```
In [ ]:
import numpy as np
import tensorflow as tf
import cv2
from keras import layers, regularizers
from keras.preprocessing.image import img to array
import os
from tqdm import tqdm
import re
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
from skimage.metrics import peak signal noise ratio as psnr
from skimage.metrics import structural similarity as ssim
In [2]:
def sorted alphanumeric(data):
    convert = lambda text: int(text) if text.isdigit() else text.lower()
    alphanum key = lambda key: [convert(c) for c in re.split('([0-9]+)', key)]
    return sorted(data, key = alphanum key)
# defining the size of the image
SIZE = 160 # Image resize dimension
color img train = []
color_img_test = []
path = '/kaggle/input/landscape-image-colorization/landscape Images/color'
files = os.listdir(path)
files = sorted alphanumeric(files)
for i in tqdm(files):
    img = cv2.imread(os.path.join(path, i), 1)
    img = cv2.cvtColor(img, cv2.COLOR BGR2RGB)
    img = cv2.resize(img, (SIZE, SIZE))
    img = img.astype('float32') / 255.0
    if i < '6000.jpg':</pre>
        color_img_train.append(img_to_array(img)) # Add to training set
    else:
        color img test.append(img to array(img))
                                                   # Add to test set
# Convert lists to numpy arrays
color img train = np.array(color img train)
color img test = np.array(color img test)
print(f"Training set size: {color img train.shape}")
print(f"Test set size: {color img test.shape}")
      | 7129/7129 [00:48<00:00, 145.98it/s]
Training set size: (5559, 160, 160, 3)
Test set size: (1570, 160, 160, 3)
In [3]:
gray img train = []
gray_img_test = []
path = '/kaggle/input/landscape-image-colorization/landscape Images/gray'
files = os.listdir(path)
files = sorted alphanumeric(files)
for i in tqdm(files):
    img = cv2.imread(os.path.join(path, i), 1)
    img = cv2.resize(img, (SIZE, SIZE))
    img = img.astype('float32') / 255.0
    if i < '6000.jpg':</pre>
        gray img train.append(img to array(img)) # Add to training set
    else:
```

gray img test.append(img to array(img)) # Add to test set

```
# Convert lists to numpy arrays
gray img train = np.array(gray img train)
gray_img_test = np.array(gray_img_test)
print(f"Training set size (grayscale): {gray img train.shape}")
print(f"Test set size (grayscale): {gray img test.shape}")
              | 7129/7129 [00:49<00:00, 144.82it/s]
Training set size (grayscale): (5559, 160, 160, 3)
Test set size (grayscale): (1570, 160, 160, 3)
In [4]:
gray img train = np.array(gray img train)
gray img test = np.array(gray img test)
In [5]:
print(f"Color Training set size: {color img train.shape}")
print(f"Color Test set size: {color img test.shape}")
print(f"Gray Training set size: {gray_img_train.shape}")
print(f"Gray Test set size: {gray img test.shape}")
Color Training set size: (5559, 160, 160, 3)
Color Test set size: (1570, 160, 160, 3)
Gray Training set size: (5559, 160, 160, 3)
Gray Test set size: (1570, 160, 160, 3)
In [6]:
split index = int(len(gray img train) * 0.95)
train gray image = gray img train[:split index]
val_gray_image = gray_img_train[split_index:]
train color image = color img train[:split index]
val_color_image = color_img_train[split_index:]
# Reshape arrays to the required dimensions
train_g = np.reshape(train_gray_image, (len(train_gray_image), SIZE, SIZE, 3))
train c = np.reshape(train color image, (len(train color image), SIZE, SIZE, 3))
val g = np.reshape(val gray image, (len(val gray image), SIZE, SIZE, 3))
val c = np.reshape(val color image, (len(val color image), SIZE, SIZE, 3))
test gray image = np.reshape(gray img test, (len(gray img test), SIZE, SIZE, 3))
test color image = np.reshape(color img test, (len(color img test), SIZE, SIZE, 3))
# Check shapes to confirm they are aligned
print('Train color image shape:', train_c.shape)
print('Validation color image shape:', val_c.shape)
print('Test color image shape:', test color image.shape)
Train color image shape: (5281, 160, 160, 3)
Validation color image shape: (278, 160, 160, 3)
Test color image shape: (1570, 160, 160, 3)
In [7]:
def down(filters, kernel size, batch norm):
    def block(x):
        x = layers.Conv2D(filters, kernel size, strides=2, padding="same",
                          kernel regularizer=regularizers.12(0.00000000001))(x)
        if batch norm:
            x = layers.BatchNormalization()(x)
        x = layers.LeakyReLU()(x)
        return x
    return block
def up(filters, kernel size, batch norm):
    def block(x):
        x = layers.Conv2DTranspose(filters, kernel size, strides=2, padding="same",
                                   kernel regularizer=regularizers.12(0.00000000001))(x)
```

```
if batch_norm:
    x = layers.BatchNormalization()(x)
    x = layers.ReLU()(x)
    return x
return block
```

