DTSA-5511 Week 6 - Colorize image

A Jupyter notebook with a description of the problem/data, exploratory data analysis (EDA) procedure, analysis (model building and training), result, and discussion/conclusion.

Problem statement

Automated picture colorization of black-and-white photos has become a prominent topic in computer vision and deep learning research. The goal of this project is to take a grayscale (black and white) image as an input and outputs a colorized version of an old movie image. The output colorized film's image should represent and match the semantic colors and tones of the input.

Dataset Description

Human faces is a collection of 7.2k+ images useful for multiple use cases such image identifiers, classifier algorithms etc.

About directory

Male and female Image dataset with special attention to senior citizens' pictures and a small of portion real-like fake faces to improve identification over wide range of input pictures.

Model Architecture

I will be using U-Net architecture because it is considered as one of the standard CNN architectures for image classification tasks.

1. Exploratory Data Analysis (EDA)

1.1. Importing libraries

Loading libraries required for this project

In [1]:
```
# utilities
import os
import numpy as np

# plot
import matplotlib.pyplot as plt

# machine learning
import tensorflow as tf
import tensorflow.keras.layers as tfl
from tqdm import tqdm
import cv2
```

```
from sklearn.model_selection import train_test_split

#variables
IMAGE_SIZE = 128
```

1.2. Data inspection

Loading various face images from the dataset and converting RGB images to Grayscale with the OpenCV library. The RGB images will serve as labels, and the Grayscale images will serve as input.

In [2]:
```
path='../input/human-faces'
# uploading the images
def images_upload(path):
    images=[]
    for root,subfolders,files in os.walk(path):
        for file in tqdm(files):
            filename=root+os.sep+file
            if filename.endswith('jpg') or filename.endswith('png'):
                images.append(filename)
    return images
images=images_upload(path)
```

```
0it [00:00, ?it/s]
100%|██████████| 7219/7219 [00:00<00:00, 1090220.02it/s]
```

In [3]:
```
# converting the images to RGB
def convert_image_labels(images):
    labels=[]
    for i in tqdm(images):
        i = cv2.imread(i)
        i=cv2.cvtColor(i, cv2.COLOR_BGR2RGB)
        res_i=cv2.resize(i,(IMAGE_SIZE,IMAGE_SIZE))
        del i
        labels.append(res_i)
    return labels

# converting the images to black and white
def convert_image_inputs(images):
    inputs=[]
    for z in tqdm(images):
        z = cv2.imread(z)
        z=cv2.cvtColor(z,  cv2.COLOR_BGR2GRAY)
        res_z=cv2.resize(z,(IMAGE_SIZE,IMAGE_SIZE))
        del z
        inputs.append(res_z)
    return inputs

labels=convert_image_labels(images)
inputs=convert_image_inputs(images)
```

```
100%|██████████| 7123/7123 [03:37<00:00, 32.82it/s]
100%|██████████| 7123/7123 [02:59<00:00, 39.71it/s]
```

In [4]:
```
# showing the color images
def show_labels(labels):
```

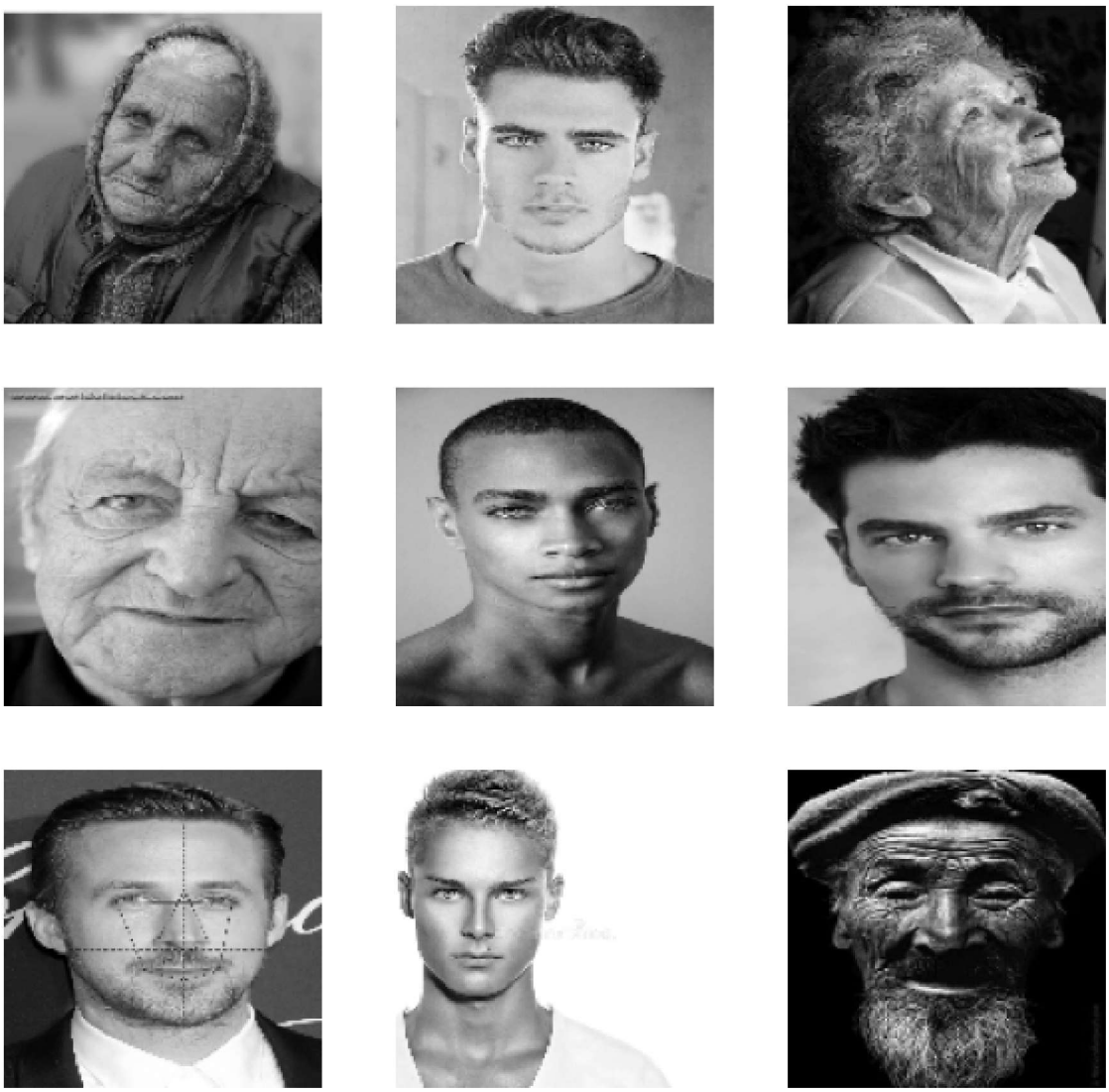
```
    plt.figure(figsize=(10,10))
    for i in range(9):
        #idx=np.random.randint(0,len(labels))
        plt.subplot(3,3,i+1)
        img=labels[i]
        plt.axis('off')
        plt.imshow(img)

show_labels(labels)
plt.suptitle("Set of color images",fontsize=20)
plt.show()
```

Although most of the images are in RGB format there are few that are in Gray scale format which can influence on the result so that should be taken into account.

In [5]:

```
# showing the images in black and white
def show_input(inputs):
    plt.figure(figsize=(10,10))
    for i in range(9):
```

```
        #idx=np.random.randint(0,len(inputs))
        plt.subplot(3,3,i+1)
        img=inputs[i]
        plt.axis('off')
        plt.imshow(img,cmap='gray')
show_input(inputs)
plt.suptitle("Set of input images",fontsize=20)
plt.show()
```



In [6]:

```
# comparing the one image from RGB to black and white
def images_compare(inputs,labels):
    idx_new=np.random.randint(0,len(labels))
    fig = plt.figure()
    ax1 = fig.add_subplot(1,2,1)
    ax1.set_title('Color')
    ax1.axis('off')
    ax1.imshow(labels[idx_new])
    ax2 = fig.add_subplot(1,2,2)
    ax2.set_title('Grayscale')
```

```
    ax2.axis('off')
    ax2.imshow(inputs[idx_new],cmap='gray')
    plt.suptitle("Color vs Grayscale image",fontsize=20)
    plt.show()
images_compare(inputs,labels)
```

2. Modeling

Training the data using U-Net architecture which is one of the CNN standard architectures for image classification tasks.

