

# Digital Restoration of Indian Traditional Paintings

Nidhi P Naik

Information Science and Engineering  
B N M Institute of Technology  
Bengaluru, India

Sanjana R

Information Science and Engineering  
B N M Institute of Technology  
Bengaluru, India

Vishwas Bhusnoor

Information Science and Engineering  
B N M Institute of Technology  
Bengaluru, India

Dr. Jagruthi H

Associate Professor  
Information Science and Engineering B  
N M Institute of Technology  
Bengaluru, India

**Abstract**—Conservation of Indian traditional paintings, a national treasure considered to be irreplaceable cultural and historical resources, is deemed to be an essential challenge. The painting works are now more exposed to natural degradation, environmental factors, and time. Conventional methods of restoration, although popularly practiced, tend to have labour intensive and expensive procedures and irreversible treatments, therefore requiring innovative alternative strategies. With the recent developments in Artificial Intelligence (AI) and deep learning, new non-destructive digital restoration processes have been proposed, which have the potential to conserve these historic masterpieces without compromising them further. In this paper, an extensive survey of the principal technologies and ideas associated with digital inpainting—a basic tool employed for virtual restoration of broken artworks is showcased. Comparisons are made between traditional image processing techniques and new deep learning techniques, such as Generative Adversarial Networks (GANs) and Diffusion Models, and their respective advantages and limitations are analysed. The involvement of human expertise in the restoration is portrayed, with focus given to ethical concerns, necessity of uncertainty quantification, and maintaining the artistic style in the course of the restoration process. Methodologies, computational complexities, and assessment measures are analysed in order to better understand the current capability provided by AI-assisted restoration. Long standing issues, like the insufficiency of datasets specifically designed for the distinctive characteristics of Indian traditional art, are noted, and directions for further studies are suggested.

**Index Terms**—Digital Restoration, Inpainting, Generative AI, Indian Traditional Paintings, Cultural Heritage, Deep Learning, Generative Adversarial Networks, Diffusion Models

## I. INTRODUCTION

Preservation of cultural heritage has been seen as an issue of significance, with historical paintings as irreplaceable art pieces that reflect human civilization, art, and societal evolution. Among these, Indian traditional paintings and drawings—praised for the variety of styles, delicate craftsmanship, and vibrant colour compositions—are especially susceptible to degradation resulting from environmental conditions, humidity, light, and the natural processes of aging. The restoration of such works has, for centuries, been performed by conservators using manual, physical, and generally invasive methods. Such

This work was supported by B N M Institute of Technology.

traditional techniques, though based on professionalism and convention, have proved to be expensive in terms of cost and labour, time-consuming, and sometimes damaging to the integrity of the original work since the risk of causing additional damage during the process of restoration cannot be eliminated.

With the rise of digital technologies, a new conservation pattern has been enabled, one that provides non-invasive, reversible, and precise means for the virtual restoration of art. At the heart of this digital revolution lies the method of digital inpainting, which entails the completion of missing or damaged areas of an image by filling them with visually coherent and contextually consistent content [14], [18]. In the initial phase, digital inpainting was limited to basic pixel-level corrections like the elimination of small blemishes or scratches [26]. However, with the accelerated development in computational power and the emergence of deep learning techniques, the area has seen a dramatic transformation [7], [14], [18]. More advanced approaches are now able to reconstruct larger missing regions automatically and create content consistent with the original artwork's style and composition [27], [29], [30].

This paper seeks to give a systematic and exhaustive overview of the evolution of digital inpainting methods, with special reference to their use in the restoration of Indian traditional paintings [21], [22], [28]. The mathematical foundations and algorithms are initially described, after which advanced AI-based methods are thoroughly discussed, with mention of their merits, drawbacks, and ethics [17]. Practical aspects like human knowledge integration, handling uncertainties, and protection of artistic integrity are also discussed [9], [25]. The survey is concluded by noting the current challenges and future opportunities, with a focus on the requirement of necessary, content-specific datasets and models specific to the unique aspects of Indian cultural heritage [10], [13], [28].

