Data Analysis & Analysis of Five 'Shot Marilyn' Images

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Abstract

This project presents a detailed analysis of five images belonging to Andy Warhol's renowned "Shot Marilyn" paintings from 1964. The examined paintings consist of the Light Blue, Sage Blue, Red, Orange, and Turquoise variations. The primary objective is to gain insights into Warhol's artistic decisions and investigate the diverse visual impacts and expressions within this series. By uncovering and emphasizing the distinctive qualities and subtleties present in each painting, a comprehensive understanding of the artistic variations within the "Shot Marilyn" series is achieved. The analysis includes color ratio computations, kernel density estimation for distribution analysis, examination of hue and saturation components, calculation of relative conditional entropy, identification of key regions of interest (lip color and eye shadow color), determination of RGB value ranges, application of edge detection using the Canny algorithm, and advanced techniques such as kernel density estimation (KDE), chromaticity, and facial feature detection for data analysis and visualization. Through this comprehensive exploration, valuable insights into the artistic choices and unique characteristics of each "Shot Marilyn" painting are revealed.

Keywords: Andy Warhol, Shot Marilyn, Color analysis, Distribution analysis, Edge detection, Face recognition, RGB normalization.

1 Introduction

In this project, we delve into the captivating world of Andy Warhol's iconic "Shot Marilyn" paintings from 1964. These artworks hold a significant place in Warhol's body of work, symbolizing a pivotal moment in his artistic journey. Inspired by Marilyn Monroe, a timeless Hollywood icon, Warhol created a series of silkscreen prints that have since become highly coveted and renowned.

Our project focuses on analyzing five specific images from the ′Shot Marilyn′ series, each showcasing different variations in color, composition, and visual impact. Through the application of various analytical methods, we aim to gain a deeper understanding of Warhol's artistic choices and shed light on the unique qualities present in each painting.

To examine the color distributions, we employ techniques such as computing color ratios, analyzing hue and saturation components, and utilizing kernel density estimation to estimate the color distributions. Additionally, we explore the interplay between different color channels by calculating the relative conditional entropy, providing insights into the relationships and interactions within the artwork.

Furthermore, we define two distinct regions of interest in the images: the lip color and eye shadow color, allowing us to examine the color ranges and variations present in these specific areas. Through edge detection using the Canny algorithm, we extract key features and patterns, further enhancing our understanding of the visual elements within the paintings. In addition to quantitative analysis, we leverage face recognition algorithms to detect and analyze key facial points within each painting. By examining how Marilyn Monroe is portrayed in these artworks, we aim to uncover additional layers of meaning and interpretation.

Through our comprehensive analysis and visualization techniques, including kernel density estimation, 3D plotting in RGB space, and RGB normalization, we aim to provide a multidimensional understanding of the "Shot Marilyn" series. Our project not only contributes to the existing body of knowledge surrounding Warhol's work but also offers valuable insights into the artistic variations and visual nuances within this iconic series of artworks.

1.1 Image Description

The project revolves around a series of five paintings from Andy Warhol's renowned "Shot Marilyn" collection, each with dimensions of 960x960 pixels. These paintings showcase unique color schemes, namely Light Blue, Sage Blue, Red, Orange, and Turquoise. The images are primarily in PNG format, except for the Light Blue painting, which was originally in JPG format. To ensure consistency, we converted the Sage Blue image into PNG format for use in our study.

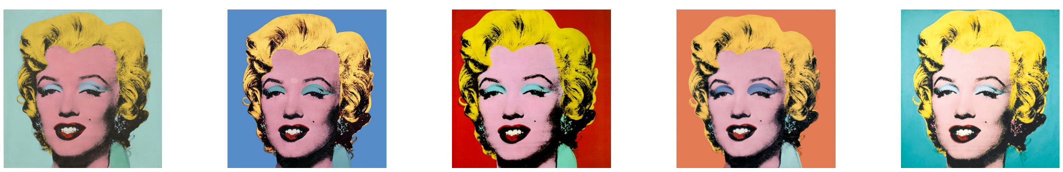


Figure 1: Five 'Shot Marilyn' Images

2 Color Spectrum Analysis

In our project, we begin with five different images. For each image, we extract the image data, which is represented as an array. Each element in the array corresponds to a pixel in the image and contains four values: [R, G, B, A]. The values represent the intensity of red, green, blue, and alpha channels of the pixel, respectively. These values are integers ranging from 0 to 255.

2.1 Basic RGB Analysis

To analyze the images and understand their color characteristics and thematic differences, our initial step is to study the pixel value distribution among five images. Figure 2 presents the histogram result for pixel distribution.

Firstly, all five images exhibit a high presence of fully saturated colors, as indicated by the extremely high pixel value of 255. This suggests a vibrant and intense color palette overall. However, the red image stands out with the second highest occurrence of pixel value 0, indicating a significant amount of black or near-black regions. This suggests the presence of shadows, dark areas, or strong contrasts in the red image. Additionally, the sage blue and orange images show three other values that stand out besides 255. This indicates a more diverse range of colors within their respective palettes, with various shades, tones, and variations. This suggests a richer and more nuanced color composition compared to the other images.

