MTH 353 Final Project

Mystery Object Recognition

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01

Project Overview

Build an Image Classification model to recognize images of artworks and predict its culture origin

Mystery Object Recognition

Machine Learning

Build a Neural Network to classify artworks into different culture

Artwork Recognition

Use the model to predict the culture of mystery objects

Art Historical Analysis

Guide art historical analysis between the mystery object & works from the culture

Approach

Data Exploration

Search for available images

Collect a small set as sample

Preliminary Model

Build preliminary models

Gather insights for data collection & processing

Data Processing

Collect & process data

Check quantity & quality

Model Training

Train 2 models

Adjust feature selections

Tune hyperparameters

Extract Insight

Generate test dataset

Produce visualizations

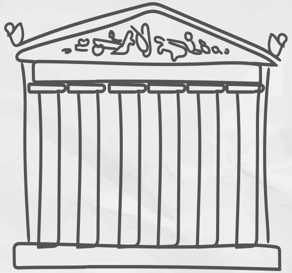
Art Historical Analysis

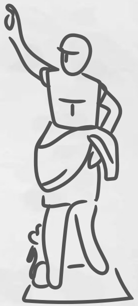
02

Data

750 Images from the collection of the Metropolitan Museum (MET)

Cultures Included & Data Distribution





Near East

150 images

Egyptian

50 images

300 images

Greek

Roman

250 images

Data Explained

WikiArt + Google Search

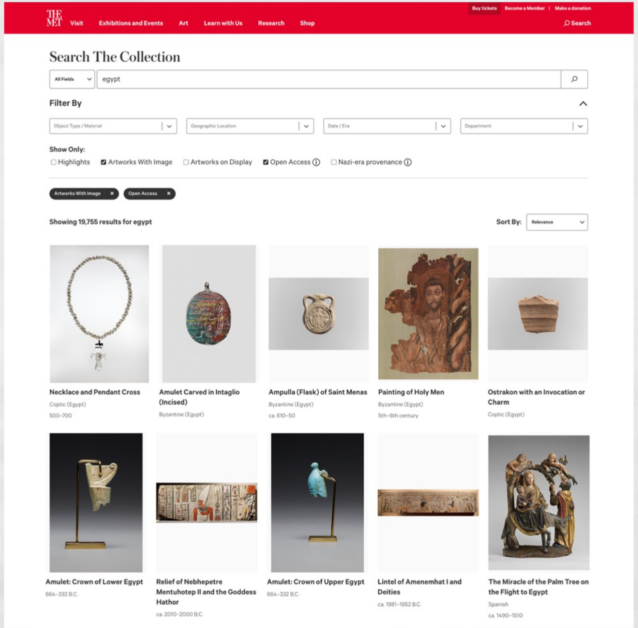
- Varied Resolution
- Different formats

MET collection

- High Resolution
- Use the same collection to reduce noise factors

Culture & Distribution

- Cultures covered in ARH 212
- Availability of artworks of different cultures
- e.g. Combine 12 cultures of similar period to “Near East”



MET Collection

Data Processing

Labeling
- Generate a dataset with images
- Put images into categories

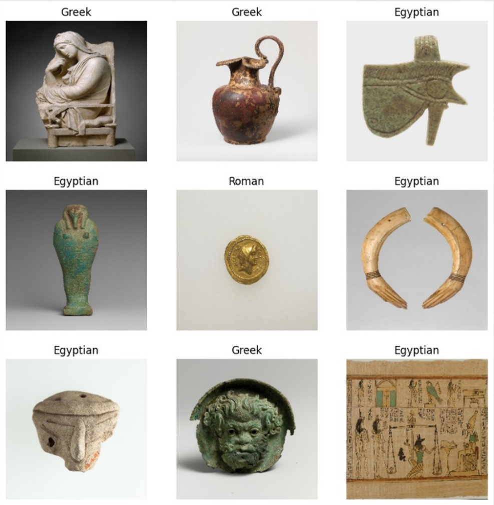


Image Data Snippet

Image Augmentation Visualization

Image Augmentation
- Rotate, mirror images
- Generate additional data to predict overfitting

