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Photorealistic Texture Contextual Fill-In

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Abstract: This paper presents a comprehensive study of the application of AI-driven inpainting techniques to the restoration of historical photographs of the Czech city Most, with a focus on restoration and reconstructing the lost architectural heritage. The project combines state-of-the-art methods, including generative adversarial networks (GANs), patch-based inpainting, and manual retouching, to restore and enhance severely degraded images. The reconstructed/restored photographs of the city Most offer an invaluable visual representation of a city that was largely destroyed for industrial purposes in the 20th century. Through a series of blind and informed user tests, we assess the subjective quality of the restored images and examine how knowledge of edited areas influences user perception. Additionally, this study addresses the technical challenges of inpainting, including computational demands, interpretability, and bias in AI models. Ethical considerations, particularly regarding historical authenticity and speculative reconstruction, are also discussed. The findings demonstrate that AI techniques can significantly contribute to the preservation of cultural heritage, but must be applied with careful oversight to maintain transparency and cultural integrity. Future work will focus on improving the interpretability and efficiency of these methods, while ensuring that reconstructions remain historically and culturally sensitive.

Keywords: cultural heritage; image reconstruction; colorization; urban; Most; inpainting; neural filters

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1. Introduction

Inpainting, or content-aware fill, has become essential in the restoration and preservation of historical images and videos, where damage due to aging or environmental factors often affects the integrity of stored media [1]. Today, inpainting is applied not only for damage restoration but also as a tool for image editing, such as in text-to-image systems like SORA [2] or simple automatic inpainting in public popular software like Photoshop or Canva.

The terms content-aware fill and inpainting [3] typically describe input data structured as a 3D matrix of RGB pixels as individual frames with textures. This well-known format better captures essential characteristics like frequency details, color consistency, and homogeneity, elements often crucial for historically faithful restoration of urban scenes like those of Most (samples of original photographs at Figure 1), where architectural and textural continuity must be preserved.

As inpainting methods grow more sophisticated [3], they introduce both benefits and difficult ethical considerations for historical preservation. Neural network-based inpainting and generative adversarial networks can convincingly reconstruct missing or restore damaged sections, but they also risk adding speculative details, which may raise questions of authenticity. Conversely, patch-based approaches generally offer conservative restorations with minimal speculative additions but may lack simplicity of use and flexibility in representing complex structures, posing challenges when reconstructing historically significant imagery where accuracy is paramount.

Figure 1. Examples of original archive photos of Most in various quality.

Currently, professional photo and video software broadly utilize modern inpainting algorithms [3–5], often termed content-aware fill, as a standard feature [6]. For historical restoration, however, the term inpainting encompasses both the recovery and synthesis of missing or unwanted data across entire images, requiring careful handling to balance visual appeal and historical fidelity.

The application of artificial intelligence in cultural heritage preservation offers unprecedented opportunities for restoration, cataloging, and enhancing public access to historically significant artifacts. AI technologies, such as machine learning and GANs, can fill in missing parts of artifacts, analyze complex historical data, and support immersive experiences that bridge the gap between past and present. However, integrating AI into this sensitive field introduces complex ethical challenges, particularly regarding authenticity, interpretative bias, and cultural ownership. Scholars emphasize the need for sector-specific ethical frameworks that address these unique concerns, as broad, generic AI principles often fall short in meeting the nuanced needs of cultural heritage preservation [7].

In the context of AI-driven digital recreation, issues of "digital colonialism" emerge [8], especially when reconstructions are created by foreign entities without input from local communities. Such practices risk decontextualizing heritage from its community, potentially eroding its cultural significance. As cultural heritage is increasingly recognized not merely as a collection of artifacts but as a dynamic social process, it is essential to balance technological advancements with respect for the social, cultural, and economic values that these artifacts embody. An inclusive ethical approach that respects local perspectives and maintains the cultural continuity of heritage is critical to ensuring that AI-driven preservation efforts do not inadvertently prioritize technology over the values of the communities represented by the artifacts.

Furthermore, recent studies underscore the importance of adopting a human-centered approach to AI in cultural heritage, advocating for frameworks that prioritize community agency, transparency, and shared responsibility. This consideration must be respected in the data collection process, especially for cases such as the city of Most, which, while transformed, remains a living and significant cultural environment.

Here, we review a range of approaches that prioritize both the quality and homogeneity of restored textures while considering the ethical implications of their application in historically sensitive contexts. Our focus is on methods that strive to minimize residual input errors, thereby preserving historical authenticity even when confronted with limited or degraded source material.

2. State-of-the-Art

Advances in artificial intelligence have brought transformative tools to the field of cultural heritage preservation, enabling new levels of accuracy and efficiency in restoration. However, these technologies also present significant ethical considerations, especially in terms of authenticity, interpretive bias, and cultural ownership. Many researchers [7,9] stress the need for sector-specific ethical frameworks that address the nuanced requirements of cultural heritage [10], as broad AI guidelines often fail to account for the unique sensitivities involved in representing historical artifacts and narratives

One of the central issues is “digital colonialism”, where foreign-led AI reconstructions risk disconnecting heritage items from their cultural context, potentially diminishing their cultural value. Ethical approaches to heritage restoration must therefore include local perspectives to safeguard the socio-cultural significance of artifacts. This is especially critical [11] when using AI models in reconstructive tasks, as such models can unintentionally impose a modernized or biased interpretation on culturally sensitive material. Scholars advocate [12] for a human-centered framework that prioritizes transparency, community input, and a balanced approach to technology adoption within heritage preservation.

Regarding photo manipulation, ethical concerns have arisen over the distinction between correction (enhancing clarity or completeness) and corruption (adding speculative or misleading content). Scholars [13] argue that transparency in restoration techniques is crucial to maintaining public trust in digital heritage projects. Historical precedents in analog manipulation are acknowledged, but the scale and subtlety enabled by digital tools amplify these risks, underscoring the need for clear standards and public awareness regarding alterations.