2.1. Splitting the data

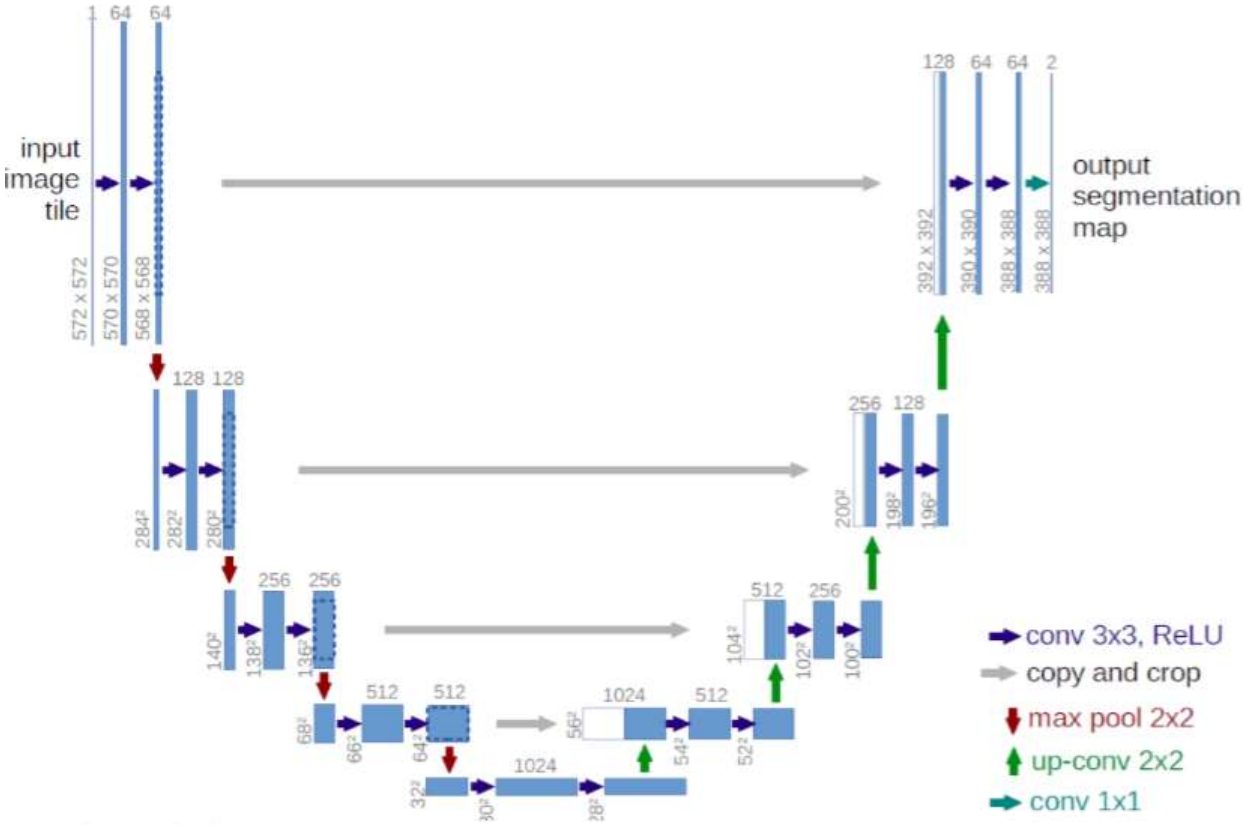
Dividing the data into two data sets.

In [7]:
```
# Splitting the data function
def split_data(inputs,labels,test_size=0.2):
    labels=np.array(labels)
    inputs=np.array(inputs)
    x_train, x_test, y_train, y_test = train_test_split(inputs, labels, test_size=test_
    x_train, x_valid, y_train, y_valid = train_test_split(x_train, y_train, test_size=0
    return x_train, x_valid,x_test ,y_train, y_valid,y_test
```

In [8]:
```
# Splitting the data
x_train, x_valid, x_test ,y_train, y_valid,y_test=split_data(inputs,labels,test_size=0.
x_train, x_valid, x_test=x_train/255.0,x_valid/255.0,x_test/255.0
y_train, y_valid, y_test=y_train/255.0,y_valid/255.0,y_test/255.0
```

2.2. Training

U-Net architecture mainly consists of two paths. One is an encoder path and other is a decoder path. The encoder path captures the context of the image producing feature maps. Encoder path is just a stack of convolution and max pooling layers. Decoder path used to enable precise localization using transposed convolutions. U-net only contains Convolutional layers and does not contain any Dense layer because of which it can accept image of any size.



U-Net architecture is used for this problem because it is considered as one of the standard CNN architectures for image classification tasks. It is considered as a best network for fast and precise segmentation of images.

