

ART CLASSIFICATION WITH DEEP LEARNING

JUSTINE PICAR, JULY 2021



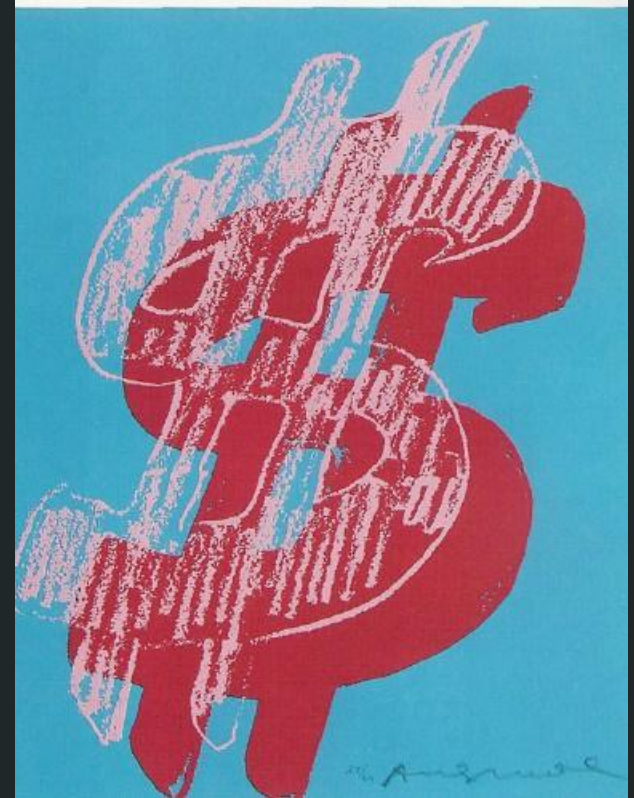
ART MUSEUMS: A BACKGROUND

- Important public institutions
- Hold a lot of cultural history
- A popular experience shared by many people with the help of the internet
- Opportunities exist to reach a broader, diverse group of people



PROBLEM

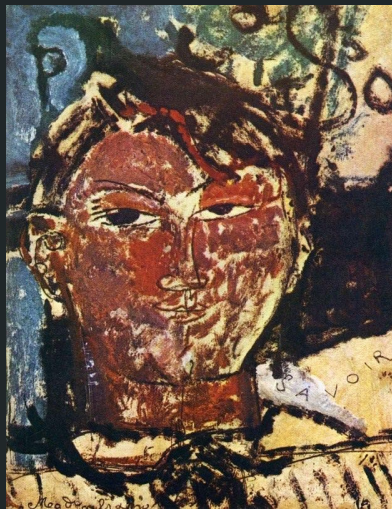
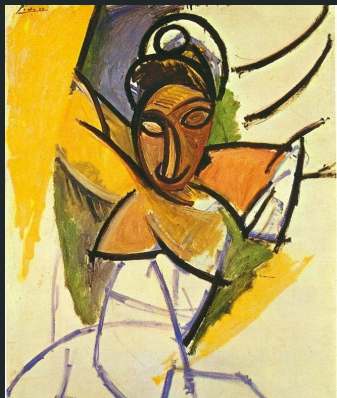
- Struggle with budget cuts
- Rely on increased audience engagement and patrons
- Lesser known museums cannot afford engaging programs and activities
- New art enthusiasts can be intimidated by art without background with knowledge
- Museums are required to label the genre of a painting before displaying it, which can be time consuming



PROJECT OBJECTIVE:

Classify the art style of a painting to use as an interactive tool for patrons and for museum curators to label new paintings before an exhibition

