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The Application and Exploration of Data Visualization Technology in Artistic Expression and Exhibition

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Abstract: - Embarking on the transformation of virtual art museums, the confluence of data visualization technology and deep learning emerges as a catalyst for redefining artistic expression. Driven by the desire to change traditional approaches, this work utilizes a sophisticated deep learning model, the self-attention-based cycle-consistent generative adversarial network (SA-CCGAN), for transformative purposes. The objective of proposed Modernizing Virtual Art: The Collaboration of Data Visualization Technology and Self-Attention-Based Cycle-Consistent Generative Adversarial Network for Artistic Expression (MVA: DVT & SA-CCGAN) is to elevate artistic expression and exhibition practices within the virtual space, marking a paradigm shift in traditional approaches. SA-CCGAN, renowned for its ability to generate realistic and coherent artistic representations, serves as the cornerstone of this transformative endeavor. The workflow intricately incorporates SA-CCGAN into the virtual art museum context, enhancing stylized outcomes and capturing global geometric features. This yields a computationally efficient representation of high-dimensional visual data, revolutionizing digital art presentation. The fusion of data visualization technology, creativity, and meticulous design not only signals innovation but also has the potential to redefine the virtual art landscape, fostering accessibility, engagement, and a deeper cultural exchange in digital art exploration.

Keywords: Virtual Art Museums, Data Visualization Technology, Self-Attention-Based Cycle-Consistent Generative Adversarial Network, Artistic Expression, Digital art Exploration

1. INTRODUCTION

Digital art spaces, also known as online art platforms, replicate the ambiance of traditional museums in a virtual setting [1]. Utilizing technology, these platforms showcase diverse art forms, such as paintings and sculptures, delivering an experience reminiscent of physical museums [2-3]. Within these digital spaces, visitors navigate through galleries, observe artworks, and engage with exhibits through computer interfaces [4-5]. This format provides a distinct avenue for art exploration, eliminating the need for physical museum visits [6-7]. Virtual art museums may feature virtual tours, interactive displays, and innovative methods of presenting art in the digital domain [8]. The rise of virtual art museums is closely tied to technological advancements, offering immersive and globally accessible experiences for art enthusiasts.

Presently, virtual museums emphasize scientific and technological system advancement, neglecting significant avenues for artistic expression [9]. To address this, there is a need to explore the future direction of virtual art museums, considering the contemporary societal requirements for both spiritual and material fulfillment [10]. The sluggish progress of domestic virtualization technology, coupled with the scarcity of scientific research institutions and limited publications in domestic academic journals, underscores the necessity for expanded investigation. Some of the recent related works are,

In 2022, Chiu, M.C.et.al., [11] have fostered university students' appreciation for artwork and enhancing their painting outcomes is the goal of an artificial intelligence-driven art education system. Utilizing ResNet50 deep learning, the system strives to elevate students' comprehension and skills in the realm of artistic expression. It attains low computation efficiency. In 2022, Bai, Y., [12] have explored the application of deep learning techniques combined with Internet of Things (IoT) technology and a visualization system, this research delves into the user experience in virtual reality (VR) concerning ceramic exhibits. The study focuses on leveraging nonlinear random matrix methodologies to enhance understanding and engagement in the realm of ceramic art. It attains low Visual Fidelity Index and User Satisfaction Score. In 2022, Arayaphan, W. et.al., [13] have transformed the ancient textiles into a digital format through the integration of virtual reality technology, the FabricVR project at the

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Wieng Yong House Museum aims to bring historical fabrics to life in a modern, immersive experience. But it attains low computation efficiency and Visual Fidelity Index. Therefore, understanding the future trajectory of virtual art museums is crucial for a more comprehensive and balanced approach.

Despite the presence of virtual museum platforms, the persisting challenge lies in the limited engagement within exhibits [14]. Present-day virtual museums, reflecting the fast-paced development era, imitate static photo presentations, providing scant involvement. The introduction of virtual reality technology in the 1980s has been widely adopted across various societal domains, yet virtual art displays fall short in dynamic interaction [15-16].

While projects such as Google's Cultural Heritage Project concentrate on preserving digital relics, there is a highlighted necessity for improved art design utilizing digital tools, specifically three-dimensional models, audio-visual components, and texture effects. The examination of the "Three-color Porcelain in the Tang Dynasty" serves as a concrete example, demonstrating a particular design approach that amalgamates theoretical concepts with practical application [17].

