

Exploring the Representativity of Art Paintings

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Abstract—Art painting evaluation is sophisticated for a novice with no or limited knowledge on art criticism, and history. In this study, we propose the concept of *representativity* to evaluate paintings instead of using professional concepts, such as genre, media, and style, which may be confusing to non-professionals. We define the concept of representativity to evaluate quantitatively the extent to which a painting can represent the characteristics of an artists creations. We begin by proposing a novel deep representation of art paintings, which is enhanced by style information through a weighted pooling feature fusion module. In contrast to existing feature extraction approaches, the proposed framework embeds painting styles, and authorship information, and learns specific artwork characteristics in a single framework. Subsequently, we propose a graph-based learning method for representativity learning, which considers intra-category, and extra-category information. In view of the significance of historical factors in the art domain, we introduce the creation time of a painting into the learning process. User studies demonstrate our approach helps the public effectively access the creation characteristics of artists through sorting paintings by representativity from highest to lowest.

Index Terms—Representativity, style enhancement, feature representation, artwork evaluation.

I. INTRODUCTION

THE recent development of artificial intelligence has created numerous opportunities for artistic aesthetic assessment, which are significant and sophisticated. The complexity of computer-assisted artwork analysis and synthesis was investigated by Zhang *et al.* [1], who proposed a four-level scheme

for utilized computational support. At Level I, people use computer painting software to create images by using digital brushes manually. At Level II, people input various attributes, styles, and possibly mathematical formulas into a computer program for a computer to automatically generate a desired image. In contrast to Level II, at Level III, people computerize paintings using machine intelligence based on generative or transformational approaches. With generative methods, artists styles can be encoded into input images intelligently. Level IV, which is the highest level, involves the automatic detection of specific styles from existing paintings and the evaluation of aesthetics and associated measurements, which can help people with different social, emotional, and cultural backgrounds appreciate paintings. Given the complexity of this last task, most recent works focus on artistic image stylization [2]–[8] at Level III. In the past few years, digital technology has enabled the public to access a large amount of digitized art collections. These artworks provide vast opportunities for conducting research at Level IV. While tools such as Google Search allow people to access large collections of paintings by particular artists, paintings recommended by search engines are repetitious and interspersed with numerous fake examples. On authoritative websites, such as *WikiArt*,¹ which features approximately 250,000 artworks by 3,000 artists, people can view the paintings of most artists. On *WikiArt*, paintings by specific artists are sorted by year or name, which is not convenient for the public to obtain substantial authorship information or gain a systematic understanding. Moreover, the website can display “famous works” that are significant to an artists creative career or to art history, thereby enabling people to understand an artists drawing characteristics. Famous works can well represent an artists creative career, thereby providing viewers with increased valuable artist-related information (e.g., texture, strokes, color, and scene). For example, among the 1,930 paintings of Vincent van Gogh (see <http://www.wikiart.org/en/vincent-van-gogh>), 13 paintings are displayed as famous works, which can help viewers generally understand his creative contributions in a short time. However, the number of selected famous works is limited. We analyze the ratio of famous works to all the paintings on the website. Fig. 1 plots the ratio of the number of famous works to other works by 208 artists. The number of famous works represents only a fraction of the total number of works. On average, only 7.3% of the paintings are identified as famous works. Under such a low percentage, people can typically acquire very limited characteristic information about an artist.

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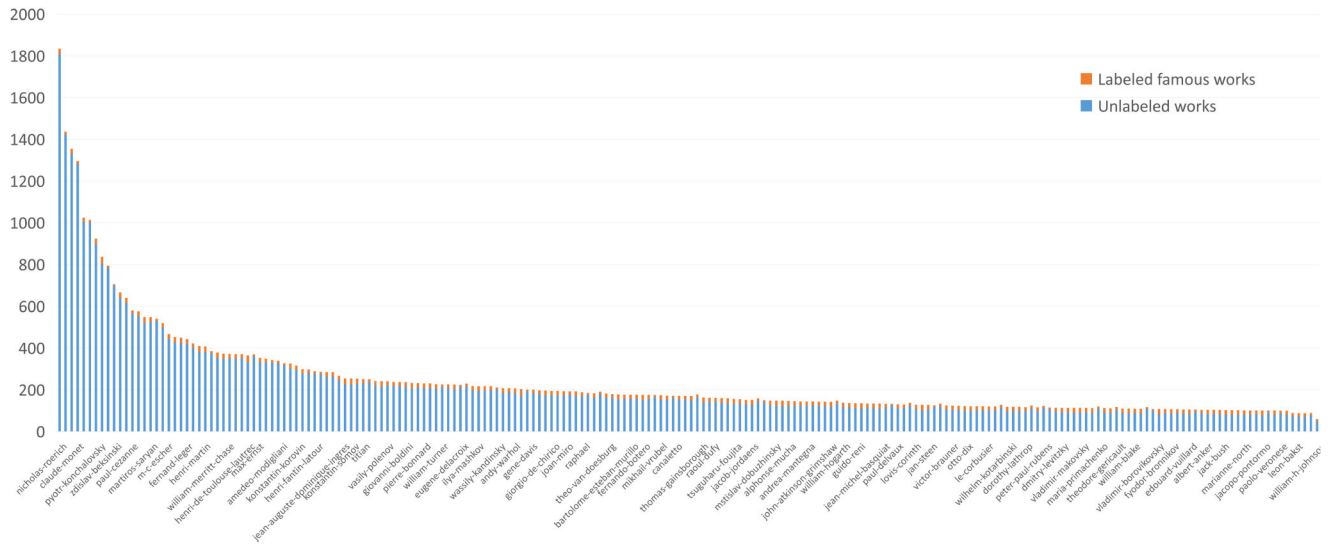


Fig. 1. Ratio of famous works to all paintings by 208 artists.

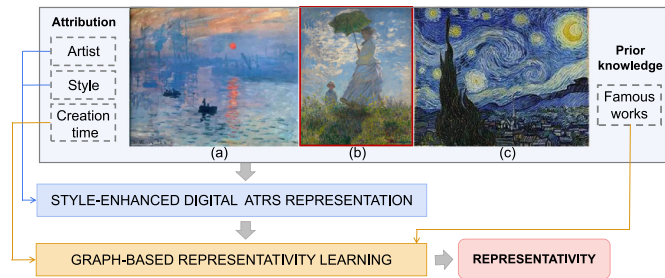


Fig. 2. Outline of our work: (a) *Impression Sunrise* by Claude Monet; (b) *La Promenade* by Claude Monet; and (c) *De Sterrennacht* by Vincent van Gogh; our system uses an efficient feature representation framework to obtain painting features; we calculate the representativity of *La Promenade*, considering an intra-category anchor (i.e., *Impression sunrise*) and an extra-category anchor (i.e., *De sterrennacht*).

To solve this deficiency in online digitized art collections, we focus on artwork evaluation in this study, which is a task in the most challenging level, that is, Level IV. We propose the concept of *representativity* to evaluate quantitatively the extent to which a painting can represent the typical characteristics of an artists body of work. The characteristics of an artists creations refer to the texture of a painting, drawing strokes, color preference, painting style, painting content, and so on. The higher the representativity of a painting, the more the artists creation characteristics can be obtained from the painting. When people want to understand an artists overall creation characteristics, the artists paintings sorted by representativity, from highest to lowest, can be viewed, which can help people obtain useful artist-related information (e.g., color, texture, stroke, content, style, and so on) in a short time.

To calculate the representativity of paintings, we propose the framework shown in Fig. 2, which consists of two parts, namely, style-enhanced art painting representation and graph-based representativity learning. We begin with feature representation learning of art paintings. According to the definition of representativity, painting features should be able to represent

artist-related characteristics. Inspired by recent works [9]–[16], we aim to train a classification network with art paintings and corresponding author information to obtain deep representations that can provide clues for artist-related creation characteristics. Moreover, for art painting analysis, *style* is a significant characteristic that can reflect the specific aspects of an artists creative personality. Therefore, we propose a style-enhanced art painting representation learning framework using text-based auxiliary style information to consummate the representation of deep image features. A weighted pooling module is proposed to map the style features to a set of weights and to apply these weights for image feature weighted pooling. Each painting is mapped to a learned feature space through the style-enhanced art painting representation framework.

