DIGITAL ART CREATION AND COPYRIGHT PROTECTION IN POLLOCK STYLE USING GANS, FRACTAL ANALYSIS, AND NFT GENERATION

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ABSTRACT

The rapid evolution of artificial intelligence has revolutionized digital art creation, enabling the development of novel methodologies that integrate artistic synthesis with robust intellectual property protection. In this study, we propose an integrated framework that combines Generative Adversarial Networks (GANs), fractal analysis, and wavelet-based turbulence modeling to generate abstract artworks inspired by Jackson Pollock's drip paintings. Beyond emulating Pollock's dynamic style via neural style transfer, our approach quantitatively characterizes the artworks' intrinsic complexity using fractal dimension and turbulence power spectrum metrics. Importantly, we introduce a comprehensive watermark robustness testing protocol that embeds imperceptible digital watermarks into the generated images and rigorously assesses their resilience against common perturbations—including Gaussian noise, JPEG compression, and spatial distortions. By merging these watermarks with NFT metadata, our framework ensures secure provenance and immutability of digital assets. Experimental results demonstrate the feasibility and efficacy of this multifaceted approach in advancing both artistic innovation and reliable digital copyright protection.

1 INTRODUCTION

Artificial intelligence has revolutionized art creation using deep learning models such as GANs and VGG19. These models simulate artistic processes, diversify styles, and digitize art production. However, traditional digital watermarks remain vulnerable to tampering and are often susceptible to degradation under various attacks, thereby compromising digital artwork copyright protection.

To address these challenges, this paper proposes an innovative method that integrates Generative Adversarial Networks (GANs) with NFT digital watermarking technology and incorporates a comprehensive watermark robustness testing framework. Our approach not only extracts and reproduces the distinctive artistic style of works—exemplified by Jackson Pollock's iconic drip paintings—but also embeds tamper-proof digital watermarks. These watermarks are rigorously tested against common attacks (such as Gaussian noise, JPEG compression, and spatial distortions) to ensure their resilience, thereby guaranteeing the continuous integrity and authenticity of the digital artwork.

By combining deep learning-based artistic style transfer with fractal and turbulence analysis for feature extraction and integrating NFT-based watermarking with robust testing mechanisms, the proposed framework addresses two fundamental challenges in digital art: creative generation and reliable protection. This integrated system provides a secure, transparent, and decentralized mechanism for artwork authentication and trading, further safeguarding the immutability and uniqueness of digital creations (Zheng et al. (2018); Belotti et al. (2019); Yli-Huumo et al. (2016)).

2 METHODS

This study proposes a comprehensive workflow for both the generation and the protection of digital artworks. The methodology capitalizes on recent advances in deep learning, fractal and turbulence analysis, robust watermark embedding, and blockchain technologies. The approach is structured into the following key components; a detailed flowchart outlining the entire process is presented in Figure 1.

