Visual Exploration of Landscape Painting Through Drone Photography Using Neural Style Transfer

Xin Cheng, Feng Wang, Muhammad Haris Muneer and Zain Anwar Ali

Abstract— **This research aims to explore the visual exploration of landscape painting through drone photography. With the rapid development of drone technology, its application in the field of photography has presented unique advantages. This paper will focus on the application potential of drone photography in landscape painting, specifically through the acquisition and image processing of aerial images, investigating its impact and value in the creative process. It also explores the integration of deep learning techniques, particularly neural style transfer, to blend aerial drone images with artistic styles. By leveraging a pre-trained deep learning model, the process extracts features from both content and style images, calculates Gram matrices to capture style information, and iteratively optimizes the target image to merge the content of aerial drone photography with the style of traditional landscape painting. This approach enhances visual expression by expanding creative possibilities for artists, offering innovative methods to transform drone images into unique artistic interpretations while maintaining content integrity and stylistic creativity.**

Index Terms— **Image processing, Deep learning, Neural Style Transfer, Artificial Intelligence**

I. Introduction

OVER time, technological advancements have led to the widespread use of unmanned systems in various fields. Nowadays, aerial photography frequently employs unmanned aerial vehicles (UAVs) and drones. Aerial photography technology has been used for military, photography, and painting purposes [1], [2]. Painting from high-altitude images is an extremely challenging and difficult task. Images in different color spaces provide high perception and inspiration for artistic creation. This technology aids in the production of landscape paintings [3]. Creating the illusion of nature on a flat surface has always been difficult. Aerial photography's visual experience breaks outdated artistic terminologies and provides more space for artistic creation [4].

Convolutional Neural Networks (CNNs) are sophisticated deep learning models designed to analyze and process images by extracting features across multiple layers [5-7]. These networks can identify increasingly complex visual elements, progressing from basic edges and textures to more intricate shapes and objects. Their remarkable ability to understand image characteristics makes them particularly powerful in various image-related applications, including classification, object detection, segmentation, and generation [8-11].

Style transfer represents an innovative technique that harnesses the feature extraction capabilities of CNNs to create novel images by combining the content of one image with the stylistic elements of another [12]. The groundbreaking work in this field was introduced by Gatys et al., who developed a method using a pre-trained VGG network to analyze and transfer image styles [13].

The core of their approach involves using a Gram matrix to capture the textural and statistical characteristics of a style image. By carefully minimizing the differences between the generated image's style and the target style while preserving the original image's content, researchers can create visually compelling transformed images.

Since its initial introduction, style transfer has undergone significant evolution. Researchers have proposed numerous enhancements to improve the technique, including by increasing network complexity, developing multi-scale transfer methods, creating real-time applications, and exploring cross-domain implementations. These advancements have expanded the potential of style transfer, making it more versatile and applicable across different domains. From artistic creation to image editing and design, technology continues to push the boundaries of how we understand and manipulate visual content.

The ongoing research in style transfer represents an exciting intersection of computer vision and artificial intelligence. By enabling the creative recombination of image content and style, this technology opens up new possibilities for digital image manipulation and artistic expression, promising continued innovation in the field.

The contributions of this research are:

- The paper bridges the gap between aerial drone photography and traditional artistic techniques by integrating advanced technologies. It showcases how high-quality aerial images captured through drones can be transformed into artistic masterpieces,

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expanding the creative possibilities for landscape painting.

- It applies neural style transfer, a deep learning technique, to merge the content of aerial photographs with the artistic styles of traditional paintings. This innovative use of technology offers a new methodology for creating art that combines modern digital imaging with classical aesthetics.
- The study emphasizes the creative potential of aerial photography in art, which provides artists with perspectives previously inaccessible, leading to fresh interpretations of landscapes.
- The research contributes to the ongoing dialogue between art and technology, demonstrating how modern tools can revolutionize traditional artistic practices. It highlights an innovative trend in the art world, where digital and traditional methods converge to redefine creative processes.

