University Of Arts London

The Impact of AI-Based Texture Synthesis and Completion Models on the Accuracy and Plausibility of Reconstructing Damaged or Incomplete Historical Artifacts

Thesis

Data Science & AI for the Creative Industries

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Contents

Abstract

Preserving and restoring historical artefacts is essential for maintaining cultural heritage, yet traditional restoration methods are often inadequate due to their reliance on manual craftsmanship, which can be labour-intensive and prone to speculative outcomes. Recent advancements in artificial intelligence, particularly in texture synthesis and completion models, offer promising new tools for reconstructing damaged or incomplete artefacts.

These AI-based techniques have the potential to analyze existing patterns, textures, and structural elements to generate plausible reconstructions that may surpass traditional methods. However, the field is still in its early stages, with significant challenges related to the accuracy of reconstructed textures, the historical plausibility of the AI-generated outcomes, and the acceptance of these methods by historians, conservators, and the public. This research seeks to evaluate the impact of AI-based texture synthesis on artefact reconstruction, focusing on the accuracy and plausibility of these techniques to better support cultural heritage preservation.

Introduction

Preserving and restoring historical artefacts is crucial for understanding and maintaining cultural heritage. However, many artefacts are often found damaged or incomplete due to the passage of time, environmental conditions, or human activities. Traditional restoration methods, which rely heavily on expert knowledge and manual craftsmanship, can be labour-intensive, time-consuming, and sometimes result in speculative reconstructions that are only sometimes satisfactory. The use of texture synthesis models in artefact restoration aims to address these challenges, but a definitive approach to image completion has yet to be established in the field of historical restoration. Speculative methods used to preserve damaged pieces may not always accurately reflect the original artefact.

Although there are numerous texture synthesis models awaiting in-depth research, the primary challenge is the use of insufficient and inconsistent methodology metrics to compare factors within the field. In order to achieve reliable results in historical artefact completion modelling, current tools must be accurately evaluated and compared according to a specific metric. To establish satisfying results in historical artefact completion modelling, current tools must be evaluated which will then enable the creation of a new tool that stands out with all features demanded from a historical artefact texture synthesis model according to a specific metric.

Recent advancements in artificial intelligence, particularly in texture synthesis and completion models, offer promising tools for reconstructing damaged or incomplete artefacts. The main expectation from AI-based techniques is the capability to analyse existing patterns, textures, and structural elements to generate plausible reconstructions that may surpass the errors of traditional methods. The key challenges are to capture the structure of complex classes of images in a concise, learnable model, and to find efficient algorithms for learning such models and synthesizing new image data [1]. Despite these advancements, the application of AI in artefact restoration is still in its nascent stages, and several challenges and limitations need to be addressed. These include the reconstructed textures' accuracy, the artefacts' historical plausibility, and the acceptance of AI-generated restorations by historians, conservators, and the public.

Relevant stakeholders in this research include historians, archaeologists, conservators, museum curators, AI researchers, and the broader community interested in cultural heritage. This research aims to explore the impact of AI-based texture synthesis and completion models on the reconstruction of historical artefacts, with a focus on accuracy and plausibility.

1.3 Significance and Broader Implications

The preservation of cultural heritage is essential, as historical artefacts provide invaluable insights into past civilizations, cultures, and histories. This research is crucial because it offers innovative solutions to the challenges of restoring damaged or incomplete artefacts, often beyond the capabilities of traditional restoration methods. By leveraging AI, this study contributes to the growing field of digital humanities, encouraging interdisciplinary collaboration between AI researchers and cultural heritage professionals, and fostering innovation at the intersection of technology and humanities. Improved reconstructions can serve as better educational tools in museums and academic settings, offering more accurate representations of historical artefacts and enhancing virtual and augmented reality applications. Moreover, AI-based restoration techniques can be more efficient and cost-effective than manual methods, allowing conservators to focus on other critical tasks and speeding up the conservation process. This efficiency makes it feasible to handle larger volumes of artefacts, leading to a more comprehensive preservation effort.

The potential benefits of this research are significant. AI-based models can achieve higher fidelity in texture synthesis and completion, resulting in reconstructions that are more accurate and plausible, which in turn deepens our understanding of historical contexts and cultural artefacts. High-quality digital reconstructions can be made widely accessible through online platforms, democratizing access to cultural heritage and promoting global education and appreciation of history. By providing new tools for conservators, this research can lead to the development of best practices that integrate AI into the restoration process, standardizing approaches across institutions. Demonstrating the accuracy and plausibility of AI-generated reconstructions through rigorous evaluation and expert validation can build trust in AI technologies within the cultural heritage community, leading to wider adoption and ensuring that more artefacts are preserved for future generations. Additionally, efficient restoration processes can reduce costs, making it more feasible for institutions with limited budgets to undertake restoration projects, while the development of AI tools for artefact restoration can create new economic opportunities, spurring innovation and job creation in both the tech and heritage sectors.

