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Recognizing Art Style by Using Neural Network

Youtube video: https://youtu.be/833KtiZLNxo

Project link(Github): https://github.com/Gabrielprogramist/Recognising-Art-Style-by-Using-Neural-Network

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Introduction

Nowadays, recognition of art styles has developed strongly by using neural networks. There are many works and research on this topic. Some of them use visual recognition and some trains data according to the large amount of data (dataset) to get the results. Image classification is improving and developing more and more. We can see it from there examples below:

1) AlexNet

The input of the AlexNet network is a $227 \times 227 \times 3$ matrix. Its structure is made of five

convolutional layers and three fully connected layers. ted layers. Convolutional layers have respectively filter of size 11×11, 5×5, 3×3, and 3×3 (Lecoutre et al., 2019).

2) ResNet

The ResNet has input dimensions of $224 \times 224 \times 3$. Its architecture is composed of different blocks, where each block uses a ”shortcut connection”. This shortcut connection can be a simple identity connection (id-block), or a connection with a convolutional layer (convblock). The shortcut-ed part of the block uses 3 convolutions, with various number of filters for each block (Lecoutre et al., 2019).

3) Inception-v3

Inception-v3 is a convolutional neural network architecture from the Inception family that makes several improvements including using Label Smoothing, Factorized 7 x 7 convolutions, and the use of an auxiliary classifer to propagate label information lower down the network (along with the use of batch normalization for layers in the sidehead) (Szegedy et al., 2015).

Problem or idea description

The idea is to use a neural network to analyze artpieces from WikiArts. We decided to concentrate on image classification to identify art style.

Our main goal is to create a convolutional neural network that will use the WikiArts dataset (including images, styles, tags etc), to identify some artistic information of the inputted art. We are planning to achieve higher accuracy rate in art style identification.

Dataset Preparation

We took the dataset from kaggle (Lopes). Dataset weights 13.25 GB and contains 176436 images, the CSV file contains classification by genre, movement and artist.

We downloaaded it and started to prepare it for model.

First, we look through general info of dataset.

	artist	style	genre	movement	tags	url	img	file_name	in
0	Byzantine Mosaics	Early Byzantine (c. 330–750)	religious painting	Byzantine Art	['Holyplaces', 'Byzantinearchitecture', 'Arch'...	https://www.wikiart.org/en/byzantine-mosaics/e...	https://uploads2.wikiart.org/00211/images/byza...	0-ravenna-cappella-arcivescovile-166.jpg	
1	Byzantine Mosaics	Early Byzantine (c. 330–750)	religious painting	Byzantine Art	['Holyplaces', 'Byzantinearchitecture', 'Arch']	https://www.wikiart.org/en/byzantine-mosaics/e...	https://uploads2.wikiart.org/00211/images/byza...	1-ravenna-cappella-arcivescovile-167.jpg	
2	Byzantine Mosaics	Early Byzantine (c. 330–750)	religious painting	Byzantine Art	['Prophet', 'History']	https://www.wikiart.org/en/byzantine-mosaics/e...	https://uploads2.wikiart.org/00211/images/byza...	2-ravenna-cappella-arcivescovile-168.jpg	
3	Byzantine Mosaics	Early Byzantine (c. 330–750)	religious painting	Byzantine Art	['Holyplaces', 'Prophet']	https://www.wikiart.org/en/byzantine-mosaics/e...	https://uploads2.wikiart.org/00211/images/byza...	3-ravenna-cappella-arcivescovile-169.jpg	
4	Byzantine Mosaics	Early Byzantine (c. 330–750)	religious painting	Byzantine Art	['Holyplaces', 'Prophet']	https://www.wikiart.org/en/byzantine-mosaics/e...	https://uploads2.wikiart.org/00211/images/byza...	4-ravenna-cappella-arcivescovile-171.jpg	

Picture 1. First five rows of csv file

Secondly, we identified how many styles are in the dataset and their amounts.

There were 193 styles.