The manuscript is organized as follows: Section 2 describes the state-of-the-art research, and section 3 presents the problem statement and solution. Section 4 discusses the methodology of this research. Section 5 presents the results and their discussion, while Section 6 presents the conclusion.

II. State of The Art

This section of the manuscript defines the recent trends in this field. In [14], the article proposes damage identification through image processing. Firstly, the segmentation process is done by thresholding and then the Markov random field technique is used to allocate labels to model the spatial needs. To determine the defective area, the RGB technique is used. Lastly, the K-means algorithm is used for clustering the images. A case study is presented in the manuscript to show the effectiveness of the used techniques. The computational results show the required detection through image processing with higher accuracy. Furthermore, in [15], the paper presents a novel method to explore the high-resolution images of ground for soil organic matter SOM estimation. Deep learning methods are used to extract the soil from the attained images. After the acquisition of sample images, ambient illumination stimulates the color of the soil. Besides, texture and color space features are extracted. Finally, the proposed method is compared to different state-of-the-art methods. The results show the effectiveness with higher accuracy of the designed scheme.

In [16], a prototype UAV has been used for the exploration of energy transmission lines. It attains the capability of viewing through different angles which provides more effective exploration. The data collected through UAV now further proceed with image processing and conventional neural network techniques. Moreover, the path of the UAV and detected objects proceeded in the Cartesian coordinate system. Through color space range, the tracking system provides conductors bidirectional tracking. To operate in rough weather conditions, PID is used. Simulation results show impressive scores in detecting many variances. Lastly, another research article [17] uses UAVs for aerial images and videos to investigate sediment plumes. The speed and motion of plumes were measured as they may affect the impact of plume turbidity. The required image is extracted and then RGB-HSV conversion takes place. Furthermore, the segmentation process takes place to determine the required plumes.

III. Problem Statement and Solution

Traditional landscape painting has long faced the challenge of accurately capturing the intricate details and vast perspectives of natural scenes. Despite advancements in painting techniques, artists often struggle to convey the expansive beauty and unique viewpoints of nature on a two-dimensional canvas. The advent of aerial photography has opened new avenues for artistic creation [18], yet integrating these aerial perspectives into artistic representations remains underexplored. Moreover, the lack of tools that seamlessly blend photographic content with artistic styles limits the creative potential for artists who wish to innovate within the medium.

In recent years, the intersection of technology and art has presented exciting opportunities, particularly through the use of drones and deep learning techniques [19]. However, there is a gap in applying these technologies cohesively to transform aerial imagery into visually compelling, stylized artworks. This research aims to address this gap by leveraging drone photography and neural style transfer, enabling the synthesis of traditional artistic elements with modern digital photography to revolutionize the process of landscape painting.

The proposed solution employs drone technology to capture high-resolution aerial images and deep learning models for style transfer to merge these images with artistic styles. Using drones like the DJI Mini Pro, artists can access unique perspectives and fine-grained details of landscapes previously unattainable through traditional means. Neural style transfer techniques are then applied to these images, extracting stylistic features from iconic works of art and combining them with the content of drone-captured photographs.

By iteratively processing these images, the solution provides a framework for transforming raw aerial photos into artistic masterpieces. This method not only preserves the integrity of the original content but also imbues the images with distinct artistic expressions. The integration of drone photography and advanced image processing thus opens a pathway for new forms of creativity, enriching the field of landscape painting and enabling artists to transcend conventional boundaries.

IV. Methodology

The methodology for the style transfer process involves leveraging the power of deep learning and computer vision techniques to blend the content of one image with the artistic style of another. This method can be broken into distinct stages:

A. Data Acquisition and Preparation

The process begins with acquiring two key inputs: a content image and a style image. The content image represents the structure and layout of the final artwork, while the style image provides the artistic textures, colors, and patterns. These images are pre-processed to ensure compatibility with the neural network. Pre-processing involves resizing images to a manageable size to balance detail and computational feasibility. Pre-processing also involves normalizing image pixel values to align with the input requirements of the pre-trained deep learning model.

