

This project aims to use image classification to predict the artists of impressionist paintings. Namely,

Camille Pissarro, Childe Hassam, Claude Monet, Edgar Degas, Henri Matisse John Singer-Sargent, Paul Cezanne, Paul Gauguin, Pierre-Auguste Renoir, and Vincent van Gogh

Importing Libraries and Mounting Dataset from Google Drive

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import glob as gb
import os
import torch
import torchvision
from torchvision import datasets, models, transforms
import torch.utils.data as data
from torch.utils.tensorboard import SummaryWriter
import torch.nn as nn
import torch.optim as optim
from torch.optim import lr_scheduler
import time, os, copy, argparse
import multiprocessing
from matplotlib import pyplot as plt
import tensorflow as tf
import cv2
from tensorflow import keras
from tensorflow.keras.models import Sequential, Model
from matplotlib import pyplot as plt
import matplotlib.image as mpimg
%matplotlib inline

from google.colab import drive
drive.mount("/content/drive", force_remount=True)
```

Mounted at /content/drive

```
# import the libraries as shown below
from tensorflow.keras.layers import Input, Lambda, Dense, Flatten
from tensorflow.keras.models import Model
from tensorflow.keras.applications.inception_v3 import InceptionV3
#from keras.applications.vgg16 import VGG16
from tensorflow.keras.applications.inception_v3 import
preprocess_input
from tensorflow.keras.preprocessing import image
from tensorflow.keras.preprocessing.image import
ImageDataGenerator, load_img
from tensorflow.keras.models import Sequential
import numpy as np
```

```
from glob import glob
#import matplotlib.pyplot as plt
```

```
!pip install pyyaml h5py
```

```
Looking in indexes: https://pypi.org/simple, https://us-
python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: pyyaml in
/usr/local/lib/python3.8/dist-packages (6.0)
Requirement already satisfied: h5py in /usr/local/lib/python3.8/dist-
packages (3.1.0)
Requirement already satisfied: numpy>=1.17.5 in
/usr/local/lib/python3.8/dist-packages (from h5py) (1.21.6)
```

Preprocessing

We standardize the image size 224 x 224, which is normal for machine learning. Then, a path is created to the training and validation folders.

```
image_size = [224, 224]
BATCH_SIZE = 32
path = '/content/drive/MyDrive/impressionist'
training_path =
'/content/drive/MyDrive/impressionist/training/training'
validation_path =
'/content/drive/MyDrive/impressionist/validation/validation'

for folder in os.listdir(training_path):
    files = gb.glob(pathname= str(training_path+ '/' + folder +
'/*.jpg'))
    print(f'For training data, found {len(files)} in folder {folder}')
```

```
For training data, found 399 in folder Monet
For training data, found 399 in folder Renoir
For training data, found 399 in folder Gauguin
For training data, found 399 in folder VanGogh
For training data, found 398 in folder Degas
For training data, found 399 in folder Matisse
For training data, found 398 in folder Pissarro
For training data, found 399 in folder Hassam
For training data, found 399 in folder Cezanne
For training data, found 399 in folder Sargent
```

```
for folder in os.listdir(validation_path):
    files = gb.glob(pathname= str(validation_path+ '/' + folder +
'/*.jpg'))
    print(f'For validation data, found {len(files)} in folder
{folder}')
```

```
For validation data, found 99 in folder Matisse
For validation data, found 99 in folder Sargent
For validation data, found 99 in folder Gauguin
```

```
For validation data, found 99 in folder Monet
For validation data, found 99 in folder Degas
For validation data, found 99 in folder Cezanne
For validation data, found 99 in folder VanGogh
For validation data, found 99 in folder Renoir
For validation data, found 99 in folder Hassam
For validation data, found 99 in folder Pissarro
```

Data Exploration

For data exploration, we can see that there is a good number of training data for the program to look at and learn the different types of artist style. The model should be able to predict who made the piece from the given training data it has looked at.

```
import random
import matplotlib.pyplot as plt
import matplotlib.image as mpimg

def view_random_image(target_dir, target_class):
    # We will view images from here
    target_folder = target_dir + target_class

    # Get a random image path
    random_image = random.sample(os.listdir(target_folder), 1)

    # read in the image and plot it using matplotlib
    img = mpimg.imread(target_folder+'/'+random_image[0])
    plt.imshow(img)
    plt.title(target_class)
    plt.axis('off')
    print(f"Image shape {img.shape}")

    return img

class_names = ['Cezanne', 'Degas', 'Gauguin', 'Hassam', 'Matisse',
               'Monet', 'Pissarro', 'Renoir', 'Sargent', 'VanGogh']

plt.figure(figsize=(20,10))
for i in range(18):
    plt.subplot(6, 6, i+1)
    class_name = random.choice(class_names)
    img =
view_random_image(target_dir="/content/drive/MyDrive/impressionist/
training/training/", target_class=class_name)

Image shape (749, 991, 3)
Image shape (877, 1119, 3)
Image shape (986, 816, 3)
Image shape (600, 726, 3)
Image shape (525, 1105, 3)
Image shape (1600, 2024, 3)
```

```

Image shape (547, 901, 3)
Image shape (1316, 1776, 3)
Image shape (518, 640, 3)
Image shape (1600, 1081, 3)
Image shape (1070, 811, 3)
Image shape (1022, 1280, 3)
Image shape (1098, 758, 3)
Image shape (1182, 1600, 3)
Image shape (1018, 1037, 3)
Image shape (942, 1226, 3)
Image shape (1988, 1451, 3)
Image shape (1123, 872, 3)

```



Creating a Sequential Model

We used the Tensorflow notebook as reference over here:

https://www.tensorflow.org/tutorials/images/classification#a_basic_keras_model

#Importing images from the dataset

```

from tensorflow.keras.preprocessing.image import ImageDataGenerator
import PIL

```

Defining pre-processing transformations on raw images of training data

```

train_datagen = ImageDataGenerator(rescale = 1./255,
                                   shear_range = 0.2,
                                   zoom_range = 0.2,
                                   horizontal_flip = True)

```

Defining pre-processing transformations on raw images of testing data

```

test_datagen = ImageDataGenerator(rescale = 1./255)

```

We import pathlib to define a path since we used Google Drive. Then to test it, we used count and data.glob to find all pathnames that match this pattern, effectively finding the number of total training files.

```

import pathlib
data = pathlib.Path('/content/drive/MyDrive/impressionist')
training =

```

```
pathlib.Path('/content/drive/MyDrive/impressionist/training/training')

validation =
pathlib.Path('/content/drive/MyDrive/impressionist/validation/validati
on')
count = len(list(training.glob('*/*.jpg')))
count

3988
```

For example, we can print a picture from any dataset.

```
Cezanne = list(training.glob('Cezanne/*'))
PIL.Image.open(str(Cezanne[0]))
```



```
training_set =
train_datagen.flow_from_directory('/content/drive/MyDrive/impressionis
t/training/training',
224),
target_size = (224,
batch_size = 32,
class_mode =
'categorical')
```

Found 3988 images belonging to 10 classes.

```

test_set =
test_datagen.flow_from_directory('/content/drive/MyDrive/impressionist
/validation/validation',
                                target_size = (224, 224),
                                batch_size = 32,
                                class_mode =
'categorical')

```

Found 990 images belonging to 10 classes.

```

batch_size = 32
img_height = 224
img_width = 224

```

```

train_ds = tf.keras.utils.image_dataset_from_directory(
    training,
    validation_split=0.2,
    subset="training",
    seed=123,
    image_size=(img_height, img_width),
    batch_size=batch_size)

```

Found 3988 files belonging to 10 classes.
Using 3191 files for training.

```

val_ds = tf.keras.utils.image_dataset_from_directory(
    training,
    validation_split=0.2,
    subset="validation",
    seed=123,
    image_size=(img_height, img_width),
    batch_size=batch_size)

```

Found 3988 files belonging to 10 classes.
Using 797 files for validation.

```

import matplotlib.pyplot as plt

```

```

plt.figure(figsize=(10, 10))
for images, labels in train_ds.take(1):
    for i in range(9):
        ax = plt.subplot(3, 3, i + 1)
        plt.imshow(images[i].numpy().astype("uint8"))
        plt.title(class_names[labels[i]])
        plt.axis("off")

```


Matisse



Sargent



Degas



Sargent



Monet



Renoir



Gauguin



Gauguin



Pissarro



```
import matplotlib.pyplot as plt
import numpy as np
import PIL
import tensorflow as tf

from tensorflow import keras
from tensorflow.keras import layers
from tensorflow.keras.models import Sequential
```

```
normalization_layer = layers.Rescaling(1./255)
```

Optimizing Data

```
normalized_ds = train_ds.map(lambda x, y: (normalization_layer(x), y))
image_batch, labels_batch = next(iter(normalized_ds))
first_image = image_batch[0]
```

```
# Notice the pixel values are now in `[0,1]`.
print(np.min(first_image), np.max(first_image))

0.0 1.0
```

Creating a Sequential CNN model

Now we create the sequential mode with 3 layers of conv2D, and a flattened layer. The last line specifies that we have 10 classes.

```
model = Sequential([
    layers.Rescaling(1./255, input_shape=(img_height, img_width, 3)),
    layers.Conv2D(16, 3, padding='same', activation='relu'),
    layers.MaxPooling2D(),
    layers.Conv2D(32, 3, padding='same', activation='relu'),
    layers.MaxPooling2D(),
    layers.Conv2D(64, 3, padding='same', activation='relu'),
    layers.MaxPooling2D(),
    layers.Flatten(),
    layers.Dense(128, activation='relu'),
    layers.Dense(10)
])
```

```
model.compile(optimizer='adam',
```

```
loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
metrics=['accuracy'])
```

```
model.summary()
```

```
Model: "sequential_4"
```

Layer (type)	Output Shape	Param #
rescaling_5 (Rescaling)	(None, 224, 224, 3)	0
conv2d (Conv2D)	(None, 224, 224, 16)	448
max_pooling2d (MaxPooling2D)	(None, 112, 112, 16)	0
conv2d_1 (Conv2D)	(None, 112, 112, 32)	4640
max_pooling2d_1 (MaxPooling2D)	(None, 56, 56, 32)	0
conv2d_2 (Conv2D)	(None, 56, 56, 64)	18496
max_pooling2d_2 (MaxPooling2D)	(None, 28, 28, 64)	0

flatten_2 (Flatten)	(None, 50176)	0
dense_12 (Dense)	(None, 128)	6422656
dense_13 (Dense)	(None, 10)	1290

```

=====
Total params: 6,447,530
Trainable params: 6,447,530
Non-trainable params: 0

```

```

epochs=10
history = model.fit(
    train_ds,
    validation_data=val_ds,
    epochs=epochs
)

```

```

Epoch 1/10
100/100 [=====] - 46s 407ms/step - loss:
2.2759 - accuracy: 0.1830 - val_loss: 2.0383 - val_accuracy: 0.2622
Epoch 2/10
100/100 [=====] - 44s 413ms/step - loss:
1.8463 - accuracy: 0.3482 - val_loss: 1.9053 - val_accuracy: 0.3275
Epoch 3/10
100/100 [=====] - 46s 439ms/step - loss:
1.4802 - accuracy: 0.4898 - val_loss: 1.8553 - val_accuracy: 0.3902
Epoch 4/10
100/100 [=====] - 47s 427ms/step - loss:
1.0361 - accuracy: 0.6684 - val_loss: 2.1404 - val_accuracy: 0.3601
Epoch 5/10
100/100 [=====] - 49s 466ms/step - loss:
0.6071 - accuracy: 0.8092 - val_loss: 2.6546 - val_accuracy: 0.3739
Epoch 6/10
100/100 [=====] - 43s 406ms/step - loss:
0.3125 - accuracy: 0.9088 - val_loss: 3.1229 - val_accuracy: 0.3463
Epoch 7/10
100/100 [=====] - 45s 426ms/step - loss:
0.1596 - accuracy: 0.9552 - val_loss: 3.8841 - val_accuracy: 0.3300
Epoch 8/10
100/100 [=====] - 42s 399ms/step - loss:
0.1058 - accuracy: 0.9718 - val_loss: 4.0829 - val_accuracy: 0.3639
Epoch 9/10
100/100 [=====] - 45s 420ms/step - loss:
0.0695 - accuracy: 0.9856 - val_loss: 4.1761 - val_accuracy: 0.3689
Epoch 10/10
100/100 [=====] - 49s 464ms/step - loss:
0.1234 - accuracy: 0.9662 - val_loss: 3.9849 - val_accuracy: 0.3388

```

```
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

loss = history.history['loss']
val_loss = history.history['val_loss']

epochs_range = range(10)

plt.figure(figsize=(8, 8))
plt.subplot(1, 2, 1)
plt.plot(epochs_range, acc, label='Training Accuracy')
plt.plot(epochs_range, val_acc, label='Validation Accuracy')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy')

plt.subplot(1, 2, 2)
plt.plot(epochs_range, loss, label='Training Loss')
plt.plot(epochs_range, val_loss, label='Validation Loss')
plt.legend(loc='upper right')
plt.title('Training and Validation Loss')
plt.show()
```