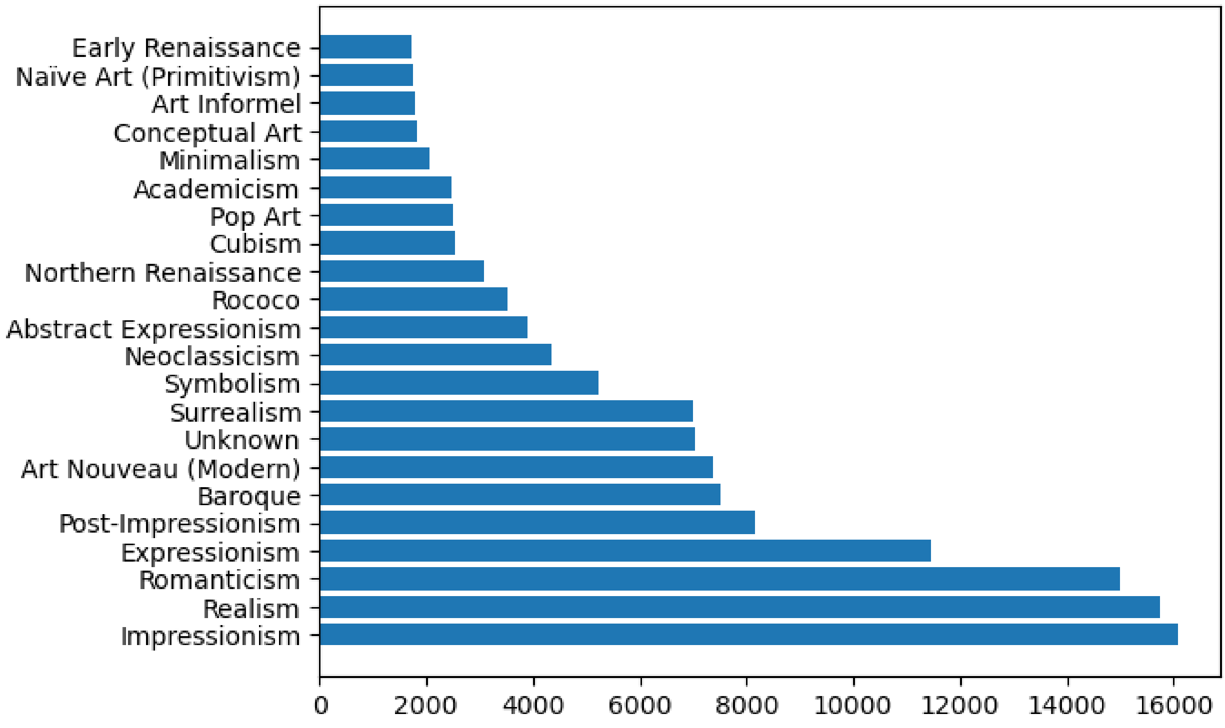
```
['Impressionism', 'Realism', 'Romanticism', 'Expressionism', 'Post-Impressionism', 'Baroque', 'Art Nouveau (Modern)', 'Unknow
n', 'Surrealism', 'Symbolism', 'Neoclassicism', 'Abstract Expressionism', 'Rococo', 'Northern Renaissance', 'Cubism', 'Pop Ar
t', 'Academicism', 'Minimalism', 'Conceptual Art', 'Art Informel', 'Naïve Art (Primitivism)', 'Early Renaissance', 'Abstract Ar
t', 'Magic Realism', 'Contemporary Realism', 'High Renaissance', 'Neo-Expressionism', 'Orientalism', 'Color Field Painting', 'O
p Art', 'Lyrical Abstraction', 'Fauvism', 'Contemporary', 'Neo-Impressionism', 'Social Realism', 'Naturalism', 'Neo-Romanticis
m', 'Kitsch', 'Post-Minimalism', 'Socialist Realism', 'Art Deco', 'Ink and wash painting', 'Tachisme', 'Neo-Dada', 'Hard Edge P
ainting', 'Regionalism', 'Pictorialism', 'Neo-Pop Art', 'Constructivism', 'Transavantgarde', 'Street art', 'Mannerism (Late Ren
aissance)', 'Tenebrism', 'Outsider art', 'Proto Renaissance', 'Feminist Art', 'Art Brut', 'Futurism', 'Biedermeier', 'Light and
Space', 'Luminism', 'Tonalism', 'New European Painting', 'Dada', 'Fantastic Realism', 'Precisionism', 'Romanesque', 'Native Ar
t', 'Divisionism', 'Concretism', 'Post-Painterly Abstraction', 'Figurative Expressionism', 'International Gothic', 'Classicis
m', 'Orphism', 'Kinetic Art', 'Synthetic Cubism', 'Neo-Figurative Art', 'Postcolonial art', 'Hyper-Realism', 'Neo-baroque', 'Me
taphysical art', 'Muralism', 'Cubo-Futurism', 'Classical Realism', 'Japonism', 'Neoplasticism', 'Pointillism', 'Cloisonnism',
'Spatialism', 'Purism', 'Digital Art', 'Ukiyo-e', 'Nouveau Réalisme', 'Modernismo', 'Documentary photography', 'Environmental
(Land) Art', 'Suprematism', 'Late Byzantine/Palaeologan Renaissance (c. 1261–1453)', 'Photorealism', 'New Realism', 'Costumbris
mo', 'Intimism', 'Confessional Art', 'Analytical Cubism', 'Early Byzantine (c. 330–750)', 'Action painting', 'Neo-Rococo', 'Str
eet Photography', 'Performance Art', 'P&D (Pattern and Decoration)', 'Neo-Concretism', 'Analytical\xa0Realism', 'Lowbrow Art',
'Neo-Minimalism', 'Mozarabic', 'Transautomatism', 'Indian Space painting', 'Stuckism', 'Macedonian Renaissance (867–1056)', 'Co
ptic art', 'Synthetism', 'Modernism', 'American Realism', 'Moscow school of icon painting', 'Fantasy Art', 'Mechanistic Cubis