Next, we perform representativity calculation in the learned feature space. Art understanding is akin to a web and involves knowing how different items are “placed” in a web of relationships (e.g., *symbolexperience* and *examplegenerality* relationships) that give the items meaning [17]. During the art educational process by [18], participants uncover similarities, differences, patterns, and discrepancies among different paintings by examining various ideas and holding them up next to one another to determine relationships. In line with such observations, we formulate the representativity learning process in the graph structure, where paintings are web-like organized in the feature space. Paintings are represented as vertices, with Euclidean distances and angles encoding relationships among instances in the feature space. We utilize “famous works,” which are officially defined as *artworks that are significant for an artist’s creative career* on the homepages of artists on *WikiArt*, as prior knowledge. Given these prior knowledge as anchor points in the feature space, the representativity calculation of one painting is based on the relationships between the painting and the anchors. Furthermore, we discover that historical factors could influence the creations of artists [19]. In analyzing paintings throughout an artists career, we determine that the number of referenced famous works is related to the age of the artist. Therefore, we

consider the creation time of an artwork when calculating representativity. In summary, we provide the following contributions.

In summary, our main contributions are:

- We present the notion of *representativity* to evaluate the extent to which a painting can represent the characteristics of the artist's creations. The higher the representativity of a painting, the more the artists creation characteristics can be obtained from the painting.
- We propose a novel method for learning *style-enhanced* representations of art paintings that involves a weighted pooling module to fuse deep image feature and style information.
- We propose a graph-based learning method for representativity calculation. In addition, we consider historical factors, such as the creation time of paintings, which can help us achieve improved performance when analyzing the representativity of artworks.

II. RELATED WORK

Analysis of artistic paintings is complex owing to a wide array of factors that may be involved, such as painting style, scene, texture, strokes, genre, historical information, artists emotions, and so on [20]. Therefore, helping the public analyze art paintings has aroused the interest of researchers.

Recently, several studies have focused on analyzing painting styles or artists automatically [21]. Motivated by the development of deep learning methods, numerous works use a convolutional neural network to address this complicated problem [22]. Noord *et al.* [10] trained a convolutional neural network to identify a paintings authorship and determine characteristic features automatically. Inspired by [2], Chu *et al.* [23] considered style representation and utilized the Gram matrix to represent style features, thereby succeeding in their style classification task. Moreover, Tarvainen *et al.* [12] modelled the relation between a large selection of low-level computational features and the perceptual stylistic, aesthetic, and affective attributes of movie clips. Chu *et al.* [16] designed a deep framework to extract correlation features for style classification. Meanwhile, Ma *et al.* [9] tried to improve the representation of a painting through multitask learning. The authors proposed a multi-range network structure consisting of local, regional, and global representations to solve the complex task of authorship identification. However, training the network is proved difficult owing to the utilized complex features. In contrast to the aforementioned methods, Jangtjik *et al.* [24] used a multilayered pyramid, rather than only one layer, based on a convolutional neural network to extract additional features. The authors achieved an outstanding result of 88.08% by categorizing 13 artists. Due to the lack of labeled art painting datasets, Carneiro *et al.* [25] proposed a new dataset for artistic paintings understanding, which contained 988 paintings with global semantic annotation, local compositional annotation, and posed annotations for human subjects and animals. However, Mao *et al.* [14] emphasized that existing art painting datasets are not well organized and thus introduced a large visual artwork dataset, namely, Art500 k, annotated with information on artists, art movements, genres, and so on. Based on this dataset, the authors proposed a unified network that learned

a joint representation of a painting containing content and style information with triplet learning. Yang *et al.* [15] presented an end-to-end framework with a multitask mechanism for style classification and added several historical context-based information, such as origin year, birthplace, and art movement. El-gammal *et al.* [26] employed style classification and analyzed the learned representation through correlation analysis with concepts derived from art history. Chen and Yang [27] proposed adaptive cross-layer correlation for style representation of visual arts.

Inspired by the aforementioned classification methods, we use convolutional neural network with multimodal information (e.g., image and text) and propose an artist classification network to obtain the representation of paintings' artist-related characteristics.

For high level applications, many researchers conducted artistic Turing test for creativity [28], artistic aesthetic assessments [29], [30] and associated measurements [31] with statistical or computational methods. Taylor *et al.* [32] used fractal analysis to characterize artworks and found that "box-counting" can be used to distinguish fractals from Euclidean objects. Kim *et al.* [33] used biologically-motivated technology to quantitatively analyze orientation, radial frequency, and color. Sartori *et al.* [34] presented a color theory-based method to analyze the color combination in abstract paintings. Kim *et al.* [35] investigated color use, color variety, and contrast, to perform statistical analysis of a large-scale database of artistic paints. Feng *et al.* [36] used a genetic algorithm to generate paintings via aesthetic evaluation. Liu *et al.* [37] used Naive Bayes classifier and BP neural network to judge the correct orientation of an abstract painting. Fraiberger *et al.* [38] used an extensive record of exhibition and auction data to study and model the career trajectory of individual artists relative to a network of galleries and museums. Sigaki *et al.* [39] estimated the permutation entropy and the statistical complexity of each painting to reveal a historical and measurable evolutionary trend in visual arts. Deng *et al.* [40] proposed a network for recommending an artists most representative works to the public and helping them master an artists painting characteristics quickly. Sargentis *et al.* [41] aimed to apply mathematical tools to describe aesthetics. The authors used a two-dimensional tool [42] to calculate differences and similarities among paintings and identify the meaning of painting regions, which are comprehensible to non-experts and can shed light on the aesthetics of artistic paintings.

In this work, we present quantitative measurements using a large dataset and propose the concept of representativity to indicate quantitatively the extent to which a painting can represent the characteristics of an artists creations. The higher the representativity of a painting, the more the artists creation characteristics can be obtained from the painting. The representativity can serve as a guide to help people appreciate artworks.

III. METHODOLOGY

Our task is calculating the representativity to quantitatively evaluate the extent to which a painting can represent the characteristics of the artist's creation. In this section, we will elaborate on the processing method of digitized arts' representativity

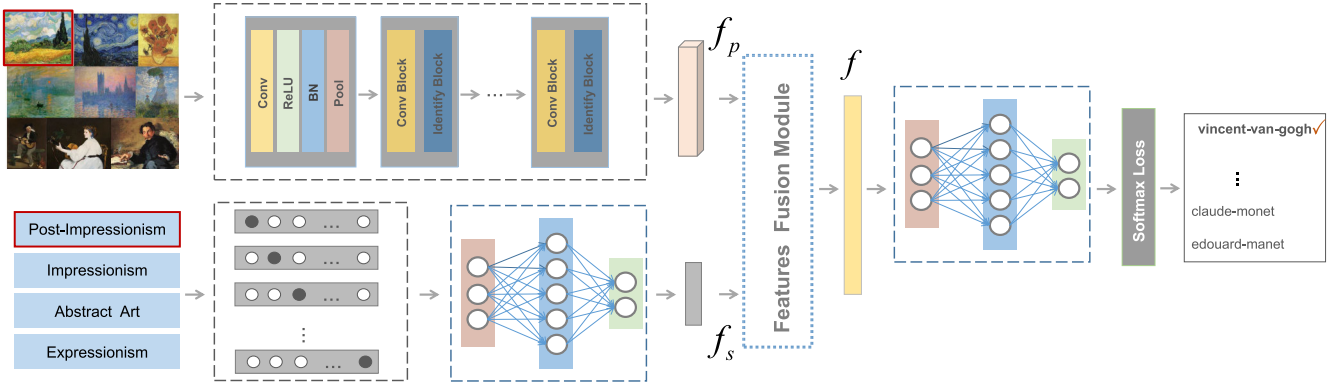


Fig. 3. Style-enhanced art painting representation framework; inputs are paintings and their corresponding text-based style information; we use fused features to conduct the artist classification task and explore the representativity of paintings.

which can be divided into two phases. We begin by obtaining the paintings' feature representation which is used for representativity calculation. The network is shown in Fig. 3. Based on its definition, we assume that representativity is artist related, and painting features should be able to represent artist-related characteristics. If features are effective for artist classification, then they should also well represent artist-related characteristics and be suitable for representativity calculation. Therefore, we present an art painting representation framework based on artist classification. Next, we calculate representativity in the feature space. We formulate representativity through a graph-based learning method to uncover similarities among different paintings by holding them up next to one another to find relationships.

