Research Article

# Artwork's Authenticity Recognition Model Using Machine Vision and Applications

## Majid Mirbod*

*Department of Industrial Management, Tehran North Branch, Azad University, Tehran, Iran*

*Corresponding Author
Majid Mirbod, Department of Industrial Management, Tehran North Branch, Azad University, Iran.

## Abstract
*This paper presents an artwork authenticity recognition model using machine vision, image processing, and a fuzzy interface system and it is an applied research category. Artworks have always been subject to copying due to their importance, uniqueness, and great financial value, and it has always been the focus of international counterfeiters worldwide. Throughout history, due to various incidents, artworks have been stolen, crossed the borders of different countries, and traded in various auctions. Therefore, recognizing and confirming an artwork's authenticity is always challenging. In this research, I try to present a model to verify the authenticity of artwork using artificial intelligence techniques. The basic assumption is that a quality image of the original artwork is available with the specifications that I will explain in the section. Indeed, two images will be compared by taking pictures of other samples, and their differences will be identified with high accuracy, which the human eye cannot recognize. So, this model cannot recognize artwork authenticity without imaging history. In other words, photographing the original artwork can be used as a basis for comparison with other fake copies of it in the future, and by using the proposed model, their authenticity can and will always be checked. This model is based on my previous research on micrographics imaging to Industrial parts change recognition, the details of which will be explained in the text of the article. In this research, seven unique and famous world artworks were used and two samples of their images were compared to the original sample. The validity and reliability of the results and the high accuracy were obtained with one pixel.*

**Keywords:** Artwork's Authenticity Recognition, Machine Vision, Image Processing, Industrial Information Integration, Artificial Intelligence.

## 1. Introduction

The global art market turns over something north of US$60 billion a year, and some experts estimate that as much as 50% of the works traded are forged [1]. Now, however, new techniques are being developed in laboratories worldwide that look set to make the forgers' lives much more difficult. Artwork authenticity is always questioned. So, for presentation of paintings or sculptures, should always be accompanied by documentation. This is also known as provenance and assures that the work you're about to acquire is genuine and made by the artist or produced by copy. Normally, the authenticity of an artwork is confirmed by getting hold of a signed certificate from the artist himself or the art seller or deciphers a few letters in the artist's signature on the artwork. However, a detailed examination of the components of the artwork requires appropriate scientific tools, and a detailed examination cannot be done using human vision. Also, using methods like x-rays of the canvas and infrared spectroscopy of the paint may have a destructive effect on the unique artwork. The purpose of research is to recognize the authenticity of an artwork by photographing its originality and comparing it with other cases. This method of image comparison has previously been used in other research like the articles below: Industrial parts change recognition model using machine vision, image processing in the framework of industrial information integration or Spatial change recognition model using artificial intelligence to remote sensing, or intelligent concrete surface cracks detection using computer vision, pattern recognition, and artificial neural networks [2-4]. Also, other research, apart from the use of comparing images, has been used to authenticity artwork recognition, of course, some of them can have a destructive effect, such as the following articles: Macro X-ray fluorescence scanning (MA-XRF) as a tool in the authentication of paintings, Identification of the authenticity of pigments in ancient polychromed artworks of China, The Impact of depth of aesthetic processing and visual-feature transformations on recognition

memory for artworks and constructed design Patterns, Art2Real: Unfolding the reality of artworks via semantically aware image to image translation, Understanding and creating art with AI: review and outlook [5-9]. Therefore, there has been no specific research on artwork's authenticity recognition model using artificial intelligence, and this became a motivation for me to research this with artificial intelligence tools and the previous research I did.

## 2. Materials
My research goal is to create a model to recognize the authenticity of unique paintings in the world. so, it is necessary to use their images to test, so the samples that have been used are as follows: Leonardo da Vinci, Portrait of Mona Lisa, 1503, The Scream 1893 by Edvard Munch; The Starry Night-Vincent van Gogh, The sunflowers-Vincent van Gogh, Two Sisters on the Terrace-Renoir, Johannes Vermeer- Girl with a Pearl Earring, Pablo Picasso, Guernica, 1937. As it is known, the images used to test the model are famous artworks in the world and were taken from the museum sites where they are kept. (Fig.1)



**Figure 1:** The model test images (material)

## 3. Methods
The following model has been used in this research to recognize the authenticity of an artwork (Fig2):
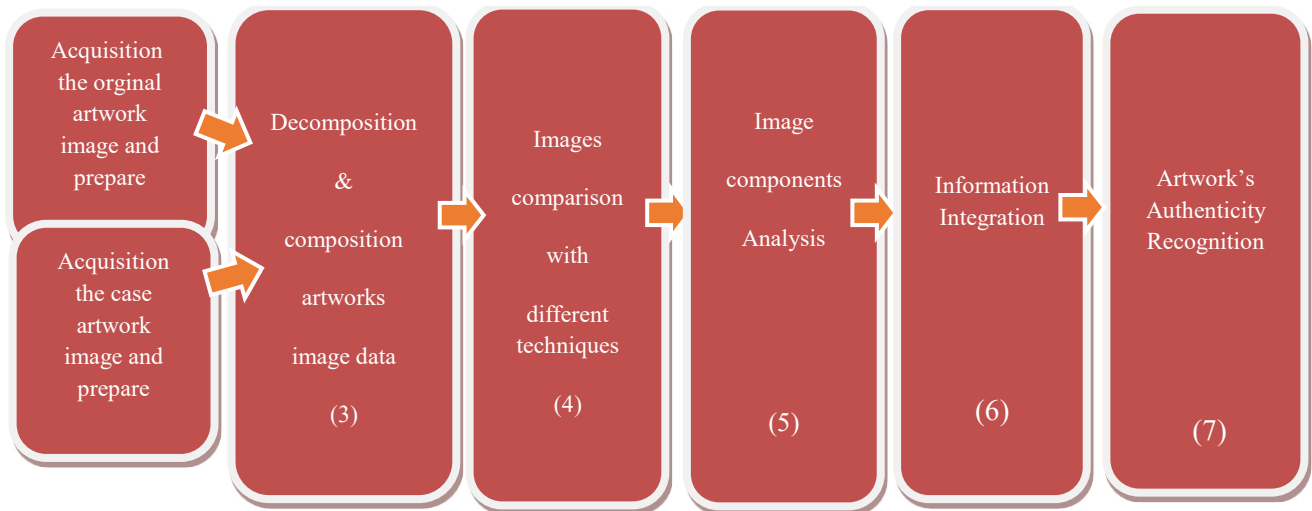


**Figure 2:** Artwork's authenticity recognition model in the framework of information integration

### 3.1 Description of Model Components
### 3.1.1 Acquisition of The Original and The Case Artwork Images and Preparation
First, we must have a picture of the original artwork with a quality of at least 24 megapixels. For this purpose, use non-destructive imaging methods, such as using a high-quality camera without flash and in natural light, or scanners that consider radiation exposure to the image. (Fig.3)
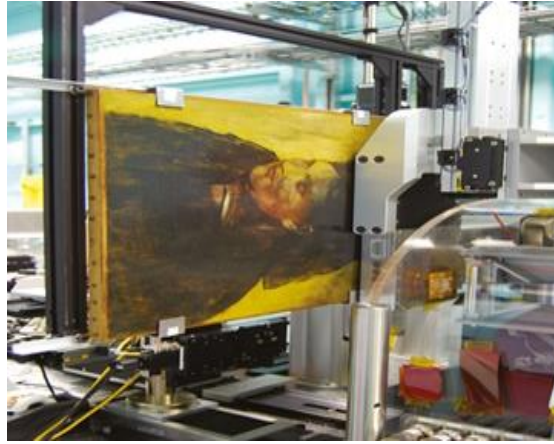
**Figure 3:** Sample artwork scanner (Source: Cosmos)

After Acquiring the image of the original artwork, we use it as a basis for comparison. Then, by Acquiring a picture of each copy, we can compare the two pictures with the provided model and check the results. The limitation that exists in this step is the size of the case images, which must be exactly equal to the size of the original, otherwise, the model will declare an error, which is also a sign of the discrepancy between the two images. Preparing two images means checking their size to be equal and ready to enter the model.

**3.1.2 Decomposition and Composition of Artwork Image Data:** I use the MATLAB image processing toolbox to decompose and compose artwork image data. In this part, I use both RGB images and grayscale images. converting RGB images to grayscale converting the intensity image to double (Pre-processing and data grayscale is to reduce the data from three dimensions to two dimensions while simplifying the problem.

**3.2 Decomposition:**
**3.2.1 RGB images pair:** In this part, two images are compared in terms of color difference. (im show pair command)

**3.2.2 subtract between two greyscale images:** In this part, I used the MATLAB image processing toolbox to convert RGB images to grayscale to reduce the data from three dimensions to two dimensions, while simplifying the problem and subtract between two greyscale images.

**3.2.3 Edge detection for original and Case images:** I used three different methods for edge detection to compare different results. The reason for using these three methods is that each has its strengths and weaknesses, so presenting different results in edge identification, and totally will lead to the model's strength in edge recognition.

**3.2.3.1 Edge detection by defining fuzzy inference system for original and Case image:** A Fuzzy Inference System (FIS) for Edge Detection is based on the subjection of a set of four pixels, part of a 2x2 window of an image to a set of fuzzy conditions that help edges highlight. The research results show that using this method increases the accuracy of edge detection. [2]. The mask used for scanning the image is shown in Fig.4.

$$Gx = [-1 \ 1], \ Gy = Gx'$$



Original image Case image

**Figure 4:** Define FIS[1]  for edge detection (The original and case image)

**3.2.3.2 Edge Detection by Defining Sobel Filter on Original and Cases Image Data:** The Sobel is a discrete differentiation operator, computing an approximation of the gradient of the image intensity function. The result of the Sobel operator is either the corresponding gradient vector or the norm of this vector. The operator is based on convolving the image with a small, separable, and integer-valued filter in the horizontal and vertical directions. The arrangement of pixels is about the pixel [i, j] shown in Table 1. The Sobel's operator is the magnitude of the gradient computed by:

$$M \sqrt{S_X^2 + S_Y^2} \, , \, S_X = (a_2 + ca_3 + a_4) - (a_0 + ca_1 + a_6), \, c = 2 \, [10].$$

Sx and Sy can be implemented using convolution masks:

$$S_X = \begin{matrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ 1 & 0 & 1 \end{matrix} \, , \, S_y = \begin{matrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{matrix}$$

**Table 1: Masks used by Sobel's Operator**

**3.2.3.3 Edge Detection by Defining Prewitt Filter on Original and Cases Image Data:** Prewitt's operator uses the same equations as Sobel's operator, where constant c = 1 [11].

$$S_X = \begin{matrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{matrix} \, , \, S_y = \begin{matrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{matrix}$$

**Table 2: Masks used by the Prewitt gradient Operator [11]**

The mask is slid over an area of the input image, changes that P4 pixel's value, and then shifts one pixel to the right and continues to the right until it reaches the end of a row. It then starts at the beginning of the next row & the process continues till the whole image is scanned. When this mask is made to slide over the image, the output is generated by the fuzzy inference system based on the rules and the value of the pixels.

a) Crisp inputs for fuzzified into various FS, having conventional crisp membership functions i.e. Black & White.
b) Firing strength is calculated using fuzzy t-norm operators (MIN or PRODUCT) on MFs.
c) Fuzzy rules are fired for each crisp input.
d) Aggregate resultant output FS for all fired rules is achieved by using the max operator (s-norm).
e) De-fuzzification is performed using the Centroid method.
f) The crisp output is the pixel value of the output image i.e. one containing the edges, black and white regions.
g) The first derivative is performed on the image output from FIS after the application of the noise removal algorithm.
h) Further refinement is performed by the second derivative and noise removal [11].