m', 'Sumi-e (Suiboku-ga)', 'Automatic Painting', 'Viking art', 'Byzantine', 'Maximalism', 'Junk Art', 'Mosan art', 'Queer art',
'Neo-Suprematism', 'Poster Art Realism', 'Lettrism', 'Komnenian style (1081-1185)', 'Verism', 'Existential Art', 'New Ink Paint
ing', 'Gongbi', 'Gothic', 'Joseon Dynasty', 'Cyber Art', 'Middle Byzantine (c. 850–1204)', 'Superflat', 'Novgorod school of ico
n painting', 'Latin Empire of Constantinople (1204-1261)', 'Cartographic Art', 'Renaissance', 'Medieval Art', 'Fiber art', 'Neo
-Orthodoxism', 'Cubo-Expressionism', 'Galicia-Volyn school', 'Tubism', 'Zen', 'Neo-Byzantine', 'Mail Art', 'Hyper-Mannerism (An
achronism)', 'Synchromism', 'Neo-Geo', 'Rayonism', 'Art Singulier', 'Kyiv school of icon painting', 'Crusader workshop', 'Yaros
lavl school of icon painting', 'Yoruba', 'Sots Art', 'Cretan school of icon painting', 'Excessivism', 'Ero guro', 'New Medievia
lism', 'Severe Style', 'Miserablism', 'Site-specific art', 'Safavid Period', 'New Casualism', 'Vologda school of icon paintin
g', 'Spectralism', 'Geometric', 'Vladimir school of icon painting', 'Chernihiv school of icon painting', 'Sky Art', 'Macedonian
school of icon painting', 'Graffiti Art', 'Pskov school of icon painting', 'Shin-hanga', 'New media art', 'Stroganov school of
icon painting', 'Early Christian']
[16083, 15764, 15010, 11455, 8147, 7496, 7382, 7039, 6988, 5224, 4360, 3909, 3537, 3089, 2530, 2517, 2474, 2077, 1818, 1797, 17
54, 1729, 1729, 1614, 1599, 1565, 1559, 1337, 1318, 1155, 1142, 1106, 992, 984, 835, 807, 805, 731, 721, 715, 714, 627, 570, 56
8, 566, 555, 524, 523, 504, 487, 487, 473, 471, 451, 442, 430, 395, 389, 387, 386, 384, 382, 378, 376, 370, 353, 348, 329, 328,
323, 314, 313, 277, 257, 256, 246, 243, 243, 241, 237, 225, 218, 211, 204, 199, 193, 178, 177, 175, 168, 162, 161, 156, 155, 15
0, 147, 145, 130, 124, 124, 122, 119, 112, 112, 109, 107, 105, 101, 97, 91, 91, 91, 90, 87, 85, 85, 82, 80, 79, 77, 77, 76, 72,
72, 69, 69, 69, 68, 68, 67, 60, 60, 59, 57, 57, 54, 53, 51, 44, 40, 36, 36, 35, 33, 33, 32, 31, 30, 29, 29, 29, 27, 25, 25, 21,
21, 21, 20, 19, 19, 18, 17, 16, 16, 15, 14, 14, 13, 13, 13, 13, 11, 11, 11, 11, 9, 9, 8, 7, 6, 5, 5, 5, 4, 4, 3, 2, 1, 1, 1, 1,
1, 1]
Number of styles: 193
```