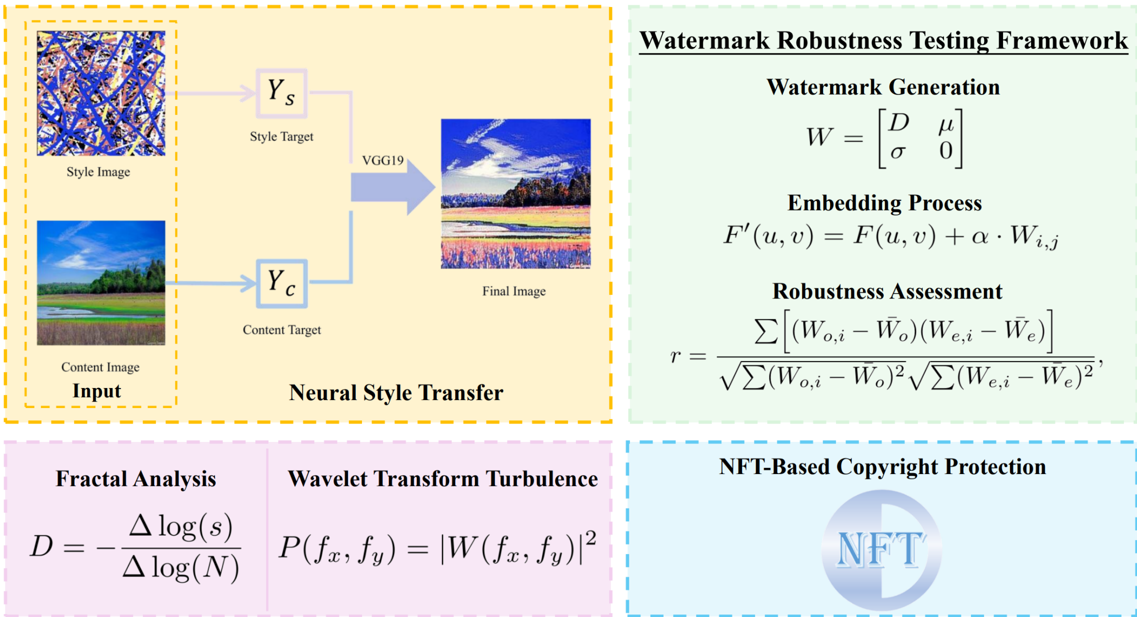

Figure 1: Flowchart for Digital Artwork Generation and Protection

2.1 NEURAL STYLE TRANSFER

At the core of the framework is a sophisticated neural style transfer algorithm implemented using the MindSpore deep learning framework (Tong et al. (2021); Chen (2021)). The pre-trained VGG19 network serves as the backbone architecture for hierarchical feature extraction from both content and style images. The image generation process is guided by a comprehensive composite loss function defined as:

$$L_{\text{total}} = \alpha L_{\text{content}} + \beta L_{\text{style}} + \gamma L_{\text{TV}} + \delta L_{\text{texture}} + \epsilon L_{\text{droplet}}, \quad (1)$$

where

- L_{content} measures the similarity between the generated and content images,
- L_{style} captures stylistic attributes,
- L_{TV} imposes spatial smoothness,
- L_{texture} enhances fine texture details, and
- L_{droplet} simulates the dynamic paint effects reminiscent of dripping.

This multi-term loss ensures that the synthesized artworks exhibit both structural coherence and stylistic fidelity.

2.2 Fractal Analysis

This study employs the differential box-counting method to quantify the fractal characteristics of the generated artworks, as outlined in references (Sarkar & Chaudhuri (1994); Panigrahy et al. (2019); Liu et al. (2014)). The Sobel filter is employed to extract edge features and perform box counting at varying scales. The number of non-empty boxes in the image is counted, and the box sizes, along with the counting results, are recorded. Subsequently, a linear regression fit is performed on the logarithmic relationship between box size and count value, thereby obtaining the fractal dimension D. The fractal dimension D indicates the structural complexity of the image, with larger values signifying more pronounced fractal features.

$$D = -\frac{\Delta \log(s)}{\Delta \log(N)}, \tag{2}$$

where N is the count of blocks at a specific box size, and s is the box size.

2.3 Wavelet Transform Turbulence Features

The dynamic texture characteristics of the artworks are further examined by performing a two-dimensional discrete wavelet transform (DWT) using the Haar basis (Selesnick (2001); Shahbahrami (2012)). This analysis decomposes the image into sub-bands, from which the local frequency content is obtained. The ensuing turbulence power spectrum $P(f_x, f_y)$ is computed as

$$P(f_x, f_y) = |W(f_x, f_y)|^2, \tag{3}$$

where $W(f_x, f_y)$ denotes the wavelet coefficient for the spatial frequencies (f_x, f_y). This metric sheds light on the spectral properties and dynamic complexity of the generated imagery.

2.4 Watermark Robustness Testing Framework

To protect intellectual property and ensure the integrity of digital artworks, a watermark robustness testing framework is integrated into the overall methodology. This framework builds upon feature extraction techniques similar to those employed in fractal and turbulence analysis but repurposes them to generate a resilient watermark. The procedure is as follows:

1. **Watermark Generation:** Extract two sets of features from the grayscale artwork—one via fractal dimension (differential box-counting) and one via texture analysis (Haar DWT)—and merge them into a compact 2×2 watermark matrix.
2. **Embedding Process:** Embed the watermark in the frequency domain by modifying select mid-frequency DCT coefficients with a predetermined strength factor to balance visibility and robustness.
3. **Robustness Assessment:** Subject the watermarked images to attacks (Gaussian noise, low-quality JPEG compression, and spatial distortions with random cropping and inpainting), re-extract the watermark, and confirm detection when the correlation exceeds a threshold (typically 0.95) across multiple trials.