A. Style-Enhanced Art Paintings Representation

We aim to obtain art paintings representation through addressing paintings' authorship identification task. The authorship identification task is complex owing to the following potential problems in the training dataset. (1) Unbalanced training samples: the number of works created by different artists varies considerably; (2) Extra-class similarity: it is common that different artists share similar creation characteristics; (3) Intra-class differences: the creation characteristics of the same artist may be changeable. Moreover, when considering the authorship of a painting, previous works [9], [13], [14] consistently neglect the significance of painting style. Style is a significant but complicated attribute that also reflects specific aspects of artists creative personalities. As shown in Fig. 4, the same artist may have different painting styles, whereas different artists may have the same painting style. For example, as illustrated in Fig. 5, the paintings of Edouard Manet may be classified into different styles, namely, realism and impressionism. Conversely, the paintings of different artists, such as Edouard Manet and Claude Monet, could be categorized in the same style. Based on such observations, we propose a novel network that integrates the advantages of a convolutional neural network and style information to extract artist-related features of art paintings. Fig. 3 presents the structure of the proposed style-enhanced deep pipeline. The upper part is based on ResNet50 [43] which is used to encode image

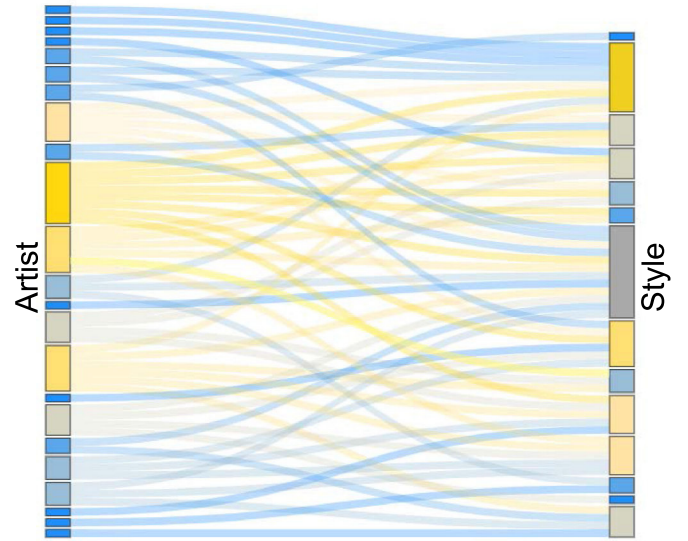


Fig. 4. Correspondence between style and artist on WikiArt23; the same artist may have different painting styles, whereas different artists may have the same painting style.



Fig. 5. Illustration of styles; paintings enclosed in the blue box are drawn by the same artist in different styles, and paintings enclosed in the grey box are in the same style by different artists.

information. The bottom part is used to encode text-based style information. Given a painting x and its corresponding text-based style information, we include both into the network. For each painting, we take the output features f_p (in the shape of $[7, 7, 2048]$) of the last identity block from the upper path. Meanwhile, we encode style information in one-hot form h in the bottom path. Next, the style features f_s is obtained by a three-layer

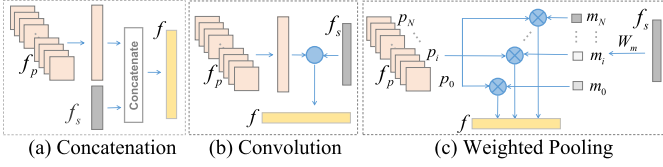


Fig. 6. Feature fusion operations.

MLP(Multilayer Perceptron), which takes h as input. We set the size of hidden layer to 256, and $d_s = 128$ is the dimension of f_s . Subsequently, we fuse f_p and f_s to obtain the ultimate feature representation f . We consider three basic mechanisms to fuse the two features, namely, the concatenation operation (*ConcatOp*), convolution operation (*ConvalOp*) and weighted pooling (*WeightOp*). The operation diagrams are illustrated in Fig. 6.

ConcatOp: Firstly, through average pooling and flattening, the shape of f_p is transformed from $[7, 7, 2048]$ to $2048-d$. Next, we concatenate f_p and f_s to obtain the features representation f whose dimension is $2048 + d_s = 2176$.

ConvalOp: Firstly, through average pooling and flattening, the shape of f_p is transformed from $[7, 7, 2048]$ to $2048-d$. Next, ultimate features representation f is obtained by applying one-dimensional convolution to f_p and f_s :

$$f(n) = \sum_{i=0}^{N-1} f_p(i) \times f_s(n-i), \quad 0 \leq n \leq N-1. \quad (1)$$

where $N = 2048 + d_s - 1 = 2175$ is the size of convolution output and $f = [f(0), \dots, f(N-1)]$.

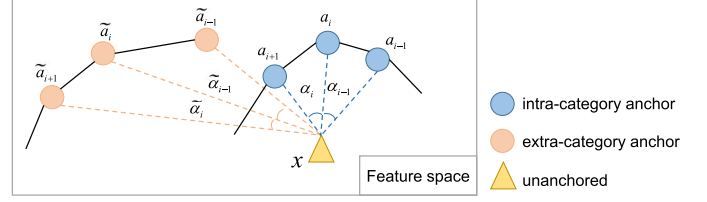
WeightOp: Firstly, we map the style features f_s to a set of weights $M = \{m_0, \dots, m_{N-1}\}$ by $M = W_m f_s$, where W_m represents the trainable parameters. Then, weights M is used to pool each feature map of f_p , and N is the number of feature maps. Next, the weighted pooling is operated by:

$$f(n) = \sum_{i=0}^{H-1} \sum_{j=0}^{W-1} p_n(i, j) m_n \quad (2)$$

where H is the height of feature map, W is the width of feature map, $p_n(i, j)$ is the pixel in position (i, j) in the n th feature map of f_p . The ultimate feature representation is $f = [f(0), \dots, f(N-1)]$, whose dimension is 2048.

Compared with simple concatenation and convolution operation on f_s and f_p , the proposed weighted pooling operation focuses on learning a transferring matrix W_m for mapping the style features to a set of weights M for weighted pooling. The influence of style feature is added adaptively to the painting representation. By pooling the features f_p with different weights, the fused feature becomes increasingly sensitive to style information. For additional comparisons of the three operations, please refer to Section IV-B.

Finally, we conduct the artist classification branch to train all the parameters. A three-layer MLP taking f as input is used. The size of output for classification task depends on the number of artists in the dataset. We adopt softmax cross entropy loss function to optimize network parameters. We train the painting representation network in a supervised manner. We use the

Fig. 7. Graph-based representativity learning, where α_i is the angle $\angle a_i, x, a_{i+1}$.

WikiArt23 and WikiArt208 as ground truth datasets for training and testing, with a ratio of 8:2. At training stage, the learning rate is initiated as 0.001, and the training batchsize is 32. After training, given the paintings and corresponding artist/style labels, we use the output of the learned feature fusion module f as the style-enhanced representations of digital paintings.

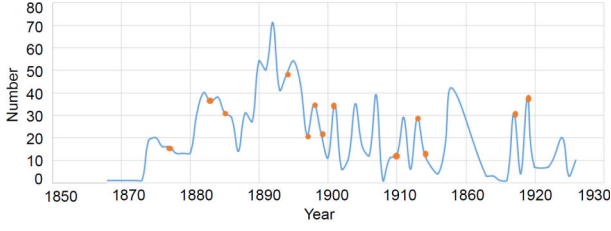
B. Graph-Based Representativity Learning

To uncover similarities among different paintings by holding them up next to one another to find relationships, we formulate the representativity through semi-supervised graph-based learning method. First, through the proposed feature representation network, each painting can be mapped to a point in the learned 2048 dimensional feature space. We select the “famous paintings” in WikiArt which are officially defined as artworks that are significant for an artist’s creative career or an art history as reference paintings (prior knowledge). For each artist, we set the representativity of reference paintings belonging to him/her to be +1 and the representativity of reference paintings belonging to other artists to be -1. Next, the representativity of a painting can be calculated based on the relationships between the painting and the reference paintings on the graph. If a painting is “close” to the reference paintings of the same artist (representativity of which are +1), then it could well represent the creative characteristic of an artist. However, a painting that is “close” to the reference paintings of other artists (representativity of which are -1) should be treated as less representative, as it lacks of unique characteristics.

