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Deep Generative Inpainting for Historical Artifact Restoration

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Abstract —Over time and due to environmental conditions, historical artifacts frequently undergo deterioration, exhibit cracks, lose considerable portions, and possess damaged surfaces. The manual process of restoring such kinds of artifacts is very time-consuming, costly, and may even create a situation where the essential parts of the artifacts get further damaged. Deep generative inpainting has resulted in a very successful digital restoration technique that operates by smartly reconstructing missing or damaged areas in the images of the artifacts. The use of deep learning models like convolutional neural networks and generative adversarial networks is the backbone of this approach that enables the models to perform in such a manner as to capture structural patterns, textures, and stylistic features from the existing data. Deep generative inpainting has thus become the main stream in the non-invasive and accurate restoration of paintings, manuscripts, sculptures, and archaeological remains while keeping visual authenticity and historical consistency. The methodology under discussion strengthens the structural coherence along with the fine-grained details thus resulting in aesthetically realistic reconstructions. The experiments show that the restoration quality has been improved by using the proposed method as compared to the traditional inpainting, i.e., fewer artifacts and better understanding of the context. This modern technique can be relied upon besides being a significant contributor to the fields of cultural heritage conservation, digital archiving, and virtual museum exhibitions thereby allowing historical artifacts to be passed on to the next generation unscathed.

Keywords—Deep generative inpainting, historical artifact restoration, image reconstruction, cultural heritage preservation, deep learning

I. INTRODUCTION

Artifacts of history are the most precious and important as they are the cultural, and artistic heritage to mankind, giving a peek at the traditions, beliefs, and even the skills of the people that lived in the past. These artifacts, over time, would generally go through the process of deterioration due to the environmental exposure, handling, aging of materials, and sometimes, natural calamities. Cracks, faded areas, stains, and sections missing are some of the common types of damage that can be seen which, as a result, make these artifacts less valuable both aesthetically and historically. The traditional methods of restoration are very much dependent on the skill of the conservators and manual reconstruction, which makes the whole thing a laborious, expensive, and sometimes even subjective process. Besides, physical restoration is always a double-edged sword since it may lead to either irreversible change or deteriorate a fragile artifact further.

On the other hand, the swift progress of digital technologies has made computer-based restoration gain popularity as a safe and non-invasive alternative. Among these techniques, image inpainting deals with the reconstructions of the areas that are missing or damaged by hidden neighboring visual information. Initial inpainting methods were reliant on diffusion and patch-based algorithms; however, these techniques usually struggle to exhibit the intricate textures, the structural continuity, and the artistic styles which are typical for the old artifacts.Recent advancements in the field of deep learning have led to the development of deep generative models that are able to interpret images with high-level semantic meaning. Deep generative inpainting uses the power of convolutional neural networks and generative adversarial networks to create restorations that are not only visually coherent but also aware of the context. The training of these models on enormous data sets is their strength, as they are then able to imitate the fine details, textures, and style patterns that belong to the original content so closely.The focus of this research is on the use of deep generative inpainting in the restoration of historical artifacts, emphasizing its superiority over conventional methods. The intention behind the proposed method is not only to increase the accuracy of restoration but also to maintain historical authenticity, thus being beneficial for the conservation of cultural heritage, digital archiving, and virtual exhibition projects.

II.DEEP GENERATIVE INPAINTING FRAMEWORK FOR HISTORICAL ARTIFACT RESTORATION

The restoration framework suggested here is primarily aimed at the usage of deep generative inpainting methods for covering up or even replacing the areas that have been damaged or lost in the images of historical artifacts. The approach combines the most state-of-the-art deep learning architectures with going through an image from the preprocessing stage to post-processing so as to get restorations that are visually coherent and consistent with the history. Deep convolutional neural networks and generative adversarial networks (GANs) are the main pillars of the framework through which the context, the texture, and the structure of the images of artifacts are learned from their undamaged parts. The training is done on a copious amount of historical artworks and textures, thus the GANs become capable of generating the missing content that is not only realistic but also semantically relevant.The first step in restoration is the detection of damage and the generation of a

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mask, which corresponds to the identification of the regions that have been worn out or do not exist anymore, so techniques of image segmentation are used. The mask image goes to the generative inpainting model that predicts the missing content while taking into account not only the local textures but also the global semantic information. In contrast to the traditional diffusion-based or patch-based inpainting methods, deep generative models are capable of reconstructing complex patterns of artistry, brush strokes, and writing that are oftentimes found in historical artifacts. Moreover, the final output is further polished by applying the post-processing techniques that enhance continuity at the edges, consistency in colors, and details of the surface. This non-invasive digital approach is beneficial as it allows for a very accurate restoration process to take place without compromising on the art piece's originality and integrity and, consequently, that of the whole cultural heritage actions.