These findings highlight the distinct color characteristics and themes of each image. The high saturation levels signify their vibrant nature, while the prominence of black areas in the red image adds contrast. The presence of multiple significant values in the sage blue and orange images suggests a broader color range.

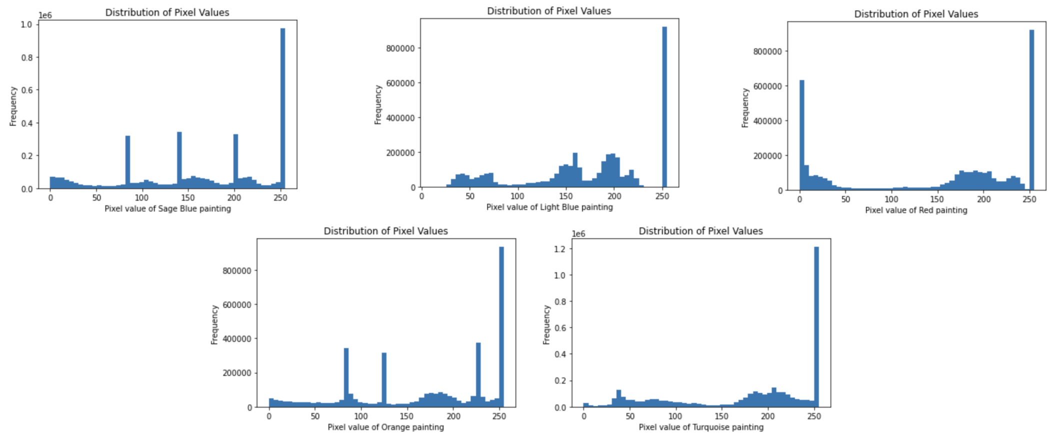


Figure 2: Pixel Value Distribution Histogram

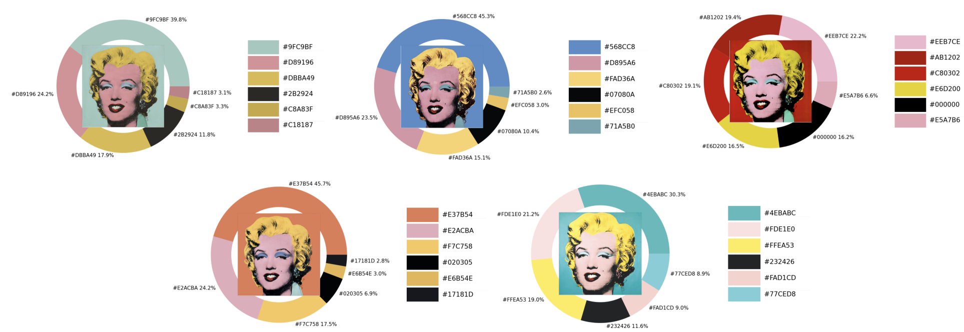


Figure 3: Color Palette with HEX Color Code

Our next step is to extract the major colors present in each image. From result shown at Figure 3. The "Sage Blue" image presents a serene and natural theme with its earthy green, brown, and gray tones. On the other hand, the "Light Blue" image creates a fresh and vibrant atmosphere with its cool blue shades and warm peach and yellow accents. In contrast, the "Red" image exudes intensity and passion through its dominant deep red hues, complemented by black and yellow accents. The "Orange" image conveys a warm and inviting ambiance with its mix of warm orange, pink, and golden tones. Lastly, the "Turquoise" image offers a sense of tranquility and elegance through its cool turquoise shades, coupled with soft pink and beige colors. These distinct color compositions not only contribute to the uniqueness of each image but also play a vital role in conveying emotions, setting the mood, and enhancing the visual impact of the artwork.

2.2 Hue & Saturation Analysis

In the next step of our project, we expanded our color analysis by performing a hue and saturation analysis, allowing us to develop a deeper comprehension of the visual attributes and variations of the five Marilyn images. Hue is defined by the predominant wavelength of the visible light spectrum, allowing us to classify colors as red, yellow, green, blue, or an intermediate color [2]. On the other hand, saturation represents the purity and intensity of a color; therefore, a high saturation value tells us that the vividness and intensity of a color is high [3].

To approach our hue and saturation analysis, we created HSV - hue and saturation values – color maps to gain information about the variations of hue and saturation values across the five paintings. For instance, our color maps aided us in visualizing the distribution and prevalence of hues in each piece, providing us more insight to better comprehend Andy Warhol's color palette choice. Additionally, our color maps also provided us with information about the variations of color intensity across the 5 paintings, helping us identify areas of high and low color saturation.

