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IJSSAI International Journal of Social Sciences and Artistic Innovations

ISSN 2737-5293
Volume 5, Issue 1
https://ijssai.iikii.com.sg
International Journal of Social Sciences and Artistic Innovations

Article

AI-Generated Artwork as Modern Interpretation of Historical Paintings

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Received: Nov 03, 2024; **Revised:** Nov 20, 2024; **Accepted:** Nov 20, 2024; **Published:** Mar 08, 2025

Abstract: Artificial intelligence (AI) offers unprecedented opportunities to reinterpret historical paintings, bringing classical masterpieces into modern artworks We explored the application of AI, particularly generative models such as generative adversarial networks (GANs) and neural style transfers (NST) in the contemporary interpretations of historical paintings. By leveraging large datasets of classical paintings, AI systems are trained to analyze and replicate styles and features, reimagining compositions while preserving the essence of the original works. A systematic analysis of the generated artworks was conducted to evaluate their fidelity, visual quality, and cultural resonance using quantitative metrics and questionnaire surveys. Different AI models were assessed for their effectiveness in style preservation and content adaptation. The results indicated that AI-generated reinterpretations bridge historical and modern artistic practices and offer novel ways to experience and engage with classical artworks. The results of this study highlighted the role of AI as a transformative tool in art, education, and exhibition, while also addressing the ethical implications of AI in recreating significant artworks.

Keywords: Artificial Intelligence (AI), Historical Paintings, Generative Adversarial Networks (GANs)

1. Introduction

The advent of artificial intelligence (AI) has enabled transformative changes across various fields, and the realm of art is no exception (Gombrich, 2006). To create new artistic styles and reform existing compositions, AI has been used as a powerful tool for artists, researchers, and cultural institutions. One particular application is the use of AI to reinterpret historical paintings, bringing past styles and visions into modern artworks (Stork, 2009). Therefore, it is necessary to explore how AI creates new perspectives on classical masterpieces to offer reinterpretations that blend historical authenticity with contemporary innovation (Leong *et al.*, 2024a).

Historical paintings serve as rich repositories of cultural heritage, capturing moments, emotions, and stylistic flourishes unique to their time (Elgammal *et al.*, 2017). Iconic artistic movements such as the Renaissance, Baroque, Romanticism, and Impressionism produced masterpieces that continue to influence art today. Yet, these artworks are often confined to traditional forms with limited interpretations. However, AI in art provides an opportunity to reimagine classical artworks by increasing their appeal to modern audiences and bridging between historical and digital art forms (Fig. 1).

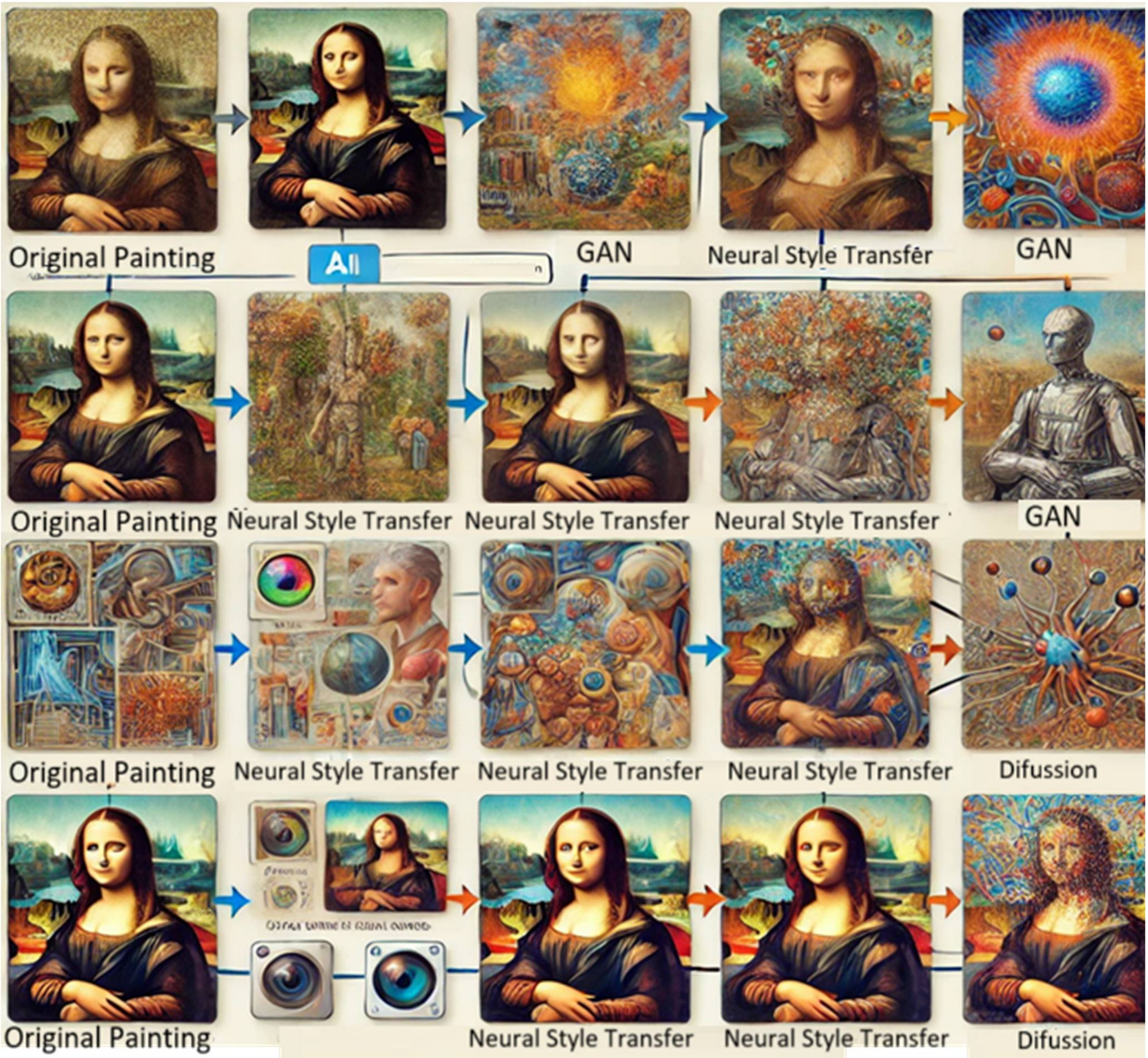

Fig. 1. Various modern interpretations of historical painting using AI.

