Visual Design from Cultural Heritage through Inpainting-based Restoration

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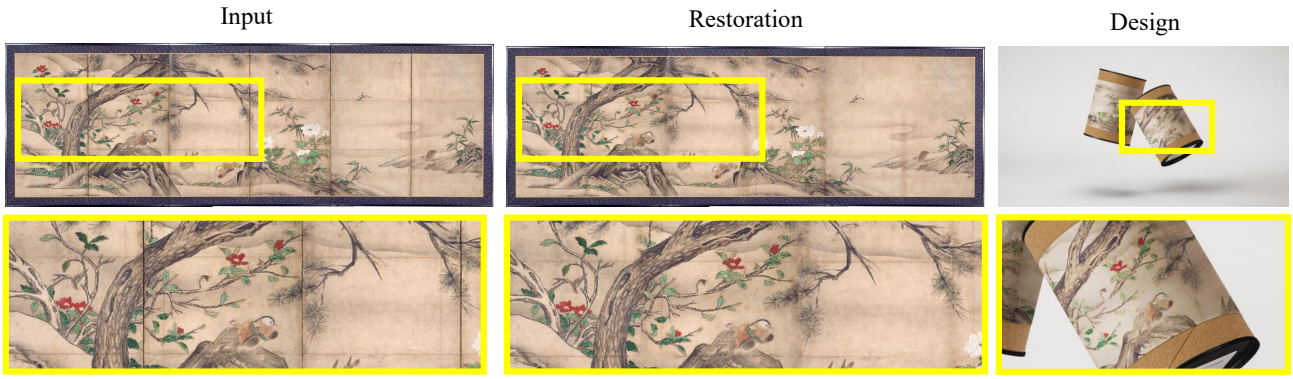

Figure 1. **Cultural product design by our framework.** We restore damaged paintings using inpainting before generating commercial package design.

Abstract

We explore an inpainting-based restoration framework for generating commercial designs from cultural heritage paintings. Cultural heritage paintings often exhibit accumulated damage, including surface contamination, color alteration, and physical deterioration, which compromises the quality of generative design outputs when processed directly. Our approach addresses this challenge by preprocessing damaged paintings through inpainting techniques before applying generative design algorithms. We employ damage-specific restoration strategies that include cleaning to remove surface contamination, coloring to restore the paint layer, and pattern extraction to isolate decorative elements. Through comparative analysis of designs generated from damaged originals and restored paintings, we demonstrate that inpainting preprocessing significantly enhances visual quality while preserving cultural authenticity. The restored designs show improved commercial viability and meet contemporary design market standards. This approach bridges historical preservation with modern design innovation, offering market-ready designs that maintain rich cultural resonance in diverse applications.

1. Introduction

Generative models fundamentally transform the digital design and creative industries [5, 7, 9]. Visual design platforms such as Adobe Firefly [1], Canva PatternedAI [3], and MYTH AI [15] revolutionize traditional design workflows, providing up to 70% cost reduction compared to conventional processes [4]. Design platforms have become essential for securing competitive advantages in the textiles, fashion, packaging, and home décor industries [2, 16].

Despite advances in generative design, applying existing systems to cultural heritage presents significant challenges. Historical paintings and cultural artifacts often exhibit accumulated damage over time, including surface contamination, color alteration, physical deterioration, restoration traces, and digital artifacts from scanning or photography. When generative design algorithms process damaged images directly, the generated designs inherit imperfections, compromising both cultural authenticity and aesthetic quality. Inherited flaws distort the original artistic intent and fail to meet contemporary design market standards, ultimately limiting commercial viability.

To address this challenge, we propose preprocessing heritage paintings with inpainting before applying generative

design algorithms. The approach, as shown in Fig. 1, first restores damaged regions using inpainting methods, then utilizes the restored paintings as a source for design generation. We examine various visual designs by comparing direct generation from damaged paintings with generation from inpainting-restored paintings. The results demonstrate that inpainting preprocessing significantly improves design quality while preserving cultural authenticity.