Technically, the field of inpainting has developed from early methods of hole filling—like the level-line techniques of Masnou and Morel [14] and the autoregressive model by Roosmalen [15]—to more sophisticated algorithms. These include texture synthesis techniques, such as quilting [16], graphcut [17], and exemplar-based inpainting [18]. Current inpainting methods apply small patches with energy-minimizing criteria to fill occluded regions, effectively segmenting images into foreground and background to accommodate camera motion and lighting changes. Techniques from Newson [19] and Wexler [20] exemplify this approach, typically requiring user-defined masks to direct inpainting.

Recent advancements in convolutional neural networks and generative adversarial networks have enabled robust inpainting over larger areas, though computational demands and training data requirements remain high. CNN models, like those by Tesfaldet [21] and Xie [22], deliver visually consistent results with minimal artifacts, while GAN-based approaches offer flexible synthesis options for reconstructing complex structures. However, they require extensive computational power and large datasets, which can limit their application in resource-constrained heritage projects.

Generative AI models, such as DALL-E [23], Midjourney [24], and the SORA model [2], demonstrate remarkable capabilities in producing high-fidelity visuals from textual descriptions. These models introduce both opportunities and risks, particularly when used to recreate or supplement heritage imagery. AI-driven reconstructions from models like SORA blur the distinction between authentic and synthetic content, necessitating careful ethical consideration in heritage settings where historical fidelity is paramount. Scholars [8] emphasize that high-quality generative models should be used with transparency to prevent misrepresentation or erosion of public trust in digitally preserved artifacts.

To address these concerns, detection methods for AI-generated media have emerged, focusing on identifying artifacts in the frequency domain. For instance, high-frequency noise analysis can help discern subtle irregularities introduced by partitioning and patch-based generation methods. This detection approach provides a preliminary mechanism for evaluating content authenticity, particularly in historical restarations and reconstructions, where the preservation of authenticity is essential.

The proliferation of generative AI models, exemplified by breakthroughs such as DALL-E [23] or Midjourney [24] and many others [25] and advancements in video synthesis like the SORA [2] open AI model, has ushered in a new era of content creation. These models, developed by organizations like OpenAI with its various models [26], demonstrate remarkable capabilities [27] in generating high-fidelity visual content from textual descriptions. While the potential applications of such technology are vast and varied, they also raise profound ethical implications and uncertainties.

Collectively, these studies contribute to a rich foundation of techniques but raise many ethical issues to consider in the use of artificial intelligence in cultural heritage inpainting. Incorporating both technical and ethical frameworks, the field aims to create responsible, transparent methods that honor cultural narratives while harnessing the potential of artificial intelligence to preserve and restore historically significant artifacts.

3. Methodology

3.1. Project Motivation

As New York Times photo critic Andy Grundberg noted, "In the future, newspaper readers and magazines are likely to view news images as illustrations rather than reporting, because they can no longer distinguish between the real image and the image that was manipulated". This prediction has become even more relevant today, as ethical concerns continue to grow, particularly with the widespread availability of powerful AI-based tools that allow for effective and seamless image manipulation.

The preservation of cultural heritage through digital restoration serves as both a safeguard for historical memory and a bridge connecting contemporary society with its past. In cities that have undergone significant transformations, digital reconstruction offers an invaluable means of visualizing and preserving historical architecture and landscapes. For the city of Most, which was largely demolished in the 1960s and 1970s to make way for coal mining, the potential for digital inpainting lies in restoring its pre-demolition appearance based on historical photographs. By removing modern elements or obstructions, such as cars, trees, and other additions, and recreating missing architectural details, these digital reconstructions enable viewers to access a representation of Most (see a simple example of retouching and coloring in Figure 2) as it once was, preserving the city's cultural identity for future generations.

Figure 2. Examples of the ability to reconstruct color an restore artificially damaged photograph.

Beyond Most, similar challenges and opportunities exist for heritage sites worldwide. In Venice, for instance, the damage caused by environmental changes and the impact of tourism endanger its architectural legacy. Digital restoration using inpainting techniques could assist in preserving the intricate details of frescoes, mosaics, and building facades.

For sites like Palmyra in Syria, which suffered substantial destruction due to conflict, AI-driven restoration could aid in reconstructing the appearance of lost monuments based on photographic and architectural records. These applications exemplify the broader value of inpainting technology in heritage contexts, where the goal is not just to restore images but to recreate spaces that hold deep cultural significance.

Technically, content-aware filling (see demonstration in Figure 3) has evolved considerably since its inception as a tool for repairing damaged images and videos due to the aging of media. Initially designed to restore degraded or corrupted areas, it has since been widely applied to remove unwanted objects from photos and videos for aesthetic, practical, or even political reasons. However, achieving a seamless edit without visible artifacts remains challenging, especially when applied to heritage content where both visual quality and historical accuracy are paramount.

Figure 3. (**Left**): A sample photo where shading obscures much of the building, making reconstruction difficult. The appearance of a large part of the building is unknown and cannot be obtained even from historical photographs; (**Right**): Objects removed and replaced with one of the possible reconstructions of the obscured content.

AI-based methods, especially those leveraging deep learning and generative models like GANs, have shown great promise in generating contextually coherent content that blends seamlessly with surrounding areas. These algorithms can "learn" the texture and structure of a scene, making them invaluable in reconstructing heritage imagery. However, they also face limitations: deep learning models require substantial computational power and large datasets, and they may exhibit bias if training data lacks variety. This bias can be problematic in heritage applications, as historical scenes often contain textures, architectural details, or artifacts that are not well-represented in standard training sets. Another challenge arises when the dataset lacks the desired textures or visuals of historical buildings. In such cases, there is a risk of introducing unintended "modernization" into the reconstructed (and not restored) images, as the inpainting algorithms may fill gaps with contemporary patterns or features not present in the original structures.