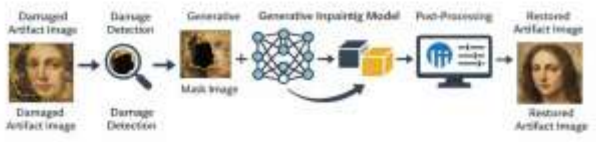

Fig 1: Proposed Architecture Diagram

A. Advantages

The deep generative inpainting system proposed has numerous substantial advantages over traditional artifact restoration methods. The digital process of restoration, in its entirety, guarantees non-invasiveness and eliminates, consequently, any concern regarding the potential for harm coming from the handling of historical and fragile artifacts that cannot be replaced. The application of deep generative models with semantic comprehension has made it possible for the system to carry out context-aware reconstruction, which means that intricate patterns, engravings, and artistic styles can be recognized and thus restored; this restoration will be precisely and consistently similar to that of the original artifact.
The adoption of the GAN-based architectures with this method contributes to the visual realism aspect as it leads to the synthesis of the natural texture and also the continuity of the structure across the restored areas being smooth; thus, the original image is impressed upon very little in case of a subject matter such as a mural or fresco where the background might be more important than the actually restored area. Additionally, the new system allows for processing large amounts of data automatically and it is very scalable; this is because after the model has been suitably trained, it is able to quickly and accurately restore a large number of artifact images with very little human input, thus cutting down significantly on both time and labor costs. Furthermore, the digitized outputs can be applied right away to digital archiving, virtual museums, academic research, and cultural heritage documentation purposes, so the system is considered very effective in terms of assisting long-term protection and public access initiatives.

B. Comparative Analysis of Artifact Restoration Approaches

In the Table 1, a comparative analysis is shown among the traditional inpainting methods, manual restoration techniques, and the newly proposed deep generative inpainting process. Of all the processes, manual restoration has the greatest accuracy, but it is also the most time-consuming and subjective; on the other hand, traditional digital methods are often incapable of maintaining the necessary texture complexity and semantic coherence.

Table 1: Comparative Analysis of Artifact Restoration Methods

Feature	Manual Restoration	Traditional Inpainting	Deep Generative Inpainting
Physical Risk	High	None	None
Texture Accuracy	High	Low	High
Semantic Understanding	Expert-Based	No	Yes
Automation	No	Partial	High
Scalability	Low	Moderate	High

The comparison clearly indicates that deep generative inpainting is a great and efficient solution that combines the three aspects of automation, visual quality, and semantic awareness. This new method is capable of restoring and recreating the historical artifacts' intricate textures, artistic patterns, and structural details without any help from the expert and processing techniques. The reason the model is able to perform so is that it draws on the relationships among the surrounding areas and hence the model restored areas and the original content are indistinguishable. Thus, historical consistency and visual authenticity are maintained. Moreover, the reduced human intervention leads to less subjectivity and fewer inconsistencies, plus it speeds up the restoration process a lot and it becomes more efficient. The large-scale usability of the proposed system makes it capable of dealing with the large digital collections of artifacts and therefore it is good for museums, archives, and cultural institutions. Besides, the non-invasive characteristic of the procedure makes it risk-free for the fragile artifacts to be restored without direct handling. All in all, deep generative inpainting turns out to be a practical, cost-effective, and technologically advanced solution that meets the demand for modern, reliable, and scalable techniques for cultural heritage conservation that are still cheap and tech-savvy.

