Wonders of The Surface

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***Abstract*—Art reflects human emotions, ideas, and experiences. While symbolic interpretation is valuable, mechanical analysis provides measurable insight into visual perception. This study uses colorfulness, hue diversity, tone balance, and image entropy to examine the visual evolution of art styles, revealing that modern styles are more colorful, complex, and cooler in tone.**

***Index Terms*—component, formatting, style, styling, insert**

I. Introduction

From prehistoric cave paintings to digital canvases, paintings have always been a profound reflection of the human spirit - a mirror to emotion, culture, and thought. Throughout centuries, humankind has used color, form, and composition not only as aesthetic tools, but also as a language to communicate identity, memory, ideology, and the shifting rhythms of society. Understanding art means understanding the people and periods that produced it: their emotional landscapes, historical contexts, and philosophical inquiries. Each brushstroke carries more than pigment; it carries a story.

The initial application of computational methods in visual art began with basic image-processing techniques, such as color histogram analysis [2], edge detection [1], [4], and texture modeling [3]–[5], aimed at digitizing and enhancing visual data. These foundational methods soon evolved into more analytical approaches, allowing researchers to explore stylistic patterns, artist-specific characteristics, and visual complexity in artworks. These early studies laid the foundation for today's intelligent systems that can explore artistic features in ways previously impossible. With the evolution of artificial intelligence, we now stand at a remarkable crossroads where we can begin to decode the visual DNA of art itself.

Recent advances have applied convolutional neural networks (CNNs) and deep learning architectures for a wide range of tasks in art analysis, from artist and style classification to automatic authentication and visual similarity retrieval. These techniques have enabled systems to detect objects and symbolic elements within paintings, uncover contextual relationships, and even analyze compositional features at scale. Applications now extend to multi-label classification, pose estimation, and the semantic interpretation of artworks, demonstrating that modern AI systems can not only quantify visual patterns but also reveal cultural, historical, and stylistic narratives embedded in the works.

Reference [7] provides a comprehensive overview of deep learning approaches applied to visual arts, particularly paintings and drawings. It has served as a valuable foundation for understanding the broader landscape of computational techniques in this domain. Reference [9] explores three practical applications: artist categorization, style classification, and saliency detection. These tasks are carried out using both global (LBP[1], GIST[2], and PHOG[3]) and local (bag-of-words) feature-based image representations. Their dataset consists of 4,266 images by 91 artists, collected from online sources which is a strategy I also plan to adopt in this project. In a broader comparative context, reference [14] evaluates various classification methodologies for the task of fine-art genre classification, focusing on intermediate-level (BoW) and semantic-level features. Their experiments were conducted on a curated dataset of 490 images across 7 categories including both classic and modern styles from artchive.com [21]. Similarly, [15] presents a comparative study between CNN-based and transformer-based models for genre, artist, and style classification using the WikiArt [6] dataset. The effectiveness of the WikiArt [6] dataset in classification tasks is reaffirmed by [16], where it outperforms other datasets in terms of model accuracy and consistency.

In parallel, several studies have adopted a statistical analysis perspective [17]–[20]. Reference [17] analyzes color semantics—specifically hue, saturation, and luminance—offering insights that can aid both classification and image retrieval. I plan to extend this work to include

[1]Local binary patterns are the most commonly used texture descriptor for image description. First described in [10], [11]

[2]GIST summarizes the gradient information (scales and orientations) for different parts of an image, which provides a rough description (the gist) of the scene. [12]

[3]Pyramid histogram of oriented gradients captures the local shape of an image along with its spatial layout. [13]

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earlier periods such as the pre-Renaissance. Reference [18] adopts an experimental approach to investigate the influence of color statistics on painting preference, particularly how similarity to natural scenes impact human perception of artworks. This study uses 1,200 paintings sourced from the WikiArt encyclopedia [6], which is the resource of this study, highlighting the relevance of color composition in artistic perception.

Conducting a quantitative analysis, [19] measures individual color usage, color variety, and brightness roughness across European art styles using a dataset of over 29,000 paintings from the Web Gallery of Art. Finally, reference [20] offers an exploratory visualization of color usage in European artworks over time, using 1,300 paintings from Freebase.com. Their work presents an engaging example of how large-scale color data can reveal stylistic transitions and aesthetic patterns across art history.

An overview of the related literature reveals that European art from the classical and Renaissance periods has been the primary focus of computational analysis, while artworks from other cultural traditions remain significantly underrepresented. Additionally, modern and contemporary art receive comparatively less attention than historical periods. To address these gaps, this study aims to include a more diverse and comprehensive range of artistic periods, with particular emphasis on both the pre-Renaissance era and the modern art movement.

The motivation of this project is to develop a comprehensive data set of artworks to investigate the evolution of artistic styles across time and cultures. By combining computer vision techniques with historical and visual features, I hope to uncover unique stylistic indicators, trace the personal evolution of individual artists, and deepen our understanding of art movements as dynamic, living phenomena.