In [8]:

```
def recolourization model():
    inputs = layers.Input(shape=(160, 160, 3))
    # Downsampling
   d1 = down(128, (3, 3), False)(inputs)
    d2 = down(128, (3, 3), False)(d1)
    d3 = down(256, (3, 3), True)(d2)
    d4 = down(512, (3, 3), True)(d3)
    d5 = down(512, (3, 3), True)(d4)
    # Upsampling
    u1 = up(512, (3, 3), False)(d5)
    u1 = layers.concatenate([u1, d4])
    u2 = up(256, (3, 3), False)(u1)
    u2 = layers.concatenate([u2, d3])
   u3 = up(128, (3, 3), False)(u2)
    u3 = layers.concatenate([u3, d2])
    u4 = up(128, (3, 3), False)(u3)
   u4 = layers.concatenate([u4, d1])
   u5 = up(3, (3, 3), False)(u4)
    u5 = layers.concatenate([u5, inputs])
    # Output layer with sigmoid activation for [0, 1] range
   output = layers.Conv2D(3, (3, 3), strides=1, padding='same', activation='sigmoid',
                           kernel regularizer=regularizers.12(0.01))(u5)
    return tf.keras.Model(inputs=inputs, outputs=output)
```

In [9]:

```
recolourization_model = recolourization_model()
recolourization_model.summary()
```

Model: "functional_1"

Layer (type)	Output Shape	Param #	Connected to
input_layer (InputLayer)	(None, 160, 160, 3)	0	-
conv2d (Conv2D)	(None, 80, 80, 128)	3,584	input_layer[0][0]
leaky_re_lu (LeakyReLU)	(None, 80, 80, 128)	0	conv2d[0][0]
conv2d_1 (Conv2D)	(None, 40, 40, 128)	147,584	leaky_re_lu[0][0]
leaky_re_lu_1 (LeakyReLU)	(None, 40, 40, 128)	0	conv2d_1[0][0]
conv2d_2 (Conv2D)	(None, 20, 20, 256)	295,168	leaky_re_lu_1[0]
batch_normalization (BatchNormalizatio	(None, 20, 20, 256)	1,024	conv2d_2[0][0]
l leaky re lu ?	(None 20 20	ค	hatch normalizat