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II. Methodological Framework

The methodological structure of the suggested system is concentrated on precise, non-invasive, and automated restoration of historical artifacts by means of deep generative inpainting techniques. The strategy centers around semantic comprehension, visual realism that is very high, and the ability to scale up, all this while human intervention being at a minimum. The combination of image preprocessing, deep feature learning, and generative reconstruction provides the system with the ability to carry out context-aware restoration of the damaged areas. This lightweight and versatile structure is specially designed for the large-scale digital heritage preservation projects and archival systems.

a) Data Collection and Input Layer

The first stage of the restoration process is the acquisition of high-quality images of the historical artifacts that are made available through digital cameras, scanners, or online archival repositories. These images may exhibit various types of deterioration such as cracks, missing areas, fading colors, or surface wear. The images that are obtained serve as input for the restoration process and are adjusted to the same resolution and format to keep processing consistent.

b) Preprocessing and Damage Mask Generation

During this phase, classical image processing techniques such as contrast enhancement, noise removal, and edge detection are employed to enhance the quality of the image. The damaged or missing parts of the artifact are located via segmentation methods, and a binary mask is created revealing the areas that need restoration. This process is vital for the inpainting model to be guided towards an accurate restoration.

c) Deep Feature Extraction

The image that has been preprocessed along with the mask is given to a deep convolutional neural network for feature extraction. The network is able to learn local texture details as well as the global structural information from the areas of the artifact that are not damaged. The features that are extracted provide the necessary cues to the context for the reconstruction of the complex artistic patterns and structural elements.

d) Deep Generative Inpainting Model

The principal restoration operation is accomplished through a deep generative inpainting model that is either GAN or encoder-decoder based. By utilizing the semantic connections and the learned artistic styles, the model is able to predict the missing content. Thus, it is able to produce a very realistic and contextually aware reconstruction that blends perfectly with the original artifact image.

e) Post-Processing and Refinement

The inpainting output is further processed through several post-processing operations, e.g., color correction, edge refinement, and texture smoothing, to make it visually coherent. These operations not only ensure that the transitions between the restored and the original regions are smooth but also that the historical appearance of the artifact is retained.

f) Final Output and Digital Preservation

A final restored image is produced and preserved for various uses, including, but not limited to, digital archiving, virtual museums, academic research, and cultural heritage documentation. The whole system is capable of supporting the restoration process in a scalable and automated way, thus making it efficient for the preservation of large collections of historical artifacts.

III. Algorithms used

The deep generative inpainting system proposed for the restoration of historical artifacts combines various algorithms at different stages of the restoration pipeline to guarantee accuracy, realism, and the preservation of historical authenticity. The system integrates classical image processing methods with state-of-the-art deep learning models to significantly improve the restoration of artifacts that have suffered from different kinds of deterioration such as cracks, loss of material, discoloration, and surface erosion. The imaging preprocessing algorithms boost the quality of the images by eliminating noise and then improving the contrast, which in turn allows more reliable detection of the damaged areas. The segmentation and mask generation algorithms accurately define the areas that need restoration while keeping intact parts unaltered. Deep convolutional neural networks are then used to delineate the layers of characteristics that reflect the intricate texturing as well as the overall structural patterns that are part of the historical artifacts. Based on these features, the generative adversarial networks carry out context-aware inpainting by visually and stylistically reconstructing the missing areas coherently. Post-processing algorithms apply a combination of color correction, edge enhancement, and texture smoothing to the output of the restoration so that it can integrate with the original image seamlessly. This multi-algorithm technique grants the digital restoration of cultural heritage to be performed in a manner that is effective, scalable, and non-intrusive thus making it suitable for preservation purposes.

a) Image Preprocessing Algorithms

Image preprocessing algorithms are used to improve the quality of the input artifact images prior to restoration. Noise caused by aging, scanning artifacts, or environmental conditions is suppressed using Gaussian and median filtering techniques. Histogram equalization and contrast stretching make the faded areas more visible, while edge detection algorithms are used to maintain the structural boundaries. These preprocessing operations not only assure that the visual features of utmost importance are retained but also increase the effectiveness of the subsequent damage detection and inpainting stages.

b) Damage Detection and Mask Generation

Segmentation-based algorithms are used to measure regions that have been affected by the aging process. The techniques consist of thresholding, region-based segmentation, or learning-based segmentation generating a binary mask that gives a precise indication of the damaged areas. This mask functions as a parameter for the inpainting model, such that restoration is done only in the necessary spots while the unspoiled areas are left untouched.