B. Feature Extraction Using a Pre-trained Model

A pre-trained VGG19 convolutional neural network (CNN) is used to extract hierarchical features from both the content and style images. This model, originally designed for image classification, is repurposed to identify patterns and abstractions at different layers, i.e., content features that are extracted from deeper layers of the model, representing the structural aspects of the image (e.g., shapes and layout); and style features which are captured from multiple layers, focusing on texture and color distributions. These features are represented using Gram matrices, which encode spatial relationships between activations in the CNN.

C. Initialization of the Target Image

The target image, which will eventually blend the content and style, is initialized as a copy of the content image. This ensures that the structural layout of the content is preserved from the start. The target image's pixel values are treated as variables that will be optimized.

D. Loss Function Design

To effectively combine the content and style into the target image, a composite loss function is defined, which includes content loss and style loss. Content loss measures the difference between the content features of the target image and those of the original content image, ensuring the structural integrity of the content is maintained. While style loss compares the style features of the target image with those of the style image. It ensures that the target image captures the textures and patterns of the style image. The total loss is a weighted sum of the content loss and style loss, with adjustable weights to balance their contributions.

E. Optimization

The target image is iteratively updated to minimize the total loss using the Adam optimizer, a gradient-based optimization algorithm. Over several iterations, the content loss guides the preservation of the structural layout, the style loss adjusts the textures and patterns to match the style image, and the optimizer computes gradients with respect to the target image's pixels, progressively transforming it to resemble a harmonious blend of content and style.

F. Iterative Refinement and Convergence

The optimization process runs for a predefined number of iterations or until the changes in loss become negligible (early stopping). At regular intervals, the target image is visualized to monitor the progress and ensure that the transformation is proceeding as expected.

G. Result Evaluation

Once the optimization completes, the final target image represents a stylized version of the content image, reflecting the artistic essence of the style image. The result is evaluated qualitatively by assessing the visual coherence and aesthetic appeal.

Figure 1 presents the methodology flowchart.

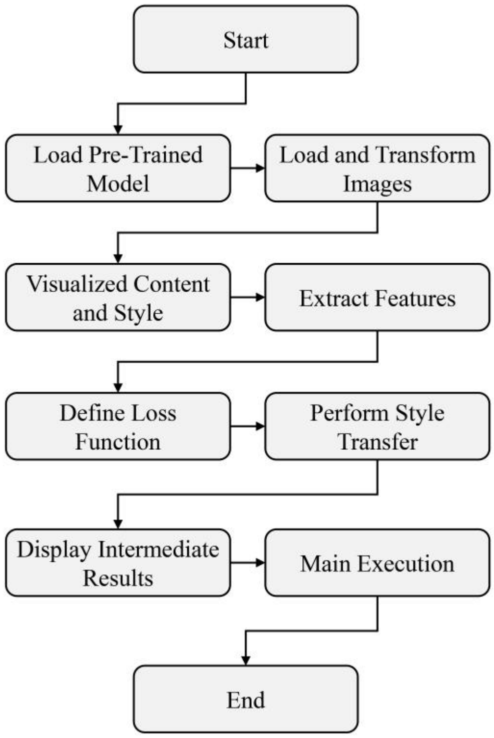


Fig. 1. Methodology Flowchart

Algorithm 1:

1: Procedure StyleTransfer(content_img, style_img, max_iter, content_weight, style_weight)
2: content_tensor ← LoadAndPreprocess(content_img)
3: style_tensor ← LoadAndPreprocess(style_img, shape = content_tensor.shape)
4: vgg_model ← LoadPretrainedVGG19()
5: FreezeParameters(vgg_model)
6: content_features ← ExtractFeatures(vgg_model, content_tensor, layers =["conv4_2"])
7: style_features ← ExtractFeatures(vgg_model, style_tensor, layers = ["conv1_1", "conv2_1", "conv3_1", "conv4_1", "conv5_1"])
8: style_grams ← ComputeGramMatrices(style_features)
9: target_img ← InitializeAs(content_tensor)
10: SetTargetTrainable(target_img)
11: Define LossFunction as:
12: content_loss ← MeanSquaredError(target_features["conv4_2"], content_features["conv4_2"])
13: style_loss ← 0
14: for each layer in style_layers do
15: target_gram ← ComputeGramMatrix(target_features[layer])
16: layer_loss ← WeightedMeanSquaredError(target_gram, style_grams[layer])
17: style_loss ← style_loss + layer_loss
18: end for
20: total_loss ← content_weight × content_loss +