**3.2 Composition**
**3.2.1 Drawing a general map:** In this section, we put the outputs together for a better comparison to get a general map, like Fig 5.
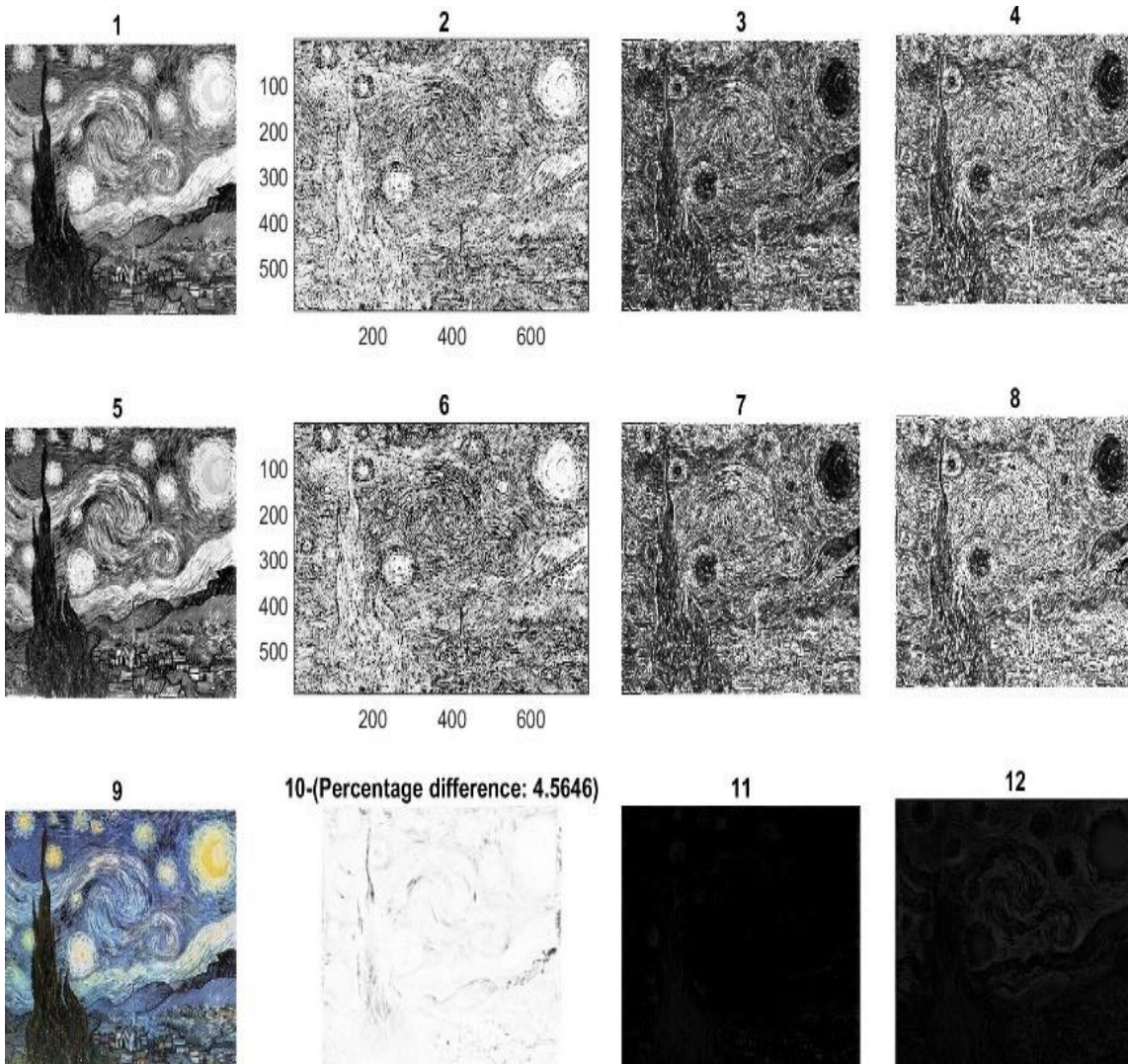
**Figure 5:** Sample of general map

The guide for the general map images is according to the table3:

| Image number | Description |
|---|---|
| 1 | artwork's original image, RGB to grayscale |
| 2 | Actions: Fuzzy interface system on the artwork's original image |
| 3 | Actions: Prewitt's operator on the artwork's original image |
| 4 | Actions: Sobel's operator on the artwork's original image |
| 5 | artwork's case image, RGB to grayscale |
| 6 | Actions: Fuzzy Interface system on artwork's case image |
| 7 | Actions: Prewitt's operator on artwork's case image |
| 8 | Actions: Sobel's operator on artwork's case image |
| 9 | artworks original image (.jpg) format |
| 10 | Difference1, between 6&2, shows a percentage difference: (1-SSIM) *100 |
| 11 | Defference2, between 7,3 - apply operator imsubtract |
| 12 | Defference3, between 8,4- apply operator imabsdiff |

**Table 3: Comparative general map description**

### 3.2.2 Images comparison with different techniques & error reduction:

### 3.2.2.1 The Structural Similarity Index measure:

The SSIM formula is based on three comparison measurements between the samples, namely the luminance term, the contrast term, and the structural term. The overall index is a multiplicative combination of the three terms. [12]

$$\text{SSIM}(x, y) = [l(x,y)]^{\alpha} \cdot [c(x,y)]^{\beta} \cdot [s(x,y)]^{\gamma}, \quad l(x,y) = \frac{2\mu x \mu y + C1}{\mu 2x + \mu 2y + C1}, \quad c(x,y) = \frac{2\sigma x \sigma y + C2}{\sigma 2x + \sigma 2y + C2}$$

$$s(x,y) = \frac{\sigma xy + C3}{\sigma x \sigma y + C3}$$

Where $\mu_x$, $\mu_y$, $\sigma_x$, $\sigma_y$, and $\sigma xy$ are the local means, standard deviations, and cross-covariance for images x, y. If $\alpha = \beta = \gamma = 1$ (the default for Exponents), and $C_3 = C_2/2$ (default selection of C3) the index simplifies to:

$$\text{SSIM}(x,y) = \frac{(2\mu x \mu y + C1)(2\sigma xy + C2)}{(\mu 2x + \mu 2y + C1)(\sigma 2x + \sigma 2y + C2)}$$

And, dissimilarity Structural is: (1- SSIM(x,y))

### 3.2.2.2 Absolute difference between the two artwork images:
In this part calculate the differences between two spatial images as the sum of the absolute difference at each pixel:

$$D(t) = \sum_{i=0}^{M} |I_{(t-T)}(i) - I_t(i)|$$

Where "M" is the resolution or number of pixels in the image. When applied to sub-regions of the image, D (t) is less noisy and may be used as a more reliable parameter for image difference.

$$\text{the Ds}(t) = \sum_{j=s}^{H/n} \sum_{i=s}^{w/n} |I_{(t-T)}(i,j) - I_t(i,j)|$$

Ds (t) is the sum of the absolute difference in a sub-region of the image, where S represents the starting position for a particular region, and n represents the number of sub-regions [13].

### 3.2.2.3 Histogram comparison:
In this section, we draw histograms of original and case images in RGB and grayscale and display them side by side for better comparison.

### 3.2.2.4 Error calculation and reduction:
To calculate the model error, it is enough to compare an original image with itself by taking two images, and whatever difference it shows is the model error and it can be removed from the calculations according to the following formula: Percentage difference= (1-SSIM) *100 – Error

### 3.2.3 Image Components Analysis:
Now, the images are both decomposition and composed, and after putting them together, the differences are revealed, and for each part, we perform our analysis in terms of color changes, size changes, image edge changes, and various histogram changes.

### 3.2.4 Information integration:
In this part, we put all the different data and the obtained outputs and information together and integrated them to get a comprehensive view of the results [14].

### 3.2.5 Artwork's Authenticity Recognition:
After information integration, using different results obtained with different algorithms, the differences between the original image and case are determined.

### 3.3 Error calculation and reduction

The steps for detecting a system error and removing it are as follows:

1- Simultaneous capture of two images of the original sample without any change in environmental conditions.

2- Comparison of two images Step 1.

3- Calculate the difference in step 2.

Since both images are taken from a fixed object at the same time, no difference should be calculated, but a value is obtained as the amount of the difference, which is the same as the system error.

Error = {Original image 1} - {Original image 2}

This error is calculated as a percentage

## Experiment 1:



A                                        B                                        C
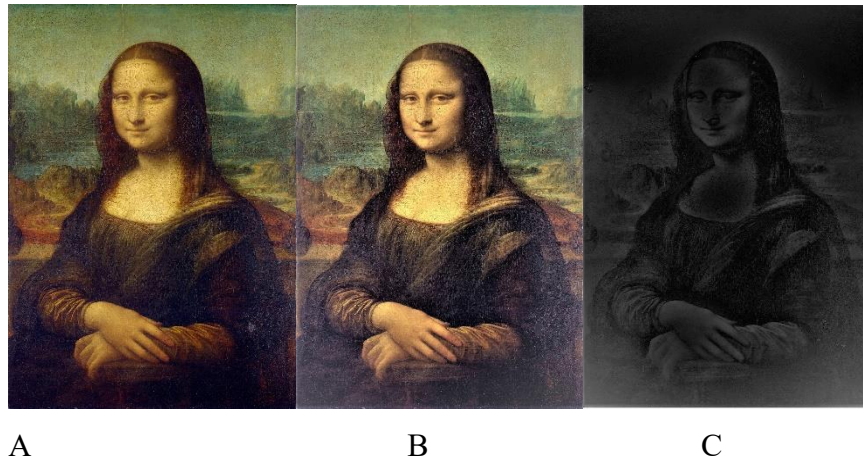
**Figure 6:** A: Original Artworks, B: Case Artworks, C: Color Difference
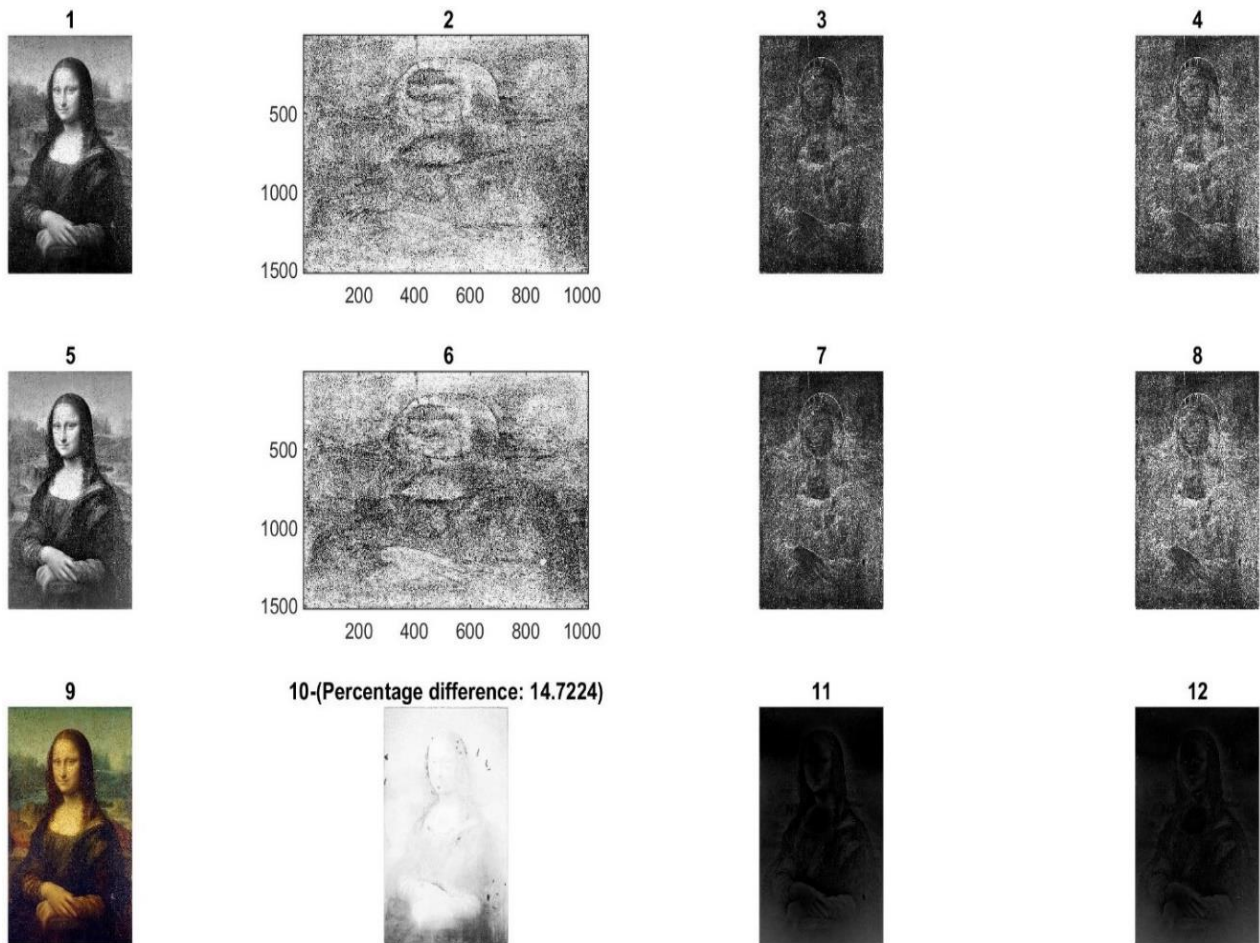