## II. LITERATURE SURVEY: KEY TECHNOLOGIES AND CONCEPTS

The terrain of computer inpainting in art restoration has been defined by an evolution over time from initial, basic

algorithms following set rules to highly advanced, generative models driven by Artificial Intelligence (AI) [14], [18]. This has followed an evolution in emphasis from mere patching of single pixels to the intelligent reconstruction of missing parts of artworks on the basis of stylistic understanding, context, and semantics [17]. Consequently, restoration methods have transitioned from surface-level repairs to full-fledged, content-based recreation that accounts for the artistic intention and historical significance of the works [21], [22].

#### A. Traditional vs. Deep Learning Methods

Early digital inpainting methods were based on traditional approaches that were strongly dependent on local information and mathematically specified procedures [26]. Such techniques, usually classified as classical techniques, were marked by local operations that were performed on small neighbourhoods of the missing area without considering higher-level image semantics.

Among these, content-based inpainting techniques, including nonparametric sampling and exemplar-based methods, were prevalent [26]. In these techniques, the repair process was achieved by taking patches or pixels from intact areas surrounding the flaw and duplicating them to replace missing portions. While such techniques were effective in coping with plain textures, homogeneous backgrounds, or minute irregularities, they were considerably constrained when charged with reconstructing large missing areas or intricate patterns [26]. The lack of contextual perception frequently resulted in irregular textures or seams where patches were blended together.

Structure-based inpainting techniques, by contrast, tried to restore the image's geometric and structure continuity. Methods like the Fast Marching Method (FMM) and Partial Differential Equations (PDEs) were utilized for extrapolating lines, edges, and boundaries into the damaged areas [11], [13]. These mathematical models provided better results when coping with shapes and patterns that called for geometric coherence. However, for all the mathematical precision they provided, such methods were inadequate when complex textures, complicated patterns, or stylistic intricacies needed to be replicated. The outcomes tended to be too simplistic or lacked accuracy [11], [26].

Eventually, classical approaches were limited by their inability to understand the higher semantics inherent in artwork. As a result, restorations conducted with these approaches often contained soft textures, artificial transitions, or structural anomalies [26]. The artistic synthesis of conceivable content in heavily compromised artwork remained elusive.

Deep learning led to a new generation of image restoration [7], [14], [18]. The advent of Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) resulted in a fundamental leap in capability [7], [29]. Through the exploitation of large datasets, the models learned not just surface-level patterns but also structural and semantic interrelations underlying images [27]. Restoration methods which could "hallucinate" missing content intelligently were

made possible through this [7], [29], [30]. These methods allowed for the computer-assisted creation of very realistic textures, forms, and patterns that conformed to the style and context of the original artwork, circumventing many of the previous methods' limitations [7], [27], [29].

#### B. Key AI Inpainting Architectures

In contemporary restoration pipelines, two major deep learning architectures have dominated the landscape: Generative Adversarial Networks (GANs) and Diffusion Models [7], [27], [19], [23]. Both models have been used to tackle particular challenges, with their individual strengths playing a role in various aspects of image reconstruction.

GAN-based methods excel at generating high-frequency, textural details and visually plausible restorations [7], [29], [24], whereas diffusion models are better at achieving global structural coherence and semantic consistency [19], [27], [30]. Hybrid approaches that combine the strengths of both have also emerged, offering a balanced trade-off between texture quality and structure fidelity [4], [23].

Transformers and Vision Transformers (ViTs) have recently introduced the ability to capture long-range dependencies across the image, making them particularly effective in understanding global artistic context [1], [20]. Diffusion models continue to evolve, with variants such as Denoising Diffusion Implicit Models (DDIMs) [16], Latent Diffusion Models [8], and Preference-Aligned Diffusion [9] introducing better efficiency, coherence, and perceptual quality.