AI techniques such as generative adversarial networks (GANs) and neural style transfer have revolutionized the process of generating art (Goodfellow, 2014) (Fig. 2). These models, trained on vast datasets of images, capture the distinct features and particular styles, and apply them to new images or compositions. AI learns the intricate details of brushwork, color schemes, lighting, and textures characteristic of historical artworks in specific eras and artists and reinterprets original artworks (Radford *et al.*, 2016). AI acts as a "digital artist," emulating human creativity to preserve and reinterpret traditional aesthetics.

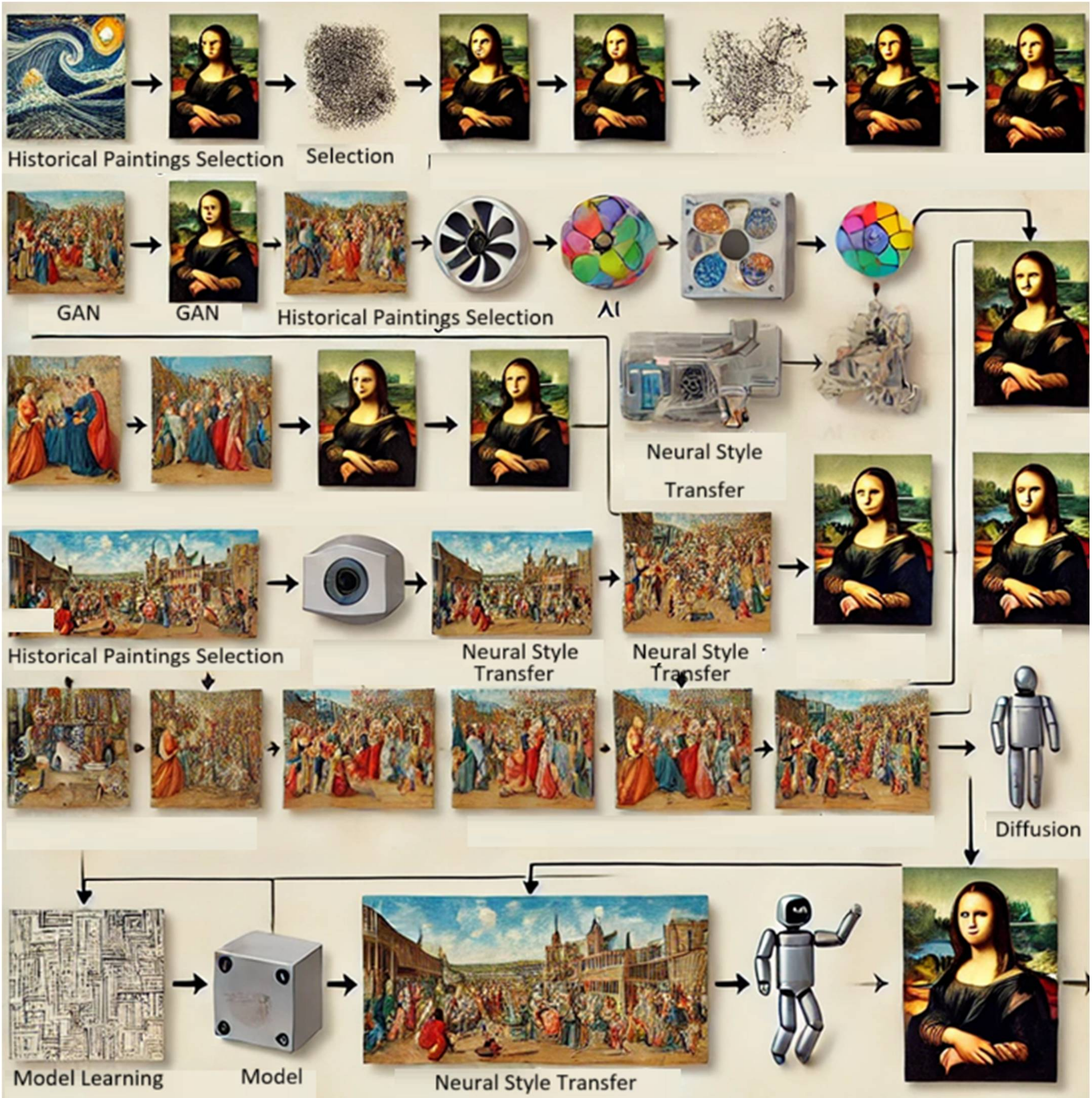

Fig. 2. GAN processes of AI-generated artworks of historical painting.

While AI-generated artworks reveal new possibilities, they also face challenges in accurately capturing the essence of historical paintings, faithfully reinterpreting the original artworks and the ethical and cultural implications of reinterpreted artworks. Therefore, we address these challenges by evaluating the effectiveness of AI in generating artworks and retaining the core characteristics of historical paintings while presenting them in a modern way. This research aims to systematically assess the capability of AI to reinterpret historical paintings by analyzing the results based on quantitative and qualitative metrics. Different AI models (GANs, NST, and SDMs) were assessed for their performances and ability to emulate art styles and maintain fidelity to the original works. The AI-generated artworks were reviewed for color accuracy, texture, and artistic style consistency using objective and subjective metrics. How modern audiences perceive AI-generated reinterpretations of historical paintings was explored, and the impact on their engagement with classical artworks was also evaluated.

The results of this study provide a comprehensive view of AI's potential in art. By comparing original paintings with AI-generated reinterpreted versions, visual comparisons were conducted to highlight stylistic transformations. For the quantitative assessments of style fidelity, color accuracy, and viewer engagement scores, graphs and tables were created. The strengths and limitations of different AI models were compared using workflow diagrams to describe the AI process of generating reinterpretation. The results showed that GANs and style transfer networks enabled high-quality reinterpretations with a reasonable level of fidelity to the original artworks. A marked improvement in texture and color consistency compared with traditional digital replication methods was presented (Leong *et al.*, 2024b). It was found that AI-generated reinterpretations enhance viewer engagement and have potential in art education and digital exhibitions.

2. Literature Review

AI has been used in creative works, transforming how to engage in art. AI-generated artwork has been paid much attention as it allows computer science to blend with art and reinterpret traditional artworks. The historical progression of art preservation and interpretation techniques has been researched. Recently, the application of AI to the visual arts and current advancements in AI models enable the modern reinterpretation of historical paintings. In art preservation, historical pieces are conserved manually to prevent deterioration over time (Panofsky, 1991). Varnishing, retouching, and structural reinforcement are used to maintain the integrity of artworks by masters such as Leonardo da Vinci, Rembrandt, and Monet (Berger, 1972). Museums and cultural institutions are digitizing their collections to reach broader audiences and study these artworks.