2.5 NFT-Based Copyright Protection

To complete the framework, a blockchain-based approach is employed for secure copyright protection. The extracted fractal and turbulence features, along with the watermark Token ID, are first hashed using a cryptographic algorithm (e.g., SHA-256) to generate a unique digital fingerprint (Gilbert & Handschuh (2003)). This fingerprint, together with timestamps and other metadata, is embedded into an NFT. By deploying the

NFT metadata via smart contracts on a blockchain platform, authenticity and provenance are guaranteed, thereby ensuring the immutability of the digital artwork's ownership records.

Collectively, these components form an integrated framework that not only generates visually compelling digital artworks but also embeds robust, imperceptible watermarks and ensures the provenance and integrity of the artwork via blockchain technology.

3 RESULTS

3.1 WATERMARK ROBUSTNESS TESTING

A series of experiments evaluated the watermarking scheme under both standard and adverse conditions. On original images, the scheme achieved an average detection rate of 87.8% with a false positive rate of 1.82%. Under attack scenarios, detection rates decreased markedly (Gaussian noise: 13.6%, JPEG compression: 19.1%, and cropping: 8.2%). With the application of image enhancement prior to watermark embedding, performance improved considerably—yielding an average detection rate of 99.3% and a false positive rate of 1.21%—while the detection rates under attacks declined to 2.3%, 2.4%, and 1.2% respectively. These outcomes are summarized in Table 1.

Table 1: Watermark Robustness Testing Results

Metric	Original Image	Enhanced Image
Average Detection Rate	87.8%	99.3%
False Positive Rate	1.82%	1.21%
Detection (Gaussian Noise)	13.6%	2.3%
Detection (JPEG Compression)	19.1%	2.4%
Detection (Cropping)	8.2%	1.2%

3.2 GENERATED ARTWORKS ANALYSIS

The proposed methodology for abstract art generation effectively captures the dynamic complexity reminiscent of Jackson Pollock's drip paintings. The generated images exhibit rich color layering and intricate textures, with a measured fractal dimension of $D = 1.88$—indicative of high structural complexity. Furthermore, turbulence analysis via wavelet transforms yielded a mean power spectrum value of 2067.82 with a variance of 3552.45, reflecting significant dynamic variability across spatial scales. The integration of NFT technology further guarantees the uniqueness and traceability of each artwork through securely embedded blockchain metadata.

4 CONCLUSION

This study presents a comprehensive approach to digital art creation and copyright protection by integrating GANs, fractal analysis, turbulence modeling, NFT technology, and a robust watermarking scheme. The methodology successfully generates abstract artworks in the style of Jackson Pollock while ensuring their authenticity and traceability through advanced digital watermarking and blockchain technology.

The integration of fractal and turbulence analysis provides a quantitative framework for assessing the structural complexity and dynamic properties of the generated artworks. In particular, the incorporation of a rigorous watermark robustness testing framework confirms that the embedded watermarks remain highly resilient against common digital attacks—such as Gaussian noise, JPEG compression, and spatial distortions (including cropping and inpainting). This robust watermarking process not only safeguards the digital artwork's copyright but also reinforces the trustworthiness of the authentication system under adverse conditions.

The use of NFTs further guarantees the immutability and uniqueness of each artwork, offering a secure solution for digital art authentication and trading. Collectively, these techniques contribute to developing secure digital art markets by providing artists and collectors with a reliable, transparent, and resilient framework for creating, protecting, and trading digital artworks. Future work could explore the application of similar methodologies to other artistic styles and investigate even more sophisticated blockchain-based solutions for enhanced digital art protection.