In [9]:

```
# Generating the U-Net model
def build_model(inputsize=(IMAGE_SIZE,IMAGE_SIZE,1)):
    input = tf.keras.Input(shape=(inputsize))

    conv = tfl.Conv2D(64, (3, 3), padding="same",kernel_initializer='he_normal', name='
        input)
    x=tfl.BatchNormalization()(conv)
    x=tfl.LeakyReLU()(x)
    x = tfl.Conv2D(64, (3, 3), padding="same",kernel_initializer='he_normal', name='Con
        x)
    x=tfl.BatchNormalization()(x)
    x=tfl.LeakyReLU()(x)
    x1 = tfl.Conv2D(64, (3, 3), padding="same",kernel_initializer='he_normal', name='Co
        x)
    x=tfl.BatchNormalization()(x1)
    x=tfl.LeakyReLU()(x)
    x = tfl.MaxPool2D(pool_size=(2, 2), strides=(2, 2), name='MaxPool1')(x)

    x = tfl.Conv2D(128, (3, 3), padding="same",kernel_initializer='he_normal', name='Co
    x=tfl.BatchNormalization()(x)
    x=tfl.LeakyReLU()(x)
    x = tfl.Conv2D(128, (3, 3), padding="same",kernel_initializer='he_normal', name='Co
    x=tfl.BatchNormalization()(x)
    x=tfl.LeakyReLU()(x)
    x2 = tfl.Conv2D(128, (3, 3), padding="same", strides=(1, 1),kernel_initializer='he_
                    name='Conv6')(x)
    x=tfl.BatchNormalization()(x2)
```

```
x=tfl.LeakyReLU()(x)
x = tfl.MaxPool2D(pool_size=(2, 2), name='MaxPool2')(x)

x = tfl.Conv2D(256, (3, 3), padding="same",kernel_initializer='he_normal', name='Co
x=tfl.BatchNormalization()(x)
x=tfl.LeakyReLU()(x)
x = tfl.Conv2D(256, (3, 3), padding="same",kernel_initializer='he_normal', name='Co
x=tfl.BatchNormalization()(x)
x=tfl.LeakyReLU()(x)
x3 = tfl.Conv2D(256, (3, 3), padding="same",kernel_initializer='he_normal', name='C
x=tfl.BatchNormalization()(x3)
x=tfl.LeakyReLU()(x)
x = tfl.MaxPool2D(pool_size=(2, 2), strides=(2, 2), name='MaxPool3')(x)


x = tfl.Conv2D(512, (3, 3), padding="same",kernel_initializer='he_normal', name='Co
x=tfl.BatchNormalization()(x)
x=tfl.LeakyReLU()(x)
x = tfl.Conv2D(512, (3, 3), padding="same",kernel_initializer='he_normal', name='Co
x=tfl.BatchNormalization()(x)
x=tfl.LeakyReLU()(x)
x4 = tfl.Conv2D(512, (3, 3), padding="same",kernel_initializer='he_normal', name='C
x=tfl.BatchNormalization()(x4)
x=tfl.LeakyReLU()(x)
x = tfl.MaxPool2D(pool_size=(2, 2), strides=(2, 2), name='MaxPool4')(x)

x = tfl.Conv2D(1024, (3, 3), padding="same",name='Conv13')(x)
x=tfl.BatchNormalization()(x)
x=tfl.LeakyReLU()(x)
x = tfl.Conv2D(1024, (3, 3), padding="same",name='Conv14')(x)
x=tfl.BatchNormalization()(x)
x=tfl.LeakyReLU()(x)
x = tfl.Conv2D(1024, (3, 3), padding="same",kernel_initializer='he_normal', name='C
x=tfl.BatchNormalization()(x)
x=tfl.LeakyReLU()(x)
x = tfl.Conv2DTranspose(512, (3, 3), strides=2, padding="same")(x)
x=tfl.BatchNormalization()(x)
x=tfl.LeakyReLU()(x)

x = tfl.concatenate([x, x4], axis=3)

x = tfl.Conv2D(512, (3, 3), padding="same",kernel_initializer='he_normal', name='Co
x=tfl.BatchNormalization()(x)
x=tfl.LeakyReLU()(x)
x = tfl.Conv2D(512, (3, 3), padding="same",kernel_initializer='he_normal', name='Co
x=tfl.BatchNormalization()(x)
x=tfl.LeakyReLU()(x)
x = tfl.Conv2D(512, (3, 3), padding="same",kernel_initializer='he_normal', name='Co
x=tfl.BatchNormalization()(x)
x=tfl.LeakyReLU()(x)
x = tfl.Conv2DTranspose(256, (3, 3), strides=2, padding="same")(x)
x=tfl.BatchNormalization()(x)
x=tfl.LeakyReLU()(x)

x = tfl.concatenate([x, x3], axis=3)

x = tfl.Conv2D(256, (3, 3), padding="same",kernel_initializer='he_normal', name='Co
x=tfl.BatchNormalization()(x)
x=tfl.LeakyReLU()(x)
x = tfl.Conv2D(256, (3, 3), padding="same",kernel_initializer='he_normal', name='Co
```

```
    x=tfl.BatchNormalization()(x)
    x=tfl.LeakyReLU()(x)
    x = tfl.Conv2D(256, (3, 3), padding="same",kernel_initializer='he_normal', name='Co
    x=tfl.BatchNormalization()(x)
    x=tfl.LeakyReLU()(x)
    x = tfl.Conv2DTranspose(128, (3, 3), strides=2, padding="same")(x)
    x=tfl.BatchNormalization()(x)
    x=tfl.LeakyReLU()(x)

    x = tfl.concatenate([x, x2], axis=3)

    x = tfl.Conv2D(128, (3, 3), padding="same",kernel_initializer='he_normal', name='Co
    x=tfl.BatchNormalization()(x)
    x=tfl.LeakyReLU()(x)
    x = tfl.Conv2D(128, (3, 3), padding="same",kernel_initializer='he_normal', name='Co
    x=tfl.BatchNormalization()(x)
    x=tfl.LeakyReLU()(x)
    x = tfl.Conv2D(128, (3, 3), padding="same",kernel_initializer='he_normal', name='Co
    x=tfl.BatchNormalization()(x)
    x=tfl.LeakyReLU()(x)
    x = tfl.Conv2DTranspose(64, (3, 3), strides=2, padding="same")(x)
    x=tfl.BatchNormalization()(x)
    x=tfl.LeakyReLU()(x)

    x = tfl.concatenate([x, x1], axis=3)

    x = tfl.Conv2D(64, (3, 3), padding="same",kernel_initializer='he_normal', name='Con
    x=tfl.BatchNormalization()(x)
    x=tfl.LeakyReLU()(x)
    x = tfl.Conv2D(64, (3, 3), padding="same",kernel_initializer='he_normal', name='Con
    x=tfl.BatchNormalization()(x)
    x=tfl.LeakyReLU()(x)
    x = tfl.Conv2D(64, (3, 3), padding="same",name='Conv27')(x)
    x=tfl.BatchNormalization()(x)
    x=tfl.LeakyReLU()(x)
    outputs = tfl.Conv2D(3, (1, 1), padding="same", activation='sigmoid', name='Outputs
    final_model = tf.keras.Model(inputs=input, outputs=outputs)
    final_model.summary()
    return final_model
```

In [10]:

```
# Setting callbacks
def callbacks(patience=5):
    # Saving the best parameters
    checkpoint = tf.keras.callbacks.ModelCheckpoint('seg_model.h5', monitor='val_loss',
    # Earlystopping callback was used to prevent from the model to be trained if there
    early=tf.keras.callbacks.EarlyStopping(monitor='val_loss',patience=patience,min_del
    callbacks_list=[checkpoint, early]
    return callbacks_list
```

In [11]:

```
# Creating the model 1
mymodel1=build_model()
```

```
2022-10-09 20:10:04.388933: I tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:937]
successful NUMA node read from SysFS had negative value (-1), but there must be at least
one NUMA node, so returning NUMA node zero
2022-10-09 20:10:04.399972: I tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:937]
successful NUMA node read from SysFS had negative value (-1), but there must be at least
```

```
one NUMA node, so returning NUMA node zero
2022-10-09 20:10:04.400736: I tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:937]
successful NUMA node read from SysFS had negative value (-1), but there must be at least
one NUMA node, so returning NUMA node zero
2022-10-09 20:10:04.401884: I tensorflow/core/platform/cpu_feature_guard.cc:142] This Te
nsorFlow binary is optimized with oneAPI Deep Neural Network Library (oneDNN) to use the
following CPU instructions in performance-critical operations:  AVX2 AVX512F FMA
To enable them in other operations, rebuild TensorFlow with the appropriate compiler fla
gs.
2022-10-09 20:10:04.402201: I tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:937]
successful NUMA node read from SysFS had negative value (-1), but there must be at least
one NUMA node, so returning NUMA node zero
2022-10-09 20:10:04.402913: I tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:937]
successful NUMA node read from SysFS had negative value (-1), but there must be at least
one NUMA node, so returning NUMA node zero
2022-10-09 20:10:04.403625: I tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:937]
successful NUMA node read from SysFS had negative value (-1), but there must be at least
one NUMA node, so returning NUMA node zero
2022-10-09 20:10:05.027072: I tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:937]
successful NUMA node read from SysFS had negative value (-1), but there must be at least
one NUMA node, so returning NUMA node zero
2022-10-09 20:10:05.027940: I tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:937]
successful NUMA node read from SysFS had negative value (-1), but there must be at least
one NUMA node, so returning NUMA node zero
2022-10-09 20:10:05.028615: I tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:937]
successful NUMA node read from SysFS had negative value (-1), but there must be at least
one NUMA node, so returning NUMA node zero
2022-10-09 20:10:05.030416: I tensorflow/core/common_runtime/gpu/gpu_device.cc:1510] Cre
ated device /job:localhost/replica:0/task:0/device:GPU:0 with 15401 MB memory:  -> devic
e: 0, name: Tesla P100-PCIE-16GB, pci bus id: 0000:00:04.0, compute capability: 6.0
Model: "model"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 128, 128, 1)]     0
_________________________________________________________________
Conv1 (Conv2D)               (None, 128, 128, 64)      640
_________________________________________________________________
batch_normalization (BatchNorma (None, 128, 128, 64)      256
_________________________________________________________________
leaky_re_lu (LeakyReLU)      (None, 128, 128, 64)      0
_________________________________________________________________
Conv2 (Conv2D)               (None, 128, 128, 64)      36928
_________________________________________________________________
batch_normalization_1 (BatchNor (None, 128, 128, 64)      256
_________________________________________________________________
leaky_re_lu_1 (LeakyReLU)    (None, 128, 128, 64)      0
_________________________________________________________________
Conv3 (Conv2D)               (None, 128, 128, 64)      36928
```

batch_normalization_2 (BatchNor	(None, 128, 128, 64)	256	Conv3[0][0]
leaky_re_lu_2 (LeakyReLU) [0][0]	(None, 128, 128, 64)	0	batch_normalization_2
MaxPool1 (MaxPooling2D)	(None, 64, 64, 64)	0	leaky_re_lu_2[0][0]
Conv4 (Conv2D)	(None, 64, 64, 128)	73856	MaxPool1[0][0]
batch_normalization_3 (BatchNor	(None, 64, 64, 128)	512	Conv4[0][0]
leaky_re_lu_3 (LeakyReLU) [0][0]	(None, 64, 64, 128)	0	batch_normalization_3
Conv5 (Conv2D)	(None, 64, 64, 128)	147584	leaky_re_lu_3[0][0]
batch_normalization_4 (BatchNor	(None, 64, 64, 128)	512	Conv5[0][0]
leaky_re_lu_4 (LeakyReLU) [0][0]	(None, 64, 64, 128)	0	batch_normalization_4
Conv6 (Conv2D)	(None, 64, 64, 128)	147584	leaky_re_lu_4[0][0]
batch_normalization_5 (BatchNor	(None, 64, 64, 128)	512	Conv6[0][0]
leaky_re_lu_5 (LeakyReLU) [0][0]	(None, 64, 64, 128)	0	batch_normalization_5
MaxPool2 (MaxPooling2D)	(None, 32, 32, 128)	0	leaky_re_lu_5[0][0]
Conv7 (Conv2D)	(None, 32, 32, 256)	295168	MaxPool2[0][0]
batch_normalization_6 (BatchNor	(None, 32, 32, 256)	1024	Conv7[0][0]
leaky_re_lu_6 (LeakyReLU) [0][0]	(None, 32, 32, 256)	0	batch_normalization_6
Conv8 (Conv2D)	(None, 32, 32, 256)	590080	leaky_re_lu_6[0][0]
batch_normalization_7 (BatchNor	(None, 32, 32, 256)	1024	Conv8[0][0]