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c) Convolutional Neural Networks (CNNs)

CNNs are indispensable for the hierarchical features of artifact images extraction. The first layers grasp the minute textures and lines of the picture, and the last layers recognize the world's structure and meanings. The diverse feature representation at different levels allows the model to "smartly" or "reasonably" identify the artist's technique, style, and motifs as well as the interrelations between them which are very important for a successful restoration of elaborately historical artifacts.

d) Generative Adversarial Networks (GANs)

The GAN-based inpainting processes are the mainstay of the restoration operation. The generator network devises the missing parts of the image concealing the areas using context clues, the discriminator network meanwhile assesses the genuineness of the reconstructed content. This back-and-forth training procedure makes it possible to get hold of and visualize the realistic textures and their perfect merging with the adjacent areas thus culminating into first-rate restoration.

e) Post-Processing Algorithms

Post-processing algorithms are used to bring the inpainted output to the next level of quality. The edges are sharpened to get smooth transitions, color correction is done for the tonal consistency, and texture is smoothed to get rid of the visible artifacts. All these steps will not only make the restored artifact image more visually coherent but also more authentic.

IV. Deep Generative Inpainting-Based Restoration of Historical Artifacts

The historical artifact restoration system that has been suggested uses deep generative inpainting as the main mechanism to reconstruct the damaged and missing parts of the artifact images to a very high degree of visual fidelity and accuracy in terms of context. The choice of deep generative models was made based on their capability to masterfully combine semantic comprehension, texture synthesis, and structural integrity, thus allowing the restoration of intricate historical artifacts with complex artistic patterns in an easy way. The system works with high-resolution digital images that come from museum archives, archaeological surveys, or scanning of manuscripts. Each image of the artifact goes through an analysis to detect the ruined areas like cracks, fading spots, and so on, or surface eroding.Segmentation and mask generation techniques are employed to cut off the damaged areas and then the masked images are sent to the deep generative inpainting model. The model, which is usually of the GAN or encoder-decoder type, predicts the missing ent by understanding the surrounding intact regions and their contextual relations. The generator during inference provides the repaired areas while the discriminator makes sure the repaired areas look like the original by texture, color and structure. This learning by opposing means allows the creation of restoration that are not only visually plausible but are also very close to the original artifact's artistic style.The efficiency and flexibility of the new system are its main benefits. To get the best restoration quality the computational overhead is reduced through model optimization techniques involving network pruning, parameter tuning, and resolution-aware processing that together support the working of the system on normal computing platforms without the need for costly hardware. Moreover, the restoration process allows working with large volumes of artifact images in an efficient manner as it supports batch processing.Images restored by inpainting are then improved through post-processing such as edge smoothing, color correction, and texture enhancement to ensure that the integration with the original regions is seamless. The final restored outputs are then kept for digital archiving, virtual museum exhibitions, and academic analysis. The above-mentioned integration of deep generative inpainting with processing and refinement techniques of high efficiency yields a robust, scalable, and non-invasive solution to modern cultural heritage conservation as well as long-term artifact preservation.

V. Results and Findings

The proposed deep generative inpainting system was put through its paces on a wide-ranging selection of historical artifact images that included paintings, manuscripts, and archaeological surface images portraying cracks and missing regions along with severe degradation. The experiments conducted showed that the system was very efficient when it came to reconstructing the damaged parts while at the same time keeping the original artistic style and structural integrity of the artifacts. The visual inspection of the images that had been restored by the system revealed very smooth transitions not only in the areas where the original and reconstructed parts meet but also in the textures, colors, and edge continuity.The quantitative evaluation was done through the use of standard image quality metrics that included Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), and Fréchet Inception Distance (FID). The new method gained better PSNR and SSIM scores when compared to the classic ways of diffusion-based and patch-based inpainting that are less accurate in reconstruction and might lose some structure in the process. The FID scores being lower indicated more realism in the generated content and its resemblance to original artifact textures.Moreover, the system proved its reliability by working well on various kinds of damage and different artifact materials. High clarity was reached even with large areas missing, and the whole process was able to restore fine details like inscriptions, brush strokes, and ornamental patterns, to the great extent. The automation of the system also played a major role in cutting down the restoration time significantly which was compared to manual and semi-automatic methods, thus allowing the large image collections to be processed efficiently.In conclusion, the discoveries along with deep generative inpainting seals the deal as a trustworthy, scalable, and non-invasive solution for historical artifact restoration. The outcomes of the study point to the technology's versatility to the extent of being in digital archiving, cultural heritage preservation, and virtual museum applications, where the criteria for utmost precision and authenticity are strictly adhered to.