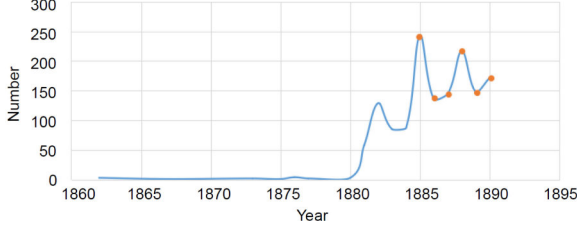
Given a painting x , we selected top- K nearest reference paintings as anchors ($K = 30$ as default in all our experiments). As illustrated in Fig. 7, R reference paintings $\{a_0, \dots, a_{R-1}\}$ by the same artist as x (intra-category anchors) and S reference paintings $\{\tilde{a}_0, \dots, \tilde{a}_{S-1}\}$ by other artists (extra-category anchors) exist, where $R + S = K$. Subsequently, the representativity of the unanchored x is calculated by measuring the similarity between x and the reference paintings. Thus, we first formulate x as a joint liner expression of the extra-category anchors and intra-category anchors, as follows:

$$x = \sum_{i=0}^{R-1} \lambda_i(x) a_i + \sum_{i=0}^{S-1} \tilde{\lambda}_i(x) \tilde{a}_i, \quad (3)$$

where $\{\lambda_0, \dots, \lambda_{R-1}, \tilde{\lambda}_0, \dots, \tilde{\lambda}_{S-1}\}$ are weights that measure the similarity between x and corresponding reference paintings $\{a_0, \dots, a_{R-1}, \tilde{a}_0, \dots, \tilde{a}_{S-1}\}$. Given that the representativity of intra-category anchors is set to +1 and the representativity of



(a) Paintings distribution of Claude Monet according to creation time



(b) Paintings distribution of Vincent van Gogh according to creation time

Fig. 8. Distribution of painting creation times; orange points present referenced famous works.

extra-category anchors is -1 , the representativity of painting x can be calculated by:

$$Rep(x) = \sum_{i=0}^{R-1} \lambda_i(x) \times (+1) + \sum_{i=0}^{S-1} \tilde{\lambda}_i(x) \times (-1). \quad (4)$$

Previous works [40], [44], [45] use Euclidean distance between points to measure similarities. However, the angle between points is also of huge significance when measuring similarities. In the feature space, each region represents a unique painting characteristic. The differences of these characteristics is encoded in the related angles between different points. Therefore, we adopt the derivative process of [46] and obtain the expression of $\lambda_i(x)$ and $\tilde{\lambda}_i(x)$ as:

$$\begin{aligned} \lambda_i(x) &= \frac{\tan(\alpha_{i-1}/2) + \tan(\alpha_i/2)}{\|a_i - x\|}, \\ \tilde{\lambda}_i(x) &= \frac{\tan(\tilde{\alpha}_{i-1}/2) + \tan(\tilde{\alpha}_i/2)}{\|\tilde{a}_i - x\|}, \end{aligned} \quad (5)$$

where both spatial distance and angle are expressed. The numerator term means that the weight of reference point a_i is proportional to the angles between it and two adjacent points. This finding indicates we reduce the weight of reference point under the situation of high density of reference points in a specific characteristic region. The denominator term means that the weight of reference point a_i is inversely proportional to the Euclidean distance between a_i and x .

Furthermore, when analyzing the paintings throughout an artist's career, we find that reference paintings consistently appear in the middle and late periods, and the density of reference paintings is proportional to the total number of paintings created (see Fig. 8). Thus, the representativity of painting x is reformulated as:

$$Rep(x) = \Psi(x) \times \left[\sum_{i=0}^{R-1} \lambda_i(x) - \sum_{i=0}^{S-1} \tilde{\lambda}_i(x) \right], \quad (6)$$

where $\Psi(x)$ is defined as:

$$\Psi(x) = \frac{y(x)}{\mathbb{Y}} \times \frac{G(x)}{G}, \quad (7)$$

where $y(x)$ is the age of the artist when painting x was created, $\mathbb{Y}$ is the age of the artist when he/she created his/her last painting. G is the number of paintings by the artist that is collected in WikiArt208, $G(x)$ is the number of paintings by the artist created in the same year as x that is collected in WikiArt208. Finally, the representativity value of painting x is normalized by:

$$Rep(x) = \frac{Rep(x) - \min(Rep(\cdot))}{\max(Rep(\cdot)) - \min(Rep(\cdot))},$$

where $\min(Rep(\cdot))$ and $\max(Rep(\cdot))$ are the minimum and maximum representativity values of all the paintings.

IV. EXPERIMENTS

A. Datasets

We collect paintings from WikiArt which is the largest online collection of over 250,000 digitized artworks. Such artworks are in museums, universities, town halls, and other civic buildings in more than 100 countries. Based on WikiArt, we construct two datasets, namely, WikiArt23 and WikiArt208. WikiArt23 is identical with the settings in [44] and contains paintings by 23 artists in 14 styles, in which each artist has at least 500 paintings. The creation time of the paintings by 23 artists ranges from 1300 to 2005. WikiArt208 contains 50,823 paintings by 208 artists in 84 styles, in which each artist has at least 100 paintings. The creation time of the paintings by 208 artists ranges from 1120 to 2014. More statistics of the WikiArt23 and WikiArt208 are available in supplementary material. WikiArt23 is used to evaluate the feature representation performance of the style-enhanced art painting representation framework. Meanwhile, WikiArt208 is employed to calculate the paintings representativity and conduct qualitative and quantitative analyses.

The training phase involves two steps. In the first step, we train the painting representation network in a supervised manner. We use the WikiArt23 and WikiArt208 as ground truth datasets for training and testing, with a ratio of 8:2. In the second step, we train the graph-based representativity learning model in a semi-supervised manner. The prior knowledge is famous works provided by WikiArt. For WikiArt208, we collect 3730 ‘‘famous works’’ from the 208 artists’ personal pages in WikiArt and divide the data into two sets, with a ratio of 7:3. Moreover, 70% of the collected famous works are used as reference paintings for representativity calculation and the rest are used as reserved paintings for model accuracy assessment.

B. Evaluation of Feature Representation

The proposed graph-based representativity learning mechanism is on the basis of the learned feature space of art paintings representation. Thus, the performance of our style-enhanced art paintings representation framework has a major impact on the calculation of $Rep(\cdot)$ in Equations (4) and (6), where $\lambda(\cdot)$ and $\tilde{\lambda}(\cdot)$ are measured by the distances and angles of different points in the feature space. We visualize the learned feature space of

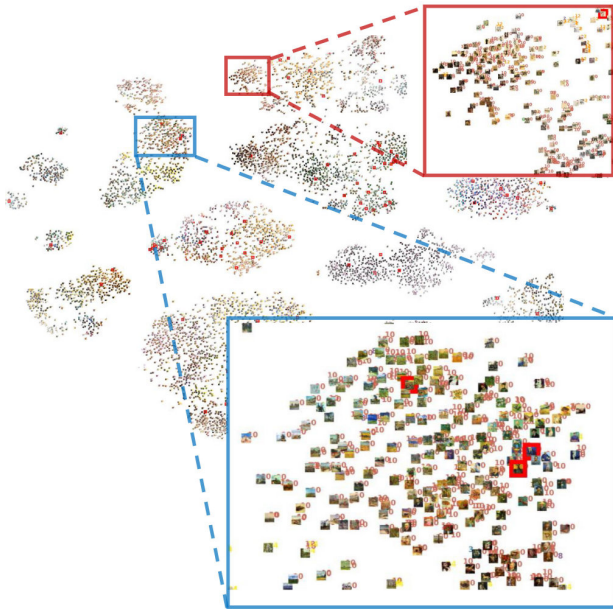


Fig. 9. Visualization of paintings representation using t-SNE [47] on WikiArt23; zoomed in parts are artworks of Vincent van Gogh.

art paintings in WikiArt23 in Fig. 9. By zooming in the figure, we can observe that paintings by the same artist are gathered together in a local area. In the case where one artist paints in more than one style, his/her paintings may be distributed in different areas. For example, in Fig. 9, several of Vincent van Goghs paintings are in the realism area (the red box), whereas other paintings are in the post impressionism area (the blue box). Nevertheless, in each area, paintings by Vincent van Gogh are close to one another. Therefore, the painting representations extracted by our network incorporate both the style information and the authorship attribute, which cover comprehensive painting characteristics (e.g., color, texture, stroke, content, style, and so on.).