leaky_re_lu_7 (LeakyReLU)	(None, 32, 32, 256)	0	batch_normalization_7[0][0]
Conv9 (Conv2D)	(None, 32, 32, 256)	590080	leaky_re_lu_7[0][0]
batch_normalization_8 (BatchNor	(None, 32, 32, 256)	1024	Conv9[0][0]
leaky_re_lu_8 (LeakyReLU)	(None, 32, 32, 256)	0	batch_normalization_8[0][0]
MaxPool3 (MaxPooling2D)	(None, 16, 16, 256)	0	leaky_re_lu_8[0][0]
Conv10 (Conv2D)	(None, 16, 16, 512)	1180160	MaxPool3[0][0]
batch_normalization_9 (BatchNor	(None, 16, 16, 512)	2048	Conv10[0][0]
leaky_re_lu_9 (LeakyReLU)	(None, 16, 16, 512)	0	batch_normalization_9[0][0]
Conv11 (Conv2D)	(None, 16, 16, 512)	2359808	leaky_re_lu_9[0][0]
batch_normalization_10 (BatchNo	(None, 16, 16, 512)	2048	Conv11[0][0]
leaky_re_lu_10 (LeakyReLU)	(None, 16, 16, 512)	0	batch_normalization_10[0][0]
Conv12 (Conv2D)	(None, 16, 16, 512)	2359808	leaky_re_lu_10[0][0]
batch_normalization_11 (BatchNo	(None, 16, 16, 512)	2048	Conv12[0][0]
leaky_re_lu_11 (LeakyReLU)	(None, 16, 16, 512)	0	batch_normalization_11[0][0]
MaxPool4 (MaxPooling2D)	(None, 8, 8, 512)	0	leaky_re_lu_11[0][0]
Conv13 (Conv2D)	(None, 8, 8, 1024)	4719616	MaxPool4[0][0]
batch_normalization_12 (BatchNo	(None, 8, 8, 1024)	4096	Conv13[0][0]
leaky_re_lu_12 (LeakyReLU)	(None, 8, 8, 1024)	0	batch_normalization_12[0][0]

Conv14 (Conv2D)	(None, 8, 8, 1024)	9438208	leaky_re_lu_12[0][0]
batch_normalization_13 (BatchNo	(None, 8, 8, 1024)	4096	Conv14[0][0]
leaky_re_lu_13 (LeakyReLU) [0][0]	(None, 8, 8, 1024)	0	batch_normalization_13
Conv15 (Conv2D)	(None, 8, 8, 1024)	9438208	leaky_re_lu_13[0][0]
batch_normalization_14 (BatchNo	(None, 8, 8, 1024)	4096	Conv15[0][0]
leaky_re_lu_14 (LeakyReLU) [0][0]	(None, 8, 8, 1024)	0	batch_normalization_14
conv2d_transpose (Conv2DTranspo	(None, 16, 16, 512)	4719104	leaky_re_lu_14[0][0]
batch_normalization_15 (BatchNo	(None, 16, 16, 512)	2048	conv2d_transpose[0][0]
leaky_re_lu_15 (LeakyReLU) [0][0]	(None, 16, 16, 512)	0	batch_normalization_15
concatenate (Concatenate)	(None, 16, 16, 1024)	0	leaky_re_lu_15[0][0] Conv12[0][0]
Conv16 (Conv2D)	(None, 16, 16, 512)	4719104	concatenate[0][0]
batch_normalization_16 (BatchNo	(None, 16, 16, 512)	2048	Conv16[0][0]
leaky_re_lu_16 (LeakyReLU) [0][0]	(None, 16, 16, 512)	0	batch_normalization_16
Conv17 (Conv2D)	(None, 16, 16, 512)	2359808	leaky_re_lu_16[0][0]
batch_normalization_17 (BatchNo	(None, 16, 16, 512)	2048	Conv17[0][0]
leaky_re_lu_17 (LeakyReLU) [0][0]	(None, 16, 16, 512)	0	batch_normalization_17
Conv18 (Conv2D)	(None, 16, 16, 512)	2359808	leaky_re_lu_17[0][0]
batch_normalization_18 (BatchNo	(None, 16, 16, 512)	2048	Conv18[0][0]

leaky_re_lu_18 (LeakyReLU)	(None, 16, 16, 512)	0	batch_normalization_18[0][0]
conv2d_transpose_1 (Conv2DTrans	(None, 32, 32, 256)	1179904	leaky_re_lu_18[0][0]
batch_normalization_19 (BatchNo	(None, 32, 32, 256)	1024	conv2d_transpose_1[0][0]
leaky_re_lu_19 (LeakyReLU)	(None, 32, 32, 256)	0	batch_normalization_19[0][0]
concatenate_1 (Concatenate)	(None, 32, 32, 512)	0	leaky_re_lu_19[0][0] Conv9[0][0]
Conv19 (Conv2D)	(None, 32, 32, 256)	1179904	concatenate_1[0][0]
batch_normalization_20 (BatchNo	(None, 32, 32, 256)	1024	Conv19[0][0]
leaky_re_lu_20 (LeakyReLU)	(None, 32, 32, 256)	0	batch_normalization_20[0][0]
Conv20 (Conv2D)	(None, 32, 32, 256)	590080	leaky_re_lu_20[0][0]
batch_normalization_21 (BatchNo	(None, 32, 32, 256)	1024	Conv20[0][0]
leaky_re_lu_21 (LeakyReLU)	(None, 32, 32, 256)	0	batch_normalization_21[0][0]
Conv21 (Conv2D)	(None, 32, 32, 256)	590080	leaky_re_lu_21[0][0]
batch_normalization_22 (BatchNo	(None, 32, 32, 256)	1024	Conv21[0][0]
leaky_re_lu_22 (LeakyReLU)	(None, 32, 32, 256)	0	batch_normalization_22[0][0]
conv2d_transpose_2 (Conv2DTrans	(None, 64, 64, 128)	295040	leaky_re_lu_22[0][0]
batch_normalization_23 (BatchNo	(None, 64, 64, 128)	512	conv2d_transpose_2[0][0]
leaky_re_lu_23 (LeakyReLU)	(None, 64, 64, 128)	0	batch_normalization_23[0][0]