DATA: KAGGLE'S BEST ARTWORKS OF ALL TIME



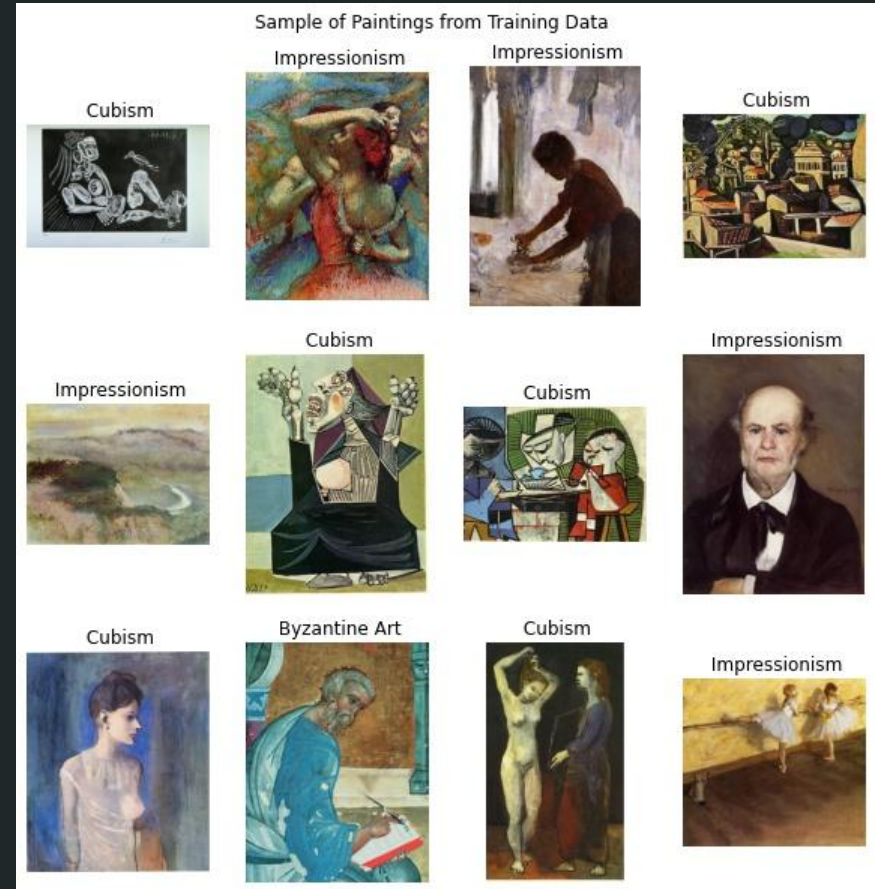
- 8,446 PAINTINGS
- FROM TOP 50 RENOWNED ARTISTS
- 20 UNIQUE ART STYLES

PACKAGES

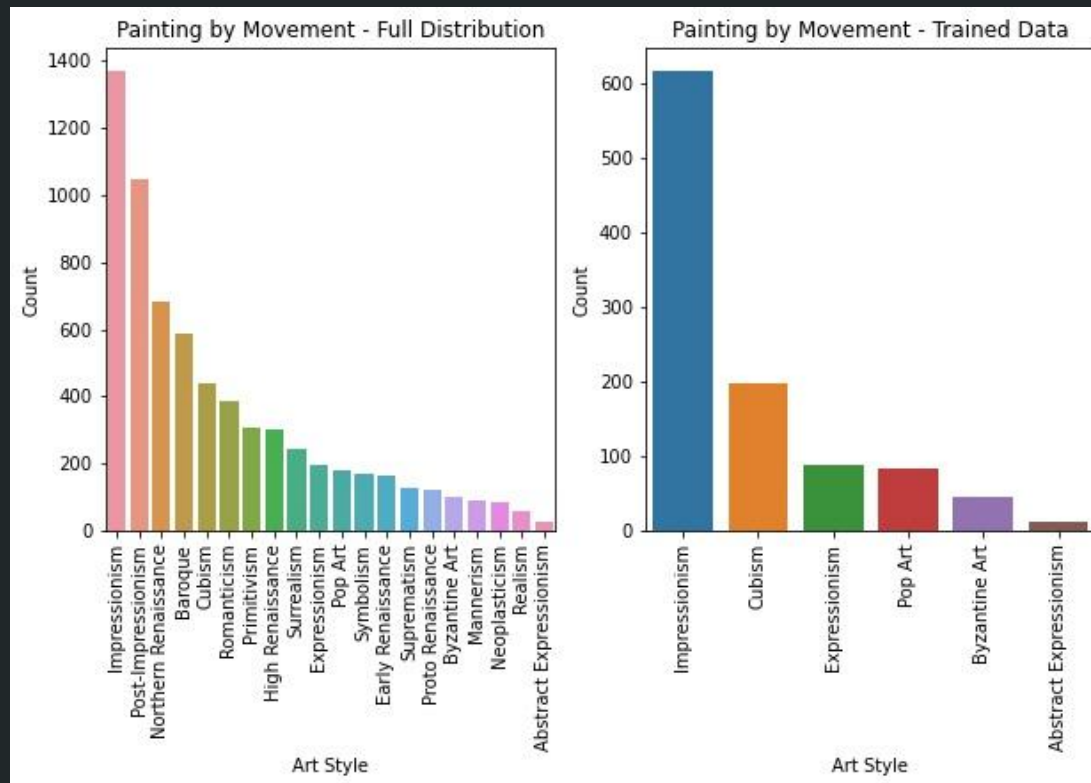
- Training and modeling the data
 - KERAS API
- EDA and Metrics Visualization
 - skimage
 - matplotlib.pyplot
 - seaborn
- Neural Network Visualization
 - graphviz
 - pydot

