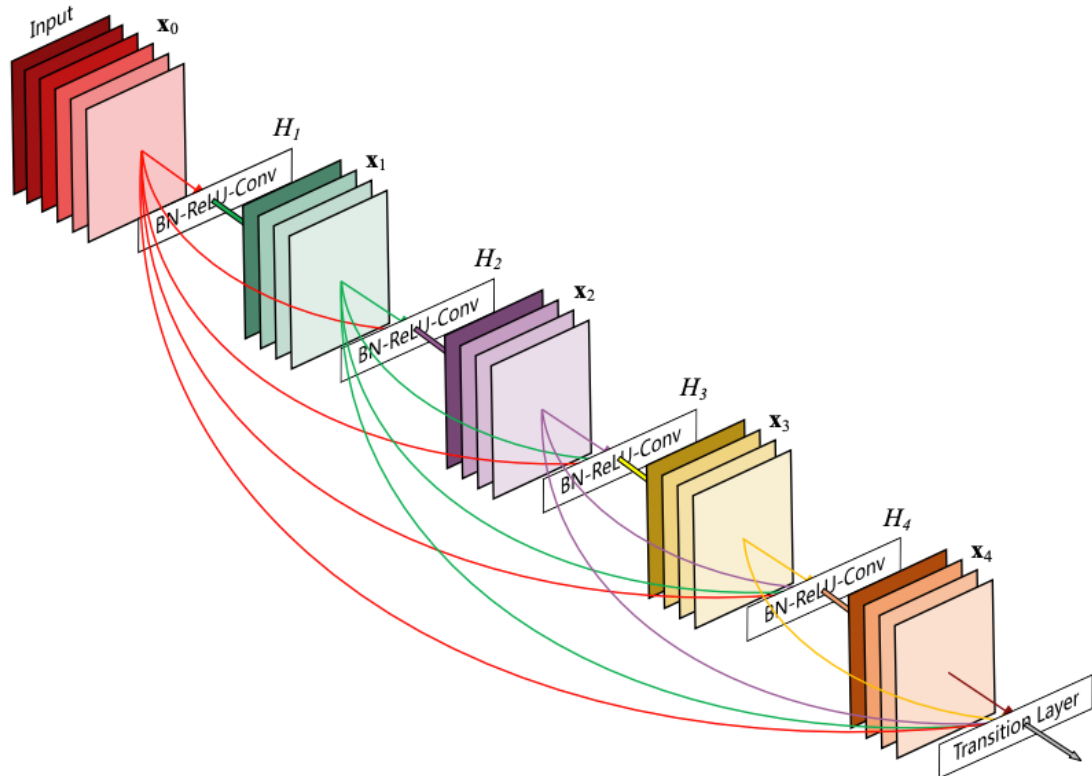
	0	1	accuracy	macro avg	weighted avg
precision	0.609418	0.946768	0.751603	0.778093	0.820262
recall	0.940171	0.638462	0.751603	0.789316	0.751603
f1-score	0.739496	0.762634	0.751603	0.751065	0.753957
support	234.000000	390.000000	0.751603	624.000000	624.000000

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 connected to the 3rd, 4th, 5th etc.



for more information about the DenseNet Architecture visit this website :

<https://keras.io/api/applications/densenet/>

In [19]:

```
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, weights='imagenet')
base_model.summary()
```

Model: "densenet121"

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	[(None, 180, 180, 3) 0		

zero_padding2d (ZeroPadding2D)	(None, 186, 186, 3)	0	input_1[0][0]
conv1/conv (Conv2D)	(None, 90, 90, 64)	9408	zero_padding2d[0][0]
conv1/bn (BatchNormalization)	(None, 90, 90, 64)	256	conv1/conv[0][0]
conv1/relu (Activation)	(None, 90, 90, 64)	0	conv1/bn[0][0]
zero_padding2d_1 (ZeroPadding2D)	(None, 92, 92, 64)	0	conv1/relu[0][0]
pool1 (MaxPooling2D)	(None, 45, 45, 64)	0	zero_padding2d_1[0][0]
conv2_block1_0_bn (BatchNormalization)	(None, 45, 45, 64)	256	pool1[0][0]
conv2_block1_0_relu (Activation)	(None, 45, 45, 64)	0	conv2_block1_0_bn[0][0]
conv2_block1_1_conv (Conv2D)	(None, 45, 45, 128)	8192	conv2_block1_0_relu[0][0]
conv2_block1_1_bn (BatchNormalization)	(None, 45, 45, 128)	512	conv2_block1_1_conv[0][0]
conv2_block1_1_relu (Activation)	(None, 45, 45, 128)	0	conv2_block1_1_bn[0][0]
conv2_block1_2_conv (Conv2D)	(None, 45, 45, 32)	36864	conv2_block1_1_relu[0][0]
conv2_block1_concat (Concatenation)	(None, 45, 45, 96)	0	pool1[0][0] conv2_block1_2_conv[0][0]
conv2_block2_0_bn (BatchNormalization)	(None, 45, 45, 96)	384	conv2_block1_concat[0][0]
conv2_block2_0_relu (Activation)	(None, 45, 45, 96)	0	conv2_block2_0_bn[0][0]
conv2_block2_1_conv (Conv2D)	(None, 45, 45, 128)	12288	conv2_block2_0_relu[0][0]
conv2_block2_1_bn (BatchNormalization)	(None, 45, 45, 128)	512	conv2_block2_1_conv[0][0]

conv2_block2_1_relu (Activation (None, 45, 45, 128) 0 [0][0])		conv2_block2_1_bn
<hr/>		
conv2_block2_2_conv (Conv2D) (None, 45, 45, 32) 36864 [0][0])		conv2_block2_1_relu
<hr/>		
conv2_block2_concat (Concatenat (None, 45, 45, 128) 0 [0][0])		conv2_block1_concat
<hr/>		
		conv2_block2_2_conv
<hr/>		
conv2_block3_0_bn (BatchNormali (None, 45, 45, 128) 512 [0][0])		conv2_block2_concat
<hr/>		
conv2_block3_0_relu (Activation (None, 45, 45, 128) 0 [0][0])		conv2_block3_0_bn
<hr/>		
conv2_block3_1_conv (Conv2D) (None, 45, 45, 128) 16384 [0][0])		conv2_block3_0_relu
<hr/>		
conv2_block3_1_bn (BatchNormali (None, 45, 45, 128) 512 [0][0])		conv2_block3_1_conv
<hr/>		
conv2_block3_1_relu (Activation (None, 45, 45, 128) 0 [0][0])		conv2_block3_1_bn
<hr/>		
conv2_block3_2_conv (Conv2D) (None, 45, 45, 32) 36864 [0][0])		conv2_block3_1_relu
<hr/>		
conv2_block3_concat (Concatenat (None, 45, 45, 160) 0 [0][0])		conv2_block2_concat
<hr/>		
		conv2_block3_2_conv
<hr/>		
conv2_block4_0_bn (BatchNormali (None, 45, 45, 160) 640 [0][0])		conv2_block3_concat
<hr/>		
conv2_block4_0_relu (Activation (None, 45, 45, 160) 0 [0][0])		conv2_block4_0_bn
<hr/>		
conv2_block4_1_conv (Conv2D) (None, 45, 45, 128) 20480 [0][0])		conv2_block4_0_relu
<hr/>		
conv2_block4_1_bn (BatchNormali (None, 45, 45, 128) 512 [0][0])		conv2_block4_1_conv
<hr/>		
conv2_block4_1_relu (Activation (None, 45, 45, 128) 0 [0][0])		conv2_block4_1_bn
<hr/>		

conv2_block4_2_conv (Conv2D)	(None, 45, 45, 32)	36864	conv2_block4_1_relu [0][0]
<hr/>			
conv2_block4_concat (Concatenat	(None, 45, 45, 192)	0	conv2_block3_concat [0][0]
<hr/>			
conv2_block4_2_conv			conv2_block4_2_conv [0][0]
<hr/>			
conv2_block5_0_bn (BatchNormali	(None, 45, 45, 192)	768	conv2_block4_concat [0][0]
<hr/>			
conv2_block5_0_relu (Activation	(None, 45, 45, 192)	0	conv2_block5_0_bn [0][0]
<hr/>			
conv2_block5_1_conv (Conv2D)	(None, 45, 45, 128)	24576	conv2_block5_0_relu [0][0]
<hr/>			
conv2_block5_1_bn (BatchNormali	(None, 45, 45, 128)	512	conv2_block5_1_conv [0][0]
<hr/>			
conv2_block5_1_relu (Activation	(None, 45, 45, 128)	0	conv2_block5_1_bn [0][0]
<hr/>			
conv2_block5_2_conv (Conv2D)	(None, 45, 45, 32)	36864	conv2_block5_1_relu [0][0]
<hr/>			
conv2_block5_concat (Concatenat	(None, 45, 45, 224)	0	conv2_block4_concat [0][0]
<hr/>			
conv2_block5_2_conv			conv2_block5_2_conv [0][0]
<hr/>			
conv2_block6_0_bn (BatchNormali	(None, 45, 45, 224)	896	conv2_block5_concat [0][0]
<hr/>			
conv2_block6_0_relu (Activation	(None, 45, 45, 224)	0	conv2_block6_0_bn [0][0]
<hr/>			
conv2_block6_1_conv (Conv2D)	(None, 45, 45, 128)	28672	conv2_block6_0_relu [0][0]
<hr/>			
conv2_block6_1_bn (BatchNormali	(None, 45, 45, 128)	512	conv2_block6_1_conv [0][0]
<hr/>			
conv2_block6_1_relu (Activation	(None, 45, 45, 128)	0	conv2_block6_1_bn [0][0]
<hr/>			
conv2_block6_2_conv (Conv2D)	(None, 45, 45, 32)	36864	conv2_block6_1_relu [0][0]
<hr/>			

conv2_block6_concat (Concatenat	(None, 45, 45, 256)	0	conv2_block5_concat [0][0]
[0][0]			conv2_block6_2_conv
<hr/>			
pool2_bn (BatchNormalization)	(None, 45, 45, 256)	1024	conv2_block6_concat [0][0]
<hr/>			
pool2_relu (Activation)	(None, 45, 45, 256)	0	pool2_bn[0][0]
<hr/>			
pool2_conv (Conv2D)	(None, 45, 45, 128)	32768	pool2_relu[0][0]
<hr/>			
pool2_pool (AveragePooling2D)	(None, 22, 22, 128)	0	pool2_conv[0][0]
<hr/>			
conv3_block1_0_bn (BatchNormali	(None, 22, 22, 128)	512	pool2_pool[0][0]
<hr/>			
conv3_block1_0_relu (Activation	(None, 22, 22, 128)	0	conv3_block1_0_bn [0][0]
<hr/>			
conv3_block1_1_conv (Conv2D)	(None, 22, 22, 128)	16384	conv3_block1_0_relu [0][0]
<hr/>			
conv3_block1_1_bn (BatchNormali	(None, 22, 22, 128)	512	conv3_block1_1_conv [0][0]
<hr/>			
conv3_block1_1_relu (Activation	(None, 22, 22, 128)	0	conv3_block1_1_bn [0][0]
<hr/>			
conv3_block1_2_conv (Conv2D)	(None, 22, 22, 32)	36864	conv3_block1_1_relu [0][0]
<hr/>			
conv3_block1_concat (Concatenat	(None, 22, 22, 160)	0	pool2_pool[0][0] conv3_block1_2_conv [0][0]
<hr/>			
conv3_block2_0_bn (BatchNormali	(None, 22, 22, 160)	640	conv3_block1_concat [0][0]
<hr/>			
conv3_block2_0_relu (Activation	(None, 22, 22, 160)	0	conv3_block2_0_bn [0][0]
<hr/>			
conv3_block2_1_conv (Conv2D)	(None, 22, 22, 128)	20480	conv3_block2_0_relu [0][0]
<hr/>			
conv3_block2_1_bn (BatchNormali	(None, 22, 22, 128)	512	conv3_block2_1_conv [0][0]
<hr/>			
conv3_block2_1_relu (Activation	(None, 22, 22, 128)	0	conv3_block2_1_bn

[0][0]

conv3_block2_2_conv (Conv2D)	(None, 22, 22, 32)	36864	conv3_block2_1_relu
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conv3_block2_concat (Concatenat	(None, 22, 22, 192)	0	conv3_block1_concat
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			conv3_block2_2_conv
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[0][0]

conv3_block3_0_bn (BatchNormali	(None, 22, 22, 192)	768	conv3_block2_concat
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[0][0]

conv3_block3_0_relu (Activation	(None, 22, 22, 192)	0	conv3_block3_0_bn
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[0][0]

conv3_block3_1_conv (Conv2D)	(None, 22, 22, 128)	24576	conv3_block3_0_relu
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[0][0]

conv3_block3_1_bn (BatchNormali	(None, 22, 22, 128)	512	conv3_block3_1_conv
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[0][0]

conv3_block3_1_relu (Activation	(None, 22, 22, 128)	0	conv3_block3_1_bn
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[0][0]

conv3_block3_2_conv (Conv2D)	(None, 22, 22, 32)	36864	conv3_block3_1_relu
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[0][0]

conv3_block3_concat (Concatenat	(None, 22, 22, 224)	0	conv3_block2_concat
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[0][0]

			conv3_block3_2_conv
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[0][0]

conv3_block4_0_bn (BatchNormali	(None, 22, 22, 224)	896	conv3_block3_concat
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[0][0]

conv3_block4_0_relu (Activation	(None, 22, 22, 224)	0	conv3_block4_0_bn
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[0][0]

conv3_block4_1_conv (Conv2D)	(None, 22, 22, 128)	28672	conv3_block4_0_relu
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[0][0]

conv3_block4_1_bn (BatchNormali	(None, 22, 22, 128)	512	conv3_block4_1_conv
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[0][0]

conv3_block4_1_relu (Activation	(None, 22, 22, 128)	0	conv3_block4_1_bn
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[0][0]

conv3_block4_2_conv (Conv2D)	(None, 22, 22, 32)	36864	conv3_block4_1_relu
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[0][0]

conv3_block4_concat (Concatenat (None, 22, 22, 256) 0	conv3_block3_concat
[0][0]	conv3_block4_2_conv