The papers referenced are summarized below highlighting their core methodologies and contributions.

**Elharrouss et al. (2025)** present a comprehensive review of Transformer-based image and video inpainting approaches, outlining key developments and challenges in the field. Their study categorizes current Transformer architectures used for restoration tasks and highlights their strengths in modeling long-range dependencies. While the work does not introduce a new model, its significance lies in identifying trends and future directions that inform ongoing research in digital art restoration.

**Zhang et al. (2025)** propose a specialized deep learning model for mural inpainting using a U-Net-based discriminator enhanced with coordinate attention and aggregated transformations. This design helps maintain structural integrity and fine textural details characteristic of mural art. The method demonstrates improved historical and stylistic fidelity, though it requires adaptation for non-mural images.

**Wang et al. (2025)** address the issue of low-resolution digital archives of ancient paintings through deep learning-based super-resolution algorithms. Their technique reconstructs lost details and enhances visual quality, aiding both research and public appreciation. A limitation is the risk of generating non-authentic details not present in the original artwork.

**Botirova et al. (2025)** combine Diffusion Models and Generative Adversarial Networks (GANs) in a hybrid framework

for historical painting restoration. The approach integrates the structural coherence of diffusion models with the textural sharpness of GANs, achieving realistic results at the expense of higher computational complexity.

**Kinakh & Voloshynovskiy (2025)** introduce a Binary Diffusion Probabilistic Model optimized for binary data such as segmentation masks. While not designed for full-color inpainting, it serves as an efficient pre-processing tool for defining damaged areas with high precision.

**Abualigah et al. (2025)** present an improved reptile search algorithm with a Gbest operator for multi-level image thresholding. Their optimization enhances segmentation accuracy, crucial for identifying damaged regions before restoration. The study, however, does not perform the inpainting itself.

**Buvaneshwaran et al. (2025)** demonstrate the application of GANs for the digital restoration of damaged paintings and artifacts. The network learns artistic styles from undamaged works to reconstruct missing regions with high-frequency detail, though it occasionally introduces structural inconsistencies across large missing areas.

**Corneanu et al. (2024)** propose *LatentPaint*, an inpainting technique operating in the latent space of an image using diffusion models. This method offers computational efficiency and global coherence, but its performance is limited by the fidelity of the autoencoder used for encoding and decoding.

**Liu et al. (2024)** introduce *PrefPaint*, a diffusion-based model fine-tuned using human feedback. By aligning model outputs with human aesthetic preferences, it produces restorations that appear more natural to viewers. The main challenge is the subjectivity and effort involved in collecting reliable human feedback.

**Sinha et al. (2024)** outline a complete digital restoration pipeline using synthetic damage generation, deep segmentation, and inpainting. This synthetic training approach addresses the scarcity of real-world damaged/undamaged artwork pairs. Its limitation lies in the gap between synthetic and real degradation patterns.

**Tint & Tin (2024)** assess the coherent transport inpainting method for mural restoration, employing damage ratio analysis to quantitatively evaluate results. The work contributes a measurable framework for restoration quality, though it focuses narrowly on one algorithm and mural type.

**Sun et al. (2024)** propose a dual-encoder inpainting architecture that processes both local textures and global structural context. The system improves compositional coherence and detail retention, although its dual-encoder design increases computational cost.

**Hu et al. (2024)** present a multi-level thresholding segmentation algorithm using an equilibrium optimizer. It efficiently isolates damaged regions, enhancing precision in restoration workflows, though it only addresses segmentation, not inpainting.

**Quan et al. (2024)** conduct a survey of deep learning-based image and video inpainting, categorizing architectures like CNNs, GANs, and Transformers. The paper provides a broad

synthesis of the field's evolution but does not include new experimental findings.

**Yang et al. (2023)** introduce *Uni-Paint*, a unified diffusion-based framework for multimodal inpainting that accepts textual or visual guidance. Its versatility offers users creative control, though this generalization may reduce task-specific performance.