Picture 2. Styles and their amount

Thirdly, we thought it is too much and that we cannot work with that amount of styles and data, therefore we decided to take biggest 22 styles.

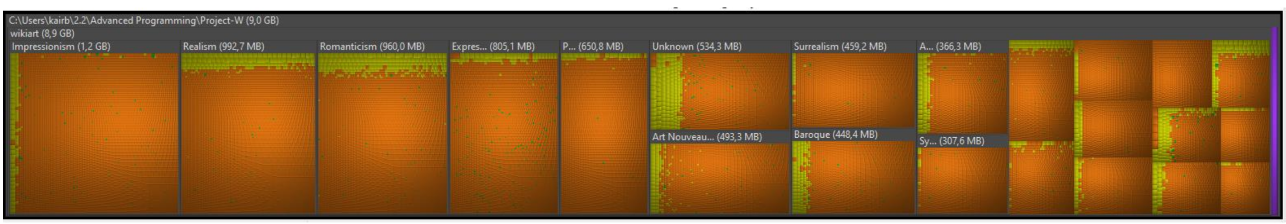
```
['Impressionism' 'Realism' 'Romanticism' 'Expressionism'
 'Post-Impressionism' 'Baroque' 'Art Nouveau (Modern)' 'Unknown'
 'Surrealism' 'Symbolism' 'Neoclassicism' 'Abstract Expressionism'
 'Rococo' 'Northern Renaissance' 'Cubism' 'Pop Art' 'Academicism'
 'Minimalism' 'Conceptual Art' 'Art Informel' 'Naïve Art (Primitivism)'
 'Early Renaissance']
[16083 15764 15010 11455  8147  7496  7382  7039  6988  5224  4360  3909
  3537  3089  2530  2517  2474  2077  1818  1797  1754  1729]
Number of styles: 22
```

Picture 3. Styles and their amount after change



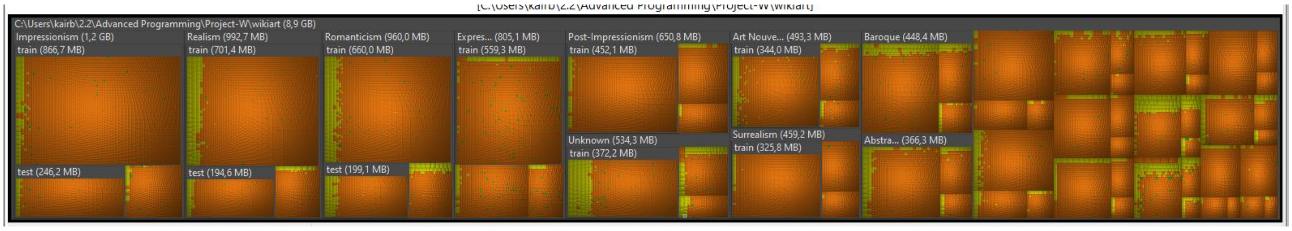
Graph 1. Styles and their amount after represented in barh chart

Everything we did to this step was the result of working with csv file. Then we started to split the dataset in “wikiart” folder, because folder contained all images without classification in styles. After running the specific code we splitted the folder into styles folder