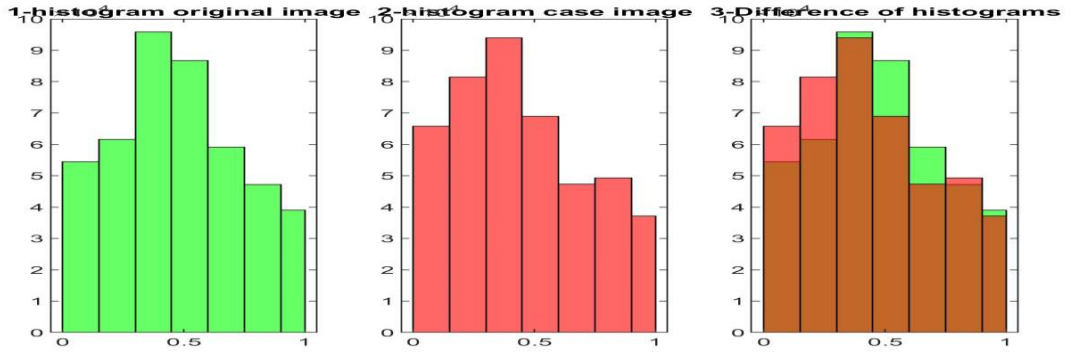**Figure 7:** Comparative general map (Table3 description)
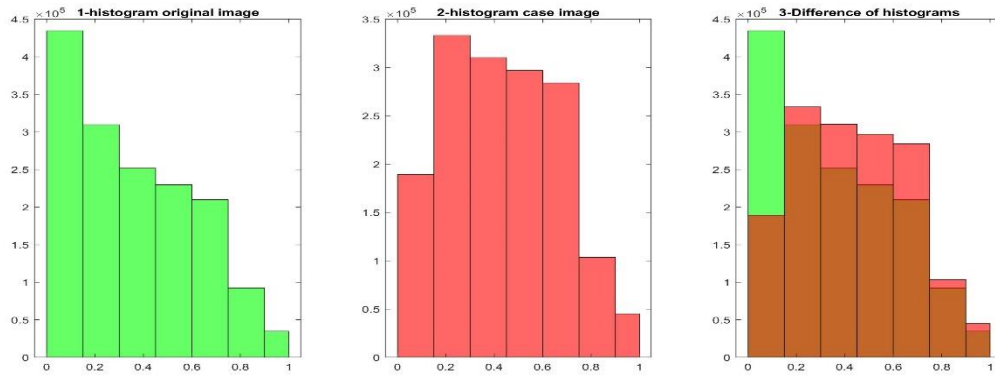
**Figure 8:** Grayscale Comparative Histogram Original & Case Artwork Image
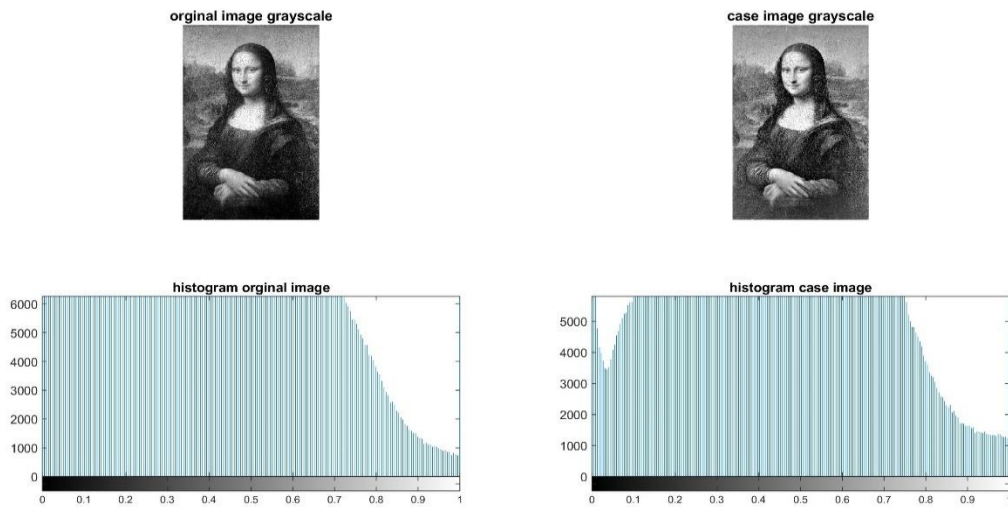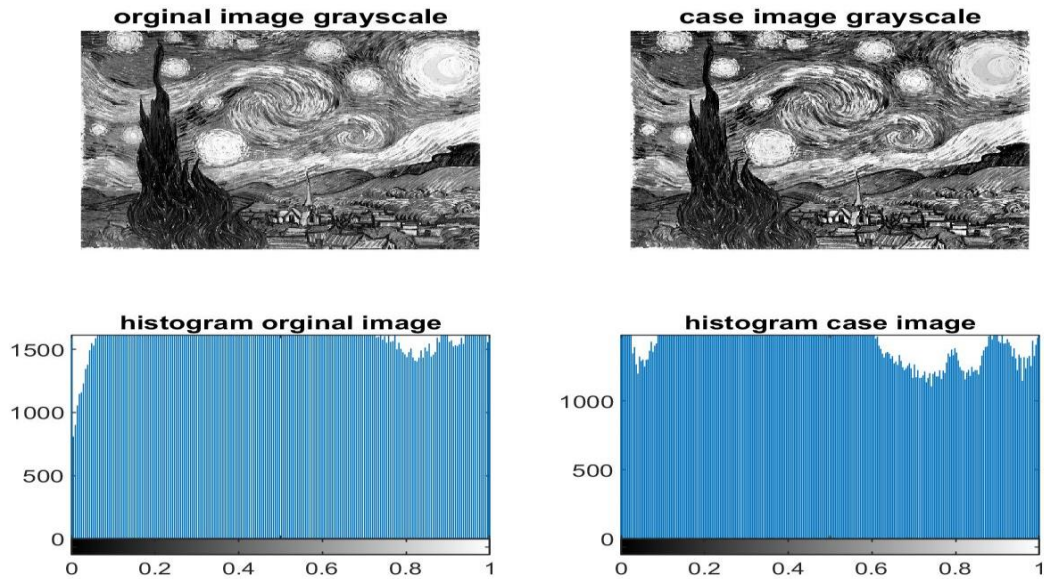


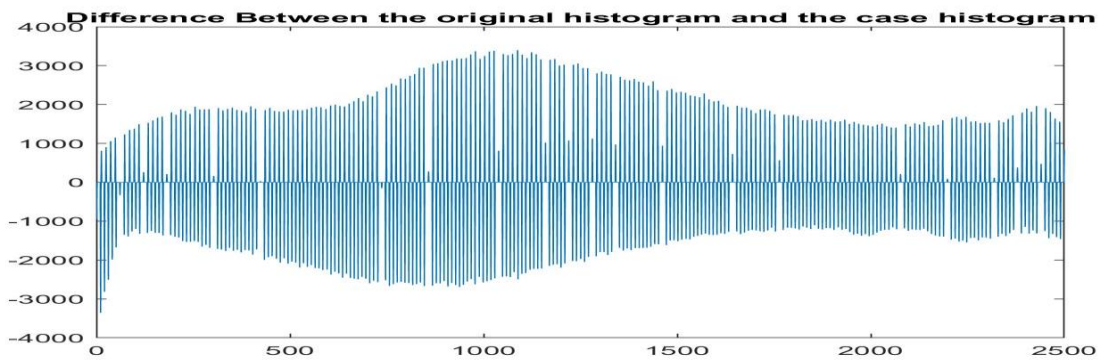**Figure 9:** Grayscale Comparative Histogram Original & Case Artwork Image
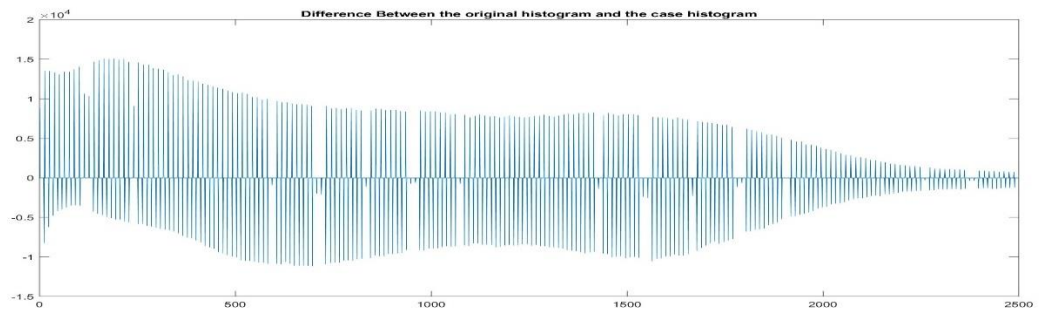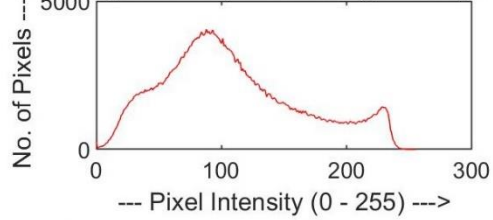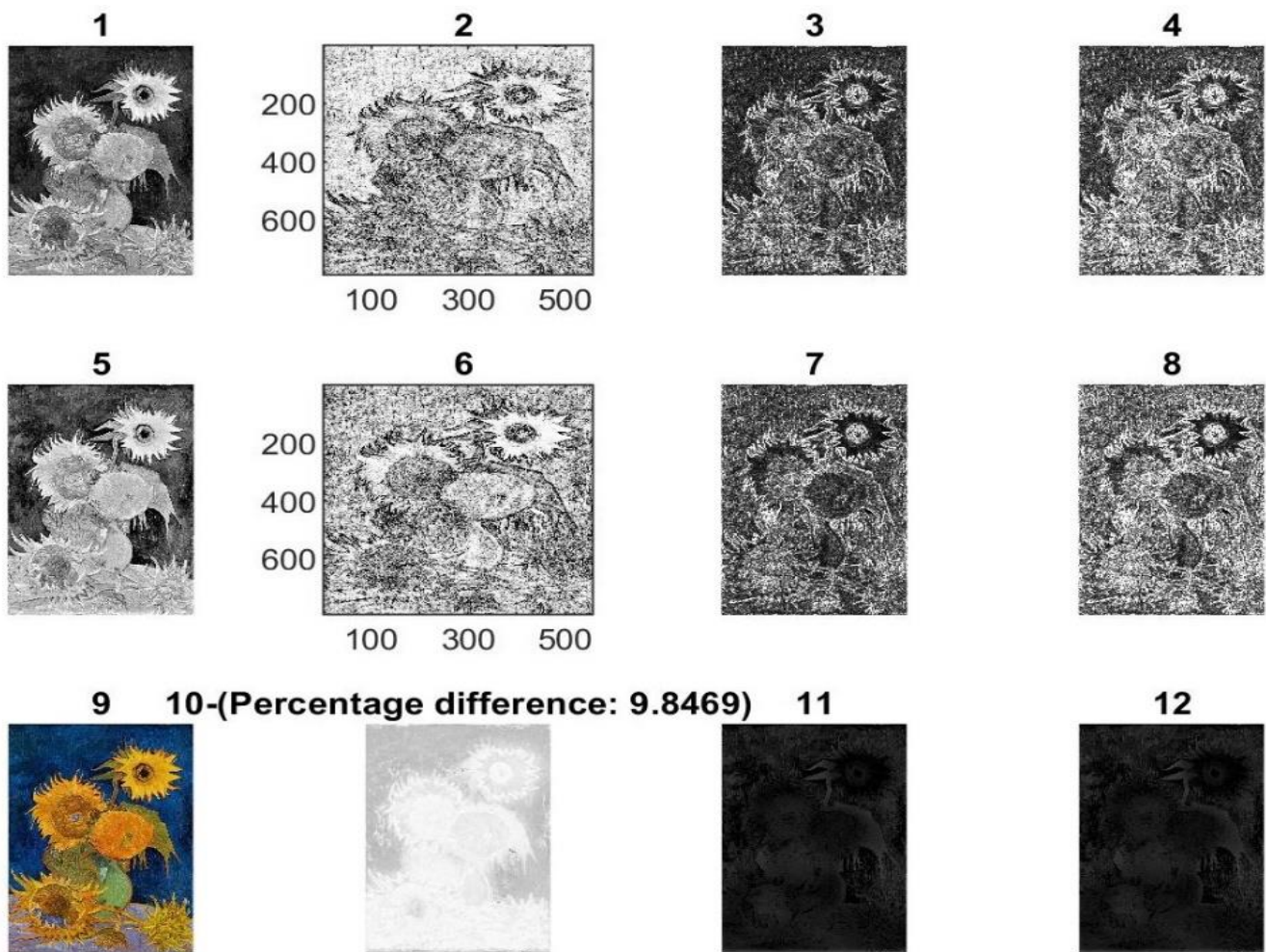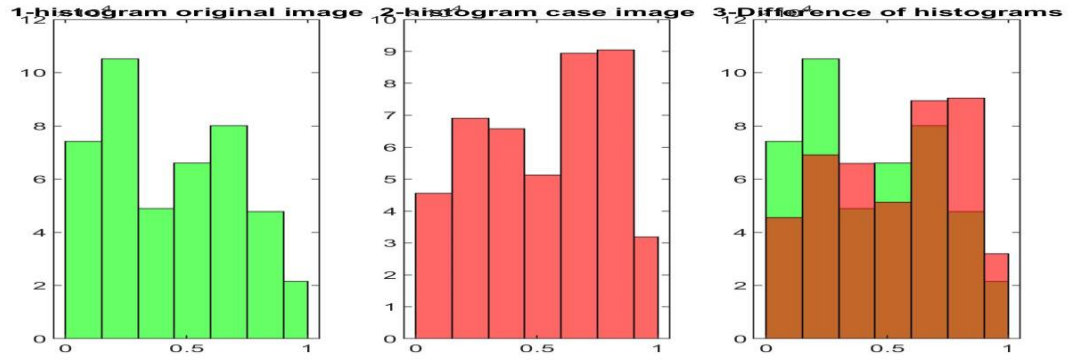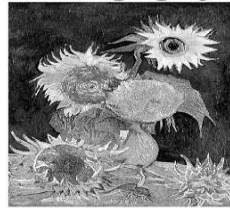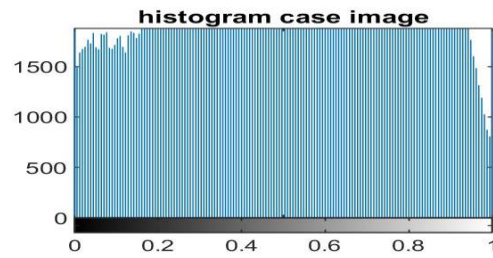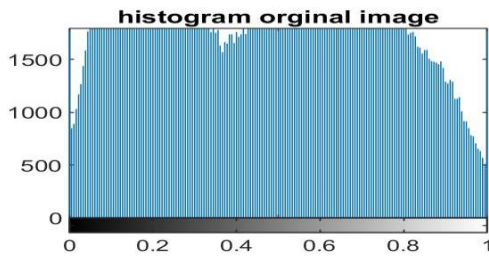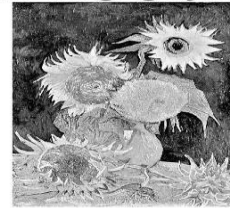