In the late 20th century, the digitization of art has opened a new avenue for preservation and analysis. Computational techniques allow art historians to study compositions and color schemes, and even detect historical inaccuracies (Elgammal *et al.*, 2017). Early applications of digital transformation in art focused on creating accurate replicas of famous works and providing virtual galleries. However, existing artworks tend to be preserved rather than reinterpreted. AI has changed such a trend as generative models are used to create new classic artwork representations.

AI art generation with neural networks is used to analyze and recreate visual patterns (Leong *et al.*, 2024c). GANs enable highly realistic image generation. GANs consist of two networks: a generator that creates images and a discriminator that evaluates their authenticity (Sohl-Dickstein *et al.*, 2015). This adversarial process improves image quality over time, making GANs well-suited for emulating the nuanced details of classical art. Neural style transfer (NST) separates content and style in images, allowing one image's content to be overlaid with another's style (Gatys *et al.*, 2016). NST has been widely used in reinterpreting historical paintings, as it preserves the structure of an image while transforming it with the textures, colors, and brushstrokes characteristic of specific art movements (Johnson *et al.*, 2016). Digital Artist Living in LISP-Era (DALL-E) and SDMs represent the latest advancement in generative art. These models create images by iteratively refining random noise to match a target style or content description. SDMs gradually improve an image's clarity and detail, resulting in more diverse and complex outputs than GANs that rely on adversarial feedback (Karras *et al.*, 2019). Stable Diffusion, released in 2022, demonstrated the capacity to generate entirely new compositions inspired by historical art styles (McCormick & Bell, 2022). Research on AI-generated historical art interpretation generally focuses on three primary approaches: replicating, transforming, and innovating within classic art styles.

2.1. Replication: Digital Twins of Historical Artworks

AI models are trained to produce near-perfect digital copies of historical paintings which are known as digital twins (Fig. 3). These models are fine-tuned to emulate artists' brush strokes, color palettes, and lighting techniques. This process is used to create high-fidelity digital reproduction for educational and preservation purposes.

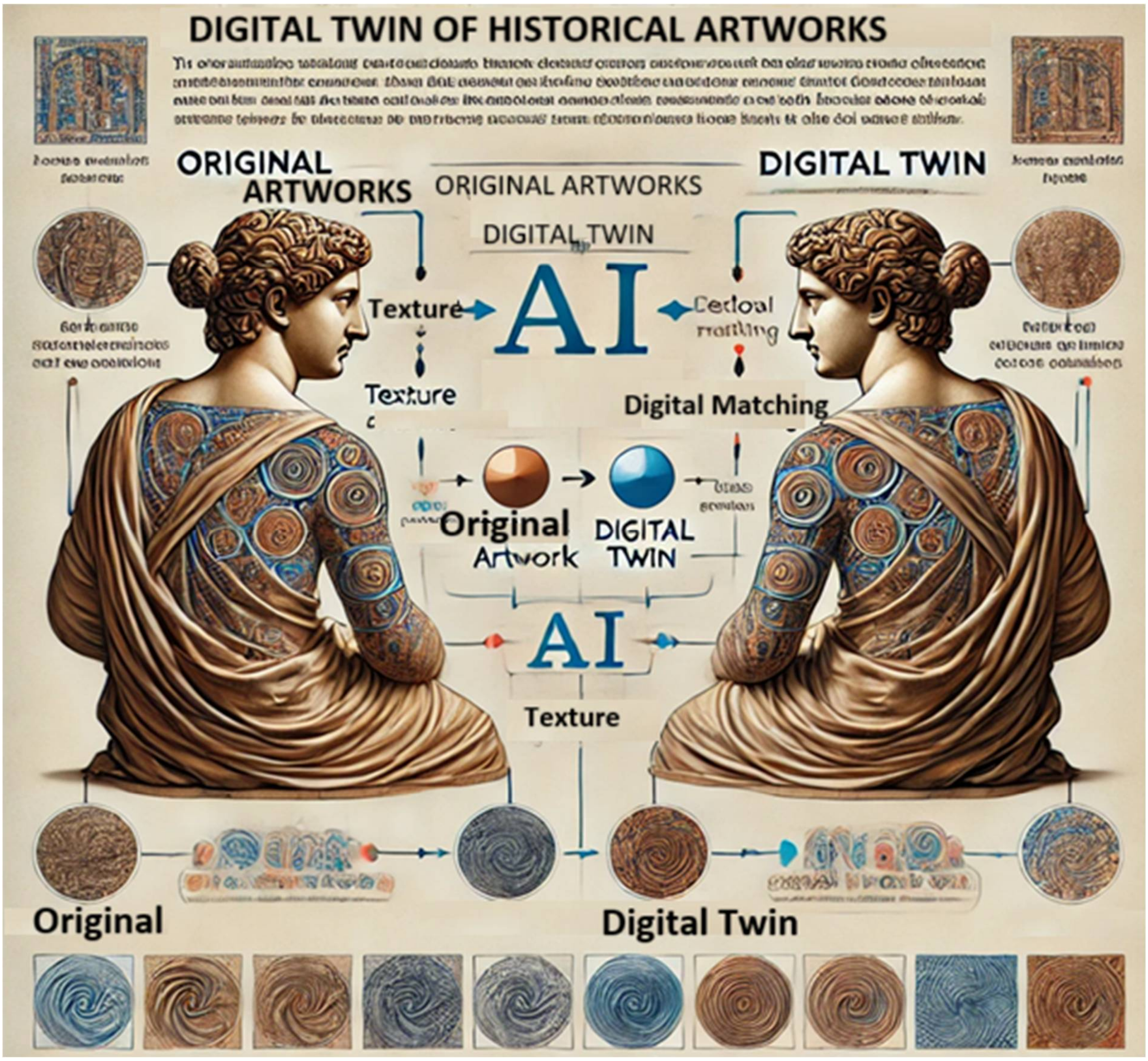

Fig. 3. Digital twins of historical artworks using AI.