concatenate_2 (Concatenate)	(None, 64, 64, 256)	0	leaky_re_lu_23[0][0] Conv6[0][0]
Conv22 (Conv2D)	(None, 64, 64, 128)	295040	concatenate_2[0][0]
batch_normalization_24 (BatchNo	(None, 64, 64, 128)	512	Conv22[0][0]
leaky_re_lu_24 (LeakyReLU) [0][0]	(None, 64, 64, 128)	0	batch_normalization_24
Conv23 (Conv2D)	(None, 64, 64, 128)	147584	leaky_re_lu_24[0][0]
batch_normalization_25 (BatchNo	(None, 64, 64, 128)	512	Conv23[0][0]
leaky_re_lu_25 (LeakyReLU) [0][0]	(None, 64, 64, 128)	0	batch_normalization_25
Conv24 (Conv2D)	(None, 64, 64, 128)	147584	leaky_re_lu_25[0][0]
batch_normalization_26 (BatchNo	(None, 64, 64, 128)	512	Conv24[0][0]
leaky_re_lu_26 (LeakyReLU) [0][0]	(None, 64, 64, 128)	0	batch_normalization_26
conv2d_transpose_3 (Conv2DTrans	(None, 128, 128, 64)	73792	leaky_re_lu_26[0][0]
batch_normalization_27 (BatchNo [0]	(None, 128, 128, 64)	256	conv2d_transpose_3[0]
leaky_re_lu_27 (LeakyReLU) [0][0]	(None, 128, 128, 64)	0	batch_normalization_27
concatenate_3 (Concatenate)	(None, 128, 128, 128	0	leaky_re_lu_27[0][0] Conv3[0][0]
Conv25 (Conv2D)	(None, 128, 128, 64)	73792	concatenate_3[0][0]
batch_normalization_28 (BatchNo	(None, 128, 128, 64)	256	Conv25[0][0]
leaky_re_lu_28 (LeakyReLU) [0][0]	(None, 128, 128, 64)	0	batch_normalization_28

```
Conv26 (Conv2D)                 (None, 128, 128, 64) 36928       leaky_re_lu_28[0][0]
__________________________________________________________________________________________
batch_normalization_29 (BatchNo (None, 128, 128, 64) 256         Conv26[0][0]
__________________________________________________________________________________________
leaky_re_lu_29 (LeakyReLU)      (None, 128, 128, 64) 0           batch_normalization_29
[0][0]
__________________________________________________________________________________________
Conv27 (Conv2D)                 (None, 128, 128, 64) 36928       leaky_re_lu_29[0][0]
__________________________________________________________________________________________
batch_normalization_30 (BatchNo (None, 128, 128, 64) 256         Conv27[0][0]
__________________________________________________________________________________________
leaky_re_lu_30 (LeakyReLU)      (None, 128, 128, 64) 0           batch_normalization_30
[0][0]
__________________________________________________________________________________________
Outputs (Conv2D)                (None, 128, 128, 3)  195         leaky_re_lu_30[0][0]
==========================================================================================
==========
Total params: 50,258,499
Trainable params: 50,238,915
Non-trainable params: 19,584
__________________________________________________________________________________________
```

In [12]:

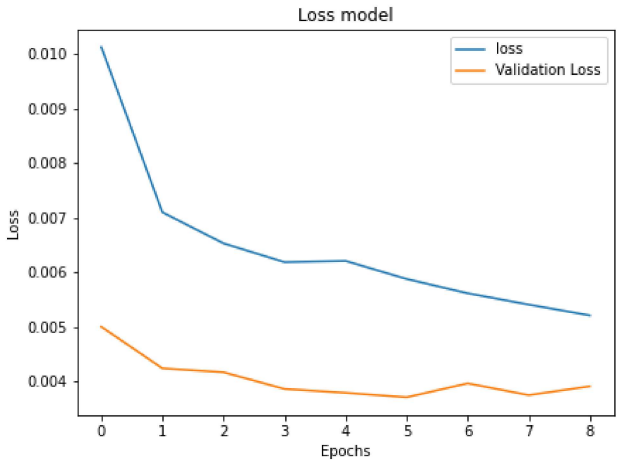
```
# Training the data with 10 EPOCHS
mymodel1.compile(optimizer=tf.keras.optimizers.SGD(lr=0.1, decay=1e-6, momentum=0.0, ne
hist1=mymodel1.fit(x_train,y_train,batch_size=8,epochs=10,validation_data=(x_valid,y_va
```

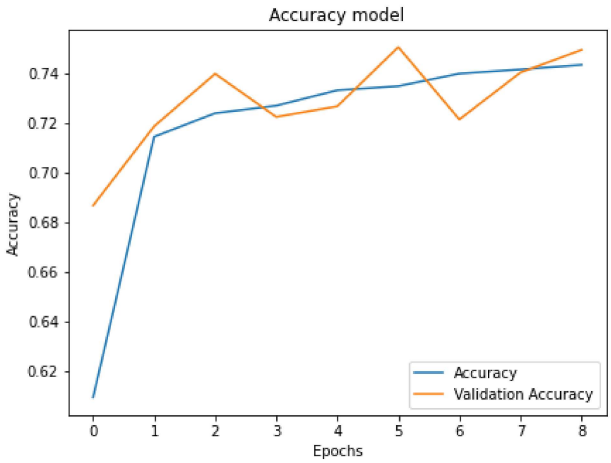
```
/opt/conda/lib/python3.7/site-packages/keras/optimizer_v2/optimizer_v2.py:356: UserWarni
ng: The `lr` argument is deprecated, use `learning_rate` instead.
  "The `lr` argument is deprecated, use `learning_rate` instead.")
2022-10-09 20:10:06.512767: W tensorflow/core/framework/cpu_allocator_impl.cc:80] Alloca
tion of 421199872 exceeds 10% of free system memory.
2022-10-09 20:10:08.242616: W tensorflow/core/framework/cpu_allocator_impl.cc:80] Alloca
tion of 1263599616 exceeds 10% of free system memory.
2022-10-09 20:10:09.793031: W tensorflow/core/framework/cpu_allocator_impl.cc:80] Alloca
tion of 421199872 exceeds 10% of free system memory.
2022-10-09 20:10:10.187993: W tensorflow/core/framework/cpu_allocator_impl.cc:80] Alloca
tion of 1263599616 exceeds 10% of free system memory.
2022-10-09 20:10:11.349787: I tensorflow/compiler/mlir/mlir_graph_optimization_pass.cc:1
85] None of the MLIR Optimization Passes are enabled (registered 2)
Epoch 1/10
2022-10-09 20:10:14.611399: I tensorflow/stream_executor/cuda/cuda_dnn.cc:369] Loaded cu
DNN version 8005
804/804 [==============================] - ETA: 0s - loss: 0.0101 - acc: 0.6093
2022-10-09 20:11:52.701824: W tensorflow/core/framework/cpu_allocator_impl.cc:80] Alloca
tion of 22216704 exceeds 10% of free system memory.
804/804 [==============================] - 104s 116ms/step - loss: 0.0101 - acc: 0.6093
- val_loss: 0.0050 - val_acc: 0.6866

Epoch 00001: val_loss improved from inf to 0.00500, saving model to seg_model.h5
Epoch 2/10
```

```
804/804 [==============================] - 92s 115ms/step - loss: 0.0071 - acc: 0.7144 -
val_loss: 0.0042 - val_acc: 0.7186

Epoch 00002: val_loss improved from 0.00500 to 0.00424, saving model to seg_model.h5
Epoch 3/10
804/804 [==============================] - 92s 114ms/step - loss: 0.0065 - acc: 0.7238 -
val_loss: 0.0042 - val_acc: 0.7397

Epoch 00003: val_loss improved from 0.00424 to 0.00417, saving model to seg_model.h5
Epoch 4/10
804/804 [==============================] - 92s 114ms/step - loss: 0.0062 - acc: 0.7269 -
val_loss: 0.0039 - val_acc: 0.7223

Epoch 00004: val_loss improved from 0.00417 to 0.00386, saving model to seg_model.h5
Epoch 5/10
804/804 [==============================] - 92s 114ms/step - loss: 0.0062 - acc: 0.7331 -
val_loss: 0.0038 - val_acc: 0.7266

Epoch 00005: val_loss improved from 0.00386 to 0.00379, saving model to seg_model.h5
Epoch 6/10
804/804 [==============================] - 92s 114ms/step - loss: 0.0059 - acc: 0.7348 -
val_loss: 0.0037 - val_acc: 0.7505

Epoch 00006: val_loss improved from 0.00379 to 0.00371, saving model to seg_model.h5
Epoch 7/10
804/804 [==============================] - 92s 114ms/step - loss: 0.0056 - acc: 0.7398 -
val_loss: 0.0040 - val_acc: 0.7213

Epoch 00007: val_loss did not improve from 0.00371
Epoch 8/10
804/804 [==============================] - 92s 114ms/step - loss: 0.0054 - acc: 0.7415 -
val_loss: 0.0037 - val_acc: 0.7403

Epoch 00008: val_loss did not improve from 0.00371
Epoch 9/10
804/804 [==============================] - 92s 114ms/step - loss: 0.0052 - acc: 0.7433 -
val_loss: 0.0039 - val_acc: 0.7494

Epoch 00009: val_loss did not improve from 0.00371
```

