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Dynamic Art Curation Method with Pretrained Models of Art Interpretation

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Abstract. In this paper, a dynamic curation method that uses pretrained models of art interpretation is proposed. The proposed method leverages exhibition catalogs (primary classifications and images) as a source of curatorial knowledge to construct a machine learning model, thereby using this model to evaluate, position, and visualize other artwork. This method enables the dynamic curation of artwork in a vast integrated art collection archive. A prototype system for the proposed method was implemented and applied to two exhibition catalogs at the Artizon Museum. In the experiment, artworks matching the purpose and art style of the modeled exhibition from the archives of the Metropolitan Museum of Art in New York City and Paris Musées were evaluated using the constructed model. The experiment demonstrated that the proposed method successfully classifies and enables the visualization of artwork and images available in the open data from the MET and Paris Musées in alignment with the intended theme of the exhibition for which the model was constructed. Feedback from curators and art professionals indicates that the proposed method can be used to compare museums with art collections of the same genre and to organize new exhibitions based on the curatorial model.

Keywords. Dynamic Art Curation, Art data processing, Machine Learning in Retrieving Museum Art Collection, Visualization of Art Collection

1. Introduction

Recently, museums have been constructing digital archives for art collections worldwide. Notably, some institutions such as The Metropolitan Museum of Art [1], Paris Musées [2], and the National Gallery of Art in Washington, D.C. [3] have released their collection of metadata and copyright-expired images as open data. Numerous methods have been proposed for establishing art collection archives, such as Artizon Cloud [4], which is a multi-database system that integrates various types of distributed art collection data, including text, images, and audio. By leveraging the data, museums can offer unprecedented virtual and physical viewing experiences. The Art Sensorium Project [5] aims to integrate various types of open data from art collections, utilizing them to produce physical and virtual dynamic art experiences in the Data Sensorium [6], which is a spatially immersive display. In this project, a prototype application for a data sensorium is proposed, featuring dynamic curation based on an individual user's art-viewing experience [7]. An implementation method integrating open art data from

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various museum archives, has also been proposed [8] for the Global Art Collection Archive as part of the Art Sensorium Project.

The challenge of utilizing open data art collections from various museums lies in selecting and ordering a vast array of artwork from diverse perspectives. These range from macro viewpoints, such as art style and movement, to micro viewpoints, including museum policies, historical context, and artists' backgrounds. In brief, the issue entails how to implement the “curation” of Global Art Collection Archives. Traditionally, the task of curation has been carried out by museum curators whose approaches naturally vary based on their interpretations, research positions, the museum’s philosophy, exhibition concept, and other factors. In other words, artwork selection, categorization, and presentation processes are dynamic and naturally differ among museums, curators, and exhibitions. Such diverse art interpretations should be included in automatic and dynamic curation.

In searching within the massive integrated archive of art collections, selecting artwork based on basic information (title, artist name, material/technique, dimensions, year, place of production, etc.) can be easily achieved. Additionally, in a virtual exhibition space, the display of artwork can be varied by tracking visitors' preferences and behaviors [7]. However, a curator's selection of artwork for an exhibition is more complex. For example, Vincent Van Gogh's 'Windmills on Montmartre'[2] is generally categorized in the Impressionism genre. However, in one exhibition, it was associated with the emergence of abstract painting; as an example of landscape painting in another exhibition; and as depicting 19th-century Parisian cityscapes in still another. A dynamic curation method encompassing diverse interpretations of art such as those mentioned above must be employed. It is anticipated that these methods can be realized by applying various curatorial insights (e.g., classifications from exhibition catalogs) to pretrained models, whereby machine learning can be used to classify artwork based on these models.

In this paper, a dynamic curation method that uses pretrained models of art interpretation is proposed. The proposed method leverages exhibition catalogs (primary classifications and images) as a source of curatorial knowledge to construct a machine learning model and uses this model to evaluate, position, and visualize other artworks. Applying this method enables the dynamic curation of artworks in a vast integrated art collection archive. A prototype system for the proposed method was implemented and applied to two exhibition catalogs at the Artizon Museum. In the experiment, artwork matching the purpose and art style of the modeled exhibition from the archives of the Metropolitan Museum of Art in New York City and Paris Musées were evaluated using the constructed model. The experiment demonstrated that the proposed method successfully classifies and visualizes artwork available from the MET and Paris Musées in alignment with the intended theme of the exhibition for which the model was constructed. Feedback from curators and art professionals indicates that the proposed method can be used to compare museums holding art collections of the same genre or for organizing new exhibitions based on the curatorial model.

2. Related Works

Research on AI and in the arts has accelerated the digitization and archiving of art collections. Studies involving art and AI are divided into two fields: "Understanding Art

[2] ‘Windmills on Montmartre’: https://www.artizon.museum/en/collection/art/22565

with AI" and "Creating Art with AI" [9]. Over the past few decades, various methods have been proposed for the automated classification of artwork based on categories such as artists, genres, and artistic schools. Most of these methods involve extracting features from artwork and applying machine-learning algorithms to create classification models. In the early stages, these methods addressed classification issues by extracting specific handcrafted image features, such as schools of art [10] or artists' brushstrokes [11]. Recently, numerous methods that leverage convolutional neural networks (CNNs) have been proposed to improve classification accuracy. Karayev [12] was the first to employ CNNs as feature extractors for classifying various art styles, such as Impressionism and Cubism. The superiority of CNN-based feature extraction over handcrafted features was indicated in classifying art styles [13] and artists [14]. CNN-based approaches have also been adopted in other studies, such as object detection, similarity retrieval of art [15], and knowledge discovery in art history [16]. Recent studies have explored multimodal modeling that incorporates both image and commentaries associated with the paintings. Datasets such as SemArt [17], BibleVSA [18], and Artpedia [19] have been developed to map artwork images and their explanatory texts into a unified model space. In addition, multimodal architectures that simultaneously process images and text have been proposed [20].

In AI and art research, datasets on artwork images are crucial across various domains and can serve as benchmarks for model building. Consequently, several datasets were introduced. Painting-91 [21] features approximately 4,000 artworks from 91 painters, categorized by artist and style. Panda [22] encompasses over 7,700 images from 12 artistic movements, with a focus on the movements. With the advent of CNN, the scales of datasets have expanded significantly. Art500k [23] includes over 500,000 artworks sorted by artist, genre, medium, and movement, whereas the OmniArt [24] dataset covers two million images. There are also specialized datasets concentrating on painting genres and features, such as iconography [25,26], portraits [27], and sentiments/emotions [28].

Most previous studies focused on creating a general-purpose classification model for artists, schools of art, or art styles based on applying machine learning to a large amount of artwork from ImageNet and WikiArt. General-purpose models are useful for classifying various types of artwork from a common perspective. In particular, because the effectiveness of CNN-based models has been demonstrated, the size of datasets used to examine art classification models has significantly increased. However, as mentioned in the Introduction, artwork selection, classification, and presentation are dynamic processes and vary among museums. Applying previous studies to artwork selection and classification in a virtual museum may lead to homogenized exhibits, potentially limiting the stimulation of visitor creativity.