style_weight × style_loss
21: optimizer ← InitializeOptimizer(target_img, learning_rate)
22: for i ← 1 to max_iter do
23: target_features ← ExtractFeatures(vgg_model, target_img, style_layers + ["conv4_2"])
24: loss ← LossFunction(target_features, content_features, style_grams)
25: Backpropagate(loss)
26: UpdateTargetImage(optimizer)
27: if ConvergenceCheck(loss) then
28: break
29: end if
30: if i % show_every == 0 then
31: Display(target_img)
32: end if
33: end for
34: return ConvertToImage(target_img)
35: End Procedure

V. RESULTS/ DISCUSSION

This section of the manuscript provides the image processing and re-creation results. Table 1 below shows the drone used for aerial images, along with performance indicators.

TABLE I
DRONE PERFORMANCE INDICATORS

Drone Type	Parameters
Drone – DJI Mini Pro	
Dimension	148×94×64 mm (L×W×H)
Maximum Speed	17 m/s
Maximum Flight Time	45 mins
Image Sensor	1/1.3 Inch CMOS, Pixel 48MP
Stabilization	3-axis mechanical gimbal (roll, pitch, yaw)
Battery Capacity	3900 mAh

Figure 2 illustrates the progressive transformation of the first content image through neural style transfer. Subfigure (a) shows the original aerial photograph. Subfigures (b), (c), and (d) represent the stylized outputs after 1000, 2000, and 3000 iterations, respectively, showcasing an increasing integration of artistic style with each iteration.

(a) Original Image

(b) Processed image after 1000 iterations

(c) Processed image after 2000 iterations

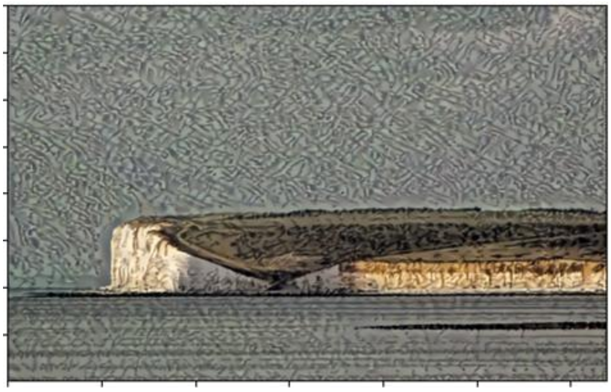
(d) Processed image after 3000 iterations

Fig. 2. Transformation of Original Image 1

Similarly, figure 3 demonstrates the evolution of the second content image under the style transfer process. The initial raw image is displayed in subfigure (a), while subsequent subfigures (b), (c), and (d) show the refined stylized results at different iteration milestones, highlighting the deepening effect of the applied artistic style.

(a) Original Image

(b) Processed image after 1000 iterations



(c) Processed image after 2000 iterations

(d) Processed image after 3000 iterations

Fig. 3. Transformation of Original Image 2

Figure 4 depicts the third image transformation. Subfigure (a) presents the original image captured by the drone. Subfigures (b), (c), and (d) show the intermediate results after successive iterations, illustrating the gradual blending of content and style through iterative optimization.

(a) Original Image

(b) Processed image after 1000 iterations

(c) Processed image after 2000 iterations

(d) Processed image after 3000 iterations

Fig. 4. Transformation of Original Image 3

Figure 5 portrays the transformation of the fourth image in the dataset. Starting with the unaltered photograph in subfigure (a), subfigures (b), (c), and (d) display the stylized outputs at increasing iteration counts, emphasizing the progressive enhancement of stylistic features.