Data Categorizations

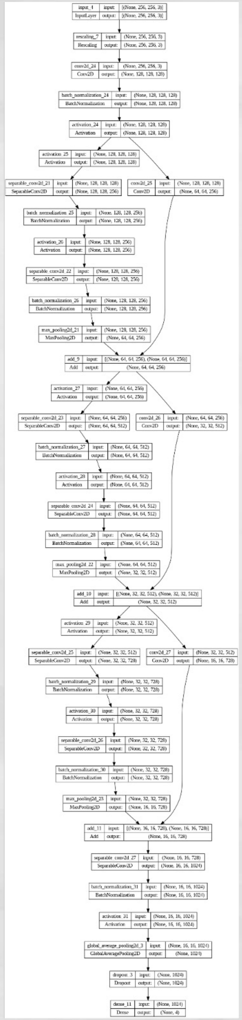
The combination of categories we included:

1.original dataset	Egyptian	Near East	Greek	Roman
	300	150	250	50
2.offset Roman's imbalance	Egyptian	Near East	Greek	
	300	150	250	
3.binary classification	Egyptian		Greek + Roman	
	300		250 + 50 = 300	

03

Model

A Convolution Neural Network that takes in images and classify artworks into its cultures



Our Model

Convolutional Neural Network (CNN)