**Zhang et al. (2023)** utilize Denoising Diffusion Implicit Models (DDIMs) to enhance global coherence and sampling speed in image inpainting. While maintaining realism and structural plausibility, challenges remain for very large missing regions.

**Gaber et al. (2023)** discuss the impact of AI and machine learning on cultural heritage preservation. Though conceptual rather than technical, it emphasizes AI's transformative role in safeguarding artworks and artifacts through virtual restoration.

**Xu et al. (2023)** review deep learning-based inpainting methods, analyzing GAN-, CNN-, and Transformer-based architectures. The study summarizes advancements and challenges such as edge artifacts and texture continuity, serving as a key resource for restoration researchers.

**Fein-Ashley & Fein-Ashley (2023)** enhance diffusion-based inpainting by introducing anisotropic Gaussian splatting, which models directional textures like brushstrokes. The method improves realism but increases computational overhead.

**Duan et al. (2023)** apply Vision Transformers to historical painting restoration, leveraging their global context modeling to maintain stylistic coherence. Although computationally expensive, this approach is highly effective for large, complex compositions.

**Singh et al. (2023)** focus on digital restoration of ancient Indian murals through adapted inpainting algorithms. Their work highlights how AI can be tailored to culturally specific art forms, though results may not generalize across diverse painting styles.

**Tribhuvan & Abdullah (2023)** present a real-world AI restoration of the Ajanta Cave paintings, demonstrating digital heritage preservation at scale. While context-specific, the study underscores the viability of AI for ancient artwork reconstruction.

**Grechka et al. (2023)** propose *GradPaint*, a gradient-guided diffusion inpainting method that leverages edge and texture gradients for sharper boundary alignment. This guidance enhances detail accuracy but can limit creative flexibility in more abstract tasks.

**Zuo et al. (2023)** combine contrastive learning and segmentation confusion adversarial training to improve semantic and structural realism in generative inpainting. The complex training setup yields strong results but demands significant computational resources.

**Yu et al. (2023)** introduce *Inpaint Anything*, integrating the Segment Anything Model (SAM) with diffusion-based inpainting. The system simplifies mask creation and improves user experience, although final quality depends on SAM's segmentation accuracy.

**Zhao et al. (2022)** enhance exemplar-based inpainting by incorporating boundary priors to guide patch selection, improving structure consistency in classical algorithms. Despite improvements, exemplar-based methods remain limited for large missing regions.

**Lugmayr et al. (2022)** present *RePaint*, one of the earliest applications of Denoising Diffusion Probabilistic Models (DDPMs) for inpainting. The model produces highly realistic results through iterative resampling but at the cost of long inference times.

**Poornapushpakala et al. (2022)** design a segmentation-plus-inpainting framework for restoring Tanjore paintings, respecting the distinct materials and textures involved. The approach is effective but tailored specifically to this art form.

**Zhao et al. (2021)** develop co-modulated GANs for large-scale image completion, achieving global structural consistency in extensive missing regions. However, GANs' training instability remains a challenge.

**Suvorov et al. (2021)** propose resolution-robust inpainting using Fourier convolutions, improving global consistency across varying resolutions. The trade-off is reduced capability in fine-texture reconstruction.

1) *Generative Adversarial Networks (GANs)*: GANs have been generally seen as one of the most effective tools for inpainting and generating images [7], [14], [29]. The architecture consists of two adversarial networks: a generator, which tries to generate inpainted images that are indistinguishable from real art, and a discriminator, which learns to recognize the difference between real and generated images [7], [27]. Through the adversarial process, both networks are progressively improved, producing progressively more realistic outputs [7], [29].

**Context Encoders**: These were some of the first methods used. They work by using an encoder-decoder setup in which the encoder looks at the parts of the image that are still there, while the decoder tries to fill in the missing spots. Using adversarial training helps make the new content blend in better with the existing parts, though it still struggles with really detailed patterns [14], [18], [26].