Another critical issue is the interpretability of AI-based techniques, which is often limited, making it difficult to verify how the algorithm produces certain results. In heritage contexts, where accuracy and oversight are essential, this lack of transparency can hinder the validation process. Additionally, ensuring that the inpainted areas appear natural and free from artifacts is paramount, as the human visual impression is the ultimate measure of success. In the context of Most, for instance, reconstructed scenes must look historically authentic and consistent with remaining archival materials to serve their educational and commemorative purposes.

These technical and ethical challenges highlight the need for carefully considered methods in digital heritage restoration. Through responsible application of AI-based inpainting, projects like the digital restoration of Most can contribute to preserving history while mitigating the risks of introducing unintended distortions. In so doing, digital heritage projects offer a powerful way to honor and communicate the cultural identities embedded in historical artifacts and sites, ensuring that they remain accessible and meaningful for future generations.

3.2. Restoration and Reconstruction

Restoration traditionally refers to the process of returning an artifact, building, or object to a known earlier state by removing later additions or repairing damage without introducing speculative elements. We use it here in this sense.

The goal is to preserve the authentic material as much as possible, maintaining the integrity and continuity of cultural heritage. In our project, restoration involves correcting degraded historical data—such as scratches, overexposure, and other forms of damage using AI-based techniques to enhance the original images. The interpretability of AI methods in restoration is generally more straightforward (or even unnecessary) because the role of AI is to identify and correct known defects while closely adhering to the original material. Techniques like noise reduction and scratch removal can be validated against undamaged portions of the data, making AI decision-making more transparent and easier to interpret.

Reconstruction involves recreating missing parts (see Figure 3) when direct restoration is impossible due to extensive damage or lack of original materials. This includes filling missing areas of photographs or rebuilding structures without precise documentation. The aim is not only visual restoration but also the re-establishing of cultural and historical significance. In the Most project, reconstruction seeks to restore physical structures and the city's memory and identity. AI interpretability here is more complex, as algorithms generate content based on learned patterns, introducing potential speculation. This raises concerns about authenticity, necessitating transparency about AI models, training data, and associated uncertainties.

Colorizing black-and-white photographs lies between restoration and reconstruction, adding interpretive information that enhances historical connection but introduces speculation due to the (usually) unknown exact colors, as AI adds speculative information to non-speculative, original data. Moreover, different methods can produce very different [28] results.

By explicitly expressing these distinctions and addressing the interpretability of AI-based techniques, the project can better communicate the challenges and limitations associated with restoring and reconstructing historical buildings and photographs using digital methods. This underscores the importance of transparency and interpretability in AI applications to maintain a dynamic and evolving understanding of authenticity, balancing historical accuracy with the necessity of speculative reconstruction.

3.3. Corrupt or Not Corrupt?

In the context of the Most reconstruction project, a case could be made where "corruption" in the form of photo manipulation may not necessarily be problematic or ethically wrong, particularly when serving the goals of historical education and preservation. Here's a reasoned counterargument:

3.3.1. Corruption as a Tool for Reconstructing Lost History

While photojournalism prioritizes truth-telling and accuracy in representing current events, in the case of the city of Most, the goal is not merely to preserve an unaltered historical truth but to reconstruct a historical narrative that has been lost. The destruction of Most, including its buildings and urban layout, means that visual records may be incomplete or insufficient. In this context, certain "corruptions"—in other words, purposeful alterations or speculative reconstructions—might be necessary and justifiable for the following reasons:

Restoring a Complete Visual Representation

Many historical photos of Most before its demolition may be obstructed by modern elements like cars, trees, or passersby, preventing an accurate view of the city's architectural details. Removing these elements and reconstructing what likely existed beneath them may involve educated guesses based on available data. While this process introduces speculative elements (and thus can be seen as a form of "corruption"), it serves to rebuild an otherwise lost view of the city as it once stood, which is critical for cultural memory and historical understanding.

Filling in Gaps Where No Visual Data Exists

In cases where no complete photographic records exist, speculative reconstruction may be the only option to provide a coherent and holistic view of the city. For instance, if only fragmented records of a particular street or building remain, "corruption" in the form of recreating missing sections (see Figure 4) based on architectural patterns or historical descriptions may serve a legitimate educational purpose. While this introduces non-historical elements, the intent is not deception but offering a plausible version of a lost historical reality.

Enhancing Public Engagement and Accessibility

Reconstructing lost historical spaces can help make cultural heritage accessible to a broader audience. For instance, a digital reconstruction of Most, even with speculative elements, may allow individuals to interact with and learn about the city's history in ways that a fragmented or incomplete representation could not achieve. Here, corruption is not intended to deceive but to engage, educate, and preserve cultural heritage through visualization, acknowledging that some interpretative leaps are needed to restore lost content.

Acknowledging Speculative Elements Transparently

One way to mitigate concerns about "corruption" is to clearly differentiate between what is factual (based on historical evidence) and what is speculative reconstruction. By transparently labeling which parts of the image or video have been altered or reconstructed, the potential ethical issues of "corruption" are addressed upfront. This transparency allows viewers to understand that while certain elements are speculative, they serve a historical and educational purpose rather than an intent to deceive.

Figure 4. Four possible results of filling the obscured area using the content-aware fill method [6].

3.4. Reflections on Speculative Reconstruction

In the context of Most's historical reconstruction, "corruption" in the form of speculative reconstruction can be justified when it is used responsibly to recreate lost cultural heritage and is clearly labeled and communicated. The key is ensuring that any manipulations are transparent and well-intentioned, aiming to restore history for public education rather than distort it. In this case, the primary goal is to recover and preserve an understanding of the past rather than adhere strictly to the raw photographic truth of incomplete or obstructed records.