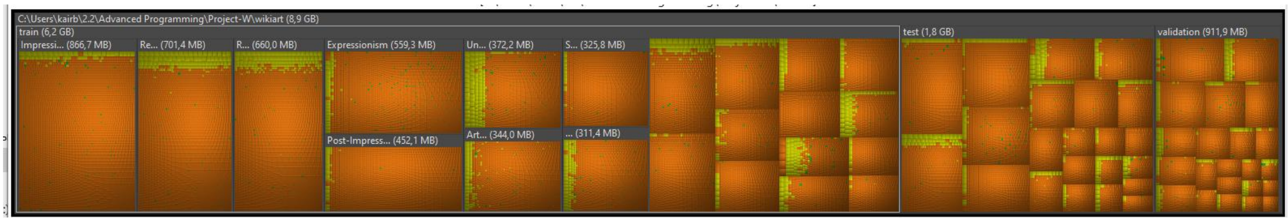
Picture 4. Splitting the dataset by styles – visualisation: WIZTREE program

Then again after running the specific code we splitted each style into train/test/validation folders by 70/20/10 percentage.



Picture 5. Splitting each style to train, validation and test datasets – visualisation: WIZTREE program

After moving and deleting operations we took three folders: train, test and validation. Each of them containing all art styles.



Picture 6. Final train, test and validation folders – visualisation: WIZTREE program

After those steps dataset were prepared for the model.

Creating the model

We took the input dimensions 224 ×224×3 as similar to ResNet. In a model we used 9 layers: 3 2D convolutional layer with 32, 64, 128 filters with ReLU activation; 3 max pooling layers; 1 flatten layer that converts the 2D feature maps to a 1D vector and 2 layer with 128 neurons and 22 neurons according to our number of classes.

```
import tensorflow as tf
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense
from tensorflow.keras.models import Sequential
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from PIL import Image

# Data generators
train_datagen = ImageDataGenerator(rescale=1./255)
test_datagen = ImageDataGenerator(rescale=1./255)

train_generator = train_datagen.flow_from_directory(
    'wikiart\\train',
    target_size=(224, 224),
    batch_size=32,
    class_mode='categorical',
    )

val_generator = train_datagen.flow_from_directory(
    'wikiart\\validation',
    target_size=(224, 224),
    batch_size=32,
    class_mode='categorical',
    )

test_generator = test_datagen.flow_from_directory(
    'wikiart\\test',
    target_size=(224, 224),
    batch_size=32,
    class_mode='categorical')

# Model
model = Sequential()
model.add(Conv2D(32, (3, 3), activation='relu', input_shape=(224, 224, 3)))
model.add(MaxPooling2D((2, 2)))
model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(MaxPooling2D((2, 2)))
model.add(Conv2D(128, (3, 3), activation='relu'))
model.add(MaxPooling2D((2, 2)))
model.add(Flatten())
model.add(Dense(128, activation='relu'))
model.add(Dense(22, activation='softmax'))

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

# Training the model
history = model.fit(train_generator, epochs=5, validation_data=val_generator)
```

Picture 7. Code for model

```
Found 92269 images belonging to 22 classes.
Found 13065 images belonging to 22 classes.
Found 26492 images belonging to 22 classes.
Epoch 1/5
2884/2884 [==============================] - 2537s 879ms/step - loss: 2.4654 - accuracy: 0.2283 - val_loss: 2.2841 - val_accu
racy: 0.2779
Epoch 2/5
2884/2884 [==============================] - 2495s 865ms/step - loss: 2.1471 - accuracy: 0.3234 - val_loss: 2.2337 - val_accu
racy: 0.3015
Epoch 3/5
2884/2884 [==============================] - 2604s 903ms/step - loss: 1.7798 - accuracy: 0.4321 - val_loss: 2.3526 - val_accu
racy: 0.2983
Epoch 4/5
2884/2884 [==============================] - 2517s 873ms/step - loss: 1.1996 - accuracy: 0.6130 - val_loss: 2.8589 - val_accu
racy: 0.2770
Epoch 5/5
2884/2884 [==============================] - 2473s 857ms/step - loss: 0.6556 - accuracy: 0.7903 - val_loss: 3.9902 - val_accu
racy: 0.2589
```

Picture 8. Training the model

After 3 hours and 30 minutes of training the model, the results showed us around 80% accuracy. Those were good results.