- Classic Image Classification models
- Available library Tensorflow & Keras

Model 1

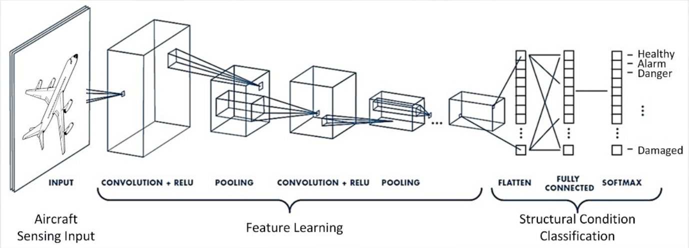
Keras Model Prototype

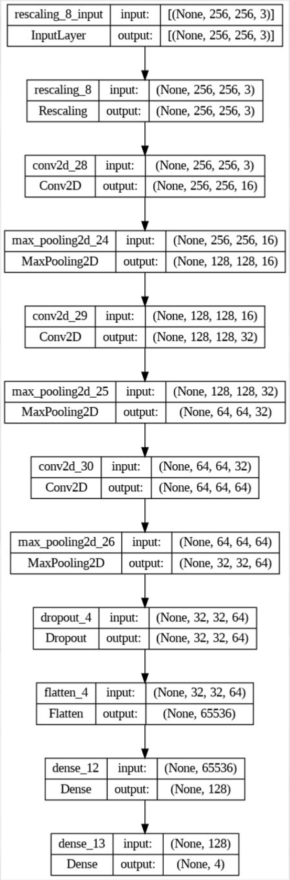
- hard to interpret
- slow training

Model 2

High Level Tensorflow model

- very basic CNN



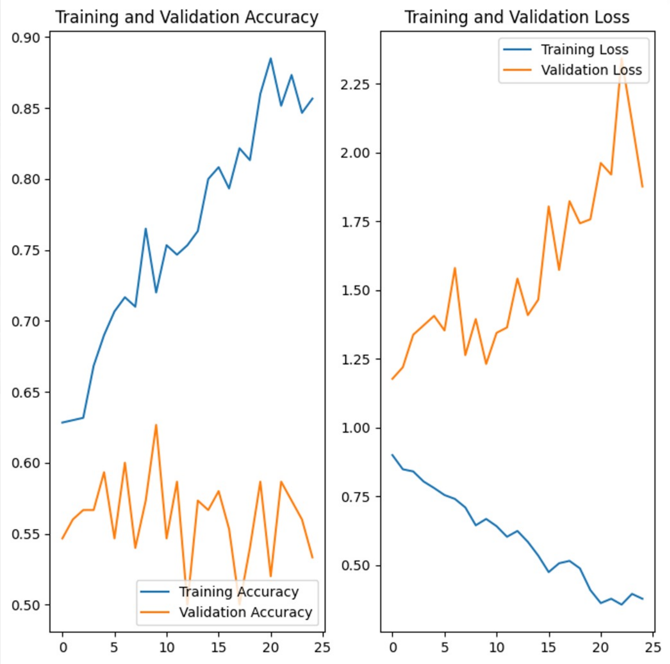


Model Performance

Model	Data	Accuracy
Model 2, epoch 10	Wiki Art	0.77
Model 1, epoch 15	MET Collection	0.64
Model 2, epoch 25	MET Collection	0.53
Model 2, epoch 25	MET: Egyptian, Near East, Greek	0.57
Model 2, epoch 25	MET: Egyptian, Greek+Roman	0.63

