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Noam Schmitt, Yoann Loesch, Nesma Houmani, Sonia Garcia-Salicetti

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# Transfer Learning for Artwork Attribution: Assessing the Importance of the Artist's Signature

Noam Schmitt  
Télécom SudParis, Institut  
Polytechnique de Paris  
91120 Palaiseau, France

Yoann Loesch  
Télécom SudParis, Institut  
Polytechnique de Paris  
91120 Palaiseau, France

Nesma Houmani  
SAMOVAR  
Télécom SudParis, Institut  
Polytechnique de Paris  
91120 Palaiseau, France  
<https://orcid.org/0000-0002-5048-9313>

Sonia Garcia-Salicetti  
SAMOVAR  
Télécom SudParis, Institut  
Polytechnique de Paris  
91120 Palaiseau, France  
<https://orcid.org/0000-0001-5257-8216>

**Abstract**— In this paper, we propose a Transfer Learning approach for artwork attribution investigating the importance of the artist's signature. We consider AlexNet Convolutional Neural Network and different fully connected layers after  $fc7$ . Three architectures are compared for authenticating paintings from Monet and classifying other artworks into the “Non-Monet” class. We considered paintings with a similar style and artist's signature to Monet's, as well as paintings with a very different style and signature. We assess the model's performance on images with the artist's signature extracted from the artwork, as well as on images of its near background not containing the artist's signature. Results demonstrate the importance of considering the artist's signature for art attribution, reaching a classification rate of 85.6% against 82% on images without signature. The analysis of the obtained feature maps allows highlighting the power of our approach based on Transfer Learning in extracting high-level features that simultaneously capture information from the artist's signature and the artist's style.

**Keywords**—Transfer Learning, AlexNet model, handwritten signature images, background images, artwork authentication, feature maps.

## I. INTRODUCTION

Artwork authentication is a complex and multifaceted process of great importance to academic art history and commercial art market. Not surprisingly, determining authenticity and authorship of the artwork is an essential prerequisite for sales and acquisitions. It is mainly carried out through visual inspection performed by human experts [1,2,3]. This process relying on established best practices requires highly experienced experts and a background knowledge about the artist's life and work. This traditional examination methodology is often criticized: it is very time-consuming, and makes the result dependent on the expert; indeed, the process inherently integrates subjective elements based on each expert's experience.

Authenticating artwork is a very challenging task in which artificial intelligence (AI) and computer vision techniques may be relevant for automatic decision-aid. Recent advances in capturing high-resolution artwork images powered by machine learning algorithms, make very promising the contribution of AI in fine artwork authentication.

There are few works addressing automatic classification for artwork attribution. Since 2015, some have exploited Deep

Transfer Learning for automatic visual analysis of paintings. In [4], the authors combined ResNet50 deep neural network with Transfer Learning for feature extraction, and Support Vector Machines for the authentication of Raphael's paintings. The authors constructed two groups of images: one consisting of paintings by Raphael, the other containing other well-known artists whose style resembles Raphael's (“Not-Raphael” class). After performing data augmentation, they achieved a classification accuracy of 96%.

In [5], the authors used for the first time a Convolutional Neural Network (CNN) for automatic artist attribution. They exploited PigeoNET, corresponding to AlexNet architecture for visual feature extraction, with three additional fully connected layers for classification. They adopted an occlusion sensitivity method: the importance of the occluded region is determined according to the change in the model's output certainty score for the correct artist. This method allows detecting which regions in the entire painting are characteristic of the artist. By using the Rijksmuseum Challenge dataset [6], they obtained a mean classification accuracy of 76.3% on a dataset containing 100 artists.

Another work of the same authors [7] proposed to use a multi-scale CNN for print artworks' image classification. The adopted multi-scale approach for artist attribution allows extracting features characterizing both coarse and fine details in images. The approach was evaluated on photographic reproductions of 210 artists from the collection of the Rijksmuseum. Results showed that the multi-scale CNN leads to a mean class accuracy of 82.12% against 75.69% with the best single-scale CNN.

