

A Fine-grained Artist Identification Method for Authentication and Attribution of Drawings using Hatching Lines

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Abstract

Fine-grained image recognition (FGIR) addresses the challenging task of distinguishing between visually similar classes by learning subtle, discriminative features. In this work, we approach the problem of artist identification as a fine-grained recognition task, where the goal is to distinguish between different artists based on the nuanced visual characteristics of their hatching lines in drawings and prints. Hatching, a popular art technique used to convey tonality, shading, and volume, is often executed quickly and spontaneously, making it a potential carrier of artist-specific, unconscious stylistic signatures. We hypothesize that these subtle variations in hatching patterns encode unique artist-specific features that can be computationally modeled for automated attribution and authentication. To explore this hypothesis, we develop a deep learning-based pipeline capable of detecting hatching regions and learning fine-grained features that discriminate between artists. We evaluate our approach on a diverse collection of drawings and prints spanning multiple artists, artistic styles, and time periods. Our results demonstrate that artist identification from hatching alone is possible, achieving 90-100% accuracy in most cases, highlighting the effectiveness of fine-grained recognition techniques for artist attribution in visual art.

1. Introduction

Fine grained image recognition (FGIR) is a challenging area of research that aims to categorize highly similar classes by learning discriminative features that capture the subtle inter-class differences [59]. FGIR is a highly versatile computer vision problem with a diverse set of applications [59] such as biodiversity analysis [14, 41], transportation and vehicle surveillance [51, 58], retail product classification [3, 29], fashion [22], agriculture [60] and medical imaging [12, 23], to name a few.

In this paper, we focus on a special case of artist identification as a fine-grained recognition problem. FGIR focuses on the recognition of highly detailed and subtle variations that distinguish objects within the same category. In the context of artist identification, this means identifying unique, small-scale features that reflect the unconscious physical and stylistic attributes of an artist's work; details that are not immediately obvious but can be critical in distinguishing one artist from another.

In this work, we investigate a special case of artist identification based on drawings and prints, where recognition experiments are carefully designed to include artists with similar style, genera and mediums (see Figure 1¹). In addition, instead of relying on global coarse-grained features, such as subject matter or overall composition, we focus on detection and recognition of specific parts of drawings, i.e. hatching lines, which we hypothesize carry unique physical and unconscious characteristics of the artist. This similarity between classes, and our detection-recognition approach, make this artist identification task a unique application of FGIR in analysis of art that can facilitate authentication and attribution of drawings and prints. Authentication and attribution are two critical tasks in the art domain. Attribution assigns authorship to an artwork, while authentication confirms the validity of that attribution. Art authenticators and connoisseurs rely heavily on stylistic analysis, where human experts, influenced by Morellian Analysis [37], visually inspect works for distinctive clues such as brushwork, lines, and stylistic details unique to the artist. In contrast to expert-eye-based stylistic analysis, technical analysis uses scientific methods to analyze physical properties of an artwork such as canvas, pigment and age, to assess its authenticity [10]. Ragai [43] provided a comprehensive review of these methods.

Due to complexity of attribution and authentication, both stylistic and technical analysis have disadvantages in areas

¹Image credit and artwork information for all the pieces shown in this paper are included under Artwork Credits (Sec. 5), after references.



Figure 1. Inter-class similarities and fine-grained nature of the Rembrandt (1–4) vs. followers (5–8) identification task.

such as speed, reliability and cost. A computer vision solution alleviates these issues by automating stylistic analysis and providing extra insight when technical analysis falls short or is impractical due to cost or time limitations [10].

Several approaches have been proposed to study the application of computer vision in the problems of authentication and attribution, however with limited scope to a specific artist, or with limited data sets. Moreover, most of these studies focus on paintings. We provide an overview of these studies in Section 2.

Unlike paintings, the application of computer vision to attribution and authentication of drawings and prints is sparsely explored. We approach these two tasks by introducing a novel methodology based on the analysis of hatching lines, aiming to discover unique underlying characteristics of the artist that can be used to recognize their hand.

1.1. Hatching Technique

Hatching is a commonly used technique in drawings and prints that is done by adding quasi-parallel line segments of different lengths, thicknesses, and spacing to select parts of the overall composition (see Fig. 2a). Hatching lines can be present in various locations in the artwork, including in the background, inside the foreground, or close to the contours of objects. This change of position can evoke different feelings in the viewers. Hatching lines in the background can introduce depth, shadows, or even movement, while those appearing inside objects often create a sense of tone and volume (see Fig. 2b). There are a few different ways to use hatching with different visual effects, such as parallel-hatching, cross-hatching, and contour-hatching. For example, contour-hatchings follow the shape of objects and create a three-dimensional effect, while cross-hatchings

can add different amounts of darkness, depending on how densely they are drawn or engraved (see Fig. 2b).