LeakyReLU)	256)		
conv2d_3 (Conv2D)	(None, 10, 10, 512)	1,180,160	leaky_re_lu_2[0]
batch_normalizatio (BatchNormalizatio	(None, 10, 10, 512)	2,048	conv2d_3[0][0]
leaky_re_lu_3 (LeakyReLU)	(None, 10, 10, 512)	0	batch_normalizat…
conv2d_4 (Conv2D)	(None, 5, 5, 512)	2,359,808	leaky_re_lu_3[0]
batch_normalizatio (BatchNormalizatio	(None, 5, 5, 512)	2,048	conv2d_4[0][0]
leaky_re_lu_4 (LeakyReLU)	(None, 5, 5, 512)	0	batch_normalizat…
conv2d_transpose (Conv2DTranspose)	(None, 10, 10, 512)	2,359,808	leaky_re_lu_4[0]
re_lu (ReLU)	(None, 10, 10, 512)	0	conv2d_transpose
concatenate (Concatenate)	(None, 10, 10, 1024)	0	re_lu[0][0], leaky_re_lu_3[0]
conv2d_transpose_1 (Conv2DTranspose)	(None, 20, 20, 256)	2,359,552	concatenate[0][0]
re_lu_1 (ReLU)	(None, 20, 20, 256)	0	conv2d_transpose
concatenate_1 (Concatenate)	(None, 20, 20, 512)	0	 re_lu_1[0][0], leaky_re_lu_2[0]
conv2d_transpose_2 (Conv2DTranspose)	(None, 40, 40, 128)	589,952	concatenate_1[0]
re_lu_2 (ReLU)	(None, 40, 40, 128)	0	 conv2d_transpose
concatenate_2 (Concatenate)	(None, 40, 40, 256)	0	 re_lu_2[0][0], leaky_re_lu_1[0]
conv2d_transpose_3 (Conv2DTranspose)	(None, 80, 80, 128)	295,040	 concatenate_2[0]
re_lu_3 (ReLU)	(None, 80, 80, 128)	0	conv2d_transpose
concatenate_3 (Concatenate)	(None, 80, 80, 256)	0	 re_lu_3[0][0], leaky_re_lu[0][0]
conv2d_transpose_4 (Conv2DTranspose)	(None, 160, 160, 3)	6,915	concatenate_3[0]
re_lu_4 (ReLU)	(None, 160, 160, 3)	0	conv2d_transpose
concatenate_4 (Concatenate)	(None, 160, 160, 6)	0	re_lu_4[0][0], input_layer[0][0]

```
conv2d 5 (Conv2D)
                        (None, 160, 160,
                                                     165
                                                            concatenate 4[0]...
```

Total params: 9,602,856 (36.63 MB)

Trainable params: 9,600,296 (36.62 MB)

Non-trainable params: 2,560 (10.00 KB)

In [10]:

recolourization model.compile(optimizer = tf.keras.optimizers.Adam(learning rate = 0.001), loss='mse', metrics=['mae'])

In [11]:

history = recolourization_model.fit(train_g, train_c, epochs = 105,batch size = 50,valid ation data=(val g, val c), verbose = 1)

Epoch 1/105

WARNING: All log messages before absl::InitializeLog() is called are written to STDERR I0000 00:00:1731071934.140625 94 service.cc:145] XLA service 0x7817c80049c0 initiali zed for platform CUDA (this does not guarantee that XLA will be used). Devices: I0000 00:00:1731071934.140816 94 service.cc:153] StreamExecutor device (0): Tesla P100-PCIE-16GB, Compute Capability 6.0

1/106 -- 25:01 14s/step - loss: 0.1312 - mae: 0.2502

I0000 00:00:1731071944.172903 94 device compiler.h:188] Compiled cluster using XLA! This line is logged at most once for the lifetime of the process.

106/106 - 36s 203ms/step - loss: 0.0964 - mae: 0.1940 - val loss: 0.08 48 - val mae: 0.2185

Epoch 2/105

106/106 - 12s 110ms/step - loss: 0.0543 - mae: 0.1483 - val loss: 0.04

69 - val mae: 0.1598

Epoch 3/105

106/106 - 12s 110ms/step - loss: 0.0200 - mae: 0.0818 - val loss: 0.01

81 - val mae: 0.0946 Epoch 4/105

106/106

- 12s 110ms/step - loss: 0.0119 - mae: 0.0710 - val loss: 0.01

69 - val mae: 0.0955 Epoch 5/105

106/106

- 12s 110ms/step - loss: 0.0095 - mae: 0.0656 - val loss: 0.01 25 - val mae: 0.0807

Epoch 6/105

106/106

- 12s 110ms/step - loss: 0.0088 - mae: 0.0641 - val loss: 0.01 70 - val mae: 0.0988

Epoch 7/105

106/106

- 12s 110ms/step - loss: 0.0080 - mae: 0.0613 - val loss: 0.01 69 - val mae: 0.1001