II. Data

WikiArt visual art encyclopedia data [25] is used for the project. The data is scraped from the styles page of Wikiart.org. As shown in Table I, most of the artworks belong to the modern and post-renaissance styles. There exist 14 main styles, each have various sub-styles.

To ensure consistency in visual content, certain sub-styles that mainly featured photographs of buildings, pottery, rocks, and sculptures were excluded from the dataset. Additionally, sub-styles with a significantly lower number of artwork instances compared to others were also removed to maintain a balanced representation across categories. As a result of these eliminations, the number of sub-styles was reduced from 190 to 51. The remaining data set consists of 96,498 artwork instances, with the largest sub-style containing 3,600 entries and the smallest comprising 503. Representative examples of excluded art works are illustrated in Figure 1.

Main Style	#Sub-styles	#Artworks
Ancient Egyptian	9	181
Ancient Greek	4	275
Renaissance (West.)	6	9969
Medieval (West.)	28	2076
Post-Ren. (West.)	14	55783
Modern Art	92	109479
Contemporary	39	14201
Chinese Art	2	859
Korean Art	1	33
Japanese Art	10	3241
Islamic Art	7	327
Native Art	3	621
Pre-Columbian	2	100
No Category	4	366
Total		**197511**

TABLE I: Distribution of Artworks by Main Art Style

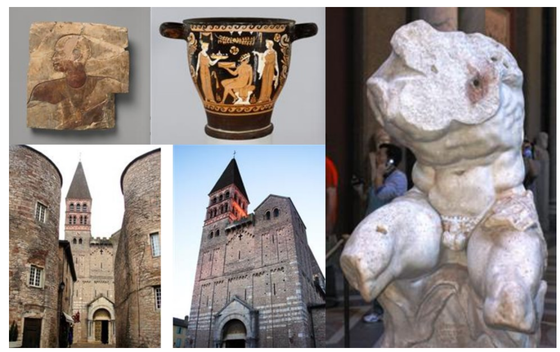


Fig. 1: Eliminated Style Examples

The scraped data set is structured and includes nine columns II The Image URL field serves as a reference to retrieve the corresponding images, which constitute the unstructured component of the dataset. Overall, the collected data can be characterized as hybrid, combining both structured metadata and unstructured visual content.

Column Name	Measurement Level
url	Nominal
artwork name	Nominal
artist name	Nominal
date	Interval (Ordinal)
style	Nominal
genre	Nominal
media	Nominal
tags	Nominal
image url	Nominal

TABLE II: Measurement Levels for Art Dataset Columns

A. Data Characteristics

An examination of the bar chart of the most frequent 50 tags in Figure 2, reveals that 17,024 artworks in the data set lack any associated tags. Among the tagged entries, the most frequently occurring tag is *lady* with a frequency of 5,211, followed closely by *male-portraits* and *female-portraits*. This suggests that human figures, particularly women, are the most commonly depicted subjects in the collection.

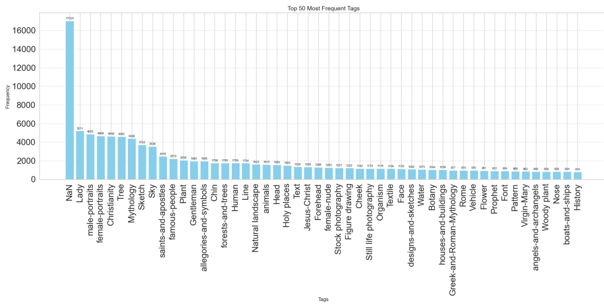


Fig. 2: Top 50 Most Frequent Tags

These are followed by tags such as *Christianity* and *mythology*, indicating that religious and mythological scenes represent the most prevalent thematic content. Natural elements like *tree*, *sky*, and *plant* also appear frequently, pointing to nature as the second most represented theme in the artworks.

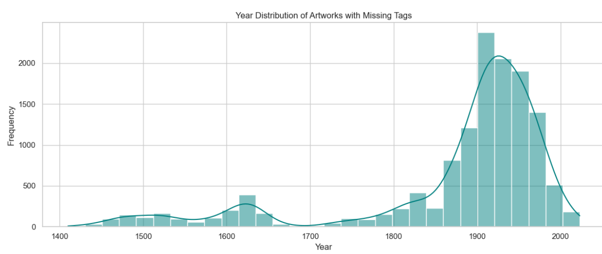


Fig. 3: Tear Distribution of Artworks Without Tags

When the untagged artworks are examined, it becomes apparent that the majority originate from the period between 1900 and 1950, as illustrated in Figure 3. A significant portion of these works have an unknown medium, and many belong to stylistic movements such as Abstract Expressionism, followed by Cubism, Baroque, Surrealism, Academicism, Expressionism, and Abstract Art (see Figure 4 and Figure 5).