We hypothesize that hatching lines carry an unintentional artist signature that holds key information about the unique physical and unconscious characteristics of artist’s hand which can be used for identification. Compared to the detailing of figure’s contours, execution of hatching lines is quite trivial for a seasoned artist and typically requires less conscious attention. In addition, hatching lines are rarely essential to the subject matter, which gives the artist the leeway to execute their hatchings quickly and usually in batches. Consequently, hatching lines tend to be spontaneous. We further hypothesize that the signatory characteristics of hatchings can be computationally modeled to facilitate automatic attribution and authentication.

To test these hypotheses, we propose a multi-step process that automates the detection, computational modeling, and analysis of hatching lines in drawings and prints. Our methodology relies on two major tasks: 1. learning a representation of hatching lines that enables hatching detection. 2. Training artist identification models that learn to distinguish between artists based solely on their hatching lines. We investigated the application of deep convolutional neural networks to the two tasks of hatching detection and hatching-based artist identification.

1.2. Challenges

Analysis of hatching lines is challenging for several reasons. First, artworks differ significantly in their physical properties, including size, drawing or printmaking technique, medium and color tone of papers. Considering medium alone, artists use a variety of techniques in their drawings, such as pencil, pen, ink, ink wash, chalk, water-

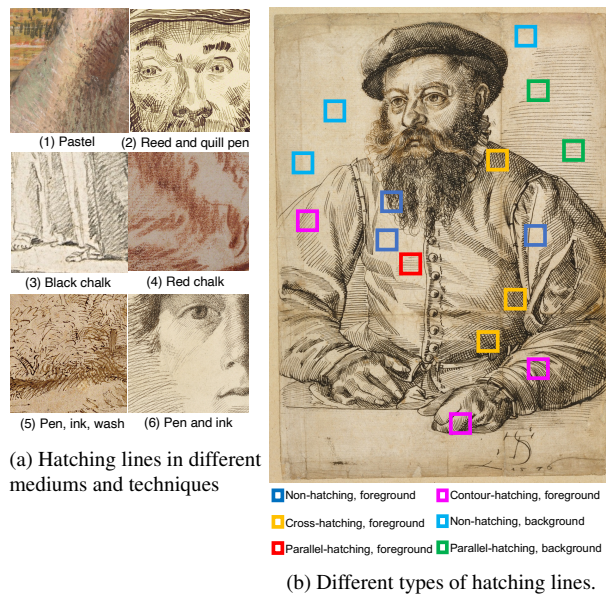


Figure 2. Hatching technique and its variations

color, and others, or a mixture of them. Additionally, different digitization technologies result in various spatial resolutions in the digitized reproduction of original art. These inconsistencies introduce complications and biases in quantifying hatching lines, which need to be addressed. Moreover, hatching lines are relatively sparse compared to contours, fillings, and background areas. This sparsity translates to an imbalance in the data. Another important challenge is the lack of data, since the number of available images of drawings of good enough resolution by each artist can be significantly small compared to datasets needed to train deep neural networks.

Given the aforementioned challenges, this paper focuses on developing an approach for artist identification using hatching lines, based on a comprehensive comparison of several deep learning models. It designs experiments to thoroughly investigate the problem and ensure that the trained models do not learn shortcuts or biases from the data (paper tone, genre, resolution, digitization artifacts). Additionally, the paper analyzes the robustness of the proposed methods against variations in medium.

To test the capacity of hatching lines in drawings as a marker for artists' hand, we designed several artist identification experiments, involving pairs or triplets of artists with similar styles, from same school or movement, with similar genre and medium. The experiments spanned different eras and nationalities, and with drawings and prints made using a variety of mediums and techniques. Overall, the main result of this study is that we can indeed identify artists based solely on their hatching lines, with very high accuracy, reaching 100% in some cases.

2. Related Work

Several approaches studied the application of computer vision to the problems of authentication and attribution. Some of these techniques extend the technical analysis paradigm by using image processing to study physical properties such as analysis of canvas weaves [26, 27, 56]. In contrast, stylistic analysis using computer vision aims at discovering patterns and repeated visual characteristics of the artist's body of work and can take several different routes. Many studies have focused on the task of artist identification on different datasets (e.g. [8, 9, 11, 32, 35, 42, 45, 46, 48]). The majority of these studies perform coarse-grained recognition of artworks based on high-level global features, such as the overall composition or subject matter. These approaches work particularly well on artists with distinguishable styles. However, such coarse-grained methods are not suitable for distinguishing artists with close styles, who worked in the same era, belong to the same school or movement, or used similar mediums. Therefore, such methods are not suitable for attribution and not effective for authentication.

Alternatively, studies on analysis of lower-level features, like line segments or brush strokes, are more likely to locate unique characteristics of an artist's hand that are independent of the subject matter or overall composition. Fine-grained features such as pressure or connectedness of line segments are the byproducts of a more subconscious artistic process, and hence harder to forge, providing an opportunity for authentication and attribution. For example, multiple studies [5, 19, 47, 54, 55] suggest fractal analysis of Jackson Pollock's drip work for authentication of his work while others [28, 52] challenged the idea. In addition, several studies have pursued brushstroke-level analysis of paintings. In particular, analysis of Van Gogh's brushstrokes has been a common theme in several studies in recent years [20, 24, 25, 31, 40]. Two recent studies applied deep learning techniques at the texture level to the authentication of action paintings by J. Pollack [50], and the recognition of Rembrandt vs. Van Dyke based on material rendering in their paintings [17].