In [13]:

```
plt.figure(figsize=(15,5))
plt.subplot(1,2,1)
plt.plot(hist1.history['loss'])
plt.plot(hist1.history['val_loss'])
plt.title("Loss model")
plt.ylabel("Loss")
plt.xlabel("Epochs")
plt.legend(["loss","Validation Loss"])

plt.subplot(1,2,2)
plt.plot(hist1.history["acc"])
plt.plot(hist1.history['val_acc'])
plt.title("Accuracy model")
plt.ylabel("Accuracy")
plt.xlabel("Epochs")
plt.legend(["Accuracy","Validation Accuracy"])

plt.show()
```





Loss model

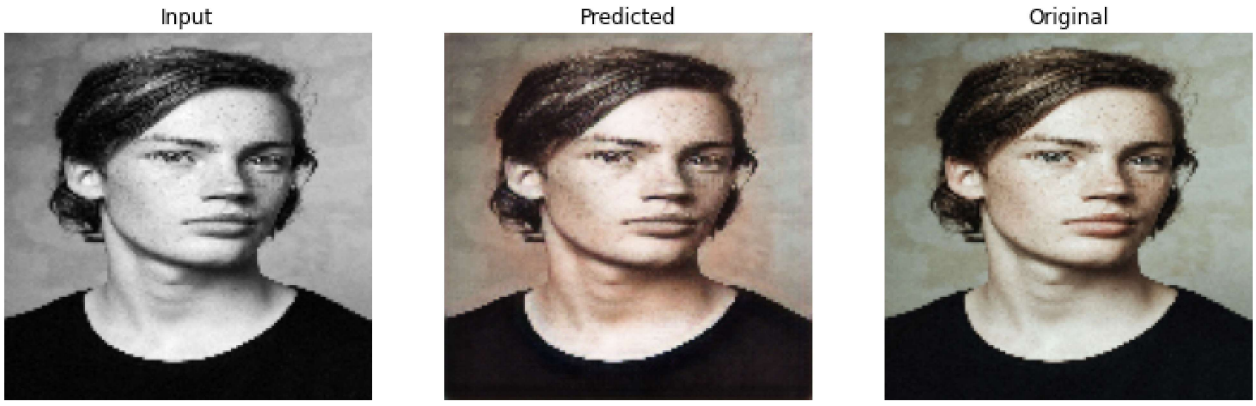
The loss model shows that the validation loss is much lower than the training loss which suggest that the model is underfitting since the model is not able to perform on the training set.

Accuracy model

The validation accuracy decreases at epoch number 2 and 5. The accuracy increases but it meets with validation accuracy at epoch 2.5, 4, 5 and 7.

In [14]:
```
# Prediction
pred1=mymodel1.predict(x_test)
```

In [15]:
```
# Plotting the results
plt.figure(figsize=(13,5))
plt.subplot(1,3,1)
plt.title('Input')
plt.axis('off')
plt.imshow(x_test[4], cmap='gray')

plt.subplot(1,3,2)
plt.title('Predicted')
plt.axis('off')
plt.imshow(pred1[4])

plt.subplot(1,3,3)
plt.title('Original')
plt.axis('off')
plt.imshow(y_test[4])
plt.show()
```



3. Tuning the hyperparameters

As I started with a low number of epochs to get quick feedback on the rest of hyperparameters. I will increase the number of epochs to 200 and batch size to 32.

In [16]:
```
# Creating the model 2
mymodel2=build_model()
```

```
Model: "model_1"
_________________________________________________________________________________________________
Layer (type)                 Output Shape              Param #     Connected to
==================================================================================================
input_2 (InputLayer)         [(None, 128, 128, 1) 0
_________________________________________________________________________________________________
Conv1 (Conv2D)               (None, 128, 128, 64) 640         input_2[0][0]
_________________________________________________________________________________________________
batch_normalization_31 (BatchNo (None, 128, 128, 64) 256         Conv1[0][0]
_________________________________________________________________________________________________
leaky_re_lu_31 (LeakyReLU)   (None, 128, 128, 64) 0           batch_normalization_31
[0][0]
_________________________________________________________________________________________________
Conv2 (Conv2D)               (None, 128, 128, 64) 36928       leaky_re_lu_31[0][0]
_________________________________________________________________________________________________
batch_normalization_32 (BatchNo (None, 128, 128, 64) 256         Conv2[0][0]
_________________________________________________________________________________________________
leaky_re_lu_32 (LeakyReLU)   (None, 128, 128, 64) 0           batch_normalization_32
[0][0]
_________________________________________________________________________________________________
Conv3 (Conv2D)               (None, 128, 128, 64) 36928       leaky_re_lu_32[0][0]
_________________________________________________________________________________________________
batch_normalization_33 (BatchNo (None, 128, 128, 64) 256         Conv3[0][0]
_________________________________________________________________________________________________
```

leaky_re_lu_33 (LeakyReLU)	(None, 128, 128, 64)	0	batch_normalization_33[0][0]
MaxPool1 (MaxPooling2D)	(None, 64, 64, 64)	0	leaky_re_lu_33[0][0]
Conv4 (Conv2D)	(None, 64, 64, 128)	73856	MaxPool1[0][0]
batch_normalization_34 (BatchNo	(None, 64, 64, 128)	512	Conv4[0][0]
leaky_re_lu_34 (LeakyReLU)	(None, 64, 64, 128)	0	batch_normalization_34[0][0]
Conv5 (Conv2D)	(None, 64, 64, 128)	147584	leaky_re_lu_34[0][0]
batch_normalization_35 (BatchNo	(None, 64, 64, 128)	512	Conv5[0][0]
leaky_re_lu_35 (LeakyReLU)	(None, 64, 64, 128)	0	batch_normalization_35[0][0]
Conv6 (Conv2D)	(None, 64, 64, 128)	147584	leaky_re_lu_35[0][0]
batch_normalization_36 (BatchNo	(None, 64, 64, 128)	512	Conv6[0][0]
leaky_re_lu_36 (LeakyReLU)	(None, 64, 64, 128)	0	batch_normalization_36[0][0]
MaxPool2 (MaxPooling2D)	(None, 32, 32, 128)	0	leaky_re_lu_36[0][0]
Conv7 (Conv2D)	(None, 32, 32, 256)	295168	MaxPool2[0][0]
batch_normalization_37 (BatchNo	(None, 32, 32, 256)	1024	Conv7[0][0]
leaky_re_lu_37 (LeakyReLU)	(None, 32, 32, 256)	0	batch_normalization_37[0][0]
Conv8 (Conv2D)	(None, 32, 32, 256)	590080	leaky_re_lu_37[0][0]
batch_normalization_38 (BatchNo	(None, 32, 32, 256)	1024	Conv8[0][0]
leaky_re_lu_38 (LeakyReLU)	(None, 32, 32, 256)	0	batch_normalization_38[0][0]

Conv9 (Conv2D)	(None, 32, 32, 256)	590080	leaky_re_lu_38[0][0]
batch_normalization_39 (BatchNo	(None, 32, 32, 256)	1024	Conv9[0][0]
leaky_re_lu_39 (LeakyReLU) [0][0]	(None, 32, 32, 256)	0	batch_normalization_39
MaxPool3 (MaxPooling2D)	(None, 16, 16, 256)	0	leaky_re_lu_39[0][0]
Conv10 (Conv2D)	(None, 16, 16, 512)	1180160	MaxPool3[0][0]
batch_normalization_40 (BatchNo	(None, 16, 16, 512)	2048	Conv10[0][0]
leaky_re_lu_40 (LeakyReLU) [0][0]	(None, 16, 16, 512)	0	batch_normalization_40
Conv11 (Conv2D)	(None, 16, 16, 512)	2359808	leaky_re_lu_40[0][0]
batch_normalization_41 (BatchNo	(None, 16, 16, 512)	2048	Conv11[0][0]
leaky_re_lu_41 (LeakyReLU) [0][0]	(None, 16, 16, 512)	0	batch_normalization_41
Conv12 (Conv2D)	(None, 16, 16, 512)	2359808	leaky_re_lu_41[0][0]
batch_normalization_42 (BatchNo	(None, 16, 16, 512)	2048	Conv12[0][0]
leaky_re_lu_42 (LeakyReLU) [0][0]	(None, 16, 16, 512)	0	batch_normalization_42
MaxPool4 (MaxPooling2D)	(None, 8, 8, 512)	0	leaky_re_lu_42[0][0]
Conv13 (Conv2D)	(None, 8, 8, 1024)	4719616	MaxPool4[0][0]
batch_normalization_43 (BatchNo	(None, 8, 8, 1024)	4096	Conv13[0][0]
leaky_re_lu_43 (LeakyReLU) [0][0]	(None, 8, 8, 1024)	0	batch_normalization_43
Conv14 (Conv2D)	(None, 8, 8, 1024)	9438208	leaky_re_lu_43[0][0]
batch_normalization_44 (BatchNo	(None, 8, 8, 1024)	4096	Conv14[0][0]