3. Dynamic Art Curation Method with Pretrained Models of Art Interpretation

Our goal is to create a viewing environment that would allow users to visualize artwork from multiple perspectives, not just based on a single interpretation. This approach enables users to experience the creativity of the artwork, enhancing their understanding and the visual experience, thereby inspiring a new era of creation. To achieve this, as illustrated in Figure 1, a dynamic art curation method is proposed to implement diverse art interpretations. This method creates models pretrained on the art collection classification from one museum and applies these models to the art collection of another museum, thereby enabling dynamic curation. Employing this method in the

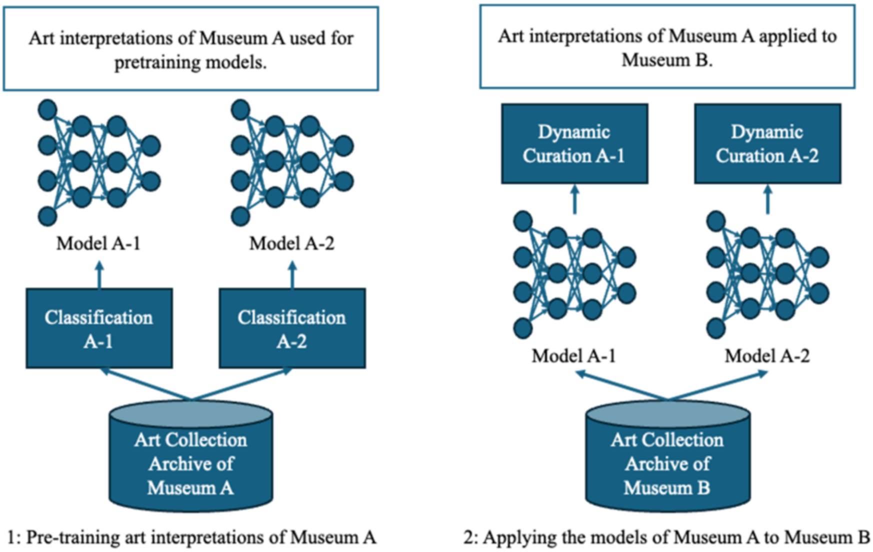

Figure 1. Idea of A Dynamic Art Curation Method

curation of a virtual museum enables the creation of a dynamically changing virtual exhibition that reflects the unique characteristics of each museum and its curators.

Figure 2 provides an overview of the proposed method, which is designed to build an art interpretation model based on the curator's knowledge, for mapping and visualizing other artwork. This method consists of the following five components:

3.1. Source Museum Archive

The *source museum archive* serves as a collection database for building a pretrained model of art interpretation based on the curator's knowledge. By selecting training data from this archive, a machine-learning model is created using the *model creation function*. Consequently, resources are essential for classifying the *source museum archive*. These resources may include the archive's internal classifications (such as art style and genre) or exhibition catalogs that list the displayed artwork. Museum curators typically perform these classifications. Exhibition classifications are particularly valuable for modeling specific art interpretations. This method assumes that an exhibition catalog is the primary source of classification. An exhibition lacking clear categorizations, requires at least two classifications: one for the exhibited artworks and another for those not exhibited. More importantly, the *source museum archive* should provide images of the artwork corresponding to these classifications.

3.2. Model Creation Function

The *model creation function* is designed to create the *art interpretation model*. This model presents the distribution of artwork based on the exhibition catalog in the *source museum archive* and curator's knowledge. The model learns from artwork data, comprising images and classification labels. The model should be constructed using methods appropriate for the image dataset of the artwork source. Therefore, during the

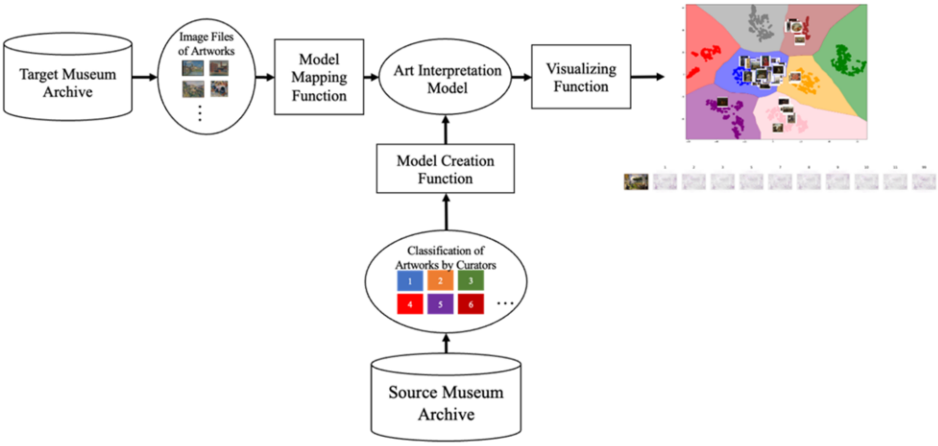

Figure 2. Overview of the proposed method

model creation process, it is essential to implement features that can test multiple pretrained architectures, as in VGG [29], ResNet [30], and vision transformer [31]. Additionally, given that the size of the artwork dataset is often not extensive, and image augmentation is crucial for enhancing the performance of CNN models [32], image augmentation should also be implemented.

3.3. Target Museum Archives

The *target museum archive* is an art collection archive that includes the artwork to be evaluated by the *art interpretation model*. Selected artwork from the *target museum archive* are mapped onto the art interpretation model using the *model-mapping function*.

The *target museum archive* is not subject to any specific restrictions. However, this method is expected to retain works that are comparable to those in the *source museum archive*. For instance, if the comparison is with the *source museum archive*'s Impressionist collection, the target is the artwork selected from another museum archive with an Impressionist collection. Similarly, to analyze the trends in artwork highlighted by the *source museum archive*, artwork highlighted by the *target museum archive* would be selected. It is preferable that both the *source* and *target museum archives* provide images under an open license (e.g., public domain or Creative Commons CC0 license) and an API for data access.

3.4. Model Mapping Function

The model-mapping function is designed to map artwork from the *target museum archive* into the *art interpretation model*. This function should incorporate at least two features. The first is an image downloader to retrieve artwork images through an API provided by the archive. During this process, the downloader must check the status of the artwork, such as 'is highlighted' or 'is public domain,' and download the appropriate images. The second feature is the capability to input images of artwork into the model. When images are input, their sizes must be adjusted to fit the model architecture. Additionally, the output of the model mapping, including the scores from the output layer and final label selection, should be stored for visualization.

3.5. Visualization Function

The *visualization function* illustrates the interpretation of artwork in the *target museum archive* as perceived by the *art interpretation model.* Thus, how the model classifies the artwork selected from the *target museum archive*, the rationale behind the classifications, and the relationship between these classifications and the artwork in the *source museum archive* can be visualized, considering both broad and detailed perspectives.

Two key features must be implemented for this function. The first feature is for visualizing the overarching trends of artwork in the *target museum archive*, such as similarities and differences, compared to the *source museum archive*. Utilizing dimensionality reduction algorithms such as principal component analysis (PCA) and t-distributed stochastic neighbor embedding (t-SNE), 2D/3D graphs can be generated from the scores obtained through the *mapping function*. This feature that helps visualize the relationship between artwork in the *source* and *target museum archives* is crucial. The second feature aims to elucidate the basis for the classifications selected by the model. Incorporating explainable artificial intelligence (XAI) [33] techniques is vital for an understanding of 'how the model interprets art,' in line with the method's focus on the diversity of art interpretation. A feature that visualizes the model's internal behavior using existing XAI techniques (such as SHapley Additive exPlanations (SHAP) [34], Gradient-weighted Class Activation Mapping (GradCAM++)[35], and Approximate Inverse Model Explanations (AIME)[36]) should also be incorporated.