DATA WRANGLING

- Reclassified data to genre then dropped all other columns
- 20/31 art styles are unique; drop columns with multiple genres
- Focus on 6 particular classes:
 - Impressionism
 - Cubism
 - Expressionism
 - Pop Art
 - Byzantine Art
 - Abstract Expressionism
- Total of 2,206 images
- 60% training, 9% validation, 10% testing



EDA: PAINTING DISTRIBUTION

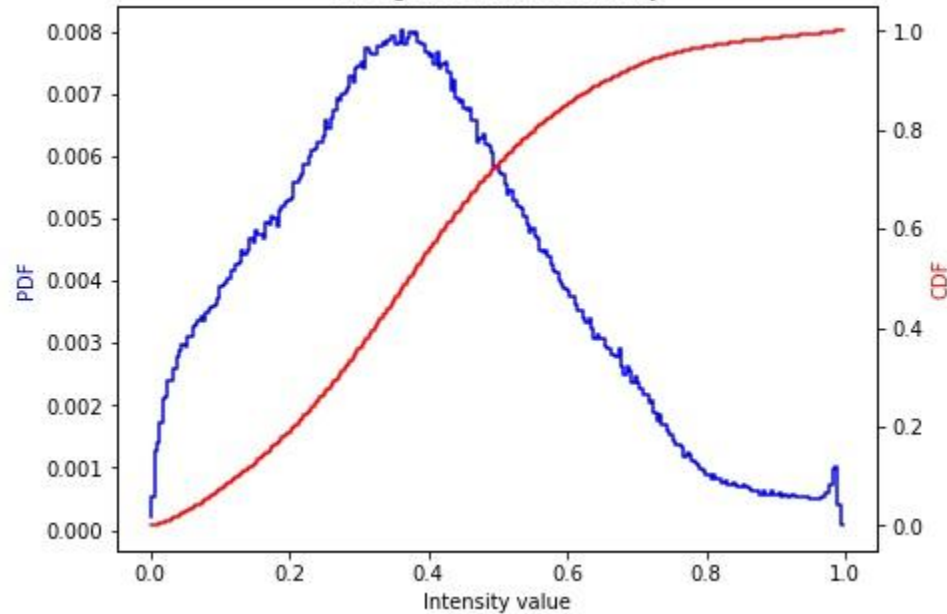


EDA: PIXEL INTENSITY

Grayscale Image

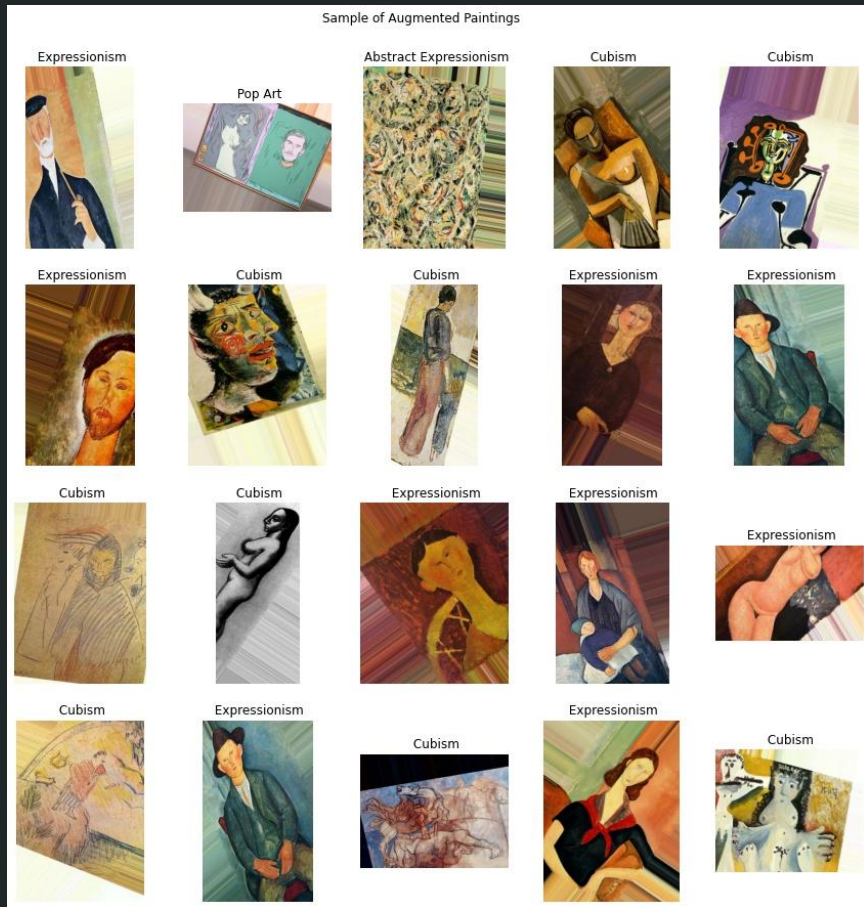


Histogram of Pixel Intensity



METHODOLOGY: DATA AUGMENTATION & PRE-PROCESSING

- Increase robustness of models and ability to generalize data
- Maintain distribution
- Apply distortions randomly
 - Rotations
 - Nearest 'fill' method
 - Horizontal flip
 - Zoom
 - Stretch (width and height)
 - Shear
 - Brightness
 - Normalization



METHODOLOGY

WEIGHT INITIALIZATION

- `class_weights` from `sklearn.utils`
- balance the distribution between art styles in the training data

PRE-TRAINING

- Transfer learning with the ImageNet database
- Train on top of a RESNET50 model

FINE TUNING

- Re-train last 20% of layers
- Freeze all other layers
- Slower learning rate
- Use Stochastic Gradient Descent (SGD) Optimizer

NEURAL NETWORK ARCHITECTURES

Convolutional Neural Network

- Input shape: 200 x 200 x 3
- 3 stages with structure:
 - Conv2D
 - RELU Activation
 - MaxPooling2D
 - Filters at each stage: 32, 64, 128 respectively
- Final Stage:
 - Flatten
 - Dense Layer with 128 feature maps
 - Dropout ~40% of the parameters to prevent overfitting
 - Dense layer = the number of classes (6)
 - Softmax activation for multi-classification

[Click Here for Visual](#)

Residual Neural Network

- Input shape: 200 x 200 x 3
- Identity Block with skip connection
 - Conv2D -> BatchNormalization
- Convolutional Block with skip connection
 - Conv2D -> BatchNormalization
- Residual Neural Network
 - Conv2D
 - BatchNormalization
 - MaxPooling2D
 - 4 stages of convolutional and identity block
 - AveragePooling
 - Dense layer = the number of classes (6)
 - Softmax activation for multi-classification
- Total: 53 layers