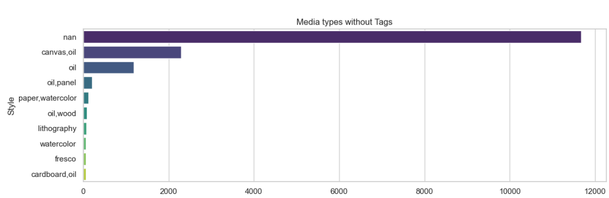


Fig. 4: Media Types Without Tags

Regarding genre, the most common categories include painting, abstract, portrait, religious painting, and landscape, as shown in Figure 6. This suggests that the

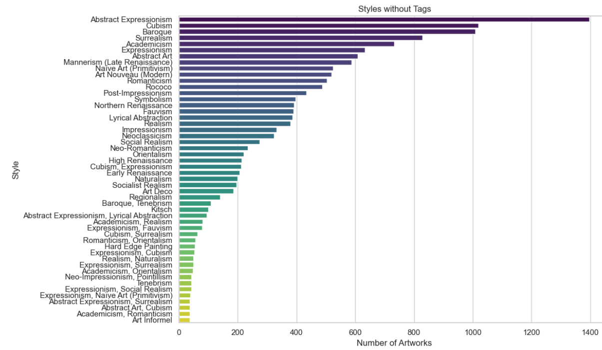


Fig. 5: Styles Without Tags

untagged artworks tend to be stylistically abstract or conceptually complex, which likely contributes to the difficulty in assigning definitive tags.

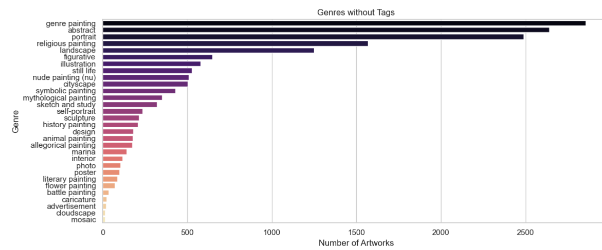


Fig. 6: Genres Without Tags

The histogram of styles (Figure 7) reveals a noticeable decline in artwork frequency following the Mannerism and Tenebrism periods. This observation will guide the selection of styles for further analysis by narrowing the dataset accordingly. Notably, within the top ten most frequent styles, there is a presence of styles from more recent art movements such as Art Nouveau, Symbolism, and Cubism. This diversity is promising, as it allows exploration in both classical and modern artistic periods, aligning well with the objective of the study of encompassing a broader temporal and stylistic range.

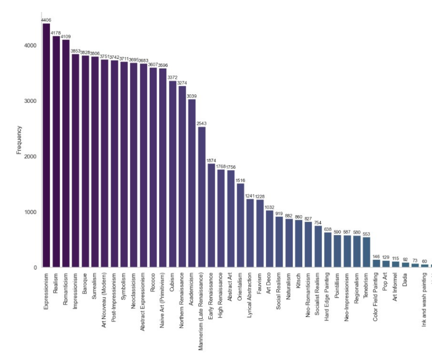


Fig. 7: Histogram of Styles (first 40)

Following the abstract genre, the frequency of artworks drops by nearly half, with the majority belonging to the portrait genre, followed by painting, religious painting, and landscape (Figure 8). This observation will also guide the narrowing of the data set for subsequent analysis.

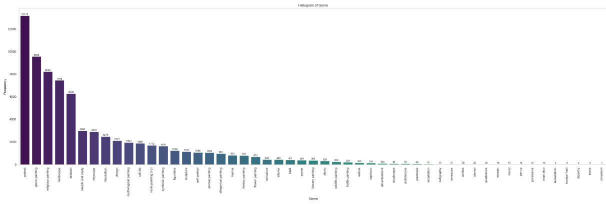


Fig. 8: Histogram of Genres

Regarding the media analysis in Figure 9, nearly half of the collected artworks lack specified media information. Among those with available data, oil is the most frequently used medium, followed by watercolor and tempera. Some media types such as photography, marble, plaster and porcelain suggests that the artwork is not on a surface but a sculpture, pot or a photograph and therefore should be eliminated from data.

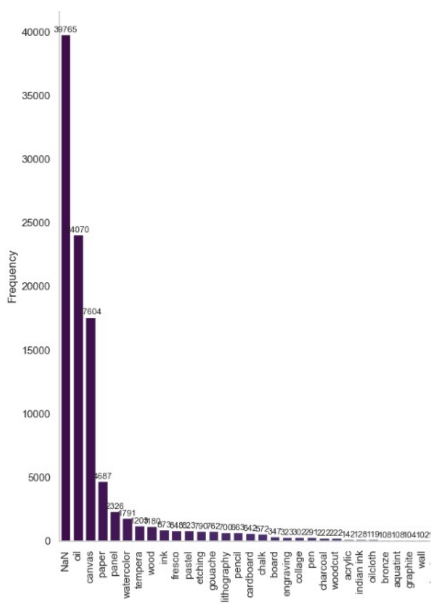


Fig. 9: Media Histogram (first 30)

Some media types, such as canvas, paper, and wood, primarily refer to the surface rather than the technique and therefore may not significantly affect the visual appearance of the artwork; as such, they might be excluded from further analysis. There are also various artistic techniques represented in the data, such as fresco and etching, alongside different labels that refer to similar or identical processes. For example, etching, lithography, linocut, engraving, and aquatint are all types of printmaking techniques, while pencil, ink, pen, charcoal, drawing, and metalpoint are commonly used in drawing techniques that often produce visually similar results, as shown in Figure 10 and Figure 11. This issue of media naming inconsistencies will be addressed in the [insert chapter name] chapter.

