Markov Chain-based Art Authentication Modeling with Convolution Neural Network

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Abstract

Consider the increasing number of digitized artworks, this work proposes a computational evidence to assist the connoisseur [2]. in their authentication assessment. Convolution Neural Network (CNN) is used for feature extraction and thus to unveil the hidden stylometry which might not be obvious to human perception. The extracted features from both genuine artworks and known forgeries are used to train the classifier. Rather than solely relying on a single classifier to distinguish an artwork from the forgery, a hierarchy of multiple classifiers are used to model the authentication process. We approach the above modeling with Markov Chain and quantify the computational evidence in terms of probability measurement. A dataset consists of artworks by Renaissance master Raphael and known forgery are used for experiment. Furthermore, a total of 7 disputed artworks are tested with our proposed approach and their computational evidences are quantified. To this end, this work hopes to provide the connoisseur an additional yet solid evidence from a more scientific perspective.

1 Introduction

Over the years, the authenticity of an artwork is always accomplished with a thorough assessment from a connoisseur. However, even though the connoisseur can reach a conclusion regarding the authenticity of an artwork with their in-depth and profound knowledge on a large collection of historical artworks; often, their judgement might prone to error and different connoisseur might hold on to their differing opinions. Such subjective judgement, undoubtedly, lead to controversial artwork in which further effort is required to authenticate a genuine artwork. Furthermore, with today's advance technology, most artworks has been digitized with an objective to preserve their value. This further creates plenty of opportunities for imitator to recreate a highly similar artwork by making use the high end processing of professional computer software.

Motivated by the increasing disputed issues in artwork authentication, researchers have started to exploit the visual stylometry analysis to discover the painting style of an artwork and thus get an insight into the habitually style of a famous artist. The active involvement of researchers in art authentication has lead to an extensive development of image processing systems to distinguish the forgery from the genuine artwork, one can refer to [1] for a survey on a various image processing tools for art authentication. It is deemed that each artist has their own unique painting style and behavior which is hard to be imitated by a forger. That is, although two artworks might highly similar

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[2]a person who is especially competent to pass critical judgments in an art, particularly one of the fine arts, or in matters of taste, "http://www.dictionary.com/browse/connoisseurship"

in first perception and could not be discerned through naked human's eye, it is still possible to unveil a forgery artwork from a genuine one by examine the hidden painting style By making use of the recent advancement in image processing, machine learning and statistical analysis, this work aims to propose an efficient artwork authentication system by quantifying the painting style based on the extracted feature vectors such that to assist the connoisseur in their profound artwork judgement.

In this work, we consider the dataset provided by Prof. Wang Yang. The dataset consists of 35 high resolution digitized artpieces attributed to the Renaissance master Raphael in which 18 are genuine works of Raphael, 10 are known as forgeries, and 7 are disputed. Figure 1 depicts the example of the artwork in each category, i.e., (a) is the genuine artwork from the Renaissance master Raphael, (b) is verified as the forgery and (c) is the disputed artwork which yet to be further justified. Among them 18 images are in the form of 'jpg', whereas the rest are in 'tif' format. Since each image has different bit depth, i.e., some were encoded in 8 bits and some in 16 bits, to ensure each image has the same bit depth and format, a quick preprocessing was performed before further process the image. A division operator (i.e., divide by 256 in this case) is imposed to convert the image with 16 bits per pixel to 8 bits per pixel. After the conversion, each image is reorganize automatically into three sub-folder: Raphael, nonRaphael, disputed.

The main contributions of this work is summarized as follows:

- **Feature Extraction**: Deep learning based feature extraction - Convolution Neural Network (CNN) is used to extract the feature of a digitized artwork and thus to unveil its hidden stylometry.
- **Hierarchy of Multi-classifiers**: A multi-classifiers compose of Support Vector Machine (SVM), Adaboost and Multi-Layers Perception (MLP) is established as an aid to the authentication process.
- **Markov Chain Modeling**: Based on the multiple results produces by the multi-classifiers, Markov Chain is adopted to model the entire process and quantify the final computational evidence for a disputed/questionable artwork.

The rest of the paper is organized as follows. Section 2 reviews the related works. Section 3 set forth the problem formulation; Section 4 describes the proposed solution and our approach to the above problem with the proposed justification metric; Section 5 presents the experiment results and compares the performance of classification with few baselines, we further discuss the disputed artworks according to the proposed justification metric; and Section 6 concludes the paper with future work.

Figure 1: The example of artwork painting from (a) Genuine Raphael, (b) Know forgery and (c) Disputed/Questionable.