Only a few studies have addressed drawings and prints. Lyu et al. [36] proposed an authentication method for drawings that was tested on a small dataset of 13 drawings either by Bruegel or attributed to him. Leonarduzzi et al. [33] proposed a methodology for authentication and attribution of both drawings and paintings, however, their drawing dataset was limited to 21 Raphael and non-Raphael works in total. Elgammal et al. [10] introduced a methodology for analyzing strokes in line drawings, emphasizing its potential in forgery detection and authentication based on stroke analysis, trained and tested on 300 images [10]. In addition, two recent studies proposed deep learning based approaches for classification tasks on datasets of prints. One of these studies was focused on classification of prints to their printing

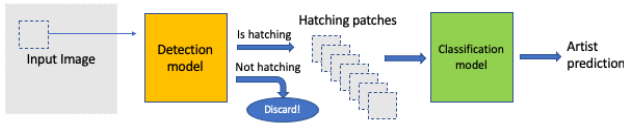


Figure 3. Hatching detection-artist classification pipeline

techniques and suggested a shallow architecture for this task [18]. The second study was focused on artist classification, exclusively prints of portraits, and compared a transformer-based architecture to a CNN-based model for this task [7].

3. Methodology

Our methodology for artist identification based on hatching can be summarized as follows. First, using supervised learning, we trained a deep neural network to quantify the characteristics of hatching lines in small patches of drawings. We call such a network a hatching detection model, as it can predict the presence of hatching lines. Next, we trained and tested several classification models that distinguish among artists at the patch level, solely based on the patches that include hatching lines. The inputs for these classification models are areas that are detected as hatching by the detection model (see Fig. 3). Finally patch-wise results are aggregated to obtain final image-level prediction of the artist. In this paper, patches refer to small parts of the image that are 50x50 pixels, which roughly maps to an average physical size of 60x60 mm.

Our patch-based approach serves several purposes. First, it isolates hatching lines to test our hypothesis mentioned above. Second, it prevents the artist classification models from relying on high-level global features such as subject matter and overall style or composition of artwork, which are easier to imitate, and thus focus on learning to distinguish the artists based on fine-grain characteristics of hatchings which are spontaneous and harder to forge. In addition, this approach increases the size of training sets substantially (e.g. by a factor of 500), providing more data for training deep learning models that generalize better. We used overlapping patches in both detection and identification. This allows the networks to learn a shift-invariant representation of hatching. It is important to note that images were transformed into grayscale as a preprocessing step, to minimize the color-related bias, such as paper tone, and ink/pigment color, and emphasis on learning the concept of hatching lines and structural differences between hatchings of different artists.

3.1. Hatching Detection and Artist Identification

We approach our hypotheses with a two-stage process: First, detection of hatching areas by labeling the images at the pixel level to hatching and non-hatching. Second, for

areas labeled as hatching, an artist classifier model is used to predict the artist. To achieve that, our pipeline consists of four components:

1. A detection model is trained to predict the probability of being a hatching patch for image patches.
2. A trained detection model is applied to each drawing in a sliding window manner and the detector’s hatching probability predictions are accumulated to achieve pixel-level prediction of hatching, i.e. segmentation masks.
3. An artist identification model then takes patches labeled as hatching and is trained to predict artist class probabilities based on hatching patches of the artists.
4. Patch-level artist class predictions are aggregated over the whole image to come up with a final image-level artist prediction.

To achieve that we need to train a hatching detection network and an artist prediction network.

3.2. Hatching Detection

Since hatching is characterized by quasi-parallel or cross lines, it is natural to think of hatching as textured areas in the image. Conversely, the negative class are either background areas or main drawing parts which do not exhibit this textural quality. Notice that hatching can appear both in the background or within the foreground area. Therefore, hatching detection reduces to training a model to identify the hatching texture apart from other areas that don’t include such texture.

Given the texture-like nature of hatching, we chose two baselines: First, we used Gabor Filters [38], which are widely used for texture classification (e.g.[21]). Applying Gabor banks to every patch results in a large feature vector, which is then classified using a Support Vector Machine (SVM) classifier. The second baseline is derived from ScatNet [4], a notable approach in texture representation that computes translation-invariant texture features using pre-defined wavelet transform filters, including Gabor. We found that both these baselines performed poorly on the task of hatching detection and could achieve test accuracy of 62%-70%.

