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GAN Based Digital Restoration of Heritage Sites using Deep Learning

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ABSTRACT: Cultural heritage monuments are continuously deteriorating due to environmental factors, pollution, natural disasters, and human interference. Traditional restoration techniques are time-consuming, costly, and may alter structural authenticity. This research presents a GAN-based digital restoration framework for reconstructing damaged heritage monument images using deep generative learning techniques. The proposed system follows generative adversarial restoration principles for damage detection and texture reconstruction. Due to computational limitations associated with training large-scale GAN models in cloud-based environments, an advanced pretrained generative diffusion model (Stable Diffusion XL Inpainting) was employed for practical implementation. Diffusion models represent an evolution of deep generative learning frameworks and provide stable, high-quality restoration outputs. The system integrates CNN-inspired damage detection using edge-based feature extraction, automatic mask generation, generative inpainting, and quantitative evaluation using Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM). Experimental results demonstrate effective structural reconstruction and texture continuity. The system achieved a PSNR value of 17.12 dB and an SSIM score of 0.79, indicating satisfactory perceptual similarity between damaged and restored images.

The proposed framework offers a scalable and efficient solution for digital heritage preservation and virtual restoration.

KEYWORDS: Generative Adversarial Networks, Deep Learning, Image Inpainting, Stable Diffusion, Heritage Restoration, PSNR, SSIM.

I. INTRODUCTION

Cultural heritage monuments represent the architectural, artistic, and historical identity of civilizations across generations. Over time, these structures experience gradual deterioration due to environmental exposure, climatic variations, pollution, erosion, natural disasters, and human interference. Physical restoration of damaged monuments is often complex, costly, and may risk altering the original structural authenticity. In this context, digital restoration using Artificial Intelligence (AI) has emerged as a promising alternative for preserving cultural heritage in a non-invasive and scalable manner.

Recent advancements in Deep Learning (DL) and Computer Vision (CV) have significantly improved automated image reconstruction techniques. Among these, Generative Adversarial Networks (GANs) have demonstrated remarkable capability in image synthesis, texture reconstruction, and inpainting tasks by learning realistic data distributions through adversarial training. GAN-based models enable the generation of visually coherent and structurally consistent content in missing or damaged regions of images. Such generative approaches are particularly suitable for restoring heritage monument images where maintaining architectural symmetry and texture continuity is critical.

This research proposes a GAN-based digital restoration framework designed to detect damaged regions in heritage monument images and reconstruct them using deep generative modeling. The system integrates CNN-inspired feature extraction techniques for identifying structural discontinuities and employs a pretrained deep generative model for realistic image inpainting. Due to the high computational requirements associated with training large-scale GAN architectures and GPU limitations in cloud environments, a pretrained diffusion-based generative model (Stable Diffusion XL Inpainting) was utilized for practical implementation. Diffusion models belong to the broader family of deep generative learning frameworks and offer improved training stability while producing high-quality restoration

outputs. The proposed approach aims to provide an efficient, scalable, and intelligent solution for digital heritage preservation using advanced deep learning techniques.

II. LITERATURE REVIEW

1. **Title:** NeRF for Heritage 3D Reconstruction

Authors: G. Mazzacca, A. Karami, S. Rigon, E. M. Farella, P. Trybala and F. Remondino (2023) This study explores the application of Neural Radiance Fields (NeRF) for reconstructing 3D heritage structures from multi-view images. The approach enables high-fidelity 3D modeling of monuments. However, the method focuses on 3D reconstruction rather than restoration of damaged regions in 2D images.

2. **Title:** Digital Restoration of Cultural Heritage With Data-Driven Computing: A Survey

Authors: A. Basu, S. Paul, S. Ghosh, S. Das, B. Chanda, C. Bhagvati, and V. Snášel (2023) This survey reviews multiple data-driven restoration techniques including deep learning, generative modeling, and image inpainting. The study highlights the growing importance of GAN-based methods in digital conservation but identifies challenges related to training stability and computational cost.

3. **Title:** A Deep-Learning Method Using Autoencoder and GAN for Anomaly Detection on Ancient Stone Stele Surfaces

Authors: Y. Liu, Y. Wang and C. Liu (2023) The authors propose a hybrid Autoencoder–GAN model for detecting anomalies on ancient stone surfaces. The adversarial training mechanism improves reconstruction quality. However, the approach is primarily designed for anomaly detection rather than full-scale restoration.