But after testing the model on test dataset, the results showed us 25% accuracy. It was unexpected. Therefore we tested the model on the pictures that we took from the internet and some that was made by AI - DALL ·E.

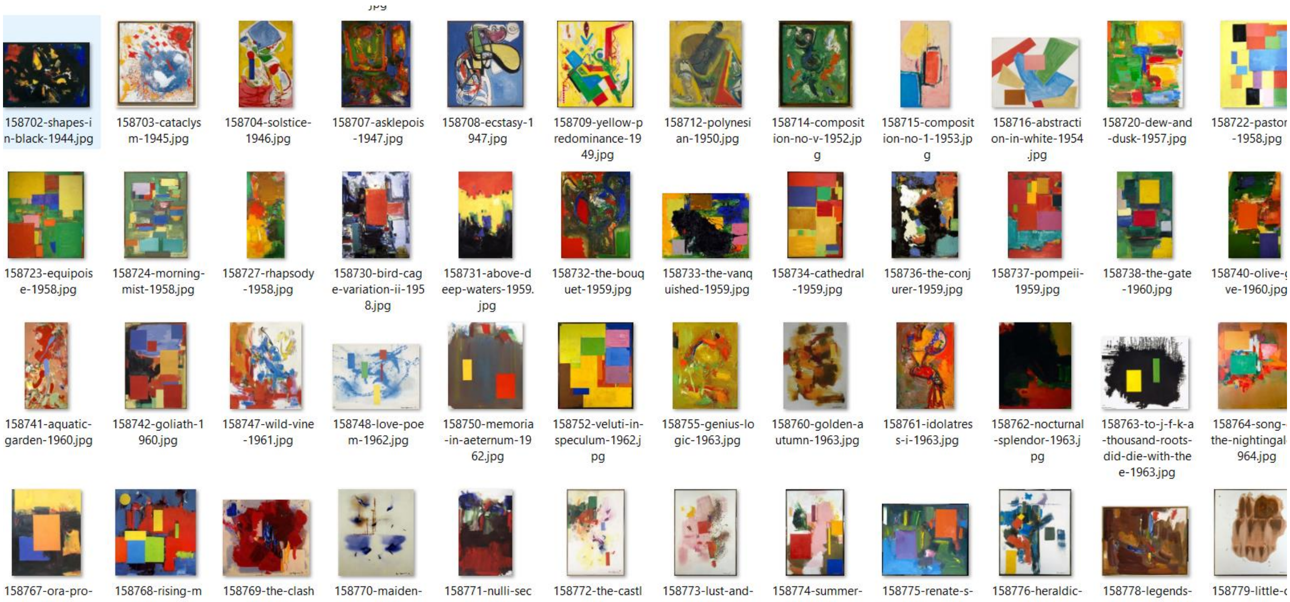
Testing

Test #1

```
1/1 [==============================] - 0s 30ms/step
Impressionism: 9.99%
Realism: 0.00%
Romanticism: 0.00%
Expressionism: 0.00%
Post-Impressionism: 0.00%
Baroque: 0.00%
Art Nouveau (Modern): 0.00%
Unknown: 0.00%
Surrealism: 0.00%
Symbolism: 0.00%
Neoclassicism: 0.00%
Abstract Expressionism: 34.26%
Rococo: 0.00%
Northern Renaissance: 0.00%
Cubism: 55.76%
Pop Art: 0.00%
Academicism: 0.00%
Minimalism: 0.00%
Conceptual Art: 0.00%
Art Informel: 0.00%
Naïve Art (Primitivism): 0.00%
Early Renaissance: 0.00%
```

Picture 9. PopArt - DALL·E *Picture 10. Results of test #1*

As we can see model does not give us any percentage for *PopArt* style, but gives for *Cubism* - 55.76% and *Abstract Expressionism* - 34.26%. The main reason is that model see the figures in picture, therefore, thinks that the style is more likely *Cubism*. Also, if we see the dataset of *Abstract Expressionism*, we may see next pictures:



Picture 11. Abstract Expressionism dataset

It also contains bright spectre of colors and abstract figures. This may explain its choice.