(a) Original Image

(b) Processed image after 1000 iterations

(c) Processed image after 2000 iterations

(d) Processed image after 3000 iterations

Fig. 5. Transformation of Original Image 4

Figure 6 shows the transformation of the fifth image in the dataset. Starting with the original image in subfigure (a), subfigures (b), (c), and (d) display the stylized outputs at increasing iteration counts, emphasizing the progressive enhancement of stylistic features.

(a) Original Image


(b) Processed image after 1000 iterations


(c) Processed image after 2000 iterations

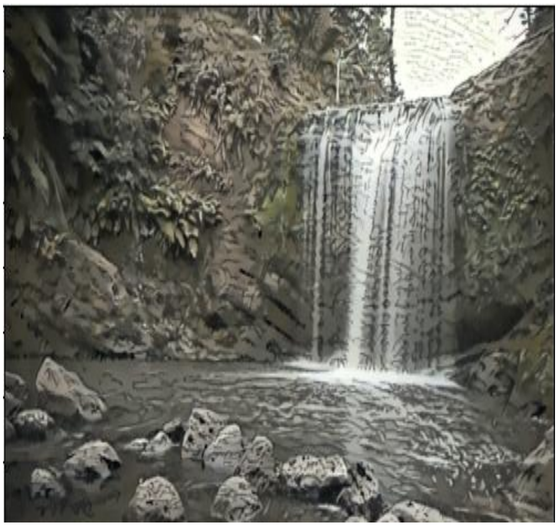
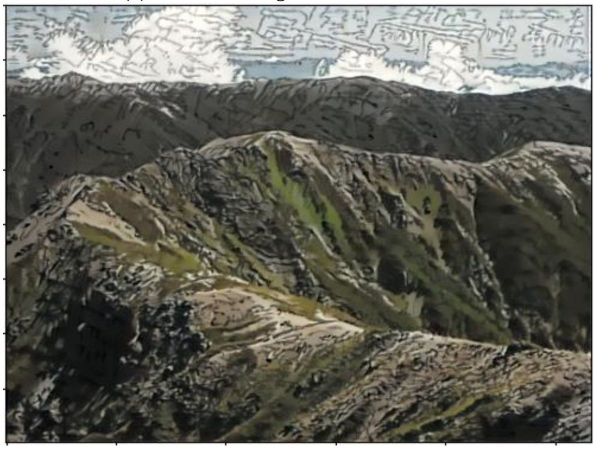

(d) Processed image after 3000 iterations

Fig. 6. Transformation of Original Image 5

Figure 7 shows the transformation of the sixth image in the dataset. Starting with the original image in subfigure (a), subfigures (b), (c), and (d) display the stylized outputs at increasing iteration counts, emphasizing the progressive enhancement of stylistic features.


(a) Original Image


(b) Processed image after 1000 iterations


(c) Processed image after 2000 iterations


(d) Processed image after 3000 iterations

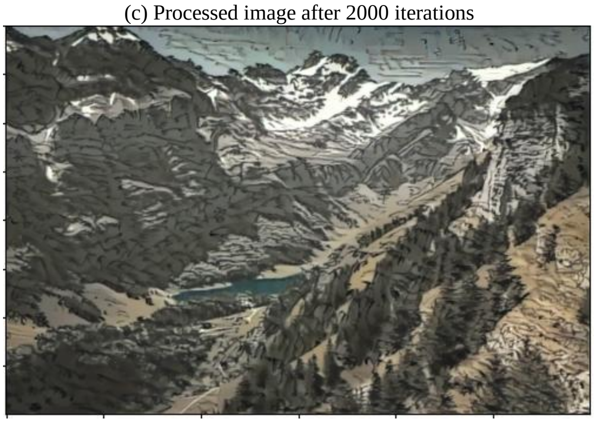
Fig. 7. Transformation of Original Image 6

Figure 8 shows the transformation of the seventh image in the dataset. Starting with the original image in subfigure (a), subfigures (b), (c), and (d) display the stylized outputs at increasing iteration counts, emphasizing the progressive enhancement of stylistic features.