[Click Here for Visual](#)

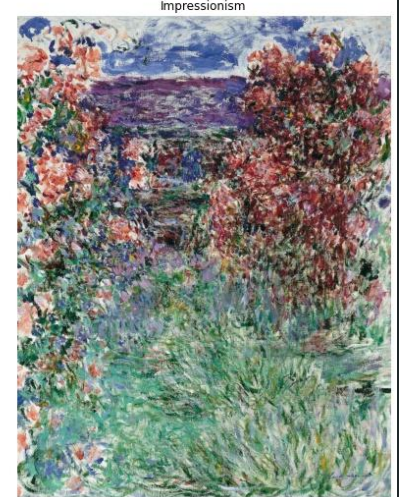
Key Findings

- Abstract Expressionism labels misclassified as Cubism and Impressionism
- Impressionism has a very open composition that appears abstract up close
- Cubism is specific, yet abstract form of art

Abstract Expressionism v. Cubism v. Impressionism

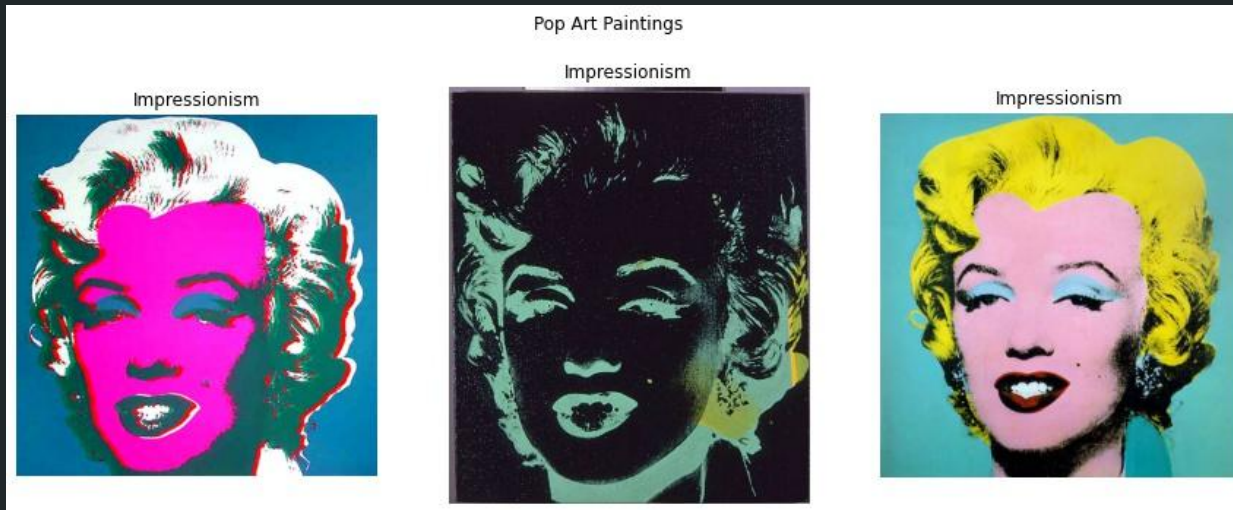


Abstract Expressionism v. Impressionism

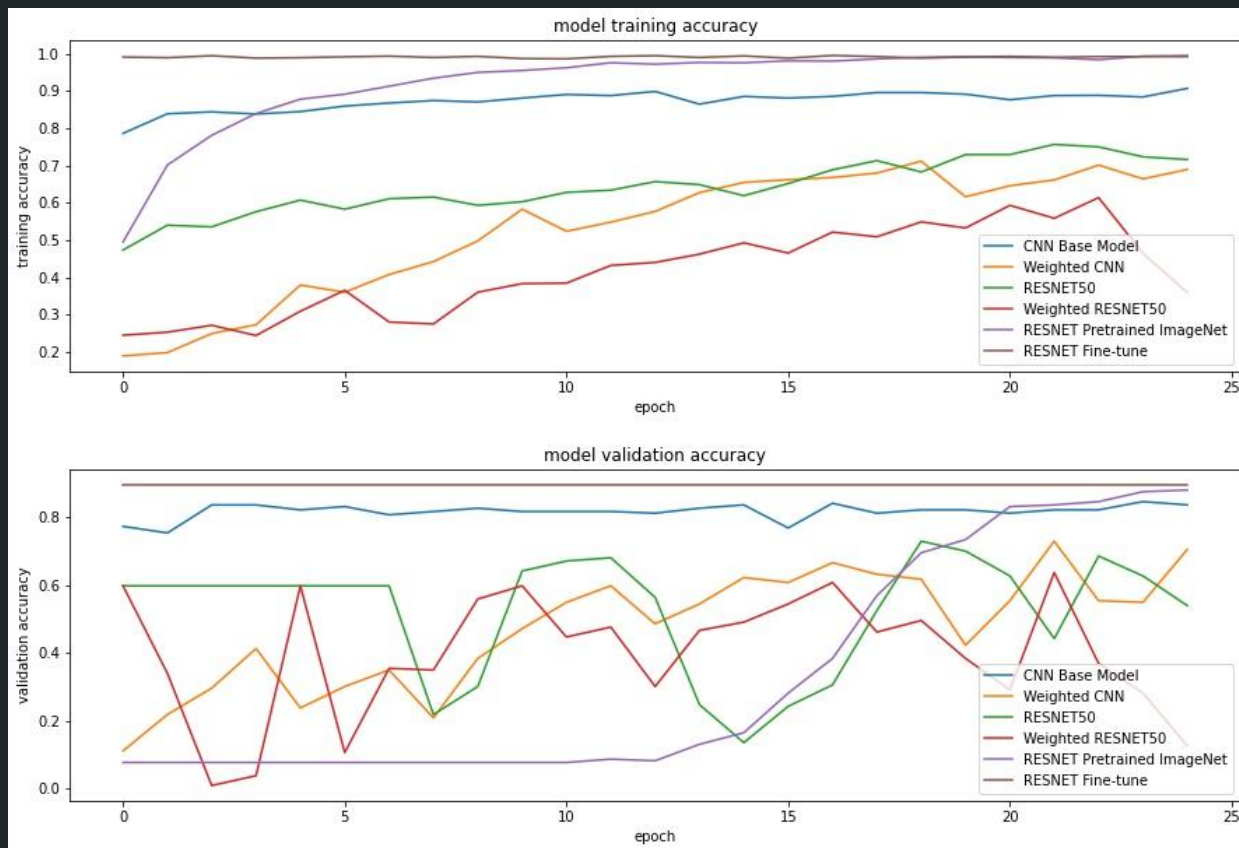


Key Findings

- Pop Art highly recognizable due to unique style (repeating patterns)
- Model detects styles with distinct repeating patterns
- Struggles with styles closer to one another, much like a person