Fig. 10: Print Examples

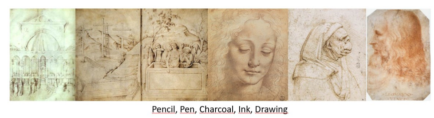


Fig. 11: Drawing Examples

Since some media types appear together in combinations (such as (oil, canvas), (ink, paper), and (oil, wood)) an analysis was carried out without separating the individual media elements, as shown in Figure 12. Excluding artworks with missing media information (NaN), the three most common combinations all involve oil paint applied on different surfaces, followed by watercolor. This observation further supports the decision to exclude surface materials from media classification, as the technique itself contributes more significantly to the visual characteristics of the artwork.

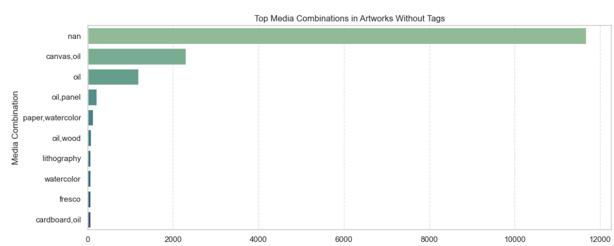


Fig. 12: media combinations

B. Preprocessing

As discussed in the Data Characteristics section, using tags or media as primary features is not ideal due to the high proportion of missing or inconsistent values. Therefore, the style attribute was selected as the main feature for further analysis.

To ensure both representativeness and temporal diversity, the 24 most frequent styles were selected, and external time period information was added to the dataset. These styles, grouped by their corresponding art periods, are presented in Table VI.

Media Category	Existing Media Instances
Oil Color	oil, magna
Watercolor	watercolor, sepia
Pastel	pastel, crayon
Tempera	tempera
Pencil	pencil, ink, charcoal, pen, drawing, graphite, leadpoint, metalpoint, sanguine, coal, colored pencils
Printing-Tinting	lithography, etching, engraving, aquatint, drypoint, linocut, mezzotint
Fresco	fresco
Gouache	gouache, acrylic
Chalk	chalk
Mixed	mixed technique, mixed media

TABLE III: Art Medium Categories and Techniques

Similar media types are combined into one representative media as shown in Table III.

After this selection, only artworks associated with a single style were retained to create a clearly categorized dataset. Artworks that listed multiple styles were excluded. To achieve a balanced dataset across styles, those with fewer examples were supplemented or recovered where possible. The final distribution of artworks by period and style is shown in Table IV.

TABLE IV: Elected Data

Time Period	**Style**	**Number of Artworks**
Pre-1600	Early Renaissance	1852
	Northern Renaissance	3218
	Mannerism	2447
1600-1800	Baroque	3354
	Rococo	3391
	Neoclassicism	3388
	Romanticism	3429
	Academicism	2304
1800-1900	Realism	3372
	Naturalism	882
	Impressionism	3495
	Post-Impressionism	3419
	Symbolism	3132
	Art Nouveau	3269
	Naïve Art	3125
1900-1950	Fauvism	1228
	Cubism	2307
	Expressionism	3125
	Abstract Art	1756
	Surrealism	3085
	Social Realism	919
1950-Present	Abstract Expressionism	3063
	Lyrical Abstraction	1241
	Neo-Romanticism	827
	Art Deco	1032

The 1800–1900 period contains significantly more artworks than the other periods, while the 1950–Present period has the fewest (Table V). To create a balanced and representative dataset, the data will be down-sampled so that each time period includes an equal number of artworks. Furthermore, within each period, an equal number of artworks will be randomly selected for each style to ensure uniform representation across styles.

The artworks which has 'sculpture' or 'photo' genres are deleted and then randomly sampled to have 816 artworks for each style since it is the least amount of artworks for a style after deletion. As a result, data will include 195834 artworks, which will be refered to as "research data" from now on.

Time Period	**Amount of artworks**
Pre-1600	7517
1600-1800	15866
1800-1900	20694
1900-1950	12420
1950-present	6163

TABLE V: Total Artwork Amount of Periods

III. Methods and Results

Although the media feature offers limited information (Figure 13) due to a high proportion of missing values, some general trends can still be observed. For instance, oil painting became the dominant medium during the 1800–1900 period, largely replacing earlier techniques such as tempera and fresco. However, its popularity began to decline in the 20th century with the rise of new artistic movements and materials [26].