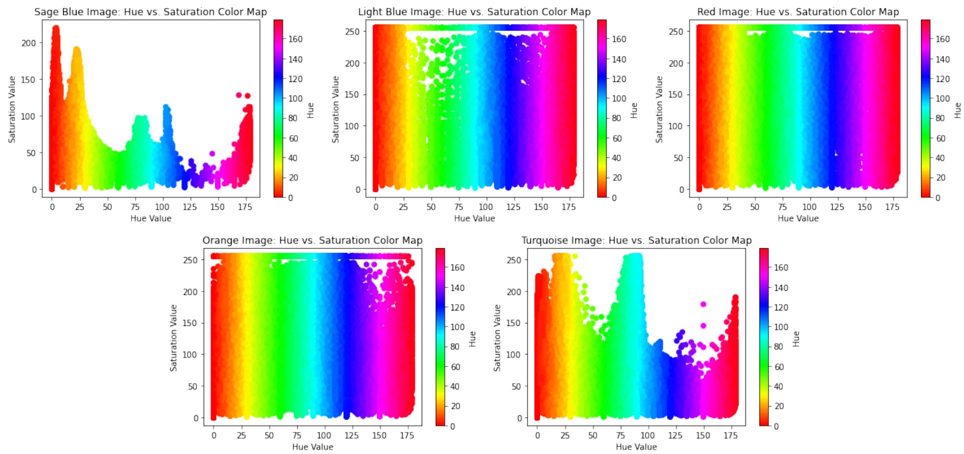


Figure 4: HSV Color Maps for Five Images

Through analyzing the hue and saturation color maps of the Marilyn images, we were able to uncover interesting patterns and artistic choices made by Warhol. To elaborate, in Figure 4, it is evident that the red painting has the highest color intensity among the 5 paintings; the presence of nearly every hue across the spectrum is observed. Similarly, the color map for the orange painting depicts high color intensity and the presence of nearly every hue, indicating Warhol's choice of the broad use of the color palette. The color map for the light blue image also exhibits the presence of nearly every hue with high color intensity except for greens. Next, the color map for the turquoise painting illustrates the predominant concentration of hues in the turquoise, red, orange, and yellow spectrums. Lastly, the color map for the sage blue painting displays low saturation values except for the red spectrums, indicating low color intensity.

2.3 Relative Conditional entropy

The conditional entropy of a random variable Y given another random variable X is defined as:

$$H(Y|X) = -\sum_{x\in X}\sum_{y\in Y} p(x,y)\log\left(\frac{p(x,y)}{p(x)}\right)$$

where p(x, y) is the joint probability mass function of X and Y, and p(x) is the marginal probability mass function of X.

In this project, we conducted an analysis of the relative conditional entropy values for the five images, which provide valuable insights into the relationships between the red, green, and blue color channels. By creating a table that showcases the relative conditional entropy between different channels for each image, we aimed to understand the interplay and dependencies between these channels.

The results revealed that the sage blue and light blue images exhibit a moderate level of dependency and a well-balanced distribution of colors across the channels. This suggests a harmonious blending of colors in these images.

On the other hand, the red image demonstrated a stronger correlation between the color channels, with the red channel dominating the overall color composition. This indicates a more prominent emphasis on red tones in the image. The orange image, similar to the blue images, displayed a moderate level of dependency between the channels, indicating a balanced distribution of colors with no dominant channel. Similarly, the turquoise image also exhibited a moderate level of dependency between the channels, suggesting a harmonious interplay of colors without any significant dominance.

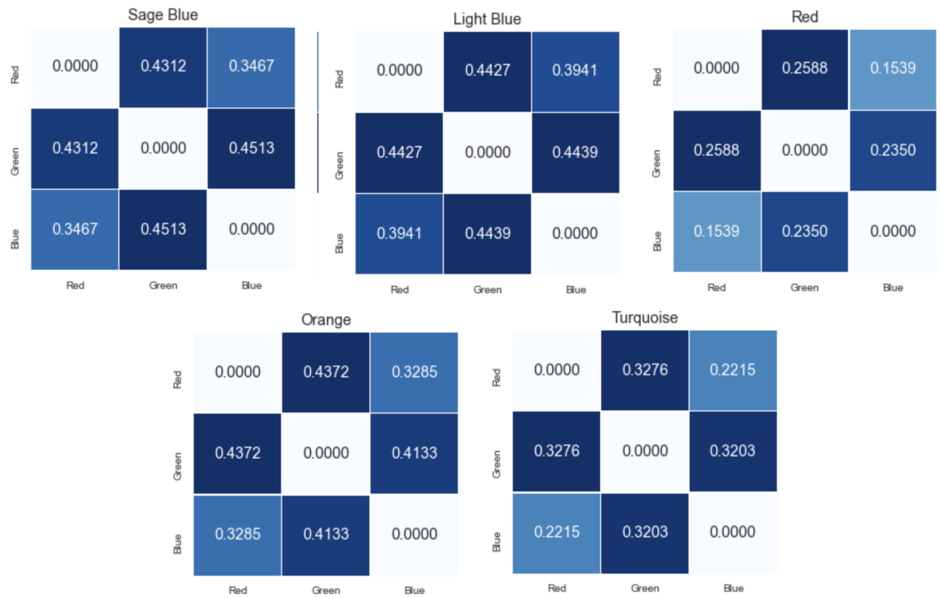


Figure 5: Relative Conditional Entropy for Five Images

Overall, these relative conditional entropy values provide valuable quantitative insights into the color composition and relationships within each image. They contribute to our understanding of how colors interact and blend in these artworks, enhancing our appreciation and interpretation of the visual elements present.