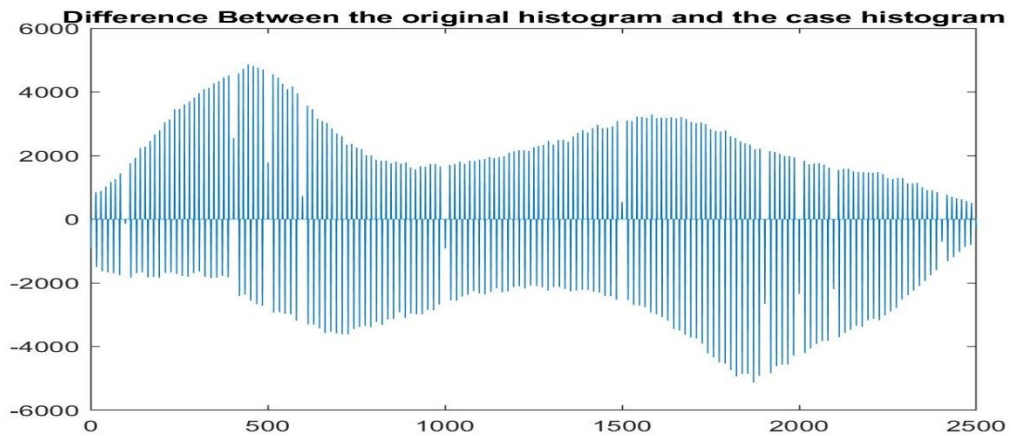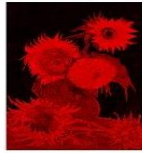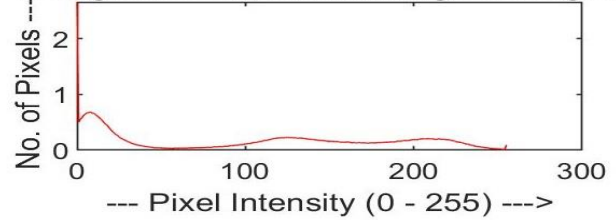**Figure 10:** Grayscale Comparative Histogram Original & Case Artwork Image
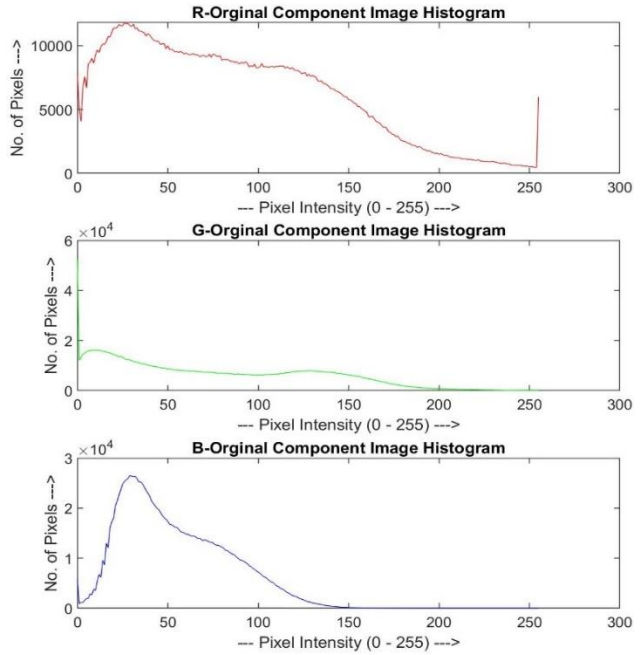
**Figure 11:** RGB analysis of the image of the original artwork image
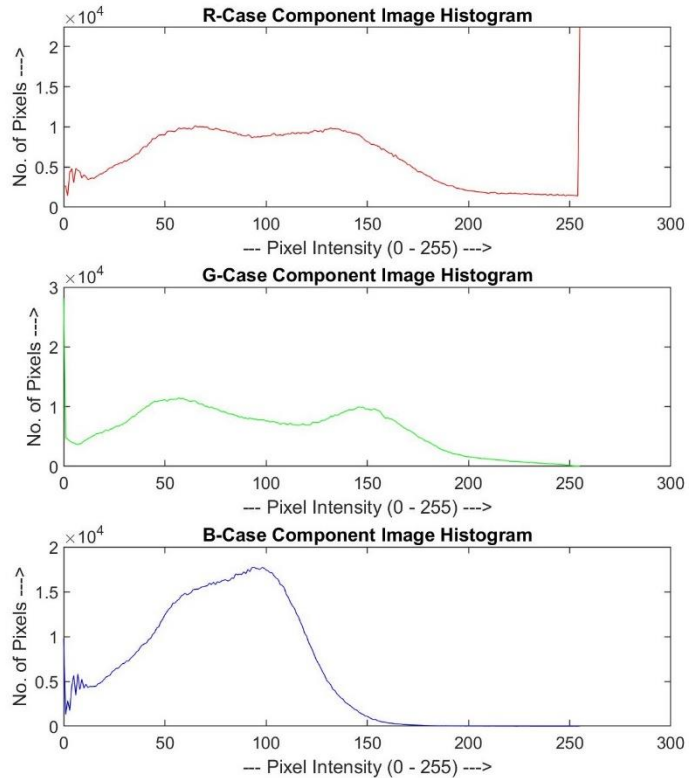


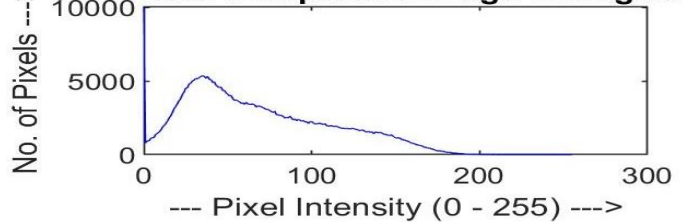**Figure 12:** RGB analysis of the image of the case artwork image

## Experiment 2:



<center>A               B               C</center>

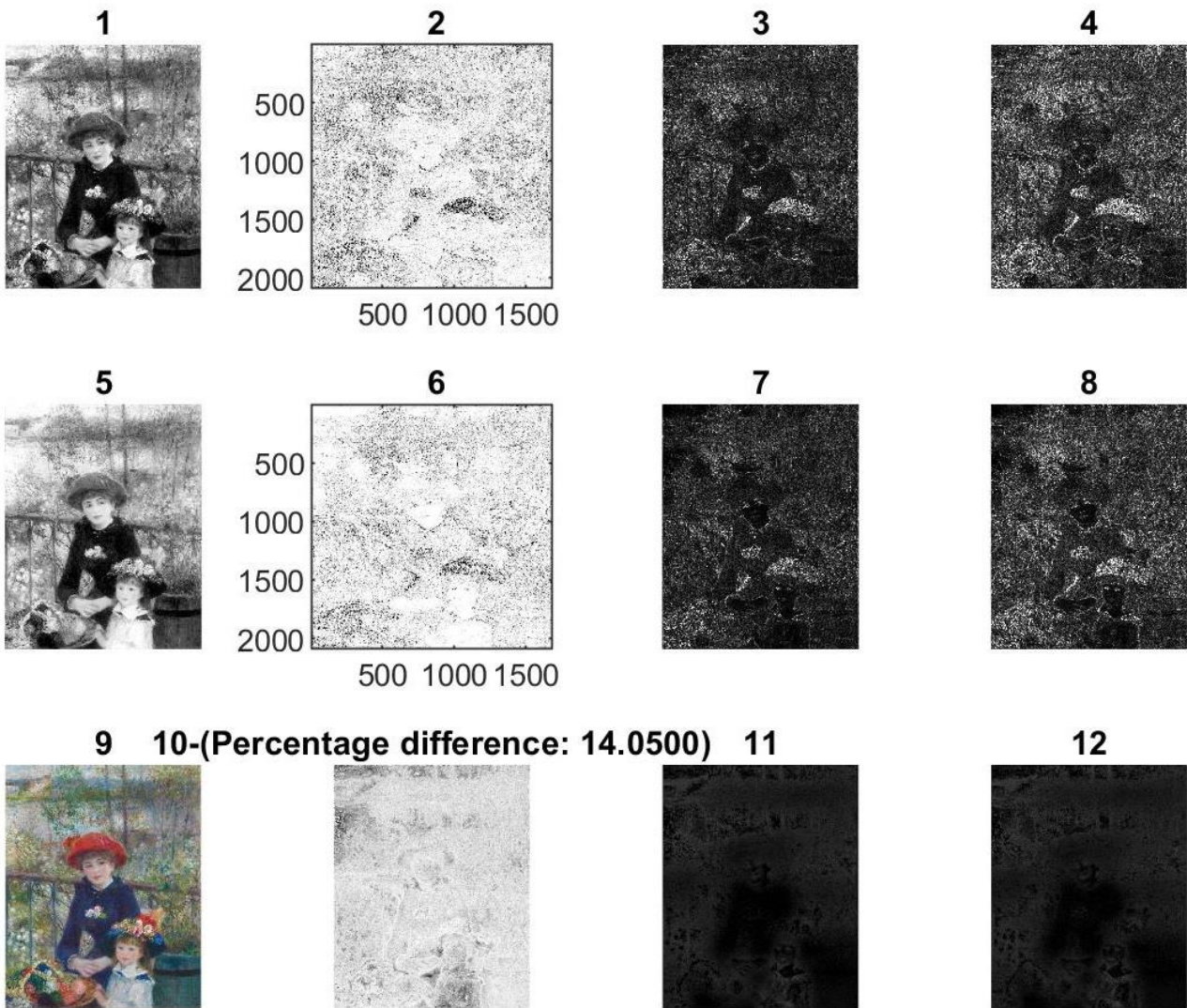**Figure 13:** A: Original Artworks, B: Case Artworks, C: Color Difference
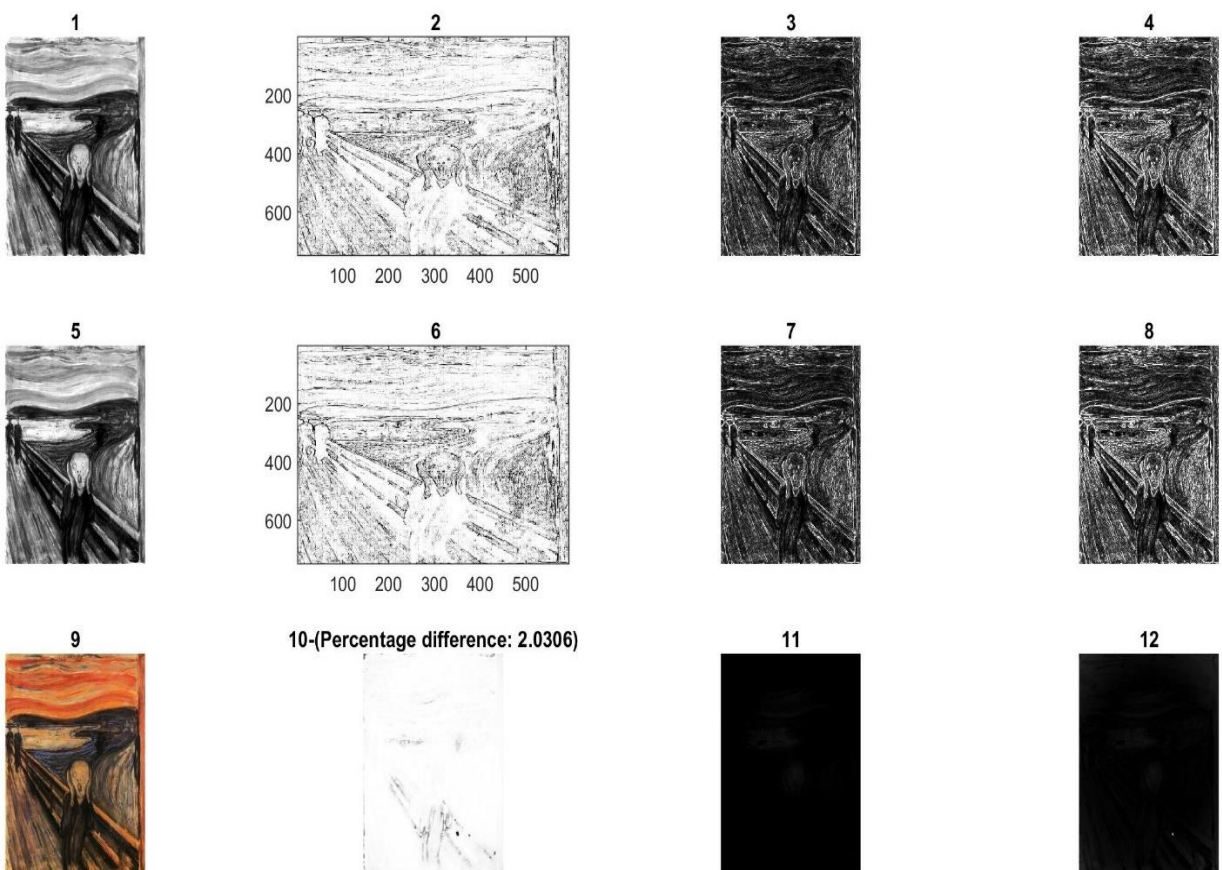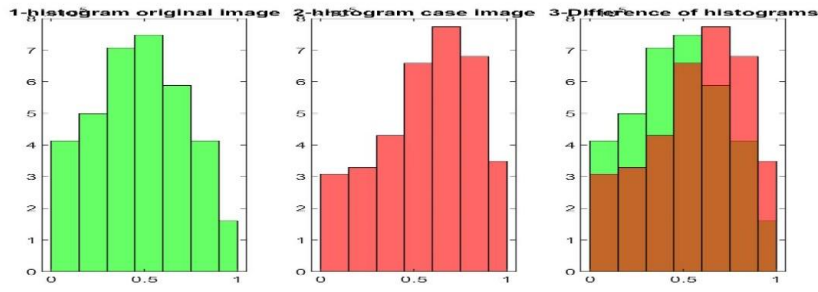