4. Implementation of Prototype Method

A prototype of the proposed method was implemented, as shown in Figure 3. Presently, the method considers the art collections that are integrated into our Global Art Collection Archive [8]. In this study, Artizon Cloud [4] was selected as the *source museum archive* and MET [1] and Paris Musees [2] as the *target museum archives*.

Three functions (model creation, model mapping, and visualization) were implemented using the prototype method under the conditions listed in Table 1.

Table 1. System Environment of Prototype Method.

Software	Python 3.11.6
	Pytorch 2.1.0
	Torch Vision 0.16.0
	Sckit-learn 1.3.1
	Matplotlib 3.8.0
	OpenCV 4.8.0.76
Hardware	Mac Book Pro (Apple Silicon M1 Pro Model) Num of CPU Core: 10 Num of GPU Core: 16 RAM: 32 GB

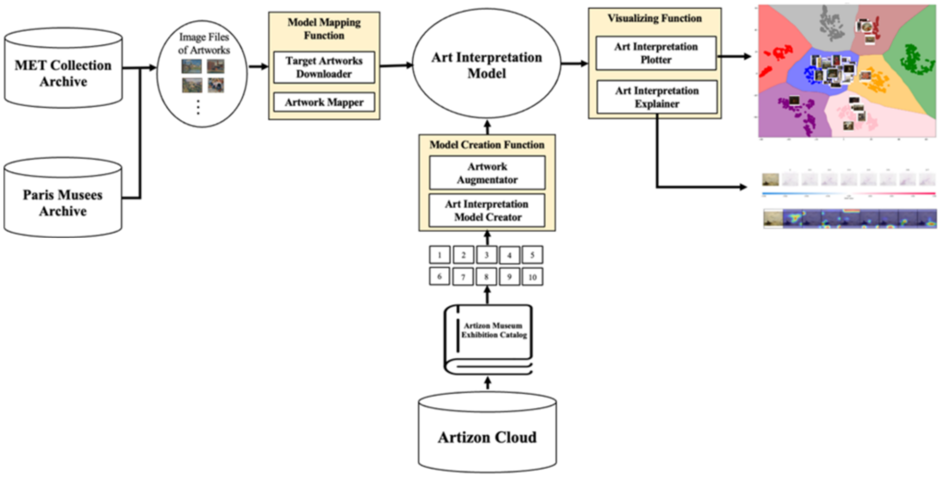

Figure 3. Implementation of the proposed method

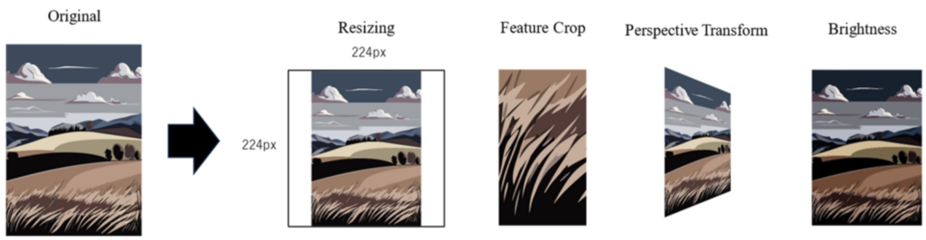

Figure 4. Artwork augmentator

4.1. Implementation of Model Creation Function

The task of the *model creation function* is to build an art interpretation model using a small image dataset and pretrained models, such as VGG, ResNet, and vision transformer. In this prototype, the model creation function employed the following two features to create the model.

Artwork Augmentator

The *artwork augmentator* feature is designed to perform image augmentation while preserving the characteristics of the artwork. The prototype method implemented the following four types of image augmentation techniques, as shown in Figure 4:

- Resizing to a uniform dimension (e.g., 224 × 224) was entered into the pretrained model while maintaining the aspect ratio of the artwork to preserve a sense of the original scale.
- Manual cropping was used to highlight distinctive features of the artwork, as identified from a description of the artwork or other sources.

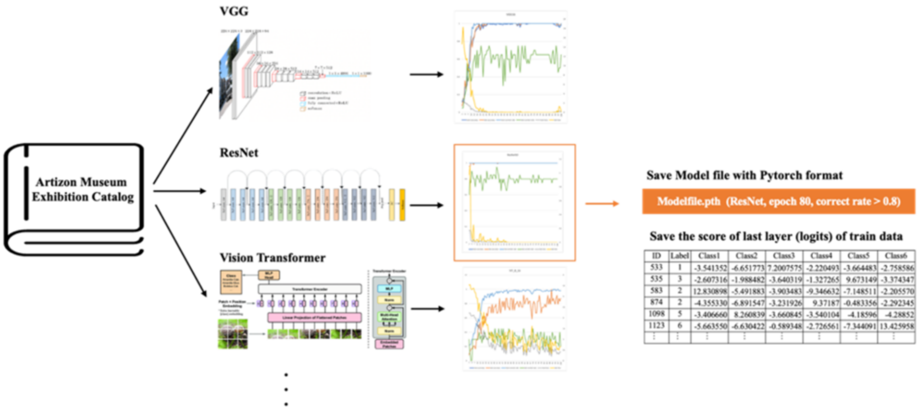

Figure 5. Art interpretation model creator

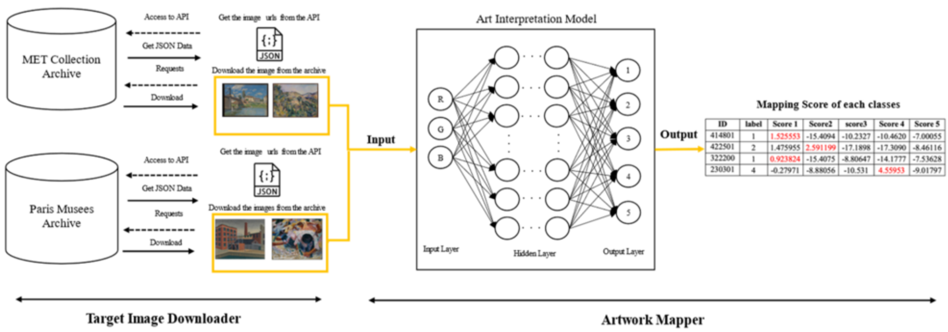

Figure 6. Model mapping function

- Perspective transformations, such as shifting the viewpoint, were used to simulate viewing from the right or left.
- Brightness adjustments were made to replicate the appearance of the artwork under various lighting conditions, such as dark or brightly lit spaces.

Art Interpretation Model Creator

The *art interpretation model creator* is the primary feature of the *model creation function*. As shown in Fig. 5, this feature can construct models by switching between a variety of pretrained model architectures. The model architecture, optimization algorithm, batch size, and number of training cycles are set before creating the model, whereby a graph illustrating the accuracy and loss values for each training cycle is generated, along with the correct response rate (image correction rate). Finally, models which achieve a specified level of accuracy are saved. In addition, the scores of the last layers (logits) of the training data that were input into the saved model are stored as a CSV file.

4.2. Implementation of Model Mapping Function

The task of the *model mapping function* is to download target artwork images from museum archives and input them into the art interpretation model constructed using the *model creation function*. As shown in Figure 6, the prototype method implements two features within this function.

Target Image Downloader

The *target image downloader* is designed to download images of the target artwork for mapping. It connects to the APIs of various archives and retrieves a list of image URLs. The downloader then retrieves the image files from the archives. During this process, the *target image downloader* checks the status of the image licenses, as defined in the APIs, and selects images in the public domain for downloading.