Unlike ScatNet, we found that adding a learnable convolution network on top of a Gabor filter bank can boost the results significantly. Inspired by this observation, we experimented with a wide range of state-of-the-art deep convolutional neural networks (CNNs) as our hatching detection model adapted and trained to distinguish between hatching and non-hatching patches. We conducted extensive evaluations of various model architectures, including MobileNet [15], VGG16 and VGG19 [49], ResNet50 [13], EfficientNetB0 [53], DenseNet121, DenseNet169 and DenseNet201 [16], and experimented with different hyperparameters and regularization methods. Moreover, we evaluated different pre-processing and training strategies, for example, trans-

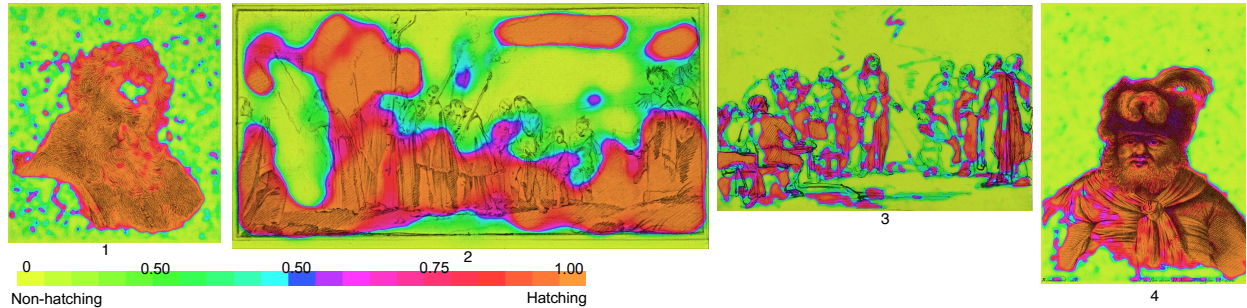


Figure 4. Hatching segmentation results are shown as a heatmap of pixel-level hatching probabilities overlaid on the original images

fer learning [61] from models pre-trained on the ImageNet dataset [6] vs. training from scratch on our data.

The overall architecture of a CNN-based hatching detection model consists of the following: a base deep neural network, such as MobileNet (i.e., without the top classification layers), a global average pooling layer, a dropout layer, and a final fully connected layer with a sigmoid activation. The base model is initialized by transfer learning from a model pre-trained on ImageNet, and the top classification layer is trained from scratch. The model is trained using the binary cross-entropy loss function and optimized using the Adam [30] optimizer with default hyperparameters, except for the learning rate which we decreased to mitigate overfitting.

In contrast to CNN-based architectures, we also experimented with a transformer-based architecture, namely, using a SWIN Transformer [34] as the feature extractor for hatching detection. SWIN Transformers have become prominent in solving diverse computer vision tasks by leveraging an efficient application of self-attention mechanism across their hierarchical levels.

3.3. Hatching Segmentation

Following the training of hatching detection models, we designed a pipeline to translate the patch-level hatching predictions to pixel-level labeling of hatching areas. We used a sliding window approach to predict hatching segmentation masks based on hatching detection results. For each pixel, we aggregated patch-level detections of its intersecting patches to create these masks. (More details in Sec. 7)

We explored multiple aggregation functions, including the minimum, median, and a learned mapping function trained to predict a pixel’s label from patch-level detections on its overlapping patches. The results showed that the median and the learned mapping function performed similarly and were more effective than the minimum function in estimating hatching segmentation masks. Using five DenseNet121-base detectors, trained in a cross-validation setting, we calculated hatching segmentation masks for our

dataset of 670 images². We evaluated these predictions using the Intersection over Union [44] metric for both hatching and non-hatching classes and computed the mean IoU (MeanIoU) metric.

3.4. Artist Prediction Network

We trained artist classifiers based solely on the hatching areas of the images. Our classification model’s architecture is similar to that of the detector model and consists of a base deep neural network, a global average pooling layer, a dropout layer and a fully connected layer with the softmax activation function. We applied transfer learning, initializing the classifier with the pre-trained hatching detector’s weights and finetuning these weights, except for the top classification layers which are trained from scratch for each experiment. We used the cross-entropy loss function and trained the artist classification models using the Adam optimizer.

We applied a sliding window with a stride of 5–35 pixels, depending on the experiment, to extract overlapping image patches, which were fed into a pre-trained detection model to locate hatching regions. Overlapping was allowed due to the sparsity of hatching lines in drawings to ensure relevant regions were not missed. Extracted patches were assigned artist labels, and the larger classes were randomly down-sampled to balance the dataset before training the artist classification model. Test sets were processed using the same procedure for consistent evaluation.