2 Related Works

This section reviews the related works and tabulates them according to their tested dataset.

Table 1: Summary of Related Works

Paper	Dataset	Methodologies	Ref
A Digital Technique for Art Authentication	13 artpieces attributed to Pieter Bruegel the Elder	Wavelet decomposition + MDS	[2]
Authentic: Computerized Brushstroke Analysis	169 artpieces attributed to Van Gogh	Circular Filter + Contour enhancement	[3]
Authenticating Pollock Paintings using Fractal Geometry	7 artpieces attributed to Jackson Pollock	Fractal analysis	[4]
Detection of Forgery in Paintings using Supervised Learning	101 artpieces attributed to Van Gogh	wavelet + HMT	[5]
Quantification of Artistic Style through Sparse Coding Analysis in the Drawings of Pieter Bruegel the Elder	13 artpieces attributed to Pieter Bruegel	Curvelet + Sparse coding	[6]
A New Method for Visual Stylometry on Impressionist Paintings	101 artpieces attributed to Van Gogh	HMT + Fisher Information	[7]
Empirical Mode Decomposition Analysis for Visual Stylometry	13 artpieces attributed to Pieter Bruegel + 20 artpieces attributed to Rembrandt van Rijn	EMD + SVM	[8]
Simultaneous forgery identification and localization in paintings using advanced correlation filters	7 artpieces attributed to Charlotte Caspers	optimal trade-off synthetic discriminant function (OTSDF)	[9]
A proposed method on painting authentication using Contourelet transform (PAUCT)	20 artpieces attributed to Van Gogh	Contourelet transform + HMT	[10]
Geometric Tight Frame based Stylometry for Art Authentication of Van Gogh Paintings	76 artpieces attributed to Van Gogh	Geometric tight frame	[11]

Art authentication based on visual stylometry, as an emerging research field, has attracted great attention from related research community since 2004. The ever first success in authenticate the genuine artworks from its forgery was published in [2]. The developed authentication system modeling always compose of several image transform, classification and statistical analysis tool including wavelets [7], fractal [4], curvelets [6], Hidden Markov Tree [5], geometry tight frame [11], empirical mode decomposition [8], etc. The details of each related work subject to their tested dataset and methodology are tabulated in Table 1, accordingly. Clearly, the combination of various advance computing tools from image processing, machine learning and statistical analysis undoubtedly demonstrate a promising authentication method in addition to the conventional authentication performed by connoisseur.

Despite the encouraging results achieved by the prior works, further work is needed to provide a move diverse methodologies as an aid to connoisseur in making their judgement as we deem that the work of authentication should not based on a single source or computing method, rather by combining the results obtained from various aspects, connoisseur can have a more holistic evidence to justify a genuine artwork. To this end, this work approach the problem from a holistic manner by classifying the known dataset and further quantify a computational evidence for the disputed artwork through a Markov Chain Modeling process with a hierarchy of multi-classifiers.

3 Problem Formulation

This section set forth the problem formulation for the art authentication problem and defines all the notations which are to be used thorough the paper.

Assume that a digital art database consists of a set of genuine artworks attributed to a known artist with index set of $I = \{1, 2, ..., n\}$, a set of forgery artworks by unknown forger with index set of $I^c = \{1, 2, ..., m\}$, and a set of disputed artworks which receive different opinions regarding its genuineness with index set of $J = \{1, 2, ..., o\}$, where the total art collection is equal to $n + m + o$, then for a given an artwork with index $j \in J$, there are only two possibilities: (1) j is also an element of set I, or (2) j is an element of set I^c. In other words, it is impossible for jth artwork to be in both set I and I^c at the same time.

Suppose each element in index set of I, I^c and J is mapped to a feature vector of size k (which is to be determined by the corresponding feature extraction), mathematically, these feature vectors can be represented as follows:

$$\mathbf{x}_i = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_k \end{pmatrix} \in \mathbb{R}^k, \forall i \in I; \qquad \mathbf{x}_i^c = \begin{pmatrix} x_1^c \\ x_2^c \\ \vdots \\ x_k^c \end{pmatrix} \in \mathbb{R}^k, \forall i \in I^c;$$
$$\mathbf{y}_j = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_k \end{pmatrix} \in \mathbb{R}^k, \forall j \in J \tag{1}$$

Since each features vector $\mathbf{x}_i$ is in the same set I, rather than represent all n artwork in I with all k elements in features vector (which is equal to total size of $k \times n$), we only use the first moment (mean) to describe the feature for n artworks, i.e.,

$$\bar{\mathbf{x}}_i = \frac{1}{k} \sum_{r=1}^{k} x_r, \forall i \in I \tag{2}$$

then the feature representation for each artwork in I can be reduced to matrix $\mathbf{X} = [\bar{\mathbf{x}}_1, \bar{\mathbf{x}}_2, ...\bar{\mathbf{x}}_n]$. Similar argument applies for artwork in I^c and artwork in J, i.e., $\mathbf{X^c}$ and $\mathbf{Y}$, respectively.