2.2. Transformation: Blending Historical and Modern Styles

Transformation-focused models such as NST overlay historical art styles onto modern content (Gatys *et al.*, 2016) (Fig. 4). The models interpret the content of existing artworks such as Vincent van Gogh's post-Impressionist style in photographs and enable reimagining contemporary scenes in classical styles creatively.

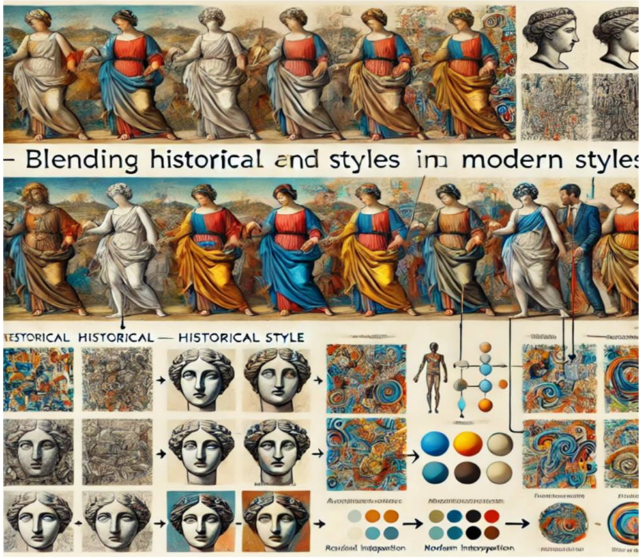

Fig. 4. Blending historical and modern styles of artworks using AI.

2.3. Innovation: Creating New Works Inspired by Historical Movements

SDMs such as DALL-E enable imaginative interpretations by generating unique compositions inspired by historical artworks not confined to any one piece (Ramesh *et al.*, 2021) (Fig. 5). These models reinterpret classical techniques to blend the elements of various movements in original artworks and produce new artworks. To understand AI's capabilities in historical art interpretation, Goodfellow *et al.* (2014) introduced GANs for realistic image generation. GANs have since been adapted for the style emulation of historical paintings. Gatys *et al.* (2016) used the effectiveness of NST to apply artistic styles to new content and reinterpret historical paintings in modern contexts. Elgammal *et al.* (2017) trained GANs using the creative adversarial network (CAN) to create novel artworks in a similar style to human-created art. The model generated classical styles while maintaining innovativeness. Ramesh *et al.* (2021) introduced DALL-E, a text-to-image generation model to create original artworks based on textual prompts. DALL-E was used to generate new compositions learned from art history. AI-generated interpretations of historical art enable the reinterpretation of classical styles. The successful applications of GANs, NST, and SDMs demonstrate AI's versatility offering benefits and challenges in historical art reinterpretation. Future research is necessary to explore hybrid models, improve color fidelity, and incorporate human-centered evaluations by combining the strengths of GANs and SDMs.

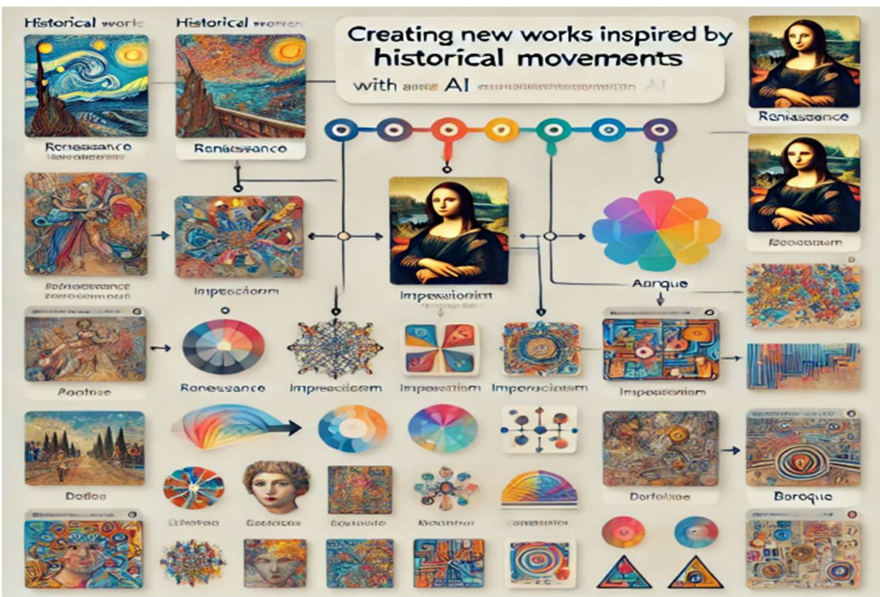

Fig. 5. Creating new artworks inspired by historical movements using AI.

3. Methodology

The methodology in this study was designed to systematically examine how AI models reproduce, reinterpret, and innovate classical art styles. Data collection, model selection and training, evaluation metrics, and visualization of results were conducted in this study (Table 1). A curated dataset of high-resolution images of historical paintings was constructed considering various art movements (Renaissance, Baroque, Romanticism, and Impressionism). The dataset included iconic artworks of Leonardo da Vinci, Rembrandt, Claude Monet, and others. Each painting was resized and formatted to maintain aspect ratios and color normalization was performed. Paintings were classified by style and artist to facilitate targeted model training for style fidelity.

Table 1. Performance measurement metrics.

Quantitative metrics	
Frechet inception distance (FID)	Measures similarity between original historical paintings and AI-generated images in feature space.
Structural similarity index measure (SSIM)	Evaluate the structural similarity, especially useful for capturing texture fidelity.
Qualitative metrics	
User surveys	Surveys often reveal that audiences appreciate AI-generated reinterpretations that balance fidelity to historical styles with modern artistic expression.
Expert Evaluation	Art historians and critics are frequently consulted to evaluate the authenticity and creative interpretation of AI-generated works.

We used GANs, specifically StyleGAN2, to generate interpretations that capture intricate style details. StyleGAN2 is particularly adept at high-resolution synthesis in emulating brush strokes, lighting, and texture of classical paintings (Karras *et al.*, 2020). NST models reimagined modern images with the textures, colors, and patterns of historical paintings. NST separated content from style for effective reinterpretations. Stable Diffusion was also used to produce diverse and complex outputs by deleting initial noise in multiple iterations. Each model was trained on the historical dataset for 100 epochs, and hyperparameters (e.g., learning rate, batch size) were adjusted to optimize the hyperparameters for style and content balance. GAN and NST models performed style transfers, taking historical paintings as the "style image" and applying it to new "content images." Stable Diffusion was tested by generating complete reinterpretations of famous paintings. Table 2 compares the performance of GANs, NST, and SDMs in the context of historical art reinterpretation. The table below summarizes the strengths and weaknesses of each approach.