**Figure 14:** Comparative general map (Table3 description)
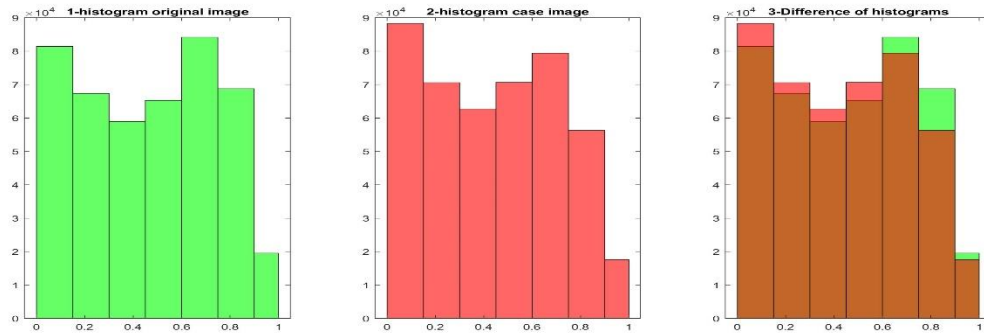
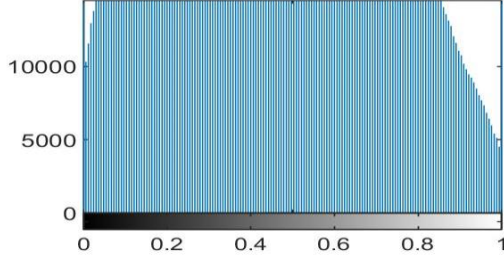**Figure 15:** Grayscale Comparative Histogram Original & Case Artwork Image
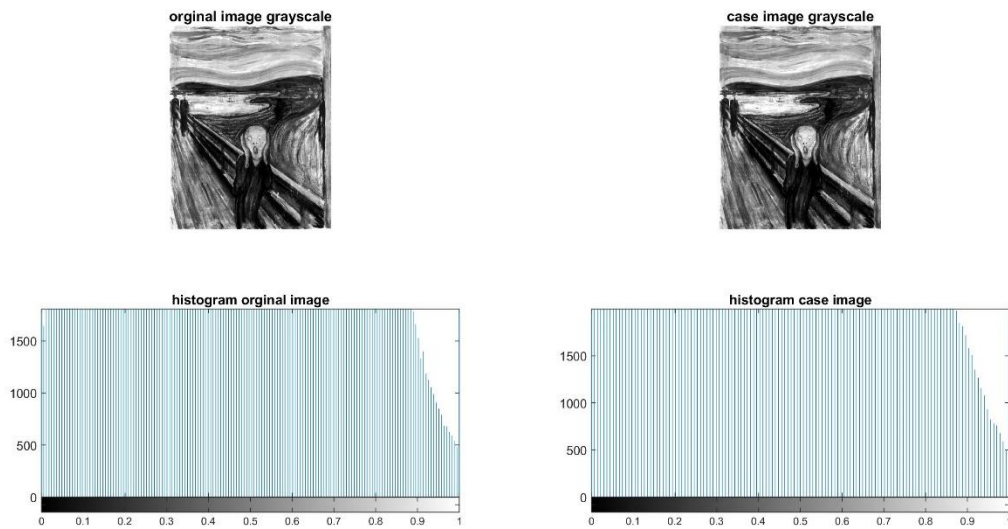


**Figure 16:** Grayscale Comparative Histogram Original & Case Artwork Image
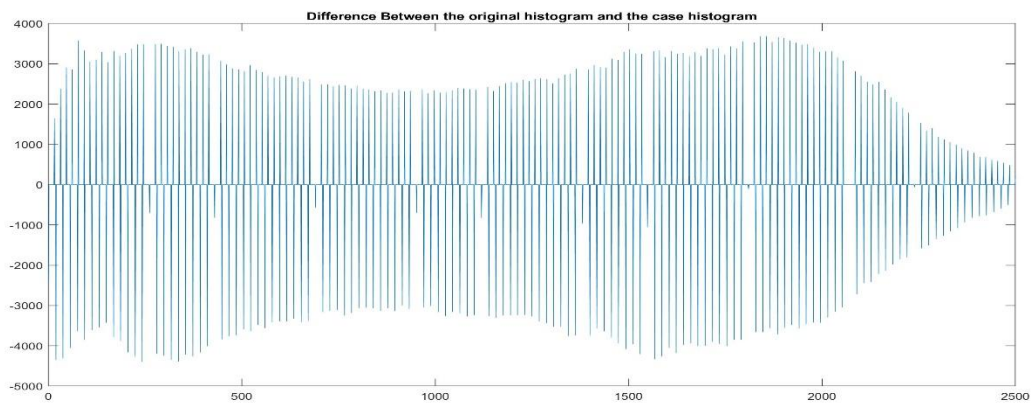


**Figure 17:** Grayscale Comparative Histogram Original & Case Artwork Image
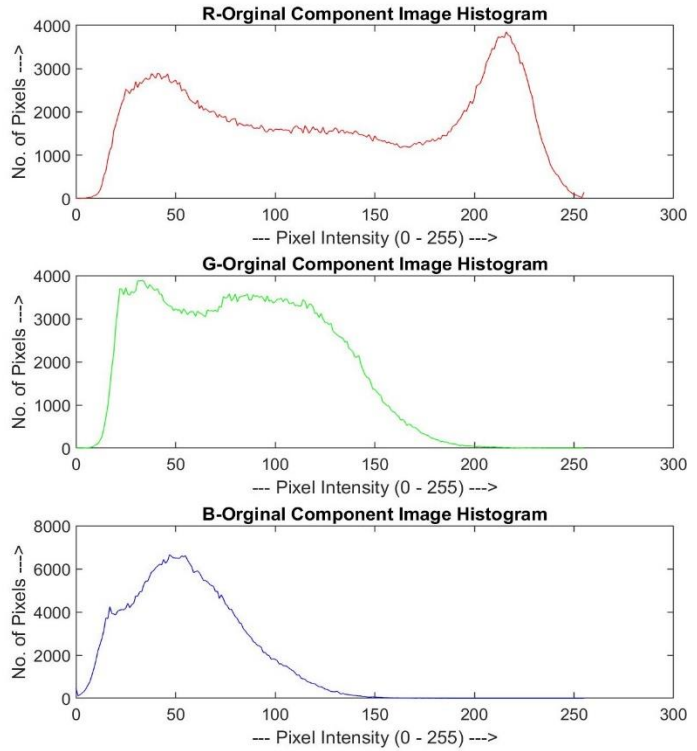
**Figure 18:** RGB analysis of the image of the original artwork image
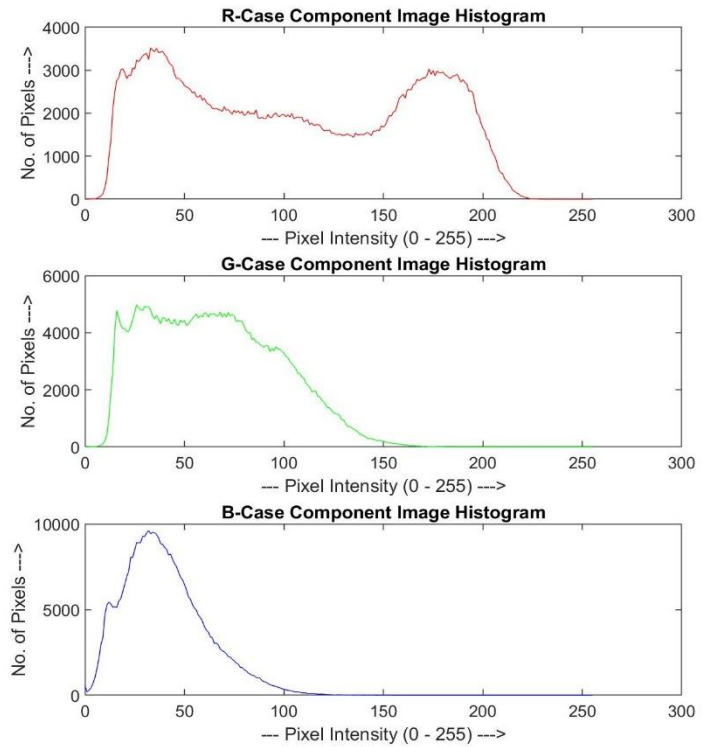