With this a classifier can be trained to distinguish the artwork in J. That is to say that, by supplying the disputed artwork to trained classifier, the probability of a disputed artwork j to be likely belong to the set I is:

$$P(j \in I) = \{p : p = ||\mathbf{y} - \mathbf{X}^T||^2 > ||\mathbf{y} - \mathbf{X^c}^T||^2\} \tag{3}$$

where p is the classification score by comparing the feature vector of $\mathbf{y}$ to all the feature vectors $\bar{\mathbf{x}}_i$.

Since Markov Chain is to be used to model the authentication process, we denote the disputed artwork j belong to the set I as state 1, or else state 0. Hence with Markov Chain context, Eq. (3) also denote the probability of state 1, then the probability of state 0 is simply $P_0 = P(state = 0) = 1 - p$, and the transition probability from state 0 to state 1 and vice versa can be represented as follows:

$$P = \begin{pmatrix} P_{00} & P_{01} \\ P_{10} & P_{11} \end{pmatrix} \quad \text{and} \quad \sum P_{ij} = 1, \forall i \neq j \tag{4}$$

Note that a steady state will be achieved after few iterations, i.e., the process will settle down at certain state with certain probability. In other words, the process converges to a certain probability at steady state.

4 Proposed Solution

This section presents our proposed solution and describes the Markov Chain Modeling with hierarchy multi-classifiers toward quantifying a computational evidence for art authentication.

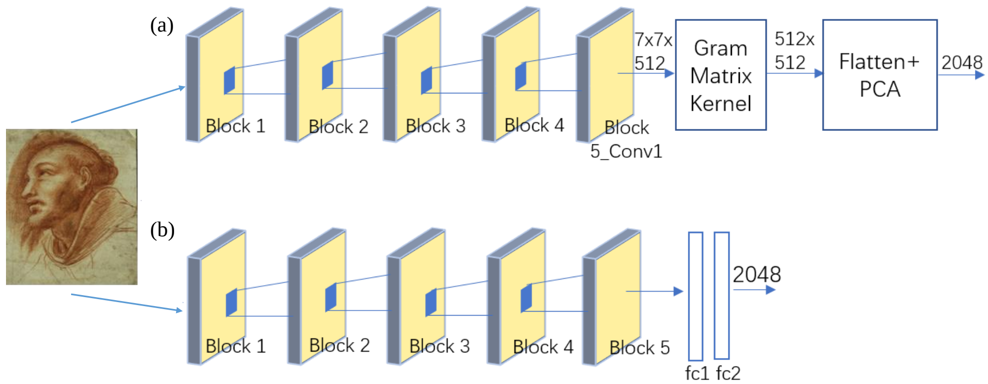

Figure 2: CNN featurare extraction with (a) style-based feature and (b) content-based feature

4.1 Feature Extraction

This work adopts two deep learning based feature extraction methods (see Figure 2) to extract hidden information from digital artworks which might not so obvious to naked eye. One artwork usually consists content part and style part, that is, artist use content to express the main subject of one artwork and use style to express the emotion of one artwork. Intuitively, these two important features might reveal the habitual style of an artist which is useful for artworks authentication. To approach the challenging artistic problem, a deep learning based feature extracting architecture is constructed to extract stylometry. We design a feature space on top of the CNN filter response layer of, and Gram matrix kernel is used to filter maps of the first convolutional layer in the fifth convolutional block (see Figure 2(a)). The output of Gram matrix $G^l \in R^{N_l \times N_l}$ in layer l contains the correlations between those filter maps, where F^l are filter maps in layer l and F^l_{ik} is the value in k^{th} position of flattened i^{th} filter map.

$$G^l_{ij} = \sum_k F^l_{ik} F^l_{jk} \tag{5}$$

The output of the Gram matrix is a symmetrical matrix which we further flatten into a vector. This yield a high dimensional vector, i.e, $13,1328$ $(512 \times 513/2)$, thus principal component analysis (PCA) is used to reduce the dimension before further export the feature for classification training. We also design a deep learning based feature extraction architecture to extract content feature which are generated on the basis of VGG-16 network. All five convolutional blocks are used and the dimension of two fully connected layers are reduced from 4,096 to 2,048 (see Figure 2(b)). More details on VGG-16 can be found in following works [12] [13]. After the fully connected layer learned non-linear combinations of features from previous layers, the output representations capture the high-level content informations which can serve as a further add-on to visual stylometry.

