Machine Learning Approach to Art Authentication

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INTRODUCTION

When buying or selling a piece of art, it is common to require proof of the artwork's authenticity. Proof of authenticity is normally accomplished through artifact provenance which consist of documentation such as certificate of authenticity, past ownership, artist signature, and other physical attributes such as dimension, medium, and title. The value of artwork is directly proportional to proper authentication. Therefore, proper art authentication impacts all parties involved with a piece of art such as artist, buyer, seller, curator, appraiser, and insurance adjuster.

Conversely, there are issues with artwork authentication when artifact provenance is fraudulent or missing. For 15 years, Ann Freedman, the president of Knoedler & Company, unknowingly owned $80 million of fraudulent art. Glafira Rosales commissioned fraudulent reproductions of Rothko, Motherwell, and Pollock masterpieces from a local artist and sold them to Freedman. Rosales walked away with $20 million before FBI forensics on the masterpieces revealed historically inconsistent chemicals (Panero, 2013). The German army stole numerous amounts of art between 1938 and 1945 during their invasion of Europe (Henson, 2001). Paris and Vienna were areas of interest for the German army due to the lavish collections held by private collectors and galleries in the area (Feliciano & Felliciano, 1997). Wissbroecker (2004) discuss the litigation attempts of recovering art during this time period. Some of this art that was not destroyed still exists by holders aware and unaware of the art asset. When one of these missing pieces of art surfaces, provenance may be missing.

Blockchain and digital rights management (DRM) are new ways to address art authentication. Wang et al. (2019) developed a system that leverages the provenance capability of blockchain to protect a unique identifier assigned to a digital art asset. Zhaofeng, Weihua, and Hongmin (2018) developed a digital watermarking algorithm to protect digital assets. This algorithm is based on discrete cosine transfer (DCT), the Arnold transform, the human vision system (HVS) model, and Watson model. Both methods address art authentication of digital assets and are easily applied to contemporary art or art with existing authentication and digital representation. However, these methods cannot be used for physical art that is fraudulent, has missing provenance, or is produced by an artist unwilling to use a supervised technical method for art authentication. The need for a supervised method to authenticate digital art assets derived from physical art still exists. The objective of this chapter is to discuss the state-of-the-art approach to meet this need.

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BACKGROUND

With the popularity of digital image processing and supervised machine learning, Johnson et al. (2008) provides objective measures for determining Van Gogh's artistic style. This work branched off into numerous research efforts analyzing artistic style thus providing a basis to mitigate the issues of missing provenance with a digital signature of an artist's work. The success of Russakovsky et al. (2015) winning the ImageNet challenge pushed image classification to new performance standards. From an artist classification perspective, Viswanathan and Stanford (2017) and Dobbs, Benedict, and Ras (2021) build on the success of ImageNet winners by applying residual neural networks to increase the performance of artist classification using the WikiArt data set. Likewise, Mensink and van Gemert (2014) and van Noord, Hendriks, and Postma (2015) apply machine learning algorithms to increase the performance of artist classification using the Rijksmuseum data set. The Rijksmuseum is the national museum of the Netherlands. They tell the story of 800 years of Dutch history, from 1200 to now. In addition, they organize several exhibitions per year from their own collection and with (inter) national loans (Rijksmuseum, 2021). The focus of this chapter relates to the Rijksmuseum dataset and ResNet 101 algorithm. (Dobbs et al., 2021) discuss additional background related to the OmniArt and WikiArt datasets and lower performing algorithms.

MACHINE LEARNING ART AUTHENTICATOIN METHODOLOGY

Applying machine learning to the art authentication problem requires five things. First, a source of data with sufficient samples for experiments is required. Second, a residual neural network method that can be customized is needed. Third, a custom method of annealing results between data subsets is required. Fourth, a high-performance cluster is needed to run experiments. Last, a method for measuring the performance of experiments is needed. These five requirements should be constructed in a manner that is easy to repeat if any step needs to be redone.

Data Source

The data source for experiments should be publicly available for research. For example, data available from the Rijksmuseum consists of 112,039 artworks from 6,629 artists. Each artwork has a corresponding image and xml metadata file. The high-quality images are stored as 300 dpi compressed jpeg and were taken in a controlled environment (Mensink & van Gemert, 2014). Special organization and translation scripts developed in Matlab can prepare the data for experimentation. For experiments, images from all types of artworks can be used for artists with more than ten artworks. Artwork types can include images of paintings, prints, photographs, ceramics, furniture, silverware, doll's houses, and miniatures. Artworks from anonymous and unknown artists can be included in experiments even though these two categories are not relevant to art authentication. Since both anonymous and unknown classes contain multiple artists, they provide a group for which an artist should not identify.

Residual Neural Network

Like Kim (2017), Matlab's implementation of Residual Neural Networks (He, Zhang, Ren, & Sun, 2016) can be used to train, validate, and test output models. Matlab provides an extensible scripting method

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