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APPENDIX

A RELATED WORK

A.1 FRACTAL FEATURES OF POLLOCK'S PAINTINGS

In 1999, Richard Taylor's team made the initial discovery that Pollock's drip paintings (illustrated in Figure 2) exhibited notable fractal characteristics (Taylor et al. (1999; 2002)). The fractal analysis of Pollock's works, conducted through the box counting method, yielded fractal dimensions indicative of a self-similar fractal structure, analogous to that observed in natural phenomena. Taylor's study posited that Pollock may have unconsciously emulated the fractal pattern observed in nature during the creative process. This discovery constituted a pivotal foundation for the subsequent numerical simulation study.

A.2 APPLICATION OF AI IN ART CREATION

With the rapid development of AI technology, the application of deep learning models in art creation has attracted increasing attention, particularly the convolutional neural network (CNN)-driven neural style migration technique (Wang et al. (2017); Deng et al. (2022); Chen et al. (2017)). The neural style migration technique enables the generation of images with different artistic styles by extracting the features of content images and style images. The VGG19 model, a pre-trained deep convolutional network, is a popular choice for advanced feature extraction. In 2016, Leon Gatys et al. proposed a neural style migration method based on the VGG19, which generates a high-quality style through the optimisation of the content loss and the style loss migration images (Gatys et al. (2016); Vedaldi & Zisserman (2016)). This method outperforms Generative Adversarial Networks (GANs) in controlling the generated details and maintaining content consistency, and thus becomes an ideal tool for artistic image processing and is widely used in art creation and digital style simulation.

(a) (b) (c)

Figure 2: Pollock Drop Painting

A.3 Physical Properties in Works of Art

In 2024, Yinxiang et al. demonstrated that the vortex flow characteristics observed in Van Gogh's Night of the Stars and Moon are highly compatible with the phenomenon of turbulence in physics, particularly in accordance with Kolmogorov's theory of turbulence (Ma et al. (2024)). In accordance with the theory, energy is transferred from large-scale vortices to small-scale vortices in a gradual manner, and ultimately dissipated. It was observed that the vortices present in the work not only align with the Kolmogorov turbulence scalar law, but also with the scalar turbulence power spectrum proposed by George Batchelor in 1959.

A.4 NFT Technique

The advent of NFT technology commenced in 2017 (Wang et al. (2021)), when Dieter Shirley's team initiated the CryptoKitties project on the Ether blockchain, which facilitated the inaugural large-scale NFT deployment. The FT application (Serada et al. (2021)) provides a technological guarantee for the uniqueness and ownership authentication of digital assets based on the tamper-proof nature of the blockchain. In 2021, Beeple's NFT artwork *Everydays: The First 5000 Days* achieved a high price at Christie's auction house, indicating that NFT has become a significant presence in the art market. However, the effective integration of the distinctive attributes of artworks with NFT technology remains a topic of ongoing research interest (Nadini et al. (2021)).

B Detailed Methods

In this study, we propose a comprehensive framework that integrates a neural style migration algorithm with a robust watermarking scheme. This dual-faceted approach not only synthesizes high-quality artistic images through deep optimization but also enables secure digital asset management via embedded watermarks. The following sections detail the theoretical formulations and practical implementations of both components.

B.1 Neural Style Migration Framework

The image synthesis procedure is based on a pre-trained VGG19 network implemented within the MindSpore deep learning framework. During training, the convolutional layers remain frozen, thereby serving as robust feature extractors that yield multilevel representations for both content and style images. The final synthesized image is generated by iteratively minimizing a composite loss function comprising several constituent terms. For clarity, the pseudocode detailing the algorithm design is presented below for reference.