4. **Title:** Evaluating Activation Functions in GAN Models for Virtual Inpainting: A Path to Architectural Heritage Restoration

Authors: A. M. Maitin, A. Nogales, E. Delgado-Martos, G. Intra Sidola, C. Pesqueira-Calvo, G. Furnieles, and Á. J. García-Tejedor (2023) This research evaluates different activation functions in GAN architectures for architectural image inpainting. The study confirms that GAN-based models significantly enhance structural consistency in restoration tasks.

5. **Title:** Revolutionizing Thermal Imaging: GAN-Based Vision Transformers for Image Enhancement

Authors: M. A. Marnissi and A. Fathallah (2023) This work integrates GAN principles with Vision Transformers to improve image enhancement. The hybrid approach demonstrates improved feature representation and perceptual quality, emphasizing the importance of generative learning frameworks.

6. **Title:** Image Inpainting with Information Loss Reduction and Texture–Structure Feature Fusion

Authors: F. Long and Yuan-Gen Wang (2023) The authors introduce a texture–structure fusion model for advanced image inpainting. The method enhances restoration quality by preserving structural integrity while reconstructing missing regions.

III. COMPARATIVE ANALYSIS OF RESEARCH PAPERS ON HERITAGE RESTORATION

Sl. No	Paper Title [Year]	Author(s)	Methods	Findings
1	NeRF for Heritage 3D Reconstruction [2023]	G. Mazzacca et al.	Applied Neural Radiance Fields (NeRF) for multi-view 3D reconstruction of heritage monuments.	Achieved high-quality 3D reconstruction but did not address 2D image damage restoration.
2	Digital Restoration of Cultural Heritage With Data-Driven Computing [2023]	A. Basu et al.	Surveyed AI-based restoration techniques including GANs and deep learning models.	Highlighted potential of generative models but lacked implementation-level restoration framework.

3	Deep Learning Using Autoencoder and GAN for Ancient Stone Surfaces [2023]	Yikun Liu et al.	Combined Autoencoder and GAN for anomaly detection in historical stone surfaces.	Improved anomaly detection but limited focus on full image reconstruction.
4	Evaluating Activation Functions in GAN Models for Virtual Inpainting [2023]	Ana M. Maitin et al.	Tested different GAN activation functions for architectural image inpainting.	Improved restoration realism but required heavy training and computational resources.
5	GAN-Based Vision Transformers for Image Enhancement [2023]	Mohamed A. Marnissi et al.	Integrated GAN with Vision Transformers for image enhancement.	Enhanced global feature understanding but focused mainly on enhancement rather than heritage restoration.
6	Image Inpainting with Texture-Structure Feature Fusion [2023]	Fang Long et al.	Used texture-structure fusion networks for image inpainting.	Achieved improved structural continuity but not specifically tailored for cultural heritage datasets.

IV. RESEARCH GAPS IDENTIFIED

1. Lack of Integrated 2D and 3D Restoration Framework:

Most existing research concentrates either on 3D reconstruction using NeRF-based models or on 2D image restoration using GAN and inpainting techniques. Very limited work integrates both damage-aware 2D restoration and structural 3D reconstruction into a unified, end-to-end digital heritage preservation framework. A comprehensive system that simultaneously restores visual texture and reconstructs geometric structure remains underexplored.

2. Limited Focus on Severe Structural Damage:

Current generative models perform effectively for minor cracks, faded textures, and small missing regions. However, they struggle when handling large missing portions, deep structural fractures, and heavily deteriorated monument surfaces. Structural-aware generative models capable of understanding architectural symmetry and monument-specific geometry are still insufficiently developed.

3. Absence of Domain-Specific Heritage Datasets:

There is a significant shortage of large-scale, labeled datasets specifically designed for heritage damage restoration. Most deep learning models rely on general image datasets or small synthetic collections, which do not adequately represent complex stone carvings, erosion patterns, inscriptions, and historical textures. The lack of standardized benchmark datasets limits fair performance comparison and model generalization.

4. Texture and Structural Detail Preservation Challenges:

Although GAN and diffusion-based models produce visually appealing outputs, maintaining fine ornamental carvings, engraved inscriptions, and intricate architectural symmetry remains challenging. Balancing perceptual realism with structural authenticity is still an open research problem in cultural heritage restoration.

