Deep Learning Techniques for Archaeological Image Restoration

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Abstract: Archaeological sites, rich in historical and cultural significance, face deterioration from invasive, environmental, biological and natural factors, necessitating innovative restoration methods. The proposed paper introduces a U-Net-based Generative Adversarial Network (GAN) framework to reconstruct damaged temple images, ensuring the preservation of intricate architectural details. A custom dataset of masked images was created, and the model was trained to reconstruct missing sections while balancing adversarial and reconstruction losses for realistic outputs. The proposed approach addresses challenges in traditional techniques by restoring complex textures, enhancing fine details and producing visually coherent results, achieving a Structural Similarity Index Measure (SSIM) of 0.7128. Furthermore, the framework demonstrates robustness in handling various levels of damage and noise, paving the way for scalable applications in heritage conservation. The proposed work contributes significantly to cultural heritage preservation by combining advanced deep learning methodologies with precise evaluation metrics to achieve impactful results.

1 INTRODUCTION

India's rich history, encapsulated in its archaeological sites, particularly temples, reflects immense historical, cultural, and spiritual significance. These temples, however, face substantial degradation due to invasions, natural disasters and environmental factors like earthquakes, climatic fluctuations and biological factors such as algae and fungal growth, leading to the loss of invaluable architectural and artistic details (Smith and Patel, 2021; Sharma and Hassan, 2022). Restoration and preservation of these monuments have become a global priority, emphasizing their historical and cultural importance (Park and Wang, 2021), and the need for scalable and precise techniques to combat widespread deterioration.

Traditional restoration approaches, though effective to an extent, struggle with complex patterns and textures. Advances in Artificial Intelligence (AI), specifically Deep Neural Networks (DNNs), offer transformative solutions (Mishra, 2021; El Masri and Rakha, 2021). DNNs excel in learning patterns from datasets to reconstruct damaged areas with remarkable precision(Kumar and Wang, 2020), preserving intricate details such as temple carvings (Jones and Alvi, 2022; Chen and Smith, 2022). Techniques like Convolutional Neural Networks (CNNs) (Lee and Gupta, 2023) and Generative Adversarial Networks (GANs) (Gupta and Lee, 2023) provide exceptional capabilities in feature extraction, structural inpainting, texture generation, and reconstructing the missing areas (Hassan and Sharma, 2022), ensuring authenticity and structural fidelity in archaeological applications (Chen and Gupta, 2023).

U-Net architectures have demonstrated exceptional promise in restoring intricate temple carvings and architectural details, thanks to their encoder-decoder structure with skip connections, enabling fine-grained reconstructions. The proposed approach employs an optimized U-Net architecture within a GAN framework, incorporating a U-Net-based generator and a PatchGAN discriminator. The U-Net generator ensures detailed texture and structural alignment, while the PatchGAN discriminator enhances output realism. The proposed combination addresses unique challenges, such as varying textures and complex architectural features, resulting in visually convincing and structurally accurate reconstructions.

Section 2 reviews recent advancements in deep learning for image restoration. Section 3 details the proposed methodology, which integrates U-Net for structural restoration and GAN for realistic texture synthesis, enabling the reconstruction of damaged and missing features in ancient temple imagery.

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Section 4 describes the dataset and analyzes the results, demonstrating the approach's effectiveness in preserving the architectural essence of heritage sites. Section 5 concludes by summarizing the contributions of the proposed approach.

2 BACKGROUND STUDY

A comprehensive review of literature highlights advancements in using deep learning techniques such as U-Net architectures and GANs for tasks like reconstruction, restoration and in-painting (Zuo and Tiddeman, 2024; Kulkarni et al., 2023). U-Net's encoder-decoder structure, with skip connections, has been extensively applied to image-to-image tasks, including restoring damaged archaeological sites and facial image voids (Zhao et al., 2024; Schonfeld et al., 2020). Multi-task approaches, such as multi-scale fusion, enable models to address diverse objectives while preserving high-resolution details and semantic coherence (Kwabena Patrick et al., 2022). Quality evaluation metrics like Structural Similarity Index Measure (SSIM) and Peak Signal-to-Noise Ratio (PSNR) are critical for assessing model performance (Feng Cai, 2024).