3.5. Problem Statement

The core challenge addressed in this article lies in the restoration and reconstruction of historical imagery using AI-driven inpainting methods, with a specific focus on the city of Most. Due to its near-total demolition, Most represents a unique case of lost urban history that can only be recovered through the careful restoration of existing photographs. However, the restoration of these historical images involves significant technical and ethical challenges.

Technologically, modern inpainting methods—ranging from patch-based techniques to deep learning algorithms—must seamlessly reconstruct missing parts of the city's architectural and urban features while maintaining visual coherence and historical authenticity. The removal of modern-day obstructions (such as cars, trees, and people) further complicates the task, as it requires the algorithm to fill in these gaps with accurate reconstructions of what may have existed in the past.

From an ethical perspective, the use of AI to reconstruct historical imagery introduces questions of authenticity and speculative reconstruction. While AI-driven inpainting offers the potential to recreate lost details, it also risks introducing elements that may not have been present, raising concerns about the historical fidelity of the final product. These challenges are compounded by the inherent biases in AI training data, which may fail to represent the unique textures, colors, and architectural styles of historical environments like Most. Thus, the primary problem addressed in this article is how to effectively leverage AI-driven inpainting for historical restoration while minimizing technical flaws and ethical concerns.

The source data consists of high-resolution color scans of physical black-and-white photographs and negatives in digital TIFF format. In some cases, the photographs are supplemented with annotated metadata, such as house numbers, street names, dates when the photographs were taken, and periods when buildings were reconstructed or demolished. However, metadata are available for only a portion of the photographs; for the majority, such information is lacking. Consequently, photographs depicting the same houses or streets need to be detected and matched using image analysis techniques.

Given that all buildings were documented during the demolition of the city, the number of available photographs is substantial. These images have been provided by both citizens of the city and, more predominantly, by museum and geodetic institutions (the process of scanning these photographs is still in its early stages; about a thousand more images are expected to become available as the project progresses).

The scans are performed at a color depth of 24 bits, with resolutions tailored to the exact format of each photograph, typically around 12,000 $\times$ 14,300 pixels with our given standard at 2400 dpi, resulting in a memory size of about half a gigabyte per image. This high resolution ensures that the scans capture the photographic grain, allowing restoration algorithms to operate effectively at the grain level.

3.6. Objectives

The objectives of this article are as follows:

1. Showcase Capability of Corrupting Inpainting Methods for Historical Accuracy: Assess different AI-driven inpainting techniques, such as patch-based methods and neural network approaches like GANs, for their ability to accurately reconstruct missing portions or restore damaged areas of historical photographs. The evaluation will focus on how well users perceive the quality of these reconstructed materials.
2. Assess Technical Performance: Analyze the computational performance and visual quality of inpainting techniques applied to historical photographs, taking into account issues such as computational demands, artifact reduction, and boundary error minimization.
3. Address Ethical Implications of AI-based Reconstruction: Explore the ethical concerns surrounding AI-driven restoration, particularly the balance between reconstructing lost historical imagery and the potential introduction of speculative elements that may not reflect the original scene. This will include a discussion on transparency, ensuring that viewers understand where AI-generated content begins and historical fact ends.
4. Propose Guidelines for Future Applications: Based on the evaluation of inpainting methods and ethical considerations, the article will propose best practices for the responsible use of AI in historical restoration.

3.7. Integrating the Concept of Authenticity with the Most Reconstruction Project

The concept of authenticity plays a crucial role [29] in the digital reconstruction of historical artifacts, particularly in heritage conservation projects such as the restoration of the city of Most. The use of AI-driven inpainting techniques, such as generative adversarial networks (GANs) and patch-based methods, is essential in restoring degraded historical photographs and reconstructing the lost urban heritage of Most. However, these technologies introduce complexities and challenges related to maintaining historical authenticity, especially when dealing with speculative reconstructions.

3.7.1. Evolution of Authenticity in Digital Heritage

Authenticity in the digital context is far from being a clear-cut or static concept [30,31]. In the process of digitizing cultural artifacts and heritage sites, authenticity transforms from a purely physical attribute into a more intellectual and epistemological question. Digital reproductions must maintain the integrity of their origin, history, and cultural significance. The digitization process often leads to debates over the "aura" and "originality" of cultural heritage, as digital representations may lose some visceral and sensory elements inherent in the original objects.

Professionals in cultural heritage increasingly recognize the necessity for a more refined approach to authenticity when addressing digital versions of cultural artifacts. A core element of conservation is the identification of heritage values, which serves to evaluate significance, allocate resources effectively, and guide decision-making processes. These values are central to understanding authenticity—a multifaceted concept developed to assess how cultural heritage communicates its attributed values. This notion has evolved through numerous international charters and conventions. Heritage values evolve alongside social changes and can frequently conflict with one another; a typical example is the tension in architectural heritage between archaeological significance and functional use.

3.7.2. Balancing Authenticity and Technological Capability

The integration of AI technologies in heritage preservation brings an evolving interpretation of authenticity. In traditional conservation, authenticity was concerned mainly with the material integrity of heritage. In the digital era, however, it has come to mean how accurately digital reconstructions represent the original cultural and historical significance [30,32]. For the Most reconstruction project, achieving this balance involves multiple technical methods, ranging from AI-driven neural networks for complex inpainting to patch-based methods for more straightforward tasks. These technologies aim to ensure that reconstructions are as faithful as possible to the original historical context, but their limitations also highlight the challenges of adhering to authenticity.

Despite some theorists are less [33] or more [34] against the emerging ideas, the importance of material authenticity and criticizing imitations, we recognize the need for the project outcome to be accessible and usable for the general public. Addressing concerns from historians within our project about the dangers of creating false, non-authentic data, allowing users to identify which data are original (and view their sources) and which are synthesized.