**Figure 19:** RGB analysis of the image of the case artwork image

**Experiment 3:**



A B C
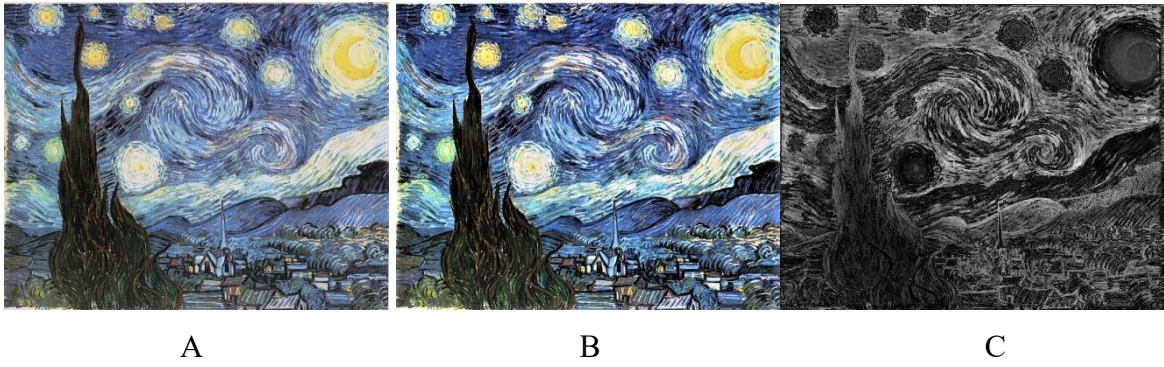
**Figure 20: A:** Original Artworks, B: Case Artworks C: Color Difference
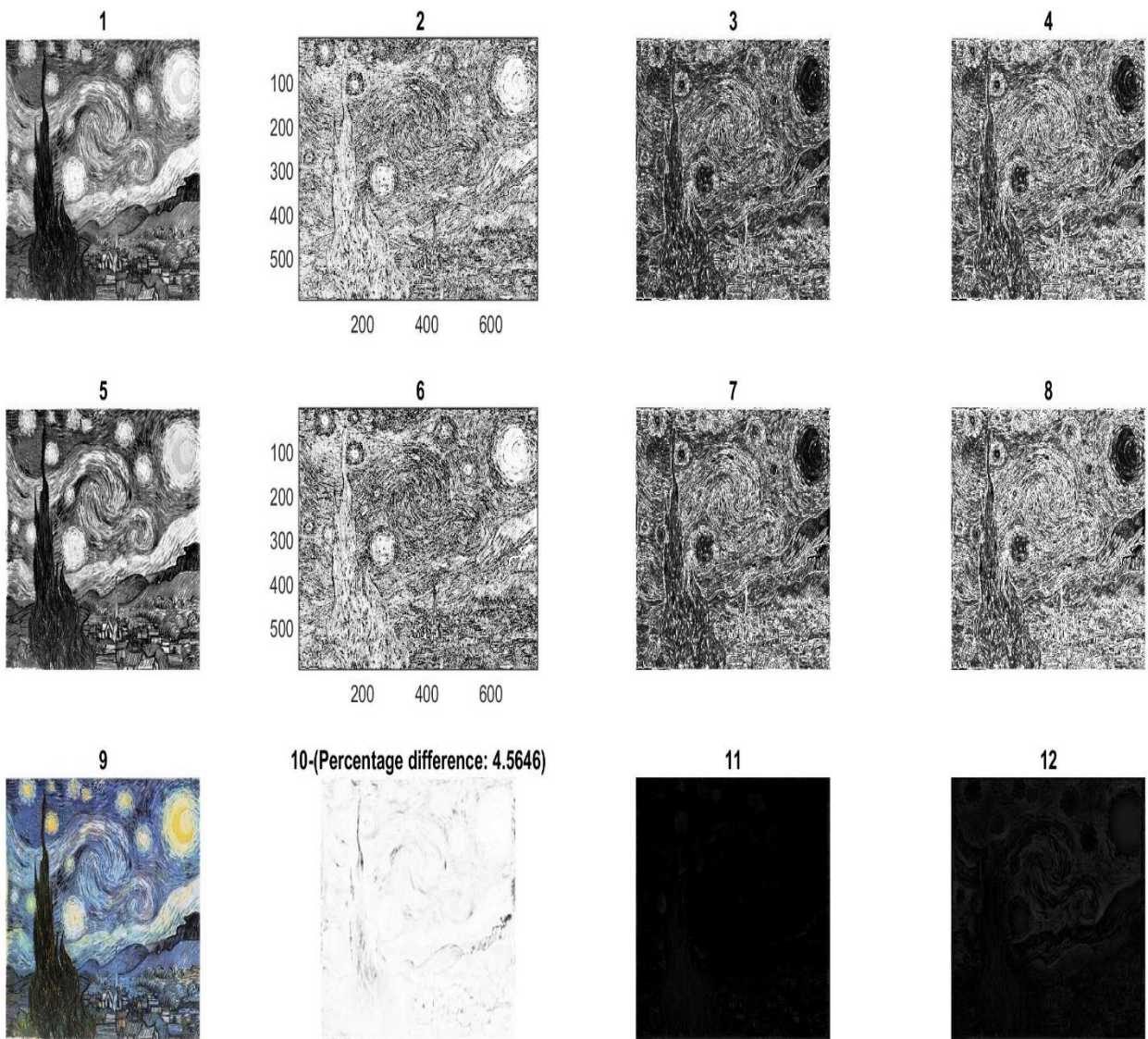


**Figure 21:** Comparative general map (Table3 description)

**Figure 22:** Grayscale Comparative Histogram Original & Case Artwork Image



**Figure 23:** Grayscale Comparative Histogram Original & Case Artwork Image



**Figure 24:** Grayscale Comparative Histogram Original & Case Artwork Image
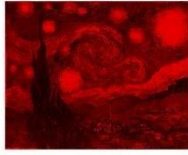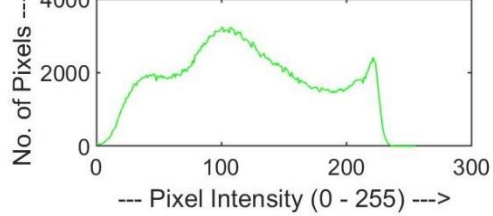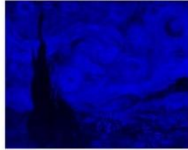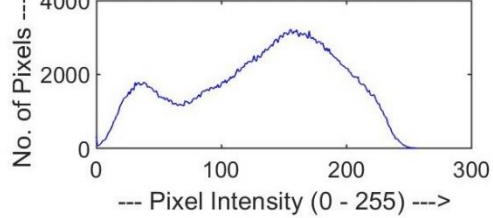
**Figure 25:** RGB analysis of the image of the original artwork image
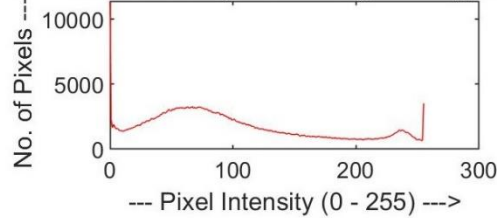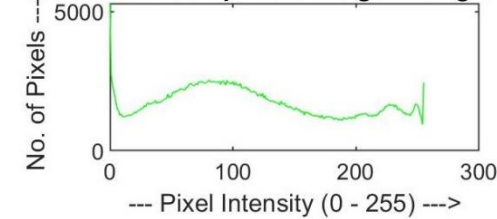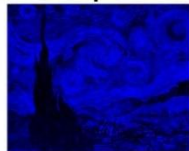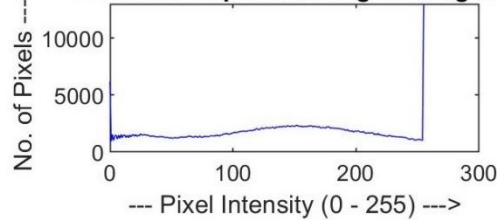


**Figure 26:** RGB analysis of the image of the case artwork image

**Experiment 4:**



A            B            C

**Figure 27:** A: Original Artworks, B: Case Artworks, C: Color Difference



**Figure 28:** Comparative general map (Table3 description)

**Figure 29:** Grayscale Comparative Histogram Original & Case Artwork Image



**Figure 30:** Grayscale Comparative Histogram Original & Case Artwork Image



**Figure 31:** Grayscale Comparative Histogram Original & Case Artwork Image
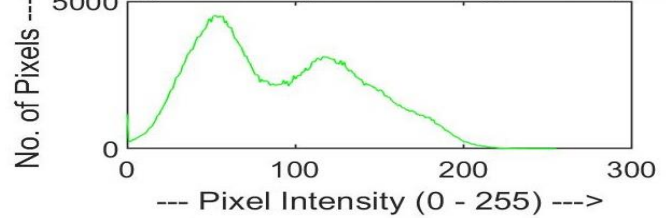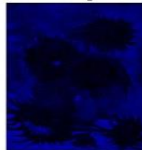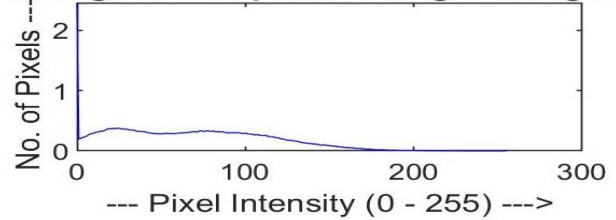
**Figure 32:** RGB analysis of the image of the original artwork image
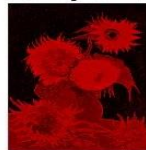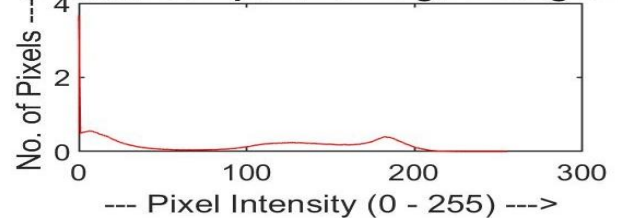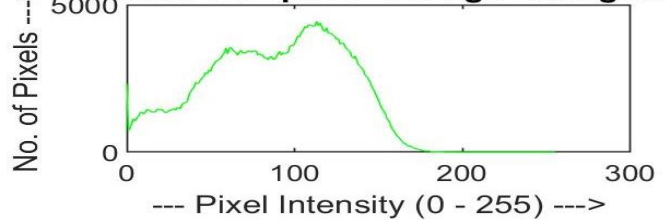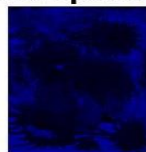


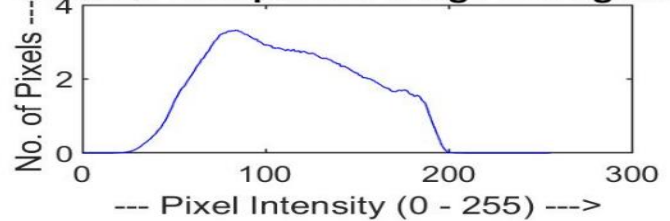**Figure 33:** RGB analysis of the image of the case artwork image

**Experiment 5:**



A                  B                  C

**Figure 34:** A: Original Artworks, B: Case Artworks, C: Color Difference



**Figure 35:** Comparative general map (Table3 description)

**Figure 36:** Grayscale Comparative Histogram Original & Case Artwork Image
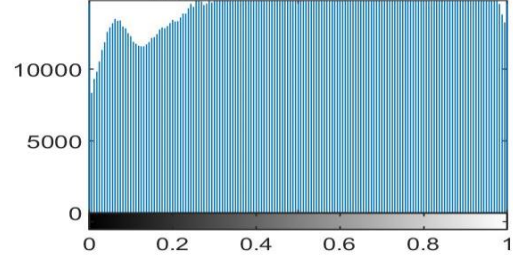


**Figure 37:** Grayscale Comparative Histogram Original & Case Artwork Image
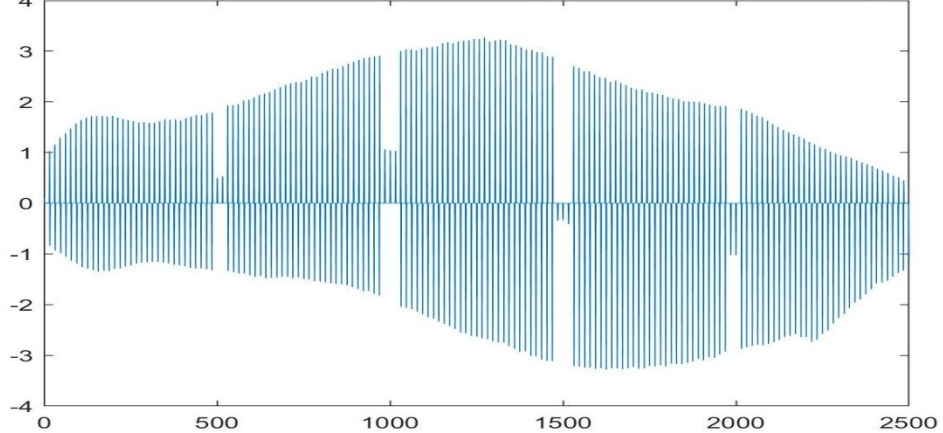


**Figure 38:** Grayscale Comparative Histogram Original & Case Artwork Image
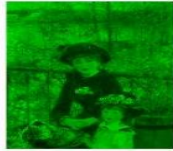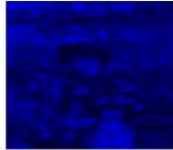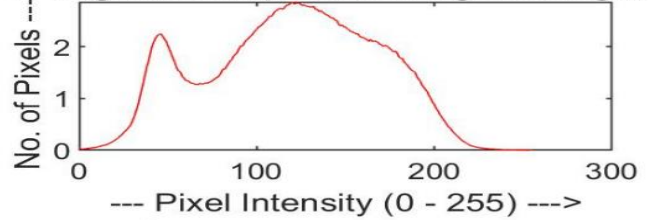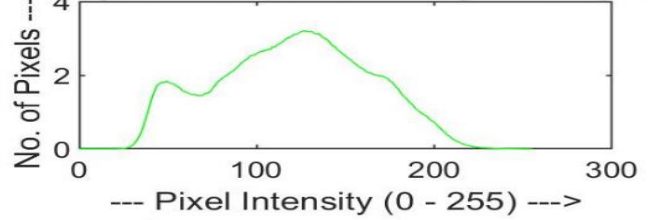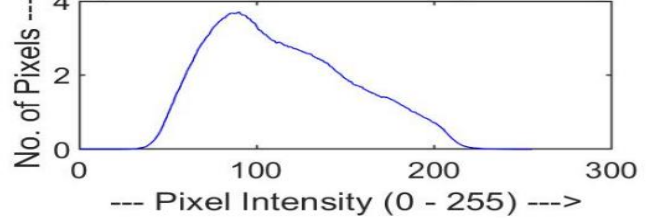
**Figure 39:** RGB analysis of the image of the original artwork image
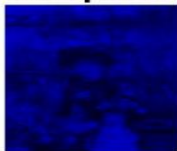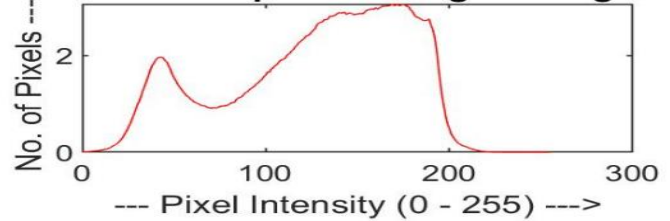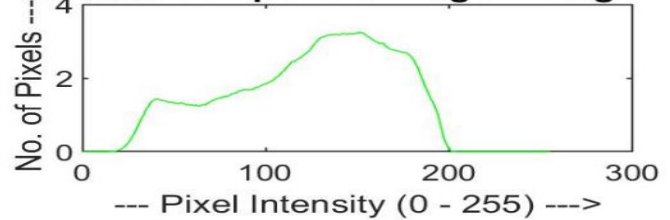