[0][0]

conv3_block5_0_bn (BatchNormali (None, 22, 22, 256) 1024	conv3_block4_concat
[0][0]	

conv3_block5_0_relu (Activation (None, 22, 22, 256) 0	conv3_block5_0_bn
[0][0]	

conv3_block5_1_conv (Conv2D) (None, 22, 22, 128) 32768	conv3_block5_0_relu
[0][0]	

conv3_block5_1_bn (BatchNormali (None, 22, 22, 128) 512	conv3_block5_1_conv
[0][0]	

conv3_block5_1_relu (Activation (None, 22, 22, 128) 0	conv3_block5_1_bn
[0][0]	

conv3_block5_2_conv (Conv2D) (None, 22, 22, 32) 36864	conv3_block5_1_relu
[0][0]	

conv3_block5_concat (Concatenat (None, 22, 22, 288) 0	conv3_block4_concat
[0][0]	conv3_block5_2_conv
[0][0]	

conv3_block6_0_bn (BatchNormali (None, 22, 22, 288) 1152	conv3_block5_concat
[0][0]	

conv3_block6_0_relu (Activation (None, 22, 22, 288) 0	conv3_block6_0_bn
[0][0]	

conv3_block6_1_conv (Conv2D) (None, 22, 22, 128) 36864	conv3_block6_0_relu
[0][0]	

conv3_block6_1_bn (BatchNormali (None, 22, 22, 128) 512	conv3_block6_1_conv
[0][0]	

conv3_block6_1_relu (Activation (None, 22, 22, 128) 0	conv3_block6_1_bn
[0][0]	

conv3_block6_2_conv (Conv2D) (None, 22, 22, 32) 36864	conv3_block6_1_relu
[0][0]	

conv3_block6_concat (Concatenat (None, 22, 22, 320) 0	conv3_block5_concat
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[0][0]		
[0][0]		conv3_block6_2_conv
<hr/>		
conv3_block7_0_bn (BatchNormali [0][0])	(None, 22, 22, 320) 1280	conv3_block6_concat
<hr/>		
conv3_block7_0_relu (Activation [0][0])	(None, 22, 22, 320) 0	conv3_block7_0_bn
<hr/>		
conv3_block7_1_conv (Conv2D) [0][0]	(None, 22, 22, 128) 40960	conv3_block7_0_relu
<hr/>		
conv3_block7_1_bn (BatchNormali [0][0])	(None, 22, 22, 128) 512	conv3_block7_1_conv
<hr/>		
conv3_block7_1_relu (Activation [0][0])	(None, 22, 22, 128) 0	conv3_block7_1_bn
<hr/>		
conv3_block7_2_conv (Conv2D) [0][0]	(None, 22, 22, 32) 36864	conv3_block7_1_relu
<hr/>		
conv3_block7_concat (Concatenat [0][0])	(None, 22, 22, 352) 0	conv3_block6_concat
[0][0]		conv3_block7_2_conv
<hr/>		
conv3_block8_0_bn (BatchNormali [0][0])	(None, 22, 22, 352) 1408	conv3_block7_concat
<hr/>		
conv3_block8_0_relu (Activation [0][0])	(None, 22, 22, 352) 0	conv3_block8_0_bn
<hr/>		
conv3_block8_1_conv (Conv2D) [0][0]	(None, 22, 22, 128) 45056	conv3_block8_0_relu
<hr/>		
conv3_block8_1_bn (BatchNormali [0][0])	(None, 22, 22, 128) 512	conv3_block8_1_conv
<hr/>		
conv3_block8_1_relu (Activation [0][0])	(None, 22, 22, 128) 0	conv3_block8_1_bn
<hr/>		
conv3_block8_2_conv (Conv2D) [0][0]	(None, 22, 22, 32) 36864	conv3_block8_1_relu
<hr/>		
conv3_block8_concat (Concatenat [0][0])	(None, 22, 22, 384) 0	conv3_block7_concat
[0][0]		conv3_block8_2_conv
<hr/>		

conv3_block9_0_bn (BatchNormali [0][0])	(None, 22, 22, 384)	1536	conv3_block8_concat [0][0]
conv3_block9_0_relu (Activation [0][0])	(None, 22, 22, 384)	0	conv3_block9_0_bn [0][0]
conv3_block9_1_conv (Conv2D) [0][0])	(None, 22, 22, 128)	49152	conv3_block9_0_relu [0][0]
conv3_block9_1_bn (BatchNormali [0][0])	(None, 22, 22, 128)	512	conv3_block9_1_conv [0][0]
conv3_block9_1_relu (Activation [0][0])	(None, 22, 22, 128)	0	conv3_block9_1_bn [0][0]
conv3_block9_2_conv (Conv2D) [0][0])	(None, 22, 22, 32)	36864	conv3_block9_1_relu [0][0]
conv3_block9_concat (Concatenat [0][0])	(None, 22, 22, 416)	0	conv3_block8_concat [0][0] conv3_block9_2_conv [0][0]
conv3_block10_0_bn (BatchNormal [0][0])	(None, 22, 22, 416)	1664	conv3_block9_concat [0][0]
conv3_block10_0_relu (Activatio [0][0])	(None, 22, 22, 416)	0	conv3_block10_0_bn [0][0]
conv3_block10_1_conv (Conv2D) u[0][0])	(None, 22, 22, 128)	53248	conv3_block10_0_rel u[0][0]
conv3_block10_1_bn (BatchNormal v[0][0])	(None, 22, 22, 128)	512	conv3_block10_1_con v[0][0]
conv3_block10_1_relu (Activatio [0][0])	(None, 22, 22, 128)	0	conv3_block10_1_bn [0][0]
conv3_block10_2_conv (Conv2D) u[0][0])	(None, 22, 22, 32)	36864	conv3_block10_1_rel u[0][0]
conv3_block10_concat (Concatena [0][0])	(None, 22, 22, 448)	0	conv3_block9_concat [0][0] conv3_block10_2_con v[0][0]
conv3_block11_0_bn (BatchNormal t[0][0])	(None, 22, 22, 448)	1792	conv3_block10_conca t[0][0]

conv3_block11_0_relu (Activation)	(None, 22, 22, 448)	0	conv3_block11_0_bn
conv3_block11_1_conv (Conv2D)	(None, 22, 22, 128)	57344	conv3_block11_0_relu[0][0]
conv3_block11_1_bn (Batch Normalization)	(None, 22, 22, 128)	512	conv3_block11_1_conv
conv3_block11_1_relu (Activation)	(None, 22, 22, 128)	0	conv3_block11_1_bn
conv3_block11_2_conv (Conv2D)	(None, 22, 22, 32)	36864	conv3_block11_1_relu[0][0]
conv3_block11_concat (Concatenation)	(None, 22, 22, 480)	0	conv3_block11_2_conv
conv3_block12_0_bn (Batch Normalization)	(None, 22, 22, 480)	1920	conv3_block11_concat
conv3_block12_0_relu (Activation)	(None, 22, 22, 480)	0	conv3_block12_0_bn
conv3_block12_1_conv (Conv2D)	(None, 22, 22, 128)	61440	conv3_block12_0_relu[0][0]
conv3_block12_1_bn (Batch Normalization)	(None, 22, 22, 128)	512	conv3_block12_1_conv
conv3_block12_1_relu (Activation)	(None, 22, 22, 128)	0	conv3_block12_1_bn
conv3_block12_2_conv (Conv2D)	(None, 22, 22, 32)	36864	conv3_block12_1_relu[0][0]
conv3_block12_concat (Concatenation)	(None, 22, 22, 512)	0	conv3_block12_2_conv
pool3_bn (Batch Normalization)	(None, 22, 22, 512)	2048	conv3_block12_concat
pool3_relu (Activation)	(None, 22, 22, 512)	0	pool3_bn[0][0]

pool3_conv (Conv2D)	(None, 22, 22, 256)	131072	pool3_relu[0][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]
conv4_block1_1_conv (Conv2D)	(None, 11, 11, 128)	32768	conv4_block1_0_relu [0][0]
conv4_block1_1_bn (BatchNormali	(None, 11, 11, 128)	512	conv4_block1_1_conv [0][0]
conv4_block1_1_relu (Activation	(None, 11, 11, 128)	0	conv4_block1_1_bn [0][0]
conv4_block1_2_conv (Conv2D)	(None, 11, 11, 32)	36864	conv4_block1_1_relu [0][0]
conv4_block1_concat (Concatenat	(None, 11, 11, 288)	0	pool3_pool[0][0] conv4_block1_2_conv [0][0]
conv4_block2_0_bn (BatchNormali	(None, 11, 11, 288)	1152	conv4_block1_concat [0][0]
conv4_block2_0_relu (Activation	(None, 11, 11, 288)	0	conv4_block2_0_bn [0][0]
conv4_block2_1_conv (Conv2D)	(None, 11, 11, 128)	36864	conv4_block2_0_relu [0][0]
conv4_block2_1_bn (BatchNormali	(None, 11, 11, 128)	512	conv4_block2_1_conv [0][0]
conv4_block2_1_relu (Activation	(None, 11, 11, 128)	0	conv4_block2_1_bn [0][0]
conv4_block2_2_conv (Conv2D)	(None, 11, 11, 32)	36864	conv4_block2_1_relu [0][0]
conv4_block2_concat (Concatenat	(None, 11, 11, 320)	0	conv4_block1_concat [0][0] conv4_block2_2_conv [0][0]

conv4_block3_0_bn (BatchNormali [0][0])	(None, 11, 11, 320) 1280	conv4_block2_concat [0][0]
conv4_block3_0_relu (Activation [0][0])	(None, 11, 11, 320) 0	conv4_block3_0_bn [0][0]
conv4_block3_1_conv (Conv2D) [0][0]	(None, 11, 11, 128) 40960	conv4_block3_0_relu [0][0]
conv4_block3_1_bn (BatchNormali [0][0])	(None, 11, 11, 128) 512	conv4_block3_1_conv [0][0]
conv4_block3_1_relu (Activation [0][0])	(None, 11, 11, 128) 0	conv4_block3_1_bn [0][0]
conv4_block3_2_conv (Conv2D) [0][0]	(None, 11, 11, 32) 36864	conv4_block3_1_relu [0][0]
conv4_block3_concat (Concatenat [0][0])	(None, 11, 11, 352) 0	conv4_block2_concat [0][0] conv4_block3_2_conv [0][0]
conv4_block4_0_bn (BatchNormali [0][0])	(None, 11, 11, 352) 1408	conv4_block3_concat [0][0]
conv4_block4_0_relu (Activation [0][0])	(None, 11, 11, 352) 0	conv4_block4_0_bn [0][0]
conv4_block4_1_conv (Conv2D) [0][0]	(None, 11, 11, 128) 45056	conv4_block4_0_relu [0][0]
conv4_block4_1_bn (BatchNormali [0][0])	(None, 11, 11, 128) 512	conv4_block4_1_conv [0][0]
conv4_block4_1_relu (Activation [0][0])	(None, 11, 11, 128) 0	conv4_block4_1_bn [0][0]
conv4_block4_2_conv (Conv2D) [0][0]	(None, 11, 11, 32) 36864	conv4_block4_1_relu [0][0]
conv4_block4_concat (Concatenat [0][0])	(None, 11, 11, 384) 0	conv4_block3_concat [0][0] conv4_block4_2_conv [0][0]
conv4_block5_0_bn (BatchNormali [0][0])	(None, 11, 11, 384) 1536	conv4_block4_concat [0][0]

conv4_block5_0_relu (Activation (None, 11, 11, 384) 0 [0][0])		conv4_block5_0_bn
conv4_block5_1_conv (Conv2D) (None, 11, 11, 128) 49152 [0][0])		conv4_block5_0_relu
conv4_block5_1_bn (BatchNormali (None, 11, 11, 128) 512 [0][0])		conv4_block5_1_conv
conv4_block5_1_relu (Activation (None, 11, 11, 128) 0 [0][0])		conv4_block5_1_bn
conv4_block5_2_conv (Conv2D) (None, 11, 11, 32) 36864 [0][0])		conv4_block5_1_relu
conv4_block5_concat (Concatenat (None, 11, 11, 416) 0 [0][0])		conv4_block4_concat
		conv4_block5_2_conv
conv4_block6_0_bn (BatchNormali (None, 11, 11, 416) 1664 [0][0])		conv4_block5_concat
conv4_block6_0_relu (Activation (None, 11, 11, 416) 0 [0][0])		conv4_block6_0_bn
conv4_block6_1_conv (Conv2D) (None, 11, 11, 128) 53248 [0][0])		conv4_block6_0_relu
conv4_block6_1_bn (BatchNormali (None, 11, 11, 128) 512 [0][0])		conv4_block6_1_conv
conv4_block6_1_relu (Activation (None, 11, 11, 128) 0 [0][0])		conv4_block6_1_bn
conv4_block6_2_conv (Conv2D) (None, 11, 11, 32) 36864 [0][0])		conv4_block6_1_relu
conv4_block6_concat (Concatenat (None, 11, 11, 448) 0 [0][0])		conv4_block5_concat
		conv4_block6_2_conv
conv4_block7_0_bn (BatchNormali (None, 11, 11, 448) 1792 [0][0])		conv4_block6_concat
conv4_block7_0_relu (Activation (None, 11, 11, 448) 0 [0][0])		conv4_block7_0_bn