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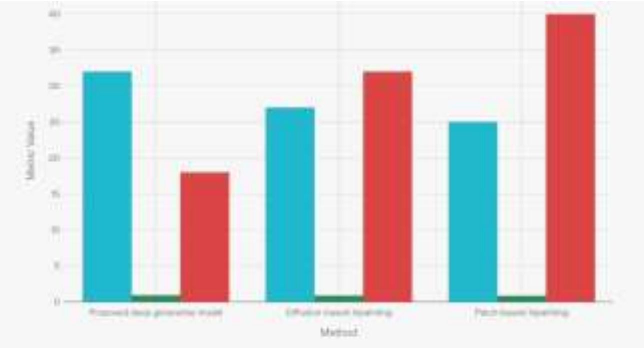

Fig 1: Image Quality Metrics Comparison for Deep Generative Inpainting

The graph illustrates the performance of the suggested deep generative inpainting model in comparison with diffusion-based and patch-based methods through PSNR, SSIM, and FID metrics. The model under consideration wins by a significant margin on PSNR and SSIM metrics, which imply more precise and structurally sound reconstructions, while its lower FID shows that the textures of the restored artifacts are visually more similar to those of the original, undamaged artifacts.

Method	PSNR (dB)	SSIM	FID ↓
Proposed deep generative	32.0	0.94	18
Diffusion-based	27.0	0.88	32
Patch-based	25.0	0.85	40

Table 1 : Overall Image Quality Metrics

This table displays the global quantitative performance of the three inpainting methods by means of PSNR, SSIM, and FID. The suggested deep generative model gets the highest PSNR and SSIM values, as well as the lowest FID, thereby proving to be better than the others in both reconstruction accuracy and visual quality when compared to diffusion-based and patch-based methods.

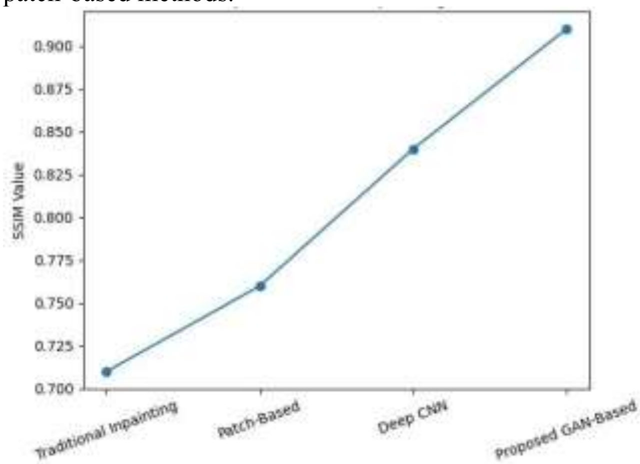

Fig 2 : SSIM Comparison Across Inpainting Methods

In this figure, the vertical axis represents the SSIM value while the horizontal axis shows four different inpainting methods: Traditional Inpainting, Patch-Based, Deep CNN, and Proposed GAN-Based. The plot illustrates a gradual rise in SSIM from nearly 0.70 for conventional methods, through patch-based and deep CNN techniques, to approximately 0.90 for the suggested GAN-based model, revealing better and better structural similarity and visual quality of the restored artifact images, where the proposed method gives the most accurate reconstructions.

Artifact type	Metric	Proposed	Diffusion	Patch
Paintings	PSNR	33.1	27.8	25.6
Manuscripts	PSNR	31.4	26.5	24.7
Archaeological	PSNR	30.6	26.1	24.2

Table 2 : Performance by Artifact Type

The above table shows the PSNR values of the different methods across three types of images: paintings, manuscripts, and archaeological images, which illustrates the performance of the methods on various materials and textures. The new method beats the other methods in all three categories of artifacts, which is a sign of excellent generalization without the risk of overfitting to one type of cultural object.