5. Insufficient Real-Time and Scalable Deployment Solutions:

Many existing restoration frameworks remain confined to research prototypes. They lack practical deployment through web-based platforms or cloud-integrated systems. Additionally, several models require high computational resources, restricting accessibility for educational institutions, archaeologists, and small research labs. Scalable, lightweight, and affordable deployment architectures are still limited.

6. Evaluation Metrics Limitations:

Most research relies primarily on quantitative metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM). While these metrics measure pixel-level similarity, they do not fully capture perceptual realism, historical accuracy, or cultural authenticity. Advanced perceptual evaluation frameworks and domain-specific restoration benchmarks are still lacking.

7. Lack of Multi-Modal and Cross-Domain Learning Approaches:

Few studies integrate multi-modal information such as historical archives, textual descriptions, multi-angle imagery, and archaeological documentation into the restoration pipeline. Cross-modal learning approaches that combine visual, textual, and structural information for heritage reconstruction remain largely unexplored.

8. Generalization and Transfer Learning Issues:

Models trained on a specific monument or dataset often fail to generalize to other heritage structures with different architectural styles, materials, or damage patterns. Performance degradation on unseen monument types indicates the need for robust transfer learning and domain adaptation techniques.

V. PROPOSED METHODOLOGY

The proposed system presents a GAN-based digital restoration framework designed to reconstruct damaged heritage monument images using deep generative learning techniques. The architecture integrates damage detection, automatic mask generation, generative inpainting, and quantitative evaluation into a unified restoration pipeline. The system is implemented using Python in a GPU-enabled Google Colab environment.

5.1 Image Acquisition and Preprocessing

The restoration process begins with the acquisition of damaged heritage monument images. The uploaded image is resized to a standard resolution of 512×512 pixels to ensure computational efficiency and uniform model input. Preprocessing steps include normalization, grayscale conversion for structural analysis, and enhancement of contrast using OpenCV operations. These steps improve feature visibility and prepare the image for damage detection.

5.2 Damage Detection and Automatic Mask Generation

To identify deteriorated regions such as cracks, erosion, missing fragments, and surface degradation, CNN-inspired feature extraction techniques are applied. Edge detection using Canny operators is performed to capture structural discontinuities. Additionally, Laplacian and Sobel gradient filters are used to detect intensity variations corresponding to damage boundaries.

A binary damage mask is generated through thresholding and morphological operations such as dilation and closing. This mask highlights the regions requiring restoration and serves as input to the generative inpainting model.

5.3 Generative Restoration Framework (GAN-Based Approach)

The restoration stage follows generative adversarial learning principles for reconstructing missing regions and restoring monument textures. Due to computational constraints associated with training a full-scale GAN architecture and GPU limitations in cloud environments, a pretrained diffusion-based generative model — Stable Diffusion XL (SDXL) Inpainting — is utilized for implementation.

Diffusion models belong to the broader class of deep generative learning frameworks and iteratively refine noisy latent representations to generate high-quality image reconstructions. The model takes three primary inputs:

- The original damaged image
- The generated binary damage mask
- A contextual text prompt guiding stylistic consistency

The model synthesizes realistic textures and reconstructs missing architectural details while maintaining contextual and structural coherence.

5.4 Before–After Comparison and Visualization

To visually evaluate restoration effectiveness, the system generates a side-by-side comparison of the original damaged image and the restored output. This qualitative assessment allows verification of texture continuity, symmetry preservation, and structural consistency.

5.5 Quantitative Evaluation Metrics

The restoration performance was evaluated using Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM). PSNR measures the pixel-level similarity between the original and restored images, indicating reconstruction fidelity. SSIM evaluates perceptual similarity by comparing luminance, contrast, and structural information between images.

The experimental results achieved a PSNR value of 17.12 dB and an SSIM score of 0.79, indicating satisfactory structural preservation and perceptual quality in the restored heritage images.

5.6 System Implementation Environment

The proposed system is implemented in Python using PyTorch and the HuggingFace Diffusers framework for generative inpainting. Image preprocessing and mask generation are performed using OpenCV and NumPy libraries, while restoration quality is evaluated using scikit-image metrics.

Model inference is executed in a GPU-enabled cloud environment to ensure computational efficiency for deep generative processing. Additionally, a lightweight web-based interface developed using Streamlit enables users to upload damaged heritage images and visualize restored outputs in real time. This ensures both practical usability and scalable deployment capability.