A more recent work [8] compares different CNNs architectures to Vision Transformers for authenticating paintings by Van Gogh, using different evaluation sets in terms of imitations. On a “Standard contrast” set including imitations and paintings (called “proxies”) whose style resembles Van Gogh's, the authors show that EfficientNetB5 achieves the best performance in average, both on patches and on entire images. More precisely, although the accuracy of EfficientNetB5 on real imitations is around 52%, the accuracy on authentic paintings is of 95.4% and of 97.5% on “proxies”. On imitations and additional images inspired by Van Gogh's style (“Refined contrast” set), Swin-Tiny Transformer gives the best average performance of 85.8%, against 84.3% with

EfficientNetB5. Nevertheless, the latter gives better results on authentic paintings (95.6% versus 85.8%).

The above-mentioned works on Deep Learning considered the entire paintings' images for artist attribution or artwork authentication, without taking into account the artist's signature. The handwritten signature is not always present in paintings, but still can be found in several well-known artworks. In this case, it is usually affixed by the artist in a personalized manner, often at the bottom right of the painting. When present, the artist's handwritten signature carries valuable information for investigating the authenticity and authorship of the painting. Indeed, in forensics, handwritten signatures are widely investigated to authenticate documents and determine authorship [9-13].

In this study, we propose to investigate the potential use of handwritten signatures for artwork attribution, with a Transfer Learning approach. The paper delves into the specific task of artist attribution using Monet's paintings as a case study. Our article aims at comparing performance between the two following cases: (i) when considering the artist's signature with its background; (ii) when only the artwork's near background of the signature is taken into account. This framework is not usual in the literature of automated artist attribution, in which the whole painting is analyzed and the signature is excluded.

This paper is organized as follows: Section II presents the dataset and the conducted methodology. Results are presented in Section III. Our conclusions and perspectives are stated and discussed in Section IV.

## II. MATERIAL AND METHODS

### A. Database collection

We constructed our dataset based on paintings from the public domain, available online on Google Arts and Culture, National Gallery of Art, Philadelphia Museum of Art, Art Institute of Chicago, Munch Museum, Musée d'Orsay, among other.

The dataset consists of 500 signed artworks of different well-known artists, captured in high-resolution images. We constructed two groups of images: the first consists of 250 paintings by Monet (see an example in Fig. 1), referred as "Monet" class; while the second consists of 250 paintings from other artists, referred as "Not-Monet" class.



Fig. 1 : Example of a signed Monet's artwork with a zoom on his signature.

For the "Not-Monet" class, we have chosen some artists with a style similar to that of Monet, as Manet, Sisley and

Munch, as well as other paintings with a different style, as Klimt, Miro and Dali. In that respect, we considered 250 paintings for the "Not-Monet" class: 92 paintings from Manet, 51 from Sisley, 12 from Klimt, 75 from Munch, 8 from Miro and 12 from Dali. Fig. 2 and Fig. 3 show the different styles considered in this class.



Fig. 2 : Examples of signed artworks by Manet (left) and Sisley (right) with similar styles to Monet's.



Fig. 3 : Examples of signed artworks by Miro (left) and Dali (right) with different styles from Monet's.

### B. Creation of two data subsets

To evaluate the contribution of the signature in art attribution, we propose to study two different cases. The first case considers 227 x 227 RGB images including the artist's handwritten signature (image with signature). The second case considers 227 x 227 RGB images without the artist's signature (image without signature). For the latter case, we ensure a strong similarity with the style of the signature's background in the former case. Fig. 4 shows some examples of the extracted images in both cases.

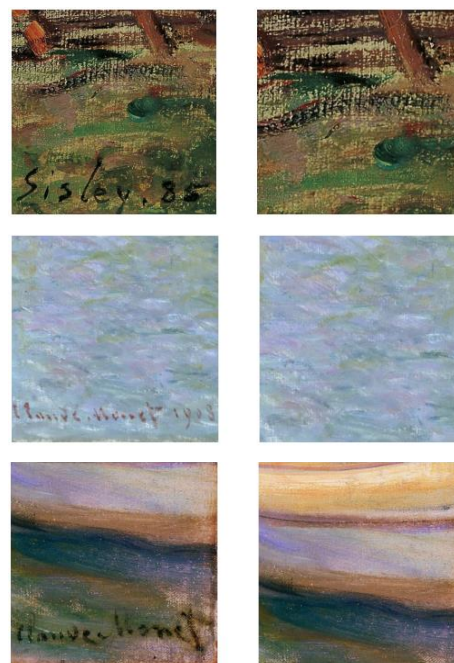


Fig. 4: Examples of the 227 x 227 extracted images with the artist's signature (left) and without the artist's signature (right).