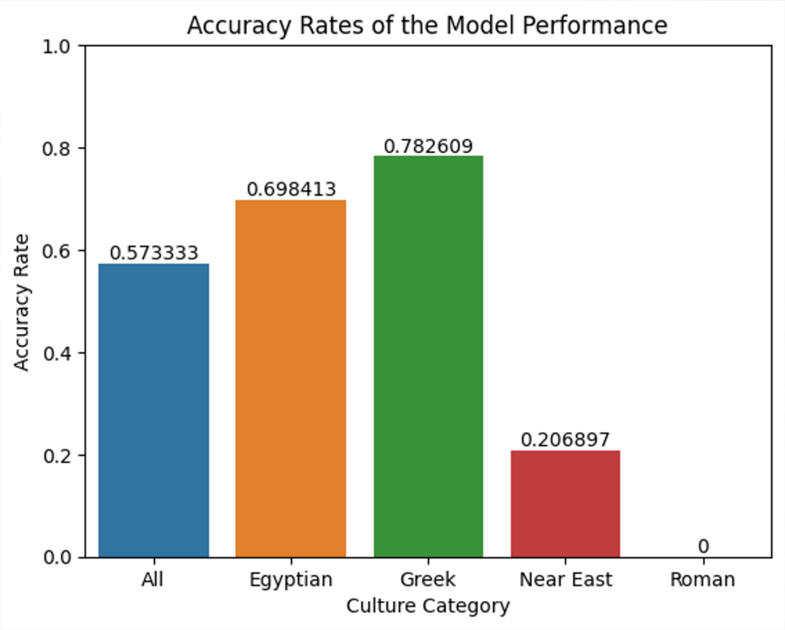
2 Models' Training Visualization

Model 1, epoch 15

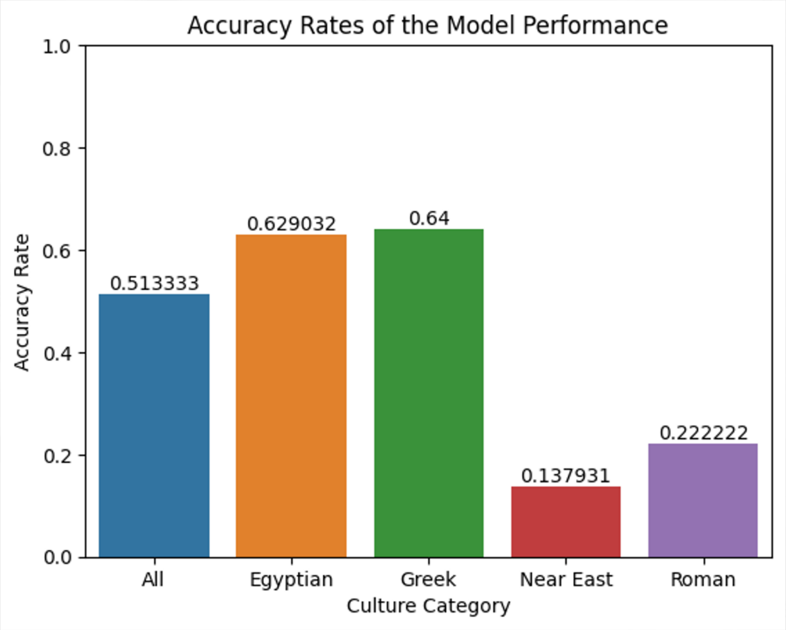


Model 2, epoch 25

2 Models' Accuracy Rates

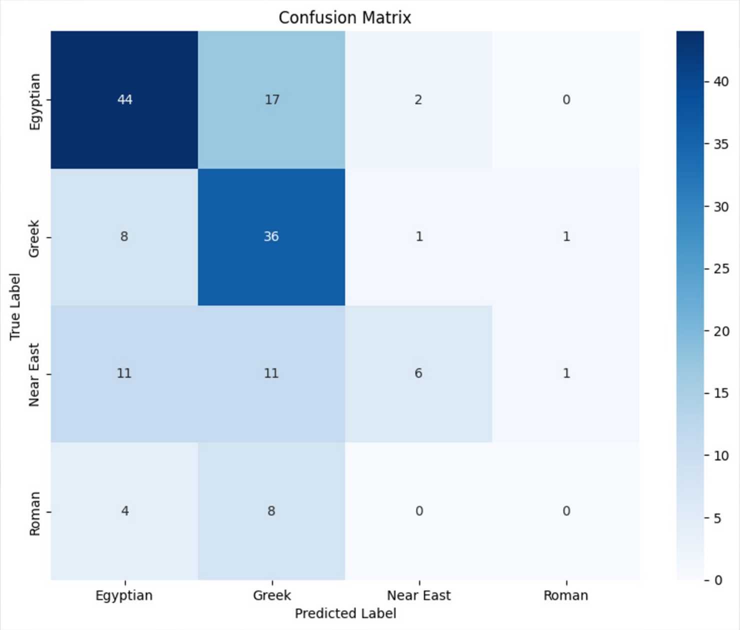


Model 1, epoch 15

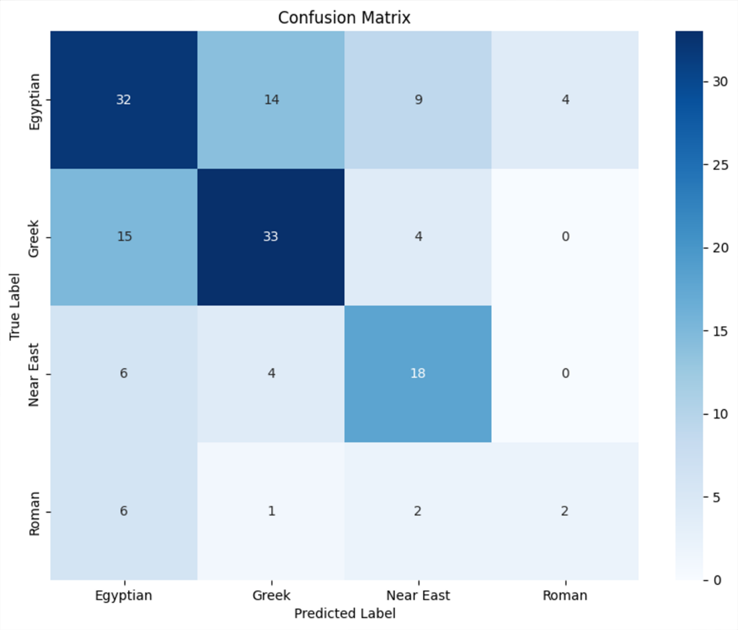


Model 2, epoch 25

2 Models' Confusion Matrix

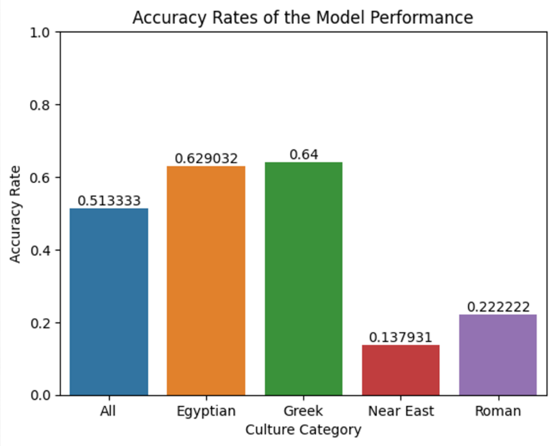


Model 1, epoch 15

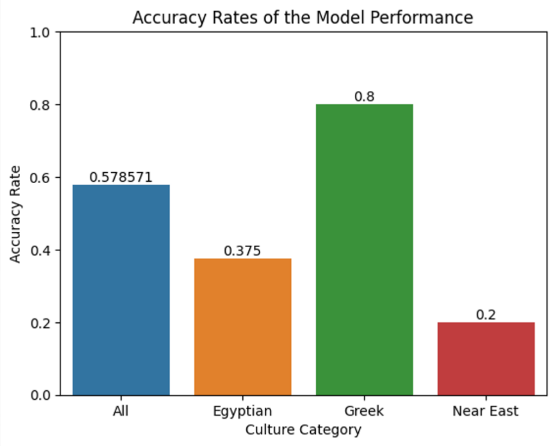


Model 2, epoch 25

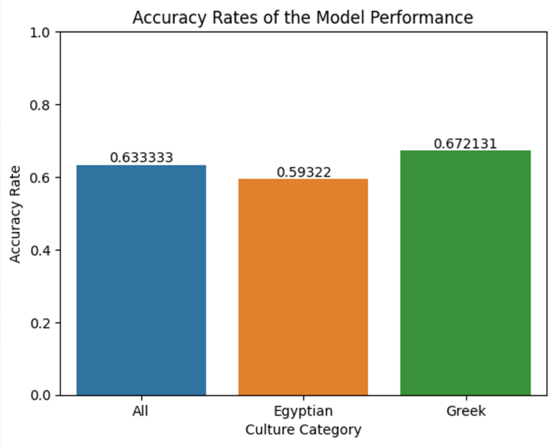
3 Data Categorization Visualization