Transparency in presenting the reconstructed images is thus a vital aspect of authenticity. By marking speculative areas and providing additional contextual information, the project aims to avoid misleading viewers. However, authenticity is challenged by the need to address gaps in historical data, making speculative reconstructions necessary.

3.8. Data Collection and Preparation

The primary data sources used for this project consist of black and white historical photographs of the city of Most, captured before its large-scale demolition in the 1960s and 1970s. These photographs are crucial for digitally reconstructing the lost architectural heritage of the city. The photos, often degraded over time due to factors such as aging, exposure to light, and physical damage, are digitized at a high resolution (minimum 600 dpi) to ensure that the restoration process captures as much detail as possible. Only a few colorized postcards are available as source data (see Figure 5)

Once digitized, a detailed analysis of the photographs is conducted to identify visible damage such as scratches, dust, and fading. Preprocessing techniques such as noise reduction, contrast enhancement, and scratch removal are applied to restore the photographs. Several tools are employed for this process, including Adobe Photoshop and neural filters [35] for automated restoration, alongside manual retouching techniques where necessary.

Figure 5. Reference data for the colorization process. Unfortunately, the amount of similar, usually hand-colored photographs is extremely small.

3.9. Technical Approaches

Various AI-based and traditional techniques are employed for inpainting and restoration of the historical photographs of Most:

- Neural Networks: Convolutional neural networks (CNNs) are utilized to remove noise and reconstruct damaged or missing areas in the photographs. These deep learning models are trained [35] on large datasets of historical imagery to learn the textures, structures, and patterns of the photos. GANs are also used for more complex restoration tasks, such as reconstructing missing architectural elements based on historical data. As we aim to create workflows for wider audiences, we currently don't use GANs to produce results but are training a GAN for future purposes to achieve better results.
- Patch-based Inpainting: For simpler restoration tasks, patch-based inpainting is applied. This method works by copying patches from undamaged regions of the photograph and pasting them into the damaged areas, ensuring that the new textures match the surrounding content. This method is particularly effective for restoring uniform areas, such as walls or skies.
- Manual and Semi-Automatic Retouching: In some cases, manual retouching techniques are necessary to ensure the highest quality restoration. Tools like the clone stamp and healing brush in Adobe Photoshop are used to manually correct defects that AI algorithms may overlook. Semi-automatic methods combine neural networks with user input to adjust and refine the restoration process.
- Colorization: Initially, the restoration process is applied to the black-and-white photographs. Tools like DeOldify [36] are employed, which utilize neural networks to predict the original colors based on contextual cues from the photographs. An alternative is semi-automatic colorization (for results see Figure 6) using neural filters [35].

Figure 6. Sample of several colored complex photographs of Most city.

4. Discussion

4.1. Technical Challenges

One of the key technical challenges encountered in the reconstruction of Most's historical photographs involves the computational demands of AI-driven inpainting techniques. GANs and other neural networks require significant processing power, particularly when reconstructing large or complex areas of the images. The high-resolution nature of the photographs further increases the computational load, resulting in longer processing times. While patch-based inpainting methods are less computationally intensive, they often produce less accurate results, especially in more intricate sections of the images such as architectural details. Reducing these computational requirements without sacrificing visual quality remains a major challenge. Notably, considerable computing time is required due to the large volume of data (up to 1 GB per photo scan) that needs to be processed.

Another challenge lies in the interpretability of the AI models used for reconstruction. Deep learning models can generate realistic visual content, but understanding exactly how the model makes certain decisions—such as how it fills in missing architectural elements—is often unclear. This lack of transparency can be problematic, especially when ensuring the historical authenticity of the reconstructed content. There is an ongoing need for more interpretable AI models that can provide explanations for the choices made during the inpainting process.

Lastly, bias in AI models presents a significant challenge. The models used for this project were trained on datasets that may not fully represent the specific architectural and cultural nuances of Most. As a result, some reconstructed areas may reflect a modern or generalized aesthetic that is not fully aligned with the city's historical reality. Although manual intervention mitigates this issue, there is a need for more tailored datasets that can help reduce the risk of biased outputs and improve the cultural specificity of AI-generated content.

4.2. Ethical and Cultural Implications

The ethical considerations in reconstructing historical artifacts, particularly using AI, are multifaceted. One of the main concerns is authenticity. AI-generated reconstructions, while visually impressive, can introduce speculative or inaccurate details that did not exist in the original artifacts. This raises questions about the fidelity of the restored images to the historical record. In the case of Most, where much of the original city has been destroyed, these reconstructions play a vital role in shaping how future generations perceive the city's history. However, it is crucial that these reconstructions remain as accurate as possible to avoid misrepresentation of historical events or architectural details.

Transparency is essential when dealing with AI-generated content in cultural heritage. The project's approach of clearly marking which areas are based on factual historical data and which involve speculative reconstruction helps mitigate some of the ethical risks. However, the potential for misleading the public—especially when AI reconstructions are presented without sufficient context—remains a concern. Ensuring that these reconstructions are labeled and accompanied by explanations of their limitations is a critical step toward maintaining the integrity of cultural heritage.

Another consideration is the cultural ownership of the restored content. AI-driven reconstruction, especially when applied to culturally significant artifacts, must respect the rights and perspectives of the communities to whom the artifacts belong. In the case of Most, the project engages with local historians and experts to ensure that the reconstructed images align with the cultural memory of the city's residents. Future work should continue to involve community stakeholders in the reconstruction process to ensure that the AI-generated artifacts are not only technically accurate but also culturally sensitive.