Epoch 8/105

106/106

89 - val mae: 0.0675

- 12s 110ms/step - loss: 0.0077 - mae: 0.0604 - val loss: 0.00

Epoch 9/105

106/106 • - 12s 110ms/step - loss: 0.0073 - mae: 0.0583 - val loss: 0.00

84 - val mae: 0.0629 Epoch 10/105

106/106 - 12s 110ms/step - loss: 0.0069 - mae: 0.0569 - val loss: 0.00

91 - val mae: 0.0639 Epoch 11/105

106/106 - 12s 110ms/step - loss: 0.0068 - mae: 0.0568 - val loss: 0.00

79 - val mae: 0.0617

Epoch 12/105

106/106 - 12s 109ms/step - loss: 0.0064 - mae: 0.0549 - val loss: 0.01

24 - val mae: 0.0831 Epoch 13/105

106/106 - 12s 110ms/step - loss: 0.0068 - mae: 0.0566 - val_loss: 0.00

87 - val mae: 0.0646

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Fbocu T4/Tn2
106/106 -
                            - 12s 110ms/step - loss: 0.0062 - mae: 0.0540 - val loss: 0.00
87 - val mae: 0.0656
Epoch 15/105
106/106
                            - 12s 110ms/step - loss: 0.0062 - mae: 0.0542 - val loss: 0.00
81 - val mae: 0.0631
Epoch 16/105
106/106
                            - 12s 110ms/step - loss: 0.0061 - mae: 0.0537 - val loss: 0.00
82 - val mae: 0.0652
Epoch 17/105
106/106
                            - 12s 110ms/step - loss: 0.0059 - mae: 0.0520 - val loss: 0.00
80 - val mae: 0.0637
Epoch 18/105
106/106
                            - 12s 110ms/step - loss: 0.0058 - mae: 0.0524 - val loss: 0.00
68 - val_mae: 0.0544
Epoch 19/105
106/106
                            - 12s 110ms/step - loss: 0.0059 - mae: 0.0536 - val loss: 0.00
90 - val mae: 0.0633
Epoch 20/105
106/106 •
                            - 12s 110ms/step - loss: 0.0058 - mae: 0.0524 - val loss: 0.00
67 - val mae: 0.0548
Epoch 21/105
106/106 -
                            - 12s 110ms/step - loss: 0.0052 - mae: 0.0489 - val loss: 0.00
68 - val mae: 0.0559
Epoch 22/105
106/106
                            - 12s 110ms/step - loss: 0.0052 - mae: 0.0496 - val loss: 0.00
67 - val mae: 0.0543
Epoch 23/105
                            - 12s 110ms/step - loss: 0.0048 - mae: 0.0474 - val loss: 0.00
106/106
68 - val mae: 0.0547
Epoch 24/105
106/106
                            - 12s 110ms/step - loss: 0.0047 - mae: 0.0475 - val loss: 0.00
93 - val_mae: 0.0689
Epoch 25/105
106/106
                            - 12s 109ms/step - loss: 0.0046 - mae: 0.0472 - val loss: 0.00
68 - val mae: 0.0540
Epoch 26/105
106/106
                            - 12s 110ms/step - loss: 0.0045 - mae: 0.0462 - val loss: 0.00
67 - val mae: 0.0544
Epoch 27/105
106/106
                            - 12s 110ms/step - loss: 0.0042 - mae: 0.0448 - val loss: 0.00
92 - val mae: 0.0685
Epoch 28/105
106/106
                            - 12s 110ms/step - loss: 0.0042 - mae: 0.0449 - val loss: 0.00
66 - val mae: 0.0532
Epoch 297105
106/106
                            - 12s 109ms/step - loss: 0.0038 - mae: 0.0426 - val loss: 0.00
81 - val mae: 0.0637
Epoch 30/105
106/106
                            • 12s 110ms/step - loss: 0.0042 - mae: 0.0452 - val loss: 0.00
80 - val mae: 0.0610
Epoch 31/105
106/106
                            - 12s 110ms/step - loss: 0.0036 - mae: 0.0414 - val loss: 0.00
80 - val mae: 0.0608
Epoch 32/105
106/106
                            - 12s 110ms/step - loss: 0.0035 - mae: 0.0414 - val loss: 0.00
73 - val mae: 0.0590
Epoch 33/105
106/106 •
                            - 12s 110ms/step - loss: 0.0032 - mae: 0.0394 - val loss: 0.00
86 - val mae: 0.0658
Epoch 34/105
106/106
                            - 12s 110ms/step - loss: 0.0033 - mae: 0.0404 - val loss: 0.00
66 - val mae: 0.0529
Epoch 35/105
106/106
                            - 12s 110ms/step - loss: 0.0031 - mae: 0.0383 - val loss: 0.00