In addition to the experiments that followed the discussed pipeline, we also conducted baseline experiments when the hatching annotation masks were available. In these experiments, we extracted the hatching patches directly from ground-truth annotations and bypassed the use of the detection model. This approach provides an upper bound for the achievable artist classification accuracy, assuming perfect detection, while also allowing us to measure how much the performance can drop if we use the detection network. We kept all the other steps the same to com-

²For details on data collection please see Sec. 6

Detection Model	Train Acc (%)	Test Acc (%)
Gabor Bank + SVM	62.15 (0.12)	61.79 (0.64)
WST ¹ (J=1) + SVM	63.08 (0.16)	62.02 (0.82)
WST ¹ (J=3) + SVM	70.36 (0.49)	69.63 (2.43)
Gabor Bank + CNN ²	81.27 (0.23)	78.80 (1.33)
Gabor Bank + VGG16	79.93 (0.19)	75.96 (1.21)
MobileNet	83.93 (0.19)	82.01 (1.03)
VGG16	86.73 (0.11)	82.61 (0.92)
EfficientNetB0	83.71 (0.19)	82.32 (1.03)
DenseNet121	86.13 (0.19)	82.81 (0.89)
SWIN Transformer ³	78.58 (0.18)	79.21 (1.39)

Table 1. Hatching detection results. For each model, the mean and standard deviation of accuracy across five folds are reported.

¹ Wavelet Scattering Transformation [2] ² CNN: 2 Conv layers, 1 Pooling, 2 Dropouts and 2 FC layers ³ "Tiny" base model [34]

pare the results of these baseline experiments to those of the detection-classification pipeline. Finally, we aggregated the patch-level predictions using a voting strategy [10] to obtain image-level artist predictions. We tested 4 voting methods: majority; k-certain, which ignores uncertain patches; posterior aggregate, which uses raw posterior class probabilities as weights; and certainty-weighted, which applies a gamma function to these probabilities for weighting. (see Sec. 8)

4. Experiments

4.1. Hatching Detection

We used an 80%-20% split for training and testing, respectively, where the split was done at the image-level to ensure that training and test patches did not originate from the same drawing, as this could superficially inflate the test performance. Table 1 reports the results for the hatching detection models. We performed five-fold cross-validation experiments for select base models and reported the mean and standard deviation of accuracies over five folds of data.

Overall, cross-validated over the five folds, we achieved patch-level hatching detection accuracies in the range of 82-83% across different CNN base models. We also concluded that the choice of base architecture, e.g. MobileNet vs. DenseNet121, in the CNN-based detection models does not make a significant difference in the performance. The detection results of SWIN Transformer did not improve over CNN-based architecture and had a 79.21% test accuracy.

In addition, we used hatching detection results to predict hatching segmentation masks (see Fig. 4). We evaluated our performance on this task using the Intersection over Union metric (IoU) [44], a standard metric used in similar problems. Table 2 shows these results. Overall, we achieved a mean MeanIoU of 0.61 (61%) with a standard deviation of 0.11 (11%) across a dataset of 670 images.

Hatching detection model was trained on drawings and

Tech/Material	Count	IoU C0	IoU C1	Mean IoU
Pen/Brush (Ink)	205	0.81 (0.14)	0.45 (0.19)	0.63 (0.10)
Chalk	184	0.70 (0.21)	0.50 (0.19)	0.60 (0.12)
Pencil/Graphite	105	0.81 (0.15)	0.45 (0.20)	0.63 (0.10)
Watercolor/Wash	105	0.89 (0.14)	0.24 (0.23)	0.56 (0.09)
Pastel/Charcoal	34	0.77 (0.14)	0.45 (0.10)	0.61 (0.09)
Printmaking	15	0.69 (0.12)	0.54 (0.12)	0.62 (0.11)
Unknown	22	0.70 (0.30)	0.42 (0.23)	0.56 (0.09)
All	670	0.78 (0.18)	0.44 (0.21)	0.61 (0.11)

Table 2. Hatching segmentation results across techniques and materials. For each category, the mean and standard deviation of IoU for non-hatching (C0) and hatching (C1) classes are reported.

prints made in a variety of mediums/techniques including different types of pens (e.g. conventional pen, reed pen, silverpoint, quill pen), pencil, brush, chalks of different colors, graphite, charcoal, ink of different colors, pastel, watercolor, wash, lithograph, etchings and engravings. In most cases, a sample artwork includes a mixture of these mediums/techniques. Our experiments showed that our model is capable of detecting hatching lines in a variety of mediums. Table 2 summarizes the distribution of techniques and materials in our dataset, along with segmentation results in each category. In comparing the IoU outcomes for hatching class in Tab. 2, we observe that except for watercolor/wash medium, mostly similar hatching segmentation results are achieved across other mediums, which shows the detection model is able to learn the concept of hatching from a diverse training data and detect it on different mediums. The lower rate of detection for hatching lines in watercolor/wash is expected given the less-defined, fuzzier nature of these hatchings, making them more difficult to discern from background and other drawing parts.

4.2. Artist Identification Based on Hatching Lines

We conducted various artist classification experiments using a diverse collection of 442 drawings, sketches, and prints from 7 artists, spanning different nationalities, art schools, genres, mediums, and techniques. The artists from the Italian and Dutch schools, lived from the early 17th to early 19th centuries. They created works in genres like religious scenes, portraits, and architectural designs, using mediums such as pencil, ink, chalk, watercolor, and printmaking techniques like etching.