4.3. Ethical and Interpretative Considerations

A significant challenge in AI-based inpainting is maintaining historical authenticity. Since neural networks and GANs can generate new content to fill missing areas, there is a risk of introducing speculative or inaccurate details into the restoration. To mitigate this, each inpainted image is carefully reviewed by historians to ensure that the reconstructed areas are as faithful as possible to the original context.

Furthermore, transparency is a critical component of this process. The project clearly delineates which parts of the restored image are based on factual evidence and which are speculative reconstructions. This distinction ensures that viewers are not misled into believing that fully reconstructed areas are necessarily historically accurate.

Additionally, we continually strive to balance the use of AI-generated content with ethical guidelines that uphold historical integrity. The potential for AI to generate convincing yet fictional elements requires that the results be rigorously vetted and that metadata accompanying the images reflects any non-historical reconstructions.

4.4. Case Study: Digital Reconstruction of the City of Most Historical Photography

Background Information

The city of Most in the Czech Republic underwent a significant transformation in the mid-20th century, when large parts of the historic city were demolished to facilitate coal mining operations. This destruction erased many of the architectural and cultural landmarks that defined the city for centuries. However, historical photographs from before the demolition provide a valuable window into the past, offering the opportunity to digitally reconstruct these lost landmarks. Reconstructing Most is not only a technical challenge but also a cultural responsibility, as it allows future generations to visualize and understand the city's historical significance before its physical disappearance.

The preservation of Most's visual history has broader implications for understanding how urban landscapes can be transformed by industrial development. The project to digitally restore these historical photographs is essential to preserving Most's architectural and cultural legacy, making it accessible to the public through exhibitions, virtual archives, and educational resources.

4.5. Application of Methods

For the digital reconstruction of Most photographs, the project employed several inpainting techniques tailored to the specific challenges posed by the historical photographs. Unlike more generalized restoration efforts, the unique characteristics of Most's urban layout—combined with the extensive damage to the photographic material—necessitated a multi-layered approach. The current best workflow for most urban photographs is:

1. Removing Modern Elements: Many of the photographs of Most were taken in the decades leading up to the demolition, often featuring modern-day objects like cars, streetlights, or passersby that obscured important architectural features. The primary goal was to remove these obstructive elements while preserving the historical integrity of the buildings and streets beneath. Patch-based inpainting was used to replace these elements with textures drawn from surrounding areas, while GANs were employed to recreate missing details based on architectural patterns that were consistent across multiple photographs of the same area.
2. Reconstructing Missing Architectural Details: In many cases, key architectural elements were obscured by damage or missing entirely from the photographs. Neural networks were used to recreate windows, arches, and facades that were vital to maintaining the aesthetic continuity of the reconstructed city. This required cross-referencing with historical documentation and consultation with historians to ensure fidelity to the original structures. Additionally, the architectural plans of the buildings, if available, served as suitable control inputs.
3. Automated and Semi-Automated Retouching: The project also developed automated and semi-automated workflows for retouching and colorizing images. These methods used a combination of AI tools, like Photoshop's neural filters, and manual adjustments to fine-tune results with varying complexity for various target audiences. These workflows ranged from a simple process for complete laypeople—consisting only of loading the image, running the automatic process, and saving the results—to manual and semi-manual workflows. The step-by-step process involved defining areas of correction, and exact tools to use. Similarly, it consists of empirical color values best suited for the Most project. It is therefore beneficial to have a range of detailed procedures for users with different knowledge and abilities. In addition, it is desirable to have multiple procedures reflecting the state of various technological and software options.
4. Handling Texture and Lighting Variations: One of the significant technical challenges encountered during the restoration process was dealing with variations in texture and lighting across different sections of the photographs. Older images often have uneven lighting due to the limitations of the photographic technology of the time. Neural networks and manual retouching techniques were used to balance these inconsistencies and ensure smooth transitions between different sections of the inpainted areas to create consistent results.
5. Historical Colorization: Applying historically accurate colors to black-and-white images required deep analysis of available color documentation and contemporary references (see Figure 5). Neural network-based tools like DeOldify [36] were employed to colorize the photographs, but with significant manual oversight to ensure the chosen color schemes were reflective of the time period. For example, exact color values of materials such as thatched roofs, burnt bricks, or car paint colors were used. This was particularly important for public-facing exhibitions where colorized images (see Figure 6) can enhance viewer engagement and provide a more immersive historical experience. For instance, externally obtained values used for colorization included

the colors of shop signs on the square—obtained from colorized postcards—and the colors of buses traveling outside the city and public transport buses.

- Time aspect: On average, this process could take around 10–15 min for simpler images, but for more complex cases with significant damage or obscure textures, it could take up to 60 or more minutes or more in case of photography with many small cracks.

4.6. Conclusions

The results of the reconstruction efforts for Most were generally successful, with many of the restored photographs achieving a level of visual coherence and historical authenticity that allows for accurate public representation. The combination of AI-driven inpainting and manual intervention enabled the project team to reconstruct key parts of the city, including important architectural landmarks that had been partially or fully obscured in the original photographs (see Figure 7).

Figure 7. (**First row**): Original black and white photograph and reconstructed color image without obscuring objects; (**Second row left**): colorized photo with photos with marked obstructing objects; (**rest**): gradually removed objects, content supplemented by generative AI. Objects must be removed in order from the most distant obscuring object to the object closest to the reconstructed object.

On average, retouching a photograph using these methods required 10–15 min, depending on the complexity of the scene. However, in more challenging cases where the image quality was particularly poor or contained intricate textures, the time required for restoration could extend up to 60 min or more, depending on the complexity. This variation highlights the importance of both automation and manual effort in achieving high-quality restorations.

Despite the success, several challenges remain. In cases where there was little reference material for the missing elements, the reconstructions relied on best-guess estimations, albeit supported by historical data and expert reviews.