Test #2

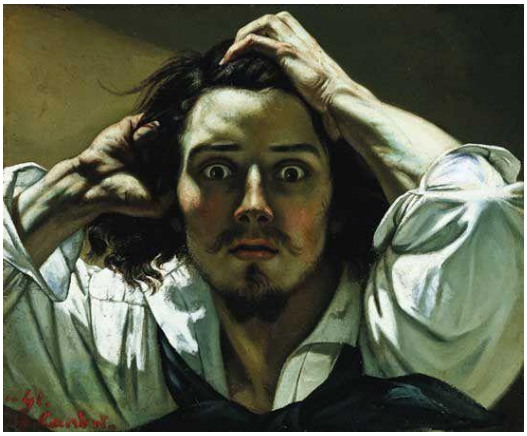
Impressionism: 0.01%
Realism: 0.00%
Romanticism: 0.00%
Expressionism: 0.01%
Post-Impressionism: 0.00%
Baroque: 0.00%
Art Nouveau (Modern): 0.00%
Unknown: 0.59%
Surrealism: 77.40%
Symbolism: 0.00%
Neoclassicism: 0.00%
Abstract Expressionism: 17.59%
Rococo: 0.00%
Northern Renaissance: 0.00%
Cubism: 0.01%
Pop Art: 0.09%
Academicism: 0.00%
Minimalism: 0.00%
Conceptual Art: 0.00%
Art Informel: 4.13%
Naïve Art (Primitivism): 0.00%
Early Renaissance: 0.18%

Picture 12. Surrealism - DALL·E

Picture 13. Results of test #2

In this test we can see that model evaluates the picture as *Surrealism* - 77.40% and *Abstract Expressionism* – 17.59%. The results is satistfying.

Test #3

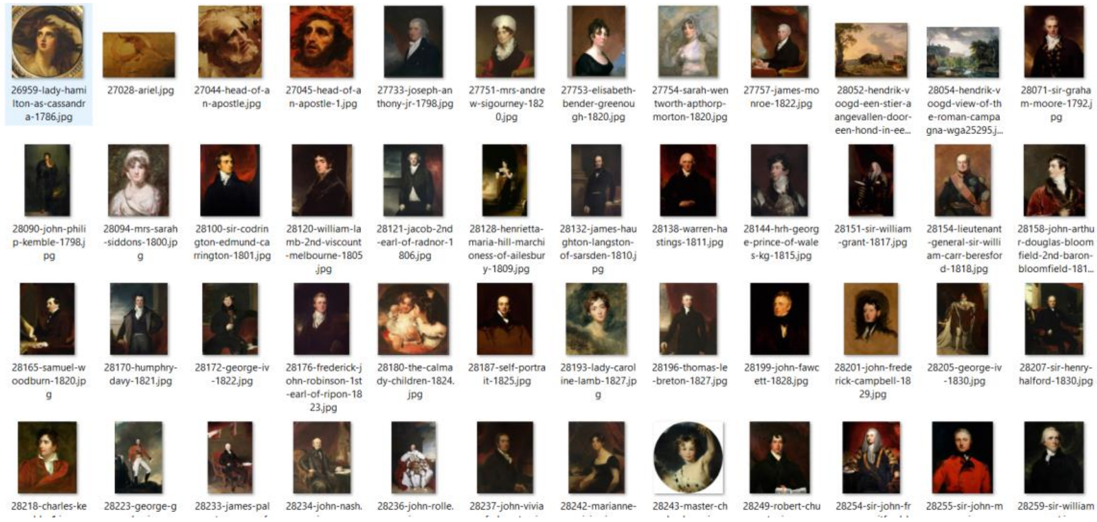


Impressionism: 0.00%
Realism: 75.06%
Romanticism: 0.00%
Expressionism: 0.00%
Post-Impressionism: 0.02%
Baroque: 0.00%
Art Nouveau (Modern): 0.06%
Unknown: 0.02%
Surrealism: 19.71%
Symbolism: 0.05%
Neoclassicism: 0.00%
Abstract Expressionism: 0.00%
Rococo: 0.00%
Northern Renaissance: 0.00%
Cubism: 0.00%
Pop Art: 0.00%
Academicism: 5.05%
Minimalism: 0.00%
Conceptual Art: 0.01%
Art Informel: 0.00%
Naïve Art (Primitivism): 0.01%
Early Renaissance: 0.01%