### C. Transfer Learning with AlexNet

We perform Transfer Learning with AlexNet, a well-known Deep Convolutional Neural Network pre-trained on the ImageNet dataset [14]. This architecture has been evaluated in [5] with success for the artist attribution task on a large dataset.

AlexNet contains eight layers: the first five are convolutional layers, and the next three are fully connected layers. It was pre-trained to classify the LSVRC-2010 ImageNet, containing 1.3 million high-resolution images, into 1000 classes. Fig. 5 shows the structure of AlexNet.

We use AlexNet architecture to extract automatically a high-level feature representation vector for each  $227 \times 227$  RGB image. We consider *fc7* representations from AlexNet leading to a feature vector of size 4096.

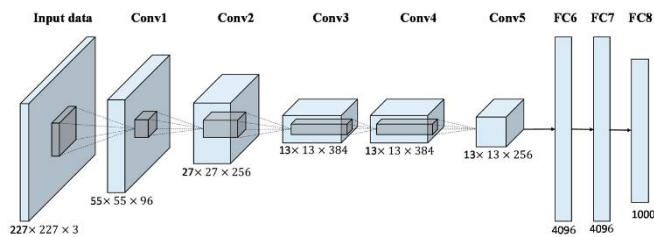


Fig. 5: Architecture of the AlexNet Convolutional Neural Network.

As above-mentioned, AlexNet was pre-trained for 1000-class classification problem, whereas we tackle a two-class problem (“Monet” versus “Not-Monet”). Therefore, we study three architectures with a different number of fully connected layers between *fc7* and the output layer of two units. More precisely, we consider: (i) one extra hidden layer of size 1024 (referred as *Architecture1*); (ii) two extra hidden layers of sizes 1024 and 512 (referred as *Architecture2*); (iii) three extra hidden layers of sizes 2048, 1024 and 512 (referred as *Architecture3*). Then, we perform the training of the model only on the additional fully connected layers.

### D. Performance assessment

To evaluate the models’ performance in terms of classification of “Monet” and “Not-Monet” images, we perform a 3-fold cross validation procedure to train, validate and test our three architectures.

Hyper-parameters of the models, such as the number of epochs, the initial learning rate initial, the batch size, the step size, and Gamma are optimized with a Grid-search procedure, considering only the training and the validation sets.

We report in next section the average performance computed on all the test sets, for “Monet” and “Not-Monet” classes.

## III. EXPERIMENTAL RESULTS

### A. Performance assessment on Images with signature

We report in Table I the performance of each architecture on Monet’s paintings when including his signature. We observe that *Architecture2* leads to the best classification rate of 88%. This architecture seems well adjusted to our classification problem when exploiting Transfer Learning. It appears as a tradeoff between *Architecture1* and *Architecture3*

in terms of number of parameters given the size of our dataset. In the sequel, we report detailed results and analyses only with *Architecture2*.

TABLE I. PERFORMANCE OF THE THREE ARCHITECTURES ON MONET’S IMAGES INCLUDING HIS SIGNATURE

	<i>Monet correctly classified</i>
<i>Architecture1</i>	81.6%
<i>Architecture2</i>	88%
<i>Architecture3</i>	83.6%

Table II shows image classification results per artist in each class (“Monet” and “Not-Monet”), with *Architecture2*, when considering the artist’s signature. We display in Fig. 6 the model’s output probabilities of belonging to “Monet” class for images from Monet. We also display in Fig. 7 to Fig. 9 the model’s output probabilities of belonging to “Not-Monet” class for images from the other artists.

TABLE II. IMAGE CLASSIFICATION RESULTS PER ARTIST IN THE TWO CLASSES “MONET” AND “NOT-MONET” ON IMAGES WITH THE SIGNATURE.