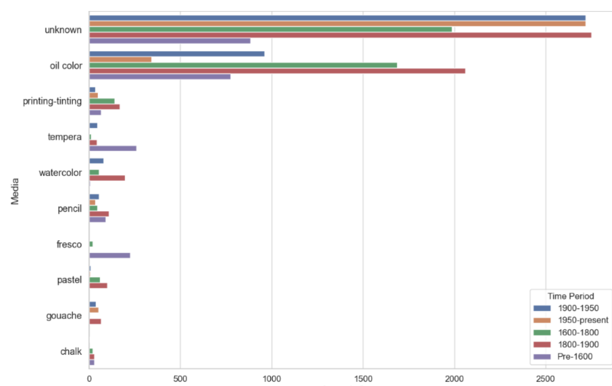


Fig. 13: Top 10 Media Distribution Across Time Periods

In contrast, the genre feature provides a more informative dimension for understanding the evolution of artistic focus across time (Figure 14). Prior to 1600, religious paintings dominated the art scene, reflecting the influence of the Church as the primary patron of the arts during the medieval and early Renaissance periods [27]. During this time, portraiture also emerged, particularly among wealthy patrons seeking to display their status and lineage.

Between 1600 and 1800, portraiture gained widespread popularity, accompanied by the rise of

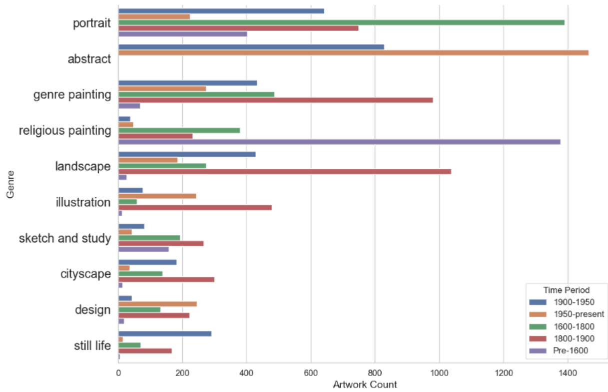


Fig. 14: Top 10 Genre Distribution Across Time Periods

genre painting[4] and landscapes[5] [28]. The shift from religious to secular themes in this era reflects broader social changes, including the Reformation and the Enlightenment, which emphasized human experience and empirical observation.

In the 1800–1900 period, genre painting and landscapes continued to flourish, while portraiture began to decline; probably influenced by the invention of photography in the 1830s, which provided a faster and more accurate means of capturing likenesses [29]. Meanwhile, illustration emerged as a genre, reflecting the growth of print media, publishing, and mass communication during the Industrial Revolution [30].

During the 1900–1950 period, the abstract genre began to emerge along with an increasing interest in still life, allowing artists to experiment with color, form, and composition in new ways. This shift reflected the influence of modernist movements such as Cubism, Expressionism, and Futurism [31]. At the same time, genre painting and landscape gradually lost their dominance.

From 1950 to the present, abstract art has become one of the most prominent genres, especially with the rise of movements like Abstract Expressionism and Minimalism, marking a departure from representational art toward more conceptual and experimental forms [32].

The confidence and lift values are calculated using the apriori algorithm (Figure 15 and Figure 16). After Jesus-Christ, Virgin-Mary, Virgin-and-Child and saints-and-apostles tags Christianity tag appears with a confidence of 0.9. With similar confidences (woody-plant,tree), (flower,plant), (figure-drawing, sketch), (boat, vehicle) tags occur together. Hence, most of their lift is quite low.

[4]Genre painting (or petit genre) is the painting of genre art, which depicts aspects of everyday life by portraying ordinary people engaged in common activities.

[5]Landscape as a genre is the depiction of a natural scene not subordinated to the description of a story

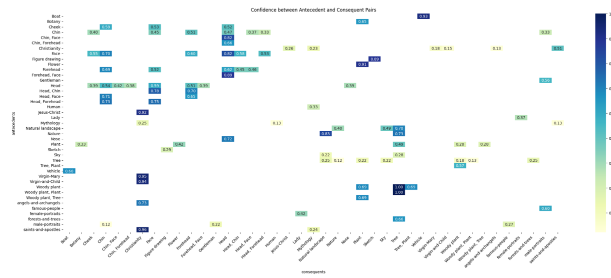


Fig. 15: Confidence Heatmap of Tag Pairs

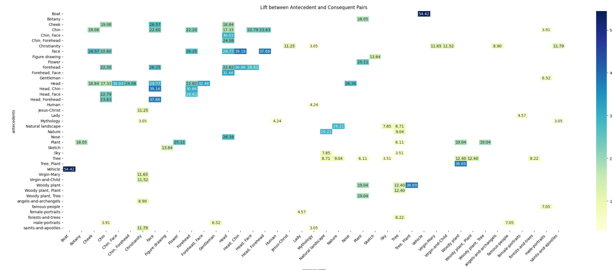


Fig. 16: Lift Heatmap of Tag Pairs

To analyze dominant color usage across different art styles, a color clustering analysis was conducted using the K-Means algorithm on the pixel data extracted from selected artwork images. Due to hardware limitations, images were resized to half of their original edge lengths before processing.

For each style, all images belonging to that style were converted into one-dimensional arrays. This step effectively merges all pixels from all paintings within a style into a single large array, enabling the treatment of the entire style as a unified color dataset and capturing its overall color distribution.