70 - val mae: 0.0563
Epoch 36/105
106/106
                            • 12s 110ms/step - loss: 0.0028 - mae: 0.0365 - val loss: 0.00
64 - val mae: 0.0521
Epoch 37/105
106/106
                            - 12s 110ms/step - loss: 0.0027 - mae: 0.0361 - val_loss: 0.00
70 - val mae: 0.0549
```

P---- 20 /10E

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Fbocu 20/102
106/106 -
                            - 12s 110ms/step - loss: 0.0027 - mae: 0.0357 - val loss: 0.00
67 - val mae: 0.0539
Epoch 39/105
106/106
                            - 12s 110ms/step - loss: 0.0027 - mae: 0.0361 - val loss: 0.00
76 - val mae: 0.0611
Epoch 40/105
106/106 •
                            - 12s 110ms/step - loss: 0.0026 - mae: 0.0351 - val loss: 0.00
82 - val mae: 0.0641
Epoch 41/105
106/106
                            - 12s 110ms/step - loss: 0.0025 - mae: 0.0343 - val loss: 0.00
66 - val mae: 0.0532
Epoch 42/105
106/106
                            - 12s 110ms/step - loss: 0.0025 - mae: 0.0348 - val loss: 0.00
66 - val_mae: 0.0528
Epoch 43/105
106/106
                            - 12s 110ms/step - loss: 0.0023 - mae: 0.0332 - val loss: 0.00
66 - val mae: 0.0539
Epoch 44/105
106/106 •
                            - 12s 110ms/step - loss: 0.0023 - mae: 0.0333 - val loss: 0.00
69 - val mae: 0.0540
Epoch 45/105
106/106 -
                            - 12s 110ms/step - loss: 0.0022 - mae: 0.0324 - val loss: 0.00
75 - val mae: 0.0599
Epoch 46/105
106/106
                            - 12s 110ms/step - loss: 0.0021 - mae: 0.0314 - val loss: 0.00
64 - val mae: 0.0519
Epoch 47/105
106/106
                            - 12s 110ms/step - loss: 0.0020 - mae: 0.0306 - val loss: 0.00
64 - val mae: 0.0517
Epoch 48/105
106/106
                            - 12s 110ms/step - loss: 0.0020 - mae: 0.0305 - val loss: 0.00
68 - val mae: 0.0529
Epoch 49/105
106/106
                            - 12s 110ms/step - loss: 0.0020 - mae: 0.0309 - val loss: 0.00
65 - val mae: 0.0521
Epoch 50/105
106/106
                            - 12s 110ms/step - loss: 0.0020 - mae: 0.0306 - val loss: 0.00
64 - val mae: 0.0516
Epoch 51/105
106/106
                            - 12s 110ms/step - loss: 0.0018 - mae: 0.0295 - val loss: 0.00
65 - val mae: 0.0526
Epoch 52/105
106/106
                            - 12s 110ms/step - loss: 0.0019 - mae: 0.0300 - val loss: 0.00
62 - val mae: 0.0511
Epoch 53/105
106/106 •
                            - 12s 110ms/step - loss: 0.0018 - mae: 0.0295 - val loss: 0.00
67 - val_mae: 0.0557
Epoch 54/105
106/106
                            • 12s 110ms/step - loss: 0.0018 - mae: 0.0297 - val loss: 0.00
66 - val mae: 0.0528
Epoch 55/105
106/106
                            - 12s 109ms/step - loss: 0.0018 - mae: 0.0290 - val loss: 0.00
64 - val mae: 0.0521
Epoch 56/105
106/106
                            - 12s 110ms/step - loss: 0.0018 - mae: 0.0294 - val loss: 0.00
65 - val mae: 0.0520
Epoch 57/105
106/106 •
                            - 12s 110ms/step - loss: 0.0016 - mae: 0.0273 - val loss: 0.00
64 - val mae: 0.0513
Epoch 58/105
106/106
                            - 12s 110ms/step - loss: 0.0016 - mae: 0.0273 - val loss: 0.00
62 - val mae: 0.0512
Epoch 59/105
106/106
                            - 12s 110ms/step - loss: 0.0016 - mae: 0.0276 - val loss: 0.00
67 - val mae: 0.0539
Epoch 60/105
106/106
                            • 12s 110ms/step - loss: 0.0015 - mae: 0.0265 - val loss: 0.00
63 - val mae: 0.0508
Epoch 61/105
106/106
                            - 12s 110ms/step - loss: 0.0016 - mae: 0.0273 - val_loss: 0.00
67 - val mae: 0.0537
```