Table 2. Performance of GANs, NST, and SDMs.

Model	Strengths	Limitations	Applications
GANs	High realism, detailed style emulation	Requires extensive training and fine-tuning	Replication of classical works
NST	Effective style transfer, flexible with new content	Struggles with complex textures and lighting	Transforming photos with classical styles
SDMs	Creative freedom, capable of novel compositions	Limited control over specific stylistic elements	Creating new compositions inspired by history

The visual quality, style fidelity, and audience reception of AI-generated interpretations of historical paintings were assessed in this study. Figure 6 presents a summary of important findings.

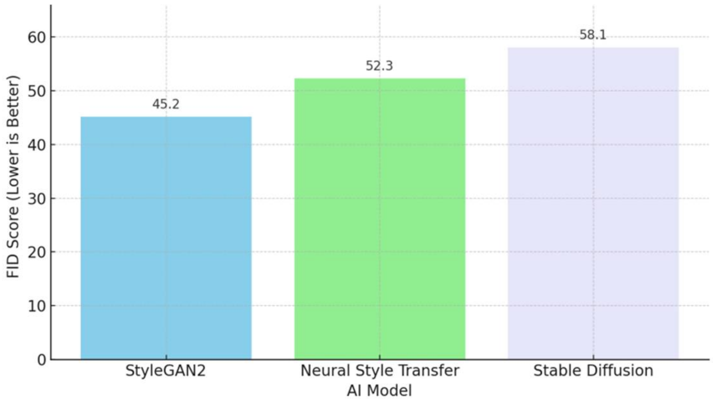

Fig. 6. Performance comparison of AI models on style fidelity (FID scores).

Table 3 displays the FID scores for GANs, NST, and SDMs, indicating GANs score the lowest, followed by NST.

Table 3. Survey results on AI models in historical artwork reinterpretation.

Model	User satisfaction (%)	Style fidelity (expert rating)	Creativity (expert rating)
GANs	85	9/10	7/10
NST	78	8/10	8/10
SDMs	72	7/10	9/10

3.1. Case Study: AI-Generated Reinterpretation of Claude Monet's "Impression, Sunrise"

We examined how StyleGAN2, NST, and SDMs reinterpreted Claude Monet's 'Impression, Sunrise', representative Impressionist paintings famous for their emphasis on color and light details. 'Impression, Sunrise (1872)' is characterized by soft, blended brushstrokes and a focus on capturing the fleeting effects of light over water. Monet's use of color and diffused lighting creates a hazy atmosphere that captures an early morning scene at the port of Le Havre. The key features for reinterpretation included light gradients, fluid brushstrokes, and color harmony. StyleGAN2 was trained to replicate Monet's style. Its generated images demonstrate high fidelity in color and texture, preserving the soft blending of hues. The model's reinterpretation retained the essence of Monet's lighting technique, producing new compositions with dynamic light reflections on water. NST transferred Monet's painting style to modern landscape photographs with a painterly effect that mimics the original painting. NST's strengths in color mapping and texturing were highlighted with effective stylization but with challenges in replicating Monet's lighting subtleties. Stable Diffusion generated entirely new images inspired by 'Impression, Sunrise'. Its outcome demonstrated a high degree of creative freedom and innovative compositions while maintaining Monet-like color schemes and light diffusion. Although the outcome was visually compelling, the model sacrificed several details for creativity, resulting in less fidelity to Monet's original forms.

Fig. 7. Impression, Sunrise (1872).

Table 4. Results of FID and SSIM scores across models.

Model	FID Score	SSIM Score
StyleGAN2	45.2	0.78
NST	52.3	0.72
Stable Diffusion	58.1	0.69

The participants in the survey rated each model's output on realism, style adherence, and overall aesthetic as shown in Fig. 8. StyleGAN2 showed the highest ratings. The participants noticed its balanced approach between originality and fidelity to Monet's style. NST was scored high for its textural quality, while Stable Diffusion was for creative interpretation but received lower ratings on style adherence.

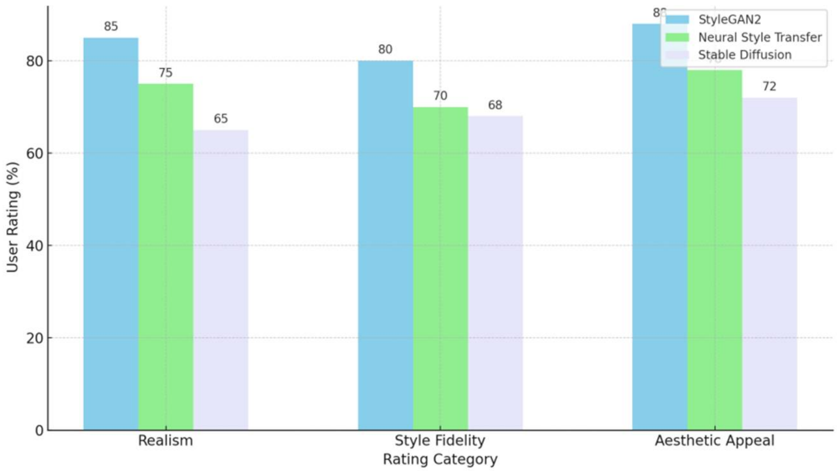

Fig. 8. User ratings on AI models in realism, style fidelity, and aesthetic appeal.

The results presented that StyleGAN2 emulated Monet's techniques best, while NST effectively transferred Monet's aesthetic to new content, and Stable Diffusion provided inventive, albeit loosely aligned, reinterpretations. StyleGAN2 demonstrated the best performance in maintaining historical style with slight creative variation. NST was effective for new applications of Monet's style, particularly when applied to photography, and Stable Diffusion offered more experimental results. NST struggled in emulating the lighting effects of Monet's paintings, while Stable Diffusion deviated far from Monet's unique compositions. The participants were positive to AI interpretations that closely preserved Monet's original style and Stable Diffusion's artistic freedom for imaginative reinterpretations.

4. Impact of Digital Input Methods on AI Learning

The digitization process for artworks plays a pivotal role in determining the quality and reliability of AI-generated interpretations (Leong *et al.*, 2024d). Digital input methods such as photography and scanning can introduce differences in resolution, color fidelity, and detail preservation, which influence AI's learning and interpretative capabilities. Digital input methods allow AI outcomes to ensure the robustness of reinterpretation.