Building upon these advancements, recent studies have demonstrated the potential of hybrid architectures that combine U-Net and GAN capabilities to enhance restoration accuracy. By leveraging GANs' adversarial training paradigm, these hybrid models generate outputs that are not only structurally consistent but also visually realistic, addressing common challenges such as texture smoothness and color discrepancies. Additionally, the inclusion of attention mechanisms and transformer-based layers has further improved the ability of these networks to focus on critical features while ignoring irrelevant artifacts. Such innovations have shown significant promise in handling complex restorations, such as recreating intricate carvings or patterns on archaeological artifacts, ensuring a seamless integration of modern technology with cultural preservation efforts.

The proposed methodology addresses limitations in traditional architectures like autoencoders and CNNs, which struggle with complex patterns and fluctuating datasets (Zhou et al., 2021; Nguyen and Tran, 2022). By leveraging U-Net and incorporating GAN frameworks with adversarial and reconstruction losses, more realistic and high-fidelity outputs are achieved (Wang and Tang, 2021; Shen and Li, 2021). Metrics like SSIM and PSNR provide structural similarity and noise-level evaluation, essential for validating results in real-world scenarios, including denoising, in-painting, and restoration of corrupted images (Lee and Kim, 2022; Huang and Zhang, 2021). Optimization strategies like curriculum learning and attention mechanisms further enhance outcomes in low-context scenarios(Patel and Gupta, 2022).

Furthermore, the integration of domain-specific pretraining and transfer learning techniques has been instrumental in improving the model's adaptability to niche datasets, such as those featuring archaeological artifacts. These techniques enable the model to generalize effectively from limited training data by leveraging knowledge from larger, more diverse datasets. In addition, advanced loss functions, such as perceptual loss and contextual loss, have been adopted to prioritize the preservation of fine-grained details and contextual relevance during reconstruction. This ensures that the restored images maintain their historical and cultural authenticity while achieving superior quantitative performance across evaluation metrics. The proposed methodology also demonstrates potential scalability, making it feasible for large-scale restoration projects involving extensive datasets.

Training stability in GAN-based models is maintained by balancing adversarial and reconstruction losses, mitigating challenges like mode collapse and vanishing gradients (Chen and Zhao, 2021). The Adam optimizer, with parameters tuned to a learning rate of 1e-4 and betas of 0.5 and 0.999, ensures efficient convergence and avoids instability associated with Stochastic Gradient Descent (SGD) (Singh and Verma, 2021; Liu and Sun, 2022). By integrating U-Net and GAN architectures with advanced optimization techniques, the approach facilitates robust restorations tailored to demanding scenarios involving missing or noisy data (Zhang and Luo, 2022).

In addition to optimization strategies, regularization techniques such as spectral normalization and gradient penalty have been employed to further enhance the stability of GAN training. These methods effectively constrain the discriminator's learning process, preventing it from becoming overly dominant, which can disrupt the generator's performance. Moreover, progressive training methodologies, where models are trained in incremental stages with increasing complexity, have shown significant improvements in handling high-resolution image restoration tasks. By combining these approaches with data augmentation strategies, such as random masking and noise injection, the framework ensures robust performance across diverse datasets while preserving computational efficiency and generalization capabilities.

3 PROPOSED WORK

The combination of the U-Net architecture with the GAN framework provides a robust approach to precise and realistic cultural heritage restoration. The U-Net-based generator excels at capturing fine-grained features while preserving spatial information, whereas the PatchGAN (Isola et al., 2018) discriminator ensures that the outputs are both realistic and structurally coherent. The proposed combination enables the model to effectively learn and reconstruct intricate architectural patterns, establishing a new standard for precision in restoration tasks.