3 ROI Analysis

Figure 7: Clustered Image

Region of Interest (ROI) is a crucial concept in image analysis and computer vision. In the context of images, ROI refers to a specific region or subset of the image that is selected for further analysis or processing. It represents a portion of the image that contains the objects, features, or areas of interest that are relevant to the specific task or objective at hand. For instance, the images above were generated with Cluster Analysis.The selection of an ROI is typically based on its significance or relevance to the analysis, and it allows for focused examination or manipulation of specific image content. ROI can be defined manually by drawing bounding boxes or polygons around the desired region, or it can be determined automatically using various image processing techniques, such as segmentation algorithms. By isolating and extracting the ROI from an image, researchers and practitioners can concentrate their efforts on specific areas of interest, improving efficiency, reducing computational resources, and enabling targeted analysis or feature extraction. ROI plays a vital role in numerous applications, including object recognition, image enhancement, medical imaging, surveillance, and more, facilitating precise and efficient image analysis and interpretation

3.1 Segmentation

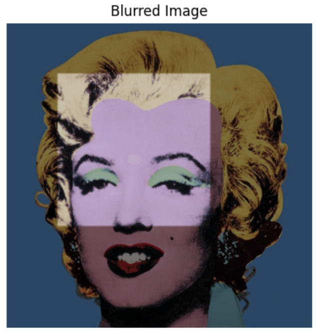


Figure 8: Segmented Image

Image segmentation plays a fundamental role in image analysis, serving as a crucial step in various computer vision tasks. Its primary objective is to partition an image into visually distinct regions or objects. This process enables the separation of objects of interest from the background or other objects within the image. By segmenting an image, it becomes possible to recognize, classify, and understand objects based on their visual properties. This is particularly important in statistical analysis, as it allows for focused examination and interpretation of specific regions or objects. Image segmentation also enables the detection of object boundaries, providing valuable information for edge detection, shape analysis, and object tracking. Furthermore, it facilitates image-based measurements and analysis by extracting features and attributes from segmented regions. The quantitative analysis of these regions allows for statistical measurements, comparisons, and inferences. Overall, image segmentation serves as a foundational step in image analysis, facilitating the understanding, interpretation, and utilization of visual data in a wide range of statistical applications.

We decided to select eye shadow and lip area as two ROI (Region of Interest) to study for. For each ROI, we will construct scatter plot to display the distribution of colors of the pixels associated with those ROIs in the red-green, red-blue, and green- blue planes. By examining the plots, we can observe the dominant color and its intensity in each image. The narrow and straight distributions in the red vs green plots indicate a clear dominance of a particular color. The transition from black to light grey suggests a gradual change in intensity. The spreading patterns in the red vs blue and blue vs green plots provide information about the variation and range of colors present in the ROI.

3.1.1 Eye Shadow ROI

For the Eye shadow ROI, the presence of a dominant color in the "Sage Blue" image, indicated by a narrow and straight distribution, suggests a focused and consistent use of a specific shade of blue in the eye shadow. This implies a cohesive color theme and intentional color selection. Similarly, the "Light Blue" image exhibits a dominant color with slight variations. The thicker distribution at the bottom left of the red vs green plot suggests a broader range of color shades, possibly indicating a gradient effect or multiple shades of blue used in the eye shadow application. In contrast, the "Red" image demonstrates a more complex color composition. The separate points and darker concentration in the red vs green and red vs blue plots indicate the presence of additional colors or color variations within the eye shadow. This suggests a more intricate and diverse use of colors, possibly incorporating multiple shades or blending techniques. The "Orange" image shows similarities to the "Red" image in terms of color distribution. However, the narrower bottom left region and linear spreading of separate points suggest a more concentrated and focused use of the dominant orange color, potentially resulting in a bold and vibrant eye shadow appearance.

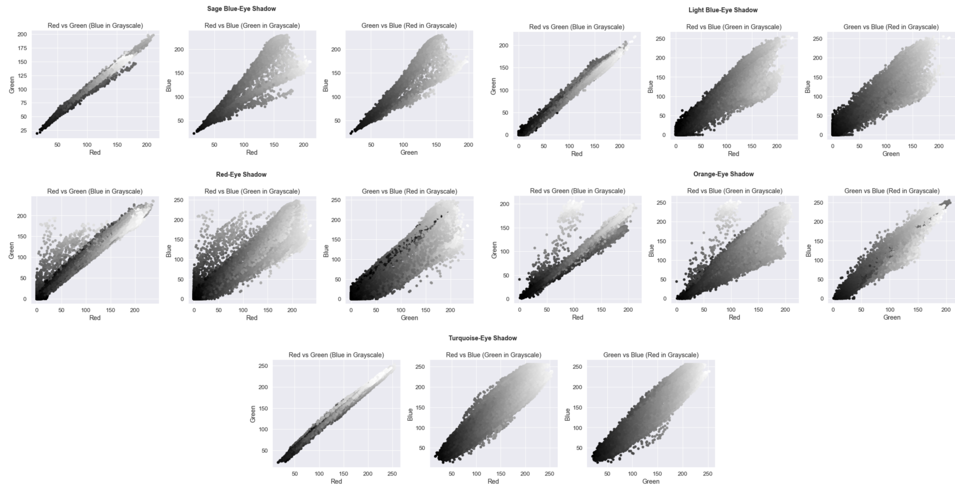


Figure 9: RGB Pixel of Eye Shadow ROI

Finally, the "Turquoise" image shares similarities with the "Light Blue" image but with a narrower color range and lighter colors. This indicates a more subtle and delicate use of turquoise shades in the eye shadow application, possibly aiming for a softer and more ethereal look.