```
model.save('/content/drive/MyDrive/model_saving')
```

WARNING:absl:Found untraced functions such as _jit_compiled_convolution_op, _jit_compiled_convolution_op, _jit_compiled_convolution_op while saving (showing 3 of 3). These functions will not be directly callable after loading.

Restoring the Model

```
# new_model = tf.keras.models.load_model('saved_model/my_model')

# Check its architecture
# new_model.summary()
```

Predicting on New Data

Let's make sure to make text classes for all 10 artists

```

target_Cezanne= 'Cezanne'
target_Degas = 'Degas'
target_Gauguin = 'Gauguin'
target_Hassam = 'Hassam'
target_Matisse= 'Matisse'
target_Monet = 'Monet'
target_Pissarro = 'Pissarro'
target_Renoir = 'Renoir'
target_Sargent = 'Sargent'
target_VanGogh = 'VanGogh'

target_dir =
"/content/drive/MyDrive/impressionist/validation/validation/"

```

Creating a function

```

def testPaintings(target_dir, target_class):
    images = []
    class_name = []
    scores = []

    target_folder = target_dir + target_class
    random_image = random.sample(os.listdir(target_folder), 25)

    for x in range(25):
        painting_url = target_folder + '/' + random_image[x]
        img = tf.keras.utils.load_img(
            painting_url, target_size=(img_height, img_width)
        )

        img_array = tf.keras.utils.img_to_array(img)
        img_array = tf.expand_dims(img_array, 0) # Create a batch
        predictions = model.predict(img_array)
        score = tf.nn.softmax(predictions[0])
        # print("This image most likely belongs to {} with a {:.2f}
percent confidence.".format(class_names[np.argmax(score)], 100 *
np.max(score)))
        images.append(img)
        class_name.append(class_names[np.argmax(score)])
        scores.append(np.max(score))

import matplotlib.pyplot as plt
import matplotlib.pyplot as plt

wrongPredict = {'family':'serif','color':'darkred','size':15}
rightPredict = {'family':'serif','color':'green','size':15}

plt.figure(figsize=(10, 10))
for i in range(25):

```

```

ax = plt.subplot(5, 5, i + 1)
plt.imshow(images[i])
if (class_name[i] == target_class):
    plt.title(class_name[i], fontdict = rightPredict)
else:
    plt.title(class_name[i], fontdict = wrongPredict)
plt.axis("off")

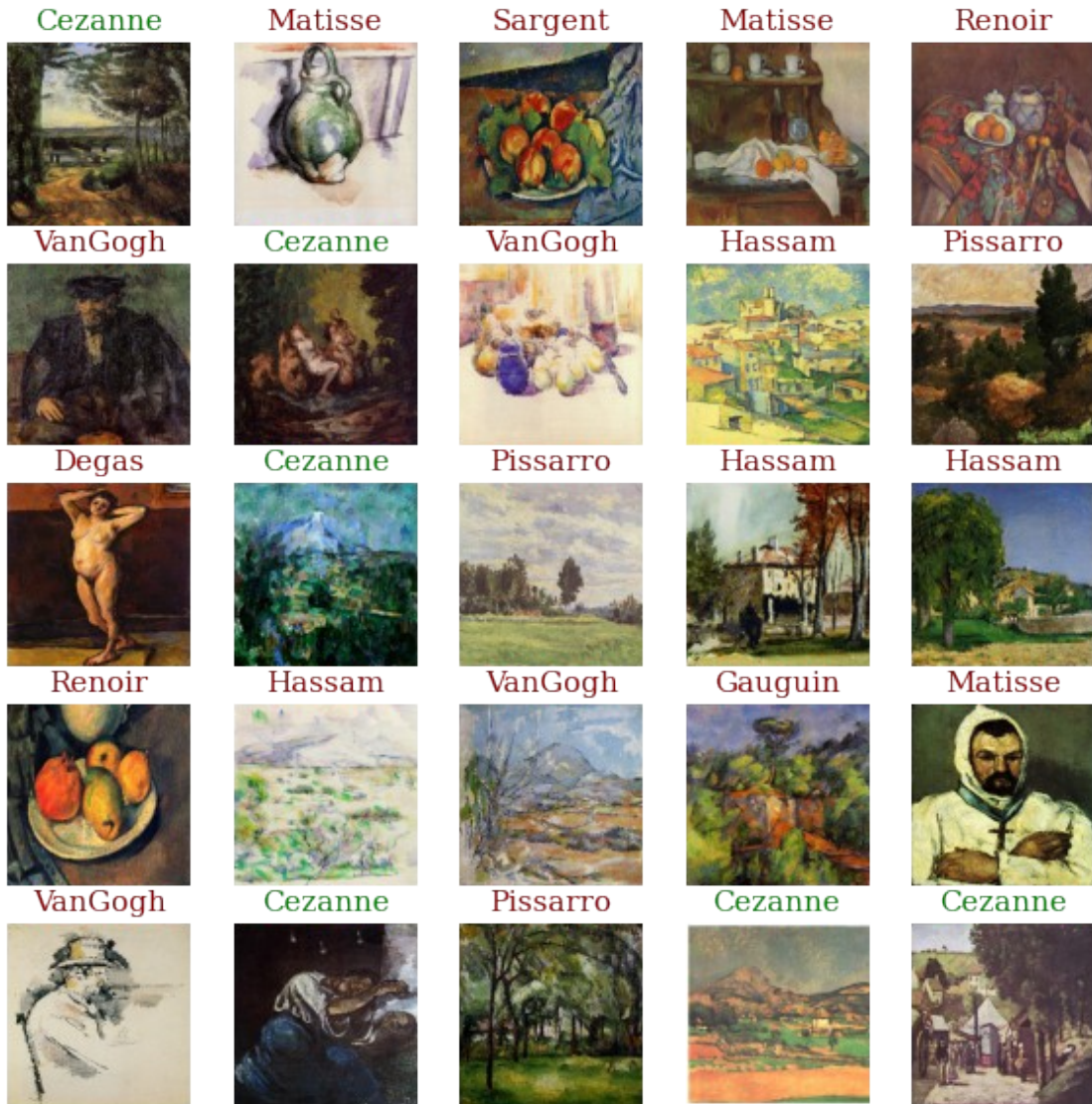
```

```
testPaintings(target_dir, target_Cezanne)
```

```

1/1 [=====] - 0s 20ms/step
1/1 [=====] - 0s 16ms/step
1/1 [=====] - 0s 21ms/step
1/1 [=====] - 0s 21ms/step
1/1 [=====] - 0s 18ms/step
1/1 [=====] - 0s 16ms/step
1/1 [=====] - 0s 21ms/step
1/1 [=====] - 0s 22ms/step
1/1 [=====] - 0s 19ms/step
1/1 [=====] - 0s 20ms/step
1/1 [=====] - 0s 18ms/step
1/1 [=====] - 0s 18ms/step
1/1 [=====] - 0s 16ms/step
1/1 [=====] - 0s 19ms/step
1/1 [=====] - 0s 17ms/step
1/1 [=====] - 0s 16ms/step
1/1 [=====] - 0s 20ms/step
1/1 [=====] - 0s 16ms/step
1/1 [=====] - 0s 22ms/step
1/1 [=====] - 0s 17ms/step
1/1 [=====] - 0s 16ms/step
1/1 [=====] - 0s 17ms/step
1/1 [=====] - 0s 16ms/step
1/1 [=====] - 0s 16ms/step
1/1 [=====] - 0s 17ms/step

```

Testing on Degas's Paintings

testPaintings(target_dir, target_Degas)

```

1/1 [=====] - 0s 19ms/step
1/1 [=====] - 0s 17ms/step
1/1 [=====] - 0s 18ms/step
1/1 [=====] - 0s 22ms/step
1/1 [=====] - 0s 18ms/step
1/1 [=====] - 0s 17ms/step
1/1 [=====] - 0s 18ms/step
1/1 [=====] - 0s 17ms/step
1/1 [=====] - 0s 16ms/step
1/1 [=====] - 0s 16ms/step
1/1 [=====] - 0s 16ms/step
1/1 [=====] - 0s 18ms/step
1/1 [=====] - 0s 20ms/step

```

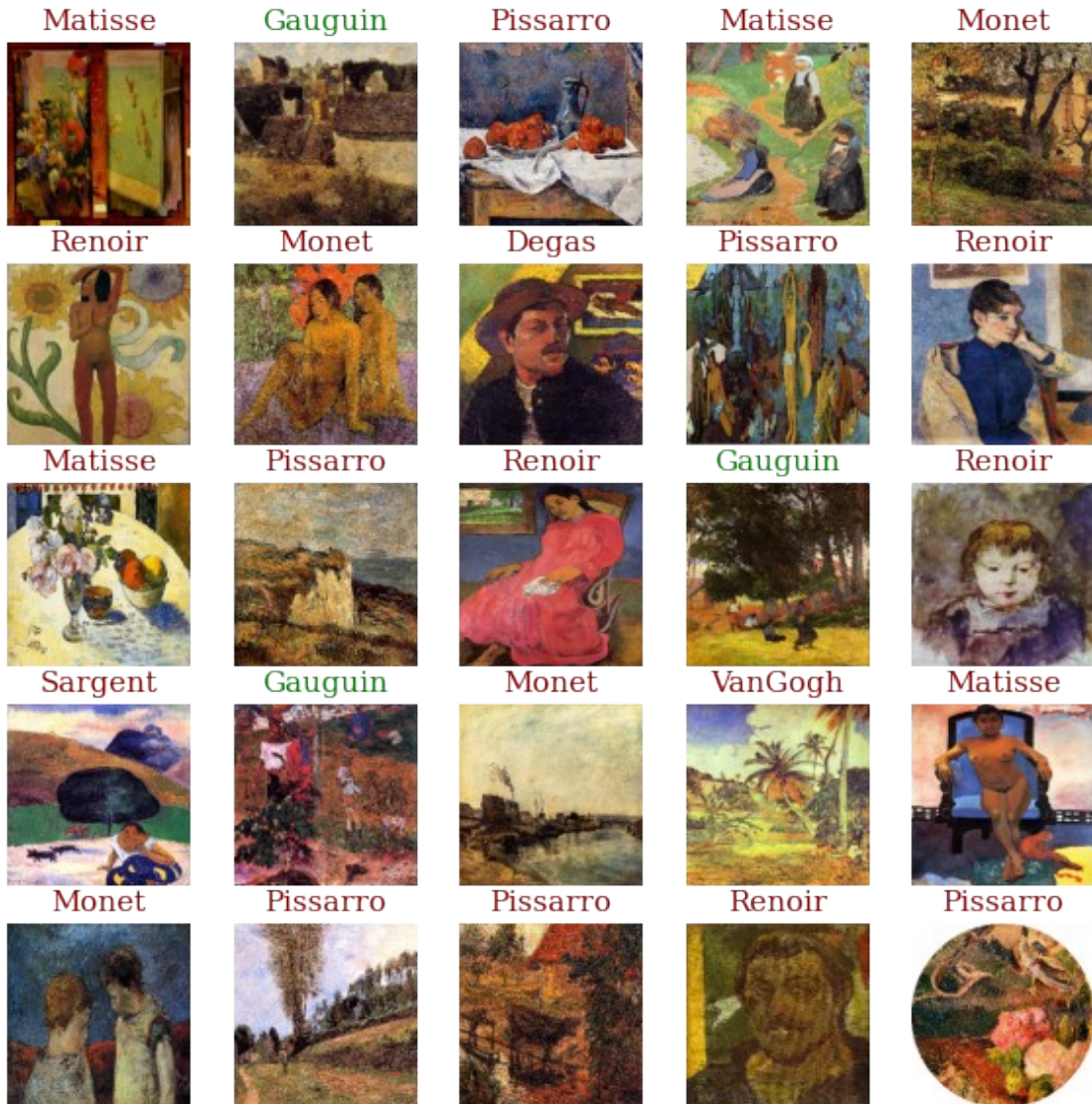
1/1 [=====] - 0s 18ms/step
 1/1 [=====] - 0s 16ms/step
 1/1 [=====] - 0s 18ms/step
 1/1 [=====] - 0s 23ms/step
 1/1 [=====] - 0s 26ms/step
 1/1 [=====] - 0s 23ms/step
 1/1 [=====] - 0s 23ms/step
 1/1 [=====] - 0s 28ms/step
 1/1 [=====] - 0s 17ms/step
 1/1 [=====] - 0s 16ms/step
 1/1 [=====] - 0s 19ms/step
 1/1 [=====] - 0s 16ms/step



Testing on Gauguin Paintings

testPaintings(target_dir, target_Gauguin)

1/1	[=====]	- 0s 19ms/step
1/1	[=====]	- 0s 20ms/step
1/1	[=====]	- 0s 27ms/step
1/1	[=====]	- 0s 18ms/step
1/1	[=====]	- 0s 18ms/step
1/1	[=====]	- 0s 16ms/step
1/1	[=====]	- 0s 16ms/step
1/1	[=====]	- 0s 18ms/step
1/1	[=====]	- 0s 16ms/step
1/1	[=====]	- 0s 18ms/step
1/1	[=====]	- 0s 19ms/step
1/1	[=====]	- 0s 15ms/step
1/1	[=====]	- 0s 17ms/step
1/1	[=====]	- 0s 17ms/step
1/1	[=====]	- 0s 19ms/step
1/1	[=====]	- 0s 17ms/step
1/1	[=====]	- 0s 15ms/step
1/1	[=====]	- 0s 20ms/step
1/1	[=====]	- 0s 17ms/step
1/1	[=====]	- 0s 16ms/step
1/1	[=====]	- 0s 19ms/step
1/1	[=====]	- 0s 19ms/step
1/1	[=====]	- 0s 19ms/step
1/1	[=====]	- 0s 16ms/step
1/1	[=====]	- 0s 16ms/step



Testing on Hassam Paintings

testPaintings(target_dir, target_Hassam)