The problem is that current virtual art exhibits are not interactive or dynamic. This prompts the exploration of new ways to use deep learning for a more lively and engaging experience in virtual art museums. So, this study introduces a contribution by suggesting the integration of data visualization technology with a Self-Attention-Based Cycle-Consistent Generative Adversarial Network (SA-CCGAN) [18] to enrich artistic expression and amplify user involvement within the virtual art realm. The main contributions of the proposed MVA: DVT & SA-CCGAN methodology are outlined below:

- Dynamically enhancing static virtual art displays using data visualization technology and the SA-CCGAN network.
- Implementing the proposed SA-CCGAN network to elevate virtual art, bridging the gap with traditional forms for a more visually appealing experience by refining artistic expression.
- Applying the proposed MVA: DVT & SA-CCGAN methodology to "Three-color Porcelain in the Tang Dynasty" for enhancing the digital representation and emphasizing cultural significance.
- Introducing a data-driven system for User-Centric Evaluation and Enhancement, enabling advanced evaluation and user feedback to ensure a personalized and satisfying virtual art experience.
- Reshaping the virtual art landscape with the proposed MVA: DVT & SA-CCGAN approach, fostering cultural exchange and offering fresh perspectives on historical artifacts in the digital realm.

The manuscript proceeds with an exploration of the proposed methodology in Section 2, results and discussion are explained in Section 3, and ultimately concludes in Section 4.

2. PROPOSED METHODOLOGY

The fusion of data visualization technology, especially with deep learning, has profoundly impacted artistic expression in virtual art museums, sparking the creation of innovative solutions and expanding creative possibilities for artists. This integration, driven by SA-CCGAN, revolutionizes the appearance and interaction of virtual art museums, providing users with a distinctive and immersive journey through history and art. The block diagram of the proposed MVA: DVT & SA-CCGAN methodology are given in Figure 1. The detail discussion regarding the proposed methodology is given below,

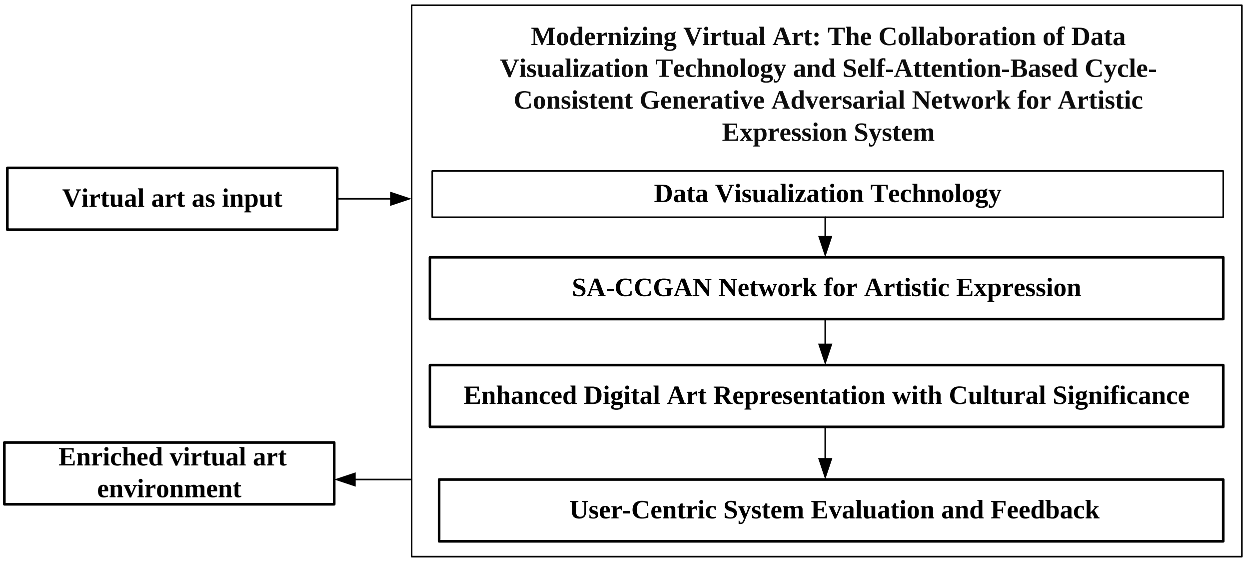

Figure 1: Block diagram of proposed MVA: DVT & SA-CCGAN methodology

2.1 Application of Deep Learning in Artistic Representation

Initially Virtual art represents the initial digital content that serves as the basis for the artistic transformation are given as the input for deep learning. In this section, the intricate integration of deep learning techniques, particularly the utilization of self-attention-based cycle-consistent generative adversarial network (SA-CCGAN), shaping transformative aspects within the artistic representation framework are discussed. SA-CCGAN, renowned for realistic and coherent artistic generation, incorporates self-attention, a generator, discriminator, and loss function in its architecture, enhancing virtual art exhibition practices.