<i>Architecture2</i>	“Monet” class	“Not-Monet” class
Monet ( $n=250$ )	220 (88%)	30 (12%)
Manet ( $n=92$ )	13 (14.13%)	79 (85.87%)
Sisley ( $n=51$ )	10 (19.6%)	41 (80.4%)
Klimt ( $n=12$ )	3 (25%)	9 (75%)
Munch ( $n=75$ )	6 (8%)	69 (92%)
Miro ( $n=8$ )	0 (0%)	8 (100%)
Dali ( $n=12$ )	0 (0%)	12 (100%)

First, we remark in Table II that 88% (220 among 250) of Monet’s images are well classified and with a probability score higher than 0.85, as shown in Fig. 6.

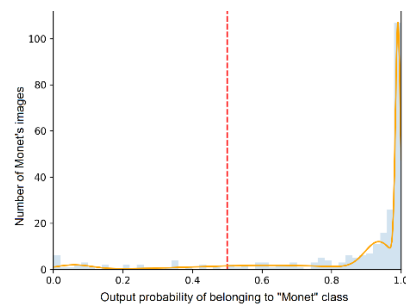
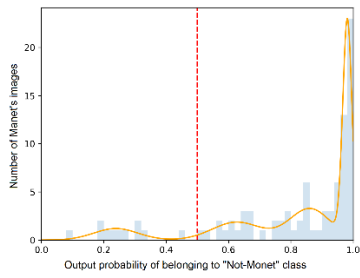
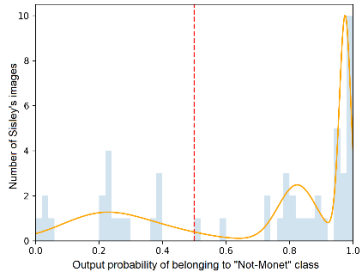


Fig. 6: Probability distribution of Monet’s paintings to belong to “Monet” class, when considering images with the artist’s signature.

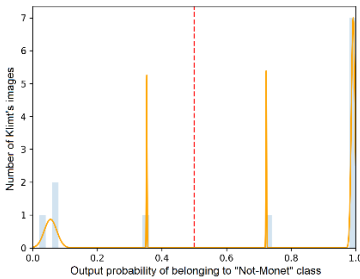
Also, we note in Table II that the highest errors that the model makes correspond to images from Manet, Sisley and Klimt. This is confirmed by the low probability values of being in “Not-Monet” class, as observed in Fig. 7 for the three artists.



(a)



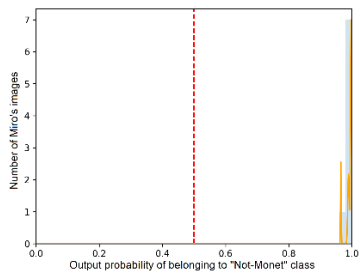
(b)



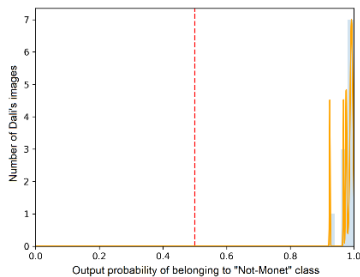
(c)

Fig. 7: Probability distribution of : (a) Manet's, (b) Sisley's and (c) Klimt's paintings, to be classified as "Not-Monet".

On the other hand, we see in Table II that Miro's and Dali's images are all correctly classified as "Not-Monet", with high probability values displayed in Fig. 8. Finally, Munch's images are in majority classified as "Not-Monet" with high probability scores (see Fig. 9).



(a)



(b)

Fig. 8: Probability distribution of Miro's (a) and Dali's (b) painting to be classified as "Not-Monet".

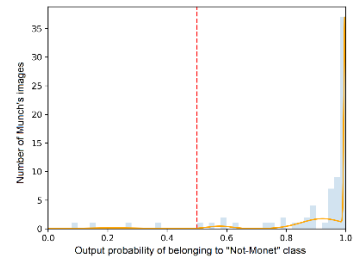


Fig. 9: Probability distribution of Munch's painting to be classified as "Not-Monet".

We display in Fig. 10 and Fig. 11 examples of Monet's images with signatures that are, respectively, correctly and wrongly classified. Their probability of belonging to the "Monet" class and "Not-Monet" class is also reported in the figures' captions.