```

1/1 [=====] - 0s 19ms/step
1/1 [=====] - 0s 19ms/step
1/1 [=====] - 0s 16ms/step
1/1 [=====] - 0s 18ms/step
1/1 [=====] - 0s 19ms/step
1/1 [=====] - 0s 16ms/step
1/1 [=====] - 0s 17ms/step
1/1 [=====] - 0s 18ms/step
1/1 [=====] - 0s 19ms/step
1/1 [=====] - 0s 21ms/step
1/1 [=====] - 0s 16ms/step
1/1 [=====] - 0s 18ms/step
1/1 [=====] - 0s 23ms/step

```

```

1/1 [=====] - 0s 16ms/step
1/1 [=====] - 0s 16ms/step
1/1 [=====] - 0s 20ms/step
1/1 [=====] - 0s 16ms/step
1/1 [=====] - 0s 15ms/step
1/1 [=====] - 0s 16ms/step
1/1 [=====] - 0s 16ms/step
1/1 [=====] - 0s 21ms/step
1/1 [=====] - 0s 17ms/step
1/1 [=====] - 0s 16ms/step
1/1 [=====] - 0s 16ms/step
1/1 [=====] - 0s 16ms/step

```



Testing Monet's Paintings

```
testPaintings(target_dir, target_VanGogh)
```


1/1	[=====]	- 0s 17ms/step
1/1	[=====]	- 0s 16ms/step
1/1	[=====]	- 0s 18ms/step
1/1	[=====]	- 0s 17ms/step
1/1	[=====]	- 0s 17ms/step
1/1	[=====]	- 0s 17ms/step
1/1	[=====]	- 0s 17ms/step
1/1	[=====]	- 0s 16ms/step
1/1	[=====]	- 0s 27ms/step
1/1	[=====]	- 0s 26ms/step
1/1	[=====]	- 0s 26ms/step
1/1	[=====]	- 0s 20ms/step
1/1	[=====]	- 0s 17ms/step
1/1	[=====]	- 0s 16ms/step
1/1	[=====]	- 0s 17ms/step
1/1	[=====]	- 0s 16ms/step
1/1	[=====]	- 0s 20ms/step
1/1	[=====]	- 0s 16ms/step
1/1	[=====]	- 0s 16ms/step
1/1	[=====]	- 0s 22ms/step
1/1	[=====]	- 0s 17ms/step
1/1	[=====]	- 0s 16ms/step
1/1	[=====]	- 0s 21ms/step
1/1	[=====]	- 0s 19ms/step
1/1	[=====]	- 0s 19ms/step



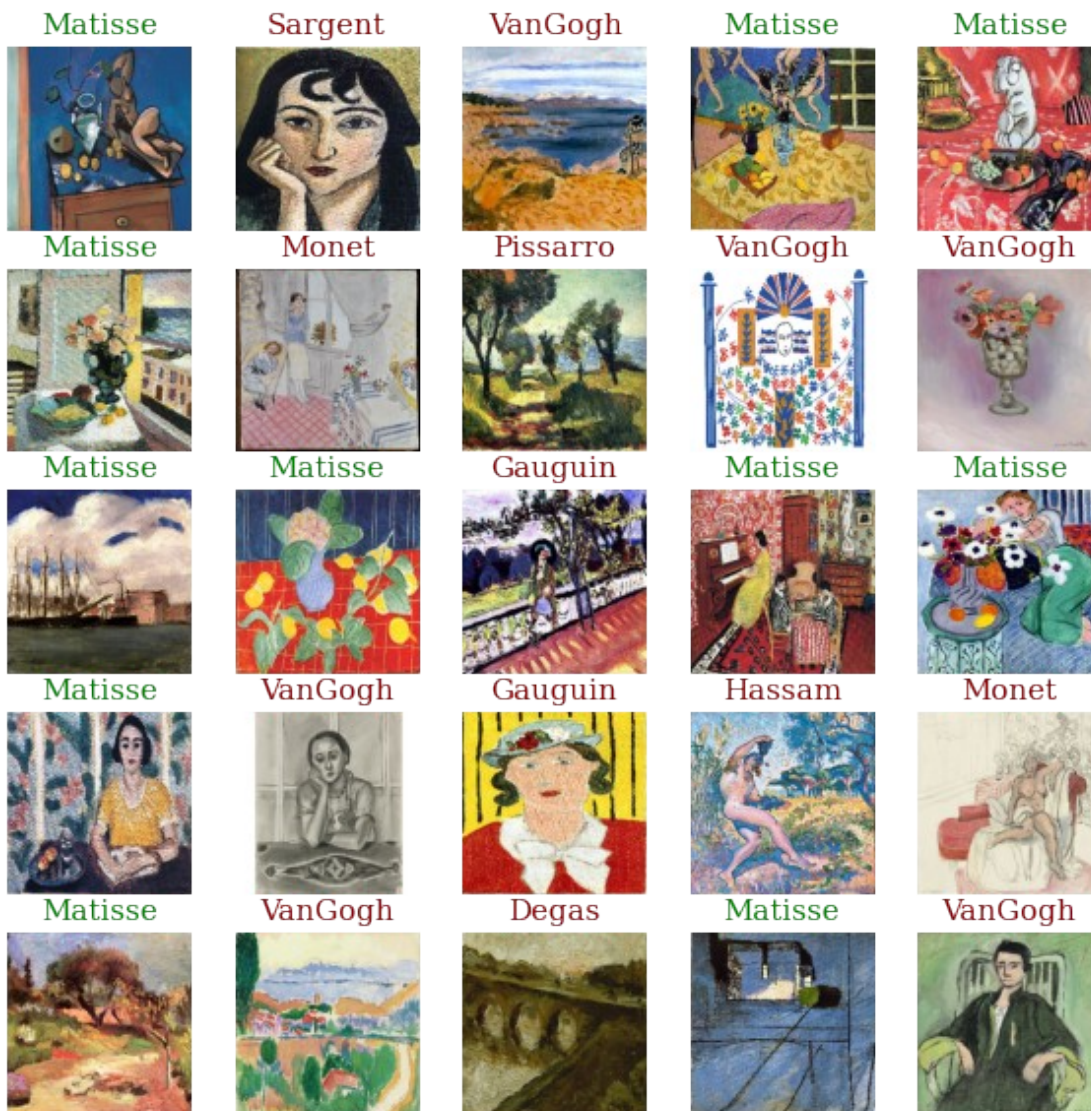
testPaintings(target_dir, target_Matisse)

```

1/1 [=====] - 0s 18ms/step
1/1 [=====] - 0s 16ms/step
1/1 [=====] - 0s 19ms/step
1/1 [=====] - 0s 16ms/step
1/1 [=====] - 0s 19ms/step
1/1 [=====] - 0s 16ms/step
1/1 [=====] - 0s 16ms/step
1/1 [=====] - 0s 16ms/step
1/1 [=====] - 0s 19ms/step
1/1 [=====] - 0s 18ms/step
1/1 [=====] - 0s 17ms/step
1/1 [=====] - 0s 16ms/step
1/1 [=====] - 0s 16ms/step
1/1 [=====] - 0s 20ms/step

```

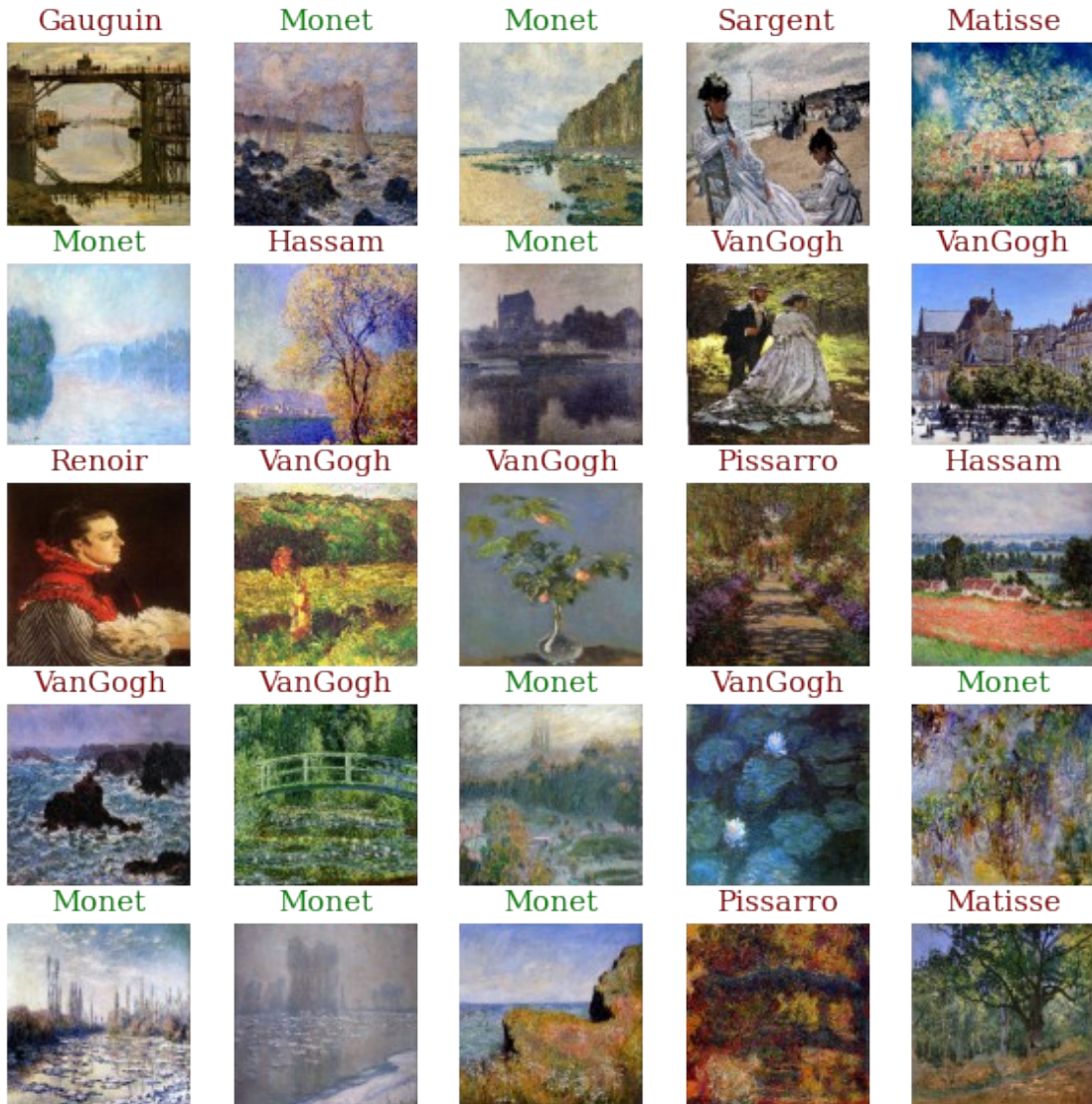
1/1 [=====] - 0s 18ms/step
 1/1 [=====] - 0s 17ms/step
 1/1 [=====] - 0s 16ms/step
 1/1 [=====] - 0s 17ms/step
 1/1 [=====] - 0s 18ms/step
 1/1 [=====] - 0s 17ms/step
 1/1 [=====] - 0s 15ms/step
 1/1 [=====] - 0s 17ms/step
 1/1 [=====] - 0s 17ms/step
 1/1 [=====] - 0s 16ms/step
 1/1 [=====] - 0s 18ms/step



Predicting Pissarro's Paintings

testPaintings(target_dir, target_Monet)

1/1	[=====]	- 0s 17ms/step
1/1	[=====]	- 0s 18ms/step
1/1	[=====]	- 0s 16ms/step
1/1	[=====]	- 0s 18ms/step
1/1	[=====]	- 0s 16ms/step
1/1	[=====]	- 0s 16ms/step
1/1	[=====]	- 0s 20ms/step
1/1	[=====]	- 0s 17ms/step
1/1	[=====]	- 0s 16ms/step
1/1	[=====]	- 0s 17ms/step
1/1	[=====]	- 0s 16ms/step
1/1	[=====]	- 0s 16ms/step
1/1	[=====]	- 0s 16ms/step
1/1	[=====]	- 0s 20ms/step
1/1	[=====]	- 0s 16ms/step
1/1	[=====]	- 0s 16ms/step
1/1	[=====]	- 0s 17ms/step
1/1	[=====]	- 0s 20ms/step
1/1	[=====]	- 0s 16ms/step
1/1	[=====]	- 0s 16ms/step
1/1	[=====]	- 0s 17ms/step
1/1	[=====]	- 0s 19ms/step
1/1	[=====]	- 0s 18ms/step



Predicting Pissarro's Paintings

testPaintings(target_dir, target_Pissarro)