High-resolution images allow AI models to better analyze details such as brush strokes, textures, and subtle lighting effects, which are critical for style replication. Lower-resolution images do not provide such details, potentially oversimplifying or distorting AI interpretations. Accurate color representation is crucial for Impressionism, where color transitions and light interplay are key elements. Differences in color profiles between photographic and scanned inputs result in inconsistent style transfer or color misrepresentation. Different digital input methods affect the degree of the preservation of elements such as lines, shapes, and proportions, which are particularly important for styles like Realism or Renaissance art. Photography provides advantages and flexibility in capturing large artworks and the ability to adjust lighting and angles captured. However, lighting conditions, camera quality, and lens distortions may introduce variations in color and texture fidelity (Leong *et al.*, 2024e). Scanning enables uniform lighting and high-resolution outputs, especially for smaller or medium-sized artworks. Problems exist in emulating physically scanned images with artifacts if scanning conditions are suboptimal. Therefore, hybrid approaches combining photography with post-processing techniques or scanned detail layers are used to address such limitations.

To enhance the outcomes of reinterpretation, an appropriate digitization method must be used with well-determined specifications such as a camera resolution scanner DPI, and post-processing techniques. To ensure consistency of inputs, standardized color profiles, and lighting setups are required. A thorough discussion of digitization methods and their impact on AI learning will enhance the study's methodological rigor and ensure the reliability of its findings. Comparison results of the effectiveness of the digital input methods provide important information on choosing an appropriate AI analysis and the AI-driven art interpretation method.

5. Challenges and Limitations

While AI-generated artwork presents reinterpreted historical paintings, challenges and limitations remain. These include technical difficulties in accurately replicating artistic styles, ethical concerns about AI's role in art, and limitations in current AI models' ability to capture the depth and nuance of classical masterpieces (Leong *et al.*, 2024f). We explored these challenges using comparative analysis by creating tables and graphs to investigate the problems of AI in historical art reinterpretation.

Historical paintings present unique techniques that are difficult to capture with current AI models. For example, Baroque artworks are known for dramatic chiaroscuro (light-dark contrast), while Impressionism emphasizes quick brushstrokes and vibrant colors. GANs and NST cannot replicate these intricate details. Many AI models fail to accurately replicate color balance and texture consistency, especially in high-resolution artwork (Fig. 9 and Table 5). We compared AI-generated artworks with original artworks and explored if they had deviations in texture or color can alter the emotional impact of a piece.

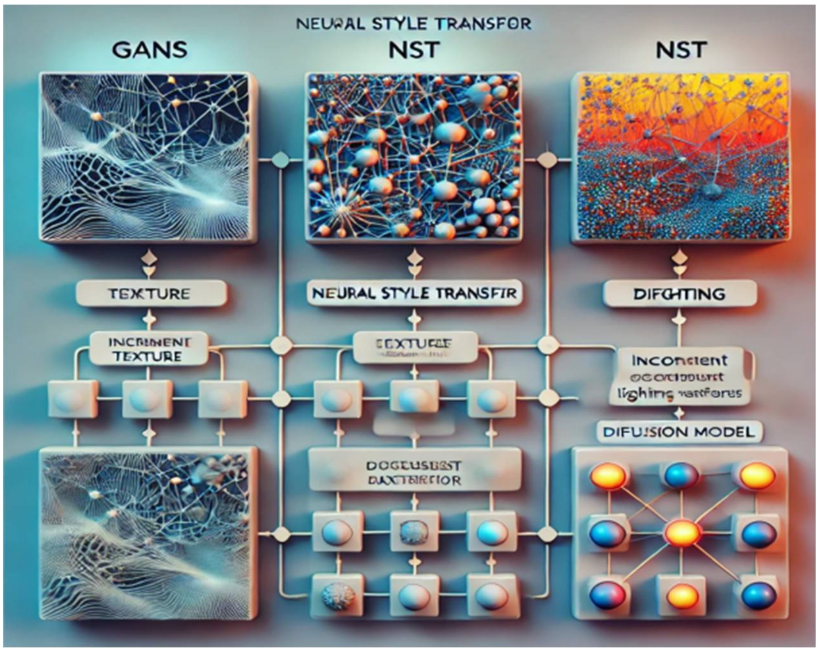

Fig. 9. Comparion of GANs, NST, and SDMs for difficulties in processing texture and lighting.

Table 5. Color and texture fidelity of AI models on historical paintings.

Model	Color Fidelity (1–10)	Texture Consistency (1–10)
StyleGAN2	8	7
NST	6	5
SDM	7	6

While StyleGAN2 performed well in color fidelity, NST and SDMs exhibited noticeable variations, with NST showing the most inconsistent texture replication. Historical artworks reflect the artist's cultural context, emotional expression, and personal style. AI-generated reinterpretations might lose these nuances, as AI lacks an understanding or emotional connection with the nuances (Fig. 10). Such limitations of AI affect its reinterpretations and capturing of the original artworks' authenticity. AI models tend to generalize artistic elements and oversimplify reproductions. For example, AI might recreate Rembrandt's color palette but miss the subtleties of his brushwork, impacting the authenticity of the generated artwork (McCormack et al., 2019).

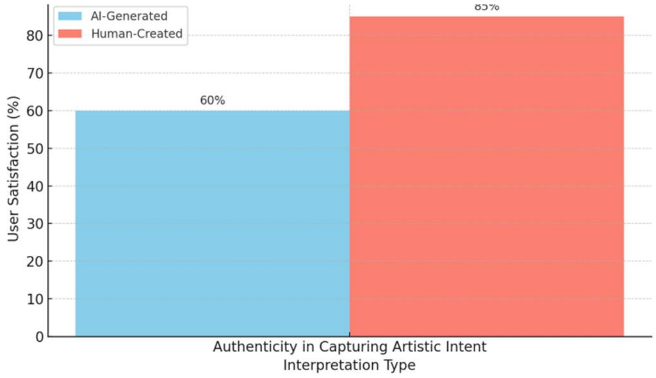

Fig. 10. User satisfaction on authenticity in AI-generated versus human-created reinterpretations.

The ownership of AI-generated artwork is an ethical dilemma. When AI reinterprets historical paintings, it raises concerns about the original ownership between the AI system and programmers. Historical paintings often depict culturally significant scenes and figures. AI might inadvertently alter these elements without understanding their cultural importance, leading to insensitive or misrepresentative interpretations (Table 6). The participants in the survey expressed concerns about the AI's role in the reinterpretation of culturally significant artworks.