conv4_block7_1_conv (Conv2D)	(None, 11, 11, 128)	57344	conv4_block7_0_relu [0][0]
conv4_block7_1_bn (BatchNormali	(None, 11, 11, 128)	512	conv4_block7_1_conv [0][0]
conv4_block7_1_relu (Activation	(None, 11, 11, 128)	0	conv4_block7_1_bn [0][0]
conv4_block7_2_conv (Conv2D)	(None, 11, 11, 32)	36864	conv4_block7_1_relu [0][0]
conv4_block7_concat (Concatenat	(None, 11, 11, 480)	0	conv4_block6_concat [0][0] conv4_block7_2_conv [0][0]
conv4_block8_0_bn (BatchNormali	(None, 11, 11, 480)	1920	conv4_block7_concat [0][0]
conv4_block8_0_relu (Activation	(None, 11, 11, 480)	0	conv4_block8_0_bn [0][0]
conv4_block8_1_conv (Conv2D)	(None, 11, 11, 128)	61440	conv4_block8_0_relu [0][0]
conv4_block8_1_bn (BatchNormali	(None, 11, 11, 128)	512	conv4_block8_1_conv [0][0]
conv4_block8_1_relu (Activation	(None, 11, 11, 128)	0	conv4_block8_1_bn [0][0]
conv4_block8_2_conv (Conv2D)	(None, 11, 11, 32)	36864	conv4_block8_1_relu [0][0]
conv4_block8_concat (Concatenat	(None, 11, 11, 512)	0	conv4_block7_concat [0][0] conv4_block8_2_conv [0][0]
conv4_block9_0_bn (BatchNormali	(None, 11, 11, 512)	2048	conv4_block8_concat [0][0]
conv4_block9_0_relu (Activation	(None, 11, 11, 512)	0	conv4_block9_0_bn [0][0]
conv4_block9_1_conv (Conv2D)	(None, 11, 11, 128)	65536	conv4_block9_0_relu [0][0]

conv4_block9_1_bn (BatchNormali [0][0])	(None, 11, 11, 128)	512	conv4_block9_1_conv
conv4_block9_1_relu (Activation [0][0])	(None, 11, 11, 128)	0	conv4_block9_1_bn
conv4_block9_2_conv (Conv2D) [0][0])	(None, 11, 11, 32)	36864	conv4_block9_1_relu
conv4_block9_concat (Concatenat [0][0])	(None, 11, 11, 544)	0	conv4_block8_concat
conv4_block10_0_bn (BatchNormal [0][0])	(None, 11, 11, 544)	2176	conv4_block9_2_conv
conv4_block10_0_relu (Activatio [0][0])	(None, 11, 11, 544)	0	conv4_block9_concat
conv4_block10_1_conv (Conv2D) u[0][0])	(None, 11, 11, 128)	69632	conv4_block10_0_bn
conv4_block10_1_bn (BatchNormal v[0][0])	(None, 11, 11, 128)	512	conv4_block10_0_relu
conv4_block10_1_relu (Activatio [0][0])	(None, 11, 11, 128)	0	conv4_block10_1_bn
conv4_block10_2_conv (Conv2D) u[0][0])	(None, 11, 11, 32)	36864	conv4_block10_1_relu
conv4_block10_concat (Concatena [0][0])	(None, 11, 11, 576)	0	conv4_block9_concat
conv4_block11_0_bn (BatchNormal t[0][0])	(None, 11, 11, 576)	2304	conv4_block10_2_con v[0][0])
conv4_block11_0_relu (Activatio [0][0])	(None, 11, 11, 576)	0	conv4_block10_concat
conv4_block11_1_conv (Conv2D) u[0][0])	(None, 11, 11, 128)	73728	conv4_block11_0_bn
conv4_block11_1_bn (BatchNormal v[0][0])	(None, 11, 11, 128)	512	conv4_block11_0_relu
			conv4_block11_1_con v[0][0])

conv4_block11_1_relu (Activatio [0][0])	(None, 11, 11, 128)	0	conv4_block11_1_bn
conv4_block11_2_conv (Conv2D) u[0][0])	(None, 11, 11, 32)	36864	conv4_block11_1_relu[0][0]
conv4_block11_concat (Concatena t[0][0])	(None, 11, 11, 608)	0	conv4_block10_concat[0][0]
v[0][0])			conv4_block11_2_conv[0][0]
conv4_block12_0_bn (BatchNormal t[0][0])	(None, 11, 11, 608)	2432	conv4_block11_concat[0][0]
conv4_block12_0_relu (Activatio [0][0])	(None, 11, 11, 608)	0	conv4_block12_0_bn[0][0]
conv4_block12_1_conv (Conv2D) u[0][0])	(None, 11, 11, 128)	77824	conv4_block12_0_relu[0][0]
conv4_block12_1_bn (BatchNormal v[0][0])	(None, 11, 11, 128)	512	conv4_block12_1_conv[0][0]
conv4_block12_1_relu (Activatio [0][0])	(None, 11, 11, 128)	0	conv4_block12_1_bn[0][0]
conv4_block12_2_conv (Conv2D) u[0][0])	(None, 11, 11, 32)	36864	conv4_block12_1_relu[0][0]
conv4_block12_concat (Concatena t[0][0])	(None, 11, 11, 640)	0	conv4_block11_concat[0][0]
v[0][0])			conv4_block12_2_conv[0][0]
conv4_block13_0_bn (BatchNormal t[0][0])	(None, 11, 11, 640)	2560	conv4_block12_concat[0][0]
conv4_block13_0_relu (Activatio [0][0])	(None, 11, 11, 640)	0	conv4_block13_0_bn[0][0]
conv4_block13_1_conv (Conv2D) u[0][0])	(None, 11, 11, 128)	81920	conv4_block13_0_relu[0][0]
conv4_block13_1_bn (BatchNormal v[0][0])	(None, 11, 11, 128)	512	conv4_block13_1_conv[0][0]
conv4_block13_1_relu (Activatio [0][0])	(None, 11, 11, 128)	0	conv4_block13_1_bn[0][0]

conv4_block13_2_conv (Conv2D)	(None, 11, 11, 32)	36864	conv4_block13_1_relu[0][0]
<hr/>			
conv4_block13_concat (Concatenation)	(None, 11, 11, 672)	0	conv4_block12_concat[0][0]
<hr/>			
conv4_block13_2_conv			conv4_block13_2_conv[0][0]
<hr/>			
conv4_block14_0_bn (Batch Normalization)	(None, 11, 11, 672)	2688	conv4_block13_concat[0][0]
<hr/>			
conv4_block14_0_relu (Activation)	(None, 11, 11, 672)	0	conv4_block14_0_bn[0][0]
<hr/>			
conv4_block14_1_conv (Conv2D)	(None, 11, 11, 128)	86016	conv4_block14_0_relu[0][0]
<hr/>			
conv4_block14_1_bn (Batch Normalization)	(None, 11, 11, 128)	512	conv4_block14_1_conv[0][0]
<hr/>			
conv4_block14_1_relu (Activation)	(None, 11, 11, 128)	0	conv4_block14_1_bn[0][0]
<hr/>			
conv4_block14_2_conv (Conv2D)	(None, 11, 11, 32)	36864	conv4_block14_1_relu[0][0]
<hr/>			
conv4_block14_concat (Concatenation)	(None, 11, 11, 704)	0	conv4_block13_concat[0][0]
<hr/>			
conv4_block14_2_conv			conv4_block14_2_conv[0][0]
<hr/>			
conv4_block15_0_bn (Batch Normalization)	(None, 11, 11, 704)	2816	conv4_block14_concat[0][0]
<hr/>			
conv4_block15_0_relu (Activation)	(None, 11, 11, 704)	0	conv4_block15_0_bn[0][0]
<hr/>			
conv4_block15_1_conv (Conv2D)	(None, 11, 11, 128)	90112	conv4_block15_0_relu[0][0]
<hr/>			
conv4_block15_1_bn (Batch Normalization)	(None, 11, 11, 128)	512	conv4_block15_1_conv[0][0]
<hr/>			
conv4_block15_1_relu (Activation)	(None, 11, 11, 128)	0	conv4_block15_1_bn[0][0]
<hr/>			
conv4_block15_2_conv (Conv2D)	(None, 11, 11, 32)	36864	conv4_block15_1_relu[0][0]
<hr/>			

conv4_block15_concat (Concatena (None, 11, 11, 736) 0 t[0][0]	conv4_block14_conca
v[0][0]	conv4_block15_2_con
conv4_block16_0_bn (BatchNormal (None, 11, 11, 736) 2944 t[0][0]	conv4_block15_conca
conv4_block16_0_relu (Activatio (None, 11, 11, 736) 0 [0][0]	conv4_block16_0_bn
conv4_block16_1_conv (Conv2D) (None, 11, 11, 128) 94208 u[0][0]	conv4_block16_0_rel
conv4_block16_1_bn (BatchNormal (None, 11, 11, 128) 512 v[0][0]	conv4_block16_1_con
conv4_block16_1_relu (Activatio (None, 11, 11, 128) 0 [0][0]	conv4_block16_1_bn
conv4_block16_2_conv (Conv2D) (None, 11, 11, 32) 36864 u[0][0]	conv4_block16_1_rel
conv4_block16_concat (Concatena (None, 11, 11, 768) 0 t[0][0]	conv4_block15_conca
v[0][0]	conv4_block16_2_con
conv4_block17_0_bn (BatchNormal (None, 11, 11, 768) 3072 t[0][0]	conv4_block16_conca
conv4_block17_0_relu (Activatio (None, 11, 11, 768) 0 [0][0]	conv4_block17_0_bn
conv4_block17_1_conv (Conv2D) (None, 11, 11, 128) 98304 u[0][0]	conv4_block17_0_rel
conv4_block17_1_bn (BatchNormal (None, 11, 11, 128) 512 v[0][0]	conv4_block17_1_con
conv4_block17_1_relu (Activatio (None, 11, 11, 128) 0 [0][0]	conv4_block17_1_bn
conv4_block17_2_conv (Conv2D) (None, 11, 11, 32) 36864 u[0][0]	conv4_block17_1_rel
conv4_block17_concat (Concatena (None, 11, 11, 800) 0 t[0][0]	conv4_block16_conca
v[0][0]	conv4_block17_2_con

conv4_block18_0_bn (BatchNormal (None, 11, 11, 800)	3200	conv4_block17_concat[0][0]
conv4_block18_0_relu (Activatio (None, 11, 11, 800)	0	conv4_block18_0_bn [0][0]
conv4_block18_1_conv (Conv2D) (None, 11, 11, 128)	102400	conv4_block18_0_relu[0][0]
conv4_block18_1_bn (BatchNormal (None, 11, 11, 128)	512	conv4_block18_1_conv[0][0]
conv4_block18_1_relu (Activatio (None, 11, 11, 128)	0	conv4_block18_1_bn [0][0]
conv4_block18_2_conv (Conv2D) (None, 11, 11, 32)	36864	conv4_block18_1_relu[0][0]
conv4_block18_concat (Concatena (None, 11, 11, 832)	0	conv4_block17_concat[0][0]
conv4_block19_0_bn (BatchNormal (None, 11, 11, 832)	3328	conv4_block18_concat[0][0]
conv4_block19_0_relu (Activatio (None, 11, 11, 832)	0	conv4_block19_0_bn [0][0]
conv4_block19_1_conv (Conv2D) (None, 11, 11, 128)	106496	conv4_block19_0_relu[0][0]
conv4_block19_1_bn (BatchNormal (None, 11, 11, 128)	512	conv4_block19_1_conv[0][0]
conv4_block19_1_relu (Activatio (None, 11, 11, 128)	0	conv4_block19_1_bn [0][0]
conv4_block19_2_conv (Conv2D) (None, 11, 11, 32)	36864	conv4_block19_1_relu[0][0]
conv4_block19_concat (Concatena (None, 11, 11, 864)	0	conv4_block18_concat[0][0]
conv4_block20_0_bn (BatchNormal (None, 11, 11, 864)	3456	conv4_block19_concat[0][0]

