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<p style="text-align:center">AI-guided Art Classifier</p>

As Artificial Intelligence (AI) has become increasingly powerful and popular nowadays, I want to build a machine learning (ML) model, a simple version of AI, to classify artworks from cultures covered in this course. I hope that the model can successfully classify artworks into different styles or at least provide a probability of how likely one mystery object is from one style, which can guide visual analysis across cultures.

After reading through 5 research papers on similar topics, I decided to gather 150 pictures from WikiArt and Google search engine as referred to in the papers, and chose TensorFlow, a Python library for image classification models, to train the actual model. I built a preliminary model that reaches an accuracy rate of 0.77, which is very promising given the poor quality and imbalance of the image data. Based on this observation, I decided to put more effort into data gathering and preparation.

Finally, I found a rich collection of high-quality images from the database of the Metropolitan Museum (MET.) To minimize the noises in the images (e.g. light, background), I decided to collect data solely from the MET collection. I spent about 6 hours downloading and labeling a total of 750 pictures:

300 from Egyptian, 250 from Greek, 50 from Roman, and 150 from Near East. (see Figure 1 for a snippet of the image data) The Roman category contains several artworks from Etruscan, and the Near East category is a discrete set
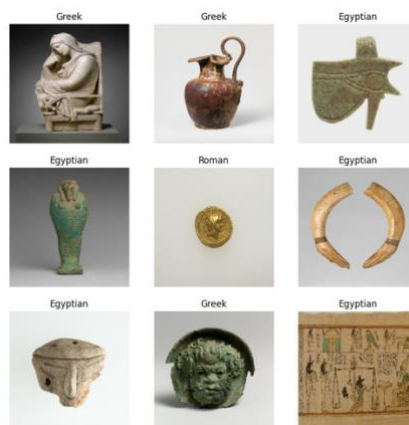

Figure 1, Sample Image Data   *Figure 2, Image Augmentation Visualization*

of 12 cultures[1]. The labeling decision is based on the availability of artworks of different cultures and the fact that data for different classes should be balanced in number so that the model learns equally from every class. I excluded artworks that have labels of multiple cultures (which are put into test data as mystery objects) and pictures that have resolutions smaller than 72*72 pixels. The data is automatically resized in the training of the model[2], and random image augmentation is applied to generate new data to help the model's generalization. (Figure 2)

For the ML classifier, I used 2 models – one sophisticated prototype from the Keras website (Model 1) and one very basic Image Classification model (Model 2). Model 1 yields a 64% accuracy rate from the MET collection data, and Model 2 yields 53%. The model can predict well on Egyptian and Greek with higher than 60% accuracy but works badly on Roman and Near East. (Figure 3)
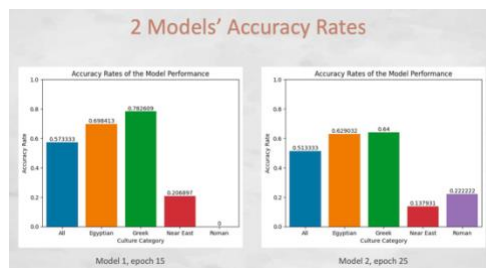

Figure 3, Accuracy Rate of Model 1 & Model 2   *Figure 4, Accuracy Rate of Model 2 on 3 categorization*

Model 1 being more complicated performed well on the prediction of Egyptian and Greek. As the Roman category is significantly low in number, I decided to try 2 different categorizations to offset the imbalance: one eliminating Roman[3], and one combining Greek with Roman against Egyptian[4]. Since Model 1 requires more than 3 hours to train, I only used Model 2 for data categorization testing. For the "Egyptian, Greek, Near East" categorization, the model performed great on Greek with an accuracy of 0.8, and the overall accuracy rate rose to 0.57; for the "Egyptian, Greek + Roman" one, the accuracy rate grew to 0.63, with Greek also outperformed a little. (Figure 4)

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[1] Phrygian, Assyrian, Iran, Achaemenid, Urartian, Israelite, Scythian, Babylonian, Parthian, Cypriot, Hillite, and Xiong Nu

[2] The resizing process stretches the pictures, which yields better training results than resizing while preserving the ratio. This might indicate that the overall shape of the artwork matters more for the model than the detailed features of the artwork.

[3] Eliminating Roman case would be Egyptian 300 images, Greek 250 images, and Near East 150 images.

[4] This case is Egyptian 300 images versus Greek + Roman 300 images. This is an interesting case given that the data is equally distributed, and my belief that Greek and Roman are highly resemblant.

Now coming to the mystery object recognition, I gathered around 50 images of artworks that have multiple categories or are indeed mystery objects. The model's prediction on these images appeared to be a little random or dependent on the availability of the data of one culture. Greek and Egyptian are the two that are predicted the most, while Roman is never predicted as the highest probable culture origin. To officially implement the model in real art recognition, more work is needed to decipher how the model predicts, which will more effectively provide insights about what features link to what prediction.

This project concludes my study of art of ancient cities and of machine learning in general. The prolonged data collection phase allowed me to go over a huge number of artworks in different cultures, and the overall digging of data also provides insights about the number of artworks we have in record for different cultures– Egyptian being the most abundant. Moreover, the model is an innovative foundation for future application of ML to analyze artworks of ancient cities. It is transferable to similar research and will be more informative if fed with abundant high-quality data. Lastly, the models' performance indicates the fact that artworks of ancient cities are highly related and share similarities in many aspects– material, pattern, subject matter, and so on. Greek being the culture in between Egyptian and Roman has equal resemblance to both styles in the model's eyes, but the fact that the model performs well in predicting Greek also points out some unique features of Greek artworks in the model's perception. Also, when concluding the model's prediction, I only looked at the class with the highest probability, but it will be interesting to examine the probability distribution and analyze the artwork as a collection of styles. Overall, the project intersects art history with computer science and effectively utilizes modern technology to scientifically analyze artworks in their contexts, and I am excited to continue similar approaches for creative exploration of art through the computer's perception.

Resources:

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