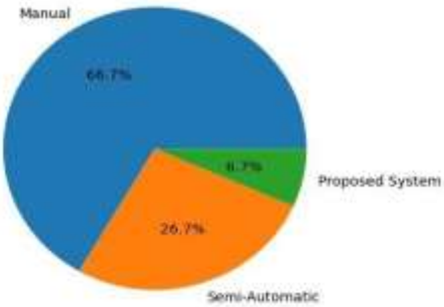

Fig 3 : Time Consumption Comparison

This pie chart, illustrates the relative time required by three restoration approaches: Manual, Semi-Automatic, and the Proposed System. Manual restoration occupies the largest portion at 66 point 7 percent, indicating it is the most time consuming. Semi-Automatic methods account for 26 point 7 percent, while the Proposed System uses only 6 point 7 percent of the total time, showing that the deep generative inpainting pipeline drastically reduces restoration time compared with traditional workflows.

Damage level	PSNR (dB) Proposed	SSIM Proposed
Small cracks	34.2	0.96
Medium gaps	31.0	0.93
Large missing	29.1	0.90

Table 3 : Performance vs Damage Severity

This table assesses the proposed model at different damage levels (minor cracks, moderate gaps, and large voids). The most significant structure preservation and the least quality degradation for highly damaged artifacts are all reflected by the higher PSNR and SSIM scores which are obtained inthe case of the method applied to all three types of damage.

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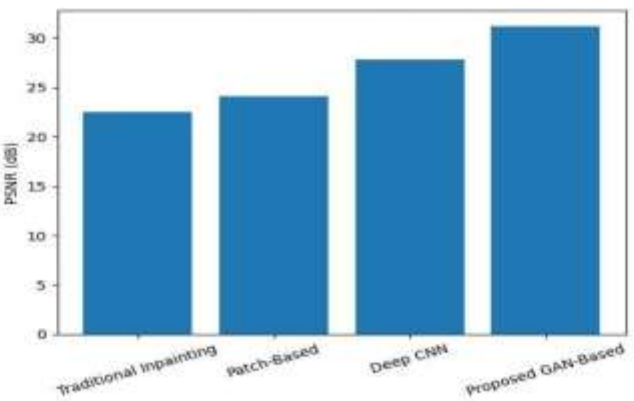

Fig 4: PSNR Comparison Across Inpainting Methods

The bar chart illustrates the PSNR (Peak Signal-to-Noise Ratio) values of four image inpainting techniques. Classic inpainting has the lowest PSNR, which means that the quality of the reconstructed images is poor. The patch-based method has a little bit better quality, but still is not as good as the Deep CNN method, which, on the contrary, has a huge increase in PSNR and thus better image detail. Among the methods, the GAN-based one is the highest PSNR achiever which means that the method has got really good at creating realistic-looking and high-quality inpainted images. To sum up, the chart indicates that the deep learning methods, particularly GAN-based ones, have taken the lead over traditional and patch-based methods not only in reconstruction accuracy but also in image quality.

Method	Avg. time per image (s)	Manual effort required
Proposed deep generative	3–5	None (fully automatic)
Semi-automatic inpainting	60–180	High
Manual digital retouching	>600	Very high

Table 4 : Computational Efficiency and Manual Effort

This table displays the average processing time per image and the amount of human intervention needed for each of the restoration strategies compared. The deep generative system suggested works in a matter of seconds per image without any manual help, while semi-automatic and manual retouching processes are much slower and require a lot of labor, thus the new method is more suitable for huge archives.