2. Related Works

2.1. Generative Design

Recent advances in generative models have revolutionized visual design capabilities in commercial applications. StyleGAN [12] established controllable image generation through style manipulation, while Diffusion models [18] have further enhanced the quality and diversity of generated visual content. These foundational architectures have spawned numerous commercial design platforms [1, 3, 14, 22] that democratize creative workflows and enable rapid prototyping of visual concepts. This democratization of design expertise accelerates innovation cycles and allows exploration of novel aesthetic approaches that emerge from AI-human collaborative processes.

However, applying these generative design systems to cultural heritage presents distinct challenges that current commercial tools inadequately address. Historical paintings and cultural artifacts exhibit various forms of deterioration accumulated over time. When contemporary generative design algorithms process damaged heritage paintings directly, the generated outputs inherit and amplify imperfections. The generative models trained to recognize and reproduce visual patterns cannot distinguish between authentic artistic elements and damage-induced artifacts. This inheritance of imperfections creates a dual problem: the resulting designs fail to accurately represent cultural heritage while falling short of contemporary design market standards. Consequently, direct application of existing generative design tools to damaged heritage materials produces commercially unviable outputs that neither honor the source culture nor meet modern consumer expectations.

2.2. Inpainting

Cultural heritage paintings present unique challenges due to accumulated deterioration from environmental factors, aging, and historical damage. Traditional digitization efforts often capture artifacts with visible deterioration, creating datasets that inadequately support downstream applications. These damaged source materials limit the effectiveness of creative applications that require high-quality visual input.

Inpainting has become an essential tool for the preservation of cultural heritage, enabling the restoration of damaged artifacts. Early restoration methods relied on manual techniques that required specialized expertise and a large investment of time [6, 8, 20]. Recent advances in deep learning have revolutionized this field, with AI frameworks combining Diffusion [18] and LoRA [10] demonstrating superior performance in reconstructing damaged areas compared to traditional approaches [24].

Contemporary applications span diverse cultural contexts, from European medieval frescoes [13] to Asian traditional paintings [17], with specialized models such as SGR-GAN [11] achieving significant improvements in restoration quality. However, current inpainting research primarily targets restoration as an end goal rather than as preprocessing for creative applications. The potential for combining heritage restoration with generative design workflows remains largely unexplored, creating a significant gap between cultural preservation and contemporary commercial design needs.

3. Methodology

Our method apply inpainting to restore damaged cultural heritage paintings, then use restored paintings for commercial visual design generation. We employ damage-specific restoration models to address surface contamination, paint deterioration, and pattern extraction, followed by generating market-ready designs. This approach demonstrates how heritage restoration improves the quality and commercial viability of culturally-inspired designs.

3.1. Restoration

We utilize IOPaint [19], an open-source image inpainting tool powered by state-of-the-art models. IOPaint employs various inpainting and segmentation models to perform cleaning, coloring, and pattern extraction tasks on paintings. We select the tool for high flexibility and support for diverse inpainting models. IOPaint provides a web-based interface that allows conservators and designers to intuitively upload images and perform various restoration tasks without requiring technical expertise. The platform offers preview functionality for step-by-step verification and adjustment of the restoration process and enables sequential application of multiple models to effectively handle complex damage patterns.

3.1.1. Damage Type-Specific Strategies

Cleaning Cultural heritage paintings often contain various forms of surface contamination that obscure original artistic details. To address these cleaning tasks, we employ the Large Mask Inpainting (LaMa) [21] model. Users employ the brush tool to manually mask contaminated regions, then apply LaMa to reconstruct the underlying content. LaMa utilizes fast Fourier convolution to generate consistent texture and structure even across large masked areas. This approach effectively removes irregular damage such as surface