leaky_re_lu_44 (LeakyReLU)	(None, 8, 8, 1024)	0	batch_normalization_44[0][0]
Conv15 (Conv2D)	(None, 8, 8, 1024)	9438208	leaky_re_lu_44[0][0]
batch_normalization_45 (BatchNo	(None, 8, 8, 1024)	4096	Conv15[0][0]
leaky_re_lu_45 (LeakyReLU)	(None, 8, 8, 1024)	0	batch_normalization_45[0][0]
conv2d_transpose_4 (Conv2DTrans	(None, 16, 16, 512)	4719104	leaky_re_lu_45[0][0]
batch_normalization_46 (BatchNo	(None, 16, 16, 512)	2048	conv2d_transpose_4[0][0]
leaky_re_lu_46 (LeakyReLU)	(None, 16, 16, 512)	0	batch_normalization_46[0][0]
concatenate_4 (Concatenate)	(None, 16, 16, 1024)	0	leaky_re_lu_46[0][0] Conv12[0][0]
Conv16 (Conv2D)	(None, 16, 16, 512)	4719104	concatenate_4[0][0]
batch_normalization_47 (BatchNo	(None, 16, 16, 512)	2048	Conv16[0][0]
leaky_re_lu_47 (LeakyReLU)	(None, 16, 16, 512)	0	batch_normalization_47[0][0]
Conv17 (Conv2D)	(None, 16, 16, 512)	2359808	leaky_re_lu_47[0][0]
batch_normalization_48 (BatchNo	(None, 16, 16, 512)	2048	Conv17[0][0]
leaky_re_lu_48 (LeakyReLU)	(None, 16, 16, 512)	0	batch_normalization_48[0][0]
Conv18 (Conv2D)	(None, 16, 16, 512)	2359808	leaky_re_lu_48[0][0]
batch_normalization_49 (BatchNo	(None, 16, 16, 512)	2048	Conv18[0][0]
leaky_re_lu_49 (LeakyReLU)	(None, 16, 16, 512)	0	batch_normalization_49[0][0]

conv2d_transpose_5 (Conv2DTrans	(None, 32, 32, 256)	1179904	leaky_re_lu_49[0][0]
batch_normalization_50 (BatchNo	(None, 32, 32, 256)	1024	conv2d_transpose_5[0][0]
leaky_re_lu_50 (LeakyReLU)	(None, 32, 32, 256)	0	batch_normalization_50[0][0]
concatenate_5 (Concatenate)	(None, 32, 32, 512)	0	leaky_re_lu_50[0][0] Conv9[0][0]
Conv19 (Conv2D)	(None, 32, 32, 256)	1179904	concatenate_5[0][0]
batch_normalization_51 (BatchNo	(None, 32, 32, 256)	1024	Conv19[0][0]
leaky_re_lu_51 (LeakyReLU)	(None, 32, 32, 256)	0	batch_normalization_51[0][0]
Conv20 (Conv2D)	(None, 32, 32, 256)	590080	leaky_re_lu_51[0][0]
batch_normalization_52 (BatchNo	(None, 32, 32, 256)	1024	Conv20[0][0]
leaky_re_lu_52 (LeakyReLU)	(None, 32, 32, 256)	0	batch_normalization_52[0][0]
Conv21 (Conv2D)	(None, 32, 32, 256)	590080	leaky_re_lu_52[0][0]
batch_normalization_53 (BatchNo	(None, 32, 32, 256)	1024	Conv21[0][0]
leaky_re_lu_53 (LeakyReLU)	(None, 32, 32, 256)	0	batch_normalization_53[0][0]
conv2d_transpose_6 (Conv2DTrans	(None, 64, 64, 128)	295040	leaky_re_lu_53[0][0]
batch_normalization_54 (BatchNo	(None, 64, 64, 128)	512	conv2d_transpose_6[0][0]
leaky_re_lu_54 (LeakyReLU)	(None, 64, 64, 128)	0	batch_normalization_54[0][0]
concatenate_6 (Concatenate)	(None, 64, 64, 256)	0	leaky_re_lu_54[0][0] Conv6[0][0]

Conv22 (Conv2D)	(None, 64, 64, 128)	295040	concatenate_6[0][0]
batch_normalization_55 (BatchNo	(None, 64, 64, 128)	512	Conv22[0][0]
leaky_re_lu_55 (LeakyReLU) [0][0]	(None, 64, 64, 128)	0	batch_normalization_55
Conv23 (Conv2D)	(None, 64, 64, 128)	147584	leaky_re_lu_55[0][0]
batch_normalization_56 (BatchNo	(None, 64, 64, 128)	512	Conv23[0][0]
leaky_re_lu_56 (LeakyReLU) [0][0]	(None, 64, 64, 128)	0	batch_normalization_56
Conv24 (Conv2D)	(None, 64, 64, 128)	147584	leaky_re_lu_56[0][0]
batch_normalization_57 (BatchNo	(None, 64, 64, 128)	512	Conv24[0][0]
leaky_re_lu_57 (LeakyReLU) [0][0]	(None, 64, 64, 128)	0	batch_normalization_57
conv2d_transpose_7 (Conv2DTrans	(None, 128, 128, 64)	73792	leaky_re_lu_57[0][0]
batch_normalization_58 (BatchNo [0]	(None, 128, 128, 64)	256	conv2d_transpose_7[0]
leaky_re_lu_58 (LeakyReLU) [0][0]	(None, 128, 128, 64)	0	batch_normalization_58
concatenate_7 (Concatenate)	(None, 128, 128, 128	0	leaky_re_lu_58[0][0] Conv3[0][0]
Conv25 (Conv2D)	(None, 128, 128, 64)	73792	concatenate_7[0][0]
batch_normalization_59 (BatchNo	(None, 128, 128, 64)	256	Conv25[0][0]
leaky_re_lu_59 (LeakyReLU) [0][0]	(None, 128, 128, 64)	0	batch_normalization_59
Conv26 (Conv2D)	(None, 128, 128, 64)	36928	leaky_re_lu_59[0][0]
batch_normalization_60 (BatchNo	(None, 128, 128, 64)	256	Conv26[0][0]

```
leaky_re_lu_60 (LeakyReLU)      (None, 128, 128, 64) 0           batch_normalization_60
[0][0]
__________________________________________________________________________________________
Conv27 (Conv2D)                 (None, 128, 128, 64) 36928       leaky_re_lu_60[0][0]
__________________________________________________________________________________________
batch_normalization_61 (BatchNo (None, 128, 128, 64) 256         Conv27[0][0]
__________________________________________________________________________________________
leaky_re_lu_61 (LeakyReLU)      (None, 128, 128, 64) 0           batch_normalization_61
[0][0]
__________________________________________________________________________________________
Outputs (Conv2D)                (None, 128, 128, 3)  195         leaky_re_lu_61[0][0]
==========================================================================================
==========
Total params: 50,258,499
Trainable params: 50,238,915
Non-trainable params: 19,584
__________________________________________________________________________________________
```

In [17]:

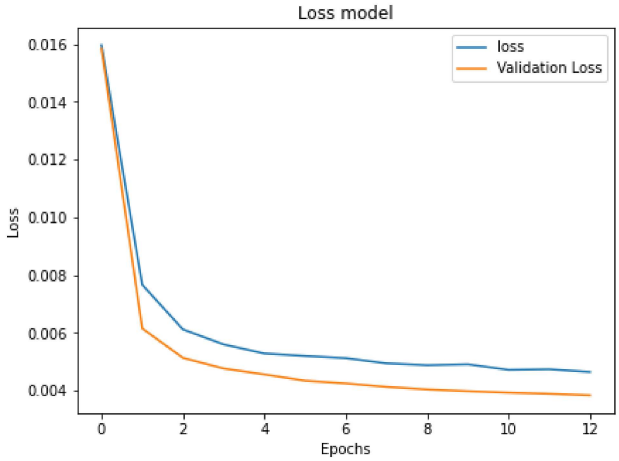
```
mymodel2.compile(optimizer=tf.keras.optimizers.SGD(lr=0.1, decay=1e-6, momentum=0.0, ne
hist2=mymodel2.fit(x_train,y_train,batch_size=32,epochs=200,validation_data=(x_valid,y_
```