**CAAT-GAN**: This model is made specifically for fixing murals. It introduces something called the Coordinated Attention Aggregation Transformation (CAAT) block, which helps the model gather information from distant parts of the image. This way, it can better rebuild damaged areas [23]. It also uses a U-Net-based discriminator that checks both the big picture and small details, reducing errors and making the results sharper and more textured [23], [24].

**User-Guided GANs**: These models let people guide the restoration process. For example, when restoring ancient Chinese paintings, users can give hints about the structure of the image [19]. This helps the AI make restorations that stay true to the original style and meaning, keeping cultural and historical details intact [21], [22], [28].

**Multi-Stage GANs**: These are more advanced systems that work in steps. The first stage fixes the basic structure, and the next stage adds textures and details [7], [29]. This approach

helps handle large, complex missing areas and creates results that look both accurate and visually pleasing [27], [30].

2) *Diffusion Models*: Along with GANs, diffusion models are another category of potent inpainting architectures [8], [9], [16], [19]. They operate by initially introducing controlled noise to an image in iterative steps and then figuring out the reverse procedure [16], [27]. This denoising process allows the retrieval of images with high textures and subtle information often hard to realize through other means [19], [30].

Numerous diffusion-based solutions have been able to successfully implement image restoration:

**Palette**: A generic architecture that utilizes conditional diffusion models to accomplish diverse image-to-image translation tasks, such as inpainting [19]. Without the need for task-specific modifications, Palette has been demonstrated to produce state-of-the-art outcomes on a large range of restoration tasks and is a valuable tool in the conservation realm [19], [27].

**BDPM (Binary Diffusion Probabilistic Model)**: This model presented an innovative solution by modelling images in binary form using decomposition into bitplanes. The model used an XOR-based noise transform, enabling more efficient and accurate control of the restoration, especially beneficial in handling fine detail and high-frequency texture [8], [16].

**PrefPaint**: In appreciation of the significance of beauty, PrefPaint combined reinforcement learning with diffusion modelling by training a reward model over a huge dataset of human-annotated images [9]. By optimizing restoration as per human preferences, the model made the outcome technically accurate as well as beautiful [9], [19]. The model was tested on a dataset of 51,000 annotated inpainted images and showed regular perceptual quality improvements [9].

**Hybrid GAN-Diffusion Models**: Recent developments have also seen attempts to hybridize GANs and diffusion models to take advantage of their strengths complementarily [4], [23]. Although GANs are far better at reconstructing texture and structural information, diffusion models are best suited to controlling noise and refining fine details [8], [19], [27]. These hybrid methods have been demonstrated to achieve restorations with very high perceptual quality while maintaining the artistic style integrity of the work [23], [30].

### C. Human-Centric Restoration and Ethical Considerations

With the evolution of restoration methods, the focus is now more and more on ethical and practical issues that come with AI-based methods [9], [17]. The most sophisticated pipelines today also incorporate human knowledge and quantifying uncertainty to facilitate responsible and culturally appropriate restoration [21], [22], [28].

1) *Human-in-the-Loop and User Guidance*: Since artworks not only contain visual patterns but also history and culture, human professionals have been considered irreplaceable in the restoration process [17], [21]. AI algorithms that have user-guidance features enable conservators to intervene throughout the restoration by giving structural suggestions or correcting generated images [9], [25]. This cooperation ensures that the

restored image not only produces technical accuracy but also artistic and cultural authenticity [17], [28].

Models such as PrefPaint have highlighted the significance of ensuring alignment of AI-generated results with human aesthetically grounded judgments, since restoration is not only about structural fidelity but also about perceptual harmony [9]. Human-in-the-loop approaches guarantee that restoration is transparent, interpretable, and accountable [17], [21].