(a)

(b)

(c)

Fig. 10: Examples of Monet's images correctly classified as "Monet" with a probability of 0.85, 0.91 and 0.59 respectively.

We remark that Monet's images with high probability values show a pronounced contrast between the signature and its background (Fig. 10a and Fig. 10b). Also, we note that the signature is completely distinguishable and legible.

For the Monet's image in Fig. 10c, it is clearly more difficult to distinguish the signature from the background, which is highly textured. Also, the signature was affixed in similar colors as the background; it is actually integrated in the painting. Despite these visual characteristics, the model was able to well classify this image but with a lower probability value compared to images in Fig. 10a and Fig. 10b.



(a)

(b)

(c)

Fig. 11: Examples of Monet's images wrongly classified as "Not-Monet" with a probability of 0.98, 0.88 and 0.99 respectively.

On the other hand, the model was unable to classify some Monet's images, as those shown in Fig.11. In Fig. 11a, the model faces the same problem encountered in Fig. 10c: indeed, the signature is not distinct from the background since they share similar colors. In Fig. 11b, we observe a lack of contrast between the signature and its very dark background. Finally, the signature in Fig. 11c, is very different from the former Monet's signatures displayed: although well contrasted, it suffers from a lack of legibility due to its coarse trace; besides it is slanted to the right.

Fig. 12 show examples of Manet's and Sisley's images wrongly classified.

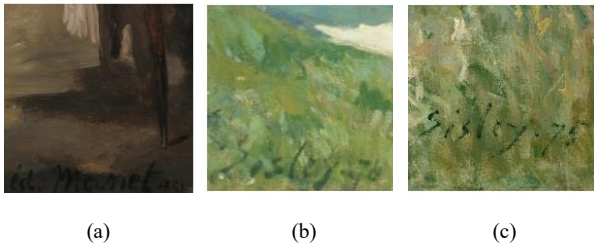


Fig. 12: One example of Manet's and two examples of Sisley's images classified as "Monet" with a probability of 0.72, 0.76 and 0.77 respectively.

In Fig 12.a, the signature is hardly distinguishable from the background, which explains the classification error. For the images in Fig. 12b and Fig. 12c, Sisley's signature was affixed on a highly textured background of similar colors. Moreover, both backgrounds show a similar style to some Monet's paintings, as illustrated in Fig. 13.

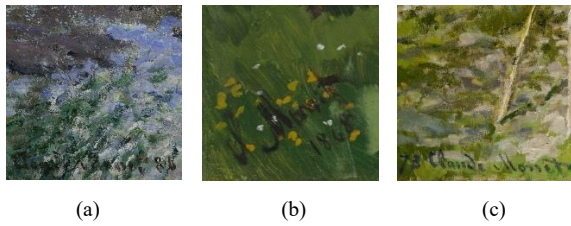


Fig. 13: Examples of Monet's images with the artist's signature.

We display in Fig. 14 examples of images correctly classified as "Not-Monet". We remark that both the signature and the background clearly differ from Monet's paintings. Besides, for Miro and Dali (Fig. 14a and Fig. 14b) in particular, the used signing tool is often of another type from that of Monet's.

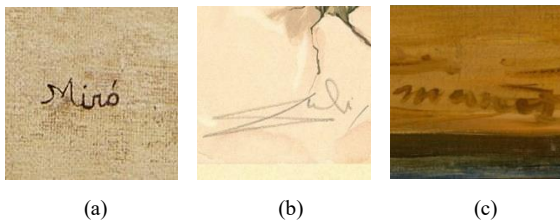


Fig. 14: Examples of images with the artist's signature correctly classified as "Not-Monet".

### B. Comparison between Images with and without signature

In order to evaluate the contribution of the artist's signature in model performance, we also considered background images without signatures, as explained in Section II.B and illustrated in Fig. 4.

We report in Table III the correct classification rates for "Monet" and "Not-Monet" classes, when considering images with and without signature.