1.4 Challenges and Limitations

The use of completion models in artefact restoration shows great promise, but it is in a nascent stage and encounters several noteworthy challenges that require attention for wider adoption. These challenges can be classified into three primary areas: the precision of reconstructed textures, historical authenticity, and acceptance by stakeholders.

1. Accuracy of Reconstructed Textures: One of the main challenges of using AI for artefact restoration is achieving a high level of accuracy in the generated textures that remains faithful to the original piece. Although AI tools have advanced, particularly in texture synthesis and completion models, they are not yet perfect. The textures generated by AI may lack the subtle details of the original materials or may introduce historically inaccurate artefacts. This is a critical issue as inaccuracies can mislead researchers and the public about the original appearance of the artefact. To address this limitation, it is important to select the appropriate texture synthesis approach that works well on rough or damaged surfaces. Studies such as TileGAN by Frühstuck et al.[2] demonstrate both the potential and the current limitations in creating large-scale, non-homogeneous textures that accurately represent the original artefacts. The study implements a texture tool that allows users to adjust local characteristics of the synthesized texture using co-occurrence values directly, highlighting the importance of accuracy when modelling a texture.

2. Historical Plausibility: Beyond mere accuracy, there is the challenge of ensuring that AI-generated reconstructions are historically plausible. This involves not just replicating textures and structures but also understanding and respecting the historical context of the artefact. AI models may generate technically accurate reconstructions that are not historically authentic if they fail to consider the cultural, temporal, and stylistic contexts in which the original artefact was created. For instance, a model might produce a texture that looks visually coherent but does not align with the known historical or artistic conventions of the period when the artefact was originally made. This raises concerns about the potential for AI to create reconstructions that, while visually impressive, may distort historical understanding.

3. Acceptance by Historians, Conservators, and the Public: The third challenge is the acceptance of AI-generated restorations by key stakeholders, including historians, conservators, and the public. Traditional methods of restoration are deeply rooted in expert knowledge, manual skill, and respect for the authenticity of the artefact. The introduction of AI into this process may be viewed with scepticism by professionals who are concerned about the loss of human expertise and the potential for AI to introduce inaccuracies or oversights. Additionally, there may be resistance from the public, who might question the authenticity and cultural value of an artefact that has been partially reconstructed by AI. Studies on the ethical implications of AI in cultural heritage, such as those discussed by UNESCO, emphasize the importance of transparency and collaboration between AI developers and cultural heritage professionals to ensure that these technologies are used responsibly and are accepted by the broader community.

Research Findings

2.1 Overview of Texture Synthesis and Completion Models

Since the field dedicated specifically to architectural completion models is still open to new findings, current research outcomes become a pathway to the final destination. AI-based texture synthesis and completion models for reconstructing damaged or incomplete historical artefacts is a burgeoning field, demonstrating significant advancements and challenges. Different AI approaches, such as Generative Adversarial Networks (GANs) and Convolutional Neural Networks (CNNs), have shown promise in generating high-quality, visually coherent textures that can restore artefacts' aesthetic and structural integrity which lead the project to create a new outcome regarding previous research.

For example, a study on the use of high-resolution art painting completion [3] explores a new AI method for preserving and restoring invaluable artworks, which stands close to architectural completion modelling. The specified approach known as Weighted Similarity-Confidence Laplacian Synthesis, mixes both traditional image processing techniques and deep learning to enhance common issues with damaged paintings. Making further connections to texture synthesis in artefact restoration, the article addresses challenges such as colour discrepancies, blurriness and texture inconsistencies, which is the common objective. The study's focus on overcoming this issue is by using nearest neighbour algorithms, highlighting the approach as a method to be explored in the current project. Giving more importance to print details rather than the painting also is highly relevant to this project's scope since the main goal is to improve textural consistency with fine details. The presented method's ability to handle complex structures and textures while minimizing restoration artefacts makes it a valuable tool for adapting the accuracy and plausibility usage in architectural restoration efforts, where accurate texture synthesis and detail preservation are critical.

Additionally, research into co-occurrence based texture synthesis emphasizes the use of neural networks to enhance texture generation [4]. This method integrates patch-based synthesis to improve the coherence of the completed images, effectively dealing with complex textures and structural elements which can be adapted to historical artefacts. The MGANs model used in the study on "Precomputed Real-Time Texture Synthesis with Markovian Generative Adversarial Networks (MGANs)", introduces a structure that is highly relevant for artefact texture synthesis. By using precomputed convolutional networks that allow real-time generation, the structure operates to generate high-quality textures at faster rates compared to traditional methods. Where large surface areas require consistent and detailed texture replication without long processing time in architectural restoration, the efficiency and adaptability seem promising. Despite the quality, MGANs being designed to capture intricate details of texture through adversarial training, do not compromise on scalability. This benefit is particularly important when relating to our current project, where both visual coherency and structural integrity of textures must be preserved.