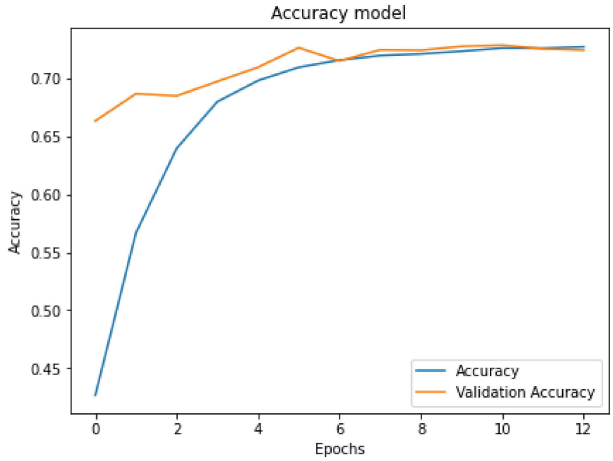
```
Epoch 1/200
201/201 [==============================] - 74s 349ms/step - loss: 0.0160 - acc: 0.4267 -
val_loss: 0.0158 - val_acc: 0.6633

Epoch 00001: val_loss improved from inf to 0.01583, saving model to seg_model.h5
Epoch 2/200
201/201 [==============================] - 67s 333ms/step - loss: 0.0077 - acc: 0.5667 -
val_loss: 0.0062 - val_acc: 0.6868

Epoch 00002: val_loss improved from 0.01583 to 0.00616, saving model to seg_model.h5
Epoch 3/200
201/201 [==============================] - 67s 333ms/step - loss: 0.0061 - acc: 0.6396 -
val_loss: 0.0051 - val_acc: 0.6849

Epoch 00003: val_loss improved from 0.00616 to 0.00514, saving model to seg_model.h5
Epoch 4/200
201/201 [==============================] - 67s 333ms/step - loss: 0.0056 - acc: 0.6799 -
val_loss: 0.0048 - val_acc: 0.6974

Epoch 00004: val_loss improved from 0.00514 to 0.00477, saving model to seg_model.h5
Epoch 5/200
201/201 [==============================] - 67s 332ms/step - loss: 0.0053 - acc: 0.6981 -
val_loss: 0.0046 - val_acc: 0.7096

Epoch 00005: val_loss improved from 0.00477 to 0.00456, saving model to seg_model.h5
Epoch 6/200
201/201 [==============================] - 67s 333ms/step - loss: 0.0052 - acc: 0.7096 -
val_loss: 0.0043 - val_acc: 0.7264

Epoch 00006: val_loss improved from 0.00456 to 0.00435, saving model to seg_model.h5
```

```
Epoch 7/200
201/201 [==============================] - 67s 333ms/step - loss: 0.0051 - acc: 0.7157 -
val_loss: 0.0043 - val_acc: 0.7150

Epoch 00007: val_loss improved from 0.00435 to 0.00425, saving model to seg_model.h5
Epoch 8/200
201/201 [==============================] - 67s 333ms/step - loss: 0.0049 - acc: 0.7197 -
val_loss: 0.0041 - val_acc: 0.7246

Epoch 00008: val_loss improved from 0.00425 to 0.00413, saving model to seg_model.h5
Epoch 9/200
201/201 [==============================] - 67s 333ms/step - loss: 0.0049 - acc: 0.7211 -
val_loss: 0.0040 - val_acc: 0.7243

Epoch 00009: val_loss improved from 0.00413 to 0.00404, saving model to seg_model.h5
Epoch 10/200
201/201 [==============================] - 67s 333ms/step - loss: 0.0049 - acc: 0.7234 -
val_loss: 0.0040 - val_acc: 0.7277

Epoch 00010: val_loss improved from 0.00404 to 0.00398, saving model to seg_model.h5
Epoch 11/200
201/201 [==============================] - 67s 333ms/step - loss: 0.0047 - acc: 0.7262 -
val_loss: 0.0039 - val_acc: 0.7287

Epoch 00011: val_loss improved from 0.00398 to 0.00393, saving model to seg_model.h5
Epoch 12/200
201/201 [==============================] - 67s 332ms/step - loss: 0.0047 - acc: 0.7260 -
val_loss: 0.0039 - val_acc: 0.7256

Epoch 00012: val_loss improved from 0.00393 to 0.00389, saving model to seg_model.h5
Epoch 13/200
201/201 [==============================] - 67s 332ms/step - loss: 0.0046 - acc: 0.7272 -
val_loss: 0.0038 - val_acc: 0.7244

Epoch 00013: val_loss improved from 0.00389 to 0.00384, saving model to seg_model.h5
```

In [18]:

```
plt.figure(figsize=(15,5))
plt.subplot(1,2,1)
plt.plot(hist2.history['loss'])
plt.plot(hist2.history['val_loss'])
plt.title("Loss model")
plt.ylabel("Loss")
plt.xlabel("Epochs")
plt.legend(["loss","Validation Loss"])

plt.subplot(1,2,2)
plt.plot(hist2.history["acc"])
plt.plot(hist2.history['val_acc'])
plt.title("Accuracy model")
plt.ylabel("Accuracy")
plt.xlabel("Epochs")
plt.legend(["Accuracy","Validation Accuracy"])

plt.show()
```





Loss model

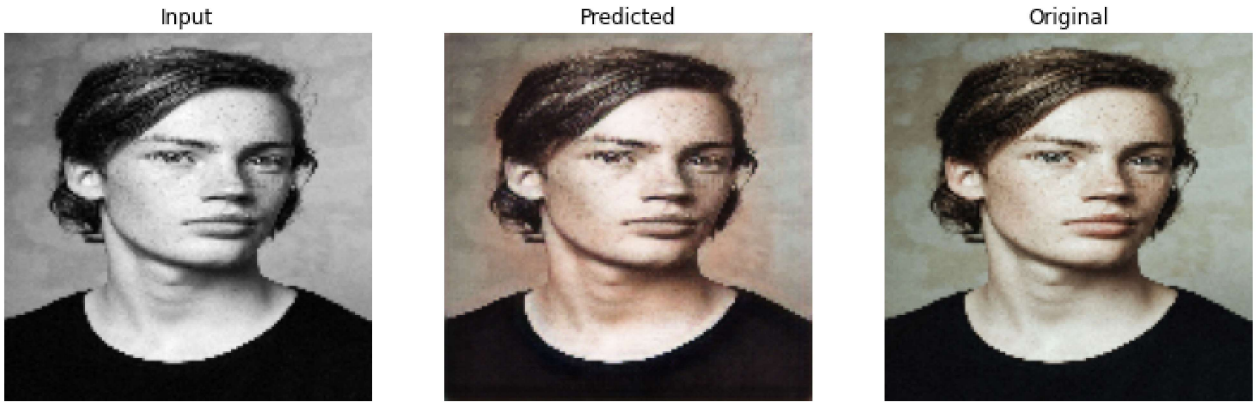
At certain epochs the validation loss is lower than the validation loss which suggest that the model is underfitting since the model is not able to perform on the training set.

Accuracy model

The accuracy and validation accuracy stabilizes at epoch number 6.

In [19]:
```
# Prediction
pred2=mymodel1.predict(x_test)
```

In [20]:
```
# Plotting the results
plt.figure(figsize=(13,5))
plt.subplot(1,3,1)
plt.title('Input')
plt.axis('off')
plt.imshow(x_test[4], cmap='gray')

plt.subplot(1,3,2)
plt.title('Predicted')
plt.axis('off')
plt.imshow(pred2[4])

plt.subplot(1,3,3)
plt.title('Original')
plt.axis('off')
plt.imshow(y_test[4])
plt.show()
```



4. Discussion

4.1. Conclusion

I used the U-Net architecture which is one of the CNN standard architectures for image classification tasks and it is considered as a best network for fast and precise segmentation of images. For the first try, I used 10 epochs with 8 batch size. The model performed poorly to colorize a grayscale image. Then, I tuned the hyperparameters using 200 epochs and 32 batch size. However, the results are nearly identical.

4.2. Further improvement

For further improvement, I would like to use GAN and try other colorization techniques. With GAN, the model can predict whether an image is "real" in terms of colorization.