# Digital Dating

## Dating Historical Art using Machine Learning

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## Introduction

Dating historical art is a necessity for museums and historians alike. When it comes to dating historical art there are many methods used such as microscopic analysis, thermoluminescence, and carbon dating. However, when these methods fail, historians are left with two options, to either estimate based on style and comparison to other art, which takes a trained eye and a lot of time, or the poorer option to leave a piece of art undated. In most museums, they will estimate a wide range of time for when a piece could have been created, however, some precision is better, whether it is a smaller range of numbers or a specific year.

## Goals and Purpose

Our goal is to train a convolutional neural network to date historical art such as pottery, paintings, and small artifacts. This is currently a project that it seems like no one has ever attempted to do so before, possibly due to the complexities of the details and the instability that is using the style and details of art to attempt to date it, however even if our model remains off by some level of forgiveness, such as being off by 100 years or so, it can prove to be quite useful and hopefully speed up the process of dating art.

## Data

Our data was generously given to use from the Carlos Museum at Emory University in Atlanta, Georgia, which is an on-campus historical art museum containing art from Egypt, Nubia, the Near East, Greece, Rome, the Americas, Africa, and Asia. We were given an Excel sheet containing around 25,000 entries of different art objects. Each object containing either all or a mix of object number, the culture it belongs to, the estimated time period, the medium, and the dimensions. After scraping images from the Carlos Museum's online catalog, we had around 2,000 usable pieces of data, which was simplified to only be the image and the date of the art. Future work will be done to see if including the culture, medium, and dimensions will improve the accuracy of the network.

Images were preprocessed to a 150x150 size and clarified changing the contrast, sharpness, and threshold.

*Figure 1.* Showing the transformation applied to images during processing

## Model

Our model is a Convolutional Neural Network which includes three convolutional layers with ReLU activation, one hidden layer, and our final output layer with softmax activation. The model was completely built-in TensorFlow with Keras and has a high learning rate of 0.1. In less than 20 epochs, the model reaches 100% accuracy.

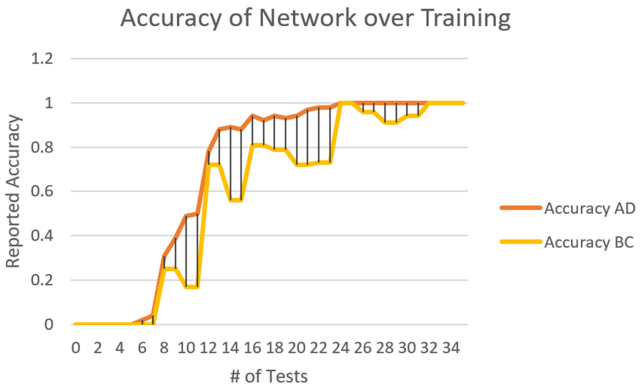


*Figure 2.* Graph showing the increase of accuracy for both AD and BC networks as time goes on

In the end, however, due to the complexities of dealing with dates in BC and AD, we built two models, one capable of dating art in BC and one capable of dating art in AD which we hope to combine via an attention network. Another possibility to get through these complexities is to instead devise an offset and then recalculating the results from the network into something easier to read.

## Conclusion

We were firstly surprised that the accuracy was able to reach such a high-level, let alone in such a short period of time. There is, however, some fear of overfitting. All results generated so far are strictly for the separated AD and BC networks, not including the future attention model due to time constraints.

Additionally, we ran some pieces of undated art through the network alongside performing our own research on similar art from the same culture.

*Table 1.* Showing the Possible Researched and predicted dates for objects

| Object # | Research | AD | BC |
|---|---|---|---|
| 1994.004.529 | 1900 AD | 1900 | 700 |
| 2004.065.001 | 150 BC | 0 | 0 |
| 2009.042.013 | 1900 AD | 2000 | 700 |
| 2011.038.003 | 1800 AD | 1200 | 300 |
| 2012.054.001 | 1900 AD | 1100 | 1076 |
| 2017.035.099 | 1200 AD | 1900 | 2950 |

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