(a) Original Image

(b) Processed image after 1000 iterations

(c) Processed image after 2000 iterations



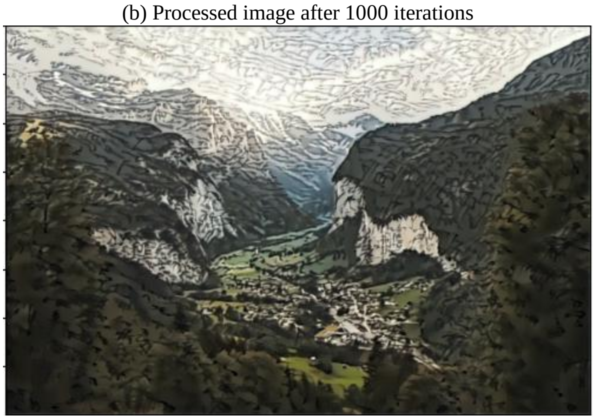
(d) Processed image after 3000 iterations

Fig. 8. Transformation of Original Image 7

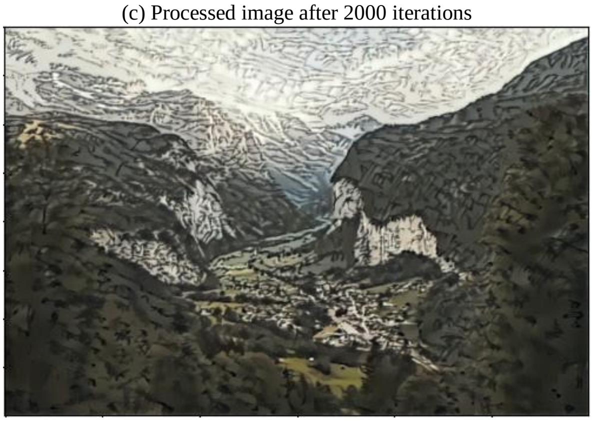
Figure 9 shows the transformation of the eighth image in the dataset. Starting with the original image in subfigure (a), subfigures (b), (c), and (d) display the stylized outputs at increasing iteration counts, emphasizing the progressive enhancement of stylistic features.

(a) Original Image

(b) Processed image after 1000 iterations



(c) Processed image after 2000 iterations



(d) Processed image after 3000 iterations

Fig. 9. Transformation of Original Image 8

Figure 10 plots the total loss values over the course of the style transfer process for each image. The graph demonstrates the convergence of the optimization, with loss values decreasing as the iterations progress, indicating the successful blending of content and style elements while refining the target images.

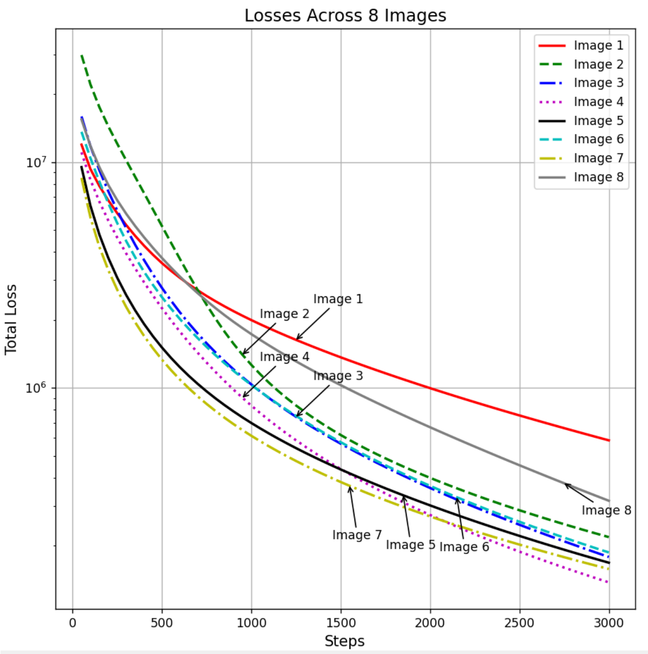
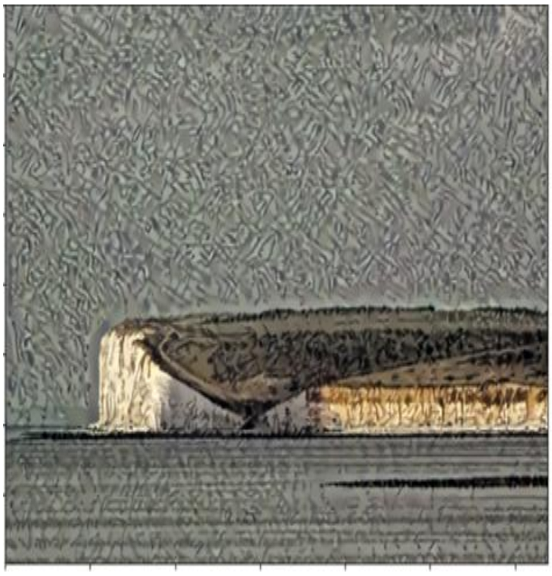