**Figure 40:** RGB analysis of the image of the case artwork image

**Experiment 6:**



A       B       C

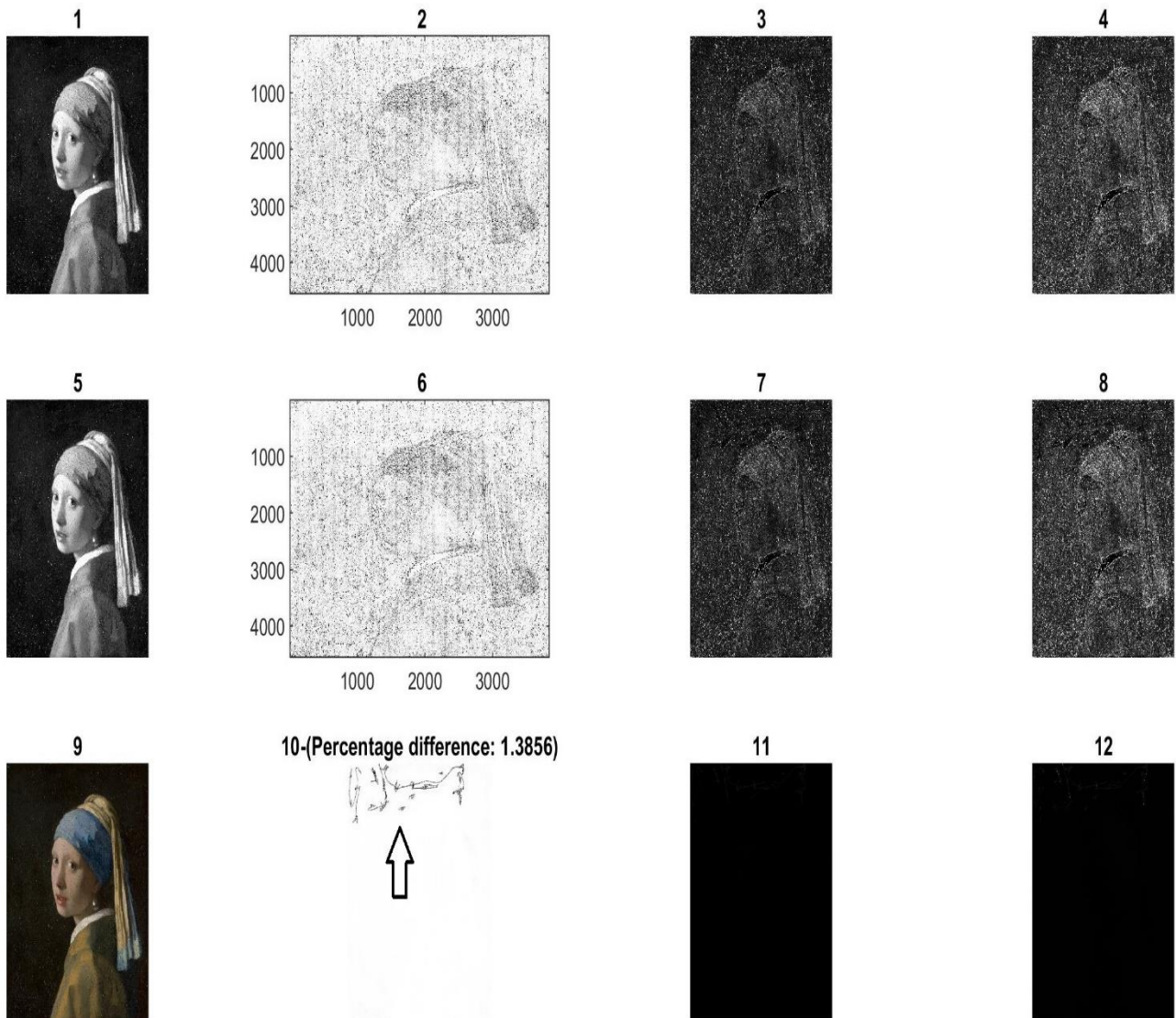**Figure 41:** A: Original Artworks, B: Case Artworks C: Color Difference



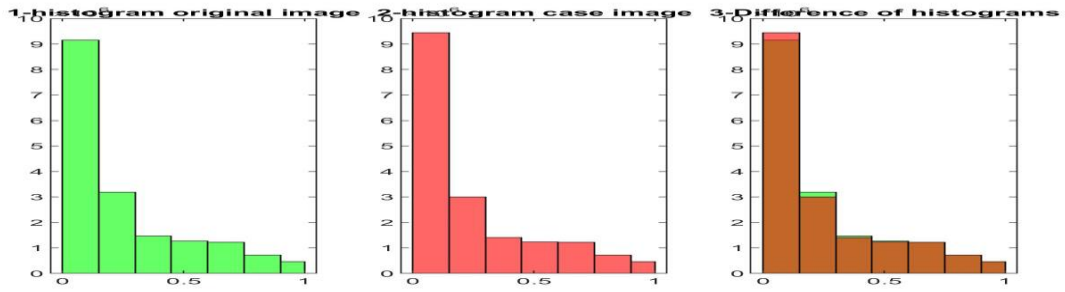**Figure 42:** Comparative general map (Table3 description)

**Figure 43:** Grayscale Comparative Histogram Original & Case Artwork Image
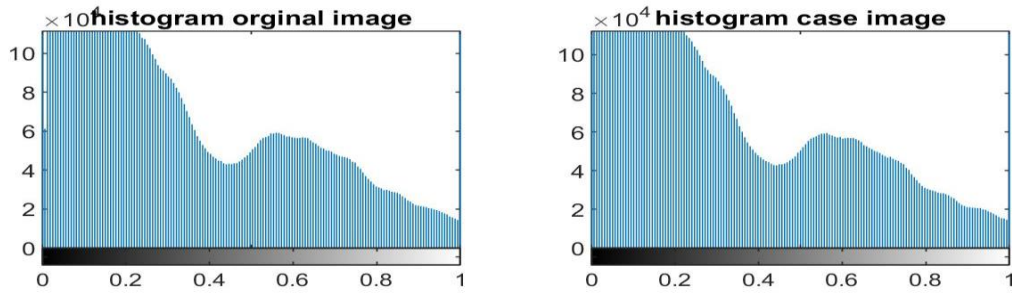


**Figure 44:** Grayscale Comparative Histogram Original & Case Artwork Image
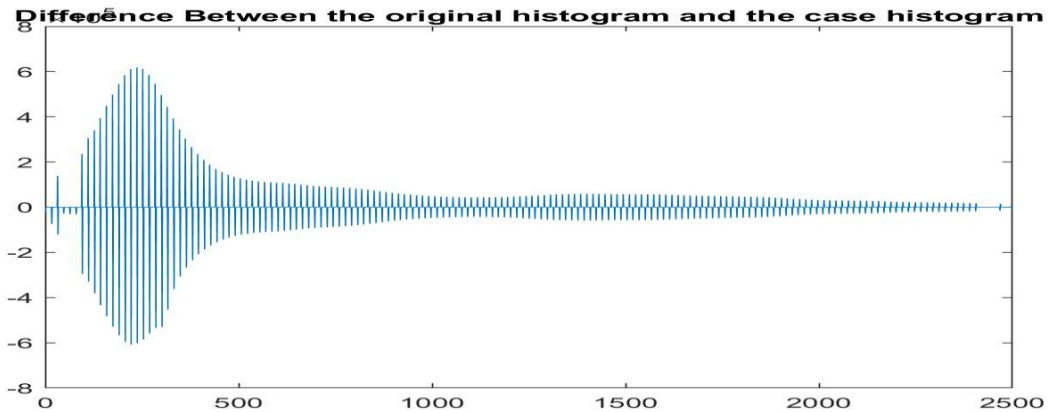


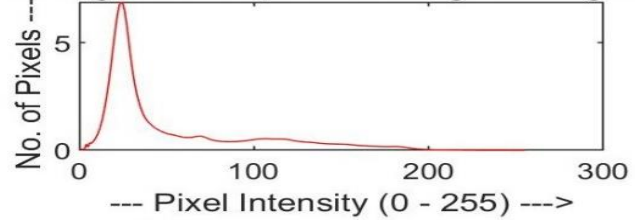**Figure 45:** Grayscale Comparative Histogram Original & Case Artwork Image
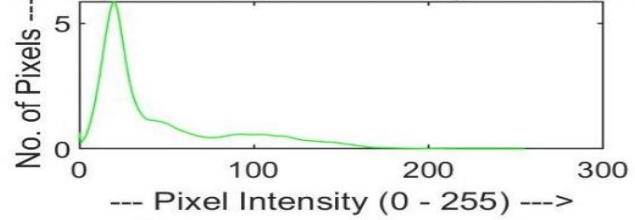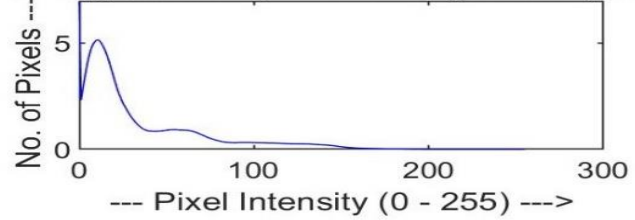
**Figure 46:** RGB analysis of the image of the original artwork image
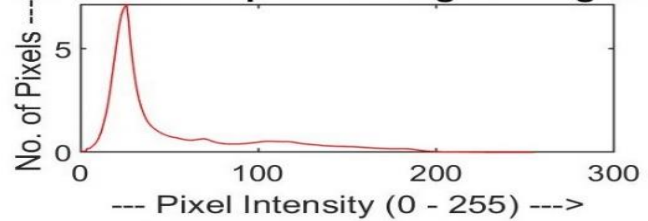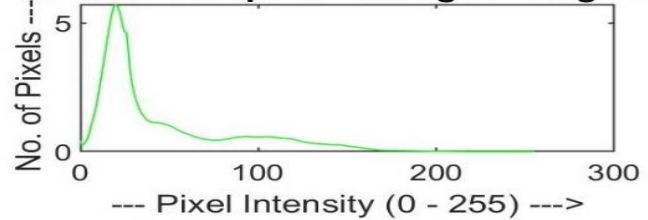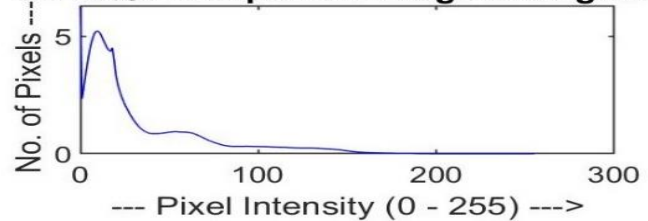