Pasab (0/10E

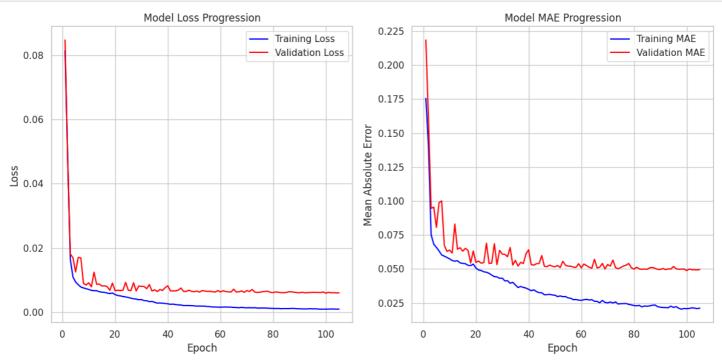
```
Fbocu 05/102
106/106 -
                            - 12s 110ms/step - loss: 0.0016 - mae: 0.0277 - val loss: 0.00
64 - val mae: 0.0524
Epoch 63/105
106/106
                            - 12s 110ms/step - loss: 0.0016 - mae: 0.0278 - val loss: 0.00
63 - val mae: 0.0513
Epoch 64/105
106/106 •
                            - 12s 110ms/step - loss: 0.0016 - mae: 0.0278 - val loss: 0.00
62 - val mae: 0.0505
Epoch 65/105
106/106
                            - 12s 110ms/step - loss: 0.0014 - mae: 0.0261 - val loss: 0.00
72 - val mae: 0.0572
Epoch 66/105
106/106
                            - 12s 110ms/step - loss: 0.0015 - mae: 0.0269 - val loss: 0.00
63 - val_mae: 0.0508
Epoch 67/105
106/106
                            - 12s 110ms/step - loss: 0.0013 - mae: 0.0248 - val loss: 0.00
63 - val mae: 0.0514
Epoch 68/105
106/106 •
                            - 12s 110ms/step - loss: 0.0015 - mae: 0.0266 - val loss: 0.00
66 - val mae: 0.0541
Epoch 69/105
106/106 -
                            - 12s 110ms/step - loss: 0.0014 - mae: 0.0261 - val loss: 0.00
62 - val mae: 0.0500
Epoch 70/105
106/106
                            - 12s 109ms/step - loss: 0.0013 - mae: 0.0245 - val loss: 0.00
67 - val mae: 0.0533
Epoch 71/105
                            - 12s 110ms/step - loss: 0.0014 - mae: 0.0254 - val loss: 0.00
106/106 •
64 - val mae: 0.0521
Epoch 72/105
106/106
                            - 12s 110ms/step - loss: 0.0013 - mae: 0.0250 - val loss: 0.00
71 - val_mae: 0.0566
Epoch 73/105
106/106
                            - 12s 110ms/step - loss: 0.0015 - mae: 0.0274 - val loss: 0.00
63 - val mae: 0.0510
Epoch 74/105
106/106
                            - 12s 110ms/step - loss: 0.0013 - mae: 0.0243 - val loss: 0.00
61 - val mae: 0.0502
Epoch 75/105
106/106
                            - 12s 110ms/step - loss: 0.0013 - mae: 0.0242 - val loss: 0.00
62 - val mae: 0.0511
Epoch 76/105
106/106
                            - 12s 110ms/step - loss: 0.0012 - mae: 0.0241 - val loss: 0.00
64 - val mae: 0.0522
Epoch 77/105
106/106 •
                            - 12s 110ms/step - loss: 0.0013 - mae: 0.0245 - val loss: 0.00
64 - val mae: 0.0528
Epoch 78/105
106/106
                            • 12s 110ms/step - loss: 0.0012 - mae: 0.0236 - val loss: 0.00
65 - val mae: 0.0541
Epoch 79/105
106/106
                            - 12s 110ms/step - loss: 0.0012 - mae: 0.0240 - val loss: 0.00
62 - val mae: 0.0510
Epoch 80/105
106/106
                            - 21s 110ms/step - loss: 0.0012 - mae: 0.0239 - val loss: 0.00
61 - val mae: 0.0499
Epoch 81/105
106/106 •
                            - 12s 110ms/step - loss: 0.0011 - mae: 0.0225 - val loss: 0.00
63 - val mae: 0.0513
Epoch 82/105
106/106
                            - 12s 110ms/step - loss: 0.0011 - mae: 0.0226 - val_loss: 0.00
62 - val mae: 0.0501
Epoch 83/105
106/106
                            - 12s 110ms/step - loss: 0.0011 - mae: 0.0221 - val loss: 0.00
61 - val mae: 0.0497
Epoch 84/105
106/106
                            • 12s 110ms/step - loss: 0.0011 - mae: 0.0228 - val loss: 0.00