2) *Uncertainty Quantification*: Inpainting techniques necessarily carry an element of guesswork when considerable parts of an image are lost, necessitating the creation of new material based on no guidance from the original object [11], [26]. In response to this problem, uncertainty quantification techniques have been developed [23], [25]. For example, CAAT-GAN's U-Net discriminator is able to generate both global and local confidence scores, giving conservators a signpost of which reconstructed regions are more trustworthy and which will need further inspection or human correction [23], [25].

Through provision of this interpretability, uncertainty quantification avoids over-reliance on the automated process and enables users to make intelligent decisions in restoration [17], [25].

#### D. Evaluation and Practical Considerations

The successful use of AI models in actual restoration contexts not only relies on algorithmic complexity but also upon the existence of suitable datasets and metrics of assessment, as well as computational efficiency [10], [13], [21].

1) *Datasets and Metrics*: The result of AI-based restoration methods is heavily dependent on the training datasets [10], [13]. For example, the DunHuang-Mural dataset, with 7,983 high-resolution images of murals depicting historical scenes from the Mogao Caves, has offered a valuable asset for training and testing models related to culturally relevant paintings [19], [21].

A variety of evaluation metrics is used to measure the efficacy of restoration techniques [14], [18]. Pixel-based measurements, including PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index), are employed to assess pixel-level precision and structural similarity. Though helpful in contrasting output with reference images, these measurements are not necessarily correlated with human intuition, particularly in applications where creative reconstruction is necessary [18], [26].

Perceptual measures, such as LPIPS (Learned Perceptual Image Patch Similarity) and FID (Fréchet Inception Distance), are more appropriate for measuring the perceptual quality of generative samples [14], [18], [27]. The measures compare similarities in feature distributions and have been found to more closely align with human judgment [9], [19].

Specialized metrics, including symmetry concentration scores for facial reconstruction and style consistency measures, have been designed to overcome the specific challenges of certain types of artworks [10], [13]. Increased recognition

of domain-specific evaluation highlights the call for metrics tailored to art restoration [21], [28].

2) *Computational and Accessibility Aspects*: Deep learning restoration models tend to be computationally expensive, demanding heavy resources for training as well as inference [19], [27], [30]. All these notwithstanding, attempts have been made at designing more efficient and accessible architectures [8], [16]. Some models have even been optimized to run in real time on consumer-grade hardware, paving the way for wider adoption in museums, archives, and cultural institutions [21], [28].

In addition, the open-source nature of most AI models has promoted collaborative research and real-world application [10], [13], [19]. By releasing datasets, codebases, and pretrained models to the public, researchers have facilitated broader experimentation, accelerated iterations, and easier access for conservation professionals with limited resources [19], [27].

### III. CONCLUSION

The survey has shown that AI-powered digital restoration, specifically focusing on inpainting methods, has become a highly developed and revolutionary field of research and practice [7], [14], [18]. The discipline has seen a significant evolution from initial rule-based algorithms that were constrained by their ability to correct only basic, localized image flaws towards advanced deep learning architectures that can effectively reconstruct distorted or missing parts with high accuracy and visual consistency [26], [27].

With the creation of sophisticated architectures like Generative Adversarial Networks (GANs) and Diffusion Models, restoration abilities have greatly improved—not just enabling the insertion of missing parts but also enabling the creation of content following the semantic, structural, and stylistic features of the original work [7], [8], [19], [29].

They have been seen to be adjusted to include human judgment and expertise such that restorations are not automated but are informed by artistic intention and the knowledge of conservators about historical context [9], [17], [25]. Uncertainty quantification techniques have been incorporated, which provide conservators with more transparency and confidence in AI outputs [23], [25]. Likewise, attempts have been made to retain the soft texture, brushwork, and symbolic aspects that are organic to old paintings, thus maintaining the integrity of the works of art [21], [22], [28].