Algorithm 1 Image Style Transfer by MindSpore

```
Import libraries
Set context and random seed
Start timer
Define VGG19 model with Conv2d, ReLU, AvgPool2d
Instantiate VGG19, set batch size, freeze parameters, set to eval mode
Define normalization and transformations
Load and transform content and style images
Define variable image with requires_grad=True
Define ShuntModel (modify VGG19 with AvgPool2d)
Extract features from content and style images
Define loss functions (content, style, texture, drip effect)
Set loss weights
Define learning rate schedule and Adam optimizer
Define forward function to compute total loss
for iteration = 0 to 1000 do
    Update learning rate
    Compute loss and gradients
    Update variable image, clamp values
    if iteration mod 100 == 0 then
        Print loss, save image
    end if
end for
```

- **Content Loss:**
  This term measures the discrepancy between the high-level features of the generated image and those of the content image. It is expressed as:

$$\mathcal{L}_{content} = \sum_i \text{MSE}(C_i, C_{\text{target},i}), \tag{4}$$

  where C_i and $C_{\text{target},i}$ represent the feature maps at layer i for the generated and content images, respectively.

- **Style Loss:**
  To capture the stylistic attributes, the style loss is computed by comparing the Gram matrices of the feature maps extracted from multiple convolutional layers:

$$\mathcal{L}_{style} = \sum_j \text{MSE}\Big(\text{Gram}(S_j), \text{Gram}(S_{\text{target},j})\Big), \tag{5}$$

  with S_j and $S_{\text{target},j}$ referring to the style feature representations.

- **Total Variation (TV) Loss:**
  To enhance spatial smoothness and suppress high-frequency artifacts, the TV loss is defined as:

$$\mathcal{L}_{TV} = \frac{1}{BCHW}\left(\sum_{b,c,h,w} |I_{b,c,h,w} - I_{b,c,h,w+1}| + \sum_{b,c,h,w} |I_{b,c,h,w} - I_{b,c,h+1,w}|\right), \tag{6}$$

  where B, C, H, and W denote the batch size, number of channels, height, and width of the image, respectively.

- **Texture & Drip Effect Losses:**
  To further refine the visual output, a texture loss based on local gradient magnitudes is integrated along with a special drip effect loss that simulates the dynamic ink-dripping patterns reminiscent of abstract expressionism:

$$\mathcal{L}_{texture} = \frac{1}{CHW}\left(\text{mean}(\|dx\|^2) + \text{mean}(\|dy\|^2)\right), \tag{7}$$

$$\mathcal{L}_{drip} = -\frac{1}{CHW}\text{mean}(|dy|) + \frac{1}{CHW}\text{mean}\Big(|dy - \text{mean}(dy)|\Big). \tag{8}$$

B.2 Fractal Dimension

In addition to the loss terms, multiscale characteristics of the images are quantified by estimating local fractal properties via the differential box-counting method. For a grayscale image partitioned into boxes of size s, the fractal dimension D is approximated as

$$D = -\frac{d\log\big(N(s)\big)}{d\log(s)}, \tag{9}$$

where $N(s)$ is the number of boxes that capture part of the image structure. Complementarily, a two-dimensional Discrete Wavelet Transform (DWT) using the Haar wavelet is employed to extract turbulence and fine texture details, thereby enriching the overall feature representation.

B.3 Watermark Robustness Testing

To ensure digital authenticity, a watermark is embedded into the synthesized images using a method that leverages features extracted from the image itself. This watermarking process is composed of three integral stages:

1. **Feature Extraction & Watermark Construction:**
   Two key features are computed from the watermarked image:
   - The **fractal dimension** D is determined using the differential box-counting method as described above.
   - Statistical features, namely the mean μ and standard deviation σ, are derived from the high-frequency sub-bands obtained via a two-dimensional DWT.

   Together, these features form a watermark matrix defined as:

$$W = \begin{bmatrix} D & \mu \\ \sigma & 0 \end{bmatrix}. \tag{10}$$

2. **Watermark Embedding:**
   The host image is segmented into non-overlapping blocks, and each block undergoes a Discrete Cosine Transform (DCT). The watermark matrix is embedded by modifying selected mid-frequency DCT coefficients according to:

$$F'(u,v) = F(u,v) + \alpha \cdot W_{i,j}, \tag{11}$$

   where α is a scaling factor controlling the strength of the watermark, and $F(u,v)$ represents the original DCT coefficient at coordinates (u,v).
3. **Robustness Evaluation:**
   The resilience of the watermark is assessed under multiple distortion scenarios:

- **Gaussian Noise Attack:**
  The watermarked image is perturbed as
  $$I'(x, y) = I(x, y) + \epsilon \cdot n(x, y), \tag{12}$$
  where $n(x, y)$ is a normally distributed random variable and ϵ controls the noise intensity.
- **JPEG Compression:**
  The image is subjected to successive rounds of high-compression to simulate quality degradation.
- **Cropping Attacks:**
  Portions of the image are arbitrarily removed, followed by inpainting to reconstruct the missing regions.