```

1/1 [=====] - 0s 21ms/step
1/1 [=====] - 0s 19ms/step
1/1 [=====] - 0s 16ms/step
1/1 [=====] - 0s 18ms/step
1/1 [=====] - 0s 17ms/step
1/1 [=====] - 0s 16ms/step
1/1 [=====] - 0s 16ms/step
1/1 [=====] - 0s 16ms/step
1/1 [=====] - 0s 19ms/step
1/1 [=====] - 0s 16ms/step
1/1 [=====] - 0s 19ms/step
1/1 [=====] - 0s 19ms/step
1/1 [=====] - 0s 21ms/step

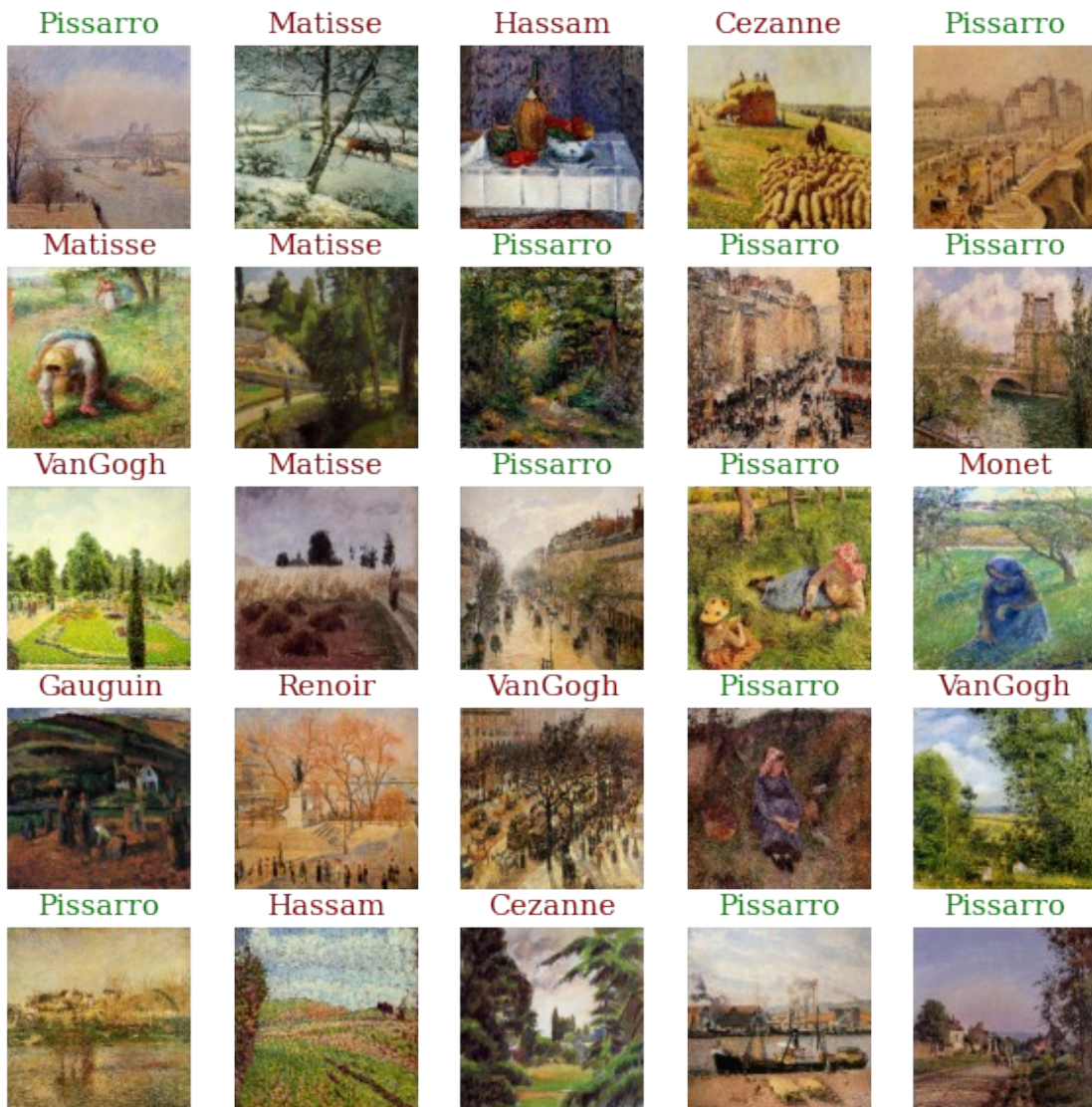
```



```

1/1 [=====] - 0s 17ms/step
1/1 [=====] - 0s 15ms/step
1/1 [=====] - 0s 16ms/step
1/1 [=====] - 0s 18ms/step
1/1 [=====] - 0s 18ms/step
1/1 [=====] - 0s 16ms/step
1/1 [=====] - 0s 16ms/step
1/1 [=====] - 0s 20ms/step
1/1 [=====] - 0s 15ms/step
1/1 [=====] - 0s 17ms/step
1/1 [=====] - 0s 20ms/step
1/1 [=====] - 0s 17ms/step

```



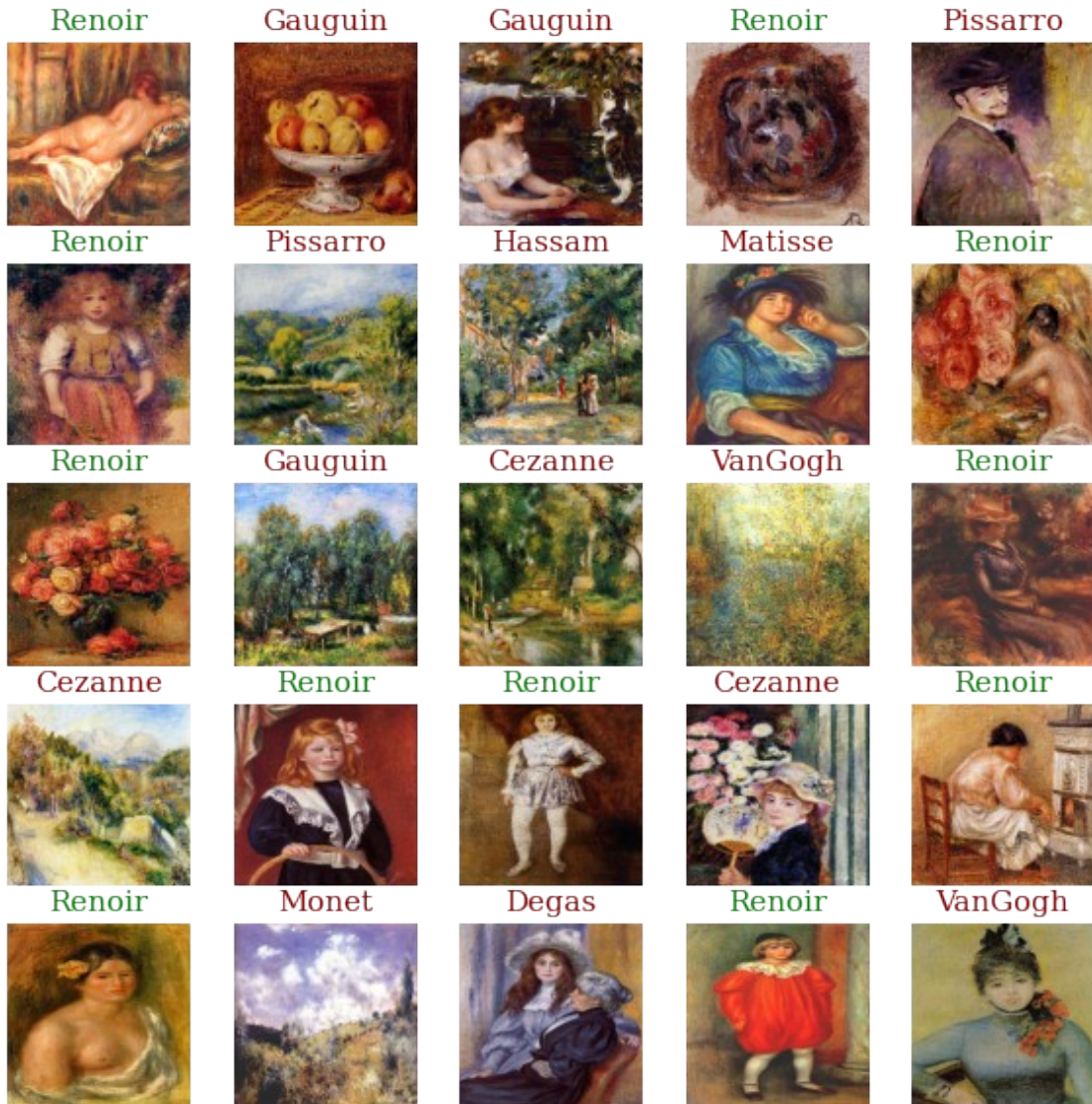
```
testPaintings(target_dir, target_Renoir)
```

```

1/1 [=====] - 0s 18ms/step
1/1 [=====] - 0s 22ms/step

```

1/1	[=====]	- 0s 16ms/step
1/1	[=====]	- 0s 17ms/step
1/1	[=====]	- 0s 16ms/step
1/1	[=====]	- 0s 16ms/step
1/1	[=====]	- 0s 19ms/step
1/1	[=====]	- 0s 19ms/step
1/1	[=====]	- 0s 16ms/step
1/1	[=====]	- 0s 18ms/step
1/1	[=====]	- 0s 17ms/step
1/1	[=====]	- 0s 19ms/step
1/1	[=====]	- 0s 16ms/step
1/1	[=====]	- 0s 16ms/step
1/1	[=====]	- 0s 16ms/step
1/1	[=====]	- 0s 19ms/step
1/1	[=====]	- 0s 16ms/step
1/1	[=====]	- 0s 17ms/step
1/1	[=====]	- 0s 17ms/step
1/1	[=====]	- 0s 19ms/step
1/1	[=====]	- 0s 16ms/step
1/1	[=====]	- 0s 19ms/step
1/1	[=====]	- 0s 31ms/step
1/1	[=====]	- 0s 17ms/step
1/1	[=====]	- 0s 22ms/step



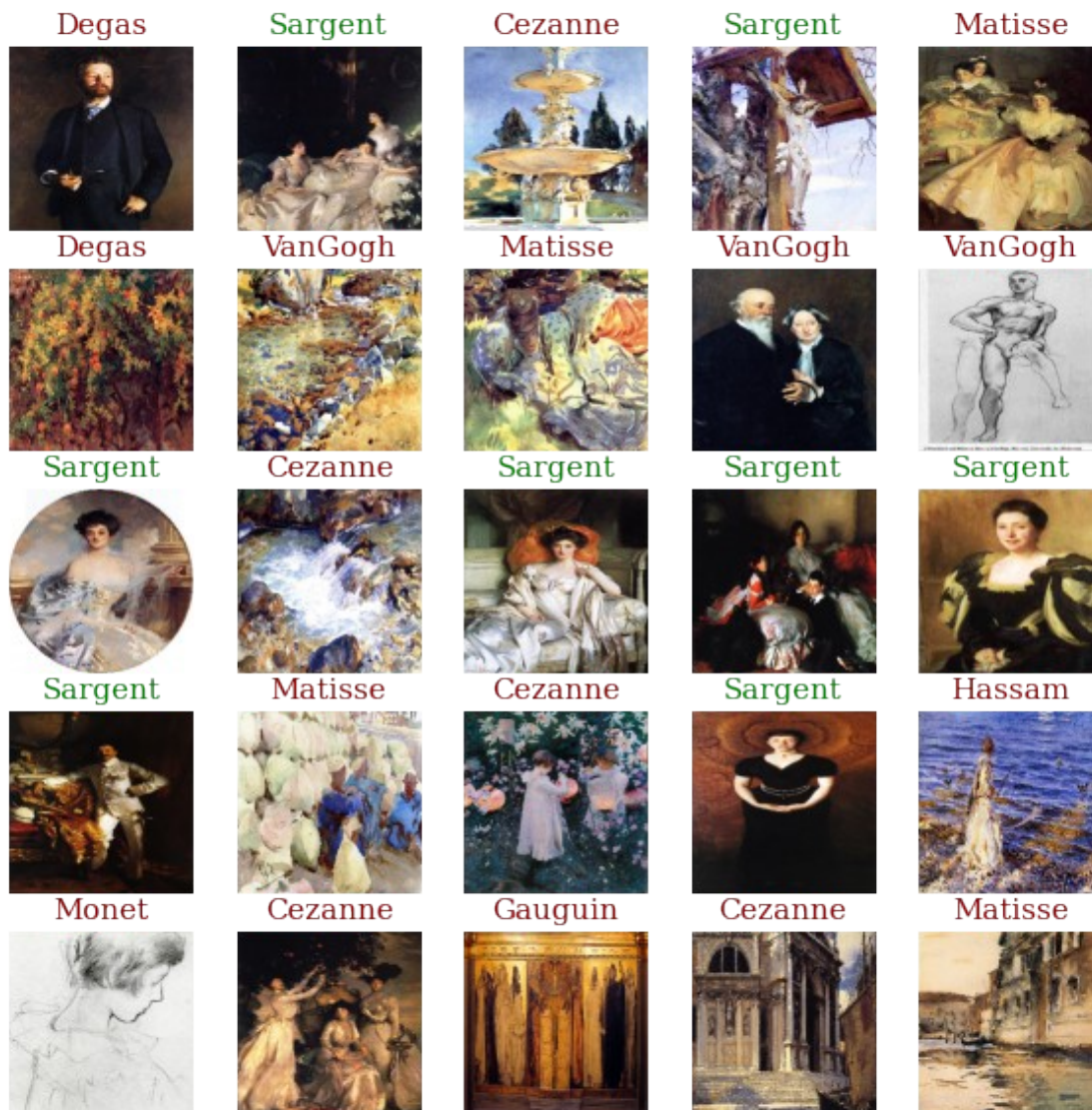
testPaintings(target_dir, target_Sargent)