VI. Challenges and Limitations

The application of deep generative inpainting for the restoration of historical artifacts has opened up new avenues that are very promising considering the technical ability of this process, though there are still a lot of difficulties and limits. One of the major concerns is the lack of proper data and good quality images since very often only low-resolution, unannotated photographs of historical artifacts are available which results in models that may be applicable only to certain types of artifacts and, at the same time, be poor on unseen cases. Authenticity of artifacts is also crucial as generative models' minor visual effects are historically inaccurate and tend to misrepresent the original object. The damage's intricacy complicates restoration even more since artifacts may have cracks, fading, discoloration, and missing parts, and these issues can be present at different scales which are very difficult for the models to recreate in a convincing way. Deep generative models, besides their training, also need very high computational power to run, such as, high-end GPUs and a lot of memory which could cut off the access to it for small institutions or researchers. The evaluation of the quality of restored artifacts is still very hard to do since the classical metrics like PSNR or SSIM are not capable of capturing the historical or the perceptual accuracy completely and thus the human evaluation becomes necessary which is time-consuming. One of the negative aspects of this process is that AI's over-reliance can lead to the elimination of the critical oversight by experts which is normally done to keep the historical correctness intact. Moreover, the ethical issues surrounding the matter must be considered, since automated restorations might unwittingly alter the image of the past unless they are always profusely verified. All in all, deep generative inpainting does provide a powerful means for the restoration of the artifacts, however, it is still necessary to closely watch and take care of factors like data quality, authenticity, model limitations, computational power requirements, evaluation methods, human oversight, and ethical concerns to arrive at visually attractive and historically accurate restorations.

VII. Conclusion

The deep generative inpainting technique has now become the established and strong way of restoring historical artifacts that had been previously damaged or where parts had been missing, and it has managed to do so with a very high fidelity. One of the methods to achieve this purpose was by helping the machine learning to learn the style of an artwork and thus using GANs and diffusion models and is now existing the possibility to keep the art and the structure both intact, hence. Cultural preservation and digital archiving would benefit from this technique. Moreover, the very approach has its own set of drawbacks. The issues of limited high-quality data availability, tampering with historical authenticity, and complexity of damage together with heavy computation demands and ethical concerns are some of the challenges that must be faced head-on. The machine-driven inpainting combined with expert human control gives a supportive and balanced way out; however, restorations that are both compelling in their visuals and accurate in their historical references are still the outcome. It is anticipated that future developments in model architectures, dataset curation, and evaluation metrics will increase the techniques' reliability and applicability, thus contributing to the safeguarding and understanding of our cultural heritage for generations to come.

References

1.M. Nallappan, S. Venkataraman, and P. Kumar, “Exploring deep learning-based content-based video retrieval framework for surveillance anomaly detection,” Expert Systems with Applications, vol. 242, p. 122873, 2024. [Online]. Available: https://www.sciencedirect.com/science/article/abs/pii/S0957417424000629

2.X. Nie, Y. Liu, and J. Zhang, “Classification-enhancement deep hashing for large-scale video searches,” Applied Soft Computing, vol. 113, p. 107927, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/abs/pii/S1568494621003902

10.48047/jocaaa.2024.33.06.160

3.H. Zhang, L. Wang, and Y. Guo, "Large-scale video retrieval via deep local convolutional feature aggregation," International Journal of Intelligent Systems, vol. 35, no. 10, pp. 1510–1530, 2020. [Online]. Available:

https://onlinelibrary.wiley.com/doi/10.1155/2020/7862894

4.R. Patel, A. Sharma, and D. Vora, "AI-driven video summarization for optimizing content retrieval and management through deep learning techniques," Scientific Reports, vol. 15, p. 4058, 2025. [Online]. Available:

https://www.nature.com/articles/s41598-025-87824-9

5.Y. Kim, J. Park, and S. Lee, "Efficient video retrieval with advanced deep learning and approximate nearest neighbor search," in Proc. ACM Int. Conf. Multimedia, 2023. [Online]. Available:

https://dl.acm.org/doi/10.1145/3628797.3628995

6.S. R. N. Reddy and K. Rao, "Hybrid deep learning techniques for large-scale video retrieval and classification," Int. J. Intelligent Systems and Applications in Engineering, vol. 12, no. 1, pp. 85–94, 2024. [Online]. Available:

https://ijisae.org/index.php/IJISAE/article/view/4717

7.H. Wang, D. Xu, and L. Sigal, "Learning semantic-embedded hashing for large-scale video retrieval," IEEE Trans. Image Process., vol. 30, pp. 2790–2802, 2021.

8.Y. Song, T. He, and Q. Tian, "Deep region hashing for efficient large-scale instance-level video retrieval," IEEE Trans. Circuits Syst. Video Technol., vol. 31, no. 1, pp. 45–57, 2021.