The project also highlighted the limits of current AI-based restoration methods. While neural networks and GANs were effective in reconstructing large areas, finer details often required manual retouching to meet the desired level of historical accuracy. The balance between visual appeal and authenticity was carefully managed to ensure that the final images were not only aesthetically pleasing but also credible representations of the city's past.

Ultimately, the reconstructed photographs of Most have been successfully used in educational programs, exhibitions, and virtual tours, providing a vivid and accessible way for people to engage with the city's lost heritage. The project demonstrates how AI-powered restoration techniques, when used in combination with historical expertise and ethical guidelines, can contribute to preserving cultural heritage in ways that were previously impossible.

4.7. Results and Evaluation

4.7.1. Comparative Control Using Known Color Photographs

In the digital reconstruction of the city of Most, a critical aspect of the evaluation process involved comparing the restored images against a small set of known historical color photographs. These reference photos provided a reliable benchmark to assess the accuracy and quality of the inpainting methods applied to the black-and-white images. The comparison focused on how well the reconstructed areas, particularly in terms of architectural details and colorization, matched the verified color references.

- Color Accuracy: Using the known color photographs as a control, we evaluated the colorization of the inpainted black-and-white images. Neural network-based tools generated color schemes based on contextual information, but the comparison revealed some inconsistencies with the reference images. For example, building facades and rooftops in the reconstructed images often displayed slight color shifts compared to the known historical colors. These deviations were more prominent in cases where GANs were used for large-scale reconstructions, leading to subtle but noticeable differences in hue and saturation. Manual adjustments were necessary to correct these discrepancies, ensuring that the final colorized images aligned more closely with historical evidence. Similar color shifts were detected in the case of signs with shop names (see Figure 8).
- Architectural Detail Consistency: The known color photographs also served as a means to test the fidelity of reconstructed architectural details. GAN-based inpainting performed well in recreating intricate elements such as windows and facades, but comparison with the color references highlighted occasional over-smoothing or loss of texture in some areas. Patch-based methods, while faster, struggled more with consistency in finer architectural features. In particular, the comparison revealed that neural filters provided more accurate representations of these details, but still required fine-tuning to avoid artificial or overly uniform textures.

Figure 8. Two possible results of shop signs color on the Peace square.

4.7.2. Visual Quality Testing with Human Users

To evaluate the visual quality of the restored images, we conducted human subject testing involving two main components: assessing the perceived authenticity of the reconstructions and determining viewer satisfaction with the colorization and inpainting results.

Perceived Authenticity: A group of test subjects, including both experts, students of computer graphics, and general users, were asked to rate the visual authenticity of the reconstructed images on a scale from 1 to 5. The evaluation focused on how well the restored images conveyed the look and feel of the historical city. Though some users noted a lack of texture variability in certain areas, which affected the perception of authenticity, the testing showed that the results were visually plausible overall.

4.7.3. Psychophysical Tests

To evaluate the visual quality of the inpainted images, we conducted two types of psychophysical tests with participants in a controlled environment within a usability laboratory. The controlled environment ensured that all potential disruptive influences were eliminated, such as differences in perception due to varying monitors, lighting conditions, and other environmental factors. Additionally, to prevent any potential bias, the moderator had no prior involvement in the project. The goal was to compare the subjective perception of image quality in scenarios where participants were either unaware of the retouched areas (blind test) or were informed about them (informed test). Participants were asked to rate the quality of the images on a scale from 1 to 5, where 5 represents the highest visual quality. The results from both tests (see Figure 9) provide valuable insights into how awareness of inpainting affects the perception of quality.

Blind Test

In the blind test, participants were shown images without being informed which parts had been altered or retouched, along with some unedited images as control samples. Their task was to assess the overall quality of the image based on visual coherence and whether they detected any artifacts or inconsistencies. The goal was to determine whether the inpainting was successful in creating a seamless visual experience where the modifications were imperceptible.

The results of the blind test indicated a generally positive reception of the inpainted images. Most participants rated the images highly, with the majority of scores falling between 4 and 5. The average rating was 4.45, with a standard deviation of 0.62. The confidence interval (95%) for the average rating was calculated as $[4.31, 4.59]$. This suggests that, in the absence of additional information, the inpainting methods effectively concealed the modified areas, resulting in high subjective quality ratings.

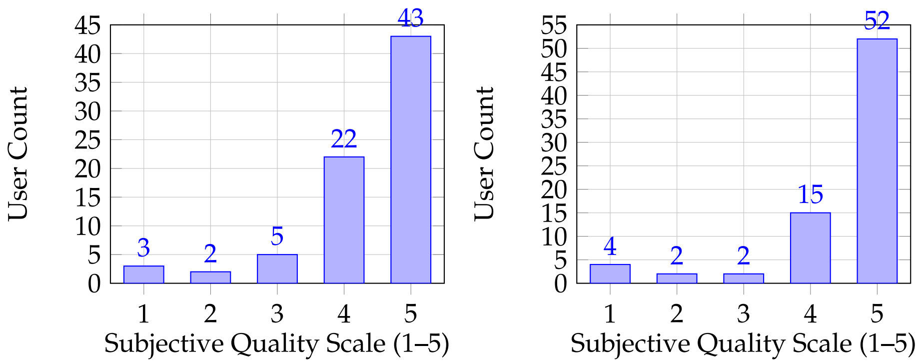

Figure 9. (**Left**): Graph of user Informed test of the quality of synthesis of photos of the Bridge (selection of twenty random photos of Peace Square and adjacent streets). Value 1 is the minimum

(unsuccessful retouching, obvious manipulation) value 5 is the maximum (high-quality and successful retouching, imperceptible manipulation); (**Right**): Graph of user Blind test of the quality of synthesis of photos of the Bridge (selection of twenty random photos of Peace Square and adjacent streets). Value 1 is the minimum (unsuccessful retouching, obvious manipulation) value 5 is the maximum (high-quality and successful retouching, imperceptible manipulation)

Informed Test

In the informed test, participants were provided with additional information about the retouched areas. The images were presented alongside their corresponding masks, allowing participants to see exactly which portions had been altered through inpainting. This allowed us to assess whether knowledge of the edited areas would affect participants' perception of the visual quality.