Post-attack, watermark detection is performed by re-extracting the embedded watermark W_e. Its fidelity is quantified via the correlation coefficient with the original watermark W_o:

$$r = \frac{\sum\Big[(W_{o,i} - \bar{W}_o)(W_{e,i} - \bar{W}_e)\Big]}{\sqrt{\sum(W_{o,i} - \bar{W}_o)^2}\sqrt{\sum(W_{e,i} - \bar{W}_e)^2}}, \tag{13}$$

where $\bar{W}_o$ and $\bar{W}_e$ are the mean values of the corresponding watermark matrices. A correlation above a predetermined threshold (typically $T \approx 0.95$) indicates successful watermark detection. The overall performance is evaluated using the Detection Rate (DR) over multiple trials and analysis of the False Positive Rate (FPR) on unwatermarked images.

B.4 Integration and Optimization

The proposed framework is implemented in a modular fashion, thereby enabling the simultaneous optimization of both neural style migration and watermark embedding processes. Batch processing methods, utilizing multiprocessing via ProcessPoolExecutor, allow for the efficient handling of large-scale image datasets. Moreover, the fractal and turbulence metrics, combined with secure watermark features, are hashed using cryptographic techniques (e.g., SHA-256) to generate unique Token IDs. These IDs are then incorporated into NFT metadata compliant with ERC-721/1155 standards, ensuring an immutable and traceable digital asset registration process. This integrated approach not only achieves a high aesthetic quality in digital art creation but also guarantees the provenance and integrity of the artworks, thereby facilitating robust authentication and secure distribution in digital art marketplaces.

C Results

C.1 Neural Style Migration Results

The Pollock-inspired paintings generated on the basis of the MindSpore framework exhibit a multitude of layers of colour and intricate textural structures, effectively mimicking the distinctive style of abstraction evident in Jackson Pollock's drip paintings. The resulting images evince a clear sense of dynamism and spontaneity, presenting a kaleidoscope of colour tones and interwoven lines. As shown in Figure 3, these images fully reflect the fractal and turbulent characteristics of Pollock's work, thereby proving the high effectiveness of the algorithm in capturing Pollock's artistic expression techniques.

C.2 Fractal Dimension Results

The fractal dimension, calculated using the difference box counting method, is approximately $D = 1.88$, which demonstrates the self-similarity and complex fractal structure of the generated artworks. The estimate