TABLE III. PERFORMANCE OF ARCHITECTURE2 IN TERMS OF "MONET" AND "NOT-MONET" IMAGES CORRECTLY CLASSIFIED, WITH AND WITHOUT THE ARTIST'S SIGNATURE

Architecture2	Monet correctly classified	Not-Monet correctly classified
With signature	88%	87.2%
Without signature	86%	78%

Table III shows a 2% degradation of performance when the signature is not included in Monet's images, and a strong degradation of 9.2% on the other artists' images. This result indicates the importance of the signature for artwork authentication. This is confirmed by the examples displayed in Fig. 15: the output probability of belonging to the "Monet" class is degraded when the signature is not considered. This is also illustrated in Fig. 16 for the "Not-Monet" class.

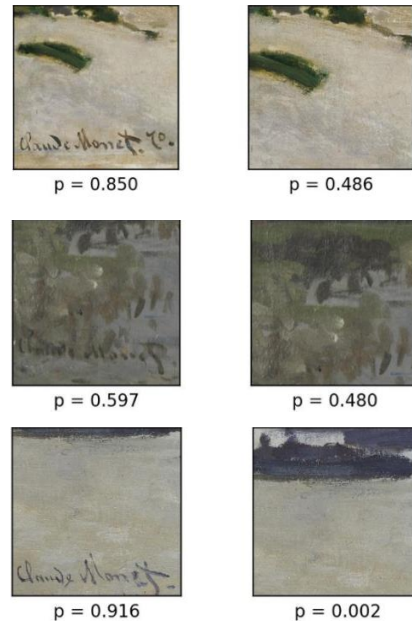


Fig. 15: Examples of Monet's images with (left) and without (right) the artist's signature. Their output probability to be classified as "Not-Monet" is reported below each image.



Fig. 16: Examples of Monet's images with (left) and without (right) the artist's signature. Their output probability to be classified as "Not-Monet" is reported below each image.

Table IV details the image classification results per artist without the signature. It shows a slight degradation for Monet images with respect to Table II (when considering the signature).

TABLE IV. PERFORMANCE PER ARTIST IN THE TWO CLASSES “MONET” AND “NOT-MONET” ON IMAGES WITHOUT SIGNATURE.

Architecture 2	Monet	Not-Monet
Monet ( $n=250$ )	215 (86%)	35 (14%)
Manet ( $n=92$ )	15 (16.3%)	77 (83.7%)
Sisley ( $n=51$ )	33 (64.7%)	18 (35.3%)
Klimt ( $n=12$ )	3 (25%)	9 (75%)
Munch ( $n=75$ )	4 (5.33%)	71 (94.67%)
Miro ( $n=8$ )	0 (0%)	8 (100%)
Dali ( $n=12$ )	0 (0%)	12 (100%)

On the other hand, we see a strong degradation in the classification of Sisley’s images. Indeed, 33 Sisley’s images (64.7%) without signature are classified in the “Monet” class, whereas only 10 Sisley’s images (19.6%) were wrongly classified as “Monet” when considering the signature (refer to Table II). This may be explained by the fact that many Sisley’s images have a highly textured background as some Monet’s images, as those shown in Fig. 12b and Fig. 12c. In this precise case, the handwritten artist’s signature may convey additional authorship information for artist attribution.

We remark that for Miro’s and Dali’s images, as expected, there is no impact of suppressing the signature. This is explainable by the fact that the background’s style is very different from Monet’s: for Miro’s and Dali’s images, the background is usually uniform (see Fig. 14a and Fig. 14b). Concerning the other artists, there is no drastic change in performance.

Finally, back to Table IV we compute the total correct classification rate on images without signature and obtain 82%. When considering the signature (Table II), we enhance the performance to 85.6%. This result underlines on one hand the effectiveness of Transfer Learning for artwork attribution considering images without signatures. This confirms the results in the literature [4-6]. On the other hand, by including the artist’s signature, the model becomes more accurate to discriminate the two classes. The contribution of the signature is further highlighted in next section.

### C. Feature map visualization

For a better understanding on feature extraction performed by Transfer Learning, we display in Fig. 18 and Fig. 19 feature maps obtained on Munch’s painting in Fig. 17, without and with the artist’s signature respectively.



Fig. 17: Example of Munch’s image without and with the artist’s signature.