4.2 Hierarchy of Multi-classifiers

As discussed in Section 3, classifier is trained to distinguish the genuine artwork from the forgery. The output of a classifier is generalized in Eq. (3). In this work, we construct a hierarchy of multi-classifiers to classifier a disputed artwork and quantify the classification with a classification score. This score can then be used as a computational evidence to aid the connoisseur in assess an artwork. The proposed hierarchy of multi-classifiers are constructed based on three famous classifiers: Support Vector Machine (SVM) [14], Adaboost [15] and Multi-Layers Perception (MLP) [16]. For details working principle of each classifiers, one can always refer to the above cited references, this work focus on the hierarchy flow of each classifiers and how the classification score generated from each classifier support the authentication modeling using conventional Markov Model.

4.3 Authentication Modeling with Markov Chain

Suppose an artwork has been questioned by many art expert regarding its authenticity and create a hard time for connoisseur to gather sufficient evidence to assess the particular artwork, this work proposes a quantify score for each disputed artwork based on probability measures conditioned on a

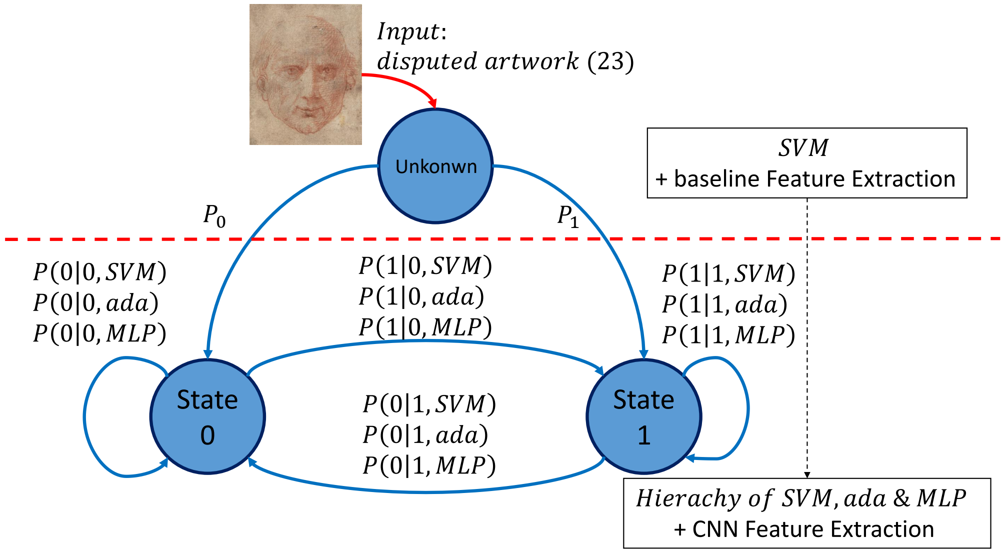

Figure 3: A hierarchy multi-classifiers aid to authentication modeling with Markov Chain

hierarchy of multi-classifier discussed above. As illustrated in Figure 3, we initialize a probability for the disputed artwork based on SVM classifier, which has been trained based on a collection of past known forgery as well as authentic artwork. Based on this initial probability, the disputed artwork might probably end up in either two states. Then, a series of classification is iterated until the process converge to a steady state with a certain probability measure. Given this steady state, we can quantify the computational evidence, i.e.,

$$[\rho_0 \quad \rho_1] = [\sum_{i=0}^{1} \rho_0 P_{ij} \quad \sum_{i=0}^{1} \rho_1 P_{ij}], \forall j \in [0, 1] \tag{6}$$

where ρ_0 indicates the process settle at state 0 with probability ρ_0, which means that the probability for the disputed artwork to be a forgery is ρ_0. Similary argument applies to ρ_1. Note that P_{ij} is a transition probability defined previously in Section 3.

5 Experiment and Result

This section describes the dataset and baselines used in our experiment. The classification results between known genuine artwork and known forgery artwork are presented in Section 5.2, and the justification metrics used to quantify the disputed artwork is discussed in Section 5.3.