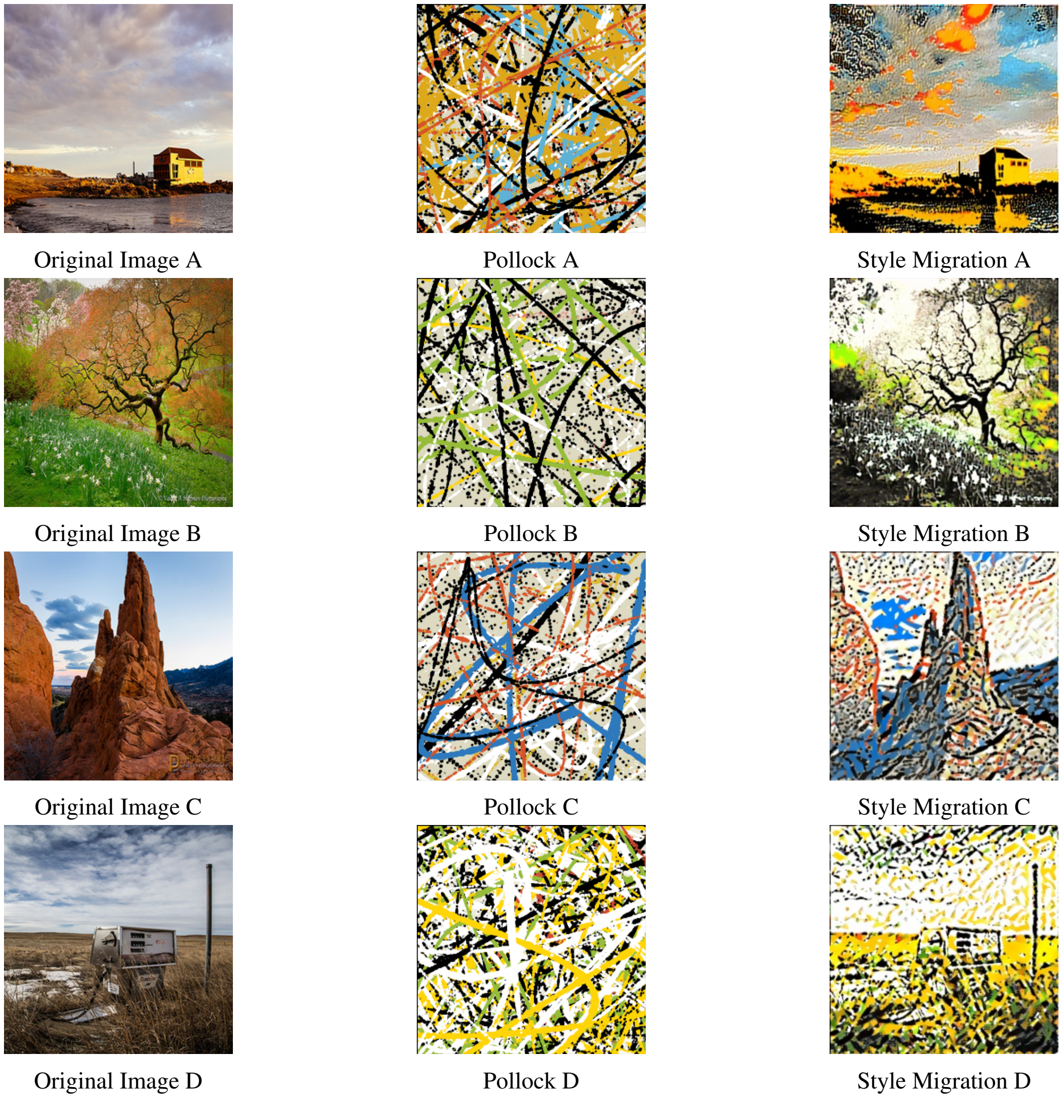

Figure 3: Example of style migration results

of the fractal dimension is highly consistent with the results of Richard Taylor et al. (1999) on Pollock's paintings, which validates the effectiveness of this study. Furthermore, the fitted curves, as shown in Figure 4, demonstrate a distinct linear trend, indicating that the box counts of the generated images adhere to a power law distribution. The image enhanced by the Sobel filter exhibits a high degree of detail and complex texture structures in the multiscale analysis, thereby substantiating the capacity of the generative algorithm in capturing the intricacies of the drip painting.