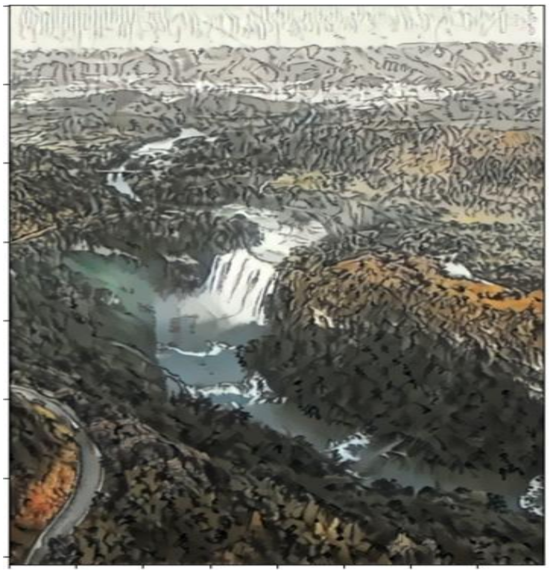
Fig. 10. Total loss for the transformation of each image

Re-Creation: The process of creating something new based on pre-existing content is known as re-creation, also called secondary creation. Fields such as art, literature, and entertainment employ this concept. It includes taking elements, characters, or themes from pre-existing work and converting them into something new by adding them in some way. It involves creating paintings and artwork inspired by existing works. It also allows artists to discover ideas and themes in new ways, contributing to ongoing creativity and culture. The aerial images are processed through the image processing process. In terms of aesthetics, the artist used processed images as a source of inspiration. This method improves the creative space, which is an inevitable trend in the coming art world. Figure 11 shows the artistic effect of all images after re-creation.