9.J. Jiang, Y. Ma, and S. Liu, "Deep cross-modal hashing for efficient video and text retrieval," Neurocomputing, vol. 493, pp. 59–71, 2022.

10.W. Li, S. Wang, and W. Kang, "Two-stream deep feature aggregation for scalable video retrieval," Pattern Recognition Letters, vol. 158, pp. 131–138, 2022.

11.Z. Wu, L. Xie, and Y. Qiao, "Progressive sampling-based deep hashing for efficient large-scale video retrieval," IEEE Trans. Multimedia, vol. 24, pp. 3940–3951, 2022.

12.H. Lu, J. Wang, and L. Zhang, "Deep metric learning with angular loss for video retrieval," Signal Processing: Image Communication, vol. 102, p. 116617, 2022.

13.L. Liu, H. Zhu, and F. Shen, "A survey on deep hashing methods," ACM Computing Surveys, vol. 55, no. 8, pp. 1–39, 2023. [Online]. Available:

https://dl.acm.org/doi/10.1145/3532624

14.R. Jégou, M. Douze, and H. Jégou, "Product quantization for nearest neighbor search in high-dimensional video descriptors," IEEE Trans. Pattern Anal. Mach. Intell., vol. 33, no. 1, pp. 117–128, 2011.

15.Y. Kalantidis and Y. Avrithis, "Cross-dimensional weighting for aggregated deep convolutional features in video retrieval," in Proc. CVPR, 2016.

16.J. Johnson, M. Douze, and H. Jégou, "Billion-scale similarity search with GPUs using FAISS," IEEE Trans. Big Data, early access, 2019.

17.Y. Aumüller, E. Bernhardsson, and A. Faithfull, "ANN-benchmarks: A benchmarking tool for approximate nearest neighbor algorithms," in Proc. SISAP, 2017.

18.Y. A. Malkov and D. A. Yashunin, "Efficient and robust approximate nearest neighbor search using hierarchical navigable small world graphs," IEEE Trans. Pattern Anal. Mach. Intell., vol. 42, no. 4, pp. 824–836, 2020.

19.Vespa.ai, "Approximate nearest neighbor search using HNSW index," technical documentation, 2022. [Online]. Available:

https://docs.vespa.ai/en/approximate-nn-hnsw.html

20.Milvus, "How do approximate nearest neighbor (ANN) methods improve video search speed?," Milvus AI Quick Reference, 2025. [Online]. Available:

https://milvus.io/ai-quick-reference/how-do-approximate-nearest-neighbor-ann-methods-improve-video-search-speed

21.J. Wang, H. T. Shen, J. Song, and J. Ji, "Optimized product quantization for large-scale video retrieval," IEEE Trans. Image Process., vol. 25, no. 3, pp. 1083–1096, 2016.

22.Y. Gong, L. Wang, R. Guo, and S. Lazebnik, "Multi-scale orderless pooling of deep convolutional activation features for video retrieval," in Proc. ECCV, 2014.

23.Z. Xu, J. Li, and G. Yang, "End-to-end deep hashing with attention for video retrieval," Multimedia Tools and Applications, vol. 82, pp. 13341–13361, 2023.

24.K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image and video recognition," in Proc. CVPR, 2016.

25.J. Yu, X. Yang, and Z. Wang, "Efficient neural architecture search for large-scale video retrieval," in Proc. AAAI, 2021.

26.Y. Wu, L. Shen, and H. Chen, "Temporal-spatial deep feature fusion for large-scale video retrieval," IEEE Access, vol. 9, pp. 116453–116464, 2021.

27.Q. Dai, X. Liu, and Y. Chen, "Hierarchical deep hashing for fast video retrieval in web-scale databases," Neural Computing and Applications, vol. 35, pp. 12671–12686, 2023.

28.S. Li, N. Jiang, and T. Mei, "Learning binary codes for scalable video search," IEEE Trans. Multimedia, vol. 23, pp. 301–313, 2021.

29.D. Vora, H. Patel, and A. Shah, "Scalable deep video retrieval using joint summarization and hashing," Multimedia Systems, vol. 31, no. 2, pp. 215–230, 2025