conv4_block20_0_relu (Activatio [0][0])	(None, 11, 11, 864) 0	conv4_block20_0_bn
conv4_block20_1_conv (Conv2D) u[0][0])	(None, 11, 11, 128) 110592	conv4_block20_0_relu[0][0]
conv4_block20_1_bn (BatchNormal v[0][0])	(None, 11, 11, 128) 512	conv4_block20_1_conv[0][0]
conv4_block20_1_relu (Activatio [0][0])	(None, 11, 11, 128) 0	conv4_block20_1_bn[0][0]
conv4_block20_2_conv (Conv2D) u[0][0])	(None, 11, 11, 32) 36864	conv4_block20_1_relu[0][0]
conv4_block20_concat (Concatena t[0][0])	(None, 11, 11, 896) 0	conv4_block19_concat[0][0]
conv4_block20_2_conv v[0][0])		conv4_block20_2_conv[0][0]
conv4_block21_0_bn (BatchNormal t[0][0])	(None, 11, 11, 896) 3584	conv4_block20_concat[0][0]
conv4_block21_0_relu (Activatio [0][0])	(None, 11, 11, 896) 0	conv4_block21_0_bn[0][0]
conv4_block21_1_conv (Conv2D) u[0][0])	(None, 11, 11, 128) 114688	conv4_block21_0_relu[0][0]
conv4_block21_1_bn (BatchNormal v[0][0])	(None, 11, 11, 128) 512	conv4_block21_1_conv[0][0]
conv4_block21_1_relu (Activatio [0][0])	(None, 11, 11, 128) 0	conv4_block21_1_bn[0][0]
conv4_block21_2_conv (Conv2D) u[0][0])	(None, 11, 11, 32) 36864	conv4_block21_1_relu[0][0]
conv4_block21_concat (Concatena t[0][0])	(None, 11, 11, 928) 0	conv4_block20_concat[0][0]
conv4_block21_2_conv v[0][0])		conv4_block21_2_conv[0][0]
conv4_block22_0_bn (BatchNormal t[0][0])	(None, 11, 11, 928) 3712	conv4_block21_concat[0][0]
conv4_block22_0_relu (Activatio [0][0])	(None, 11, 11, 928) 0	conv4_block22_0_bn[0][0]

conv4_block22_1_conv (Conv2D)	(None, 11, 11, 128)	118784	conv4_block22_0_relu[0][0]
conv4_block22_1_bn (BatchNormal	(None, 11, 11, 128)	512	conv4_block22_1_conv[0][0]
conv4_block22_1_relu (Activatio	(None, 11, 11, 128)	0	conv4_block22_1_bn[0][0]
conv4_block22_2_conv (Conv2D)	(None, 11, 11, 32)	36864	conv4_block22_1_relu[0][0]
conv4_block22_concat (Concatena	(None, 11, 11, 960)	0	conv4_block21_concat[0][0]
conv4_block23_0_bn (BatchNormal	(None, 11, 11, 960)	3840	conv4_block22_2_conv[0][0]
conv4_block23_0_relu (Activatio	(None, 11, 11, 960)	0	conv4_block22_concat[0][0]
conv4_block23_1_conv (Conv2D)	(None, 11, 11, 128)	122880	conv4_block23_0_bn[0][0]
conv4_block23_1_bn (BatchNormal	(None, 11, 11, 128)	512	conv4_block23_0_relu[0][0]
conv4_block23_1_relu (Activatio	(None, 11, 11, 128)	0	conv4_block23_1_conv[0][0]
conv4_block23_2_conv (Conv2D)	(None, 11, 11, 32)	36864	conv4_block23_1_bn[0][0]
conv4_block23_concat (Concatena	(None, 11, 11, 992)	0	conv4_block23_2_conv[0][0]
conv4_block24_0_bn (BatchNormal	(None, 11, 11, 992)	3968	conv4_block22_concat[0][0]
conv4_block24_0_relu (Activatio	(None, 11, 11, 992)	0	conv4_block23_concat[0][0]
conv4_block24_1_conv (Conv2D)	(None, 11, 11, 128)	126976	conv4_block24_0_bn[0][0]

conv4_block24_1_bn (BatchNormal (None, 11, 11, 128) 512	conv4_block24_1_con
v[0][0]	
conv4_block24_1_relu (Activatio (None, 11, 11, 128) 0	conv4_block24_1_bn
[0][0]	
conv4_block24_2_conv (Conv2D) (None, 11, 11, 32) 36864	conv4_block24_1_relu
[0][0]	
conv4_block24_concat (Concatena (None, 11, 11, 1024) 0	conv4_block23_conca
t[0][0]	
conv4_block24_2_con	
v[0][0]	
pool4_bn (BatchNormalization) (None, 11, 11, 1024) 4096	conv4_block24_conca
t[0][0]	
pool4_relu (Activation) (None, 11, 11, 1024) 0	pool4_bn[0][0]
pool4_conv (Conv2D) (None, 11, 11, 512) 524288	pool4_relu[0][0]
pool4_pool (AveragePooling2D) (None, 5, 5, 512) 0	pool4_conv[0][0]
conv5_block1_0_bn (BatchNormali (None, 5, 5, 512) 2048	pool4_pool[0][0]
conv5_block1_0_relu (Activation (None, 5, 5, 512) 0	conv5_block1_0_bn
[0][0]	
conv5_block1_1_conv (Conv2D) (None, 5, 5, 128) 65536	conv5_block1_0_relu
[0][0]	
conv5_block1_1_bn (BatchNormali (None, 5, 5, 128) 512	conv5_block1_1_conv
[0][0]	
conv5_block1_1_relu (Activation (None, 5, 5, 128) 0	conv5_block1_1_bn
[0][0]	
conv5_block1_2_conv (Conv2D) (None, 5, 5, 32) 36864	conv5_block1_1_relu
[0][0]	
conv5_block1_concat (Concatenat (None, 5, 5, 544) 0	pool4_pool[0][0]
	conv5_block1_2_conv
[0][0]	
conv5_block2_0_bn (BatchNormali (None, 5, 5, 544) 2176	conv5_block1_concat
[0][0]	

conv5_block2_0_relu (Activation (None, 5, 5, 544) [0][0])	0	conv5_block2_0_bn
conv5_block2_1_conv (Conv2D) (None, 5, 5, 128) [0][0])	69632	conv5_block2_0_relu
conv5_block2_1_bn (BatchNormali (None, 5, 5, 128) [0][0])	512	conv5_block2_1_conv
conv5_block2_1_relu (Activation (None, 5, 5, 128) [0][0])	0	conv5_block2_1_bn
conv5_block2_2_conv (Conv2D) (None, 5, 5, 32) [0][0])	36864	conv5_block2_1_relu
conv5_block2_concat (Concatenat (None, 5, 5, 576) [0][0])	0	conv5_block1_concat
		conv5_block2_2_conv
conv5_block3_0_bn (BatchNormali (None, 5, 5, 576) [0][0])	2304	conv5_block2_concat
conv5_block3_0_relu (Activation (None, 5, 5, 576) [0][0])	0	conv5_block3_0_bn
conv5_block3_1_conv (Conv2D) (None, 5, 5, 128) [0][0])	73728	conv5_block3_0_relu
conv5_block3_1_bn (BatchNormali (None, 5, 5, 128) [0][0])	512	conv5_block3_1_conv
conv5_block3_1_relu (Activation (None, 5, 5, 128) [0][0])	0	conv5_block3_1_bn
conv5_block3_2_conv (Conv2D) (None, 5, 5, 32) [0][0])	36864	conv5_block3_1_relu
conv5_block3_concat (Concatenat (None, 5, 5, 608) [0][0])	0	conv5_block2_concat
		conv5_block3_2_conv
conv5_block4_0_bn (BatchNormali (None, 5, 5, 608) [0][0])	2432	conv5_block3_concat
conv5_block4_0_relu (Activation (None, 5, 5, 608) [0][0])	0	conv5_block4_0_bn

conv5_block4_1_conv (Conv2D)	(None, 5, 5, 128)	77824	conv5_block4_0_relu [0][0]
conv5_block4_1_bn (BatchNormali	(None, 5, 5, 128)	512	conv5_block4_1_conv [0][0]
conv5_block4_1_relu (Activation	(None, 5, 5, 128)	0	conv5_block4_1_bn [0][0]
conv5_block4_2_conv (Conv2D)	(None, 5, 5, 32)	36864	conv5_block4_1_relu [0][0]
conv5_block4_concat (Concatenat	(None, 5, 5, 640)	0	conv5_block3_concat [0][0] conv5_block4_2_conv [0][0]
conv5_block5_0_bn (BatchNormali	(None, 5, 5, 640)	2560	conv5_block4_concat [0][0]
conv5_block5_0_relu (Activation	(None, 5, 5, 640)	0	conv5_block5_0_bn [0][0]
conv5_block5_1_conv (Conv2D)	(None, 5, 5, 128)	81920	conv5_block5_0_relu [0][0]
conv5_block5_1_bn (BatchNormali	(None, 5, 5, 128)	512	conv5_block5_1_conv [0][0]
conv5_block5_1_relu (Activation	(None, 5, 5, 128)	0	conv5_block5_1_bn [0][0]
conv5_block5_2_conv (Conv2D)	(None, 5, 5, 32)	36864	conv5_block5_1_relu [0][0]
conv5_block5_concat (Concatenat	(None, 5, 5, 672)	0	conv5_block4_concat [0][0] conv5_block5_2_conv [0][0]
conv5_block6_0_bn (BatchNormali	(None, 5, 5, 672)	2688	conv5_block5_concat [0][0]
conv5_block6_0_relu (Activation	(None, 5, 5, 672)	0	conv5_block6_0_bn [0][0]
conv5_block6_1_conv (Conv2D)	(None, 5, 5, 128)	86016	conv5_block6_0_relu [0][0]

conv5_block6_1_bn (BatchNormali [0][0])	(None, 5, 5, 128)	512	conv5_block6_1_conv [0][0]
conv5_block6_1_relu (Activation [0][0])	(None, 5, 5, 128)	0	conv5_block6_1_bn [0][0]
conv5_block6_2_conv (Conv2D) [0][0]	(None, 5, 5, 32)	36864	conv5_block6_1_relu [0][0]
conv5_block6_concat (Concatenat [0][0])	(None, 5, 5, 704)	0	conv5_block5_concat [0][0] conv5_block6_2_conv [0][0]
conv5_block7_0_bn (BatchNormali [0][0])	(None, 5, 5, 704)	2816	conv5_block6_concat [0][0]
conv5_block7_0_relu (Activation [0][0])	(None, 5, 5, 704)	0	conv5_block7_0_bn [0][0]
conv5_block7_1_conv (Conv2D) [0][0]	(None, 5, 5, 128)	90112	conv5_block7_0_relu [0][0]
conv5_block7_1_bn (BatchNormali [0][0])	(None, 5, 5, 128)	512	conv5_block7_1_conv [0][0]
conv5_block7_1_relu (Activation [0][0])	(None, 5, 5, 128)	0	conv5_block7_1_bn [0][0]
conv5_block7_2_conv (Conv2D) [0][0]	(None, 5, 5, 32)	36864	conv5_block7_1_relu [0][0]
conv5_block7_concat (Concatenat [0][0])	(None, 5, 5, 736)	0	conv5_block6_concat [0][0] conv5_block7_2_conv [0][0]
conv5_block8_0_bn (BatchNormali [0][0])	(None, 5, 5, 736)	2944	conv5_block7_concat [0][0]
conv5_block8_0_relu (Activation [0][0])	(None, 5, 5, 736)	0	conv5_block8_0_bn [0][0]
conv5_block8_1_conv (Conv2D) [0][0]	(None, 5, 5, 128)	94208	conv5_block8_0_relu [0][0]
conv5_block8_1_bn (BatchNormali [0][0])	(None, 5, 5, 128)	512	conv5_block8_1_conv [0][0]

conv5_block8_1_relu (Activation (None, 5, 5, 128) [0][0])	0	conv5_block8_1_bn
conv5_block8_2_conv (Conv2D) (None, 5, 5, 32) [0][0])	36864	conv5_block8_1_relu
conv5_block8_concat (Concatenat [0][0])	0	conv5_block7_concat
		conv5_block8_2_conv
conv5_block9_0_bn (BatchNormali [0][0])	3072	conv5_block8_concat
conv5_block9_0_relu (Activation (None, 5, 5, 768) [0][0])	0	conv5_block9_0_bn
conv5_block9_1_conv (Conv2D) (None, 5, 5, 128) [0][0])	98304	conv5_block9_0_relu
conv5_block9_1_bn (BatchNormali [0][0])	512	conv5_block9_1_conv
conv5_block9_1_relu (Activation (None, 5, 5, 128) [0][0])	0	conv5_block9_1_bn
conv5_block9_2_conv (Conv2D) (None, 5, 5, 32) [0][0])	36864	conv5_block9_1_relu
conv5_block9_concat (Concatenat [0][0])	0	conv5_block8_concat
		conv5_block9_2_conv
conv5_block10_0_bn (BatchNormal [0][0])	3200	conv5_block9_concat
conv5_block10_0_relu (Activatio [0][0])	0	conv5_block10_0_bn
conv5_block10_1_conv (Conv2D) (None, 5, 5, 128) u[0][0])	102400	conv5_block10_0_rel
conv5_block10_1_bn (BatchNormal [0][0])	512	conv5_block10_1_con
conv5_block10_1_relu (Activatio [0][0])	0	conv5_block10_1_bn