60 - val mae: 0.0500
Epoch 85/105
106/106
                            - 12s 110ms/step - loss: 0.0011 - mae: 0.0231 - val_loss: 0.00
61 - val mae: 0.0497
```

```
106/106 -
                            - 12s 110ms/step - loss: 0.0011 - mae: 0.0228 - val loss: 0.00
64 - val mae: 0.0509
Epoch 87/105
106/106
                            - 12s 110ms/step - loss: 0.0011 - mae: 0.0228 - val loss: 0.00
63 - val mae: 0.0511
Epoch 88/105
106/106 •
                            - 12s 110ms/step - loss: 0.0011 - mae: 0.0225 - val loss: 0.00
62 - val_mae: 0.0505
Epoch 89/105
106/106 •
                            - 12s 110ms/step - loss: 0.0011 - mae: 0.0229 - val loss: 0.00
61 - val mae: 0.0497
Epoch 90/105
106/106
                            - 12s 110ms/step - loss: 0.0010 - mae: 0.0215 - val loss: 0.00
60 - val_mae: 0.0496
Epoch 91/105
106/106 •
                            - 12s 110ms/step - loss: 9.9445e-04 - mae: 0.0216 - val loss:
0.0062 - val_mae: 0.0504
Epoch 92/105
106/106 -
                            - 12s 110ms/step - loss: 9.8137e-04 - mae: 0.0214 - val loss:
0.0060 - val mae: 0.0495
Epoch 93/105
106/106 -
                            - 12s 110ms/step - loss: 0.0010 - mae: 0.0217 - val loss: 0.00
60 - val mae: 0.0500
Epoch 94/105
106/106 -
                            - 12s 110ms/step - loss: 0.0010 - mae: 0.0219 - val loss: 0.00
61 - val mae: 0.0499
Epoch 95/105
106/106 •
                            - 12s 110ms/step - loss: 9.8219e-04 - mae: 0.0213 - val loss:
0.0062 - val mae: 0.0519
Epoch 96/105
106/106
                           - 12s 110ms/step - loss: 0.0011 - mae: 0.0228 - val loss: 0.00
61 - val mae: 0.0501
Epoch 97/105
106/106 •
                           - 12s 110ms/step - loss: 9.9584e-04 - mae: 0.0216 - val loss:
0.0061 - val_mae: 0.0497
Epoch 98/105
106/106 -
                           - 12s 110ms/step - loss: 9.1110e-04 - mae: 0.0205 - val loss:
0.0061 - val mae: 0.0499
Epoch 99/105
106/106 -
                            - 12s 110ms/step - loss: 9.4289e-04 - mae: 0.0211 - val loss:
0.0063 - val mae: 0.0500
Epoch 100/105
106/106
                            - 12s 109ms/step - loss: 9.4462e-04 - mae: 0.0212 - val loss:
0.0059 - val mae: 0.0488
Epoch 101/10\overline{5}
106/106 -
                            - 12s 110ms/step - loss: 8.9341e-04 - mae: 0.0202 - val loss:
0.0062 - val_mae: 0.0499
Epoch 102/105
106/106
                            - 12s 110ms/step - loss: 9.6895e-04 - mae: 0.0213 - val loss:
0.0060 - val mae: 0.0494
Epoch 103/105
106/106 •
                            - 12s 110ms/step - loss: 9.3705e-04 - mae: 0.0208 - val loss:
0.0061 - val mae: 0.0495
Epoch 104/105
106/106 •
                            - 12s 110ms/step - loss: 8.8685e-04 - mae: 0.0203 - val loss:
0.0060 - val mae: 0.0493
Epoch 105/105
106/106 -
                            - 12s 110ms/step - loss: 9.3598e-04 - mae: 0.0209 - val loss:
0.0060 - val mae: 0.0496
In [12]:
recolourization model.save("/kaggle/working/recolorization model.keras")
In [13]:
predicted color = recolourization model.predict(test gray image)
50/50 -
                          3s 39ms/step
```