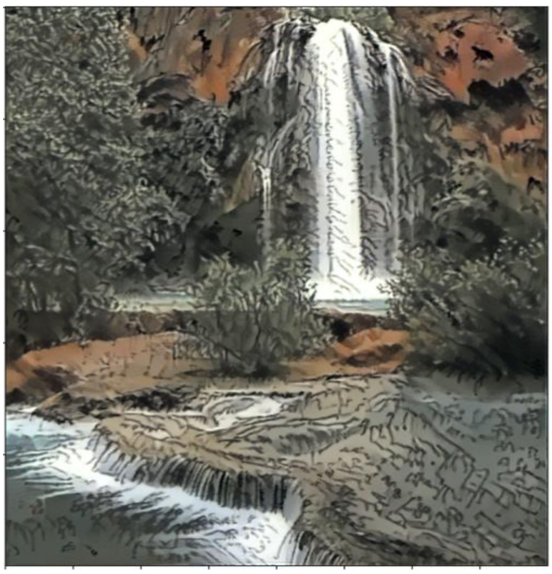
(a) Re-created Image 1



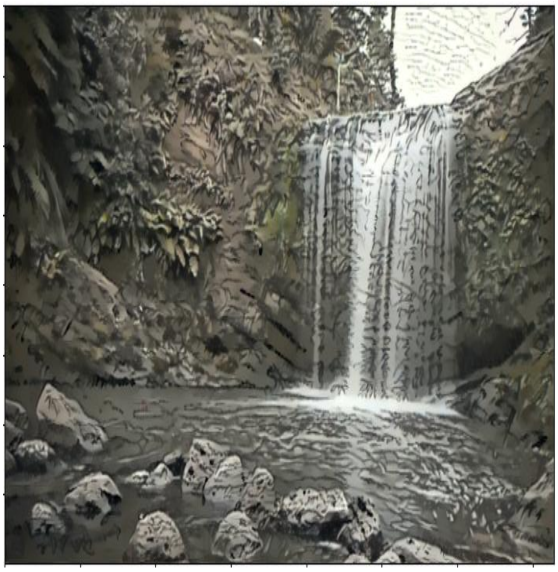
(b) Re-created Image 2



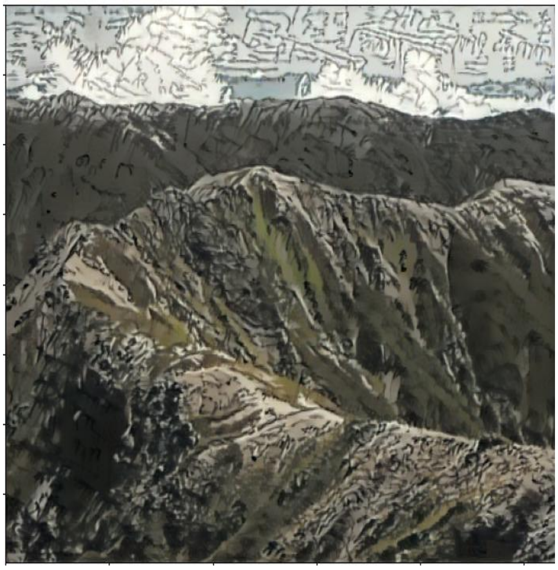
(c) Re-created Image 3



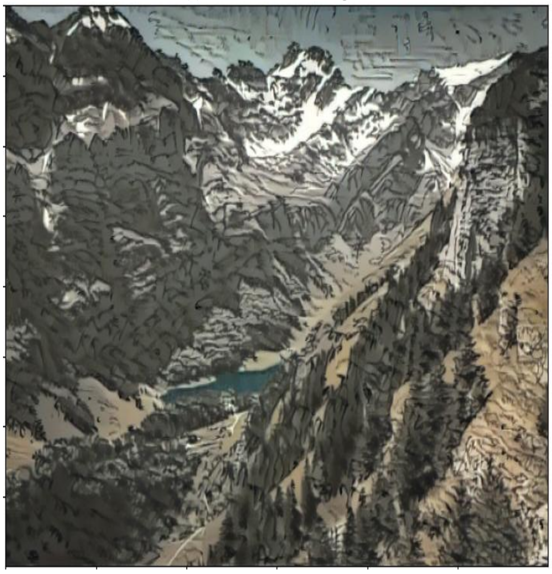
(d) Re-created Image 4



(e) Re-created Image 5



(f) Re-created Image 6



(g) Re-created Image 7

(h) Re-created Image 8

Fig. 11. Re-created Images

VI. CONCLUSION

Drone photography in the exploration of landscape painting provides a fascinating and innovative pathway for researchers and artists. The integration of advanced image processing techniques, including neural style transfer, allows artists to merge the high-resolution content of aerial drone imagery with artistic styles, offering new creative possibilities. By capturing high-altitude aerial images from perspectives previously inaccessible to humans, drone technology enables artists to explore previously unseen details and angles, inspiring fresh artistic interpretations. This innovative approach bridges the gap between traditional landscape painting and modern digital techniques, fostering a dynamic evolution of artistic expression. Moreover, the combination of drone photography with deep learning techniques presents an opportunity to reimagine nature through art, pushing the boundaries of how nature can be represented in creative works and enabling the exploration of new tactics for depicting the environment.

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