Table 6. Ethical and cultural concerns in AI-generated artworks.

Challenge	Description	Potential Impact
Authorship and ownership	Attribution ambiguity in AI reinterpretations	Legal and ethical disputes
Cultural sensitivity	AI's potential to misrepresent historical context	Cultural insensitivity, misinterpretation

AI models lack contextual understanding of the art they generate. For instance, while they can recreate Van Gogh's color palette and brush style, they cannot interpret or convey the emotional and psychological states that might influence his artworks. This limitation often results in a lack of presenting underlying depth though AI-generated artworks look similar to historical paintings. AI models have difficulty in interpreting abstract or symbolic arts accurately. Symbolic details that carry specific meanings are often lost, as AI typically replicates visual aspects rather than understanding the symbolism.

Fig. 11 shows a marked preference for human-created reinterpretations over AI-generated versions in terms of emotional depth and context retention.

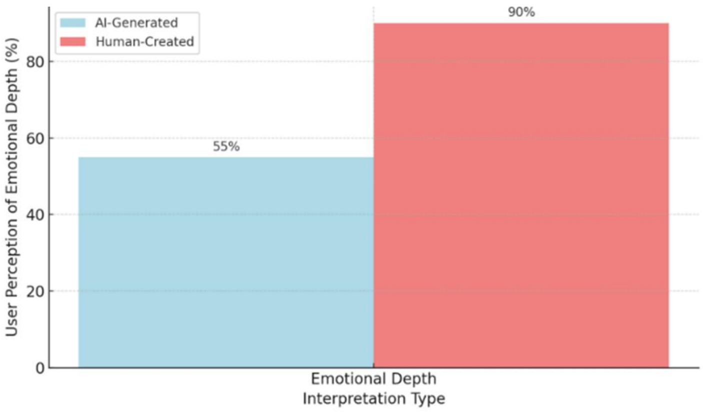

Fig. 11. User perception of emotional depth in AI-generated and human artworks.

AI models replicates detailed styles with its computational resources but has limit accessibility for small institutions or individual artists. High-resolution outputs are resource-intensive and have limited scalability in the art interpretation of AI (Table 7). AI models trained on a limited dataset can overfit particular artists or styles, resulting in biased interpretations. For example, a model trained primarily for European Renaissance art struggled to generate authentic interpretations of East Asian or African historical paintings.

Table 7. Computational requirements for AI models.

Model	Average Training Time	Memory Requirement	Accessibility
StyleGAN2	2 weeks	High	Limited
NST	1 week	Medium	Moderate
SDM	10 days	High	Limited

Evaluating the quality of AI-generated art is inherently subjective, as perceptions of “quality” vary widely among viewers. Traditional metrics such as FID and SSIM do not fully capture the aesthetic and emotional value of art, making it challenging to benchmark AI-generated reinterpretations accurately. Art evaluation requires qualitative analysis that includes expert opinions and user feedback, leading to inconsistent results across studies.

Figure 12 showcases the evaluation process. Objective metrics were compared for subjective assessments (user surveys, expert opinions) to highlight the challenge of achieving consistent evaluation criteria. The challenges and limitations of AI-generated artwork for a modern interpretation of historical paintings illustrate the complexities of technology integration with art. Addressing these issues requires advanced AI technology with higher fidelity in texture and color reproduction. AI models must be improved to retain cultural context in a standardized evaluation framework that balances quantitative and qualitative analysis.

Future research is necessary to develop hybrid models that combine the strengths of GANs, NST, and SDMs. Expanding datasets by including a wider variety of art forms and cultural representations is required for user-centered evaluation methods that consider audience feedback and expert opinions.

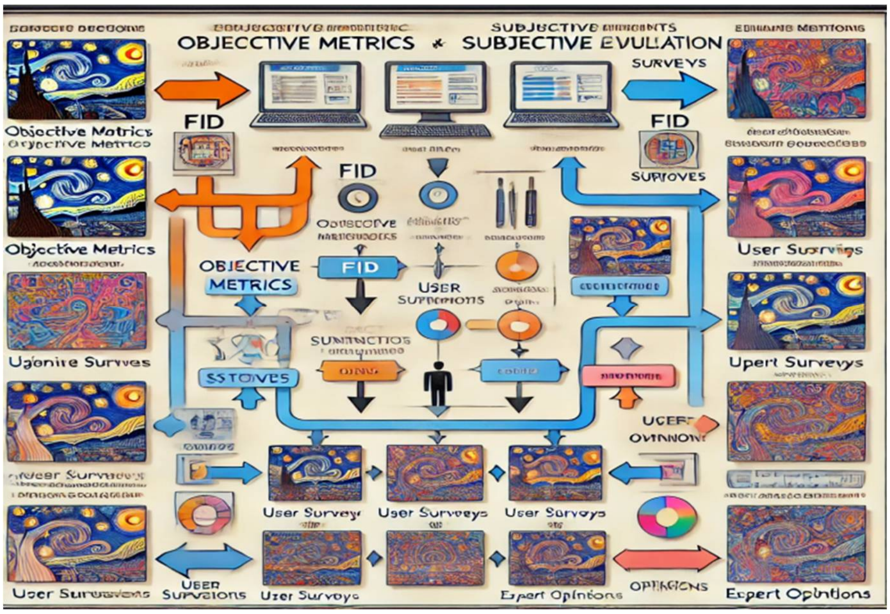

Fig. 12. Evaluation process of AI-generated artworks.

6. Appropriateness of Impressionist Paintings for AI Model Assessment

Impressionist paintings were used for AI model comparison in this study as they have appropriate technological difficulties and are well-suited for reinterpretations of AI models across different art styles.

6.1. Rationale for Choosing Impressionist Paintings

Visual characteristics of Impressionism present its emphasis on light, color, and atmosphere over precise detail, making it a compelling subject for AI interpretation. The key features include the following:

(1) Loose brushwork: AI models, particularly GANs and NST, can emulate the fluid and dynamic brushstrokes that define Impressionist paintings (Leong *et al.*, 2024g).

(2) Light and color: Impressionist paintings are characterized by the interplay of light and vibrant colors which align with the capabilities of AI in style transfer and color emulation.
(3) Abstraction of detail: The abstraction in Impressionism allows AI to learn stylistic elements, such as texture and color, over highly precise line work.