1) *Ablation Study*: In this part, we verify three advantages of our style-enhanced art paintings representation method. (1) The use of style to enhance artist-based feature representation is effective when comparing our method with the ResNet50 baseline model. (2) The way we utilize style information is more effective than that in ResNet50 with multi-task (artists and style) leaning. (3) The features fusion method (WeighOp) is highly suitable to our feature representation framework. Therefore, we change our feature representation framework by reducing or replacing several network components:

- *ResNet50*. The proposed deep pipeline is based on ResNet50 structure [43]. Thus we adopt and fine-tune the original ResNet50 for artist classification task.
- *ResNet50+MT*. The proposed deep pipeline uses style information as additional input for training. An alternative way is to use style and artist labels in a multitask fashion. We adopt the ResNet50 and add two classification branches for style and artist. The details of these two branches are the same, however, the output size of the style branch is set to the number of styles involved in the training set.

TABLE I

ABLATION STUDY RESULTS. ACCURACY OF OUR METHOD (OURS) IS BETTER THAN (1) RESNET50 BASELINE METHOD, (2) RESNET50 WITH MULTI-TASK LEARNING (STYLE AND ARTIST), (3) OUR MODEL WHERE WEIGHTOP IS REPLACED WITH CONCATOP OR CONVALOP

	ResNet50	+MT	ConcatOp	ConvalOp	Ours
WikiArt23	79.5%	80.1%	87.1%	86.5%	89.1%
WikiArt208	54.1%	63.7%	72.1%	70.6%	75.0%

TABLE II

ARTIST CLASSIFICATION COMPARISON WITH PREVIOUS METHODS

Saleh [43]	Tan [47]	Ma [8]	Cetinic [48]	CNN-MRF [49]	Ours
63.1%	76.1%	88.6%	79.8%	73.06%	89.1%

- *ConcatOp*. The feature fusion module in our model is changed from weighted pooling to concatenation, and the rest of the network structure is maintained.
- *ConvalOp*. The feature fusion module in our model is changed from weighted pooling to convolution, and the rest of the network structure is maintained.

We conduct contrast experiments on WikiArt23 and WikiArt208. The comparison results are shown in Table I. Due to the use of style information, our framework performs much better than the ResNet50 baseline method. The way we utilize style information is more effective than that in ResNet50+MT. Moreover, the selection of weighed pooling as a feature fusion operation is better than concatenation and convolution.

2) *Comparison With State-of-the-Art Methods*: We compare our style-enhanced art paintings representation framework with state-of-the-art artist classification approaches [9], [44], [48]–[50] which use the same data settings as WikiArt23. All models are trained by solving the task of artist classification, and the average accuracy results are reported in Table II. Overall, our approach achieves the best artist classification performance. Compared with [44], [48]–[50], a huge increase in accuracy is evident. Compared with [9], the improvement is marginal. However, Ma *et al.* [9] used a multitask multirange framework which combines local, regional, and global features of paintings and employs painting style and data as auxiliary tasks. While in this paper, we adopt an end-to-end framework by only using additional style information which has been demonstrated to be efficient and effective.

C. Quantitative Evaluation of Representativity

1) *Representativity Results*: The representativity value calculated by our approach ranges from 0.0 to 1.0. Fig. 10 shows the representativity value of Vincent van Goghs paintings from highest to lowest. Both the unanchored paintings and the reserved paintings are involved. We can observe that all the reserved paintings (enclosed in yellow boxes in Fig. 10) demonstrate high representativity.

Vincent van Gogh sought expressiveness in color and line [51]. When observing a painting with a high representativity value (e.g., “Still Life - Vase with Fifteen Sunflowers”), we can conclude that Vincent van Gogh’s painting creation

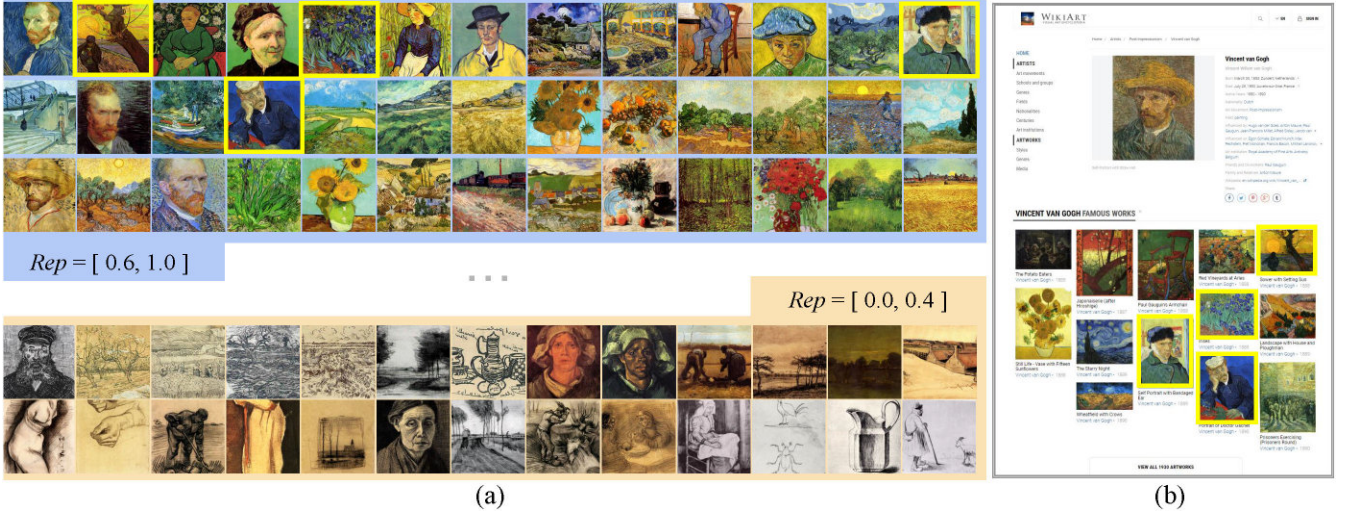


Fig. 10. (a) aintings sorted according to representativity value, from largest to smallest; (b) Famous works from artist's homepage. Paintings enclosed in a yellow box are famous works reserved for verifying the accuracy of our method; representativity of paintings against the blue background ranges from 0.6 to 1.0, representativity of paintings against the orange background ranges from 0.0 to 0.4.

characteristics are profound-colored, with dynamic strokes. However, when observing a painting by Vincent van Gogh with a low representativity value, summarizing the painters creation characteristics would be extremely difficult. In other words, the extent to which the painting represents van Goghs creative career is too low to provide people valuable information (e.g., scene, color, texture, stroke, and so on).

2) *Evaluation Metric*: We introduce the quantitative index AR to evaluate the overall accuracy of painting representativity calculated by our method for each artist. Therefore, AR should be able to measure the difference between representativity calculated by us and the ground-truth value.

In this work, we obtain a collection of “famous works” provided by *WikiArt*, and set the representativity of this works as the ground-truth value. As illustrated in Section IV-A, the collected famous works (representativity of which are +1) are divided into two sets, with a ratio of 7:3. 70% of the collected famous works are used as reference paintings for representativity calculation and the rest are used as reserved paintings for model accuracy assessment. Hence, we recalculate the representativity of reserved famous works. If the representativity value of the reserved paintings calculated by our method are near 1, then accuracy is high. Thus, we average the representativity of reserved paintings by an artist as AR to evaluate the accuracy of our method:

$$AR = \frac{1}{l} \sum_{i=0}^{l-1} Rep(rf) \quad (8)$$

where l is the number of reserved paintings from a specific artist, $Rep(rf)$ is the the representativity of reserved paintings calculated by our method.

In addition, we show the AR value for each artist in *WikiArt208* in Table III. The closer the AR value to 1, the more precise the representativity. The average AR value of 208 artists is 0.721.