3.1 U-Net Generator Architecture

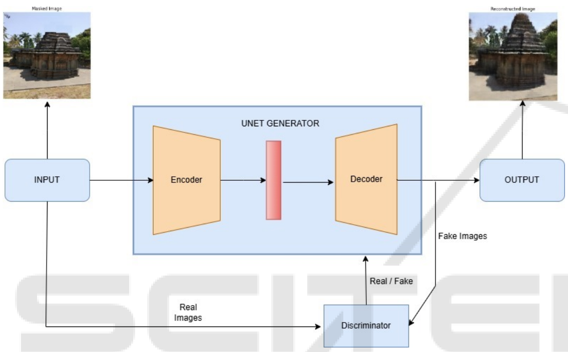


Figure 1: Architecture overview of U-Net GAN.

The U-Net architecture is integrated with the GAN framework to reconstruct damaged image regions as shown in the Figure 1. During preprocessing, the pixel values of images are normalised which are further converted into tensor formats thus making them suitable for deep learning models.

The U-Net generator operates as an encoder-decoder network which is enhanced with skip connections. With the usage of convolutional layers, batch normalization and leakyReLU activation, encoder gradually reduces the spatial dimensions of the input image while extracting complex features.The decoder is responsible for upsampling the encoded image i.e., the encoded features are upsampled to their original resolution. The decoder uses transposed convolutional layers with ReLU activation. Skip connections used in the network ensure that the feature information is transferred from corresponding encoder layers to decoder layers in a thorough way ensuring that the spatial features are retained.The generator uses a TanH activation function to generate the reconstructed images by scaling values between -1 and 1.

3.2 Discriminator Network

A discriminator network is trained alongside with generator to ensure that the generated images appear realistic. The discriminator consists of multiple convolutional layers that gradually reduce input image into a scalar probability score providing an indication of an image being real (ground truth) or fake(reconstructed by generator). The proposed adversarial design stimulates generator to improve its reconstructions, causing difficulty for discriminator to distinguish real images from fake ones.

During the forward pass for real images,the discriminator calculates the real loss as denoted in Equation 1

$$L_{\text{real}} = -\frac{1}{N}\sum_{i=1}^{N} \log D(y_i) \tag{1}$$

where $D(y_i)$ represents the discriminator's output for the real image y_i, and N is the total number of real images in the batch.The motive is to make $D(y_i)$ close to 1.

It is implemented using Binary Cross-Entropy(BCE) loss denoted below in Equation 2.

$$L_{\text{real}} = \text{BCE}(D(y_i), 1), \tag{2}$$

Then, in the forward pass of fake images, the generator first generates fake images $(G(x_i))$ from masked images(x_i). Then, the discriminator will measure those generated images to compute the fake loss(L_fake) as shown in the Equation 3

$$L_{\text{fake}} = -\frac{1}{N}\sum_{i=1}^{N} \log\left(1 - D(G(x_i))\right), \tag{3}$$

The aim is to encourage $D(G(x_i))$ to be close to 0, which means that the discriminator must identify the generated images as fake. It is also calculated using Binary Cross Entropy loss as indicated in Equation 4

$$L_{\text{fake}} = \text{BCE}(D(G(x_i)), 0), \tag{4}$$

Finally, the total discriminator loss (L_D)combines the real and fake losses to maximize the discriminator's performance at being able to distinguish between real and generated images. It is calculated as shown in Equation 5:

$$L_D = \frac{1}{2}(L_{\text{real}} + L_{\text{fake}}), \tag{5}$$

The combined loss is decreased through backward propagation which enables the discriminator to distinguish between real and fake images.

3.3 Adversarial Training

The generator is trained to fool the discriminator while simultaneously producing realistic images that resemble the target images. In the forward pass, adversarial loss L_{adv} is calculated using the output generated by the discriminator on the fake images.The adversarial loss formula ,as shown in Equation 6:

$$L_{\text{adv}} = -\frac{1}{N}\sum_{i=1}^{N} \log D(G(x_i)), \tag{6}$$

The loss aids the generator in learning to generate pictures that confuses the discriminator. It is calculated using Binary Cross-Entropy(BCE) loss, as shown in Equation 7:

$$L_{\text{adv}} = \text{BCE}(D(G(x_i)), 1), \tag{7}$$

where the target label is set to 1 for marking that the fake images should be classified as actual.