We organized 6 experiments to explore challenging scenarios of classifying artists who have similar styles, belong to the same school or era, or work in similar mediums. This experimental setup avoids performing a strawman test, i.e. comparing artists who have obviously different styles. It is evident that success in such challenging scenarios would suggest that hatching could be useful for identifying artists

in easier cases. This setting also emulates the real scenarios that experts face in attribution, where the confusion is mainly between artists from the same school.

In what follows, we cover the details of each classification experiment, along with the motivation behind them and report the achieved accuracies at both patch and image levels. Tab. 3, Tab. 4 and Fig. 5 summarize the results.

4.2.1. Piazzetta-Tiepolo-Piranesi Classification

Giovanni Battista Piazzetta (1683-1754), Giovanni Battista Tiepolo (1696-1770), Giovanni Battista Piranesi (1720-1778) were three Italian artists that lived and worked contemporaneously in Venice, Italy and shared similar stylistic characteristics in their sketches. In Piazzetta-Tiepolo-Piranesi classification, we achieved 95-96% five-fold cross validation identification accuracy at the patch level and 93.33% accuracy at the image level. Since Piazzetta’s hatching patches were subject to minimal missclassification and were classified with accuracy of 99.87%, we removed Piazzetta’s works and trained and tested two-way classification models based on sketches of Tiepolo and Piranesi. Our five-fold cross validation experiments resulted in 95.41% and 94.42% patch-level accuracy, based on hatching areas detected by the detection model and ground truth labels respectively. At the image level, we achieved 93% accuracy. These results indicate that using a non-perfect hatching detection model (i.e. 82% detection accuracy) to isolate hatching lines for training of the artist classification model produces similar results to using labeled ground truth hatching lines. We consistently observed this in every artist classification experiment reported in Table 3.

4.2.2. Canaletto vs. Piranesi

Giovanni Antonio Canal (1697-1768) known as Canaletto and Piranesi were both prominent printmakers and produced numerous etchings of city views and architectural scenes. This similarity in both subject matter and medium provided an opportunity to further evaluate the discriminative power of hatching lines in challenging artist identification tasks. We performed artist classification experiments based on both etchings and sketches of the two artists. In a five-fold cross validation setting, we achieved 93.6% and 94.2% accuracy for patch-level artist classification of Canaletto vs. Piranesi, for datasets of sketches and etchings respectively. For both datasets, the classification results were boosted to 98% accuracy at the image level.

4.2.3. Tiepolo Father and Son

Giovanni Domenico Tiepolo (1727-1804), an 18th century painter and printmaker, was the son of prolific Italian artist Giovanni Battista Tiepolo (aka Tiepolo). Domenico was trained in Tiepolo’s studio and both artists focused heavily on religious subject matter in their works. Similarities between the works of Tiepolo father and son inspired us

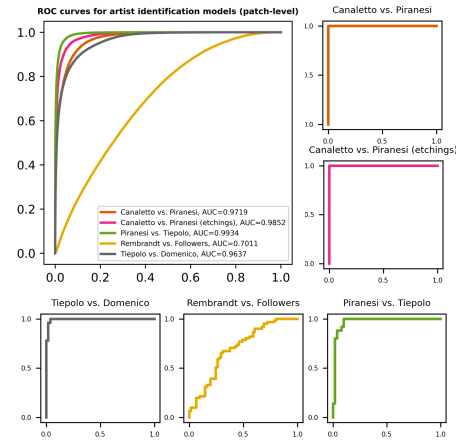


Figure 5. Patch-level (top-left) and drawing-level (smaller sub-figures) ROC curves for binary artist classification experiments.

to test our artist identification approach on these artists. In Tiepolo-Domenico classification, in five-fold cross validation setting, we achieved patch-level accuracies of 92% and 89.6% based on ground truth and detected hatching lines respectively. At the image level, we achieved 96% accuracy.

4.2.4. Rembrandt vs. Followers

Rembrandt Harmenszoon van Rijn (1606-1669), known as Rembrandt, was a prolific painter, printmaker, and draftsman of the Dutch Golden Age. Numerous assistants and students were trained in Rembrandt’s studio [1]. Moreover, Rembrandt was a profoundly influential artist of the 17th century, and many artists were inspired by him and were his followers [57]. Distinguishing Rembrandt’s art from that of his students and followers has been challenging for several reasons. He had many students and followers [1, 57], and it was common for them to copy or make minimal changes to his works. This complicates the distinction between authentic works, studio copies, and forgeries [1].

To test our approach for attribution of Rembrandt’s works we designed a binary artist classification experiment where one class includes only drawings and etchings attributed to Rembrandt himself, and the second class comprises of works that are either attributed to Rembrandt’s followers or his school or are copies after him.