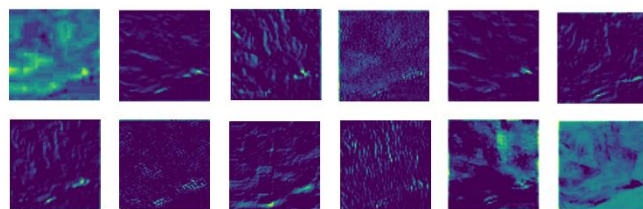


Fig. 18: Twelve features maps extracted at the first layer of the model on Munch’s image displayed in Fig. 17a.

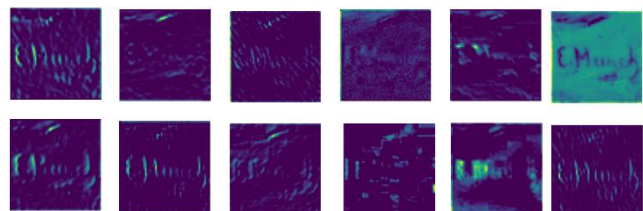


Fig. 19: Twelve features maps extracted at the first layer of the model on Munch’s image displayed in Fig. 17b.

We see in Fig. 18 that the extracted feature maps include different patterns from the background. Some correspond to coarse textural features and other capture fine details of the image background. In Fig. 19, some feature maps extract high-level features from the background, whereas other concentrate on the characteristics of the artist’s signature.

This double high-level feature extraction of the artwork fusing information from the background and from the artist’s signature, leads to a more accurate classification performance. This way, we conclude that our model allows capturing information simultaneously from the artist’s signature and the artist’s style.

## IV. CONCLUSION AND PERSPECTIVES

In this paper, we present a study on Transfer Learning for artwork attribution centered on Monet’s paintings. We evaluated the potential use of the artist’s signatures with respect to background images (images without the artist’s signature). By contrast, the literature focuses on the artist’s style characterization without taking into account the artist’s signature, although the handwritten signature is of main importance in forensic analysis.

On a data set consisting of 250 Monet’s paintings and 250 of other artists, we considered AlexNet Convolutional Neural Network and three architectures constructed by adding fully connected layers between  $fc7$  and the output layer of two units (“Monet class” and “Not-Monet” class). A three-fold cross validation was performed on our dataset to train and test the proposed architectures.

Results showed that the best architecture in terms of performance is that consisting of two hidden layers of 1024 and 512 units. Classification performance reached 88% on “Monet” signature images, and 87.2% on “Not-Monet” signature images. When analyzing classification errors, we noticed that the model mostly misclassified images from Manet, Sisley and Klimt as belonging to the “Monet” class. This can be explained by the fact that the background of Manet’s and Sisley’s signatures is more textured, as Monet’s, comparatively to the other artists in our dataset. Also, Monet, Manet and Sisley usually affixed a complex signature consisting of letter characters. Concerning Klimt, the limited

number of training samples compared to other artists of the “Not-Monet” class, does not allow the model to learn correctly the discriminant characteristics of Klimt’s images with regard to the “Monet” class.

On the other hand, Miro’s and Dali’s images are correctly classified as “Not-Monet” because their background and signature are totally different from those of Monet’s paintings. In between, Munch’s images are mostly classified as “Not-Monet”.

When considering background images without the artist’s signature, results showed a degradation of authentication performance of 2% on Monet’s paintings and 9.2% on the other artists’ paintings. In particular, we observed a strong degradation in the authentication of Sisley images; this can be due to the fact that the background of the signature in Sisley’s images is highly textured as some Monet’s images. In this case, the signature provides precious authorship information that helps for authentication. This statement was highlighted by the extracted feature maps on signature images: they convey features extracted on the signatures and on the background as well.

All these results and analysis demonstrate the importance of the handwritten signature for artwork authentication. Indeed, we obtained 82% of correct classification rate on background images without the artist’s signature, whereas performance reaches 85.6% when considering images containing the artist’s signature. These values are state-of-the-art performance: in [6], the AlexNet architecture led to 78% of classification performance and the multi-scale Convolutional Neural Network in [7] reached 82% of performance. Although the data sets are not the same in such works and in our work, these performance values reveal that our approach shows a strong potential.

In this work, we considered only the local background surrounding the signature; it would be interesting to incorporate more information about the artwork style by considering the whole painting or different regions of interest as done in [4-8]. We also plan to continue the study by evaluating other architectures for Transfer Learning and other classification schemes after feature extraction.

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