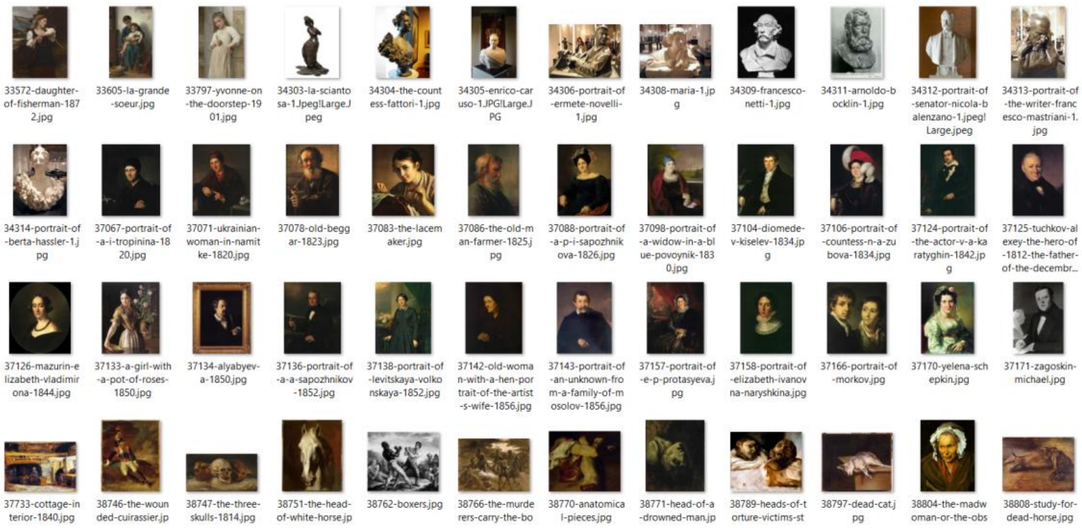
Picture 14. Romanticism

Picture 15. Results of test #3

In this test we see that model shows no *Romanticism* accuracy, but *Realism* 75.06%. Again as test #1, the reason may be in dataset that the model is learning.



Picture 16.



Picture 17.

From the 2 set up pictures above one is *Romanticism* and another one is *Realism*. Can you differ which one is one?

We think that is the problem of this model. It is really hard to identify each style, when the dataset on which model is learning are similar to each other.

Picture 16. *Romanticism.* Picture 17. R*ealism*

Discussion

After watching the tests results, we can see that model is not working as it needs to. Model works based on elements in picture. Sometimes it cannot differ which style it truly is. Some styles have similar elements in it, that is why it is hard to identify to model which one exactly it is. But still it can identify some styles very good.

The reason of inappropriate work of model may be the amount of data in dataset. 132179 pictures for 22 styles seems not enough. Therefore, it needs to be larger.

The second reason may be the small structure of the model. We think it can show better results if it would be more complicated than this. Those amount of layers are not enough for that kind of complicated task: art style recognition.

References

Lecoutre et al. (2019, February 02). Recognizing Art Style Automatically with deep learning. Retrieved from https://hal.science/hal-02004781

Lopes, S. (n.d.). WikiArt all artpieces. *2022*. Retrieved from https://www.kaggle.com/datasets/simolopes/wikiart-all-artpieces

Szegedy et al. (2015, December 2). Rethinking the Inception Architecture for Computer Vision. Retrieved from https://arxiv.org/abs/1512.00567v3

Extra:

Tech stack: Python**,** TensorFlow, numpy, pandas**,** Keras**,** Jupyter Notebook

Project link: https://github.com/Gabrielprogramist/Recognising-Art-Style-by-Using-Neural-Network