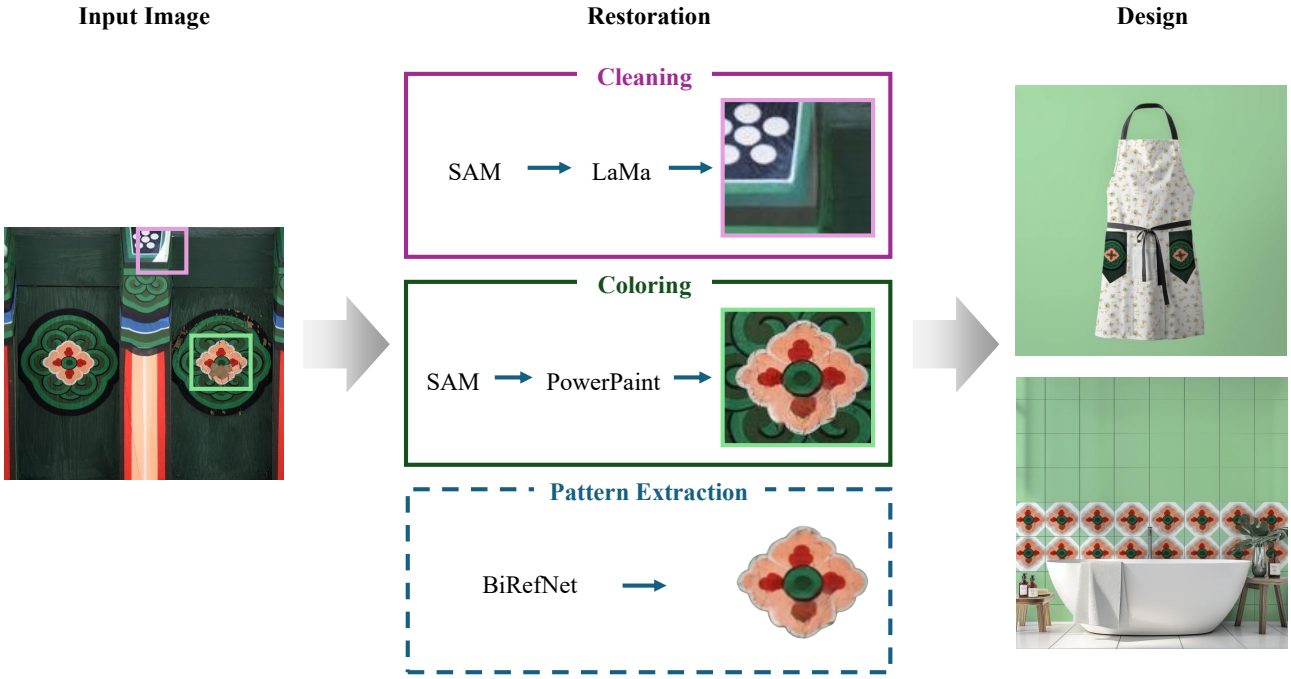

Figure 2. **Framework overview.** The pipeline employs a processing strategy that addresses different types of heritage painting deterioration. The restored outputs serve as source material for generating commercial designs.

dirt, cracks, and stains while maintaining natural visual continuity with surrounding undamaged regions.

Coloring Cultural heritage paintings frequently suffer from paint layer deterioration, including flaking, fading, and color loss that compromises their visual integrity. For restoring these damaged areas, we employ PowerPaint [26], a ControlNet [23]-based conditional generative model. Users mask the affected regions, and PowerPaint generates contextually appropriate content that maintains semantic coherence rather than relying on simple texture replication. This approach ensures visual harmony with the original painting's style and composition. For areas experiencing color loss or fading, PowerPaint's colorization functionality reconstructs missing colors by analyzing surrounding color information and considering the original work's palette.

Pattern Extraction Cultural heritage paintings often contain intricate traditional patterns and decorative elements that serve as valuable sources for contemporary design applications. For extracting specific objects and motifs, we employ BiRefNet [25], a specialized model for precise object segmentation. BiRefNet excels at background removal by accurately separating complex patterns and objects from surrounding contexts. In cases where patterns show damage or deterioration, we first apply cleaning and coloring restoration processes before proceeding with extraction to ensure optimal pattern quality. Users can leverage BiRefNet to isolate traditional patterns, decorative motifs, and other culturally significant elements required for textile design and commercial applications.

3.2. Visual Design Generation

Restored cultural heritage paintings serve as pristine source material for commercial design generation. This clean visual content provides designers with versatile resources that can be effectively utilized across multiple design contexts. Commercial design platforms process these restored paintings to generate initial concepts and develop production-ready prototypes across diverse applications, including textile patterns, packaging designs, and promotional materials.