Artwork Mapper

The *artwork mapper* is the primary feature of the *model mapping function*. It inputs the downloaded images into the *art interpretation model* and obtains the mapping score and selected class from the model. The mapping scores are the logits from the last layer of the model, and the selected class is the final result outputted by the model. The scores are stored as CSV files for use in the visualization function.

4.3. Implementation of Visualization Function

The task of the *visualization function* is to reveal the model's interpretation of the target artwork. It contains two visualization features:

Art Interpretation Plotter

The *art interpretation plotter* generates a two-dimensional scatter plot of the target artwork with a color-coded classification based on the model output to provide an overview of the biases, differences, and similarities among the target artworks across various classes within the model. As demonstrated in Figure 7, *artwork classification plotter* utilizes the scores (logits) from the last layer of the trained and target artworks, which were stored by the *model creation function* and *model mapping function,* respectively. The t-SNE algorithm was used to reduce the dimensionality of the scores. Initially, a color-coded 2D graph was produced from the scores of the trained artwork. Subsequently, a scatterplot of the target artwork was created by overlaying the images. Finally, the two generated graphs were integrated.

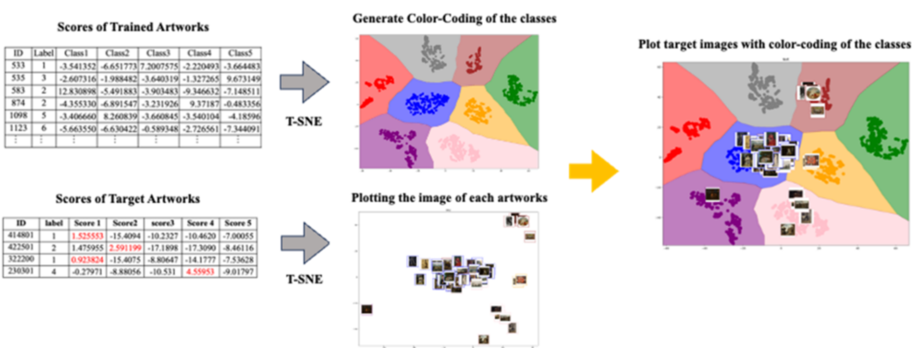

Figure 7. Overview of art interpretation plotter

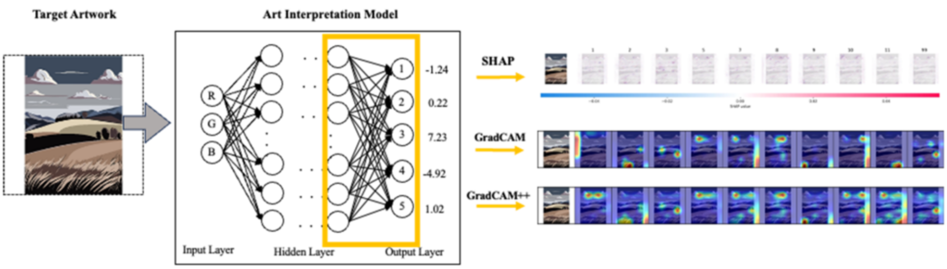

Figure 8. Overview of artwork explainer

Art Interpretation Explainer

The *artwork explainer* analyzes the model behavior by employing various XAI methods. This provides a rationale for the label selection of the model. In this prototype, SHAP and GradCAM + + were used for analysis, as shown in Figure 8.

5. Experiments

To confirm that the proposed method performed as intended, experiments were conducted on two Artizon Museum exhibitions. Table 2 presents an overview of these exhibitions[3]. In both cases, the scope was limited to 2D paintings from the Artizon Collection, excluding artwork on loan from other museums. For Exhibition A, two adjustments were made: 1) works with only a single piece remaining in the category were omitted, and 2) an 'Other' category was introduced to include works not conforming to existing classifications, such as Japanese modern art, materials, and ancient art. Consequently, the final categorization comprised ten categories. For Exhibition B, although there were two primary classifications, the latter was segmented into seven subcategories, whereby, both the major and minor categories were combined to generate eight classification categories.

Table 2. Overview of experiment's scope

	Exhibition A	Exhibition B
Title	ABSTRACTION: The Genesis and Evolution of Abstract Painting Cézanne, Fauvism, Cubism and on to Today	Inaugural Exhibition Emerging Artscape: The State of Our Collection
Period	2023/06/03 ~ 2023/08/20	2020/01/18 ~ 2020/03/31
Num of Classes	10	8
Num of Artworks	122	163

5.1. Exhibition A

Figure 9 shows the results of applying *art interpretation model creator* in *model creation function* to Exhibition A. For Exhibition A, VGG (VGG16, VGG19), ResNet (ResNet18,

3 The list of artwork in Exhibition A: https://www.artizon.museum/exhibition/download/113. The list of artwork in Exhibition B: https://www.artizon.museum/exhibition/download/14

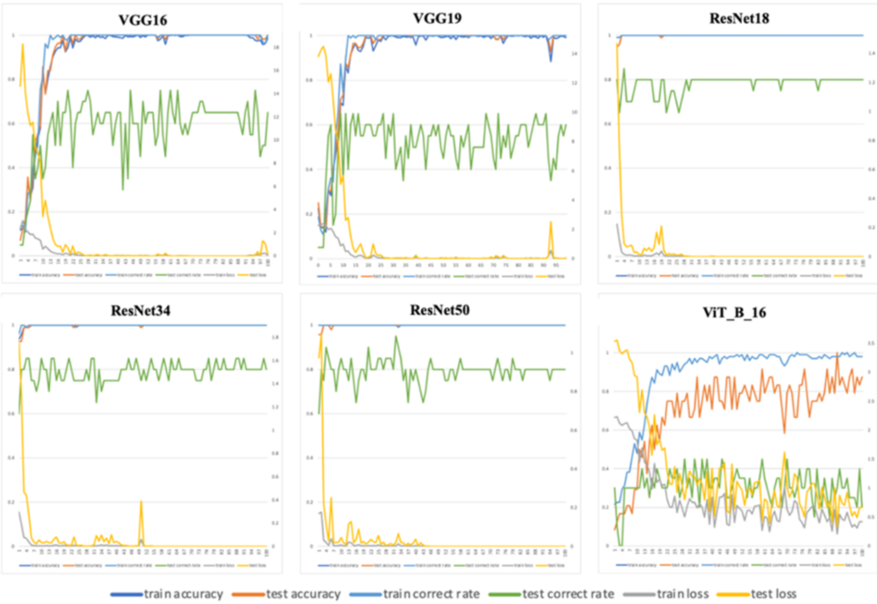

Figure 9. Model creation function results for Exhibition A

ResNet34, ResNet50), and vision transformer (ViT_B_16) were examined to build the models. All network architectures utilized Adam for optimization, and *artwork augmentator* employed all four image augmentation techniques to increase the number of images for training. The batch size was set to 128 for VGG and ResNet but was reduced to 32 for the vision transformers as memory leaks were encountered with a batch size of 128 during the vision transformer construction task. Figure 8 illustrates that although VGG and ResNet achieved favorable outcomes, the vision transformer did not demonstrate an increase in test accuracy, and its loss value did not decrease readily. Because of its superior test correct rates (rate of classification accuracy for test images processed directly through the model, represented with green line in each graph), ResNet50 was selected for subsequent experiments.