```

1/1 [=====] - 0s 17ms/step
1/1 [=====] - 0s 17ms/step
1/1 [=====] - 0s 20ms/step
1/1 [=====] - 0s 17ms/step
1/1 [=====] - 0s 15ms/step
1/1 [=====] - 0s 16ms/step
1/1 [=====] - 0s 17ms/step
1/1 [=====] - 0s 16ms/step
1/1 [=====] - 0s 15ms/step
1/1 [=====] - 0s 16ms/step
1/1 [=====] - 0s 18ms/step
1/1 [=====] - 0s 17ms/step
1/1 [=====] - 0s 16ms/step
1/1 [=====] - 0s 16ms/step

```


1/1 [=====] - 0s 20ms/step
 1/1 [=====] - 0s 19ms/step
 1/1 [=====] - 0s 18ms/step
 1/1 [=====] - 0s 16ms/step
 1/1 [=====] - 0s 19ms/step
 1/1 [=====] - 0s 16ms/step
 1/1 [=====] - 0s 17ms/step
 1/1 [=====] - 0s 16ms/step
 1/1 [=====] - 0s 18ms/step
 1/1 [=====] - 0s 18ms/step
 1/1 [=====] - 0s 16ms/step



RNN Architecture Model

max_features = 10000
 maxlen = 500
 batch_size = 32

```
from tensorflow.keras.models import Sequential
```

```
modelRNN = keras.Sequential([Input(shape=(224, 224, 3)),  
modelRNN.add(layers.Embedding(max_features, 32))  
modelRNN.add(layers.SimpleRNN(32))  
modelRNN.add(layers.Dense(1, activation='sigmoid'))
```

```
modelRNN.summary()
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv2d_3 (Conv2D)	(None, 224, 224, 16)	448
max_pooling2d_3 (MaxPooling 2D)	(None, 112, 112, 16)	0
conv2d_4 (Conv2D)	(None, 112, 112, 32)	4640
max_pooling2d_4 (MaxPooling 2D)	(None, 56, 56, 32)	0
conv2d_5 (Conv2D)	(None, 56, 56, 64)	18496
max_pooling2d_5 (MaxPooling 2D)	(None, 28, 28, 64)	0
flatten_1 (Flatten)	(None, 50176)	0
dense_2 (Dense)	(None, 128)	6422656
dense_3 (Dense)	(None, 10)	1290
embedding (Embedding)	(None, 10, 32)	320000
simple_rnn (SimpleRNN)	(None, 32)	2080
dense_4 (Dense)	(None, 1)	33

```
=====  
Total params: 6,769,643  
Trainable params: 6,769,643  
Non-trainable params: 0
```

```
=====  
modelRNN.compile(optimizer='rmsprop',  
                  loss='binary_crossentropy',  
                  metrics=['accuracy'])
```



```

historyRNN = modelRNN.fit(
    training_set,
    validation_data=test_set,
    epochs= 10,
    steps_per_epoch=len(training_set),
    validation_steps=len(test_set)
)

```

Epoch 1/10

```

WARNING:tensorflow:Gradients do not exist for variables
['conv2d_3/kernel:0', 'conv2d_3/bias:0', 'conv2d_4/kernel:0',
'conv2d_4/bias:0', 'conv2d_5/kernel:0', 'conv2d_5/bias:0',
'dense_2/kernel:0', 'dense_2/bias:0', 'dense_3/kernel:0',
'dense_3/bias:0'] when minimizing the loss. If you're using
`model.compile()`, did you forget to provide a `loss` argument?
WARNING:tensorflow:Gradients do not exist for variables
['conv2d_3/kernel:0', 'conv2d_3/bias:0', 'conv2d_4/kernel:0',
'conv2d_4/bias:0', 'conv2d_5/kernel:0', 'conv2d_5/bias:0',
'dense_2/kernel:0', 'dense_2/bias:0', 'dense_3/kernel:0',
'dense_3/bias:0'] when minimizing the loss. If you're using
`model.compile()`, did you forget to provide a `loss` argument?

```

```

125/125 [=====] - 1531s 12s/step - loss:
0.3339 - accuracy: 0.9000 - val_loss: 0.3252 - val_accuracy: 0.9000

```

Epoch 2/10

```

123/125 [=====>.] - ETA: 3s - loss: 0.3252 -
accuracy: 0.9000

```

```

acc = historyRNN.history['accuracy']
val_acc = historyRNN.history['val_accuracy']

```

```

loss = historyRNN.history['loss']
val_loss = historyRNN.history['val_loss']

```

```

epochs_range = range(10)

```

```

plt.figure(figsize=(8, 8))
plt.subplot(1, 2, 1)
plt.plot(epochs_range, acc, label='Training Accuracy')
plt.plot(epochs_range, val_acc, label='Validation Accuracy')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy')

```

```

plt.subplot(1, 2, 2)
plt.plot(epochs_range, loss, label='Training Loss')
plt.plot(epochs_range, val_loss, label='Validation Loss')
plt.legend(loc='upper right')
plt.title('Training and Validation Loss')
plt.show()

```

```

-----
NameError                                Traceback (most recent call
last)
<ipython-input-1-0ffab28fb573> in <module>
----> 1 acc = history.history['accuracy']
      2 val_acc = history.history['val_accuracy']
      3
      4 loss = history.history['loss']
      5 val_loss = history.history['val_loss']

```

NameError: name 'history' is not defined

Using Inception v3 Architecture

Using a pretrained model was trained on a large dataset, and can save time and energy. This model can serve as a general model for the visual world, and can be used as learned feature maps without starting from scratch for models we decide to train on later.

Instructions on how to apply Inception v3 and preprocessing were referenced using this tutorial: <https://www.youtube.com/watch?v=chQNuV9B-Rw&t=837s>

Here we import the Inception V3 Library, adding preprocessing layer to the front.

```
inception = InceptionV3(input_shape=image_size + [3],
weights='imagenet', include_top=False)
```

```

Downloading data from https://storage.googleapis.com/tensorflow/keras-
applications/inception_v3/
inception_v3_weights_tf_dim_ordering_tf_kernels_notop.h5
87910968/87910968 [=====] - 1s 0us/step

```

```

# don't train existing weights
for layer in inception.layers:
    layer.trainable = False

```

```
x = Flatten()(inception.output)
```

Need 10, since we have 10 classes.

```
prediction = Dense(10, activation='softmax')(x)
```

```

# create a model object
model = Model(inputs=inception.input, outputs=prediction)

```

```

# view the structure of the model
model.summary()

```

```
Model: "model"
```

Layer (type)	Output Shape	Param #
--------------	--------------	---------

Connected to

=====

input_1 (InputLayer) [(None, 224, 224, 3 0 [])
)]

conv2d_6 (Conv2D) (None, 111, 111, 32 864
['input_1[0][0]']
)

batch_normalization (BatchNorm (None, 111, 111, 32 96
['conv2d_6[0][0]']
alization)
)

activation (Activation) (None, 111, 111, 32 0
['batch_normalization[0][0]']
)

conv2d_7 (Conv2D) (None, 109, 109, 32 9216
['activation[0][0]']
)

batch_normalization_1 (BatchNo (None, 109, 109, 32 96
['conv2d_7[0][0]']
rmalization)
)

activation_1 (Activation) (None, 109, 109, 32 0
['batch_normalization_1[0][0]']
)

conv2d_8 (Conv2D) (None, 109, 109, 64 18432
['activation_1[0][0]']
)

```
batch_normalization_2 (BatchNormaliz (None, 109, 109, 64) 192
['conv2d_8[0][0]']
rmalization)
)
```

```
activation_2 (Activation) (None, 109, 109, 64) 0
['batch_normalization_2[0][0]']
)
```

```
max_pooling2d_6 (MaxPooling2D) (None, 54, 54, 64) 0
['activation_2[0][0]']
```

```
conv2d_9 (Conv2D) (None, 54, 54, 80) 5120
['max_pooling2d_6[0][0]']
```

```
batch_normalization_3 (BatchNormaliz (None, 54, 54, 80) 240
['conv2d_9[0][0]']
rmalization)
```

```
activation_3 (Activation) (None, 54, 54, 80) 0
['batch_normalization_3[0][0]']
```

```
conv2d_10 (Conv2D) (None, 52, 52, 192) 138240
['activation_3[0][0]']
```

```
batch_normalization_4 (BatchNormaliz (None, 52, 52, 192) 576
['conv2d_10[0][0]']
rmalization)
```

```
activation_4 (Activation) (None, 52, 52, 192) 0
['batch_normalization_4[0][0]']
```

```
max_pooling2d_7 (MaxPooling2D) (None, 25, 25, 192) 0
```

['activation_4[0][0]']

conv2d_14 (Conv2D) (None, 25, 25, 64) 12288
['max_pooling2d_7[0][0]']

batch_normalization_8 (BatchNormaliza (None, 25, 25, 64) 192
['conv2d_14[0][0]']
tization)

activation_8 (Activation) (None, 25, 25, 64) 0
['batch_normalization_8[0][0]']

conv2d_12 (Conv2D) (None, 25, 25, 48) 9216
['max_pooling2d_7[0][0]']

conv2d_15 (Conv2D) (None, 25, 25, 96) 55296
['activation_8[0][0]']

batch_normalization_6 (BatchNormaliza (None, 25, 25, 48) 144
['conv2d_12[0][0]']
tization)

batch_normalization_9 (BatchNormaliza (None, 25, 25, 96) 288
['conv2d_15[0][0]']
tization)

activation_6 (Activation) (None, 25, 25, 48) 0
['batch_normalization_6[0][0]']

activation_9 (Activation) (None, 25, 25, 96) 0
['batch_normalization_9[0][0]']

average_pooling2d (AveragePooling2D) (None, 25, 25, 192) 0
['max_pooling2d_7[0][0]']
ing2D)

conv2d_11 (Conv2D) ['max_pooling2d_7[0][0]']	(None, 25, 25, 64)	12288
conv2d_13 (Conv2D) ['activation_6[0][0]']	(None, 25, 25, 64)	76800
conv2d_16 (Conv2D) ['activation_9[0][0]']	(None, 25, 25, 96)	82944
conv2d_17 (Conv2D) ['average_pooling2d[0][0]']	(None, 25, 25, 32)	6144
batch_normalization_5 (BatchNormal- ization) ['conv2d_11[0][0]']	(None, 25, 25, 64)	192
batch_normalization_7 (BatchNormal- ization) ['conv2d_13[0][0]']	(None, 25, 25, 64)	192
batch_normalization_10 (BatchNormal- ization) ['conv2d_16[0][0]']	(None, 25, 25, 96)	288
batch_normalization_11 (BatchNormal- ization) ['conv2d_17[0][0]']	(None, 25, 25, 32)	96
activation_5 (Activation) ['batch_normalization_5[0][0]']	(None, 25, 25, 64)	0
activation_7 (Activation)	(None, 25, 25, 64)	0