The K-Means clustering algorithm was applied to this combined pixel dataset with k=50, with the aim of identifying the 50 most representative colors in each style. K-Means groups similar RGB values into clusters and computes the centroids, which represent the dominant colors.

Following clustering, the frequency of each color cluster was determined by counting the number of pixels assigned to each cluster. These frequencies were then normalized to reflect the relative usage of each color within the style. The resulting color distributions are visualized in Figure 17.

It can be observed that more recent art styles tend to exhibit a higher degree of colorfulness compared to earlier periods. Although black, brown, gray, and other neutral tones dominate in most styles, modern and contemporary styles demonstrate a noticeable increase in the use of vibrant and saturated colors, especially at the tail ends of the color histograms. This trend aligns with historical developments in both artistic philosophy and material technology.

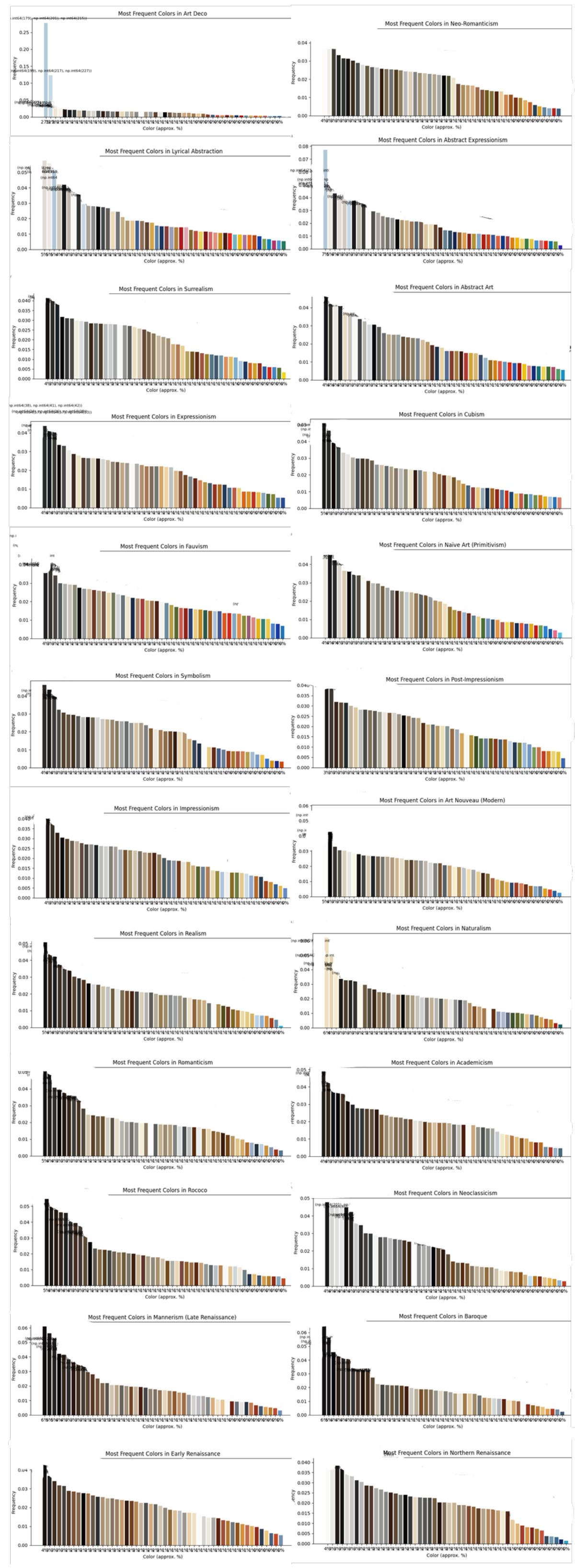


Fig. 17: Most Frequent 50 Colors of Each Style
The order of styles are from present to past, from top to down.

In earlier periods, particularly before 1800, artworks primarily focused on themes such as religious iconography, portraiture, and landscapes. These genres traditionally employed subdued palettes, as seen in Pre-1600, 1600–1800 (down from Realism), and even into the 19th century. The limited color range of these periods can be partly attributed to the availability and cost of pigments, which were derived from natural sources such as minerals and plants (Ref. [33]). These natural pigments often produced earthy and muted tones, restricting the color choices of artists.

During the 19th century, with the emergence of movements like Impressionism and Symbolism, artists began experimenting with more diverse and expressive palettes. The invention and commercialization of synthetic pigments allowed for broader chromatic freedom, enabling more vibrant artworks (Ref. [34]). This shift is visible in the greater presence of bright colors in the data from 1800–1900 (Realism to Naive Art).

The 20th century saw an even more radical departure from naturalistic color usage. With the rise of abstraction, expressionism, and conceptual art, color became a vehicle for emotion, symbolism, and form, rather than mere representation. Consequently, modern styles tend to display significantly more varied and intense colors.

An interesting exception is Art Deco, a 20th-century movement that surprisingly shows minimal color diversity in the analysis. Despite being modern, it relies heavily on two shades of bluish-gray, with very little variation. This may be attributed to the industrial and minimalist aesthetic of the style, which often emphasized geometric form, metallic finishes, and architectural symmetry over expressive coloration (Ref. [35]). As such, its limited palette reflects both its design philosophy and its close association with modernist architecture and machinery.