2.1.1 Self-attention component

Within the realm of virtual art museums, the dynamic synergy between data visualization technology and deep learning undergoes a transformative evolution through the strategic integration of a self-attention mechanism. This innovative addition, embedded within generator and discriminator architectures, amplifies stylized outcomes by adeptly capturing global geometric features. The implementation of self-attention marks a pivotal shift in artistic expression and exhibition practices.

2.1.2 Generator

In the generator component, it incorporates three essential modules: encoder, transformer, and decoder, each contributing to the intricate process of transforming visual input data in the realm of virtual art museums. Initially, the visual input data, such as images or other forms of artistic content are processed through a generator network. Here encoder is employed to transform the intricate, high-dimensional visual input information into a more compact, lower-dimensional space, thereby diminishing computational intricacies. This process involves down sampling the visual data through a stride-1 convolutional layer and two stride-2 convolutional layers. By implementing this down sampling technique, a more expansive network and an augmented effective receptive field are achieved without introducing supplementary computational expenses. Consequently, this refinement amplifies the network's proficiency. Transitioning to the transformer, nine residual blocks are applied to capture distinct characteristics of the visual data. These blocks leverage these identified features to convert the feature vector of the visual data, transitioning it from the A domain to the B domain. The decoder restores the initial size of the visual data from the transformer's output. The decoder, mirroring the encoder in reverse, meticulously restores the initial size of the visual data through deconvolution layers. This comprehensive process culminates in the generation of artistic expressions, showcasing the profound impact of data visualization technology and deep learning within the virtual art space. The Generator Internal Configuration is given in Table 1.

Table 1: Generator Internal Configuration

Component	Size of Kernel	Connection Method	Stride	Number of Filters
Encoder	7 × 7	Convolution with instance normalization and ReLU activation applied.	1	64
	3 × 3	Convolution with instance normalization and ReLU activation applied.	2	128
	3 × 3	Convolution with instance normalization and ReLU activation applied.	2	256
Transformer	Residual Blocks			
Self-Attention Module				
Decoder	3 × 3	Deconvolution with instance normalization and ReLU activation applied.	2	128
	3 × 3	Deconvolution with instance normalization and ReLU activation applied.	2	64
	7 × 7	Deconvolution with instance normalization and ReLU activation applied.	1	3

2.1.3 Discriminator

The discriminator analyzes features within the visual data, assessing whether these features correspond to a specific category. This involves incorporating convolutional layers to generate a one-dimensional output. During experimentation, a self-attention module is introduced to enhance the discriminator's capabilities. The discriminator's focus lies in distinguishing stylistic visual data, while the generator is oriented towards producing such stylistic representations. The maturation of training occurs when both entities achieve Nash equilibrium, mutually advancing each other to attain an optimal adversarial state. The discriminator Internal Configuration is given in Table 2.

Table 2: Discriminator Internal Configuration

Component	Size of Kernel	Connection Method	Stride	Number of Filters
Discriminator	4 × 4	Convolution with leaky ReLU activation function applied.	2	64
	4 × 4	Convolution with instance normalization and leaky ReLU activation applied.	2	128
	4 × 4	Convolution with instance normalization and leaky ReLU activation applied.	2	256
Self-Attention Module				
	4 × 4	Convolution with instance normalization and leaky ReLU activation applied.	1	512
	4 × 4	Convolution applied.	1	1

2.1.4 Loss function

Adversarial loss:

The style transfer model operates within the dual realms, exemplified by the transfer involving A and B domain. Employing the CycleGAN model, the generator G coordinates the mapping from the A domain to the B domain, transforming visual data and discerning their authenticity through discriminator D_B . This generative adversarial process involves establishing a generative adversarial loss, as outlined in equation (1),

$$Loss_{GAN}(G, D_B, A, B) = \mathrm{E}_{b \sim P_{Visual\ data}(b)}\left[\log\ D_B(b)\ \right] + \mathrm{E}_{a \sim P_{Visual\ data}(a)}\left[\log\left(1 - D_B(G(b))\right)\ \right] \tag{1}$$