4. Findings

We investigate the effectiveness of inpainting-based restoration with generative design to create commercial visual designs from cultural heritage paintings. We demonstrate diverse design applications and compare designs generated from damaged and restored paintings.

4.1. Heritage painting Restoration

Fig. 3 presents the restoration results demonstrating effectiveness on two distinct cultural heritage types: tradi-

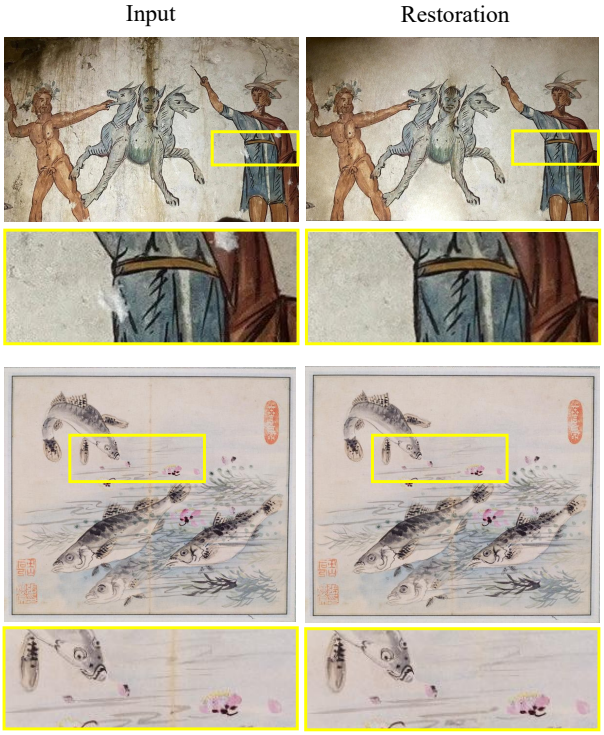

Figure 3. **Heritage painting restoration results.** The top row shows traditional mural restoration with elimination of structural cracks and brown discoloration. The bottom row presents a folk painting restoration, demonstrating the complete removal of fold line damage and seamless reconstruction. Detailed views are highlighted in yellow boxes.

tional murals and folk paintings. The mural shows structural cracks in the wall substrate, paint layer loss in decorative areas, and extensive brown discoloration from contamination. Inpainting restoration eliminates structural cracks and perfectly reconstructs missing paint layers, restoring the original decorative patterns and color schemes. While complete removal of contamination proves challenging, the cleaning process significantly enhances visual clarity, achieving substantial improvement in overall image quality.

The folk painting exhibits deterioration along fold lines, creating visible damage that disrupts the artwork's visual continuity. The inpainting process completely removes fold-related deterioration, seamlessly reconstructing the affected areas without visible artifacts. The restoration preserves the original painting and maintains color harmony throughout the composition. Both cases demonstrate that inpainting effectively addresses various damage types while preserving the cultural authenticity and artistic integrity of the original works.

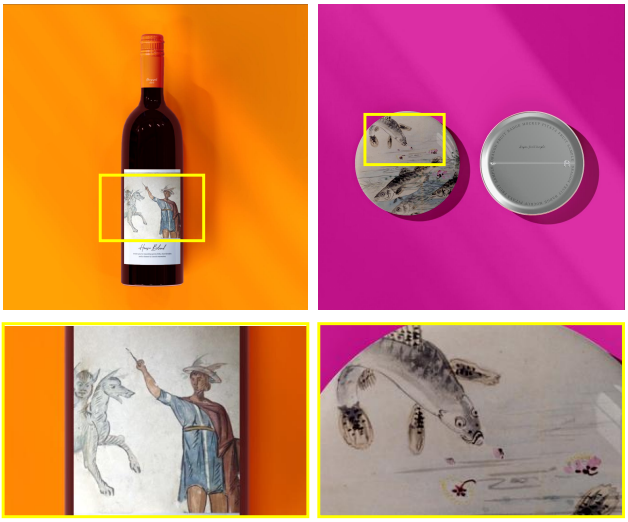

Figure 4. **Commercial design applications using restored heritage paintings.** The left column demonstrates wine bottle label design incorporating traditional mural imagery. The right column shows a badge design derived from folk painting motifs. Yellow boxes show detailed views of the heritage-sourced images.