Figure 18 shows how much space different styles take up in the RGB color space along with the covariance matrix of the color channels (R: red, G: green, B: blue).

The covariance matrices positioned above each RGB scatter plot provide insight into the statistical dependencies between the red, green, and blue color channels in different artistic styles. Diagonal elements represent the variance within individual color channels, whereas off-diagonal elements reflect the degree of covariance between pairs of channels (e.g., red-green, red-blue, green-blue).

Notably, styles such as Fauvism, Abstract Art, and Lyrical Abstraction (1950-Present period) exhibit higher variances and stronger covariances across all channels, indicating a broader and more balanced use of the RGB spectrum. This suggests that these styles employ vivid and diverse color palettes, often unconstrained by naturalistic representation.

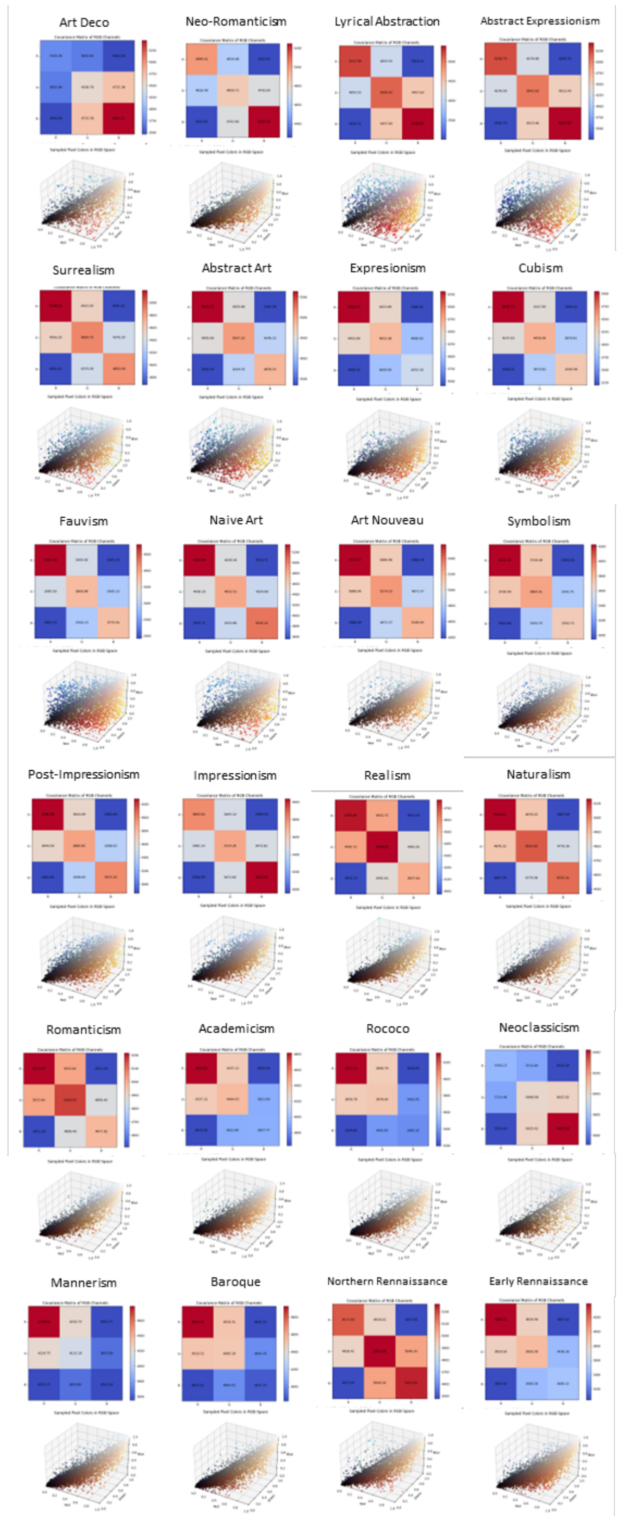


Fig. 18: RGB Colorspace Representation and Correlation Matrix of Color Channels (same order with histograms)

In contrast, traditional or realist styles, such as Realism, Naturalism, and Neoclassicism (1800-1900 period), tend to show lower overall variance and weaker covariances between channels. This pattern implies a more restrained and focused color usage.

Intermediate levels of variance and covariance observed in styles such as Symbolism, Surrealism, and Baroque suggest a moderate use of color diversity, often reflective of symbolic or compositional intentions rather than pure naturalism or abstraction.

To assess the visual richness and diversity of color usage across artistic styles, multiple complementary color metrics were used. First, the Colorfulness metric proposed by Hasler and Süsstrunk [36] was utilized. This perceptual colorfulness measure is based on opponent color channels and is designed to align closely with human visual perception, providing a robust estimation of how vibrant or saturated an image appears.