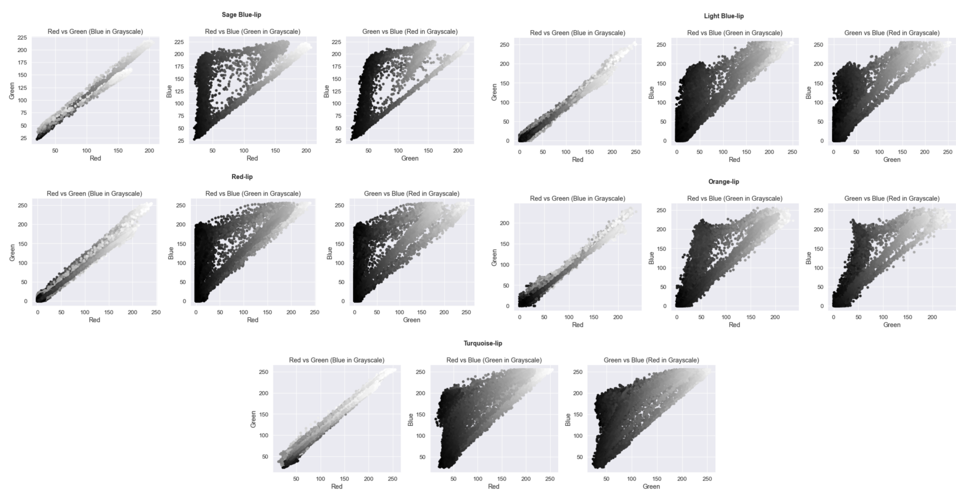


Figure 10: RGB Pixel of Lip ROI

3.1.2 Lip ROI

The analysis reveals different color compositions within the lip area of each image. The color changes from dark black to light grey in all cases, indicating a range of shades and intensities. The specific colors and their distribution vary across the images, from a predominantly grey composition in Sage Blue to darker shades in Red and Orange. Turquoise stands out with its lighter overall color composition and near-white shade at the top right. These variations in lip color contribute to the overall aesthetic and visual impact of the images. For the lip area, the linear plot in the red vs green (blue as greyscale) analysis suggests a consistent and linear shape for the lip region in all images. However, there are differences in the thickness and darkness of the lip area. Light Blue and Orange have thicker lip areas, with distinct color changes and darker regions at the bottom left. Turquoise exhibits a narrower lip area compared to the others, while Sage Blue and Red have more evenly filled lip areas.

Overall, the analysis of eye shadows and lips highlights the variations in makeup application and composition across the images. It helps us understand the specific characteristics, aesthetics, and artistic choices associated with each image's lip makeup.

3.2 Clustering

Figure 11: ROI Clustered Image

Cluster analysis is a versatile statistical technique used to classify data points into distinct groups based on their similarities or dissimilarities. It involves defining a distance or similarity measure between data points and utilizing optimization algorithms to achieve optimal data grouping. The most commonly used distance measure in cluster analysis is the Euclidean distance, which quantifies dissimilarity between data points. Given a dataset with n data points represented as $x_1, x_2, \ldots, x_n$ (where each data point is a d-dimensional vector), the Euclidean distance between two data points x_i and x_j is defined as:

$$d(x_i, x_j) = \sqrt{\sum_{k=1}^{d} (x_{ik} - x_{jk})^2}$$

where x_{ik} and x_{jk} represent the k-th components of x_i and x_j respectively. To perform cluster analysis, various algorithms such as k-means, hierarchical clustering, and DBSCAN are commonly used.

Evaluation of clustering results is essential, and two widely used metrics are the silhouette score and Davies-Bouldin index. The silhouette score assesses cluster compactness and separation by computing the average dissimilarity between data points within the same cluster and the nearest neighboring cluster. Mathematically, the silhouette score for a data point i is given by:

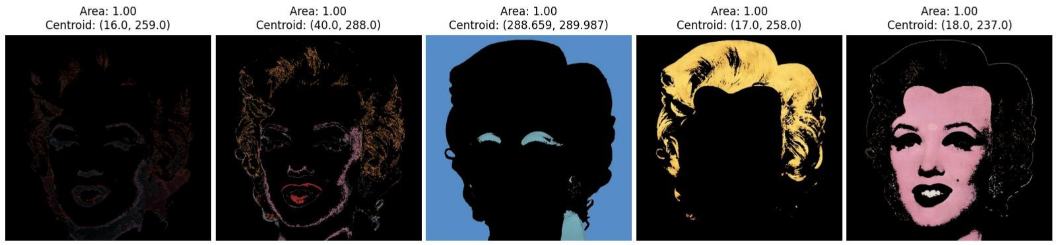
$$s(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}}$$

where $a(i)$ and $b(i)$ represent the average dissimilarity between i and other points within its cluster and neighboring cluster, respectively. The silhouette score ranges from -1 to 1, with values close to 1 indicating well-separated clusters, values near 0 indicating overlapping clusters, and negative values suggesting potential misclassifications.