['batch_normalization_7[0][0]']

activation_10 (Activation) (None, 25, 25, 96) 0
['batch_normalization_10[0][0]']

activation_11 (Activation) (None, 25, 25, 32) 0
['batch_normalization_11[0][0]']

mixed0 (Concatenate) (None, 25, 25, 256) 0
['activation_5[0][0]',
'activation_7[0][0]',
'activation_10[0][0]',
'activation_11[0][0]']

conv2d_21 (Conv2D) (None, 25, 25, 64) 16384
['mixed0[0][0]']

batch_normalization_15 (Batch Normalization) (None, 25, 25, 64) 192
['conv2d_21[0][0]']

activation_15 (Activation) (None, 25, 25, 64) 0
['batch_normalization_15[0][0]']

conv2d_19 (Conv2D) (None, 25, 25, 48) 12288
['mixed0[0][0]']

conv2d_22 (Conv2D) (None, 25, 25, 96) 55296
['activation_15[0][0]']

batch_normalization_13 (Batch Normalization) (None, 25, 25, 48) 144
['conv2d_19[0][0]']

batch_normalization_16 (BatchN (None, 25, 25, 96) 288
['conv2d_22[0][0]']
ormalization)

activation_13 (Activation) (None, 25, 25, 48) 0
['batch_normalization_13[0][0]']

activation_16 (Activation) (None, 25, 25, 96) 0
['batch_normalization_16[0][0]']

average_pooling2d_1 (AveragePo (None, 25, 25, 256) 0
['mixed0[0][0]']
oling2D)

conv2d_18 (Conv2D) (None, 25, 25, 64) 16384
['mixed0[0][0]']

conv2d_20 (Conv2D) (None, 25, 25, 64) 76800
['activation_13[0][0]']

conv2d_23 (Conv2D) (None, 25, 25, 96) 82944
['activation_16[0][0]']

conv2d_24 (Conv2D) (None, 25, 25, 64) 16384
['average_pooling2d_1[0][0]']

batch_normalization_12 (BatchN (None, 25, 25, 64) 192
['conv2d_18[0][0]']
ormalization)

batch_normalization_14 (BatchN (None, 25, 25, 64) 192
['conv2d_20[0][0]']
ormalization)

batch_normalization_17 (BatchN (None, 25, 25, 96) 288
['conv2d_23[0][0]']
ormalization)

batch_normalization_18 (BatchN (None, 25, 25, 64) 192
['conv2d_24[0][0]']
ormalization)

activation_12 (Activation) (None, 25, 25, 64) 0
['batch_normalization_12[0][0]']

activation_14 (Activation) (None, 25, 25, 64) 0
['batch_normalization_14[0][0]']

activation_17 (Activation) (None, 25, 25, 96) 0
['batch_normalization_17[0][0]']

activation_18 (Activation) (None, 25, 25, 64) 0
['batch_normalization_18[0][0]']

mixed1 (Concatenate) (None, 25, 25, 288) 0
['activation_12[0][0]',
'activation_14[0][0]',
'activation_17[0][0]',
'activation_18[0][0]']

conv2d_28 (Conv2D) (None, 25, 25, 64) 18432
['mixed1[0][0]']

batch_normalization_22 (BatchN (None, 25, 25, 64) 192
['conv2d_28[0][0]']
ormalization)

activation_22 (Activation) ['batch_normalization_22[0][0]']	(None, 25, 25, 64)	0
conv2d_26 (Conv2D) ['mixed1[0][0]']	(None, 25, 25, 48)	13824
conv2d_29 (Conv2D) ['activation_22[0][0]']	(None, 25, 25, 96)	55296
batch_normalization_20 (Batch Normalization) ['conv2d_26[0][0]']	(None, 25, 25, 48)	144
batch_normalization_23 (Batch Normalization) ['conv2d_29[0][0]']	(None, 25, 25, 96)	288
activation_20 (Activation) ['batch_normalization_20[0][0]']	(None, 25, 25, 48)	0
activation_23 (Activation) ['batch_normalization_23[0][0]']	(None, 25, 25, 96)	0
average_pooling2d_2 (Average Pooling2D) ['mixed1[0][0]']	(None, 25, 25, 288)	0
conv2d_25 (Conv2D) ['mixed1[0][0]']	(None, 25, 25, 64)	18432
conv2d_27 (Conv2D) ['activation_20[0][0]']	(None, 25, 25, 64)	76800
conv2d_30 (Conv2D)	(None, 25, 25, 96)	82944

['activation_23[0][0]']

conv2d_31 (Conv2D) (None, 25, 25, 64) 18432
['average_pooling2d_2[0][0]']

batch_normalization_19 (BatchN (None, 25, 25, 64) 192
['conv2d_25[0][0]']
ormalization)

batch_normalization_21 (BatchN (None, 25, 25, 64) 192
['conv2d_27[0][0]']
ormalization)

batch_normalization_24 (BatchN (None, 25, 25, 96) 288
['conv2d_30[0][0]']
ormalization)

batch_normalization_25 (BatchN (None, 25, 25, 64) 192
['conv2d_31[0][0]']
ormalization)

activation_19 (Activation) (None, 25, 25, 64) 0
['batch_normalization_19[0][0]']

activation_21 (Activation) (None, 25, 25, 64) 0
['batch_normalization_21[0][0]']

activation_24 (Activation) (None, 25, 25, 96) 0
['batch_normalization_24[0][0]']

activation_25 (Activation) (None, 25, 25, 64) 0
['batch_normalization_25[0][0]']

mixed2 (Concatenate) (None, 25, 25, 288) 0

```
['activation_19[0][0]',  
'activation_21[0][0]',  
'activation_24[0][0]',  
'activation_25[0][0]']
```

```
conv2d_33 (Conv2D)          (None, 25, 25, 64)    18432  
['mixed2[0][0]']
```

```
batch_normalization_27 (BatchN (None, 25, 25, 64)    192  
['conv2d_33[0][0]']  
ormalization)
```

```
activation_27 (Activation)    (None, 25, 25, 64)    0  
['batch_normalization_27[0][0]']
```

```
conv2d_34 (Conv2D)          (None, 25, 25, 96)    55296  
['activation_27[0][0]']
```

```
batch_normalization_28 (BatchN (None, 25, 25, 96)    288  
['conv2d_34[0][0]']  
ormalization)
```

```
activation_28 (Activation)    (None, 25, 25, 96)    0  
['batch_normalization_28[0][0]']
```

```
conv2d_32 (Conv2D)          (None, 12, 12, 384)   995328  
['mixed2[0][0]']
```

```
conv2d_35 (Conv2D)          (None, 12, 12, 96)    82944  
['activation_28[0][0]']
```

```
batch_normalization_26 (BatchN (None, 12, 12, 384)   1152  
['conv2d_32[0][0]']  
ormalization)
```


batch_normalization_29 (Batch Normalization) (None, 12, 12, 96) 288
['conv2d_35[0][0]']

activation_26 (Activation) (None, 12, 12, 384) 0
['batch_normalization_26[0][0]']

activation_29 (Activation) (None, 12, 12, 96) 0
['batch_normalization_29[0][0]']

max_pooling2d_8 (MaxPooling2D) (None, 12, 12, 288) 0
['mixed2[0][0]']

mixed3 (Concatenate) (None, 12, 12, 768) 0
['activation_26[0][0]',
'activation_29[0][0]',
'max_pooling2d_8[0][0]']

conv2d_40 (Conv2D) (None, 12, 12, 128) 98304
['mixed3[0][0]']

batch_normalization_34 (Batch Normalization) (None, 12, 12, 128) 384
['conv2d_40[0][0]']

activation_34 (Activation) (None, 12, 12, 128) 0
['batch_normalization_34[0][0]']

conv2d_41 (Conv2D) (None, 12, 12, 128) 114688
['activation_34[0][0]']

batch_normalization_35 (Batch Normalization) (None, 12, 12, 128) 384

['conv2d_41[0][0]']
ormalization)

activation_35 (Activation) (None, 12, 12, 128) 0
['batch_normalization_35[0][0]']

conv2d_37 (Conv2D) (None, 12, 12, 128) 98304
['mixed3[0][0]']

conv2d_42 (Conv2D) (None, 12, 12, 128) 114688
['activation_35[0][0]']

batch_normalization_31 (BatchN (None, 12, 12, 128) 384
['conv2d_37[0][0]']
ormalization)

batch_normalization_36 (BatchN (None, 12, 12, 128) 384
['conv2d_42[0][0]']
ormalization)

activation_31 (Activation) (None, 12, 12, 128) 0
['batch_normalization_31[0][0]']

activation_36 (Activation) (None, 12, 12, 128) 0
['batch_normalization_36[0][0]']

conv2d_38 (Conv2D) (None, 12, 12, 128) 114688
['activation_31[0][0]']

conv2d_43 (Conv2D) (None, 12, 12, 128) 114688
['activation_36[0][0]']

batch_normalization_32 (BatchN (None, 12, 12, 128) 384
['conv2d_38[0][0]']
ormalization)

batch_normalization_37 (BatchN (None, 12, 12, 128) 384
['conv2d_43[0][0]']
ormalization)

activation_32 (Activation) (None, 12, 12, 128) 0
['batch_normalization_32[0][0]']

activation_37 (Activation) (None, 12, 12, 128) 0
['batch_normalization_37[0][0]']

average_pooling2d_3 (AveragePo (None, 12, 12, 768) 0
['mixed3[0][0]']
oling2D)

conv2d_36 (Conv2D) (None, 12, 12, 192) 147456
['mixed3[0][0]']

conv2d_39 (Conv2D) (None, 12, 12, 192) 172032
['activation_32[0][0]']

conv2d_44 (Conv2D) (None, 12, 12, 192) 172032
['activation_37[0][0]']

conv2d_45 (Conv2D) (None, 12, 12, 192) 147456
['average_pooling2d_3[0][0]']

batch_normalization_30 (BatchN (None, 12, 12, 192) 576
['conv2d_36[0][0]']
ormalization)

batch_normalization_33 (BatchN (None, 12, 12, 192) 576
['conv2d_39[0][0]']
ormalization)

batch_normalization_38 (Batch Normalization) (None, 12, 12, 192) 576
['conv2d_44[0][0]']

batch_normalization_39 (Batch Normalization) (None, 12, 12, 192) 576
['conv2d_45[0][0]']

activation_30 (Activation) (None, 12, 12, 192) 0
['batch_normalization_30[0][0]']

activation_33 (Activation) (None, 12, 12, 192) 0
['batch_normalization_33[0][0]']

activation_38 (Activation) (None, 12, 12, 192) 0
['batch_normalization_38[0][0]']

activation_39 (Activation) (None, 12, 12, 192) 0
['batch_normalization_39[0][0]']

mixed4 (Concatenate) (None, 12, 12, 768) 0
['activation_30[0][0]',
'activation_33[0][0]',
'activation_38[0][0]',
'activation_39[0][0]']

conv2d_50 (Conv2D) (None, 12, 12, 160) 122880
['mixed4[0][0]']

batch_normalization_44 (Batch Normalization) (None, 12, 12, 160) 480
['conv2d_50[0][0]']

activation_44 (Activation) (None, 12, 12, 160) 0
['batch_normalization_44[0][0]']

conv2d_51 (Conv2D) (None, 12, 12, 160) 179200
['activation_44[0][0]']

batch_normalization_45 (BatchN (None, 12, 12, 160) 480
['conv2d_51[0][0]']
ormalization)

activation_45 (Activation) (None, 12, 12, 160) 0
['batch_normalization_45[0][0]']

conv2d_47 (Conv2D) (None, 12, 12, 160) 122880
['mixed4[0][0]']

conv2d_52 (Conv2D) (None, 12, 12, 160) 179200
['activation_45[0][0]']

batch_normalization_41 (BatchN (None, 12, 12, 160) 480
['conv2d_47[0][0]']
ormalization)

batch_normalization_46 (BatchN (None, 12, 12, 160) 480
['conv2d_52[0][0]']
ormalization)

activation_41 (Activation) (None, 12, 12, 160) 0
['batch_normalization_41[0][0]']

activation_46 (Activation) (None, 12, 12, 160) 0
['batch_normalization_46[0][0]']

conv2d_48 (Conv2D) (None, 12, 12, 160) 179200
['activation_41[0][0]']

conv2d_53 (Conv2D) (None, 12, 12, 160) 179200
['activation_46[0][0]']

batch_normalization_42 (BatchN (None, 12, 12, 160) 480
['conv2d_48[0][0]']
ormalization)

batch_normalization_47 (BatchN (None, 12, 12, 160) 480
['conv2d_53[0][0]']
ormalization)

activation_42 (Activation) (None, 12, 12, 160) 0
['batch_normalization_42[0][0]']

activation_47 (Activation) (None, 12, 12, 160) 0
['batch_normalization_47[0][0]']

average_pooling2d_4 (AveragePo (None, 12, 12, 768) 0
['mixed4[0][0]']
oling2D)

conv2d_46 (Conv2D) (None, 12, 12, 192) 147456
['mixed4[0][0]']

conv2d_49 (Conv2D) (None, 12, 12, 192) 215040
['activation_42[0][0]']

conv2d_54 (Conv2D) (None, 12, 12, 192) 215040
['activation_47[0][0]']

conv2d_55 (Conv2D) (None, 12, 12, 192) 147456

['average_pooling2d_4[0][0]']