TABLE III
PERFORMANCE (AR VALUE) ON WIKIART208

Artist	AR	Artist	AR
William Blake	0.907	Pierre-Paul Prud'hon	0.831
Giovanni Battista Piranesi	0.893	Edward Burne-Jones	0.829
Lorenzo Lotto	0.874	Frederic Leighton	0.829
John William Waterhouse	0.867	Paolo Veronese	0.827
Vasily Perov	0.864	...	
Jan Matejko	0.860		
Karl Bryullov	0.858	Jan Steen	0.588
Joshua Reynolds	0.858	Eugene Delacroix	0.586
Jack Bush	0.856	James McNeill Whistler	0.585
William H. Johnson	0.855	Henri Martin	0.583
Childe Hassam	0.849	Kazimir Malevich	0.577
Franz Marc	0.849	Guido Reni	0.575
Henri de Toulouse-Lautrec	0.846	Wilhelm Kotarbinski	0.566
Theodoros Stamos	0.844	Isaac Levitan	0.563
Maxime Maufra	0.843	Egon Schiele	0.541
Kitagawa Utamaro	0.840	Pierre Bonnard	0.506
Ellsworth Kelly	0.840	Erté	0.483
John Singleton Copley	0.835	Theodore Gericault	0.397
Frans Hals	0.833	Gustav Klimt	0.381
Vladimir Borovikovsky	0.833		
Bartolomé Esteban Murillo	0.833	Average	0.721

3) *Setting of K* : As described in Section III-B, we select Top- K nearest reference paintings as anchors. To test the effect of K value, we set K to 20, 30, 40, 50, respectively. Next, the AR value of 6 artists and the average AR value of the 6 artists in *WikiArt208* are calculated. As illustrated in Fig. 11, the system is parameter insensitive, since the average line is steady.

4) *Effectiveness of Painting's Creation Time*: To reveal the advantage of painting creation time, we calculate the representativity of reserved paintings with and without integrating creation time information then compute the AR value. The AR value of 6 artists and the average AR value of the 6 artists are shown in Table IV. Obviously, painting creation time information can help improve the precision of representativity.

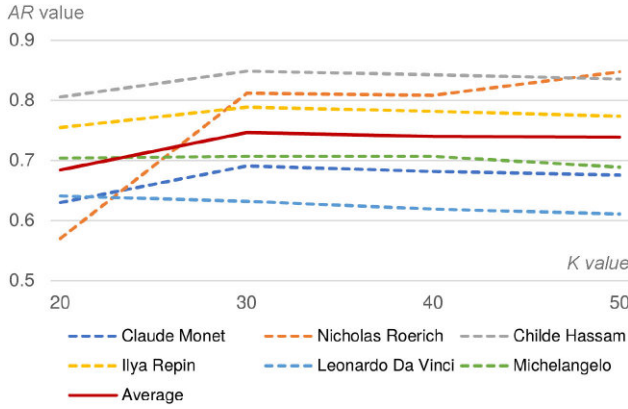


Fig. 11. AR value of our model choosing Top- K ($K = 20, 30, 40, 50$) nearest references as anchors.

TABLE IV
PERFORMANCE (AR VALUE) WITHOUT AND WITH CREATION TIME FOR
PAINTING REPRESENTATIVITY CALCULATION

	Without creation time	With creation time
Claude Monet	0.614	0.691
Nicholas Roerich	0.663	0.812
Childe Hassam	0.696	0.849
Ilya Repin	0.723	0.789
Leonardo Da Vinci	0.495	0.632
Michelangelo	0.620	0.707
Average	0.635	0.747

TABLE V
PAINTING REPRESENTATIVITY CALCULATION PERFORMANCE (AR VALUE) OF
RESNET50-MT AND OUR METHOD

	ResNet50+MT	Ours
Claude Monet	0.463	0.691
Nicholas Roerich	0.659	0.812
Childe Hassam	0.739	0.849
Ilya Repin	0.674	0.789
Leonardo Da Vinci	0.596	0.632
Michelangelo	0.651	0.707
Average	0.643	0.747

5) *Mechanism of Using Style Information*: We compare our method with *ResNet50+MT* described in Section IV-B, which utilizes style information differently. The representativity of reserved paintings are calculated using features extracted by *ResNet50+MT* and our method. The AR value of 6 artists and the average AR value of the 6 artists are shown in Table V. Obviously, our way of using style information is more effective than that of *ResNet50+MT* in improving representativity accuracy.

6) *Comparison With Correlative Method*: Recent studies aim to select the representative paintings of an artist automatically [40], [45]. Such works can recommend an artists most representative works to the public, thereby helping them master the artists painting characteristics quickly. However, these studies pay more attention to diversity than to representativity. We collect the 10 representative paintings by Vincent van Gogh recommended by [40], and calculate the paintings' representativity. As illustrated in Fig. 12, the paintings recommended by

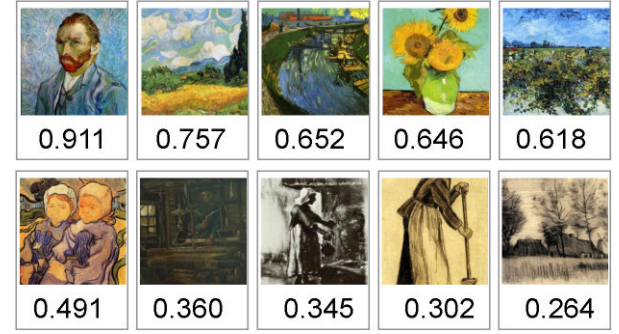


Fig. 12. Representativity value of 10 paintings by Vincent van Gogh recommended by [40].

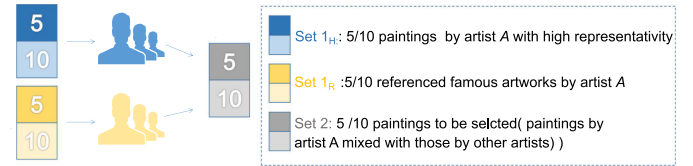


Fig. 13. Settings of user study I.

Deng *et al.* [40] are diverse in terms of painting characteristics, but some of the paintings are less representative than others; thus, their predicted representativity value is low.

D. Qualitative Evaluation of Representativity

Representativity is proposed to evaluate quantitatively the extent to which a painting can represent the characteristics of a painters creations. Therefore, paintings with high representativity would be helpful in providing additional information about an artists creation characteristics. Hence, in this section, we conduct two user studies to prove that paintings with high representativity can represent an artists creation characteristics veraciously and provide the public access to additional painting characteristics.

A total of 50 individuals (30 males, 20 females, age range of 18-40) with different educational backgrounds participated in the two user studies. In each study, a participant is asked to firstly view a set of paintings (*Set 1*) created by an artist A and then select all the paintings he/she believes were created by A from another set (*Set 2*). The two sets contain the same number of paintings. Paintings by 6 artists are used. Artist A is selected randomly, and the two painting sets are constructed randomly during each round. No time limit is given for the selection process, but the observation time should be longer than one minute. Finally, the average $accuracy = \frac{TP}{TP+FP}$ and $recall = \frac{TP}{TP+FN}$ are recorded. TP is the average true examples selected by the participants, FP is the average false examples selected by participants, FN is average true examples not selected by participants.

1) *User Study I*: As shown in Fig. 13, *Set 1* contains either P referenced "famous" works by A (*Set 1_R*) or P paintings paintings by A with high representativity values (*Set 1_H*). *Set 2* contains P paintings randomly selected from artist A and other artists. Given that the number of reference paintings is limited, for each round, we randomly set $P = 5$ or $P = 10$. Each participant is involved in 24 rounds of experiments. The selection

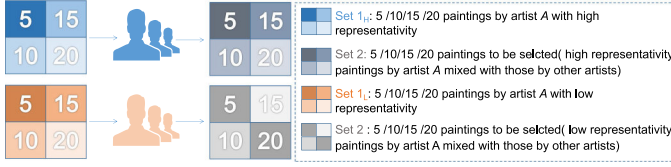


Fig. 14. Settings of user study II.