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In [14]:

```
# Extract the loss and accuracy values
train loss = history.history['loss']
val loss = history.history['val loss']
train mae = history.history['mae']
val mae = history.history['val mae']
epochs = range(1, len(train loss) + 1)
sns.set(style="whitegrid")
# Plot loss (training vs validation)
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1) # Create a 1x2 grid, first subplot for loss
sns.lineplot(x=epochs, y=train loss, label='Training Loss', color='blue')
sns.lineplot(x=epochs, y=val loss, label='Validation Loss', color='red')
plt.title('Model Loss Progression')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
# Plot mean absolute error (mae) (training vs validation)
plt.subplot(1, 2, 2) # Second subplot for mae
sns.lineplot(x=epochs, y=train_mae, label='Training MAE', color='blue')
sns.lineplot(x=epochs, y=val_mae, label='Validation MAE', color='red')
plt.title('Model MAE Progression')
plt.xlabel('Epoch')
plt.ylabel('Mean Absolute Error')
plt.legend()
# Show the plots
plt.tight layout()
plt.show()
```



In [15]:

```
n = 10  # Number of images to display
plt.figure(figsize=(20, 10))
for i in range(n):
    # Grayscale input images
    ax = plt.subplot(3, n, i + 1)
    plt.imshow(test_gray_image[i], cmap='gray')
    plt.title("Grayscale")
    plt.axis('off')

# Predicted color images
    ax = plt.subplot(3, n, i + n + 1)
    plt.imshow(predicted_color[i])
    plt.title("Predicted Color")
    plt.axis('off')
```

```
# Ground truth color images
ax = plt.subplot(3, n, i + 2 * n + 1)
plt.imshow(test_color_image[i])
plt.title("True Color")
plt.axis('off')

plt.show()
```





























































In [16]:

```
psnr_value = psnr(test_color_image[0], predicted_color[0], data_range=1.0)
ssim_value = ssim(test_color_image[0], predicted_color[0], multichannel=True, win_size=3
, channel_axis=-1, data_range=1.0)
print(f"PSNR: {psnr_value}, SSIM: {ssim_value}")
```

PSNR: 22.809714345038735, SSIM: 0.9491534233093262

In [17]:

```
recolorization model = tf.keras.models.load_model("/kaggle/working/recolorization_model.k
eras", compile=False)
SIZE = 160
def colorize image(grayscale img):
    # Resize and normalize the grayscale image to match the model's input format
    img = cv2.resize(grayscale img, (SIZE, SIZE))
    img = img.astype('float32') / 255.0 # Normalize
    img = np.stack((img, img, img), axis=-1) # Convert grayscale to 3-channel RGB forma
    img = np.expand dims(img, axis=0) # Add batch dimension for the model
    # Predict the colorized version using the model
    colorized img = recolorization model.predict(img)
    colorized img = colorized img[0] # Remove batch dimension
    colorized_img = np.clip(colorized_img, 0, 1) # Clip to valid pixel range
    # Convert colorized image to 0-255 scale for visualization
    colorized img = (colorized img * 255).astype(np.uint8)
    return colorized img
```

In []:

```
import gradio as gr
gr_interface = gr.Interface(
    fn=colorize_image,
    inputs=gr.Image(image_mode='L', label="Upload a grayscale image"),
    outputs=gr.Image(label="Colorized Image"),
    title="Image Recolorization",
```

```
description="Upload a grayscale image to see it colorized by the trained model."
)
# Launch the Gradio app
gr_interface.launch()
```