In the case of Indian traditional paintings, with their variety of regional manners, involved iconography, and vibrant color palettes, the use of AI-based restoration methods presents especially exciting options [21], [22], [28]. The development of models customized for the distinctive characteristics of Indian art—such as its aging patterns, pigment degradation, and cultural symbolism—has been recognized as a high-priority next step [10], [13], [28]. Correctly curated datasets reflecting the nuances encountered across the different schools and eras of Indian art will be used to train models that are

able to restore works of art in ways that are sensitive to their contexts and respectful of their original aesthetic [21], [28].

Realization of these goals will involve persistent cross-disciplinary collaboration. Research in AI will need to be conducted in coordination with art historians, conservators, and cultural analysts to ensure that restoration techniques are guided by profound contextual knowledge and ethical consideration [17], [21], [28]. There should be encouraged interdisciplinary models where technology is not viewed as a substitute for human expertise but as an enhancement of it [9], [25].

A hybrid strategy that leverages the generative power of AI models and applies human oversight and interpretative direction will be instrumental in ensuring restoration processes stay true to artistic authenticity and cultural value [9], [17]. Through the formation of such partnerships, Indian traditional painting preservation can be viewed not as a technical problem but as a cultural imperative—a marriage of innovation and respect for heritage [21], [22], [28].

Eventually, it is through the ethical integration of AI in art conservation that historic paintings can be conserved, researched, and enjoyed by generations to come [17], [21], [28]. The continuation of research in this area, underpinned by open datasets, ethical guidelines, and cross-disciplinary collaborations, will be invaluable in making sure the visual stories and artistic heritage contained in these works are preserved for the ages [9], [25].

#### ACKNOWLEDGMENT

The authors would like to thank all researchers whose work contributed to this survey, and acknowledge the importance of preserving cultural heritage through the application of modern technologies.