conv5_block10_2_conv (Conv2D)	(None, 5, 5, 32)	36864	conv5_block10_1_relu[0][0]
conv5_block10_concat (Concatenation)	(None, 5, 5, 832)	0	conv5_block9_concat[0][0] conv5_block10_2_conv[0][0]
conv5_block11_0_bn (Batch Normalization)	(None, 5, 5, 832)	3328	conv5_block10_concat[0][0]
conv5_block11_0_relu (Activation)	(None, 5, 5, 832)	0	conv5_block11_0_bn[0][0]
conv5_block11_1_conv (Conv2D)	(None, 5, 5, 128)	106496	conv5_block11_0_relu[0][0]
conv5_block11_1_bn (Batch Normalization)	(None, 5, 5, 128)	512	conv5_block11_1_conv[0][0]
conv5_block11_1_relu (Activation)	(None, 5, 5, 128)	0	conv5_block11_1_bn[0][0]
conv5_block11_2_conv (Conv2D)	(None, 5, 5, 32)	36864	conv5_block11_1_relu[0][0]
conv5_block11_concat (Concatenation)	(None, 5, 5, 864)	0	conv5_block10_concat[0][0] conv5_block11_2_conv[0][0]
conv5_block12_0_bn (Batch Normalization)	(None, 5, 5, 864)	3456	conv5_block11_concat[0][0]
conv5_block12_0_relu (Activation)	(None, 5, 5, 864)	0	conv5_block12_0_bn[0][0]
conv5_block12_1_conv (Conv2D)	(None, 5, 5, 128)	110592	conv5_block12_0_relu[0][0]
conv5_block12_1_bn (Batch Normalization)	(None, 5, 5, 128)	512	conv5_block12_1_conv[0][0]
conv5_block12_1_relu (Activation)	(None, 5, 5, 128)	0	conv5_block12_1_bn[0][0]
conv5_block12_2_conv (Conv2D)	(None, 5, 5, 32)	36864	conv5_block12_1_relu[0][0]

conv5_block12_concat (Concatena t[0][0]	(None, 5, 5, 896)	0	conv5_block11_conca t[0][0]
conv5_block12_2_con v[0][0]			conv5_block12_2_con
conv5_block13_0_bn (BatchNormal t[0][0]	(None, 5, 5, 896)	3584	conv5_block12_conca t[0][0]
conv5_block13_0_relu (Activatio [0][0]	(None, 5, 5, 896)	0	conv5_block13_0_bn [0][0]
conv5_block13_1_conv (Conv2D) u[0][0]	(None, 5, 5, 128)	114688	conv5_block13_0_rel u[0][0]
conv5_block13_1_bn (BatchNormal v[0][0]	(None, 5, 5, 128)	512	conv5_block13_1_con v[0][0]
conv5_block13_1_relu (Activatio [0][0]	(None, 5, 5, 128)	0	conv5_block13_1_bn [0][0]
conv5_block13_2_conv (Conv2D) u[0][0]	(None, 5, 5, 32)	36864	conv5_block13_1_rel u[0][0]
conv5_block13_concat (Concatena t[0][0]	(None, 5, 5, 928)	0	conv5_block12_conca t[0][0]
conv5_block13_2_con v[0][0]			conv5_block13_2_con
conv5_block14_0_bn (BatchNormal t[0][0]	(None, 5, 5, 928)	3712	conv5_block13_conca t[0][0]
conv5_block14_0_relu (Activatio [0][0]	(None, 5, 5, 928)	0	conv5_block14_0_bn [0][0]
conv5_block14_1_conv (Conv2D) u[0][0]	(None, 5, 5, 128)	118784	conv5_block14_0_rel u[0][0]
conv5_block14_1_bn (BatchNormal v[0][0]	(None, 5, 5, 128)	512	conv5_block14_1_con v[0][0]
conv5_block14_1_relu (Activatio [0][0]	(None, 5, 5, 128)	0	conv5_block14_1_bn [0][0]
conv5_block14_2_conv (Conv2D) u[0][0]	(None, 5, 5, 32)	36864	conv5_block14_1_rel u[0][0]
conv5_block14_concat (Concatena t[0][0]	(None, 5, 5, 960)	0	conv5_block13_conca t[0][0]
			conv5_block14_2_con

v[0][0]

conv5_block15_0_bn (BatchNormal (None, 5, 5, 960)	3840	conv5_block14_concat[0][0]
---	------	----------------------------

conv5_block15_0_relu (Activatio (None, 5, 5, 960)	0	conv5_block15_0_bn [0][0]
---	---	---------------------------

conv5_block15_1_conv (Conv2D) (None, 5, 5, 128)	122880	conv5_block15_0_relu[0][0]
---	--------	----------------------------

conv5_block15_1_bn (BatchNormal (None, 5, 5, 128)	512	conv5_block15_1_conv[0][0]
---	-----	----------------------------

conv5_block15_1_relu (Activatio (None, 5, 5, 128)	0	conv5_block15_1_bn [0][0]
---	---	---------------------------

conv5_block15_2_conv (Conv2D) (None, 5, 5, 32)	36864	conv5_block15_1_relu[0][0]
--	-------	----------------------------

conv5_block15_concat (Concatena (None, 5, 5, 992)	0	conv5_block14_concat[0][0]
		conv5_block15_2_conv[0][0]

conv5_block16_0_bn (BatchNormal (None, 5, 5, 992)	3968	conv5_block15_concat[0][0]
---	------	----------------------------

conv5_block16_0_relu (Activatio (None, 5, 5, 992)	0	conv5_block16_0_bn [0][0]
---	---	---------------------------

conv5_block16_1_conv (Conv2D) (None, 5, 5, 128)	126976	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)	0	conv5_block16_1_bn [0][0]
---	---	---------------------------

conv5_block16_2_conv (Conv2D) (None, 5, 5, 32)	36864	conv5_block16_1_relu[0][0]
--	-------	----------------------------

conv5_block16_concat (Concatena (None, 5, 5, 1024)	0	conv5_block15_concat[0][0]
		conv5_block16_2_conv[0][0]

bn (BatchNormalization) (None, 5, 5, 1024)	4096	conv5_block16_concat
--	------	----------------------

t[0][0]

relu (Activation)	(None, 5, 5, 1024)	0	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 Tensor("input_1:0", shape=(None, 180, 180, 3), dtype=float32)

The output shape Tensor("avg_pool/Mean:0", shape=(None, 1024), dtype=float32)

```
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)

model = Model(inputs=base_model.input, outputs=predictions)
#model.add(base_model)
#model.add(GlobalAveragePooling2D())
#model.add(Dense(1, activation='sigmoid'))

model.compile(loss='binary_crossentropy',
              optimizer='adam',
              metrics=['accuracy'])
```

```
In [23]: r = model.fit(
    train,
    epochs=10,
    validation_data=validation,
    class_weight=class_weight,
    steps_per_epoch=100,
    validation_steps=25,
)
```

Epoch 1/10

```
100/100 [=====] - ETA: 0s - loss: 0.1463 - accuracy: 0.8438
WARNING:tensorflow:Your input ran out of data; interrupting training. Make 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 [=====] - 700s 7s/step - loss: 0.1463 - accuracy:
```

```

0.8438 - val_loss: 13.9214 - val_accuracy: 0.5000
Epoch 2/10
100/100 [=====] - 692s 7s/step - loss: 0.0960 - accuracy:
0.9000
Epoch 3/10
100/100 [=====] - 694s 7s/step - loss: 0.0955 - accuracy:
0.9062
Epoch 4/10
100/100 [=====] - 698s 7s/step - loss: 0.0981 - accuracy:
0.8900
Epoch 5/10
100/100 [=====] - 692s 7s/step - loss: 0.1079 - accuracy:
0.8750
Epoch 6/10
100/100 [=====] - 687s 7s/step - loss: 0.0918 - accuracy:
0.9050
Epoch 7/10
100/100 [=====] - 677s 7s/step - loss: 0.0919 - accuracy:
0.8988
Epoch 8/10
100/100 [=====] - 682s 7s/step - loss: 0.0836 - accuracy:
0.9100
Epoch 9/10
100/100 [=====] - 678s 7s/step - loss: 0.0768 - accuracy:
0.9237
Epoch 10/10
100/100 [=====] - 684s 7s/step - loss: 0.0664 - accuracy:
0.9287

```

In [24]:

```

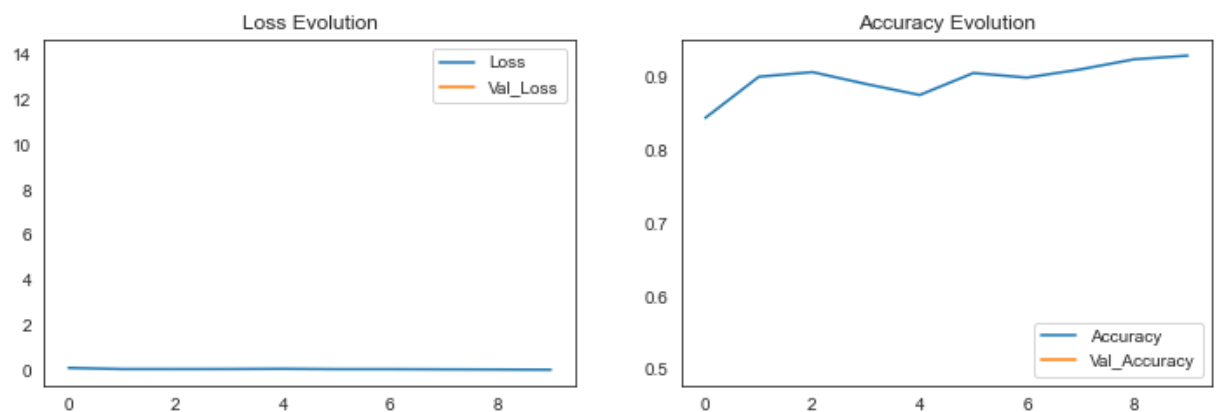
plt.figure(figsize=(12, 8))

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')



In [25]:

```

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 [=====] - 140s 224ms/step - loss: 0.5100 - accuracy: 0.7676
Test Accuracy: 76.76%
652/652 [=====] - 937s 1s/step - loss: 0.6964 - accuracy: 0.6848
Train Accuracy: 68.48%
```

Evaluation

```
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_dict=True))
```

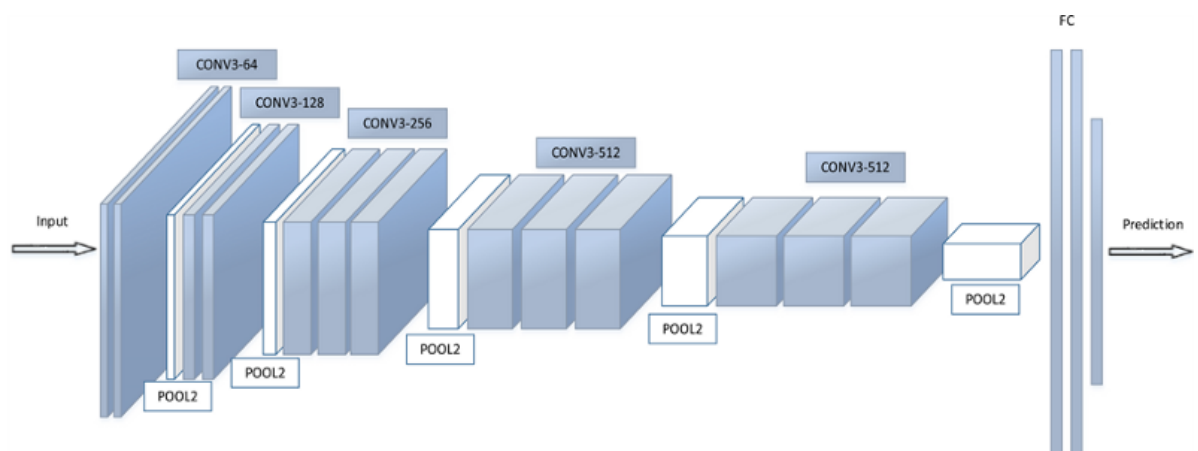
```
[[227  7]
 [150 240]]
```

```
Out[27]:
```

	0	1	accuracy	macro avg	weighted avg
precision	0.602122	0.971660	0.748397	0.786891	0.833083
recall	0.970085	0.615385	0.748397	0.792735	0.748397
f1-score	0.743044	0.753532	0.748397	0.748288	0.749599
support	234.000000	390.000000	0.748397	624.000000	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.