Paul Cézanne's artworks within the collections of the New York Metropolitan Museum and the Paris Musées were selected as the target artwork for Exhibition A. Exhibition A focuses on abstract paintings, underscoring Cézanne's role as a precursor to abstract art [37]. This experiment analyzed the positioning of Cézanne's works from the MET and Paris Musées within a previously constructed model. There were 39 artworks from MET and 9 artworks from Paris Musées.

Table 3 presents the classification results of Cézanne's work from the MET and Paris Musées, using the *model-mapping function*. Among the MET works, 15 are categorized under 'Origins of Abstract Art,' 'Fauvism and Cubism,' and 'Genesis of Abstract Painting' and 13 under 'Others.' In contrast, among Cézanne's works from the Paris Musées, five fall into the 'Origins of Abstract Art' and three into 'Others.' Table 4 and 5 display samples from the MET and Paris Musées, respectively, where 'Mapped Class' indicates the class number corresponding to Table 3.

Table 3. Classification results using Model Mapping Function for Exhibition A

Class Number	Class name	MET Artworks	Paris Musees Artworks
1	Origins of Abstract Art	5	5
2	Fauvism and Cubism	9	0
3	Genesis of Abstract Painting	1	0
5	Hot Abstraction and Lyrical Abstraction	4	1
7	Abstract Expressionism	3	0
8	Evolution of Postwar Japanese Abstract Painting	0	0
9	Gutai	1	0
10	Takiguchi Shuzo and Jikken Kobo	3	0
11	Future Paths of Postwar Abstractions	0	0
99	Others	13	3

Table 4. Sample result on Cézanne's artwork from MET for Exhibition A (total: 9)

ID	Title	Mapped Class
435869	Antoine Dominique Sauveur Aubert (born 1817), the Artist's Uncle, as a Monk	1
435877	Mont Sainte-Victoire and the Viaduct of the Arc River Valley	1
435870	Antoine Dominique Sauveur Aubert (born 1817), the Artist's Uncle	2
435868	The Card Players	2
435880	Rocks at Fontainebleau	3
⋮	⋮	⋮
435872	The Gulf of Marseilles Seen from L'Estaque	5
459092	Trees and Houses Near the Jas de Bouffan	7
438136	The Fishermen (Fantastic Scene)	9
435866	Apples	10
334257	Bathers (recto); Still Life (verso)	99

Table 5. Sample result on Cézanne's artwork from Paris Musées for Exhibition A (total: 39)

ID	Title	Mapped Class
160007458	Rochers et branches à Bibémus	1
160007659	Les quatre saisons - Le printemps	1
160007657	Les quatre saisons - L'automne	1
160007656	Les quatre saisons - L'hiver	1
160007457	Portrait d'Ambroise Vollard	1
160007455	Trois baigneuses	5
160025722	Étude d'après "David" d'Antonin Mercié (recto); Paul enfant (verso)	99
320210662	Reproduction d'un tableau de Cézanne: pommes et biscuits lors d'une vente	99
160007658	Les quatre saisons - L'été	99

Figures 10 and 11 show the results of applying *artwork classification plotter* to Cézanne's artwork at the MET and Paris Musées. The majority of the artworks correspond to the classifications outlined in Table 3, with the images displayed on a scatterplot for easy visual association with their respective categories. The graph helps visualize the model characteristics, particularly anticipating the placement of Cézanne's works, regarded as precursors of abstract art, in classes 1, 2, and 3. Additionally, some artwork considered as rough sketches or recorded works are categorized under Class 13.

On the other hand, several of the artwork from the MET are categorized as related to postwar Japanese abstract paintings (Categories 9 and 10). Further analysis using *artwork explainer* can reveal which elements of the paintings contributed to the corresponding classifications and how the model disregards the classification. Figure 12 shows that the result of the SHAP and GradCAM++ visualization for the MET artwork is classified under 'Gutai' (ID:438136). The *artwork explainer* shows that the model regards something in the top-right part as a feature, indicating the points (and how) this may have led the model to erroneously interpret the artwork.

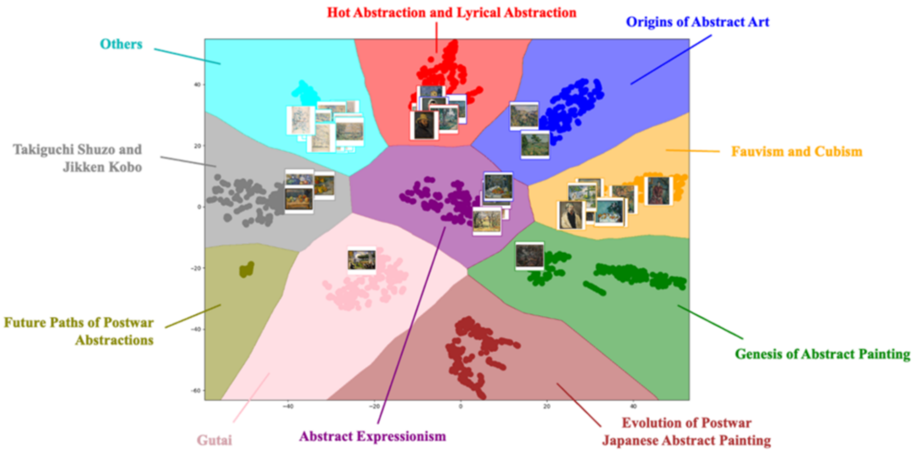

Figure 10. Visualization of MET Cezanne artwork in Exhibition A model

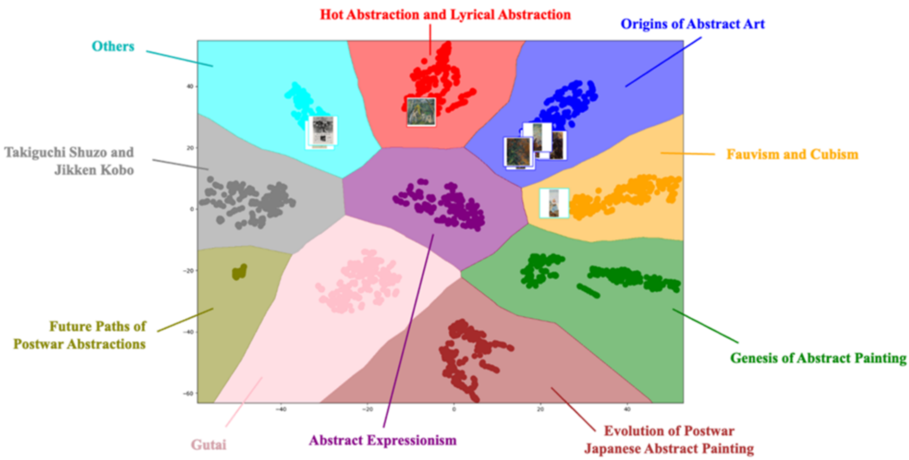

Figure 11. Visualization of Paris Musées Cezanne artwork in Exhibition A model

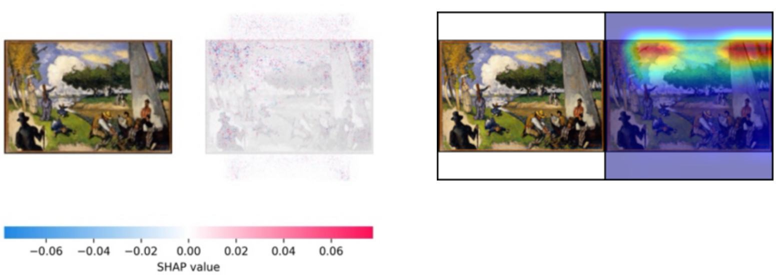

Figure 12. Sample analysis result by art explainer (Left: SHAP, Right: GradCAM++)