The results reveal that modern art styles exhibit significantly higher colorfulness scores compared to older styles. This finding again suggests that contemporary movements make broader and more expressive use of the RGB spectrum. A possible explanation lies in the shift from representational accuracy to emotional or conceptual expression, which allowed for greater experimentation with color.

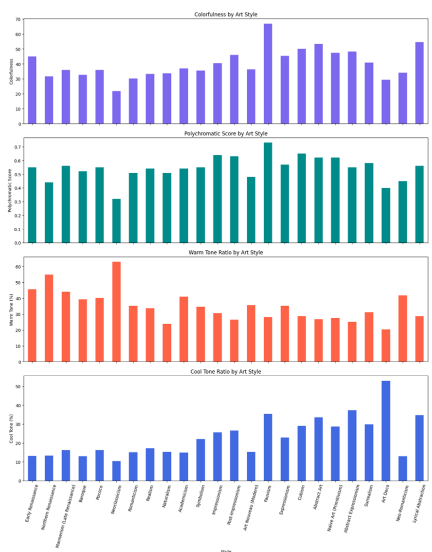


Fig. 19: Colorfullnes and Cool-Warm Tone Dominance

To further quantify color palette diversity, the Polychromatic Score was applied. This metric captures hue variation across an image, effectively measuring how diverse or monochromatic a palette is. The outcomes of this metric strongly align with the Colorfulness measure.

Finally, the percentage of warm (red, orange, yellow) and cool (blue, green, purple) tones was analyzed to understand stylistic preferences across periods. Interestingly, older styles demonstrate a greater reliance on warm tones, which may be attributed to the dominance of earth-based pigments and religious or human-centric subject matter. In contrast, modern and abstract styles increasingly incorporate cool tones, possibly reflecting shifts toward abstraction, industrial aesthetics, and more experimental color theories (Ref. [37])

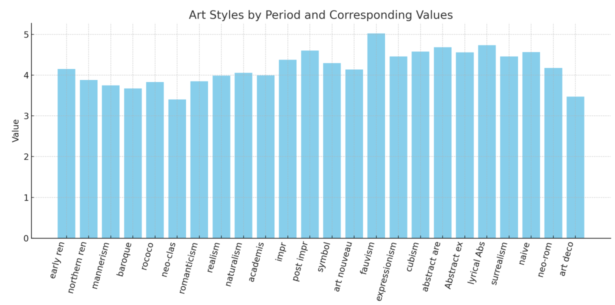


Fig. 20: Style Entropies

The image entropy of each style was calculated to quantify visual complexity, using the Shannon entropy [22] of the grayscale pixel intensity distributions. The results indicate lower entropy values in older styles and higher values in modern styles, suggesting that modern artworks exhibit more intricate and varied visual patterns. This may reflect a shift from the smoother, more blended transitions typical of early styles, where objects often merge softly toward sharper edges and more defined structures in modern movements.

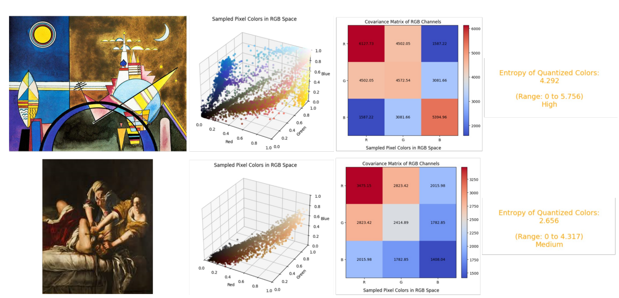
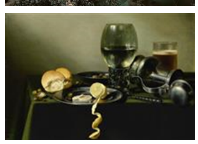
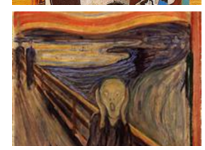
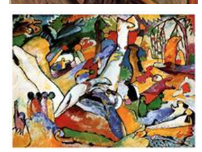
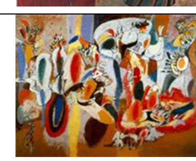
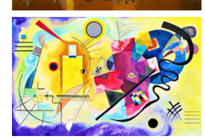
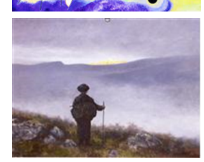


Fig. 21: Symbolism and Baroque Examples

Figure 21 shows two examples; top from symbolism and bottom from Baroque. Their RGB colo space representation, color channel covariance matrix and entropy values are as listed. The difference between older styles and newer styles can be observed clearlt with these examples.

TABLE VI: Grouped Rows with Images in Third Column

Time Period	Style	Example
Pre-1600	Early Renaissance	
	Northern Renaissance	
	Mannerism	
1600-1800	Baroque	
	Rococo	
	Neoclassizm	
	Romanticism	
	Academicism	
1800-1900	Realism	
	Naturalism	
	Impressionism	
	Post-Impressionism	
	Symbolism	
1800-1900	Art Nouveau	
	Naive Art	
1900-1950	Fauvism	
	Cubism	
	Expressionism	
	Abstract Art	
	Surrealism	
1950-Present	Abstract Expressionism	
	Lyrical Abstraction	
	Neo-Romanticism	
	Art Deco	

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