#### REFERENCES

- [1] O. Elharrouss, R. Damseh, A. N. Belkacem, E. Badidi, and A. Lakas, "Transformer-based image and video inpainting: current challenges and future directions," *Artificial Intelligence Review*, 2025.
- [2] J. Zhang et al., "Supporting historic mural image inpainting by using coordinate attention aggregated transformations with U-Net-based discriminator," *Heritage Science*, 2025.
- [3] C. Wang, D. Zhou, Y. Fu, and Z. Shi, "Super resolution reconstruction of ancient paintings," *Proc. 2025 5th Int. Conf. Neural Networks, Information and Communication Engineering (NNICE)*, 2025.
- [4] H. Botirova et al., "Restoring historical paintings using diffusion models and GANs," *Proc. 2025 Int. Conf. Computational Innovations and Engineering Sustainability (ICCIES)*, 2025.
- [5] V. Kinakh and S. Voloshynovskiy, "Binary Diffusion Probabilistic Model," *arXiv preprint arXiv*, 2025.
- [6] L. Abualigah et al., "Optimized image segmentation using an improved reptile search algorithm with Gbest operator for multi-level thresholding," *Scientific Reports*, vol. 15, p. 12713, 2025.
- [7] B. Buvaneshwaran, V. Ashwin, B. S. Abishekrupan, S. Sasidharan, and K. P. Revathi, "AI driven restoration of damaged paintings and historical artifacts using generative adversarial networks," *Proc. 2025 3rd Int. Conf. Disruptive Technologies (ICDT)*, IEEE, 2025.
- [8] C. Corneanu, R. Gadde, and A. M. Martinez, "LatentPaint: Image inpainting in latent space with diffusion models," *Proc. 2024 IEEE Winter Conf. Applications of Computer Vision (WACV)*, 2024.
- [9] K. Liu et al., "PrefPaint: Aligning image inpainting diffusion model with human preference," *Advances in Neural Information Processing Systems (NeurIPS 2024)*, 2024.
- [10] S. N. Sinha, P. J. Kühn, J. Koppe, H. Graf, and M. Weinmann, "Digital restoration of visual art using synthetic training, deep segmentation and inpainting," 2024 *Int. Conf. Cyberworlds (CW)*, IEEE, 2024.
- [11] K. K. W. Tint and M. M. Tin, "Digital restoration of ancient murals: Assessing the efficacy of coherent transport inpainting with damage ratio analysis," 2024 *IEEE Conf. Computer Applications (ICCA)*, 2024.
- [12] Z. Sun, Y. Lei, and X. Wu, "Ancient paintings inpainting based on dual encoders and contextual information," *Heritage Science*, 2024.
- [13] P. Hu, Y. Han, Z. Zhang, S.-C. Chu, and J.-S. Pan, "A multi-level thresholding image segmentation algorithm based on equilibrium optimizer," *Scientific Reports*, 2024.
- [14] W. Quan, J. Chen, Y. Liu, D.-M. Yan, and P. Wonka, "Deep learning-based image and video inpainting: A survey," *International Journal of Computer Vision*, 2024.
- [15] S. Yang, X. Chen, and J. Liao, "Uni-paint: A unified framework for multimodal image inpainting with pretrained diffusion model," *Proc. 31st ACM Int. Conf. Multimedia (ACM MM)*, 2023.
- [16] G. Zhang et al., "Towards coherent image inpainting using denoising diffusion implicit models," *Proc. 40th Int. Conf. Machine Learning (ICML)*, PMLR 202, 2023.
- [17] J. A. Gaber, S. M. Youssef, and K. M. Fathalla, "The role of artificial intelligence and machine learning in preserving cultural heritage and artworks via virtual restoration," *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, X-1/W1-2023, pp. 185-192, 2023.
- [18] Z. Xu et al., "A review of image inpainting methods based on deep learning," *Applied Sciences*, vol. 13, no. 20, p. 11189, 2023.
- [19] J. Fein-Ashley and B. Fein-Ashley, "Diffusion models with anisotropic Gaussian splatting for image inpainting," 2023.
- [20] X. Duan, C. Jiang, and Y. Fan, "Enhanced inpainting model revitalizes historical paintings with vision transformer," 2023 *9th Int. Conf. Virtual Reality (ICVR)*, IEEE, 2023.
- [21] Maiti Singh, Saini, and Dhiraj, "Ancient Indian murals digital restoration through image inpainting," 2023 *10th Int. Conf. Signal Processing and Integrated Networks (SPIN)*, IEEE, 2023.
- [22] A. P. Tribhuvan and B. A. Abdullah, "Restoration of world famous 2200-year-old paintings with AI: digital heritage of Ajanta Caves," *International Journal of Science, Engineering and Management*, vol. 10, no. 9, 2023.
- [23] A. Grechka, G. Couairon, and M. Cord, "GradPaint: gradient-guided inpainting with diffusion models," *arXiv preprint arXiv*, 2023.
- [24] Z. Zuo et al., "Generative image inpainting with segmentation confusion adversarial training and contrastive learning," *Proc. AAAI Conf. Artificial Intelligence*, 2023.
- [25] T. Yu et al., "Inpaint Anything: Segment Anything meets image inpainting," *arXiv preprint arXiv*, 2023.
- [26] J. Zhao, J. Tan, Y. Huang, and C. Lu, "Improved image inpainting exemplar-based algorithms by boundary prior knowledge," *ICPCM 2021, MATEC Web of Conferences*, 2022.
- [27] A. Lugmayr et al., "RePaint: Inpainting using denoising diffusion probabilistic models," *Computer Vision Lab, ETH Zürich*, 2022.
- [28] S. Poornapushpakala, S. Barani, M. Subramoniam, and T. Vijayashree, "Restoration of Tanjore paintings using segmentation and in-painting techniques," *Heritage Science*, 2022.
- [29] S. Zhao et al., "Large scale image completion via co-modulated generative adversarial networks," *Int. Conf. Learning Representations (ICLR)*, 2021.
- [30] R. Suvorov et al., "Resolution-robust large mask inpainting with Fourier convolutions," *Samsung AI Center, EPFL, and associated institutes*, 2021.