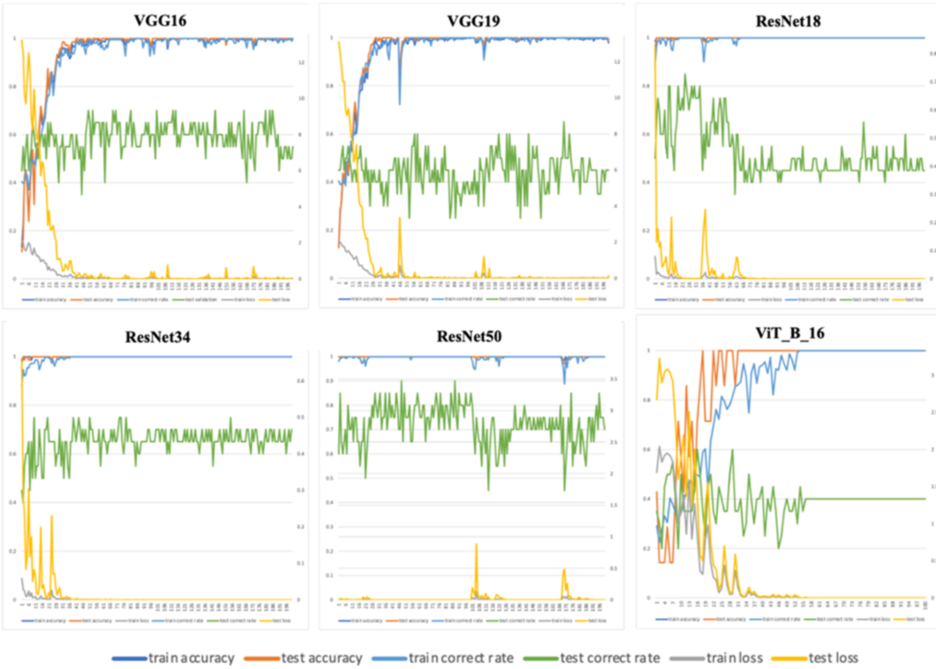

Figure 13. Model creation function result for Exhibition A

5.2. Exhibition B

Figure 13 shows the results of the *art interpretation model builder* in the *model creation function* for Exhibition B. The network architecture used in Exhibition A was examined for model building. Identical parameters and batch sizes were configured as in Exhibition A. Consequently, the model-building results were similar: VGG and ResNet yielded favorable outcomes, whereas the vision transformer did not show an increase in test accuracy, and its loss value did not decrease significantly. Therefore, ResNet50 was selected for subsequent experiments.

The target artwork for Exhibition B were selected from the works highlighted in the collection archives of the MET and Paris Musées. Exhibition B, the inaugural exhibition of the Artizon Museum, aimed to showcase the highlights of its collection [38]. The model was used to analyze the placement of artwork highlighted by the MET and Paris Musées within the context of the Artizon Museum's featured collections and their respective classification genres.

Table 6 displays the classification results obtained using the *model mapping function* for the highlighted works from the MET and Paris Musées. Of the works highlighted from the MET, 31 out of 48 are classified as Unfurling Art, representing modern and contemporary art in the Artizon Museum. Similarly, 34 out of 53 highlighted works from the Paris Musées are categorized under 'Origins of Abstract Art.' Among other highlighted works, nine of the artwork from the MET are classified under 'The Sacred and the Profane,' whereas 10 of the artwork from Paris Musées are classified under 'Records. ' Table 7 and 8 present samples from the MET and Paris Musées, respectively.

Table 6. Result of Classification using Model Mapping Function for Exhibition B

Class	Class name	MET	Paris Musées
1	Unfurling Art (modern and contemporary art selected from the collection)	31	34
2-1	Decoration	2	2
2-2	The Classics (Western Classic Artworks)	1	0
2-3	Primordials	0	0
2-4	Other Worlds	0	1
2-5	The Sacred and the Profane	9	7
2-6	Records	3	10
2-7	Happiness	2	0

Table 7. Sample Result of Highlighted Artwork from MET for Exhibition B (total: 48)

Objectid	Title	Artist Name	Class
436947	Boating	Edouard Manet	1
436282	The Crucifixion; The Last Judgment	Jan van Eyck	2-1
436918	Venus and Cupid	Lorenzo Lotto	2-2
435888	Soap Bubbles	Jean Siméon Chardin	2-5
435802	Portrait of a Young Man	Bronzino (Agnolo di Cosimo di Mariano)	2-6
436819	Mäda Primavesi (1903–2000)	Gustav Klimt	2-7

Table 8. Sample Result of Highlighted Artwork from Paris Musées for Exhibition B (total: 53)

Objectid	Title	Artist Name	Class
160007868	Les demoiselles des bords de la Seine (été)	Gustave Courbet	1
240009265	Frontispice Album Allix	Auguste Vacquerie	2-1
460000176	Portrait présumé de Marie-Emilie Baudouin, fille du peintre	François Boucher	2-2
280001425	Miranda fait une partie d'échec avec Ferdinand qu'elle accuse, en plaisantant, de tricher	Gillot Saint-Evre	2-4
320064606	La Chasse, boiserie provenant de l'hôtel du duc de Richelieu		2-5
280000452	Lénore, les morts vont vite	Ary Scheffer	2-6
320026188	Les conscrits de 1807 défilant devant la porte Saint-Denis	Louis-Léopold Boilly	2-7

Figures 14 and 15 illustrate the visualization of highlighted works from the MET and Paris Musées, respectively, using *artwork classification plotter*. Although most works correspond to the classification in Table 6, some from the MET deviate. For instance, Object ID 435888 listed in Table 7 is classified as 'The Sacred and the Profane' (2-5) by the *model mapping function* yet placed under 'Unfurling Art' (blue area) in the graph. When this painting was evaluated using the model, the values of the final output layer (LOGIT) indicated an approximation between Class 1 and Classes 2-5. Upon applying the softmax function to determine the probability for the final classification, a probability of 68% was predicted for Classes 2-5 and approximately 30% for Class 1. This suggests that this artwork posed a classification challenge for the model. Further analysis using *artwork explainer*, shown in Figure 16, depicts this challenge more clearly, revealing that Classes 1, 2-5, and 2-6 each have distinctive points for classification.