batch_normalization_40 (BatchN (None, 12, 12, 192) 576
['conv2d_46[0][0]']
ormalization)

batch_normalization_43 (BatchN (None, 12, 12, 192) 576
['conv2d_49[0][0]']
ormalization)

batch_normalization_48 (BatchN (None, 12, 12, 192) 576
['conv2d_54[0][0]']
ormalization)

batch_normalization_49 (BatchN (None, 12, 12, 192) 576
['conv2d_55[0][0]']
ormalization)

activation_40 (Activation) (None, 12, 12, 192) 0
['batch_normalization_40[0][0]']

activation_43 (Activation) (None, 12, 12, 192) 0
['batch_normalization_43[0][0]']

activation_48 (Activation) (None, 12, 12, 192) 0
['batch_normalization_48[0][0]']

activation_49 (Activation) (None, 12, 12, 192) 0
['batch_normalization_49[0][0]']

mixed5 (Concatenate) (None, 12, 12, 768) 0
['activation_40[0][0]',

'activation_43[0][0]',

'activation_48[0][0]',

'activation_49[0][0]']

conv2d_60 (Conv2D) (None, 12, 12, 160) 122880
['mixed5[0][0]']

batch_normalization_54 (BatchN (None, 12, 12, 160) 480
['conv2d_60[0][0]']
ormalization)

activation_54 (Activation) (None, 12, 12, 160) 0
['batch_normalization_54[0][0]']

conv2d_61 (Conv2D) (None, 12, 12, 160) 179200
['activation_54[0][0]']

batch_normalization_55 (BatchN (None, 12, 12, 160) 480
['conv2d_61[0][0]']
ormalization)

activation_55 (Activation) (None, 12, 12, 160) 0
['batch_normalization_55[0][0]']

conv2d_57 (Conv2D) (None, 12, 12, 160) 122880
['mixed5[0][0]']

conv2d_62 (Conv2D) (None, 12, 12, 160) 179200
['activation_55[0][0]']

batch_normalization_51 (BatchN (None, 12, 12, 160) 480
['conv2d_57[0][0]']
ormalization)

batch_normalization_56 (BatchN (None, 12, 12, 160) 480

['conv2d_62[0][0]']
ormalization)

activation_51 (Activation) (None, 12, 12, 160) 0
['batch_normalization_51[0][0]']

activation_56 (Activation) (None, 12, 12, 160) 0
['batch_normalization_56[0][0]']

conv2d_58 (Conv2D) (None, 12, 12, 160) 179200
['activation_51[0][0]']

conv2d_63 (Conv2D) (None, 12, 12, 160) 179200
['activation_56[0][0]']

batch_normalization_52 (BatchN (None, 12, 12, 160) 480
['conv2d_58[0][0]']
ormalization)

batch_normalization_57 (BatchN (None, 12, 12, 160) 480
['conv2d_63[0][0]']
ormalization)

activation_52 (Activation) (None, 12, 12, 160) 0
['batch_normalization_52[0][0]']

activation_57 (Activation) (None, 12, 12, 160) 0
['batch_normalization_57[0][0]']

average_pooling2d_5 (AveragePo (None, 12, 12, 768) 0
['mixed5[0][0]']
oling2D)

conv2d_56 (Conv2D) (None, 12, 12, 192) 147456

['mixed5[0][0]']

conv2d_59 (Conv2D) (None, 12, 12, 192) 215040
['activation_52[0][0]']

conv2d_64 (Conv2D) (None, 12, 12, 192) 215040
['activation_57[0][0]']

conv2d_65 (Conv2D) (None, 12, 12, 192) 147456
['average_pooling2d_5[0][0]']

batch_normalization_50 (Batch Normalization) (None, 12, 12, 192) 576
['conv2d_56[0][0]']

batch_normalization_53 (Batch Normalization) (None, 12, 12, 192) 576
['conv2d_59[0][0]']

batch_normalization_58 (Batch Normalization) (None, 12, 12, 192) 576
['conv2d_64[0][0]']

batch_normalization_59 (Batch Normalization) (None, 12, 12, 192) 576
['conv2d_65[0][0]']

activation_50 (Activation) (None, 12, 12, 192) 0
['batch_normalization_50[0][0]']

activation_53 (Activation) (None, 12, 12, 192) 0
['batch_normalization_53[0][0]']

activation_58 (Activation) (None, 12, 12, 192) 0

['batch_normalization_58[0][0]']

activation_59 (Activation) (None, 12, 12, 192) 0
['batch_normalization_59[0][0]']

mixed6 (Concatenate) (None, 12, 12, 768) 0
['activation_50[0][0]',

'activation_53[0][0]',

'activation_58[0][0]',

'activation_59[0][0]']

conv2d_70 (Conv2D) (None, 12, 12, 192) 147456
['mixed6[0][0]']

batch_normalization_64 (Batch Normalization) (None, 12, 12, 192) 576
['conv2d_70[0][0]']

activation_64 (Activation) (None, 12, 12, 192) 0
['batch_normalization_64[0][0]']

conv2d_71 (Conv2D) (None, 12, 12, 192) 258048
['activation_64[0][0]']

batch_normalization_65 (Batch Normalization) (None, 12, 12, 192) 576
['conv2d_71[0][0]']

activation_65 (Activation) (None, 12, 12, 192) 0
['batch_normalization_65[0][0]']

conv2d_67 (Conv2D) (None, 12, 12, 192) 147456
['mixed6[0][0]']

conv2d_72 (Conv2D) (None, 12, 12, 192) 258048
['activation_65[0][0]']

batch_normalization_61 (BatchN (None, 12, 12, 192) 576
['conv2d_67[0][0]']
ormalization)

batch_normalization_66 (BatchN (None, 12, 12, 192) 576
['conv2d_72[0][0]']
ormalization)

activation_61 (Activation) (None, 12, 12, 192) 0
['batch_normalization_61[0][0]']

activation_66 (Activation) (None, 12, 12, 192) 0
['batch_normalization_66[0][0]']

conv2d_68 (Conv2D) (None, 12, 12, 192) 258048
['activation_61[0][0]']

conv2d_73 (Conv2D) (None, 12, 12, 192) 258048
['activation_66[0][0]']

batch_normalization_62 (BatchN (None, 12, 12, 192) 576
['conv2d_68[0][0]']
ormalization)

batch_normalization_67 (BatchN (None, 12, 12, 192) 576
['conv2d_73[0][0]']
ormalization)

activation_62 (Activation) (None, 12, 12, 192) 0
['batch_normalization_62[0][0]']

```

activation_67 (Activation)      (None, 12, 12, 192)  0
['batch_normalization_67[0][0]']

average_pooling2d_6 (AveragePo (None, 12, 12, 768)  0
['mixed6[0][0]']
oling2D)

conv2d_66 (Conv2D)              (None, 12, 12, 192)  147456
['mixed6[0][0]']

conv2d_69 (Conv2D)              (None, 12, 12, 192)  258048
['activation_62[0][0]']

conv2d_74 (Conv2D)              (None, 12, 12, 192)  258048
['activation_67[0][0]']

conv2d_75 (Conv2D)              (None, 12, 12, 192)  147456
['average_pooling2d_6[0][0]']

batch_normalization_60 (BatchN (None, 12, 12, 192)  576
['conv2d_66[0][0]']
ormalization)

batch_normalization_63 (BatchN (None, 12, 12, 192)  576
['conv2d_69[0][0]']
ormalization)

batch_normalization_68 (BatchN (None, 12, 12, 192)  576
['conv2d_74[0][0]']
ormalization)

batch_normalization_69 (BatchN (None, 12, 12, 192)  576
['conv2d_75[0][0]']
ormalization)

```

activation_60 (Activation) (None, 12, 12, 192) 0
['batch_normalization_60[0][0]']

activation_63 (Activation) (None, 12, 12, 192) 0
['batch_normalization_63[0][0]']

activation_68 (Activation) (None, 12, 12, 192) 0
['batch_normalization_68[0][0]']

activation_69 (Activation) (None, 12, 12, 192) 0
['batch_normalization_69[0][0]']

mixed7 (Concatenate) (None, 12, 12, 768) 0
['activation_60[0][0]',
'activation_63[0][0]',
'activation_68[0][0]',
'activation_69[0][0]']

conv2d_78 (Conv2D) (None, 12, 12, 192) 147456
['mixed7[0][0]']

batch_normalization_72 (Batch Normalization) (None, 12, 12, 192) 576
['conv2d_78[0][0]']

activation_72 (Activation) (None, 12, 12, 192) 0
['batch_normalization_72[0][0]']

conv2d_79 (Conv2D) (None, 12, 12, 192) 258048
['activation_72[0][0]']

batch_normalization_73 (Batch Normalization) (None, 12, 12, 192) 576

['conv2d_79[0][0]']
ormalization)

activation_73 (Activation) (None, 12, 12, 192) 0
['batch_normalization_73[0][0]']

conv2d_76 (Conv2D) (None, 12, 12, 192) 147456
['mixed7[0][0]']

conv2d_80 (Conv2D) (None, 12, 12, 192) 258048
['activation_73[0][0]']

batch_normalization_70 (BatchN (None, 12, 12, 192) 576
['conv2d_76[0][0]']
ormalization)

batch_normalization_74 (BatchN (None, 12, 12, 192) 576
['conv2d_80[0][0]']
ormalization)

activation_70 (Activation) (None, 12, 12, 192) 0
['batch_normalization_70[0][0]']

activation_74 (Activation) (None, 12, 12, 192) 0
['batch_normalization_74[0][0]']

conv2d_77 (Conv2D) (None, 5, 5, 320) 552960
['activation_70[0][0]']

conv2d_81 (Conv2D) (None, 5, 5, 192) 331776
['activation_74[0][0]']

batch_normalization_71 (BatchN (None, 5, 5, 320) 960
['conv2d_77[0][0]']
ormalization)

batch_normalization_75 (Batch Normalization) ['conv2d_81[0][0]']	(None, 5, 5, 192)	576
activation_71 (Activation) ['batch_normalization_71[0][0]']	(None, 5, 5, 320)	0
activation_75 (Activation) ['batch_normalization_75[0][0]']	(None, 5, 5, 192)	0
max_pooling2d_9 (MaxPooling2D) ['mixed7[0][0]']	(None, 5, 5, 768)	0
mixed8 (Concatenate) ['activation_71[0][0]', 'activation_75[0][0]', 'max_pooling2d_9[0][0]']	(None, 5, 5, 1280)	0
conv2d_86 (Conv2D) ['mixed8[0][0]']	(None, 5, 5, 448)	573440
batch_normalization_80 (Batch Normalization) ['conv2d_86[0][0]']	(None, 5, 5, 448)	1344
activation_80 (Activation) ['batch_normalization_80[0][0]']	(None, 5, 5, 448)	0
conv2d_83 (Conv2D) ['mixed8[0][0]']	(None, 5, 5, 384)	491520
conv2d_87 (Conv2D)	(None, 5, 5, 384)	1548288

['activation_80[0][0]']

batch_normalization_77 (BatchN (None, 5, 5, 384) 1152
['conv2d_83[0][0]']
ormalization)

batch_normalization_81 (BatchN (None, 5, 5, 384) 1152
['conv2d_87[0][0]']
ormalization)

activation_77 (Activation) (None, 5, 5, 384) 0
['batch_normalization_77[0][0]']

activation_81 (Activation) (None, 5, 5, 384) 0
['batch_normalization_81[0][0]']

conv2d_84 (Conv2D) (None, 5, 5, 384) 442368
['activation_77[0][0]']

conv2d_85 (Conv2D) (None, 5, 5, 384) 442368
['activation_77[0][0]']

conv2d_88 (Conv2D) (None, 5, 5, 384) 442368
['activation_81[0][0]']

conv2d_89 (Conv2D) (None, 5, 5, 384) 442368
['activation_81[0][0]']

average_pooling2d_7 (AveragePo (None, 5, 5, 1280) 0
['mixed8[0][0]']
oling2D)

conv2d_82 (Conv2D) (None, 5, 5, 320) 409600
['mixed8[0][0]']

batch_normalization_78 (Batch Normalization) ['conv2d_84[0][0]']	(None, 5, 5, 384)	1152
batch_normalization_79 (Batch Normalization) ['conv2d_85[0][0]']	(None, 5, 5, 384)	1152
batch_normalization_82 (Batch Normalization) ['conv2d_88[0][0]']	(None, 5, 5, 384)	1152
batch_normalization_83 (Batch Normalization) ['conv2d_89[0][0]']	(None, 5, 5, 384)	1152
conv2d_90 (Conv2D) ['average_pooling2d_7[0][0]']	(None, 5, 5, 192)	245760
batch_normalization_76 (Batch Normalization) ['conv2d_82[0][0]']	(None, 5, 5, 320)	960
activation_78 (Activation) ['batch_normalization_78[0][0]']	(None, 5, 5, 384)	0
activation_79 (Activation) ['batch_normalization_79[0][0]']	(None, 5, 5, 384)	0
activation_82 (Activation) ['batch_normalization_82[0][0]']	(None, 5, 5, 384)	0
activation_83 (Activation)	(None, 5, 5, 384)	0