As anticipated, this classification task was significantly more difficult than all other artist classification tasks discussed in this paper. In a five-fold cross validation setting, we achieved patch-level classification accuracies of 63% and 62% based on ground truth hatching lines and detected ones respectively. At the image level, our best accuracy was 66%. The observation that these results are outliers compared to all the other artist classification experiments we attempted is aligned with the challenges in Rembrandt attribution. We hypothesize that this is due to impurity in

Artist Identification Experiment	Artworks per class	Identification from Hatching Detector		Identification from Hatching Annotations	
		Train Acc	Test Acc	Train Acc	Test Acc
Piazzetta vs. Piranesi vs. Tiepolo	50	96.87% (0.17%)	95.98% (1.01%)	96.40% (0.30%)	95.38% (0.91%)
Piranesi vs. Tiepolo	50	96.88% (0.28%)	95.41% (1.88%)	96.53% (0.35%)	94.42% (2.38%)
Tiepolo vs. Domenico	50	94.98% (0.61%)	89.57% (4.30%)	96.41% (0.64%)	92.01% (3.17%)
Rembrandt vs. Followers	61	69.22% (3.66%)	62.08% (6.65%)	72.94% (1.03%)	63.03% (6.98%)
Canaletto vs. Piranesi	50	96.00% (0.96%)	93.64% (3.63%)	-	-
Canaletto vs. Piranesi (etchings)	35	97.59% (0.18%)	94.21% (1.15%)	-	-

Table 3. Patch-level artist identification results. The mean and standard deviation of classification accuracy across five folds of data are reported. ‘Identification from Hatching Detector’ represents results obtained using a pre-trained detection model. ‘Identification from Hatching Annotations’ shows results achieved using ground-truth hatchings. Empty cells indicate the absence of ground-truth annotations.

Artist Identification Experiment	Majority	Posterior Aggregate	K-certain	Certainty Weighted
Piazzetta vs. Piranesi vs. Tiepolo	93.33%	93.33%	93.33%	93.33%
Piranesi vs. Tiepolo	93% (0.9796)	93% (0.9792)	93% (0.9716)	93% (0.9724)
Tiepolo vs. Domenico	97% (0.9956)	96% (0.9956)	96% (0.9932)	96% (0.9948)
Rembrandt vs. Followers	61.47% (0.6901)	64.75% (0.6904)	63.11% (0.7063)	66.39% (0.6995)
Canaletto vs. Piranesi	98% (1.00)	98% (1.00)	98% (1.00)	98% (1.00)
Canaletto vs. Piranesi (etchings)	98.57% (1.00)	98.57% (1.00)	98.57% (1.00)	98.57% (1.00)

Table 4. Artist identification results at the image level, including drawing-level artist identification accuracies and AUC for binary cases.

our training data as we are unable to verify if the works attributed to Rembrandt were solely done by his hand or include contributions by his students whose works are also present in the second class.

5. Discussion

This work introduces a novel formulation of artist identification in drawings, sketches and prints as a fine-grained image recognition problem, where the goal is to distinguish between different artists based solely on the subtle visual characteristics of their hatching lines. We conducted challenging experiments focusing on contemporaneous artists from the same school of art, working on similar subject matter and using similar mediums and techniques, which closely parallels the challenges seen in traditional FGIR tasks where inter-class differences are small [59]. Our experiments across multiple datasets and artist groups demonstrate that these fine-grained, local stylistic features can be learned by deep models to achieve artist identification accuracies of 90-100% in most cases. The only experiment where this was not achieved was the case of identifying Rembrandt from his students and followers, which we attribute to the impurity in the data discussed in Section 4.2.4.

The deep learning pipeline we employed successfully detected hatching regions and learned artist-specific patterns from these localized areas. This local feature-based approach is aligned with localization-classification [59]

paradigm in FGIR. Moreover, by isolating hatching lines we excluded compositional and thematic elements from our analysis, showing that hatching serves as a rich source of fine-grained features that allow for artist attribution.

Although the detection network performance is 82%, this gap had a minor effect on the artist identification task. Our results showed that identification accuracy does not drop when using the detected hatching area compared to using ground truth hatching. This highlights the robustness of the fine-grained features encoded in hatching, even with imperfect localization, demonstrating that coarse region proposals can still enable reliable fine-grained artist recognition.

Compared to prior work in art authentication and attribution, our approach is novel in directly modeling fine-grained signatory characteristics of hatching lines. Furthermore, our dataset spans a wide range of subject matter, periods, mediums, and techniques, demonstrating that the fine-grained features extracted from hatching lines generalize across diverse artistic contexts. While hatching is highly versatile and used widely in drawing and printmaking, some compositions are executed without hatchings or clear hatching lines. Consequently, in these scenarios, our hatching-based approach for artist identification would not be applicable.

Overall, our findings show that fine-grained image recognition techniques can successfully extend to cultural heritage applications, providing automated tools for attribution and authentication through local stylistic analysis.