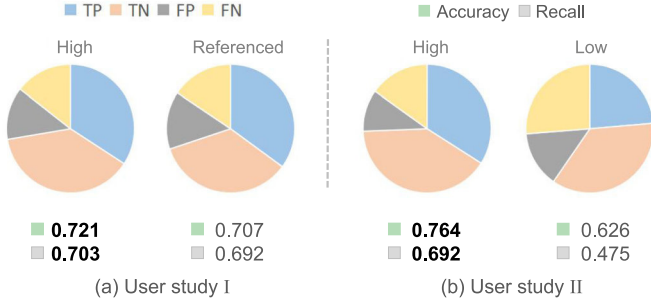


Fig. 15. Experiment results of overall contrast.

results are separated to two groups, that is, the results of participants who viewed $Set 1_R$ are placed in the “Referenced” group and the results of participants who viewed $Set 1_H$ are placed in the “High” group.

We calculate the average accuracy and recall of the two groups, and the statistical results are shown in Fig. 15(a). The overall average accuracy and recall of both groups (“Referenced” vs. “High”) are similar. We further compare the accuracy of the two groups with independent t -test to verify reliability. The p -value is 0.5969, which indicates that no significant difference exists between the two groups. Therefore, the first user study demonstrates that people can obtain similar characteristics from paintings with high representativity when compared with referenced famous works.

2) *User Study II*: As shown in Fig. 14, $Set 1$ contains either P paintings by A with high representativity ($Set 1_H$) or P paintings by A with low representativity ($Set 1_L$). $Set 2$ contains P paintings randomly selected from artist A and other artists. Notably, paintings with high and low representativity may differ completely in style. Thus, for fair comparison, paintings by A in $Set 2$ are chosen from paintings with similar representativity as $Set 1$ for observation. During each round, we randomly set the value of P to be 5, 10, 15 or 20. Each participant is involved in 48 rounds of experiments.

Similar to user study I, we place the results of participants who viewed $Set 1_H$ into the “High” group and place the results of participants who viewed $Set 1_L$ into the “Low” group. The statistical results are shown in Fig. 15(b). The average accuracy and recall of the “High” group is higher than those of “Low” group. This phenomenon illustrates that the selected paintings with high representativity can help people to grasp the painting characteristics of an artist better than those with low representativity. The p -value = $3.12e^{-7}$ of independent t -test between the two groups (“High” vs. “Low”) indicates that the performance of paintings with high representativity are significantly better than that of the paintings with low representativity. Therefore,

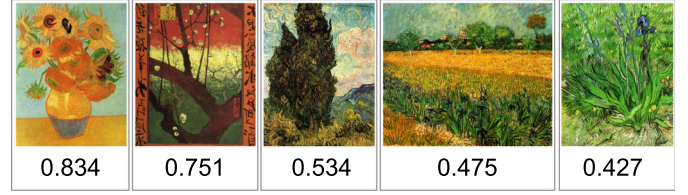


Fig. 16. Representativity of Vincent van Gogh's paintings which is calculated without inter-category anchors.

the second user study demonstrates that people can obtain additional creation characteristics of an artist from paintings with high representativity compared with paintings with low representativity.

3) *Summary*: By comparing user studies I and II, we observe a substantial improvement in accuracy in the “High” group. Given that the only difference between the two groups is that the average number of paintings (P value) used in user study II is larger than that in user study I, we can conclude that a large amount of paintings with high representativity can help the public acquire information about an artists painting characteristics. However, obtaining adequate information from *WikiArt* is difficult owing to the limited number of “famous works” on the site. In line with average accuracy and recall comparisons in different groups, by comparing overall TP, TN, FP, and FN, we can see that paintings with high representativity perform as well as referenced famous works and better than paintings with low representativity. Overall, the two user studies show that paintings with high representativity can help the public obtain artists creation characteristics. Moreover, the user studies prove that representativity can be used to evaluate quantitatively the extent to which a painting can represent the characteristics of an artists creations. The higher the representativity of a painting, the more the artists creation characteristics can be obtained from the painting.

E. Discussion

In the aforementioned experiments, 70% of famous works are used as reference paintings for representativity calculation, and 30% are reserved for verifying the performance. However, in an extreme case where no referenced famous work by an artist is available, will the proposed method still work? Under this circumstance, we represent an unanchored point only using a linear combination of extra-category anchors. Afterwards, we calculate the unanchor's representativity according to the second term in Equation (6). Fig. 16 shows the representativity of Vincent van Gogh's paintings which is calculated without inter-category anchors. In another extreme case when the paintings of an unseen artists are explored, we can fine tune the painting representation network and apply the graph-based representativity computation. Therefore, our method is scalable to most cases.

V. CONCLUSION

In this paper, we focus on analysis of art paintings, which is the most challenging Level IV delineated in [1]. We adopt

deep learning techniques for the art domain and enable effective engagement between the public and art. We present a novel concept, namely, *representativity*, to quantitatively evaluate the extent to which a painting can represent the characteristics of the artist's creations. Paintings with high representativity can help the public grasp additional creation characteristics of an artist. To this end, we propose a novel style-enhanced artist classification framework for extracting painting-specific features which uses auxiliary style information (e.g. Expression, Impression, Gongbi, and so on) to consummate feature representation. Our framework combines the style and authorship of art paintings and learns specific artwork characteristics. Then, we calculate painting representativity with a graph-based learning method.

In learning feature representations, we consider only paintings authorship and style. In the future, we plan to analyze additional descriptive attributes to compute the representativity of art paintings. Furthermore, we will explore the impact of different painting regions on representativity.