The Davies-Bouldin index complements the evaluation of clustering quality by considering both compactness and separation of clusters. It calculates the average similarity measures between each cluster and its closest neighboring cluster. Mathematically, the Davies-Bouldin index is expressed as:

$$DB = \frac{1}{k}\sum_{i=1}^{k}\max_{j\neq i}\left(\frac{s(i)+s(j)}{d(c_i,c_j)}\right)$$

where k denotes the number of clusters, $s(i)$ and $s(j)$ represent within-cluster similarity measures, and $d(c_i, c_j)$ denotes the dissimilarity between the centroids of clusters c_i and c_j. A lower Davies-Bouldin index indicates more distinct and well-separated clusters.



In the image above, texture features were computed to reveal their respective texture segmentations by utilizing a cluster number of 3, computed with both the Davies-Bouldin index and silhouette score:

- Silhouette Score: 0.5069015026092529
- Davies-Bouldin Index: 0.42186156768552463

Those segmentations reveal a more natural way of dividing the image, rather than using rectangles or manually drawn regions. The face, eye lids, most of the hair, and certain other facial characteristics become more apparent.

3.3 Kernel Density Information (KDE)

In the next step of our project, we employed the Kernel Density Estimation (KDE) method to gain a deeper understanding of the variations and color composition of the 5 paintings by visualizing the distribution and concentrations of the paintings' RGB values. The Kernel Density Estimation (KDE) estimates the probability density function:

$$\hat{f}(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x-x_i}{h}\right)$$

where $\hat{f}(x)$ is the estimated probability density function, n are the number of observations, h is the bandwidth, and K is the kernel function. In order to compute the KDE values for RGB, we utilized python's Gaussian Kernel Density Estimation library, providing us with the relative density of the RGB channels. Through computing the KDE values, we were able to generate KDE diagrams to aid in the visualization of the color composition – color intensity, color distribution, saturation, etc – for each painting. Furthermore, the KDE algorithm separated the RGB channels; therefore, the diagrams deepened our comprehension of the individual color components and its impact on the overall color distribution.

Plotting the RGB channels in a 3-dimensional space helped us explore the relationship between the individual color components from a holistic view. For each data point, the value of each individual channel represents the color intensity of each color component, providing us with a better understanding of the relationships between the RGB channels. For instance, a region that is primarily purple represents a high concentration of red and blue and a low concentration of green.

As seen in the figure above, the KDE RGB diagram for the sage blue painting reveals that there is a relatively wide range of hues that is represented with primarily large green and blue regions indicating that there is a high concentration of blue and green. Furthermore, the diagram also illustrates lower density values across the hues, especially for red, indicating that the saturation values for the sage blue painting are relatively lower. Next, in the KDE diagram for the light blue painting, there is a

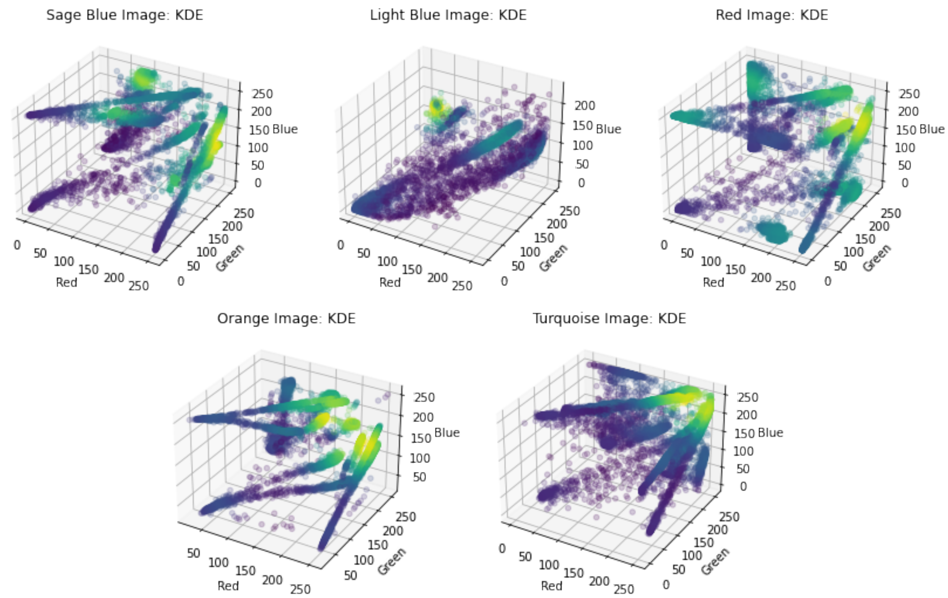


Figure 12: KDE Diagrams for the 5 Paintings

wide range of hues that are depicted, but the KDE values for the RGB channels are generally low, indicating that this painting is not highly saturated (which was revealed in the color maps). To add on, the many data points in the diagram are shown to be purple, suggesting that there is a high level of interaction between red and blue. Next, the diagram for the red painting makes it evident that there the saturation is high, through the high KDE values. The diagram also illustrates large purple, green, and yellow regions with high KDE values, which reveals that there is a high interaction between all three channels for the red painting. Next, the diagram for the orange painting suggests that the saturation levels of the painting are relatively high and that there is a higher concentration of red and green as indicated by the green and yellow regions. Lastly, the diagram for the turquoise painting makes it clear that there is a high concentration of all three channels.