Then the overall objective expressed in equation (2),

$$G^* = \arg\min_G \max_{D_B} Loss_{GAN}(G, D_B, A, B) \tag{2}$$

On the other hand, in the CycleGAN training process for converting B domain visual data to A domain, the mapping from B to A, represented by generator K, transforms B domain visual data into target A domain visual data. This transformation is evaluated by discriminator D_A, constituting a distinct generative adversarial process with a specific loss function and it is defined in equation (3),

$$Loss_{GAN}(K, D_A, B, A) = \mathrm{E}_{a \sim P_{Visual\ data}(a)}\left[\log\ D_A(a)\ \right] + \mathrm{E}_{b \sim P_{Visual\ data}(b)}\left[\log\left(1 - D_A(K(b))\right)\ \right] \tag{3}$$

Then the final objective articulated in the following equation (4)

$$K^* = \arg\min_K \max_{D_A} Loss_{GAN}(F, D_A, B, A) \tag{4}$$

Cycle consistency Loss:

CycleGAN incorporates cycle consistency loss to ensure the dual learning of mappings K and G stabilizing GAN optimization, reducing mapping space, and preserving contour features concerning visual data. This aligns with the profound impact of data-driven approaches on artistic expression and exhibition practices in virtual art museums. The cycle consistency loss is represented in the following equation (5)

$$Loss_{CCL}(G, K) = \mathrm{E}_{a \sim P_{Visual\ data}(a)}\left[\left\|K\left(G(a)\right) - a\right\|_1\right] + \mathrm{E}_{b \sim P_{Visual\ data}(b)}\left[\left\|G\left(K(b)\right) - b\right\|_1\right] \tag{5}$$

Identity loss:

Maintaining visual data integrity, identity loss enforces that the generator G, when applied to a certain style $G(b)$, closely resembles the original input b, preventing undesirable color shifts and ensuring overall coherence in visual data. The identity loss is represented in the following equation (6)

$$Loss_{IL}(G, K) = \mathrm{E}_{b \sim P_{Visual\ data}(b)}\left[\left\|\left(G(b)\right) - b\right\|_1\right] + \mathrm{E}_{a \sim P_{Visual\ data}(a)}\left[\left\|\left(K(a)\right) - a\right\|_1\right] \tag{6}$$

Perceptual loss:

Perceptual loss emphasizes maintaining high-level features by incorporating the ReLU activation layer loss from a pre-trained VGG-19 network, enhancing fidelity in visual data representation [18]. The perceptual loss is represented in the following equation (7)

$$Loss_P(G, K) = \frac{1}{Dp * Ht * Wt}\left[\left\|\phi(G(a)) - \phi(b)\right\|_2^2 + \left\|\phi(K(b)) - \phi(a)\right\|_2^2\right] \tag{7}$$

Where ϕ signifies the Visual data feature extraction mechanism, Dp, Wt, and Ht representing the Visual data feature's depth, width, and height, respectively.

By this, the total loss is calculated with the help of equation (8)

$$\begin{aligned} Loss_{Total} = Loss_{GAN}(G, D_B, A, B) + Loss_{GAN}(K, D_A, B, A) + \\ \alpha * Loss_{CCL}(G, K) + \beta * Loss_{IL}(G, K) + \gamma * Loss_P(G, K) \end{aligned} \quad (8)$$

Where α, β, and γ assign weights to cycle consistency loss, identity loss, and perceptual loss respectively.

2.2 Creative Integration of Data Visualization Technology: Empowering Artistic Expression and Exhibition

In the pursuit of elevating artistic expression and exhibition, this research work delves into the creative integration of data visualization technology, specifically focusing on Three-Color Porcelain. The selection of Virtual Ceramic Demonstrations serves as a canvas to explore innovative solutions empowered by SA-CCGAN network. This interdisciplinary approach accentuates adapted shapes, intricate textures, vibrant colors, and exceptional material quality. Primarily, 3DSMAX was employed to initiate the foundational component, employing SA-CCGAN network for enhanced model structuring in low-poly and high-poly versions. Successively, ZBrush augmented by SA-CCGAN network capabilities was employed for carving and shaping the white mold. Afterward, Substance Painter, enhanced by SA-CCGAN network, added intricate details, baked the model, and adjusted lighting and colors to achieve the final object appearance. To aid seamless application in SDK software during virtual development, the product design process considered the factors such as the number of surfaces and product size. The result is a sophisticated representation that skillfully conveys historical and cultural significance. This research not only pioneers in artistic representation but also showcases the potential of data-driven methodologies in shaping the future of virtual art experiences. The detail description about the MVA: DVT & SA-CCGAN design model is given below,