REFERENCES

- [1] K. Zhang, S. Harrell, and X. Ji, "Computational aesthetics: On the complexity of computer-generated paintings," *Leonardo*, vol. 45, no. 3, pp. 243–248, 2012.
- [2] L. A. Gatys, A. S. Ecker, and M. Bethge, "Image style transfer using convolutional neural networks," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, 2016, pp. 2414–2423.
- [3] J. Johnson, A. Alahi, and L. Fei-Fei, "Perceptual losses for real-time style transfer and super-resolution," in *Proc. Eur. Conf. Comput. Vis.*, 2016, pp. 694–711.
- [4] A. Sanakoyeu, D. Kotovenko, S. Lang, and B. Ommer, "A style-aware content loss for real-time hd style transfer," in *Proc. Eur. Conf. Comput. Vis.*, 2018, pp. 698–714.
- [5] X. Huang and B. Serge, "Arbitrary style transfer in real-time with adaptive instance normalization," in *Proc. IEEE Int. Conf. Comput. Vis.*, 2017, pp. 1501–1510.
- [6] J. Liu, W. Yang, X. Sun, and W. Zeng, "Photo stylistic brush: Robust style transfer via superpixel-based bipartite graph," *IEEE Trans. Multimedia*, vol. 20, no. 7, pp. 1724–1737, Jul. 2018.
- [7] Y. Zhou *et al.*, "BranchGAN: Unsupervised mutual image-to-image transfer with a single encoder and dual decoders," *IEEE Trans. Multimedia*, vol. 21, no. 12, pp. 3136–3149, Dec. 2019.
- [8] L. Doyle, F. Anderson, E. Choy, and D. Mould, "Automated pebble mosaic stylization of images," *Comput. Vis. Media*, vol. 5, no. 1, pp. 33–44, 2019.
- [9] D. Ma *et al.*, "From part to whole: Who is behind the painting?" in *Proc. ACM Int. Conf. Multimedia*, 2017, pp. 1174–1182.
- [10] N. Van Noord, E. Hendriks, and E. Postma, "Toward discovery of the artist's style: Learning to recognize artists by their artworks," *IEEE Signal Process. Mag.*, vol. 32, no. 4, pp. 46–54, Jul. 2015.
- [11] I.-C. Shen and W.-H. Cheng, "Gestalt rule feature points," *IEEE Trans. Multimedia*, vol. 17, no. 4, pp. 526–537, Apr. 2015.
- [12] J. Tarvainen, M. Sjberg, S. Westman, J. Laaksonen, and P. Oittinen, "Content-based prediction of movie style, aesthetics, and affect: Data set and baseline experiments," *IEEE Trans. Multimedia*, vol. 16, no. 8, pp. 2085–2098, Dec. 2014.
- [13] G. Liu *et al.*, "Inferring painting style with multi-task dictionary learning," in *Proc. Int. Conf. Artif. Intell.*, 2015, pp. 2162–2168.
- [14] H. Mao, M. Cheung, and J. She, "DeepArt: Learning joint representations of visual arts," in *Proc. ACM Int. Conf. Multimedia*, 2017, pp. 1183–1191.
- [15] J. Yang *et al.*, "Historical context-based style classification of painting images via label distribution learning," in *Proc. ACM Int. Conf. Multimedia*, 2018, pp. 1154–1162.
- [16] W.-T. Chu and Y.-L. Wu, "Image style classification based on learnt deep correlation features," *IEEE Trans. Multimedia*, vol. 20, no. 9, pp. 2491–2502, Sep. 2018.
- [17] D. Perkins, "Art as understanding," *J. Aesthetic Educ.*, vol. 22, no. 1, pp. 111–131, 1988.
- [18] M. Dewhurst, *Social Justice Art: A Framework for Activist Art Pedagogy*. Cambridge, MA, USA: Harvard Educ. Press, 2014.
- [19] E. H. Gombrich and E. Gombrich, *The Story of Art*. London, U.K.: Phaidon, 1995, vol. 12, pp. 155–159.
- [20] M. Pelowski, G. Gerger, Y. Chetouani, P. S. Markey, and H. Leder, "But is it really art? The classification of images as "art"/"not art" and correlation with appraisal and viewer interpersonal differences," *Frontiers Psychol.*, vol. 8, 2017, Art. no. 1729.
- [21] L. Shamir, T. J. Macura, N. Orlov, D. M. Eckley, and I. G. Goldberg, "Impressionism, expressionism, surrealism: Automated recognition of painters and schools of art," *ACM Trans. Appl. Perception*, vol. 7, no. 2, pp. 1–17, 2010.
- [22] D. Wynn, C. Schmid, and J. Mairal, "Unsupervised learning of artistic styles with archetypal style analysis," in *Proc. 32nd Conf. Neural Inf. Process. Syst. (NeurIPS)*, 2018, pp. 6584–6593.
- [23] W. T. Chu and Y. L. Wu, "Deep correlation features for image style classification," in *Proc. 24th ACM Int. Conf. Multimedia*, 2016, pp. 402–406.
- [24] K. A. Jangtik, M.-C. Yeh, and K.-L. Hua, "Artist-based classification via deep learning with multi-scale weighted pooling," in *Proc. ACM Int. Conf. Multimedia*, 2016, pp. 635–639.
- [25] G. Carneiro, N. P. da Silva, A. Del Bue, and J. P. Costeira, "Artistic image classification: An analysis on the printart database," in *Proc. Eur. Conf. Comput. Vis.*, 2012, pp. 143–157.
- [26] A. Elgammal, B. Liu, D. Kim, M. Elhoseiny, and M. Mazzone, "The shape of art history in the eyes of the machine," in *Proc. AAAI Conf. Artif. Intell.*, 2018, pp. 2183–2191.
- [27] L. Chen and J. Yang, "Recognizing the style of visual arts via adaptive cross-layer correlation," in *Proc. ACM Int. Conf. Multimedia*, 2019, pp. 2459–2467.
- [28] S. Ornes, "Science and culture: Computers take art in new directions, challenging the meaning of "creativity"," *Proc. Nat. Acad. Sci.*, vol. 116, no. 11, pp. 4760–4763, 2019.
- [29] Z. Kang, S. Harrell, and J. Xin, "Computational aesthetics: On the complexity of computer-generated paintings," *Leonardo*, vol. 45, no. 3, pp. 243–248, 2012.
- [30] M. Perc, "Beauty in artistic expressions through the eyes of networks and physics," *J. Roy. Soc. Interface*, vol. 17, no. 164, pp. 1–13, 2020.
- [31] B. Saleh, K. Abe, A. R. Singh, and A. Elgammal, "Toward automated discovery of artistic influence," *Multimedia Tools Appl.*, vol. 75, no. 7, pp. 3565–3591, 2016.
- [32] R. P. Taylor, A. P. Micolich, and D. Jonas, "Fractal analysis of pollock's drip paintings," *Nature*, vol. 399, no. 6735, pp. 422–422, 1999.
- [33] M. Kim and J. Kim, "Quantitative analysis of artists' characteristic styles through biologically-motivated image processing techniques: Uncovering a mentor to johannes vermeer," in *Proc. Int. Conf. Human-Comput. Interact.*, 2013, pp. 258–262.
- [34] A. Sartori, D. Culibrk, Y. Yan, and N. Sebe, "Who's afraid of itten: Using the art theory of color combination to analyze emotions in abstract paintings," in *Proc. ACM Int. Conf. Multimedia*, 2015, pp. 311–320.
- [35] D. Kim, S.-W. Son, and H. Jeong, "Large-scale quantitative analysis of painting arts," *Scientific Rep.*, vol. 4, no. 1, pp. 7370:1–7370:7, 2014.
- [36] S.-Y. Feng and C.-K. Ting, "Painting using genetic algorithm with aesthetic evaluation of visual quality," in *Proc. Int. Conf. Technologies Appl. Artif. Intell.*, 2014, pp. 124–135.
- [37] J. Liu, W. Dong, X. Zhang, and Z. Jiang, "Orientation judgment for abstract paintings," *Multimedia Tools Appl.*, vol. 76, no. 1, pp. 1017–1036, 2017.
- [38] S. P. Fraiberger, R. Sinatra, M. Resch, C. Riedl, and A.-L. Barabási, "Quantifying reputation and success in art," *Science*, vol. 362, no. 6416, pp. 825–829, 2018.
- [39] H. Y. D. Sigaki, M. Perc, and H. V. Ribeiro, "History of art paintings through the lens of entropy and complexity," *Proc. Nat. Acad. Sci.*, vol. 115, no. 37, pp. E8585–E8594, 2018.
- [40] Y. Deng *et al.*, "Selective clustering for representative paintings selection," *Multimedia Tools Appl.*, vol. 78, no. 14, pp. 19 305–19 323, 2019.
- [41] G.-F. Sargentis, P. Dimitriadis, and D. Koutsoyiannis, "Aesthetical issues of Leonardo Da Vinci's and Pablo Picasso's paintings with stochastic evaluation," *Heritage*, vol. 3, no. 2, pp. 283–305, 2020.
- [42] G. Sargentis, P. Dimitriadis, R. Ioannidis, T. Iliopoulou, and D. Koutsoyiannis, "Stochastic evaluation of landscapes transformed by renewable energy installations and civil works," *Energies*, vol. 12, no. 14, 2019, Art. no. 2817.
- [43] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, 2016, pp. 770–778.
- [44] B. Saleh and A. Elgammal, "A unified framework for painting classification," in *Proc. IEEE Int. Conf. Data Mining Workshop*, 2015, pp. 1254–1261.

- [45] Y. Deng, F. Tang, W. Dong, H. Yao, and B.-G. Hu, "Style-oriented representative paintings selection," in *Proc. SIGGRAPH Asia Posters*, 2017, pp. 12:1–12:2.
- [46] M. S. Floater, "Mean value coordinates," *Comput. Aided Geometric Des.*, vol. 20, no. 1, pp. 19–27, 2003.
- [47] L. Van Der Maaten, "Accelerating t-SNE using tree-based algorithms," *J. Mach. Learn. Res.*, vol. 15, no. 1, pp. 3221–3245, 2014.
- [48] W. R. Tan, C. S. Chan, H. E. Aguirre, and K. Tanaka, "Ceci n'est pas une pipe: A deep convolutional network for fine-art paintings classification," in *Proc. IEEE Int. Conf. Image Process.*, 2016, pp. 3703–3707.
- [49] E. Cetinic, T. Lipic, and S. Grgic, "Fine-tuning convolutional neural networks for fine art classification," *Expert Syst. Appl.*, vol. 114, pp. 107–118, 2018.
- [50] K.-L. Hua, T.-T. Ho, K.-A. Jangtjik, Y.-J. Chen, and M.-C. Yeh, "Artist-based painting classification using markov random fields with convolution neural network," *Multimedia Tools Appl.*, vol. 79, no. 17, pp. 12 635–12 658, 2020.
- [51] J. Hulsker, *The New Complete Van Gogh: Paintings, Drawings, Sketches: Revised and Enlarged Edition of the Catalogue Raisonné of the Works of Vincent Van Gogh*. Amsterdam, The Netherlands: JM Meulenhoff, 1996.



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