4.2. Design Application

Fig. 4 and Fig. 5 demonstrate commercial applications of restored cultural heritage paintings in three product categories. In Fig. 4, a restored mural is adapted for wine bottle label design, creating packaging that combines heritage aesthetics with modern commercial appeal. A folk painting is transformed into badge designs, where the traditional imagery provides distinctive visual elements for commemorative applications. In Fig. 5, Dancheong architectural decoration undergoes pattern extraction to isolate lotus motifs, which designers then scale and arrange to create bathroom tile patterns that integrate traditional Korean decorative elements into contemporary interior design. The applications demonstrate the versatility of restored heritage paintings in generating commercially viable designs across diverse product categories while preserving cultural authenticity.

Comparative Analysis Using Damaged and Restored Paintings We compare commercial design quality between products generated from damaged and restored paintings using Dancheong architectural decoration for bathroom tile pattern design. Fig. 5 presents the comparative results. Tile patterns generated from the damaged painting exhibit quality degradation, where color loss and surface contamination directly transfer to the final design. In contrast, tile patterns generated from the restored painting demonstrate superior design quality. This comparison demonstrates that restoration preprocessing significantly improves the commercial viability of heritage-inspired designs by

w/o Restoration w/ Restoration

Figure 5. **Tile pattern design comparison between using damaged and restored heritage paintings.** The left shows a design generated from the damaged Dancheong. Right demonstrates a design using restored Dancheong.

eliminating damage-related artifacts and enhancing overall design quality.

5. Discussion

Our current method reveals several important limitations that warrant careful consideration. While the approach effectively maintains artwork structure and removes contamination, the inpainting process introduces modifications to original content that may compromise cultural authenticity when applied to pure heritage preservation contexts. Extensive inpainting areas pose additional risks when large portions of historical artwork require restoration, raising questions about the balance between restoration completeness and heritage preservation integrity. The limitations necessitate the development of comprehensive approaches that can analyze the entire painting context, differentiate between various damage types, and perform targeted texture restoration while preserving cultural integrity.

Future research should explore several promising directions to advance heritage-inspired commercial design generation. The method should evolve toward unified frameworks that seamlessly integrate restoration and design generation processes in a single workflow. Additionally, expansion to three-dimensional cultural heritage artifacts such as sculptures, architectural elements, and decorative vessels would unlock rich pattern sources that remain largely unexploited in contemporary design applications. Such developments would enhance both the efficiency and scope of heritage-inspired commercial design generation.

6. Conclusion

We present an inpainting-based restoration framework that enhances the generation of commercial design from cultural heritage paintings. Our findings confirm that restoration preprocessing improves design quality compared to using damaged paintings. The restoration of traditional murals, folk paintings, and Dancheong architectural elements enables successful adaptation to diverse commercial applications, including packaging design, decorative accessories, and interior patterns. The method effectively addresses various damage types, making heritage content accessible for modern creative workflows.

We contribute to the growing intersection of digital heritage preservation and commercial design, demonstrating how restoration enhances both aesthetic quality and market viability of culturally-inspired products. The demonstrated versatility across multiple heritage types and commercial applications suggests the broad applicability of our method. This approach opens new possibilities for cultural institutions and designers to leverage heritage assets for contemporary applications while maintaining respect for the original artistic intent. By transforming damaged cultural artifacts into high-quality design resources, our study establishes a foundation for the commercialization of sustainable cultural heritage that benefits both preservation efforts and the creative industry.

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References

[1] Adobe Inc. Firefly. https://www.adobe.com/products/firefly.html, 2025. 1, 2

[2] AI Time Journal. Top 5 ai pattern generators to consider in 2024. https://www.aitimejournal.com/top-ai-pattern-generators-to-consider/, 2024. Accessed: June 30, 2025. 1

[3] Canva. Patterned ai. https://www.canva.com/features/pattern-generator/, 2025. Accessed: June 30, 2025. 1, 2

[4] McKinsey & Company. The economic potential of generative ai: The next productivity frontier. Technical report, 2023. 1

[5] The Business Research Company. Generative ai in creative industries global market report 2025. Technical report, 2025. 1