3.4 Chromaticity

To expand our color analysis, we decided to explore the paintings' Chromaticity. Chromaticity is defined as, a three-coordinate value, the quality of a color regardless of luminance, which explains how color is observed from the human eye. The two measurements that make up chromaticity are hue and colorfulness [4]. In our project, we incorporated the concept of chromaticity to generate chromaticity diagrams, providing us more valuable information about the color distribution, composition, and harmonies of each painting in a 3-dimensional space. In order to generate the diagrams, the pixel values were normalized to a [0,1] range to simply express the chromaticity values. The color of each pixel represents its RGB values; therefore, we were able to determine the dominant colors of different clusters.

Based on the chromaticity diagram for the sage blue painting, it is evident the range of hues is not as wide as compared to the light blue, red, orange, and turquoise paintings. The data points representing the chromaticity values are lower and appear in the vicinity of the blue and green axes, indicating that there is a dominance of blue and green at a lower intensity in the painting. Next, the diagram for the light blue painting displays a wide range of hues with many points in the vicinity of the blue axis, which tells us that there is a dominance of blue in the painting. To add on, both the diagrams for the red and orange diagrams display a wide range of hues, specifically within the vicinity of the red axis. Through this, we determine that red components are dominant for these paintings. Lastly, the diagram for the turquoise reveals large blue regions and many points within the vicinity of the blue axis, exhibiting that the blue component is predominantly present in the painting. Overall, these diagrams make it evident that the RGB concentrations are much higher in the red, orange, and turquoise paintings.

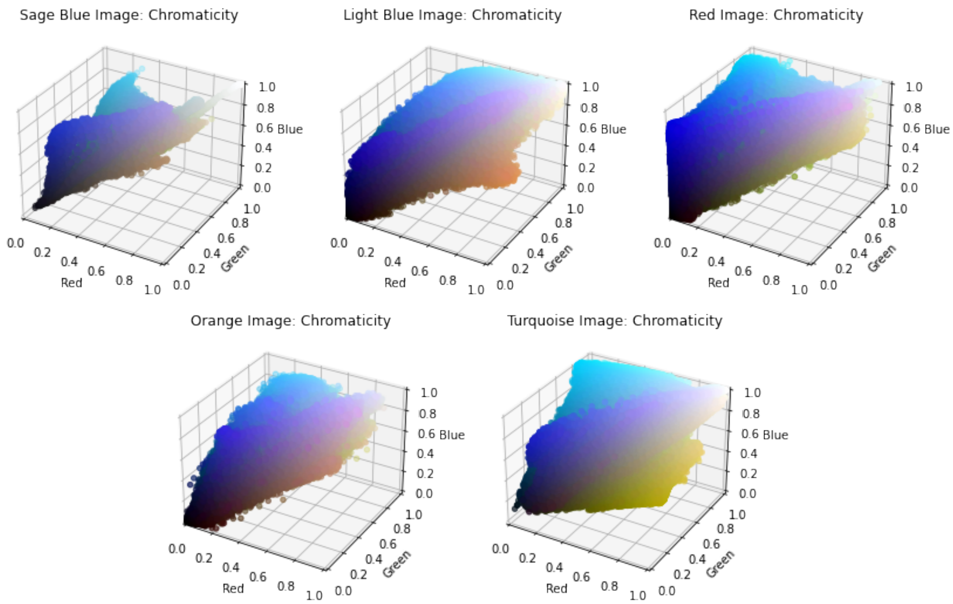


Figure 13: Chromaticity Diagrams for the 5 Paintings

4 Shape Analysis

4.1 Edge Detection

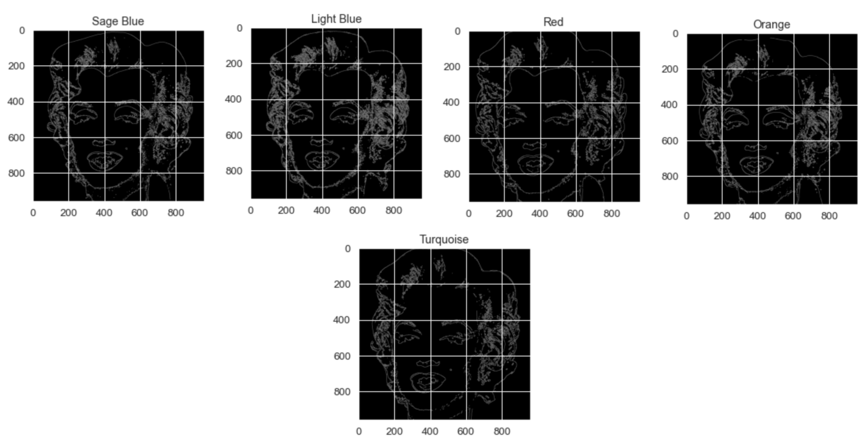


Figure 14: Outline for Images

For the analysis, the Canny Edge Detection technique was employed to extract outlines from the five images. This method effectively identifies areas of sharp contrast or brightness changes, allowing the edges within the images to be revealed. By applying a threshold between 200 and 250, a thorough examination was conducted.