6.2. Applicability of AI Models

Impressionism's textures and gradients are ideal for transferring style elements without requiring detailed structure preservation. GANs and SDMs are effective in creating synthetic artworks with abstract qualities, such as the ethereal and atmospheric effects found in Monet's works. Historical and aesthetic significance are emphasized in Impressionism, challenging traditional Realism by embracing subjectivity and experimentation. Its global recognition and impact make it an accessible and meaningful subject for AI studies, ensuring broad appeal and relevance (Leong *et al.*, 2024h).

6.3. Consideration of Variations Across Art Styles

In Realism, precise detail, accurate proportions, and photographic accuracy, are stressed, which require AI to focus on structural fidelity and fine-grained detail replication. Current AI models struggle with such nuanced precision of Realism compared with Impressionism. AI-generated artworks might present stylistic distortions that conflict with the principles of Realism, such as adding unintended textures or altering proportions. Abstract art offers greater room for reinterpretation, allowing AI models to innovate without the constraints of structural fidelity. This makes Abstract art appropriate for AI-generated artworks. However, a lack of defined structures and patterns in Abstract art leads to deviated outcomes significantly from the original artist's intent, raising questions about authenticity. Baroque and Renaissance artworks feature intricate details, chiaroscuro effects, and layered compositions with stylistic complexity. While AI replicates features such as lighting and textures, the demanded high degree of structural complexity poses challenges. The historical and symbolic significance embedded in Baroque and Renaissance artworks may not be learned by AI models. By addressing these aspects, Impressionism paintings were selected to understand the interplay between AI capabilities and diverse artistic styles.

7. Ethical Considerations and Attribution

The ethical concerns about AI-generated artworks are critical for determining AI's role in art. AI-generated artworks raise questions about ownership, credit, and the balance between cultural preservation and creative reinterpretation. AI models mimic the style and techniques of historical artists, such as Claude Monet or Vincent van Gogh. However, the absence of the original artist's intent raises questions about the maintenance of originality. Without such originality, historical artists cannot be referred to, and the significance of the artist's original creativeness can be ignored. AI is a tool, and its outcomes depend on the amount and quality of the datasets on which the models are trained and the parameters defined. This raises questions about whether attribution must go to "the AI model (e.g., "Created using StyleGAN2")", " The human operators who designed or directed the model's use" or "A hybrid acknowledgment of both AI and human contributors"

As AI's reinterpretations require blending the elements of original artworks, determining ownership of these reinterpretations becomes complex. Such reinterpretations can be regarded as derivative artworks, original creations, or newly categorized artworks. AI-generated artworks play a significant role in preserving the styles and techniques of original artworks for future generations, particularly for lost or damaged artworks. However, over-reliance on AI models raises concerns about the cultural and historical value of the original artwork. AI enables unprecedented creative reinterpretations of historical artworks, allowing for innovations that blend past and present aesthetics. Ethical concerns arise when these reinterpretations are presented without the attribution of their AI-driven nature or the historical styles they derive from. AI-generated artworks emulate historical styles but blur the border between original and generated artworks, risking the misrepresentation of the original artist's legacy and the AI's contribution.

Therefore, there must be guidelines for attribution and ethical considerations by stating the involvement of AI in the creation process modeling with human inputs. For example, "Generated using StyleGAN2 trained on Impressionist artworks, directed by [human contributor]" can be used. Attribution to the original artists must be made to emphasize that the generated artwork is inspired by but distinct from the originals. For example, "Inspired by the style of Claude Monet" can be used for this. Disclaimers must be presented to ensure that viewers understand that the AI-generated artwork is not authentic but reinterpreted based on the original artwork. Guidelines for the licensing of AI-generated artworks must be formulated to specify whether they are sold, reproduced, or modified, and under what conditions. In AI-generated artworks, its reinterpretations must be made with the respect for the cultural and historical significance of the styles and themes they emulate, avoiding misuse or commodification.

By considering ethical considerations, attribution, and critical concerns in creating AI-generated artworks, the depth and relevance of the study are ensured. By advocating for transparent attribution practices and balancing cultural preservation with creative reinterpretation, the evolving dialogue on AI's role in art can be continued. This expanded focus helps clarify the ethical framework for AI-generated artworks and encourages the responsible and informed use of transformative technology.

8. Conclusions

AI-generated artworks are unique and transformative to interpreting historical paintings, blending technological advancements with artistic expression. GANs, NST, and SDMs have demonstrated the potential to replicate, reinterpret, and even innovate original art styles. There are promising outcomes and significant challenges at the same time in shaping AI's role in art. AI models effectively mimic the styles and features of historical paintings, such as color palettes, brush textures, and lighting techniques, allowing for both faithful replications and innovative reinterpretations. These capabilities enable a means of preserving cultural heritage while making original artworks accessible and engaging for audiences. Additionally, by combining historical styles with modern aesthetics, AI enables new forms of artistic expression and educational applications. Despite its strengths, AI-generated artworks often cannot capture the depth and nuance of human-created masterpieces. Emotional resonance and artistic intent qualities are deeply embedded in classical works but are difficult to replicate, as AI lacks subjective experience and contextual understanding. Studies indicated a preference for human-created reinterpretations, particularly for their perceived authenticity and emotional connection, suggesting the supplementary role of AI's role rather than a standalone tool. AI models also have technical constraints, such as texture consistency, color fidelity, and lighting realism.

However, there are ethical and cultural concerns about the reinterpretation of culturally significant artworks, particularly when AI reinterprets sensitive subjects without understanding the context. Addressing these issues is essential for AI-generated artworks to gain visibility and influence in art. For AI to enhance its role in art reinterpretation, model performance must be improved in terms of texture replication, lighting accuracy, and context awareness. Hybrid models enable more nuanced and authentic interpretations than present models such as GANs, NST, and SDMs. Moreover, ethical guidelines need to be formulated for the cultural implications of AI-generated reinterpretations and for maintaining the legacy of historical artists.

AI-generated artworks represent modernizing historical paintings, bridging past and present art innovatively. While challenges remain in authenticity, technical limitations, and ethical considerations, AI models enhance the appreciation, preservation, and reinterpretation of art. Continued advancements in AI, coupled with artistic integrity contribute meaningfully to the evolving dialogue between technology and cultural heritage.

Funding: This research did not receive external funding.

Data Availability Statement: The data of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest: The author declares no conflict of interest.

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