5.1 Baselines

Three existing feature extraction tools are used as baselines to compare the performance of our proposed solution. The details of each baseline are briefly described as follows:

- **SURF**: Since Speeded-Up Robust Features (SURF) [17] has proven to be a robust feature extractor which is able to detect local invariant features of an image, and we deem that the artworks from same artist's hands should exhibit some invariant features across multiple artworks. For this reason, we had implemented SURF as a baseline as a comparison.
- **HOG**: The other feature extraction method that we had used as a baseline is Histogram of Gradient (HOG) [18]. Even though HOG is seldom used in extracting the style pattern of an image, the change of gradient across the surface of image did attracted our attention because the change of gradient should be smooth if the artwork if genuine, an abrupt change might indicate a forgery work.

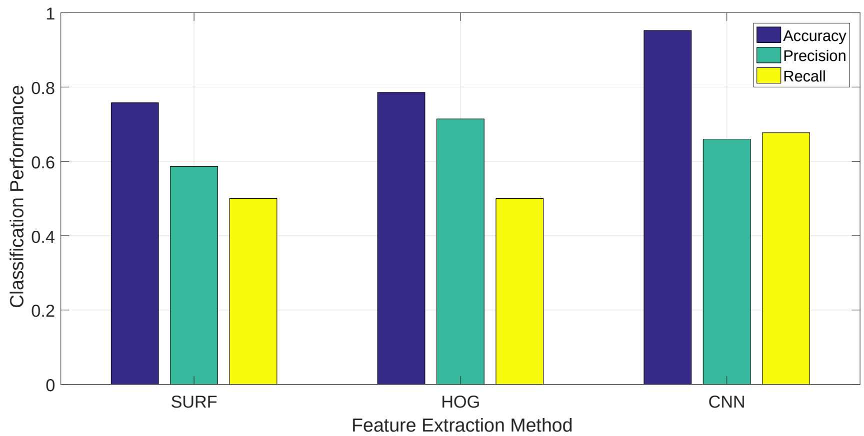

Figure 4: Classification performance in terms of accuracy, precision and recall for all the three feature extraction methods.

Table 2: Authentican Quantification with Probability Measures

Artworks	A01	A07	A10	A20	A23	A25	A26
ρ_0	0.062	0.2689	0.56	0.67	0.45	0.75	0.56
ρ_1	0.938	0.931	0.44	0.33	0.55	0.25	0.44

5.2 Classification Results

Leave-one-out cross validation is applied to the classifier training process. Only the genuine artworks and the known forgery were used in classification, whereas the disputed artworks are reserved for later evidence computation experiment. The classification accuracy for all the three feature extraction methods using SVM is summarized in From Figure 4, it is clear that CNN outperforms the rest with high classification accuracy. In the art authentication context, a high recall is deem significant as incorrect classify a forgery as genuine artwork might create great lost; whereas high precision ensures a genuine artwork can be recognized correctly. Overall, CNN still achieve better performance than the other two, even though HOG might give a slightly higher precision than CNN.

5.3 Computational Evidence Quantification

Table 2 illustrates the steady state probability for each of the six disputed artworks in Raphael's dataset. The probability measures at the steady state give an insight regarding the computational evidence of a disputed artwork from a scientific perspective. With the aid of this quantifying evidence, connoisseur can have a better idea regarding a particular artwork and further judge the artwork with their profound knowledge. If normal person would like to assess the disputed artwork with the evidence score presented in Table 2, they might conclude that with high probability that artwork A20 and A25 might be a forgery; however, it also note that artwork A10, A23 and A26 have a very similar probability which couldn't be distinguish easily. Nonetheless, the ultimate objective is to provide the connoisseur additional evidence for further assessment rather than judge a disputed artwork directly with simply some mathematical measure which might be very dangerous to art authentication. Furthermore, current probability measure is calculated manually and further work is needed to automate the process for better efficiency.

6 Conclusion and Future Work

This paper presents a computational evidence for art authentication from a scientific perspective by leveraging the current advancement techniques in image processing, machine learning and statistical analysis. Instead of judging the disputed artwork based on a single classifier, we further propose a hierarchy of multi-classifier, and together with Markov Chain modeling, we provide the connoisseur a quantify evidence which might helpful to assist them in further authentication assessment. Even though CNN is used in feature extraction and shows promising results, we also noted the potential of HOG in artworks extraction which further work can be put forth to improve the performance of HOG, for example, characterize the gradient with higher statistical order rather than simply based on the histogram. Lastly, as mentioned, current modeling process is incomplete and manual calculation is required to obtain the quantify probability measures, further work is needed to automate the authentication modeling process for better efficiency. Nonetheless, this work, undoubtedly achieves very good performance in connection to the classification accuracy using CNN, furthermore, a novel art authentication tool is presented with hopes to create a new synergy between physical authentication and scientific authentication for better authentication process.

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