Notably, the results revealed that the light blue image showcased the most intricate and detailed outlines among the five. This suggests that this particular image possesses numerous distinct edges with pronounced variations in color contrast and brightness, resulting in a visually complex composition. In contrast, the Turquoise image exhibited the cleanest and simplest outlines. This indicates that the image contains smoother transitions and fewer abrupt changes in color contrast or brightness, resulting in more refined and uncomplicated edges.

Overall, the findings from the Canny Edge Detection analysis provide insights into the level of detail and simplicity present in the outlines of the five images. The light blue image stands out as the most intricate, while the Turquoise image offers a cleaner and more streamlined outline.

4.2 Facial Feature Detection

In the last section of our project, we employed a facial feature detection technique in order to identify and locate key points of facial features in the 5 paintings. This was done through python's ORB – Oriented FAST and Rotated BRIEF – algorithm, which functions by analyzing the various characteristics of facial features in each image [5]. We utilized ORB in order to generate plots that depict the key points of each image, allowing us to analyze the prominent facial features of each painting. The key points drawn on the plot assisted us in gaining a better understanding of the distribution (size, shape, etc.) and positioning of significant facial features, such as eyes, nose, and mouth.

Figure 15: Facial Feature Keypoint Plots for the 5 Paintings

Based on the figure above, it is clear that the mouth is a key facial feature for all 5 images. Next, the plots also illustrate that the nose is a prominent feature for the following paintings: red, sage blue, orange, and turquoise. The plot for the light blue image tells us that the nose is not a key point, helping us explore the variation in facial features and ultimately, facial expressions across the 5 paintings. Additionally, it is evident that Marilyn's eyes are a prominent feature in the red, sage blue, orange, and turquoise paintings. The plot for the light blue painting indicates that Marilyn's eyes are indeed a key point; however, her eyes are not as prominent in this painting as opposed to the 4 other paintings. Lastly, the plots also suggest the corners of Marilyn's face are significant features.

Overall, utilizing facial feature detection to generate visual representations of facial feature key points provided us with more insight on the variations of facial structure across the five paintings. Furthermore, it deepened our understanding on the artistic choices made by Warhol.

5 Similarities and Dissimilarities

The similarity scores based on mean absolute difference represent the dissimilarity between pairs of images. A higher similarity score indicates that the images are more similar, while a lower score indicates greater dissimilarity. Mathematically, the mean absolute difference (MAD) between two images A and B can be computed as:

$$MAD(A, B) = \frac{1}{N} \sum_{i=1}^{N} |A_i - B_i|$$

where N represents the total number of pixels in the images, and A_i and B_i denote the pixel values at the corresponding positions. To identify the closest and most different images based on mean absolute difference, one can examine the values in the similarity scores matrix. The images with higher similarity scores (closer to 100) are more similar to each other, while images with lower similarity scores (closer to 0) are more different. The image with the highest mean similarity score can be considered the most average or representative compared to the rest.

By computing the similarity scores, our group identified the "least" dissimilar image from the others, as shown below using MAD. This means that, compared to the other paintings, it shares the most common attributes.

Figure 16: MAD Average Painting

The similarity scores based on mean squared error (MSE) also indicate the dissimilarity between pairs of images. However, in the case of MSE, lower scores indicate higher similarity, while higher scores indicate greater dissimilarity. Mathematically, the mean squared error between two images A and B can be computed as:

$$MSE(A, B) = \frac{1}{N} \sum_{i=1}^{N} (A_i - B_i)^2$$

where N represents the total number of pixels in the images, and A_i and B_i denote the pixel values at the corresponding positions. To identify the closest and most different images based on MSE, one can examine the values in the similarity scores matrix. Images with lower MSE scores (closer to 0) are more similar to each other, while images with higher MSE scores (further from 0) are more different. The image with the lowest mean MSE score can be considered the most average or representative compared to the rest.

These similarity scores provide valuable information for image comparison and can be used in various image analysis tasks, such as image retrieval, classification, or anomaly detection. By understanding the mathematical principles behind MAD and MSE, researchers and practitioners can make informed decisions based on the level of similarity or dissimilarity between images.

Just like with the similarity scores, our group identified the "least" dissimilar image from the others, as shown below using MSE. However, it corresponds to a different painting.

Figure 17: MSE Average Painting

6 Conclusion

In conclusion, our comprehensive analysis of Andy Warhol's Marilyn Monroe paintings shed light on the intricate details and artistic nuances present within each piece. Through meticulous examination, we observed the deliberate and skillful use of intense colors, creating visually captivating compositions. The color palettes employed in these paintings exhibited a remarkable range, with certain color channels assuming dominance while others displayed interdependence. Notably, the strategic placement and application of eye shadow and lip colors significantly contributed to the overall impact of each image. By employing advanced techniques such as segmentation, clustering, and kernel density estimation, we delved deeper into the intricate color compositions and underlying structures, unraveling further insights into Warhol's artistic techniques and his deliberate choices in selecting color palettes for these iconic Marilyn Monroe paintings. This analysis serves to enrich our understanding and appreciation of Warhol's artistic vision and his mastery of color.

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