Original Dataset



Egyptian, Greek, Near East



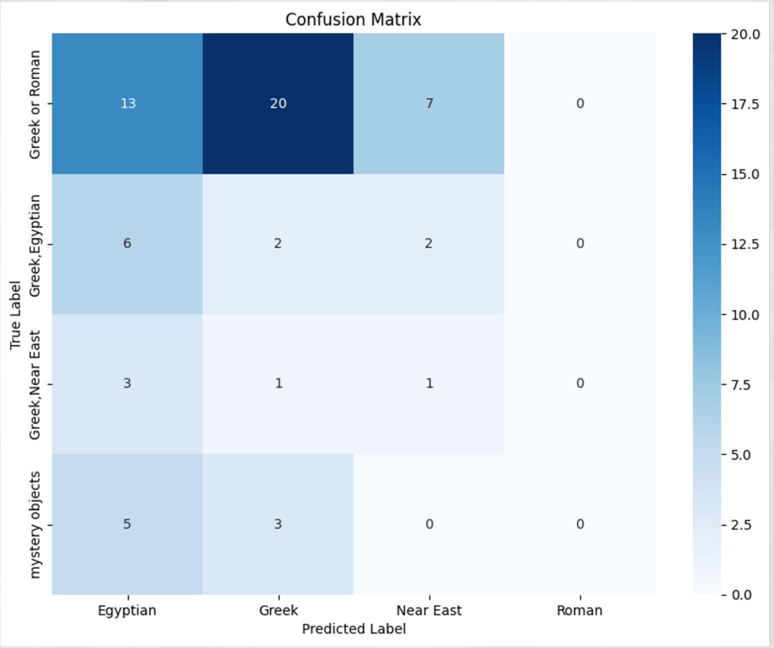
Egyptian, Greek + Roman

Model Prediction on Mystery Object

Greek/Egyptian

Greek/Roman

Greek/Near East



Confusion Matrix of Mystery objects & Prediction

Insights from the Model

Observations:

1. The model is best at distinguishing “Greek”
2. “Near East” yields good result though being a discrete collection
3. “Roman” is never predicted
4. Validation accuracy does not improve as much as the training accuracy
5. Model’s performance is not stable