MODEL RESULTS AND ANALYSIS



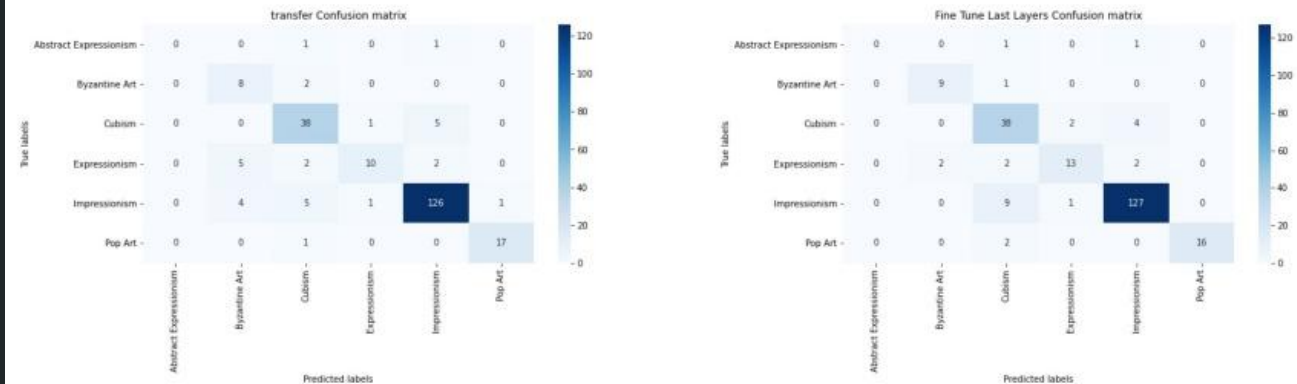
MODEL RESULTS AND ANALYSIS

	CNN	CNN_weighted	ResNet50	ResNet50_Weighted	ResNet50_Pre-Trained	ResNet50_Fine_Tune
Pop Art	0.888889	0.500000	0.888889	0.500000	0.944444	0.888889
Impressionism	0.824818	0.642336	0.547445	0.642336	0.919708	0.927007
Cubism	0.636364	0.568182	0.568182	0.568182	0.863636	0.863636
Expressionism	0.631579	0.578947	0.421053	0.578947	0.526316	0.684211
Abstract Expressionism	0.500000	0.500000	NaN	0.500000	NaN	NaN
Byzantine Art	0.400000	0.500000	NaN	0.500000	0.800000	0.900000

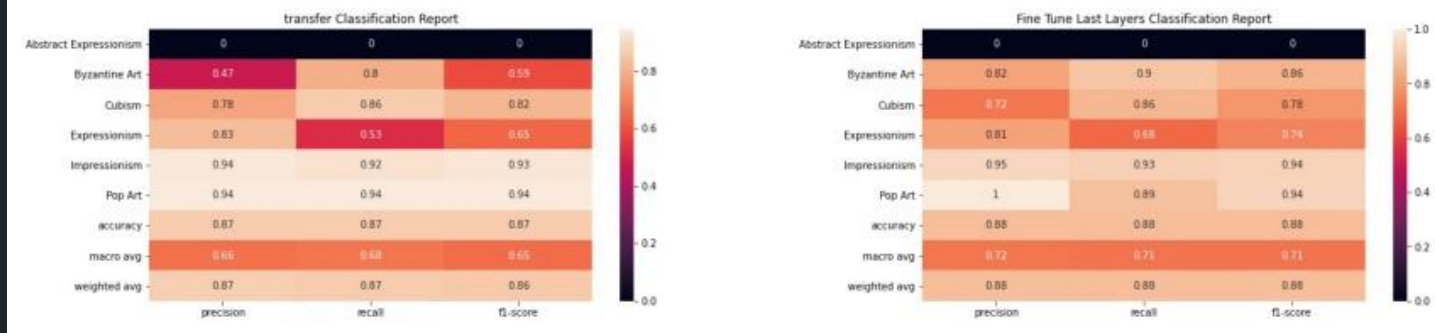
PRE-TRAINED RESNET50 WAS THE BEST MODEL
WEIGHTED RESNET50 WAS THE WORST MODEL

MODEL RESULTS AND ANALYSIS

Pre-Trained ResNet50 v. Fine-Tuned



Pre-Trained ResNet50 v. Fine-Tuned



CONCLUSION & LESSONS LEARNED



- 87% ACCURACY ON PRE-TRAINED RESNET50
 - PRE-TRAIN OTHER MODELS:
 - VGG-16
 - INCEPTIONV3
 - EFFICIENT NET
 - METHODOLOGY:
 - COMBINING CLASSES
 - BAGGING
 - CROSS-VALIDATION
 - DIVERSE DATASET
-

THANK YOU!

Thank you to my patient and wonderful mentor Nik Skhirtladze, Francois Chollet and Priya Dwivedi on their helpful tutorials, and Stack Overflow for all my troubleshooting needs.

SOURCES

- [Image Classification Using Very Little Data by Francois Chollet](#)
 - [Kaggle Best Artworks of All Time](#)
 - [Keras API](#)
 - [MOMA Contemporary Challenges](#)
 - [Stack Overflow](#)
 - [Understanding ResNet in Keras by Priya Dwivedi](#)
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