```
In [28]: from keras.models import Sequential
from keras.layers import GlobalAveragePooling2D
from keras.applications import VGG16
```

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

In [29]:

```
vgg16_base_model.summary()
```

Model: "vgg16"

Layer (type)	Output Shape	Param #
=====		
input_3 (InputLayer)	[(None, 180, 180, 3)]	0
<hr/>		
block1_conv1 (Conv2D)	(None, 180, 180, 64)	1792
<hr/>		
block1_conv2 (Conv2D)	(None, 180, 180, 64)	36928
<hr/>		
block1_pool1 (MaxPooling2D)	(None, 90, 90, 64)	0
<hr/>		
block2_conv1 (Conv2D)	(None, 90, 90, 128)	73856
<hr/>		
block2_conv2 (Conv2D)	(None, 90, 90, 128)	147584
<hr/>		
block2_pool1 (MaxPooling2D)	(None, 45, 45, 128)	0
<hr/>		
block3_conv1 (Conv2D)	(None, 45, 45, 256)	295168
<hr/>		
block3_conv2 (Conv2D)	(None, 45, 45, 256)	590080
<hr/>		
block3_conv3 (Conv2D)	(None, 45, 45, 256)	590080
<hr/>		
block3_pool1 (MaxPooling2D)	(None, 22, 22, 256)	0
<hr/>		
block4_conv1 (Conv2D)	(None, 22, 22, 512)	1180160
<hr/>		
block4_conv2 (Conv2D)	(None, 22, 22, 512)	2359808
<hr/>		
block4_conv3 (Conv2D)	(None, 22, 22, 512)	2359808
<hr/>		
block4_pool1 (MaxPooling2D)	(None, 11, 11, 512)	0
<hr/>		
block5_conv1 (Conv2D)	(None, 11, 11, 512)	2359808
<hr/>		
block5_conv2 (Conv2D)	(None, 11, 11, 512)	2359808
<hr/>		
block5_conv3 (Conv2D)	(None, 11, 11, 512)	2359808
<hr/>		
block5_pool1 (MaxPooling2D)	(None, 5, 5, 512)	0
=====		
Total params: 14,714,688		
Trainable params: 14,714,688		
Non-trainable params: 0		

In [30]:

```
vgg16_model = 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")
    ])

model = Sequential()
model.add(vgg16_model.layers[0])

```

In [31]:

```

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=METRICS)

```

In [32]:

```

r = vgg16_model.fit(train,
    epochs=10,
    validation_data=validation,
    class_weight=class_weight,
    steps_per_epoch=100,
    validation_steps=25)

```

Epoch 1/10

100/100 [=====] - ETA: 0s - loss: 0.2962 - accuracy: 0.5950
 - precision: 0.8444 - recall: 0.5672 WARNING:tensorflow:Your input ran out of data;
 interrupting training. Make 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 [=====] - 1595s 16s/step - loss: 0.2962 - accuracy:
 0.5950 - precision: 0.8444 - recall: 0.5672 - val_loss: 17.1873 - val_accuracy: 0.50
 00 - val_precision: 0.0000e+00 - val_recall: 0.0000e+00

Epoch 2/10

100/100 [=====] - 1588s 16s/step - loss: 0.1996 - accuracy:
 0.7425 - precision: 0.9212 - recall: 0.7124

Epoch 3/10

100/100 [=====] - 1993s 20s/step - loss: 0.2028 - accuracy:
 0.7312 - precision: 0.9119 - recall: 0.7212

Epoch 4/10

100/100 [=====] - 1701s 17s/step - loss: 0.1667 - accuracy:
 0.8050 - precision: 0.9335 - recall: 0.7963

Epoch 5/10

100/100 [=====] - 1620s 16s/step - loss: 0.1641 - accuracy:
 0.8100 - precision: 0.9259 - recall: 0.7951

Epoch 6/10

100/100 [=====] - 1595s 16s/step - loss: 0.1726 - accuracy:
 0.7937 - precision: 0.9395 - recall: 0.7754

Epoch 7/10

100/100 [=====] - 1593s 16s/step - loss: 0.1651 - accuracy:
 0.8250 - precision: 0.9425 - recall: 0.8106

Epoch 8/10

100/100 [=====] - 1576s 16s/step - loss: 0.1827 - accuracy:
 0.7825 - precision: 0.9217 - recall: 0.7727

Epoch 9/10

100/100 [=====] - 1789s 18s/step - loss: 0.1603 - accuracy:
 0.8000 - precision: 0.9391 - recall: 0.7808

Epoch 10/10

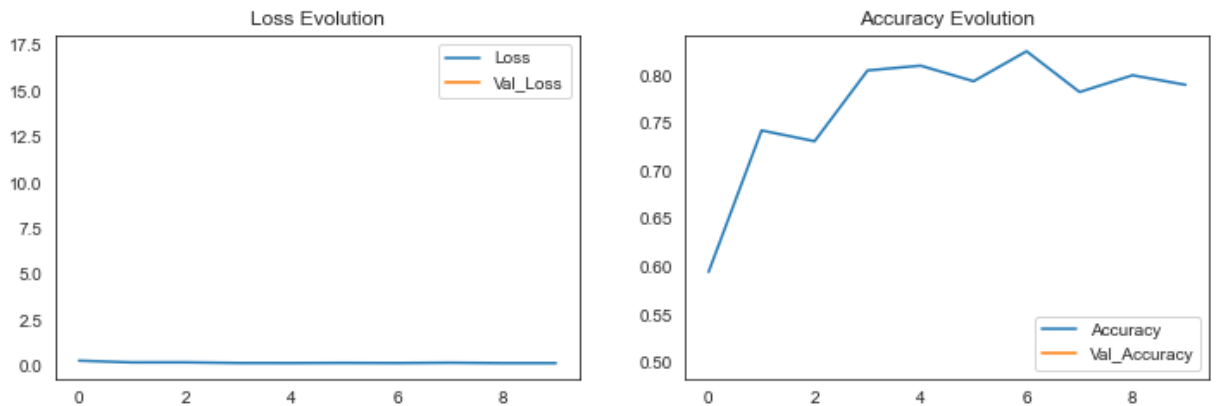
100/100 [=====] - 1650s 16s/step - loss: 0.1606 - accuracy:
 0.7900 - precision: 0.9378 - recall: 0.7661

```
In [33]: 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[33]: Text(0.5, 1.0, 'Accuracy Evolution')



```
In [34]: 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 [=====] - 416s 666ms/step - loss: 0.6091 - accuracy: 0.7163 - precision: 0.7036 - recall: 0.9436
Test Accuracy: 71.63%
652/652 [=====] - 3235s 5s/step - loss: 0.3134 - accuracy: 0.8600 - precision: 0.8803 - recall: 0.9394
Train Accuracy: 86.00%
```

ResNet

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

```
In [35]: from keras.applications import ResNet50

resnet_base_model = ResNet50(input_shape=(180,180,3), include_top=False, weights='im
```

```
In [36]: resnet_base_model.summary()
```

Model: "resnet50"

Layer (type)	Output Shape	Param #	Connected to
=====			

=====			
input_4 (InputLayer)	[(None, 180, 180, 3) 0		
conv1_pad (ZeroPadding2D)	(None, 186, 186, 3) 0		input_4[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) 0		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) 0		conv2_block1_2_bn
	[0][0]		
conv2_block1_0_conv (Conv2D)	(None, 45, 45, 256) 16640		pool1_pool[0][0]
conv2_block1_3_conv (Conv2D)	(None, 45, 45, 256) 16640		conv2_block1_2_relu
	[0][0]		
conv2_block1_0_bn (BatchNormali	(None, 45, 45, 256) 1024		conv2_block1_0_conv
	[0][0]		
conv2_block1_3_bn (BatchNormali	(None, 45, 45, 256) 1024		conv2_block1_3_conv
	[0][0]		
conv2_block1_add (Add)	(None, 45, 45, 256) 0		conv2_block1_0_bn
	[0][0]		
			conv2_block1_3_bn
			[0][0]

conv2_block1_out (Activation)	(None, 45, 45, 256)	0	conv2_block1_add[0][0]
conv2_block2_1_conv (Conv2D)	(None, 45, 45, 64)	16448	conv2_block1_out[0][0]
conv2_block2_1_bn (BatchNormali	(None, 45, 45, 64)	256	conv2_block2_1_conv[0][0]
conv2_block2_1_relu (Activation	(None, 45, 45, 64)	0	conv2_block2_1_bn[0][0]
conv2_block2_2_conv (Conv2D)	(None, 45, 45, 64)	36928	conv2_block2_1_relu[0][0]
conv2_block2_2_bn (BatchNormali	(None, 45, 45, 64)	256	conv2_block2_2_conv[0][0]
conv2_block2_2_relu (Activation	(None, 45, 45, 64)	0	conv2_block2_2_bn[0][0]
conv2_block2_3_conv (Conv2D)	(None, 45, 45, 256)	16640	conv2_block2_2_relu[0][0]
conv2_block2_3_bn (BatchNormali	(None, 45, 45, 256)	1024	conv2_block2_3_conv[0][0]
conv2_block2_add (Add)	(None, 45, 45, 256)	0	conv2_block1_out[0][0] conv2_block2_3_bn[0][0]
conv2_block2_out (Activation)	(None, 45, 45, 256)	0	conv2_block2_add[0][0]
conv2_block3_1_conv (Conv2D)	(None, 45, 45, 64)	16448	conv2_block2_out[0][0]
conv2_block3_1_bn (BatchNormali	(None, 45, 45, 64)	256	conv2_block3_1_conv[0][0]
conv2_block3_1_relu (Activation	(None, 45, 45, 64)	0	conv2_block3_1_bn[0][0]
conv2_block3_2_conv (Conv2D)	(None, 45, 45, 64)	36928	conv2_block3_1_relu[0][0]

conv2_block3_2_bn (BatchNormali	(None, 45, 45, 64)	256	conv2_block3_2_conv
[0][0]			
conv2_block3_2_relu (Activation	(None, 45, 45, 64)	0	conv2_block3_2_bn
[0][0]			
conv2_block3_3_conv (Conv2D)	(None, 45, 45, 256)	16640	conv2_block3_2_relu
[0][0]			
conv2_block3_3_bn (BatchNormali	(None, 45, 45, 256)	1024	conv2_block3_3_conv
[0][0]			
conv2_block3_add (Add)	(None, 45, 45, 256)	0	conv2_block2_out[0]
[0]			conv2_block3_3_bn
[0][0]			
conv2_block3_out (Activation)	(None, 45, 45, 256)	0	conv2_block3_add[0]
[0]			
conv3_block1_1_conv (Conv2D)	(None, 23, 23, 128)	32896	conv2_block3_out[0]
[0]			
conv3_block1_1_bn (BatchNormali	(None, 23, 23, 128)	512	conv3_block1_1_conv
[0][0]			
conv3_block1_1_relu (Activation	(None, 23, 23, 128)	0	conv3_block1_1_bn
[0][0]			
conv3_block1_2_conv (Conv2D)	(None, 23, 23, 128)	147584	conv3_block1_1_relu
[0][0]			
conv3_block1_2_bn (BatchNormali	(None, 23, 23, 128)	512	conv3_block1_2_conv
[0][0]			
conv3_block1_2_relu (Activation	(None, 23, 23, 128)	0	conv3_block1_2_bn
[0][0]			
conv3_block1_0_conv (Conv2D)	(None, 23, 23, 512)	131584	conv2_block3_out[0]
[0]			
conv3_block1_3_conv (Conv2D)	(None, 23, 23, 512)	66048	conv3_block1_2_relu
[0][0]			
conv3_block1_0_bn (BatchNormali	(None, 23, 23, 512)	2048	conv3_block1_0_conv
[0][0]			
conv3_block1_3_bn (BatchNormali	(None, 23, 23, 512)	2048	conv3_block1_3_conv
[0][0]			

conv3_block1_add (Add)	(None, 23, 23, 512)	0	conv3_block1_0_bn
[0][0]			conv3_block1_3_bn
[0][0]			
conv3_block1_out (Activation)	(None, 23, 23, 512)	0	conv3_block1_add[0]
[0]			
conv3_block2_1_conv (Conv2D)	(None, 23, 23, 128)	65664	conv3_block1_out[0]
[0]			
conv3_block2_1_bn (BatchNormali	(None, 23, 23, 128)	512	conv3_block2_1_conv
[0][0]			
conv3_block2_1_relu (Activation	(None, 23, 23, 128)	0	conv3_block2_1_bn
[0][0]			
conv3_block2_2_conv (Conv2D)	(None, 23, 23, 128)	147584	conv3_block2_1_relu
[0][0]			
conv3_block2_2_bn (BatchNormali	(None, 23, 23, 128)	512	conv3_block2_2_conv
[0][0]			
conv3_block2_2_relu (Activation	(None, 23, 23, 128)	0	conv3_block2_2_bn
[0][0]			
conv3_block2_3_conv (Conv2D)	(None, 23, 23, 512)	66048	conv3_block2_2_relu
[0][0]			
conv3_block2_3_bn (BatchNormali	(None, 23, 23, 512)	2048	conv3_block2_3_conv
[0][0]			
conv3_block2_add (Add)	(None, 23, 23, 512)	0	conv3_block1_out[0]
[0]			conv3_block2_3_bn
[0][0]			
conv3_block2_out (Activation)	(None, 23, 23, 512)	0	conv3_block2_add[0]
[0]			
conv3_block3_1_conv (Conv2D)	(None, 23, 23, 128)	65664	conv3_block2_out[0]
[0]			
conv3_block3_1_bn (BatchNormali	(None, 23, 23, 128)	512	conv3_block3_1_conv
[0][0]			
conv3_block3_1_relu (Activation	(None, 23, 23, 128)	0	conv3_block3_1_bn
[0][0]			

conv3_block3_2_conv (Conv2D)	(None, 23, 23, 128)	147584	conv3_block3_1_relu [0][0]
conv3_block3_2_bn (BatchNormali	(None, 23, 23, 128)	512	conv3_block3_2_conv [0][0]
conv3_block3_2_relu (Activation	(None, 23, 23, 128)	0	conv3_block3_2_bn [0][0]
conv3_block3_3_conv (Conv2D)	(None, 23, 23, 512)	66048	conv3_block3_2_relu [0][0]
conv3_block3_3_bn (BatchNormali	(None, 23, 23, 512)	2048	conv3_block3_3_conv [0][0]
conv3_block3_add (Add)	(None, 23, 23, 512)	0	conv3_block2_out[0] [0][0]
conv3_block3_out (Activation)	(None, 23, 23, 512)	0	conv3_block3_add[0] [0]
conv3_block4_1_conv (Conv2D)	(None, 23, 23, 128)	65664	conv3_block3_out[0] [0]
conv3_block4_1_bn (BatchNormali	(None, 23, 23, 128)	512	conv3_block4_1_conv [0][0]
conv3_block4_1_relu (Activation	(None, 23, 23, 128)	0	conv3_block4_1_bn [0][0]
conv3_block4_2_conv (Conv2D)	(None, 23, 23, 128)	147584	conv3_block4_1_relu [0][0]
conv3_block4_2_bn (BatchNormali	(None, 23, 23, 128)	512	conv3_block4_2_conv [0][0]
conv3_block4_2_relu (Activation	(None, 23, 23, 128)	0	conv3_block4_2_bn [0][0]
conv3_block4_3_conv (Conv2D)	(None, 23, 23, 512)	66048	conv3_block4_2_relu [0][0]
conv3_block4_3_bn (BatchNormali	(None, 23, 23, 512)	2048	conv3_block4_3_conv [0][0]