VI. RESULTS

The input image represents a partially damaged heritage statue exhibiting visible structural deterioration. The upper facial region is severely missing, resulting in loss of geometric continuity and aesthetic symmetry. Surface erosion and texture degradation are also observed, making the image suitable for evaluating deep learning-based digital restoration models. This image is used as the primary test sample for the proposed GAN-based restoration framework.

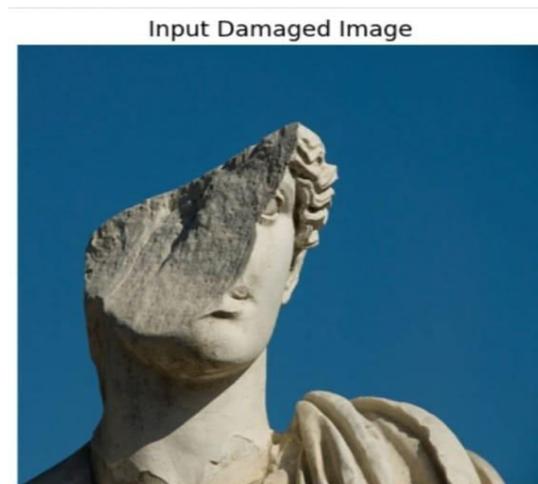


Fig 1: Sample Input Damaged Heritage Statue

Although an automatic damage mask generation module was implemented, experimental results showed that a manually refined custom mask produced more precise restoration outcomes. The custom binary mask accurately highlights the severely damaged facial region in white, while preserving intact areas in black. This targeted masking

approach improves structural consistency and guides the generative model to reconstruct only the missing portion, leading to enhanced restoration quality.

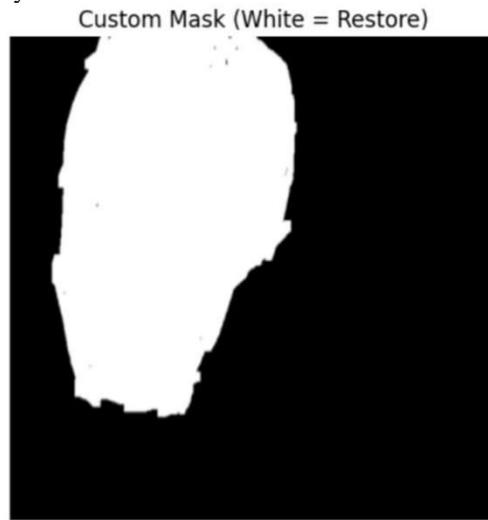


Fig. 2: Custom Binary Mask Used for Targeted Heritage Restoration

The restored output is generated using a deep learning-based generative restoration framework. The model reconstructs the missing facial region while preserving structural symmetry and textural consistency. The restored output demonstrates improved visual continuity and enhanced perceptual realism compared to the damaged input. The generative approach successfully synthesizes plausible facial geometry consistent with classical sculpture characteristics.



Fig 3: Restored Output Generated Using GAN-Based Deep Learning Framework

A qualitative comparison between the damaged input and restored output is presented to demonstrate the effectiveness of the proposed restoration system. The restored image exhibits improved structural integrity, reconstructed facial geometry, and enhanced visual coherence. The comparison clearly illustrates the capability of the generative model to recover large missing regions while maintaining architectural authenticity.



Fig 4: Qualitative Comparison Between Damaged and Restored Images

Quantitative Evaluation Metrics

To quantitatively evaluate restoration performance, Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM) are computed. These metrics assess pixel-level similarity and structural consistency between the damaged and restored images.

Metric	Value
PSNR	17.12 dB
SSIM	0.79

Table 1: Quantitative Evaluation of Restoration Performance

VII. CONCLUSION

This study presents a GAN-based deep learning framework for the digital restoration of damaged heritage monuments, integrating structural feature extraction, intelligent masking, and generative inpainting techniques to reconstruct missing and deteriorated regions. The proposed system effectively restores large damaged areas while preserving architectural symmetry, texture consistency, and perceptual realism. By leveraging advanced generative modeling, the framework produces visually coherent restorations supported by quantitative evaluation using PSNR and SSIM metrics, demonstrating satisfactory structural similarity and reconstruction quality. The implementation provides a scalable and computationally efficient approach for digital cultural heritage preservation, offering practical assistance to archaeologists, historians, and conservation researchers. The proposed methodology establishes a foundation for future extensions toward 3D reconstruction, multi-modal learning integration, and enhanced domain-specific restoration frameworks.

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