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Figure 2a:

Artwork Credits

Figure 1

1. P. Schatborn, 2017, 'Rembrandt van Rijn, *Jacob and his Sons*, Amsterdam, c. 1641', in J. Turner (ed.), *Drawings by Rembrandt and his School in the Rijksmuseum*, online collection catalog. Available: hdl.handle.net/10934/RM0001.COLLECT.28138. [Accessed 16 May 2024 00:17:20]
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5. P. Schatborn, 2018, 'school of Rembrandt van Rijn, *Seated Old Man with Tall Cap*, Amsterdam, c. 1645 - c. 1655', in J. Turner (ed.), *Drawings by Rembrandt and his School*
1. Edgar Degas (French, 1834 - 1917), *Après le bain (Femme s'essuyant)* (Detail), about 1895, Pastel, on paper laid down on board, 72 × 58 cm (28 3/8 × 22 13/16 in.), Digital image courtesy of the Getty's Open Content Program, The J. Paul Getty Museum, Los Angeles 2017.75.1, Available: <https://www.getty.edu/art/collection/object/109NER>
2. Vincent van Gogh (Dutch, 1853 - 1890), *Portrait of Joseph Roulin* (Detail), 1888, Reed and quill pen and brown ink, over black chalk, 32.1 × 24.4 cm (12 5/8 × 9 5/8 in.), Digital image courtesy of the Getty's Open Content Program, The J. Paul Getty Museum, Los Angeles, 85.GA.299, Available: <https://www.getty.edu/art/collection/object/103QZR>
3. Giovanni Battista Tiepolo, *Illustration for a Book: Reception of Monks at a City Gate* (Detail), 1696–1770, Black chalk. Horizontal and vertical centering lines ruled in faint black chalk, 7.5 × 15.9 cm (2-15/16 × 6-1/4 in), The Metropolitan Museum of Art, New York, The Elisha Whittelsey Collection, The Elisha Whittelsey Fund, 1959, 59.600.210, Available: <https://www.metmuseum.org/art/collection/search/339293>
4. Jean-Baptiste Pater (French, 1695 - 1736), *Study of a Seated Woman* (Detail), about 1730, Red chalk, on tan paper, 15.2 × 16.7 cm (6 × 6 9/16 in.), Digital image courtesy of the Getty's Open Content Program, The J. Paul Getty Museum, Los Angeles, 86.GB.613, Available: <https://www.getty.edu/art/collection/object/103R0J>
5. Rembrandt Harmensz. van Rijn (Dutch, 1606 - 1669), *A Wooded Road* (Detail), about 1650, Pen and brown ink and brown wash on paper toned with brown wash, intentionally scratched by the artist, 15.9 × 20.2 cm (6 1/4 × 7 15/16 in.), Digital image courtesy of the Getty's Open Content Program, The J. Paul Getty Museum, Los Angeles, 85.GA.95, Available: <https://www.getty.edu/art/collection/object/103QYF>

6. Charles Samuel Keene (English, 1823 - 1891) *Self-Portrait* (Detail), about 1845, Pen and brown ink over black chalk, Unframed: 24.1 × 27.9 cm (9 1/2 × 11 in.), Digital image courtesy of the Getty's Open Content Program, The J. Paul Getty Museum, Los Angeles, 2009.95, Available: <https://www.getty.edu/art/collection/object/109EEM>

Figure 2b:

Tobias Stimmer (Swiss, 1539 - 1584), *Portrait of a Bearded Man*, 1576, Pen and black and brown ink over black chalk, 29.8 × 20.8 cm (11 3/4 × 8 3/16 in.), Digital image courtesy of the Getty's Open Content Program, The J. Paul Getty Museum, Los Angeles, 92.GA.102, Available: <https://www.getty.edu/art/collection/object/103R6S>

Figure 4:

1. Cornelis van der Griendt, after print by Rembrandt van Rijn, *Head of an old man with a beard*, 1837–1918, Pen in gray and ink, 8.0 cm x 7.3 cm, Digital image courtesy of Rijksmuseum, Available: <https://id.rijksmuseum.nl/200317879>
2. Giovanni Battista Tiepolo (Italian, Venice 1696–1770 Madrid), *Illustration for a Book: Procession of Monks and Flagellants*, ca. 1696–1770. Black chalk drawing, 8.0 × 16.6 cm. The Metropolitan Museum of Art, New York, acc. no. 59.600.189. Available: <https://www.metmuseum.org/art/collection/search/339294>. [Accessed April 15, 2025.]
3. Samuel van Hoogstrate (follower of Rembrandt), *Doubting Thomas recognizes Christ*, 1650, Digital image courtesy of the Rijksmuseum, Available: <http://hdl.handle.net/10934/RM0001.COLLECT.28606>
4. Hendrik Nieuwenhuysen, after Rembrandt, *Seated man with fur hat*, 1766, Pen in black, 12.8 cm × 9.2 cm, Digital image courtesy of Rijksmuseum, Available: <http://hdl.handle.net/10934/RM0001.COLLECT.232220>