The results showed a slight drop in the perceived quality when participants were informed of the retouched areas. The average rating was 4.33, with a standard deviation of 0.68, and the confidence interval (95%) for the average rating was $[4.17, 4.49]$. The number of participants giving the images a perfect score of 5 decreased slightly, with more ratings in the 4 to 5 range. This suggests that even when participants are aware of the modified sections, the inpainting methods still perform well, though the awareness of edits does have a minor impact on subjective evaluations.

Comparison of Blind and Informed Tests

The difference between the blind and informed tests demonstrates the importance of perception in evaluating inpainting quality. The average rating decreased from 4.45 in the Blind Test to 4.33 in the Informed Test. A paired t-test was conducted to determine whether this difference was statistically significant. The p-value obtained was 0.045, indicating that the difference is statistically significant at the $\alpha = 0.05$ significance level. The standard deviations of the scores for both tests (0.62 for the Blind Test and 0.68 for the Informed Test) suggest that there was a slightly greater variability in participant ratings when they were informed of the retouched areas.

When participants are unaware of the retouched areas, they tend to rate the images more favorably. However, even when informed, the overall drop in perceived quality is minimal, indicating the robustness of the inpainting methods in producing visually cohesive results. The confidence intervals and standard deviations provide further evidence that the differences in ratings, although statistically significant, are relatively small, emphasizing the effectiveness of the inpainting methods.

4.8. Limitations and Future Work

While the project has produced high-quality reconstructions of Most, there are several limitations to the current approach. One significant limitation is the availability of data. The reconstructions rely heavily on the quality and completeness of the original photographs, many of which are damaged or incomplete. In cases where no sufficient photographic records exist, the reconstructions involve a degree of speculation, which, while informed by historical context, cannot fully capture the original state of the city.

Additionally, the computational demands of AI-based methods are a limiting factor. The processing time required for high-resolution images can slow down the restoration process, especially in large-scale projects. Future work should explore more efficient AI algorithms that can reduce the computational load without sacrificing the quality of the reconstructions, possibly by using specialized AI models trained specifically for this task. Techniques such as model optimization, distributed computing, and the use of lightweight neural networks could offer promising solutions.

Another area for future research is the improvement of interpretability in AI models. While current models produce highly realistic results, they operate largely as "black boxes", making it difficult to understand how certain reconstruction decisions are made. Developing more interpretable AI models would help increase confidence in the historical accuracy of the results and allow experts to better refine the outputs.

A particularly challenging aspect is the need for human input when coloring problematic areas, such as brightly colored house facades or shop signs. In the current workflow, the user must remember the problematic colors and manually reapply the same inputs to all photos containing the same object.

Finally, future research should continue to address the issue of bias in AI models. One potential solution is to create domain-specific datasets that better represent the architectural styles, textures, and historical contexts of the areas being reconstructed. By training AI models on data that more closely aligns with the cultural and historical specifics of the target area, future projects can produce more accurate and culturally sensitive reconstructions.

4.9. Final Conclusions

This study has demonstrated the potential of AI-driven inpainting techniques to contribute significantly to the preservation and reconstruction of cultural heritage, with a specific focus on the city of Most. By leveraging methods such as GANs, patch-based inpainting, and manual retouching, the project was able to reconstruct and restore damaged or incomplete historical photographs, offering a window into a lost urban landscape. The combination of modern AI tools with historical expertise proved to be an effective strategy in reviving cultural artifacts that otherwise might have been forgotten.

One of the key findings of this study is the importance of balancing technological capability with cultural responsibility. While AI provides powerful tools to reconstruct and enhance visual data, it also introduces challenges related to authenticity and interpretability. As the case study of Most illustrated, AI-generated content can sometimes introduce speculative elements, requiring manual oversight to ensure historical fidelity. Additionally, computational demands and the potential for biased outputs underscore the need for careful application and ongoing refinement of these technologies.

This work also highlights the need for transparency when using AI for cultural preservation. Ensuring that viewers and stakeholders understand which elements of a restoration are fact-based and which are speculative is essential for maintaining the integrity of reconstructed artifacts. In the field of heritage conservation, where the goal is not only to preserve the past but to present it truthfully, this transparency plays a critical role in ensuring public trust and academic credibility.

Moving forward, the integration of AI into cultural heritage preservation will continue to evolve. Future research should aim to refine AI models to improve interpretability, reduce computational costs, and minimize bias, ensuring that reconstructions are both technologically advanced and culturally sensitive. By adhering to ethical guidelines and involving local communities and experts in the reconstruction process, AI can become an invaluable tool in safeguarding our collective history for future generations.

While the results of psychophysical experiments appear, from a quality perspective, highly positive, it is important to recognize that they also highlight the ethical risks and the ease and effectiveness of corrupting historical photographs. Any creation of speculative content must, therefore, not only be carefully supervised by experts familiar with the specific subject matter, but also be transparently communicated and never concealed.

We therefore propose that, in addition to indicating that a given photograph has been digitally restored, it should also be clearly stated if any part of the image has been synthetically generated. Furthermore, users should have the option to view either the unedited original grayscale version or a version where the synthesized sections are highlighted (see Figure 10) with a color overlay for transparency.

Figure 10. Retouched photo example with color-coded overlays. Each colored region indicates an area where a significant object was removed and subsequently reconstructed.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial intelligence
GAN	Generative Adversarial Network
CNN	Convolutional neural networks

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