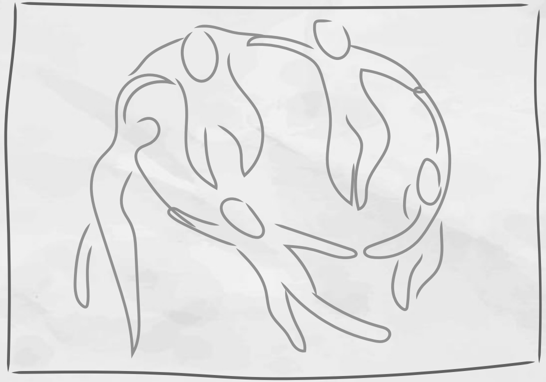
Some Insights concluded from the results:

- Model’s prediction is largely based on the distribution of data
- Model has low confidence in the category with smallest dataset
- Increasing epochs doesn’t improve the model’s performance significantly after 15 in this case
- “Near East” is quite distinct from the others
- “Greek” has very considerable similarity with “Egyptian” & “Roman”

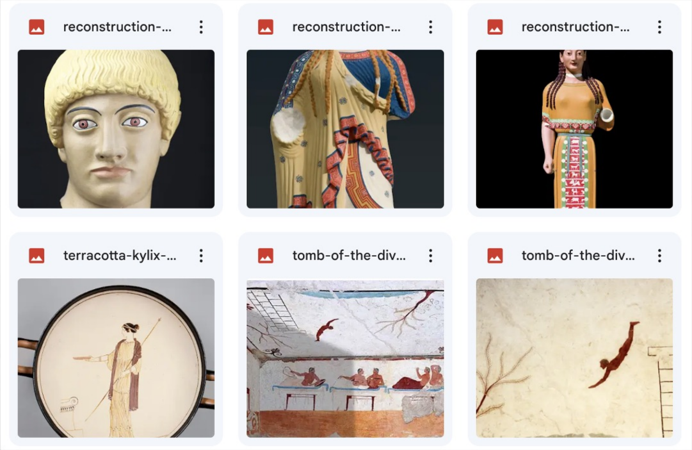
04

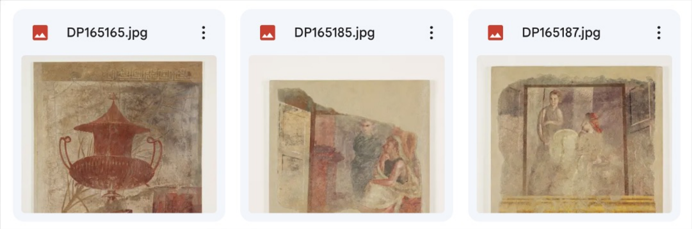
Final Thoughts

The better the data,
the merrier the result



Data Collection Reflection





Prolonged data gathering phase

- Explore artworks of ancient cities
- Gain insights about the availability of works

Artwork from Ancient Cities

- Limit Availability
- Difficult to put into 1 category
- High similarity/ influence between artworks
  - pattern
  - material
  - subject

Arbitrary choices

- Imbalance distribution
- Categories vary in the collection

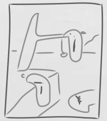
Our Thoughts about the Model

Data Quality

The quantity & quality of the data largely affect the performance of the model.

Low Explanantility

The difficulty to decipher neural networks makes it hard for us to know exactly what features to change after the training of one model.



Costy Training

The model takes around 1~3 hours to train. The time & energy required makes it difficult for us to train as many iterations as we want for the ideal feature selection, hyperparameter tuning, etc.

Lack of Experience

The high flexibility of CNN offers many possibilities for the model tuning, but also adds difficulty for our design decisions. Instead of making proactive decisions, we can only observe the effect of changes after every training iteration.

Thank you!

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Resources

DuBois, J. (n.d.). Using Conv Using Convolutional Neur olutional Neural Networks t al Networks to Classify Ar o Classify Art Genre . John Carroll University Carroll Collected. https://collected.jcu.edu/cgi/viewcontent.cgi?article=1147&context=honorspapers

Zoe Falomir, Lledó Museros, Ismael Sanz, Luis Gonzalez-Abril, Categorizing paintings in art styles based on qualitative color descriptors, quantitative global features and machine learning (QArt-Learn), Expert Systems with Applications, Volume 97, 2018, Pages 83-94, ISSN 0957-4174, https://doi.org/10.1016/j.eswa.2017.11.056.

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