conv3_block4_add (Add)	(None, 23, 23, 512) 0	conv3_block3_out[0] conv3_block4_3_bn
[0][0]		
conv3_block4_out (Activation)	(None, 23, 23, 512) 0	conv3_block4_add[0] [0]
conv4_block1_1_conv (Conv2D)	(None, 12, 12, 256) 131328	conv3_block4_out[0] [0]
conv4_block1_1_bn (BatchNormali	(None, 12, 12, 256) 1024	conv4_block1_1_conv [0][0]
conv4_block1_1_relu (Activation	(None, 12, 12, 256) 0	conv4_block1_1_bn [0][0]
conv4_block1_2_conv (Conv2D)	(None, 12, 12, 256) 590080	conv4_block1_1_relu [0][0]
conv4_block1_2_bn (BatchNormali	(None, 12, 12, 256) 1024	conv4_block1_2_conv [0][0]
conv4_block1_2_relu (Activation	(None, 12, 12, 256) 0	conv4_block1_2_bn [0][0]
conv4_block1_0_conv (Conv2D)	(None, 12, 12, 1024) 525312	conv3_block4_out[0] [0]
conv4_block1_3_conv (Conv2D)	(None, 12, 12, 1024) 263168	conv4_block1_2_relu [0][0]
conv4_block1_0_bn (BatchNormali	(None, 12, 12, 1024) 4096	conv4_block1_0_conv [0][0]
conv4_block1_3_bn (BatchNormali	(None, 12, 12, 1024) 4096	conv4_block1_3_conv [0][0]
conv4_block1_add (Add)	(None, 12, 12, 1024) 0	conv4_block1_0_bn conv4_block1_3_bn
[0][0]		
conv4_block1_out (Activation)	(None, 12, 12, 1024) 0	conv4_block1_add[0] [0]
conv4_block2_1_conv (Conv2D)	(None, 12, 12, 256) 262400	conv4_block1_out[0] [0]

conv4_block2_1_bn (BatchNormali	(None, 12, 12, 256)	1024	conv4_block2_1_conv
[0][0]			
<hr/>			
conv4_block2_1_relu (Activation	(None, 12, 12, 256)	0	conv4_block2_1_bn
[0][0]			
<hr/>			
conv4_block2_2_conv (Conv2D)	(None, 12, 12, 256)	590080	conv4_block2_1_relu
[0][0]			
<hr/>			
conv4_block2_2_bn (BatchNormali	(None, 12, 12, 256)	1024	conv4_block2_2_conv
[0][0]			
<hr/>			
conv4_block2_2_relu (Activation	(None, 12, 12, 256)	0	conv4_block2_2_bn
[0][0]			
<hr/>			
conv4_block2_3_conv (Conv2D)	(None, 12, 12, 1024)	263168	conv4_block2_2_relu
[0][0]			
<hr/>			
conv4_block2_3_bn (BatchNormali	(None, 12, 12, 1024)	4096	conv4_block2_3_conv
[0][0]			
<hr/>			
conv4_block2_add (Add)	(None, 12, 12, 1024)	0	conv4_block1_out[0]
[0]			
			conv4_block2_3_bn
[0][0]			
<hr/>			
conv4_block2_out (Activation)	(None, 12, 12, 1024)	0	conv4_block2_add[0]
[0]			
<hr/>			
conv4_block3_1_conv (Conv2D)	(None, 12, 12, 256)	262400	conv4_block2_out[0]
[0]			
<hr/>			
conv4_block3_1_bn (BatchNormali	(None, 12, 12, 256)	1024	conv4_block3_1_conv
[0][0]			
<hr/>			
conv4_block3_1_relu (Activation	(None, 12, 12, 256)	0	conv4_block3_1_bn
[0][0]			
<hr/>			
conv4_block3_2_conv (Conv2D)	(None, 12, 12, 256)	590080	conv4_block3_1_relu
[0][0]			
<hr/>			
conv4_block3_2_bn (BatchNormali	(None, 12, 12, 256)	1024	conv4_block3_2_conv
[0][0]			
<hr/>			
conv4_block3_2_relu (Activation	(None, 12, 12, 256)	0	conv4_block3_2_bn
[0][0]			
<hr/>			
conv4_block3_3_conv (Conv2D)	(None, 12, 12, 1024)	263168	conv4_block3_2_relu
[0][0]			

conv4_block3_3_bn (BatchNormali	(None, 12, 12, 1024) 4096	conv4_block3_3_conv
[0][0]		
conv4_block3_add (Add)	(None, 12, 12, 1024) 0	conv4_block2_out[0]
[0]		
		conv4_block3_3_bn
[0][0]		
conv4_block3_out (Activation)	(None, 12, 12, 1024) 0	conv4_block3_add[0]
[0]		
conv4_block4_1_conv (Conv2D)	(None, 12, 12, 256) 262400	conv4_block3_out[0]
[0]		
conv4_block4_1_bn (BatchNormali	(None, 12, 12, 256) 1024	conv4_block4_1_conv
[0][0]		
conv4_block4_1_relu (Activation	(None, 12, 12, 256) 0	conv4_block4_1_bn
[0][0]		
conv4_block4_2_conv (Conv2D)	(None, 12, 12, 256) 590080	conv4_block4_1_relu
[0][0]		
conv4_block4_2_bn (BatchNormali	(None, 12, 12, 256) 1024	conv4_block4_2_conv
[0][0]		
conv4_block4_2_relu (Activation	(None, 12, 12, 256) 0	conv4_block4_2_bn
[0][0]		
conv4_block4_3_conv (Conv2D)	(None, 12, 12, 1024) 263168	conv4_block4_2_relu
[0][0]		
conv4_block4_3_bn (BatchNormali	(None, 12, 12, 1024) 4096	conv4_block4_3_conv
[0][0]		
conv4_block4_add (Add)	(None, 12, 12, 1024) 0	conv4_block3_out[0]
[0]		
		conv4_block4_3_bn
[0][0]		
conv4_block4_out (Activation)	(None, 12, 12, 1024) 0	conv4_block4_add[0]
[0]		
conv4_block5_1_conv (Conv2D)	(None, 12, 12, 256) 262400	conv4_block4_out[0]
[0]		
conv4_block5_1_bn (BatchNormali	(None, 12, 12, 256) 1024	conv4_block5_1_conv
[0][0]		

conv4_block5_1_relu (Activation (None, 12, 12, 256) 0	conv4_block5_1_bn
[0][0]	
conv4_block5_2_conv (Conv2D) (None, 12, 12, 256) 590080	conv4_block5_1_relu
[0][0]	
conv4_block5_2_bn (BatchNormali (None, 12, 12, 256) 1024	conv4_block5_2_conv
[0][0]	
conv4_block5_2_relu (Activation (None, 12, 12, 256) 0	conv4_block5_2_bn
[0][0]	
conv4_block5_3_conv (Conv2D) (None, 12, 12, 1024) 263168	conv4_block5_2_relu
[0][0]	
conv4_block5_3_bn (BatchNormali (None, 12, 12, 1024) 4096	conv4_block5_3_conv
[0][0]	
conv4_block5_add (Add) (None, 12, 12, 1024) 0	conv4_block4_out[0]
[0]	
	conv4_block5_3_bn
[0][0]	
conv4_block5_out (Activation) (None, 12, 12, 1024) 0	conv4_block5_add[0]
[0]	
conv4_block6_1_conv (Conv2D) (None, 12, 12, 256) 262400	conv4_block5_out[0]
[0]	
conv4_block6_1_bn (BatchNormali (None, 12, 12, 256) 1024	conv4_block6_1_conv
[0][0]	
conv4_block6_1_relu (Activation (None, 12, 12, 256) 0	conv4_block6_1_bn
[0][0]	
conv4_block6_2_conv (Conv2D) (None, 12, 12, 256) 590080	conv4_block6_1_relu
[0][0]	
conv4_block6_2_bn (BatchNormali (None, 12, 12, 256) 1024	conv4_block6_2_conv
[0][0]	
conv4_block6_2_relu (Activation (None, 12, 12, 256) 0	conv4_block6_2_bn
[0][0]	
conv4_block6_3_conv (Conv2D) (None, 12, 12, 1024) 263168	conv4_block6_2_relu
[0][0]	

conv4_block6_3_bn (BatchNormali	(None, 12, 12, 1024)	4096	conv4_block6_3_conv
[0][0]			
<hr/>			
conv4_block6_add (Add)	(None, 12, 12, 1024)	0	conv4_block5_out[0]
[0]			
			conv4_block6_3_bn
[0][0]			
<hr/>			
conv4_block6_out (Activation)	(None, 12, 12, 1024)	0	conv4_block6_add[0]
[0]			
<hr/>			
conv5_block1_1_conv (Conv2D)	(None, 6, 6, 512)	524800	conv4_block6_out[0]
[0]			
<hr/>			
conv5_block1_1_bn (BatchNormali	(None, 6, 6, 512)	2048	conv5_block1_1_conv
[0][0]			
<hr/>			
conv5_block1_1_relu (Activation	(None, 6, 6, 512)	0	conv5_block1_1_bn
[0][0]			
<hr/>			
conv5_block1_2_conv (Conv2D)	(None, 6, 6, 512)	2359808	conv5_block1_1_relu
[0][0]			
<hr/>			
conv5_block1_2_bn (BatchNormali	(None, 6, 6, 512)	2048	conv5_block1_2_conv
[0][0]			
<hr/>			
conv5_block1_2_relu (Activation	(None, 6, 6, 512)	0	conv5_block1_2_bn
[0][0]			
<hr/>			
conv5_block1_0_conv (Conv2D)	(None, 6, 6, 2048)	2099200	conv4_block6_out[0]
[0]			
<hr/>			
conv5_block1_3_conv (Conv2D)	(None, 6, 6, 2048)	1050624	conv5_block1_2_relu
[0][0]			
<hr/>			
conv5_block1_0_bn (BatchNormali	(None, 6, 6, 2048)	8192	conv5_block1_0_conv
[0][0]			
<hr/>			
conv5_block1_3_bn (BatchNormali	(None, 6, 6, 2048)	8192	conv5_block1_3_conv
[0][0]			
<hr/>			
conv5_block1_add (Add)	(None, 6, 6, 2048)	0	conv5_block1_0_bn
[0][0]			
			conv5_block1_3_bn
[0][0]			
<hr/>			
conv5_block1_out (Activation)	(None, 6, 6, 2048)	0	conv5_block1_add[0]
[0]			
<hr/>			

conv5_block2_1_conv (Conv2D)	(None, 6, 6, 512)	1049088	conv5_block1_out[0] [0]
conv5_block2_1_bn (BatchNormali	(None, 6, 6, 512)	2048	conv5_block2_1_conv [0][0]
conv5_block2_1_relu (Activation	(None, 6, 6, 512)	0	conv5_block2_1_bn [0][0]
conv5_block2_2_conv (Conv2D)	(None, 6, 6, 512)	2359808	conv5_block2_1_relu [0][0]
conv5_block2_2_bn (BatchNormali	(None, 6, 6, 512)	2048	conv5_block2_2_conv [0][0]
conv5_block2_2_relu (Activation	(None, 6, 6, 512)	0	conv5_block2_2_bn [0][0]
conv5_block2_3_conv (Conv2D)	(None, 6, 6, 2048)	1050624	conv5_block2_2_relu [0][0]
conv5_block2_3_bn (BatchNormali	(None, 6, 6, 2048)	8192	conv5_block2_3_conv [0][0]
conv5_block2_add (Add)	(None, 6, 6, 2048)	0	conv5_block1_out[0] [0] conv5_block2_3_bn [0][0]
conv5_block2_out (Activation)	(None, 6, 6, 2048)	0	conv5_block2_add[0] [0]
conv5_block3_1_conv (Conv2D)	(None, 6, 6, 512)	1049088	conv5_block2_out[0] [0]
conv5_block3_1_bn (BatchNormali	(None, 6, 6, 512)	2048	conv5_block3_1_conv [0][0]
conv5_block3_1_relu (Activation	(None, 6, 6, 512)	0	conv5_block3_1_bn [0][0]
conv5_block3_2_conv (Conv2D)	(None, 6, 6, 512)	2359808	conv5_block3_1_relu [0][0]
conv5_block3_2_bn (BatchNormali	(None, 6, 6, 512)	2048	conv5_block3_2_conv [0][0]
conv5_block3_2_relu (Activation	(None, 6, 6, 512)	0	conv5_block3_2_bn [0][0]

conv5_block3_3_conv (Conv2D)	(None, 6, 6, 2048)	1050624	conv5_block3_2_relu [0][0]
conv5_block3_3_bn (BatchNormali	(None, 6, 6, 2048)	8192	conv5_block3_3_conv [0][0]
conv5_block3_add (Add)	(None, 6, 6, 2048)	0	conv5_block2_out[0] [0] conv5_block3_3_bn [0][0]
conv5_block3_out (Activation)	(None, 6, 6, 2048)	0	conv5_block3_add[0] [0]

=====
=====
Total params: 23,587,712
Trainable params: 23,534,592
Non-trainable params: 53,120

In [37]:

```
resnet_model = Sequential([
    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=METRICS)
```