['batch_normalization_83[0][0]']

batch_normalization_84 (BatchN (None, 5, 5, 192) 576
['conv2d_90[0][0]']
ormalization)

activation_76 (Activation) (None, 5, 5, 320) 0
['batch_normalization_76[0][0]']

mixed9_0 (Concatenate) (None, 5, 5, 768) 0
['activation_78[0][0]',
'activation_79[0][0]']

concatenate (Concatenate) (None, 5, 5, 768) 0
['activation_82[0][0]',
'activation_83[0][0]']

activation_84 (Activation) (None, 5, 5, 192) 0
['batch_normalization_84[0][0]']

mixed9 (Concatenate) (None, 5, 5, 2048) 0
['activation_76[0][0]',
'mixed9_0[0][0]',
'concatenate[0][0]',
'activation_84[0][0]']

conv2d_95 (Conv2D) (None, 5, 5, 448) 917504
['mixed9[0][0]']

batch_normalization_89 (BatchN (None, 5, 5, 448) 1344
['conv2d_95[0][0]']
ormalization)

activation_89 (Activation) ['batch_normalization_89[0][0]']	(None, 5, 5, 448)	0
conv2d_92 (Conv2D) ['mixed9[0][0]']	(None, 5, 5, 384)	786432
conv2d_96 (Conv2D) ['activation_89[0][0]']	(None, 5, 5, 384)	1548288
batch_normalization_86 (Batch Normalization) ['conv2d_92[0][0]']	(None, 5, 5, 384)	1152
batch_normalization_90 (Batch Normalization) ['conv2d_96[0][0]']	(None, 5, 5, 384)	1152
activation_86 (Activation) ['batch_normalization_86[0][0]']	(None, 5, 5, 384)	0
activation_90 (Activation) ['batch_normalization_90[0][0]']	(None, 5, 5, 384)	0
conv2d_93 (Conv2D) ['activation_86[0][0]']	(None, 5, 5, 384)	442368
conv2d_94 (Conv2D) ['activation_86[0][0]']	(None, 5, 5, 384)	442368
conv2d_97 (Conv2D) ['activation_90[0][0]']	(None, 5, 5, 384)	442368
conv2d_98 (Conv2D) ['activation_90[0][0]']	(None, 5, 5, 384)	442368

average_pooling2d_8 (AveragePo ['mixed9[0][0]'] oling2D)	(None, 5, 5, 2048)	0
conv2d_91 (Conv2D) ['mixed9[0][0]']	(None, 5, 5, 320)	655360
batch_normalization_87 (BatchN ['conv2d_93[0][0]'] ormalization)	(None, 5, 5, 384)	1152
batch_normalization_88 (BatchN ['conv2d_94[0][0]'] ormalization)	(None, 5, 5, 384)	1152
batch_normalization_91 (BatchN ['conv2d_97[0][0]'] ormalization)	(None, 5, 5, 384)	1152
batch_normalization_92 (BatchN ['conv2d_98[0][0]'] ormalization)	(None, 5, 5, 384)	1152
conv2d_99 (Conv2D) ['average_pooling2d_8[0][0]']	(None, 5, 5, 192)	393216
batch_normalization_85 (BatchN ['conv2d_91[0][0]'] ormalization)	(None, 5, 5, 320)	960
activation_87 (Activation) ['batch_normalization_87[0][0]']	(None, 5, 5, 384)	0

activation_88 (Activation)	(None, 5, 5, 384)	0
['batch_normalization_88[0][0]']		
activation_91 (Activation)	(None, 5, 5, 384)	0
['batch_normalization_91[0][0]']		
activation_92 (Activation)	(None, 5, 5, 384)	0
['batch_normalization_92[0][0]']		
batch_normalization_93 (BatchN	(None, 5, 5, 192)	576
['conv2d_99[0][0]']		
ormalization)		
activation_85 (Activation)	(None, 5, 5, 320)	0
['batch_normalization_85[0][0]']		
mixed9_1 (Concatenate)	(None, 5, 5, 768)	0
['activation_87[0][0]',		
'activation_88[0][0]']		
concatenate_1 (Concatenate)	(None, 5, 5, 768)	0
['activation_91[0][0]',		
'activation_92[0][0]']		
activation_93 (Activation)	(None, 5, 5, 192)	0
['batch_normalization_93[0][0]']		
mixed10 (Concatenate)	(None, 5, 5, 2048)	0
['activation_85[0][0]',		
'mixed9_1[0][0]',		
'concatenate_1[0][0]',		
'activation_93[0][0]']		

flatten_2 (Flatten)	(None, 51200)	0
['mixed10[0][0]']		
dense_4 (Dense)	(None, 10)	512010
['flatten_2[0][0]']		

```
=====
Total params: 22,314,794
Trainable params: 512,010
Non-trainable params: 21,802,784
=====
```

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

```
#Importing images from the dataset
```

```
from tensorflow.keras.preprocessing.image import ImageDataGenerator
```

```
# Defining pre-processing transformations on raw images of training data
```

```
train_datagen = ImageDataGenerator(rescale = 1./255,
                                   shear_range = 0.2,
                                   zoom_range = 0.2,
                                   horizontal_flip = True)
```

```
# Defining pre-processing transformations on raw images of testing data
```

```
test_datagen = ImageDataGenerator(rescale = 1./255)
```

```
# Load the training set and find number of images
```

```
training_set =
train_datagen.flow_from_directory('/content/drive/MyDrive/impressionist/
t/training/training',
```

```
target_size = (224,
224),
```

```
batch_size = 32,
class_mode =
```

```
'categorical')
```

```
Found 3988 images belonging to 10 classes.
```

```
test_set =
```

```
test_datagen.flow_from_directory('/content/drive/MyDrive/impressionist
```

```
/validation/validation',
```

```
target_size = (224, 224),  
batch_size = 32,  
class_mode =
```

```
'categorical')
```

Found 990 images belonging to 10 classes.

```
r = model.fit_generator(  
    training_set,  
    validation_data=test_set,  
    epochs=10,  
    steps_per_epoch=len(training_set),  
    validation_steps=len(test_set)  
)
```

<ipython-input-41-5932e3024fde>:1: UserWarning: `Model.fit_generator` is deprecated and will be removed in a future version. Please use `Model.fit`, which supports generators.

```
    r = model.fit_generator(  
    training_set,  
    validation_data=test_set,  
    epochs=10,  
    steps_per_epoch=len(training_set),  
    validation_steps=len(test_set)  
)
```

Epoch 1/10

```
125/125 [=====] - 744s 6s/step - loss: 6.9032  
- accuracy: 0.3831 - val_loss: 4.2751 - val_accuracy: 0.4727
```

Epoch 2/10

```
125/125 [=====] - 720s 6s/step - loss: 3.4511  
- accuracy: 0.5592 - val_loss: 5.8303 - val_accuracy: 0.4697
```

Epoch 3/10

```
125/125 [=====] - 668s 5s/step - loss: 3.4942  
- accuracy: 0.5983 - val_loss: 6.3525 - val_accuracy: 0.4657
```

Epoch 4/10

```
125/125 [=====] - 670s 5s/step - loss: 3.0434  
- accuracy: 0.6457 - val_loss: 4.9889 - val_accuracy: 0.5424
```

Epoch 5/10

```
125/125 [=====] - 673s 5s/step - loss: 2.7136  
- accuracy: 0.6908 - val_loss: 5.5642 - val_accuracy: 0.5424
```

Epoch 6/10

```
125/125 [=====] - 674s 5s/step - loss: 2.7595  
- accuracy: 0.6933 - val_loss: 5.1629 - val_accuracy: 0.5556
```

Epoch 7/10

```
125/125 [=====] - 670s 5s/step - loss: 2.6889  
- accuracy: 0.7144 - val_loss: 6.9475 - val_accuracy: 0.5172
```

Epoch 8/10

```
125/125 [=====] - 680s 5s/step - loss: 2.6792  
- accuracy: 0.7332 - val_loss: 6.2279 - val_accuracy: 0.5556
```

Epoch 9/10

```
125/125 [=====] - 673s 5s/step - loss: 2.5250  
- accuracy: 0.7402 - val_loss: 7.7884 - val_accuracy: 0.5111
```

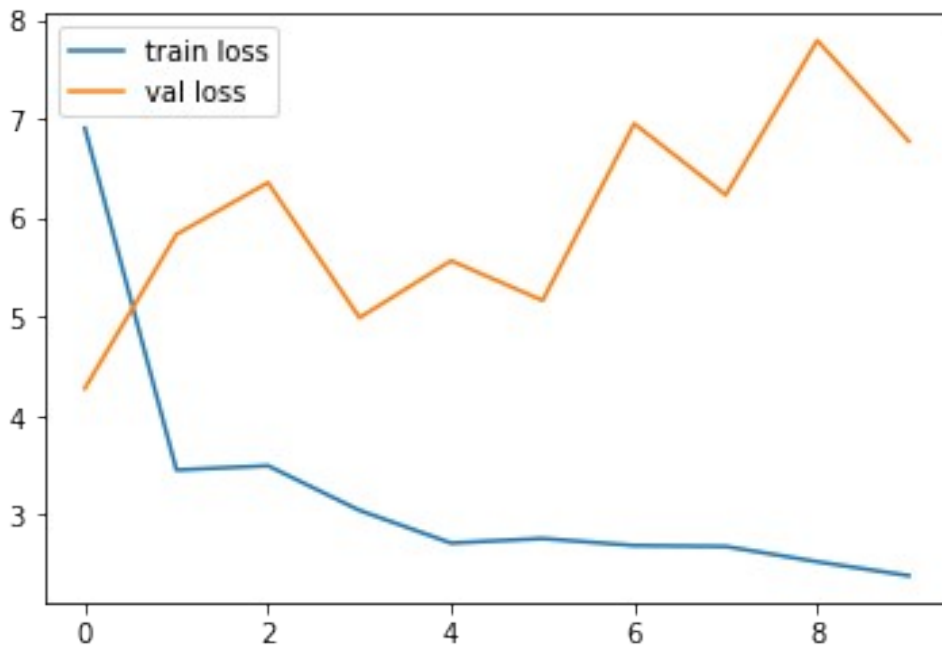
Epoch 10/10

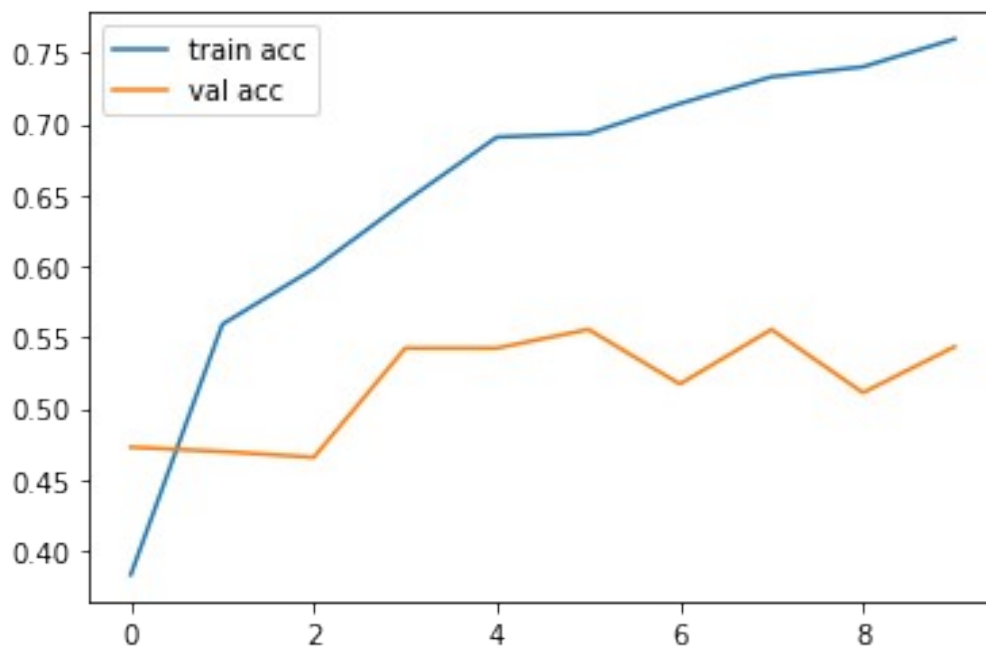
```
125/125 [=====] - 673s 5s/step - loss: 2.3841  
- accuracy: 0.7598 - val_loss: 6.7700 - val_accuracy: 0.5434
```

Plotting the Data

```
# plot the loss
plt.plot(r.history['loss'], label='train loss')
plt.plot(r.history['val_loss'], label='val loss')
plt.legend()
plt.show()
plt.savefig('LossVal_loss')

# plot the accuracy
plt.plot(r.history['accuracy'], label='train acc')
plt.plot(r.history['val_accuracy'], label='val acc')
plt.legend()
plt.show()
plt.savefig('AccVal_acc')
```





<Figure size 432x288 with 0 Axes>