2.3 Exploring Data-Driven Virtual Art Museums: Leveraging Deep Learning for Advanced Design Models

In the process of MVA: DVT & SA-CCGAN system model development, four primary steps are followed that are Crafting models, intricately carving details, illustrating textures, and performing post-editing. Initially, the 3DSMAX2018 was employed to establish a 3D modeling workspace. SA-CCGAN network play a significant role in this phase, where the ceramic is approximately contoured and categorized into "upper body" and "lower body" based on its shape, Afterward, two cubes are generated with distinct size parameters, guaranteeing a well-coordinated and visually appealing outcome.

The subsequent step encompassed the introduction of ZBrush 2018, incorporating SA-CCGAN network. Multiple practices are accessible for carving the concave mold. Utilizing the edge loop technique for the ceramic's firm texture, the normal direction is introduced for a distinct hard-edge effect. The face brush tool guided by SA-CCGAN network, breathes life into the mold, differentiating hues for every facet. The primary focus is on completing the main part, followed by separate sculpting of hands, feet, ears, and other components. The Boolean operation command is then directed to specifically inspect the grid alignment, followed by fine-tuning through manual adjustments.

In the third step, High Mode format was introduced to the 2018 version, which incorporates SA-CCGAN network. The ongoing task involves working on materials and textures, bringing in UV from 3DSMAX to the target object. Then, brush along with the application of smart mask and smart mask effects is accustomed by adding simple colors to perceive each part. In the fourth step, SA-CCGAN network is incorporated to enhance the smoothness of the target object's surface, creating a three-dimensional effect that closely matches the real object. This process encompasses two scenarios: the first captures the initial impressive appearance, and second is the physical objects enduring weather conditions. To craft the model's material, various brushes of discrete sizes were used to produce patterns like scratch, dirt, and oxidation.

2.4 Optimizing Artistic Experiences: Enhanced Evaluation and User Feedback with Data-Driven System Design

In this portrayal of "Sancai Porcelain in Tang Dynasty," a discernible lack of profound artistic expression becomes evident upon closer examination. When regarded as a standard illustration, it might not succeed in captivating the attention of observers. To imbue it with artistic vitality, Tang Dynasty three-color porcelain utilizes methodologies encompassing aspects like form, design, hue, and illumination, which introduces a novel aesthetic encounter through artistic means. This establishes a closer connection to historical contexts, providing a fresh perspective for virtual cultural exchange.

To affirm the capability of this proposed MVA: DVT & SA-CCGAN work in conveying information within the virtual art museum, user feedback was collected through a user evaluation approach, and it is provided in Table 3.

Table 3: Exploring Artistic Preferences and Technological Awareness

S. No	Question	Answer
1.	What's your main area of study or work?	
2.	How much do you like history and culture? A. Love it B. Neutral C. Not a fan	
3.	Have you ever been to a virtual museum? A. Yes B. No C. Not interested	
4.	Do you use design tools like Photoshop or 3D modeling? A. Regularly B. Occasionally C. Know about them. D. Not interested	
5.	Are you curious if virtual museum exhibits can be made more artistic? A. Very curious B. Somewhat curious C. Not curious	
6.	What's your attitude toward trying new things? A. Interested and willing to try. B. Have some creativity but need improvement. C. Neutral D. Not interested	
7.	How often do you visit virtual art museums? A. Very often B. Occasionally C. Rarely D. Never	
8.	What makes a virtual art experience immersive for you? A. Looks good. B. Interactivity C. Good stories D. Technology features	
9.	Do you know about deep learning in virtual art creation? A. Yes B. A bit C. No	

10.	Is it important to you that virtual art uses innovative technology? A. Very important B. Kind of important C. Not important	