In [38]:

```
r = resnet_model.fit(train,
    epochs=10,
    validation_data=validation,
    class_weight=class_weight,
    steps_per_epoch=100,
    validation_steps=25)
```

Epoch 1/10

```
100/100 [=====] - ETA: 0s - loss: 0.2354 - accuracy: 0.7200
- precision: 0.9000 - recall: 0.6993WARNING:tensorflow:Your input ran out of data; i
nterrupting training. Make 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 t
```


he repeat() function when building your dataset.

```
100/100 [=====] - 383s 4s/step - loss: 0.2354 - accuracy:
0.7200 - precision: 0.9000 - recall: 0.6993 - val_loss: 874.2960 - val_accuracy: 0.5
000 - val_precision: 0.5000 - val_recall: 1.0000
Epoch 2/10
100/100 [=====] - 658s 7s/step - loss: 0.1914 - accuracy:
0.7675 - precision: 0.9249 - recall: 0.7537
Epoch 3/10
100/100 [=====] - 773s 8s/step - loss: 0.1763 - accuracy:
0.7975 - precision: 0.9453 - recall: 0.7832
Epoch 4/10
100/100 [=====] - 765s 8s/step - loss: 0.2092 - accuracy:
0.7538 - precision: 0.8896 - recall: 0.7573
Epoch 5/10
100/100 [=====] - 812s 8s/step - loss: 0.2206 - accuracy:
0.7400 - precision: 0.8942 - recall: 0.7430
Epoch 6/10
100/100 [=====] - 786s 8s/step - loss: 0.2471 - accuracy:
0.6488 - precision: 0.8413 - recall: 0.6504
Epoch 7/10
100/100 [=====] - 774s 8s/step - loss: 0.2119 - accuracy:
0.6825 - precision: 0.9073 - recall: 0.6597
Epoch 8/10
100/100 [=====] - 780s 8s/step - loss: 0.2056 - accuracy:
0.7638 - precision: 0.9012 - recall: 0.7565
Epoch 9/10
100/100 [=====] - 820s 8s/step - loss: 0.1637 - accuracy:
0.8275 - precision: 0.9399 - recall: 0.8193
Epoch 10/10
100/100 [=====] - 801s 8s/step - loss: 0.1466 - accuracy:
0.8425 - precision: 0.9594 - recall: 0.8253
```

In [39]:

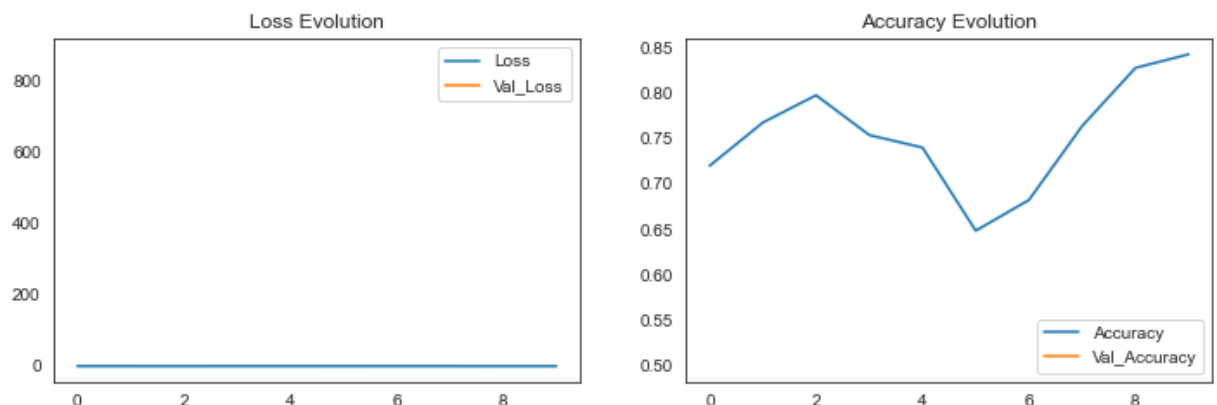
```
plt.figure(figsize=(12, 8))

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[39]:

Text(0.5, 1.0, 'Accuracy Evolution')



In [40]:

```
evaluation = resnet_model.evaluate(test)
```

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

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

```
624/624 [=====] - 207s 332ms/step - loss: 1.0688 - accuracy: 0.6378 - precision: 0.6336 - recall: 0.9974
Test Accuracy: 63.78%
652/652 [=====] - 805s 1s/step - loss: 0.5094 - accuracy: 0.7789 - precision: 0.7720 - recall: 0.9969
Train Accuracy: 77.89%
```

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>

```
In [41]: from keras.applications import InceptionV3

inception_base_model = InceptionV3(input_shape=(180,180,3),include_top=False,weights
```

```
In [42]: inception_model = 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")
])

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=METRICS
```

```
In [43]: r = inception_model.fit(train,
    epochs=10,
    validation_data=validation,
    class_weight=class_weight,
    steps_per_epoch=100,
    validation_steps=25)
```

```
Epoch 1/10
100/100 [=====] - ETA: 0s - loss: 0.2088 - accuracy: 0.7300
```

```
- precision: 0.9187 - recall: 0.7002WARNING:tensorflow:Your input ran out of data; i
nterrupting training. Make 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 t
he repeat() function when building your dataset.
100/100 [=====] - 225s 2s/step - loss: 0.2088 - accuracy:
0.7300 - precision: 0.9187 - recall: 0.7002 - val_loss: 6.1463 - val_accuracy: 0.500
0 - val_precision: 0.0000e+00 - val_recall: 0.0000e+00
Epoch 2/10
100/100 [=====] - 226s 2s/step - loss: 0.1842 - accuracy:
0.7987 - precision: 0.9369 - recall: 0.7797
Epoch 3/10
100/100 [=====] - 285s 3s/step - loss: 0.1660 - accuracy:
0.8012 - precision: 0.9499 - recall: 0.7796
Epoch 4/10
100/100 [=====] - 443s 4s/step - loss: 0.1616 - accuracy:
0.8263 - precision: 0.9339 - recall: 0.8205
Epoch 5/10
100/100 [=====] - 431s 4s/step - loss: 0.1290 - accuracy:
0.8550 - precision: 0.9662 - recall: 0.8399
Epoch 6/10
100/100 [=====] - 408s 4s/step - loss: 0.1415 - accuracy:
0.8525 - precision: 0.9519 - recall: 0.8484
Epoch 7/10
100/100 [=====] - 428s 4s/step - loss: 0.1168 - accuracy:
0.8700 - precision: 0.9643 - recall: 0.8579
Epoch 8/10
100/100 [=====] - 446s 4s/step - loss: 0.1331 - accuracy:
0.8612 - precision: 0.9467 - recall: 0.8626
Epoch 9/10
100/100 [=====] - 449s 4s/step - loss: 0.1471 - accuracy:
0.8425 - precision: 0.9378 - recall: 0.8479
Epoch 10/10
100/100 [=====] - 441s 4s/step - loss: 0.1121 - accuracy:
0.8875 - precision: 0.9696 - recall: 0.8813
```

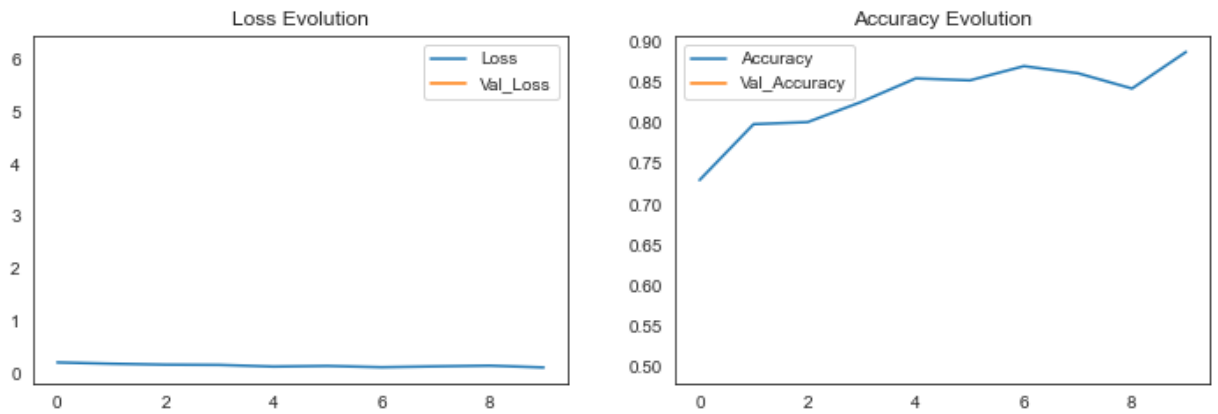
In [44]:

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



```
In [45]: 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}%")
```

```
624/624 [=====] - 119s 191ms/step - loss: 3.2893 - accuracy: 0.7532 - precision: 0.7305 - recall: 0.9590
Test Accuracy: 75.32%
652/652 [=====] - 743s 1s/step - loss: 1.6314 - accuracy: 0.9030 - precision: 0.9158 - recall: 0.9574
Train Accuracy: 90.30%
```

Comparing different models

```
In [46]: model_mae_scores_dict = {'CNN': 91.98, 'CNN_2': 68.91, 'DenseNet': 87.18, 'VGG16': 66.19, 'ResNet': 73.40, 'InceptionNet': 76.76}
```

```
In [47]: model_mae_scores = pd.Series(model_mae_scores_dict)
```

```
In [48]: model_mae_scores
```

```
Out[48]: CNN          91.98
CNN_2         68.91
DenseNet      87.18
VGG16         66.19
ResNet        73.40
InceptionNet  76.76
dtype: float64
```

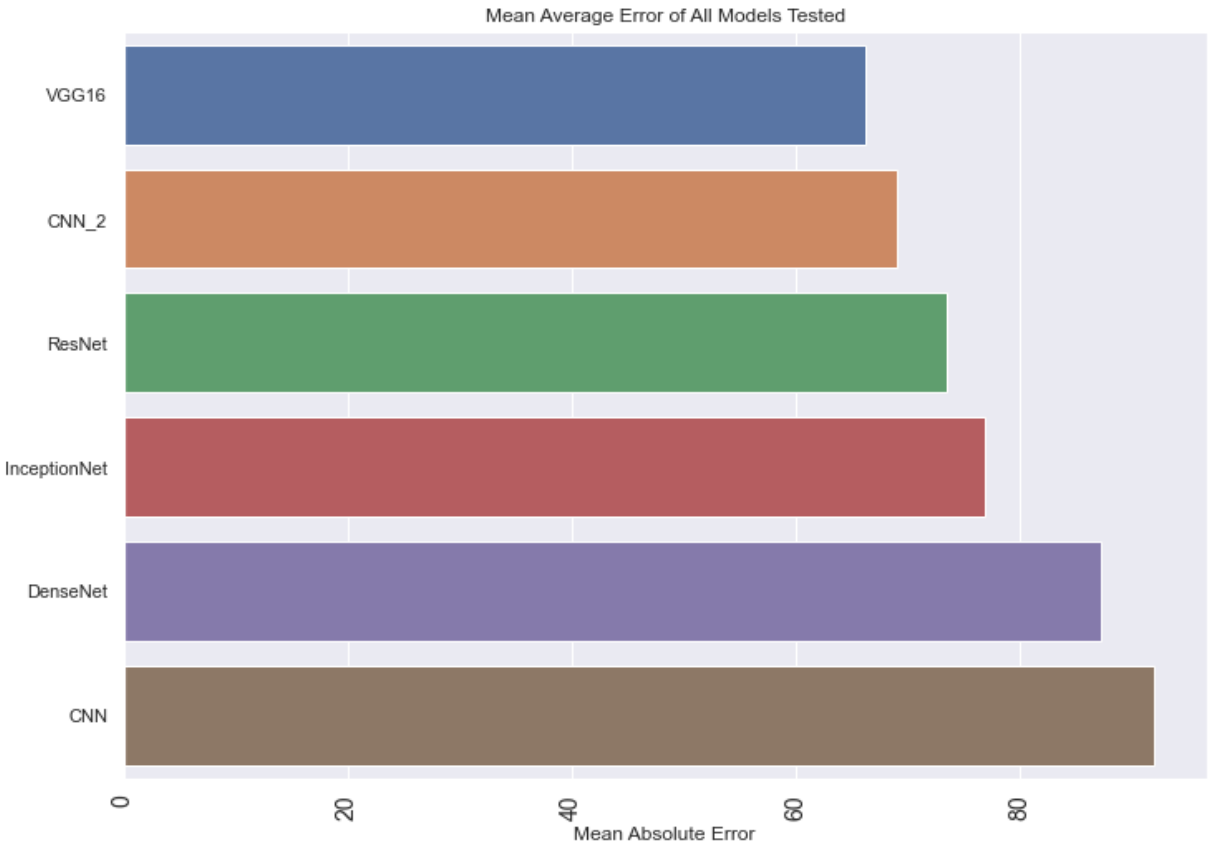
```
In [49]: order = model_mae_scores.sort_values()
```

```
In [50]: from matplotlib import pyplot
import seaborn as sns

sns.set(rc={'figure.figsize':(11.7,8.27)})
sns.barplot(x=order.values, y = order.index, orient='h')

plt.xlabel('Mean Absolute Error')
plt.xticks(rotation='vertical',fontsize=14)
plt.title('Mean Average Error of All Models Tested')
```

```
Out[50]: Text(0.5, 1.0, 'Mean Average Error of All Models Tested')
```



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