3.4 Reconstruction Loss

The reconstruction loss in-terms of pixel-wise accuracy ensures that the reconstructed images match the ground truth.The generator tries to minimize the difference between the generated and the actual target images using the reconstruction loss L_rec. the formula for the loss, as shown in Equation 8:

$$L_{\text{rec}} = \frac{1}{N}\sum_{i=1}^{N} \|G(x_i) - y_i\|_1, \tag{8}$$

where $\|G(x_i) - y_i\|_1$ denotes the L1 norm (Mean Absolute Error), which minimizes the pixel-wise difference between the generated image and the target image.

Finally, a total generator loss is calculated that combines both adversarial and reconstruction losses ,as shown in Equation 9:

$$L_G = \lambda_{\text{rec}} \cdot L_{\text{rec}} + \lambda_{\text{adv}} \cdot L_{\text{adv}}, \tag{9}$$

where λ_{rec} and λ_{adv} are the weights that control the influence of the reconstruction and adversarial losses, respectively. Using the loss, the generator adjusts its parameters to maximize both realism and fidelity to the target images.

3.5 Evaluation Metrics

The PSNR and SSIM metrics are used to evaluate the performance of the model. PSNR checks the difference between the reconstructed and target image to estimate the pixel-level accuracy. It calculates the ratio between the maximum possible pixel value of the image and the Mean Squared Error (MSE) between the generated and target images. SSIM whose value is between 0 to 1, measures the kind of structural and visual quality of the original in the reconstruction. The SSIM is responsible for measuring the visual similarity between the generated image and the target image.

The overall methodology portrays an effective blend of architectural design and adversarial training aimed at achieving high-quality image reconstructions.

4 RESULTS AND ANALYSIS

The proposed work outlines the experimental results of the proposed framework, including details on the dataset, prepossessing steps, and the training procedure. The model's performance is evaluated using SSIM as the primary metric to assess the quality of restoration and its effectiveness in addressing complex challenges.

4.1 Dataset Description

The IHDS dataset, containing 3,000 high-resolution images of temples as shown in Figure 2, was utilized to train the model. Since the dataset only provided intact temple images (target images), corresponding masked images were generated to simulate structural damage. To create realistic masked images, methods such as adding inconsistent or random patches were avoided, as they do not accurately represent true distortions. Instead, background patches were overlaid on temple regions, effectively mimicking structural damage or fragmentation. The proposed approach ensured that the masked images closely resembled real-world scenarios of temple degradation.

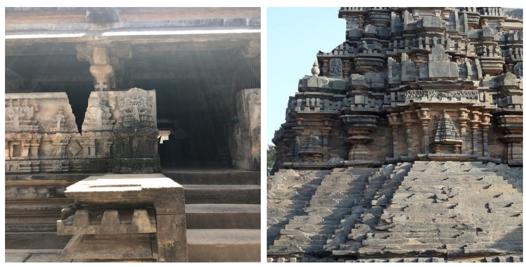
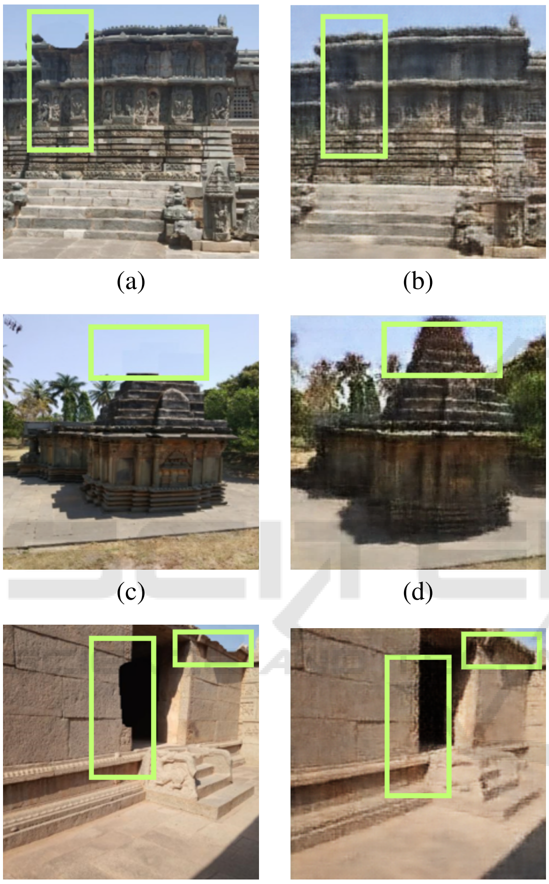