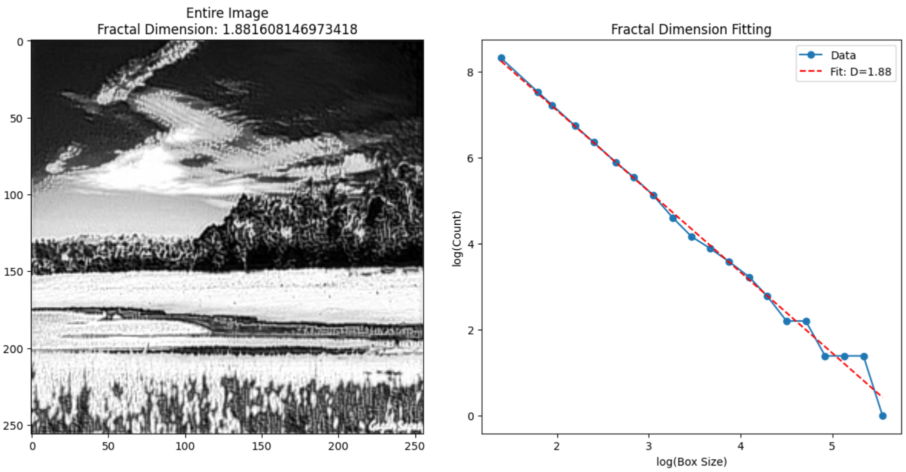

Figure 4: Fractal Dimension

C.3 Turbulence Characterisation Results

The characteristics of turbulence are revealed through the utilisation of a range of power and spectral metrics. The mean value of the turbulence power spectrum extracted using the Haar wavelet transform is 2067.82, with a variance of 3552.45. These metrics indicate the overall level of turbulence intensity and characterise the spectral properties and dynamic complexity of the generated images at different scales. As shown in Figure 5, the results demonstrate that the generated artworks exhibit significant diversity in spectral distribution, reflecting the complex nature of turbulence. These spectral characteristics complement the analysis of fractal dimension and provide a unique perspective for understanding the dynamic behaviour of the images. Compared to a traditional Fourier transform (FFT), a wavelet transform shows greater sensitivity and accuracy in capturing local frequency features, allowing for a more comprehensive depiction of the complex dynamic behaviour of the images.

C.4 Uniqueness of NFT Tags

The Token ID generated by feature hashing serves to guarantee the uniqueness and unforgeability of each digital collection. As shown in Table 2, examples of NFT metadata validate the efficacy of our method in generating reliable and unique NFT labels.

This design guarantees the singularity of each NFT on the blockchain and enables the traceability of its genesis and attributes through metadata. The findings demonstrate that the algorithm employed in this study is highly reliable in generating distinctive and verifiable NFT tags.

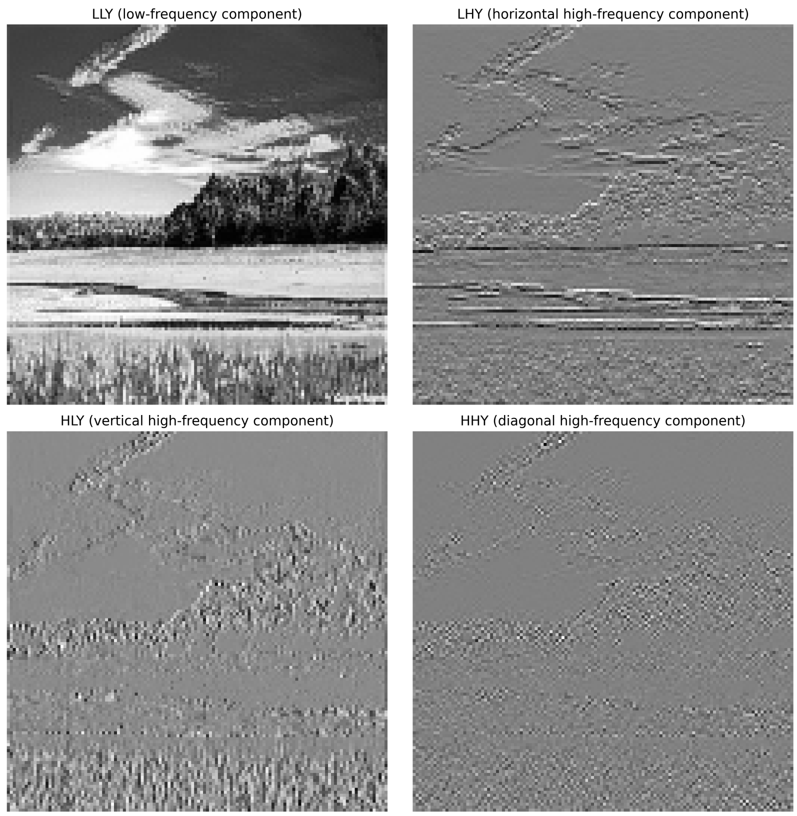

Figure 5: Turbulence Characterisation Results

Table 2: Example of NFT metadata

Field	**Value**
fractal_dimension	1.88
turbulence_mean_power	2067.82
turbulence_variance_power	3552.45
timestamp	2025-01-01 T12:34:56Z
artist	MindSpore-VGG-Pollock