[6] TL Dawson. Examination, conservation and restoration of painted art. *Coloration Technology*, 123(5):281–292, 2007. 2

[7] Digital Silk. Ai statistics in 2025: Key trends and usage data. https://www.digitalsilk.com/digital-trends/ai-statistics/, 2025. Accessed: June 30, 2025. 1

[8] International Centre for the Study of the Preservation and Restoration of Cultural Property (ICCROM). Conservation and preservation standards for paintings. Technical Report, 2015. International standards for manual conservation of paintings. 2

[9] Giiresearch. Generative ai in creative industries global market report 2025. Technical report, 2025. 1

[10] Edward J Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, Weizhu Chen, et al. Lora: Low-rank adaptation of large language models. *The International Conference on Learning Representations*, 1(2): 3, 2022. 2

[11] Qiyao Hu, Weilu Huang, Yinyin Luo, Rui Cao, Xianlin Peng, Jinye Peng, and Jianping Fan. Sgrgan: sketch-guided restoration for traditional chinese landscape paintings. *Heritage Science*, 12(1):163, 2024. 2

[12] Tero Karras, Samuli Laine, and Timo Aila. A style-based generator architecture for generative adversarial networks. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 4401–4410, 2019. 2

[13] Fabio Merizzi, Perrine Saillard, Oceane Acquier, Elena Morotti, Elena Loli Piccolomini, Luca Calatroni, and Rosa Maria Dessì. Deep image prior inpainting of ancient frescoes in the mediterranean alpine arc. *Heritage Science*, 12(1):41, 2024. 2

[14] Alexander Mordvintsev. Deep dream generator. https://deepdreamgenerator.com, 2015. Accessed: June 30, 2025. 2

[15] MYTH AI. Myth ai design generator. https://myth-ai.com/, 2025. Accessed: June 30, 2025. 1

[16] Piktochart. Top 11 best ai graphic design tools for 2025. https://piktochart.com/blog/ai-graphic-design-tools/, 2025. Accessed: June 30, 2025. 1

[17] Hui Ren, Ke Sun, Fanhua Zhao, and Xian Zhu. Dunhuang murals image restoration method based on generative adversarial network. *Heritage Science*, 12(1):39, 2024. 2

[18] Dominik Lorenz Patrick Esser Robin Rombach, Andreas Blattmann and Björn Ommer. High-resolution image synthesis with latent diffusion models. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, 2022. 2

[19] Sanster. Iopaint: Image inpainting tool powered by sota ai model. https://github.com/Sanster/IOPaint, 2024. Accessed: June 30, 2025. 2

[20] Ioannidou Stefania and Pantazis George. Conservation and preservation standards for paintings. In *International Conference on the Theory of Machines and Mechanisms*, pages 147–158. Springer, 2023. 2

[21] Roman Suvorov, Elizaveta Logacheva, Anton Mashikhin, Anastasia Remizova, Arsenii Ashukha, Aleksei Silvestrov, Naejin Kong, Harshith Goka, Kiwoong Park, and Victor Lempitsky. Resolution-robust large mask inpainting with fourier convolutions. *In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, 2022. 2

[22] WowPattern. Wowpattern: Ai-powered textile pattern generator. https://wowpattern.com, 2023. Accessed: June 30, 2025. 2

[23] Lvmin Zhang, Anyi Rao, and Maneesh Agrawala. Adding conditional control to text-to-image diffusion models. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, 2023. 3

[24] Xinyi Zhang. Ai-assisted restoration of yangshao painted pottery using lora and stable diffusion. *Heritage (2571-9408)*, 7(11), 2024. 2

[25] Peng Zheng, Dehong Gao, Deng-Ping Fan, Li Liu, Jorma Laaksonen, Wanli Ouyang, and Nicu Sebe. Bilateral reference for high-resolution dichotomous image segmentation. *CAAI Artificial Intelligence Research*, 2024. 3

[26] Junhao Zhuang, Yanhong Zeng, Wenran Liu, Chun Yuan, and Kai Chen. A task is worth one word: Learning with task prompts for high-quality versatile image inpainting. In *European Conference on Computer Vision*, pages 195–211. Springer, 2024. 3