Figure 2: Dataset of Damaged Archaeological Sites

4.2 Evaluation

After preparing the dataset of masked images, the model was trained using a UNet-based GAN architecture with a PatchGAN discriminator. During training, the U-Net generator focused on reconstructing the missing parts of the masked images, while the PatchGAN discriminator ensured the realism of these reconstructions. Once training was complete, the generator was used to produce the final reconstructed images, effectively restoring the damaged regions as shown in Figure 3.



(a) (b) (c) (d) (e) (f)

Figure 3: Examples of masked images (left column) and their corresponding reconstructed images (right column). The SSIM scores are as follows: (b): 0.7538, (d): 0.8235, (f): 0.8012.

The performance of the proposed UNetGAN model is evaluated using the Structural Similarity Index Measure (SSIM) to assess the quality of the reconstructed images. SSIM evaluates the similarity between the reconstructed image and the ground truth, reflecting the model's effectiveness in restoring visual details. For the provided archaeological images, the model achieved an overall SSIM score of 0.7128 .The score demonstrates the model's capability to restore omitted architectural details while successfully capturing the structural and textural integrity of the original images, aligning closely with the ground truth.

Upon visual inspection, the reconstructed images exhibit a high level of detail preservation, effectively capturing the intricate features of the original architectural forms. However, the analysis highlights the influence of the quality and diversity of the training data on the model's performance. Expanding the dataset with a greater variety of high-resolution ground truth images could further enhance the accuracy and reliability of the reconstructions.

Having established the model's overall performance through the SSIM, we now delve into specific examples of reconstructed images and their corresponding SSIM values in Figure 3. The first example is the Kappachenikeshwara Temple in Hassan, which achieved an SSIM of 0.7581 as shown in Figure 3(b), indicating significant reconstruction accuracy while preserving intricate architectural details. Next, the Veerabhadreshwara temple, Hangal recorded an SSIM of 0.8589 as shown in Figure 3(d) reflecting the model's ability to capture the structural and textural intricacies of this iconic monument. Further, Hazararama temple, Hampi attained an SSIM of 0.8661 as shown in Figure 3(f), showcasing exceptional fidelity in reconstructing the missing portions while closely aligning with the ground truth. These examples highlight the model's capability to effectively restore archaeological images, emphasizing the critical role of diverse and high-quality datasets in improving reconstruction accuracy and reliability.

5 CONCLUSION AND FUTURE WORK

The potential for preserving cultural property is enormous when deep learning algorithms are used to recreate damaged archaeological pictures, especially those of temples. The efficiency of integrating U-Net architecture with a GAN framework was shown in the study, allowing for excellent restoration while preserving the originals' fine architectural elements and aesthetic integrity. The suggested model outperforms conventional techniques in achieving durable and realistic image in-painting by utilizing adversarial training and reconstruction loss. Additionally, using sophisticated evaluation measure like SSIM guarantees thorough quality assessment, which strengthens the model's dependability. The proposed model has achieved an SSIM score of 0.7128. To further increase reconstruction skills for varied cultural items, future research can investigate improving training efficiency and combining multi-modal data.

The future scope can include advancement of model architectures and techniques to capture finer details and complex patterns, alongside improved data preprocessing and augmentation strategies for robust results. Expanding to diverse datasets and integrating domain-specific knowledge could enhance contextual accuracy and generalization. Additionally, smoothing the blurred areas after reconstruction can improve results.

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