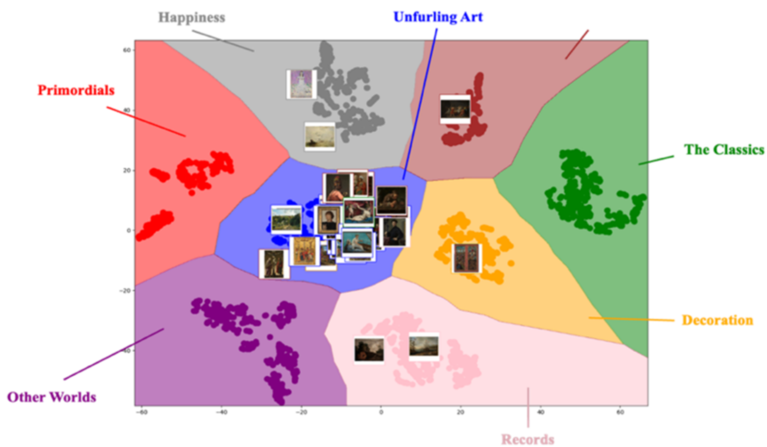

Figure 14. Visualization of MET highlighted artwork in Exhibition B

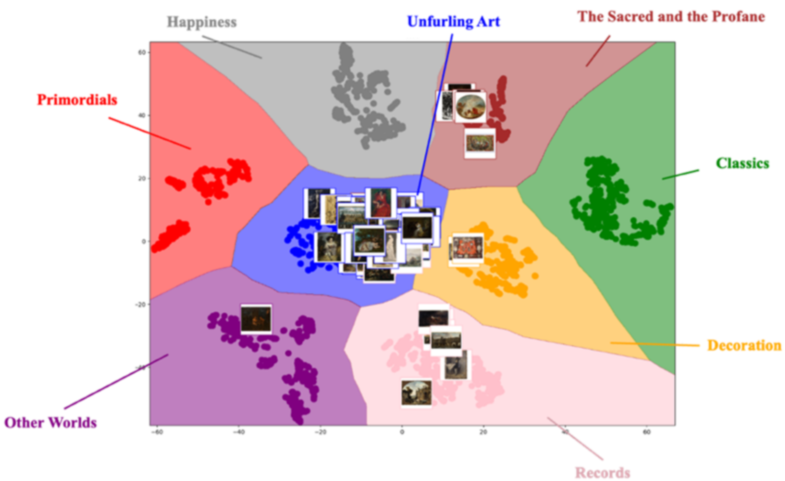

Figure 15. Visualization of Paris Musées highlighted artwork in Exhibition B

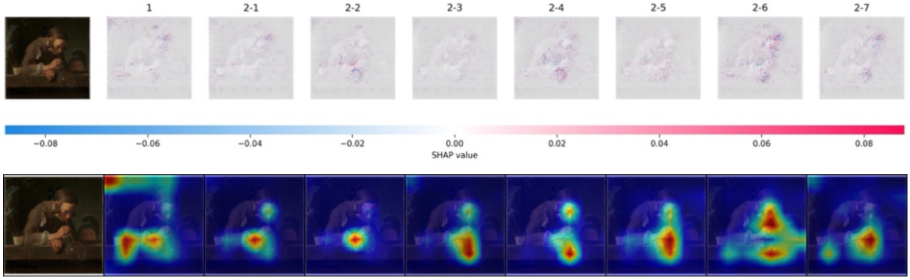

Figure 16. Sample of art explainer analysis results for artwork difficult to classify

5.3. Observations and Limitations

For this experiment, two exhibition catalogs at the Artizon Museum were used as the basis for art interpretation, in examining artwork from the MET and Paris Musées. In Exhibition A, Paul Cézanne's works, recognized as forerunners of abstract art, were analyzed. The results indicate that the model's classification of his works are to a certain extent in line with the exhibition's intention to showcase the origins and development of abstract paintings. In Exhibition B, the artwork highlighted in the MET and Paris Musées were compared with those highlighted in the Artizon Museum. The findings reveal that many highlighted artworks from the MET and Paris Musées are categorized as Unfurling Art, the featured category of modern and contemporary art in the Artizon Museum collection.

A curator who reviewed the experiments noted the utility of the method for comparing trends in specific art styles across different museum collections. In this instance, models based on the Artizon Museum collection were used to visualize artwork from the MET and Paris Musées. Additionally, models constructed from the MET and Paris Musé collections using similar exhibition classifications and artwork lists could allow for visual comparisons with the Artizon Museum collection. For instance, the Impressionist collections at the Artizon Museum, American Museum of Modern Art (MoMA), and Musée d'Orsay were acquired through unique acquisition policies. The proposed prototype method enables a comparative analysis of the similarities, differences, and tendencies within each museum's Impressionist collection. Moreover, it would be interesting to focus on the details of Impressionist artwork such as portraits and landscapes.

However, the prototype method has certain limitations. First, a relatively small number of target artwork images may not encompass all the classifiable features, potentially leading to misclassification. The *art interpretation plotter* provides a clear visualization of both successful and erroneous classifications, in associating Cézanne's artworks from the MET with postwar Japanese abstract painting. Another limitation concerns the training data. One curator pointed out that in contemporary art, including abstract paintings, the scale of the artwork is significant. However, this method does not account for scale, standardizing all images to the same size of 224 × 224 pixels, despite maintaining the aspect ratio. Furthermore, exhibition curation involves spatial considerations, such as the sequencing and placement of artwork, which this method has not yet incorporated. To mirror a curator's interpretation and knowledge more closely, integrating these spatial and scale elements of exhibitions into model building is essential.

Nevertheless, based on the feedback from art professionals, the prototype method is anticipated to facilitate unconventional classifications and exhibitions that curators may not typically encounter. For instance, classifying some of Cézanne's works from the MET as related to postwar Japanese abstract paintings is usually erroneous. However, if the model were to learn the intricate features in the images of Cézanne's artwork and elucidate the elements influencing its classification, the results could be more persuasive. Exploring XAI methods that can effectively explain these 'unexpected associations' remains a significant challenge to be addressed in the future.

6. Conclusion

In this study, a dynamic art curation method with pretrained models of art interpretation is proposed. The purpose of the dynamic curation method is to create models pretrained on the classification of the art collection from one museum, thereby applying the models to the art collection of another museum. A prototype of this method was implemented and applied to two exhibition catalogs at the Artizon Museum. The experiment demonstrated that the proposed method successfully classified and visualized artwork from the MET and Paris Musées in alignment with the intended theme of the exhibition for which the model was constructed. Discussions regarding the experiments highlight the potential of this method for unconventional classifications and exhibitions allowing vivid comparisons between museum collections. However, the results revealed areas that require improvement. These include developing models that minimize misinterpretation to more closely align with the curator's knowledge as well as enhancing XAI techniques to better elucidate model interpretations. Future work along the lines of this method will include: 1) implementing applications based on the proposed method, especially applications that stimulate the intellectual curiosity of museum visitors and 2) improving the accuracy of the art interpretation model to mirror the curator's knowledge more closely. We hope this challenging effort will lead to a new era of creativity.

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References

[1] The Metropolitan Museum of Art: The Met Collection, available via WWW, https://www.metmuseum.org/art/collection, last accessed 2024/01/10

[2] Paris Musées: Les collections en ligne des musées de la Ville de Paris, available via WWW, https://www.Paris Muséescollections.paris.fr/, last accessed 2024/01/10

[3] National Gallery of Art: Open Data at the National Gallery, https://www.nga.gov/open-access-images/open-data.html, last accessed 2024/01/10

[4] Ishibashi, N.: *Artizon Cloud:* A multidatabase system architecture for an art museum. Information Modelling and Knowledge Bases XXXIII, pp.323-331 (2021).

[5] Ishibashi,N. Fukuda, T., Tsuchiya, Y., Enzaki, Y., and Iwata, H.: Art Sensorium Project: A System Architecture of Unified Art Collection for Virtual Art Experiences. Information Modelling and Knowledge Base XXXV. pp.145-154 (2023).

[6] Iwata, H., Sasaki, S., Ishibashi, N., Sornlertlamvanich, V., Enzaki, Y., Kiyoki, Y.: Data sensorium: spatial immersive displays for atmospheric sense of place. Information Modelling and Knowledge Bases XXXIV, 247-257 (2022).