Embarking on this survey adventure involves classifying participants into two fascinating groups: the vibrant realm of undergraduate and postgraduate students aged 18–25, alongside the seasoned design practitioners aged 26–55. With a particular spotlight on individuals immersed in the world of art, the questionnaire unfolds a captivating narrative within the context of data visualization technology and deep learning's impact on virtual art museums. The questionnaire's rich content takes participants on an engaging exploration are based on the following points,

1. Exploring the knowledge depths regarding virtual museums, fine arts, and the market's virtual art galleries.
2. Evaluating proficiency in digital media art tools and the potential for simulating and creating analogous exhibition works.
3. Scrutinizing perspectives on the presentation quality of "Three-color Porcelain of the Tang Dynasty," measuring the inclination for self-directed learning, and ascertaining enthusiasm for extended learning opportunities.

This MVA: DVT & SA-CCGAN approach ensures a focused exploration of the target audience's perspectives, linking their responses to the overarching influence of data visualization technology and deep learning on artistic expression and exhibition practices in virtual art museums.

3. RESULT AND DISCUSSION

The simulation efficiency of proposed MVA: DVT & SA-CCGAN approach is discussed. The integration of ZBrush 2018, 3DSMAX 2018, Substance Painter, and the High Mode format in SDK software, incorporating SA-CCGAN network enhancements, involves a unified workflow implemented through Python scripting for seamless coordination in virtual art model development. The performance metrics like Computational Efficiency (SA-CCGAN's adept processing of complex visual data for efficient art generation), Visual Fidelity Index (Measures the close resemblance of SA-CCGAN-generated virtual art to traditional artwork in detail, color, and overall visual quality) and User Satisfaction Score (Comprehensive evaluation of user satisfaction in the virtual art experience, derived by aggregating survey scores on diverse presentation aspects) are analyzed to validate the efficiency of the proposed approach. The performance of the proposed method is estimated with existing method such as AI in art education with Data Visualization Technology (DVT) and ResNet50 (MVA: DVT & ResNet50) [11], Elevating ceramic exhibits with DVT and machine learning such as multi-level perception, feedforward neural network, Support Vector Machine and Artificial neural network (MVA: DVT & MLP-SVM-ANN-FFNN) [12] and FabricVR project with DVT (MVA: DVT & FabricVR) [13] respectively.

Table 4: Performance Metrics Analysis

Performance Metrics	Computational Efficiency (s)	Visual Fidelity Index (0-100)	User Satisfaction Score (0-100)
MVA: DVT & ResNet50	987	25	34
MVA: DVT & MLP-SVM-ANN-FFNN	678	32	65
MVA: DVT & FabricVR	562	45	54
MVA: DVT & SA-CCGAN (Proposed)	90	96	98.5

Table 4 shows the efficiency of the proposed MVA: DVT & SA-CCGAN approach is evaluated to the existing method such as MVA: DVT & ResNet50 [11], MVA: DVT & MLP-SVM-ANN-FFNN [12] and MVA: DVT &

FabricVR [13] respectively. Here the proposed MVA: DVT & SA-CCGAN approach attains low Computational Efficiency, high Visual Fidelity Index and User Satisfaction Score. The high Visual Fidelity Index of the proposed MVA: DVT & SA-CCGAN approach indicates that the generated digital representations closely match the characteristics of traditional art, demonstrating a high level of fidelity or faithfulness to the original artistic expressions. Similarly, it has a higher User Satisfaction Score which indicates that users find the virtual art experience more satisfying.

4. CONCLUSION

In this, sophisticated technology called SA-CCGAN (Self-Attention-Based Cycle-Consistent Generative Adversarial Network) was successfully implemented within virtual art museums. SA-CCGAN served as a smart tool, enhancing the realism and visual appeal of digital art. The aim was to improve how art was displayed and experienced in virtual museums. The focus of the proposed MVA: DVT & SA-CCGAN approach was on making computer-generated art more closely resemble traditional artwork, with SA-CCGAN playing a significant role in refining details, colors, and the overall appearance of digital art. Through the SA-CCGAN network, virtual art could be presented in a way that felt more natural and captivating. It wasn't just about creating images; it was about crafting a virtual art space that people could explore and enjoy as if they were in a real art museum. The proposed MVA: DVT & SA-CCGAN approach also highlighted how this technology could bring a new and exciting dimension to the world of digital art. In future work, the incorporation of the latest technologies, along with fine-tuning SA-CCGAN model architectures based on novel optimization algorithms, is envisioned to enhance the virtual art experience further.

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