**Figure 47:** RGB analysis of the image of the case artwork image

**Experiment 7:**



A



B



C

**Figure 48:** A: Original Artworks, B: Case Artworks C: Color Difference



**Figure 49:** Grayscale Comparative Histogram Original & Case Artwork Image

**Figure 50:** Comparative general map (Table3 description)



**Figure 51:** Grayscale Comparative Histogram Original & Case Artwork Image

**Figure 52:** RGB analysis of the image of the original artwork image



**Figure 53:** RGB analysis of the image of the case artwork image

## 4. Discussion

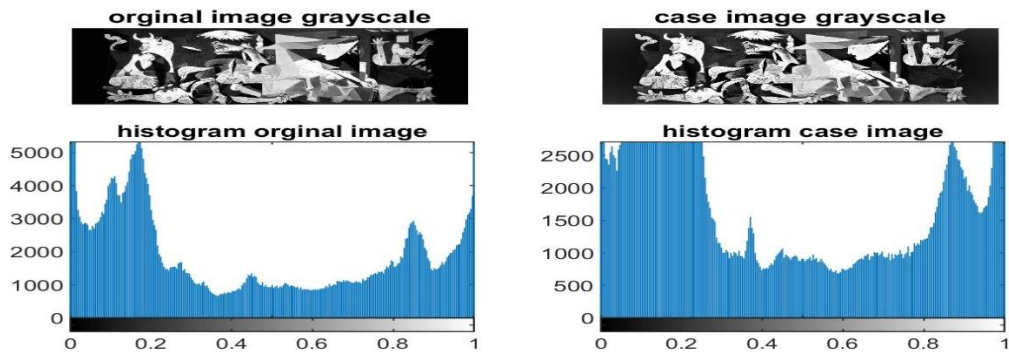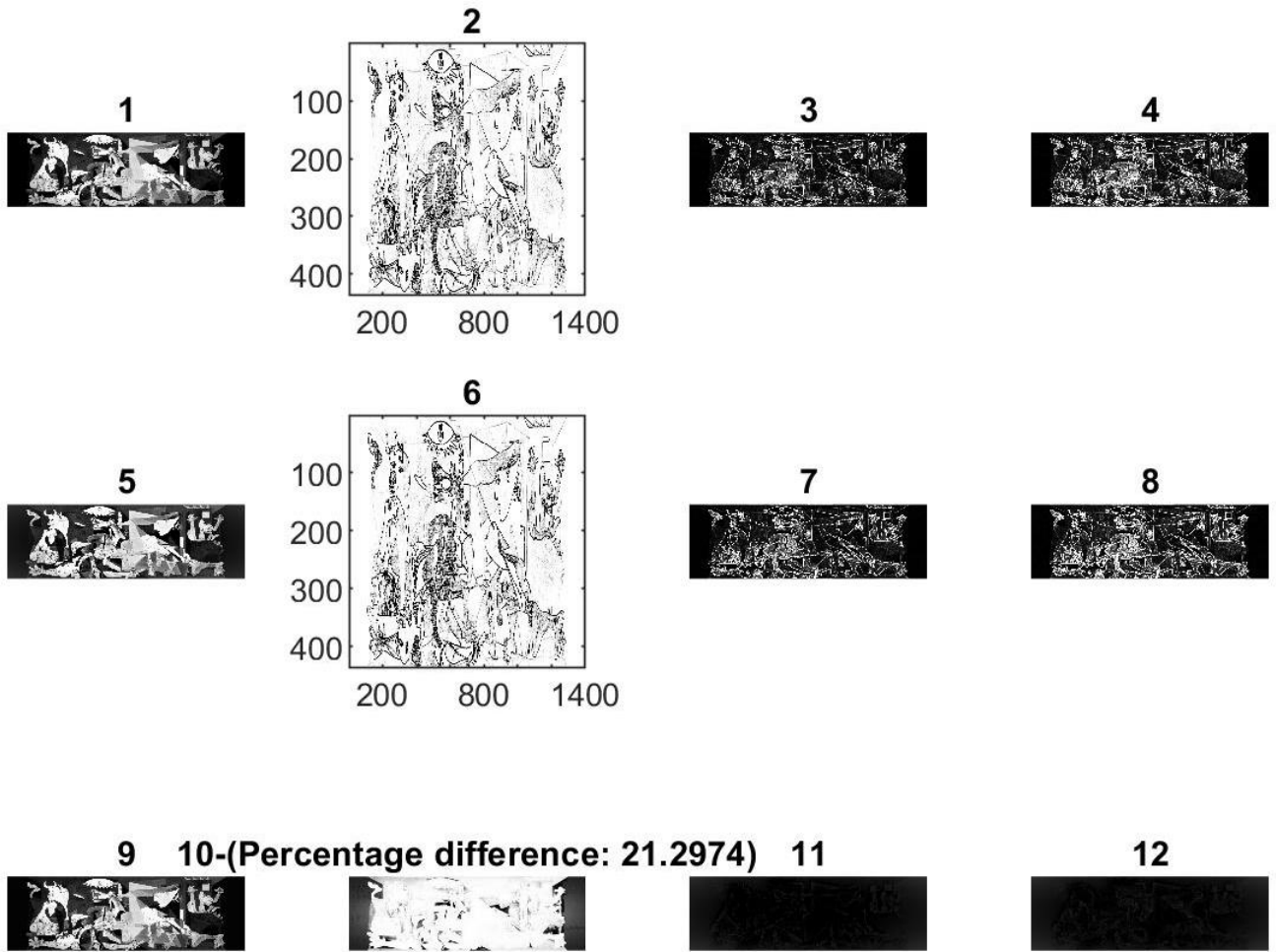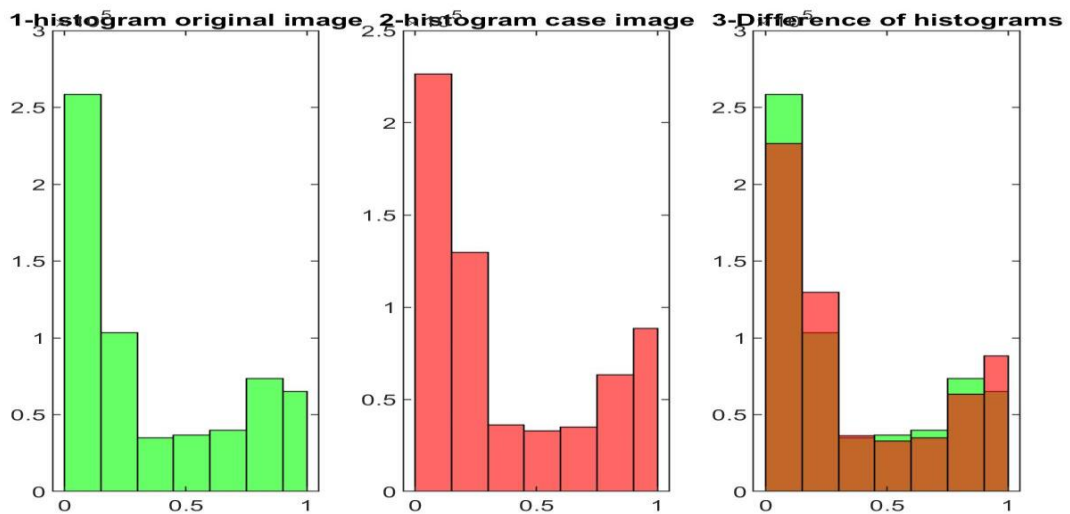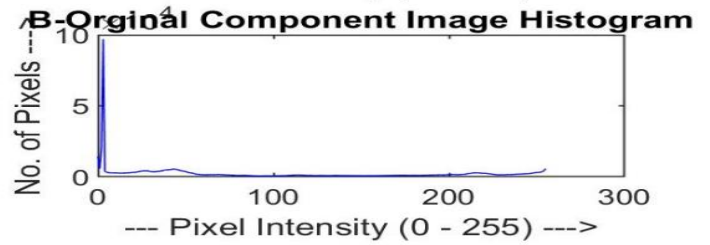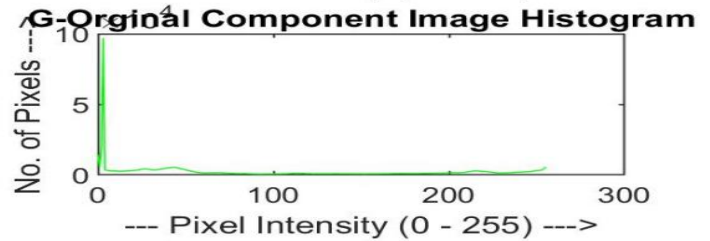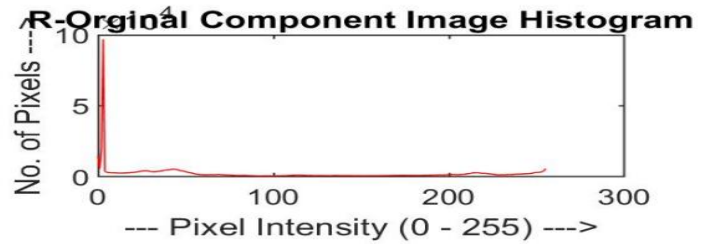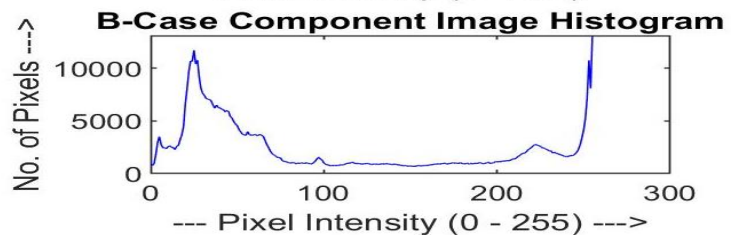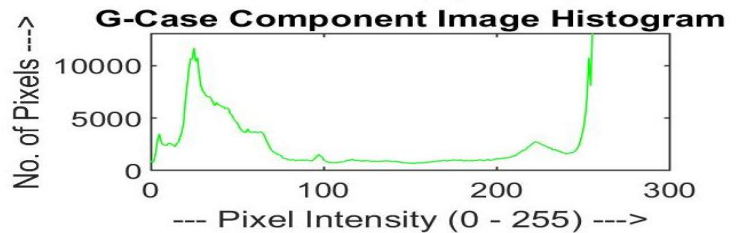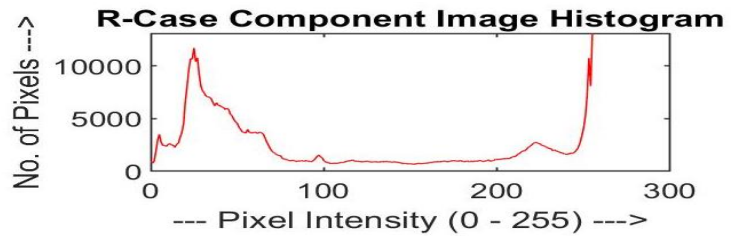In this model, non-destructive methods have been used for the authenticity recognition of artwork because the artwork is unique and the test should not have any destructive effect on them. Only when photographing the original work, safety and protection points must be carefully observed, including photographing without exposing the image to radiation and using natural light, etc. Once the image with the desired quality is obtained, the rest of the steps are done by mathematical algorithms and we have nothing to do with artwork. In the mentioned model, nine different algorithms have been used to perform the test. As it was said, due to the accuracy of the comparison within one pixel and the possible error removal part of the model, the accuracy of the results is near 100%.

## 5. Implication

The presented model can be used to authenticate recognition artworks from their fake type, and it can be a reliable method in case of limitations of imaging (respecting the size of both samples).

## 6. Conclusion

In the presented model, known artificial intelligence methods such as machine learning or neural networks are not used. But with a new approach, I have presented an intelligent tool for the artworks authenticity recognition of works of art, which is beyond the five human senses, and only an intelligent machine can have this capability.

## References

1. Science's war on art fraud. (2024). Cosmos.
2. Mirbod, M., Ghatari, A. R., Saati, S., & Shoar, M. (2022). Industrial parts change recognition model using machine vision, image processing in the framework of industrial information integration. *Journal of Industrial Information Integration, 26,* 100277.
3. Mirbod, M., Rezaei, B., & Najafi, M. (2023). Spatial change recognition model using artificial intelligence to remote sensing. *Procedia Computer Science, 217*, 62-71.
4. Mirbod, M., & Shoar, M. (2023). Intelligent concrete surface cracks detection using computer vision, pattern recognition, and artificial neural networks. *Procedia Computer Science, 217,* 52-61.
5. Saverwyns, S., Currie, C., & Lamas-Delgado, E. (2018). Macro X-ray fluorescence scanning (MA-XRF) as tool in the authentication of paintings. *Microchemical Journal, 137*, 139-147.
6. Sultan, S., Kareem, K., He, L., & Simon, S. (2017). Identification of the authenticity of pigments in ancient polychromed artworks of China. *Analytical Methods*, 9(5), 814-825.
7. Wang, T., Cant, J. S., & Cupchik, G. (2016). The impact of depth of aesthetic processing and visual-feature transformations on recognition memory for artworks and constructed design patterns. *Empirical Studies of the Arts,* 34(2), 193-220.
8. Tomei, M., Cornia, M., Baraldi, L., & Cucchiara, R. (2019). Art2real: Unfolding the reality of artworks via semantically-aware image-to-image translation. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition* (pp. 5849-5859).
9. Cetinic, E., & She, J. (2022). Understanding and creating art with AI: Review and outlook. *ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM),* 18(2), 1-22.
10. Kanopoulos, N., Vasanthavada, N., & Baker, R. L. (1988). Design of an image edge detection filter using the Sobel operator. *IEEE Journal of solid-state circuits,* 23(2), 358-367.
11. Seif, A., Salut, M. M., & Marsono, M. N. (2010, November). A hardware architecture of Prewitt edge detection. In *2010 IEEE conference on sustainable utilization and development in engineering and technology* (pp. 99-101). IEEE.
12. Wang, Z., Bovik, A. C., Sheikh, H. R., & Simoncelli, E. P. (2004). Image quality assessment: from error visibility to structural similarity. *IEEE transactions on image processing*, 13(4), 600-612.
13. Bovik, A. C. (2009). *The essential guide to video processing*. Academic Press.
14. Da Xu, L. (2014). *Enterprise integration and information architecture: A systems perspective on industrial information integration.* CRC Press.