[7] Fukuda, T. and Ishibashi, N: Virtual Art Exhibition System: An implementation method for creating an experiential museum system in a virtual space. Information Modelling and Knowledge Bases XXXIV, 38-47(2022).

[8] Tsuchiya, Y. and Ishibashi, N.: An Implementation Method of GACA: Global Art Collection Archive. Information Modelling and Knowledge Base XXXV, pp.133-144. (2023).

[9] Centic, E. She, J.: Understanding and creating art with AI: Review and outlook. ACM Transaction on Multimedia Computing, Communications, and Applications, Volume 18, Issue 2, Article No.:66, 1-22 (2022).

[10] Shamir, L. Macura, T. Orlov, N., Eckley, M. Goldberg, I.: Impressionism, expressionism, surrealism: Automated recognition of painters and schools of art. ACM Transaction on Applied Perception, Volume 7, Issue 2, Article No.:8, 1-17 (2010).

[11] Berezhnoy, I.E., Postma, E.O. & van den Herik, H.J.: Automatic extraction of brushstroke orientation from paintings. Machine Vision and Applications, Volume 20, 1–9 (2009).

[12] Karayev,S., Trentacoste, M., Han, H., Agarwala, A., Darrell, T., Hertzmann, A., Winnemoeller, H.: Recognizing image style. In: Proceedings of the 2014 British Machine Vision Conference, (2014).

[13] Bar, Y., Levy, N., Wolf, L.: Classification of artistic styles using binarized features derived from a deep neural network. In: Agapito, L., Bronstein, M., Rother, C. (eds) Computer Vision - ECCV 2014 Workshops. ECCV 2014. Lecture Notes in Computer Science, vol 8925. Springer, Cham (2014).

[14] David, E., Netanyahu, S,N.: Deep Painter: Painter classification using deep convolutional autoencoders. Artificial Neural Networks and Machine Learning. Lecture Notes in Computer Science, Vol. 9887. Springer, 20–28 (2016).

[15] Crowley, E.J., Zisserman.: A. In Search of Art. In: Agapito, L., Bronstein, M., Rother, C. (eds) Computer Vision - ECCV 2014 Workshops. ECCV 2014. Lecture Notes in Computer Science, vol 8925. pp.54-70. Springer, Cham (2015).

[16] Elgammal, A., Liu, B., Kim, D, Elhoseiny, M. Marian Mazzone, M.: The shape of art history in the eyes of the machine. In: Proceedings of the 32nd AAAI Conference on Artificial Intelligence (AAAI'18). pp. 2183–2191 (2018).

[17] Garcia, N. and Vogiatzis, G.: How to read paintings: Semantic art understanding with multi-modal retrieval. In Computer Vision—ECCV 2018 Workshops. Lecture Notes in Computer Science, Vol. 11130. Springer, 676–691 (2018).

[18] Baraldi, L., Cornia, M., Grana, C., and Cucchiara, R.: Aligning text and document illustrations: Towards visually explainable digital humanities. In Proceedings of the 24th International Conference on Pattern Recognition (ICPR'18). IEEE, Los Alamitos, CA, 1097–1102 (2018).

[19] Stefanini, M., Cornia, M., Baraldi, L., Corsini, M., and Cucchiara, R.: 2019. Artpedia: A new visual-semantic dataset with visual and contextual sentences in the artistic domain. In Image Analysis and Processing. Lecture Notes in Computer Science, Vol. 11752. Springer, 729–740.

[20] Efthymiou, A., Rudinac, S., Kackovic, M., Worring, M., and Wijnberg, N.: Graph neural networks for knowledge enhanced visual representation of paintings. arXiv preprint arXiv:2105.08190 (2021)

[21] Khan, F.S., Beigpour, S., Van de Weijer,J., and Felsberg, M.: Painting-91: A large scale database for computational painting categorization. Machine Vision and Applications 25, 6 (2014), 1385–1397.

[22] Florea, C., Condorovici, R., Vertan, C., Butnaru, R., Florea, L., and Vrânceanu, R.: Pandora: Description of a painting database for art movement recognition with baselines and perspectives. In Proceedings of the 24th European Signal Processing Conference (EUSIPCO'16). IEEE, Los Alamitos, CA, 918–922 (2014)

[23] Mao, H., Cheung, M., and She, J.: DeepArt: Learning joint representations of visual arts. In Proceedings of the 2017 ACM on Multimedia Conference (MM'17). ACM, New York, NY, 1183–1191 (2017).

[24] Strezoski, G., and Worring, M.: OmniArt: A large-scale artistic benchmark. ACM Transactions on Multimedia Computing, Communications, and Applications 14, 4,1–21 (2018).

[25] Milani, F., and Fraternali, P.: A data set and a convolutional model for iconography classification in paintings. arXiv preprint arXiv:2010.11697 (2020).

[26] Posthumus, E. Brill.: Iconclass AI Test Set. Available: https://labs.brill.com/ictestset/, last accessed 2024/01/10.

[27] Crowley, E., Omkar M., Parkhi, O., and Zisserman, A.: Face painting: Querying art with photos. In Proceedings of the 2015 British Machine Vision Conference (BMVC'15). 65.1–65.13 (2015).

[28] Mohammad, S., and Kiritchenko. S.: Wikiart emotions: An annotated dataset of emotions evoked by art. In Proceedings of the 11th International Conference on Language Resources and Evaluation (LREC'18).

[29] Simonyan, K., & Zisserman, A.: Very Deep Convolutional Networks for Large-Scale Image Recognition. CoRR, abs/1409.1556 (2014).

[30] He, K., Zhang, X., Ren, S., & Sun, J.: Deep Residual Learning for Image Recognition. IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 770-778 (2015).

[31] Dosovitskiy, A., Beyer, L., Kolesnikov, A., et.al.: An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale. ArXiv, abs/2010.11929 (2020).

[32] Shorten, C., Khoshgoftaar, T.M. A survey on Image Data Augmentation for Deep Learning. Journal of Big Data 6, 60 (2019). https://doi.org/10.1186/s40537-019-0197

[33] Saeed, W., Omlin, C.: Explainable AI (XAI): A Systematic Meta-Survey of Current Challenges and Future Opportunities. *Knowledge-Based Systems*, Volume 263, 110273 (2023).

[34] Scott M. Lundberg and Su-In Lee. 2017. A unified approach to interpreting model predictions. In Proceedings of the 31st International Conference on Neural Information Processing Systems (NIPS'17). Curran Associates Inc., Red Hook, NY, USA, 4768–4777.

[35] Chattopadhyay, A., Sarkar, A., Howlader, P., & Balasubramanian, V.N.: Grad-CAM++: Generalized Gradient-Based Visual Explanations for Deep Convolutional Networks. *2018 IEEE Winter Conference on Applications of Computer Vision (WACV)*, 839-847 (2017).

[36] Nakanishi. T.: Approximate Inverse Model Explanations (AIME): Unveiling Local and Global Insights in Machine Learning Models. in *IEEE Access*, vol. 11, pp. 101020-101044, (2023).

[37] ABSTRACTION: The genesis and evolution of abstract painting—Cézanne, fauvism, cubism and on to Today. exh. cat. (Tokyo: Artizon Museum, 2023).

[38] Inaugral Exhibition Emerging Artscape: The State of Our Collection. exh. cat. (Tokyo:Artizon Museum, 2020).