Comparing these two approaches for direct applications, both highlight different aspects of the project. While the Weighted Similarity-Confidence Laplacian Synthesis model is perfect for handling fine details and colour consistency in small areas, MGANs have a focus on scalability and real-time performance. In patch-based research, the computational intensity may limit scalability since it uses patch-based synthesis to address issues like colour discrepancies and blurriness making it less adaptable for a large-scale artefact restoration project. On the other hand, MGANs having a focus on scalability are well-suited for restoration projects for handling vast surfaces. By integrating the strengths of both methods, a hybrid approach can be developed resulting in a comprehensive tool that can accurately reconstruct artefacts with profound implications for museums, researchers, and conservators, providing a means to safeguard cultural heritage for future generations.

Similarly, the paper "Image Inpainting via Conditional Texture and Structure Dual Generation" proposes a two-stream generative network that simultaneously addresses texture synthesis and structure reconstruction for image inpainting [6]. By leveraging texture-guided structure generation and structure-constrained texture synthesis, the model ensures more plausible and consistent inpainted regions. This approach is enhanced by Bi-directional Gated Feature Fusion (Bi-GFF) and Contextual Feature Aggregation (CFA) modules, improving global consistency and spatial detail. The adaptable insights for architectural restoration involve using dual pathways to handle both textures and structural integrity in restoring damaged surfaces. This methodology can help generate realistic reconstructions in large-scale architectural projects by inpanting completion approach.

Research Questions and Hypotheses

3.1 Methodology

The research is grounded in the theory that advanced artificial intelligence (AI) models, specifically texture synthesis and completion models, can significantly improve the restoration of architectural artefacts by accurately reconstructing missing or damaged textures and structures. Traditional restoration methods rely heavily on manual craftsmanship and expert knowledge, which can be time-consuming, labour-intensive, and sometimes speculative. In contrast, AI models, particularly those based on deep learning frameworks like Generative Adversarial Networks (GANs) and Convolutional Neural Networks (CNNs), have the potential to analyze existing architectural elements, learn patterns, and generate reconstructions that are more consistent and plausible compared to traditional methods.

The key theoretical underpinning is that AI-driven models can capture and replicate architectural elements' intricate textures and structural details, even in high-resolution contexts. This theory builds on existing research that has successfully applied similar methods to art restoration, suggesting that these techniques can be adapted and extended to the domain of architectural restoration. By evaluating both study findings and applications, this research aims to overcome common restoration challenges and will build upon current limitations that specialise directly in artefact texture synthesis.

3.2 Possible Expected Results

1. Improved Accuracy and Plausibility: The algorithms are expected to produce reconstructions that closely mimic the original architectural elements, with high fidelity in texture and structure. The use of advanced techniques like Laplacian pyramid blending and patch-based propagation should result in restored surfaces that are visually consistent with the surrounding materials and free from artefacts such as blurriness or colour mismatches.

2. Efficiency in Restoration Processes: By automating the texture synthesis and completion processes, the research is expected to demonstrate significant time and labour savings compared to traditional manual restoration methods. This efficiency could make the restoration of large-scale architectural projects more feasible and cost-effective.

3. Comparison Between Tools: The research should yield quantifiable improvements in restoration quality, as measured by metrics learned from current online tools and interfaces. Taking the comparison metrics as an asset, this outcome will have an impact on the final development of the tool creation that fits the expected outcome perfectly.

By validating the theory that AI can significantly enhance the restoration of architectural elements, the research could set a new standard in the field, combining the precision of deep learning algorithms with the expertise of human conservators to preserve cultural heritage more accurately. The research questions below stand as a formulation of the expected outcomes.

3.3 Research Questions

1. How does the application of AI-based texture synthesis models affect the accuracy of reconstructed historical artefacts?

2. What is the level of historical plausibility achieved through AI-based completion models in the reconstruction of damaged or incomplete artefacts?

3. How do different stakeholders (historians, conservators, the public) perceive the use of AI in artefact restoration, and what are their acceptance levels?

3.4 Hypotheses Formulation:

Hypothesis 1: AI-based texture synthesis models significantly improve the accuracy of reconstructed historical artefacts compared to traditional methods.

- Expected Outcome: AI-based models will produce reconstructions with higher fidelity to the original artefacts, as measured by texture similarity, and structural coherence.
- Rationale: AI models can analyze and replicate intricate details that might be missed or inaccurately restored by manual methods, leveraging large datasets and advanced algorithms to achieve greater precision.

Hypothesis 2: The historical plausibility of AI-generated reconstructions is on par with or superior to that achieved through manual restoration techniques.

- Expected Outcome: AI-generated reconstructions will be evaluated as equally or more historically plausible by experts in the field, based on criteria such as stylistic consistency, material accuracy, and historical context.

- Rationale: AI models trained on extensive historical data can generate reconstructions that adhere closely to historical styles and contexts, potentially reducing human bias and error.

Hypothesis 3: Stakeholders are more likely to accept AI-generated reconstructions if they are presented with evidence of the accuracy and plausibility of these methods.

- Expected Outcome: Increased acceptance and trust in AI-generated reconstructions among historians, conservators, and the public, particularly when detailed comparisons and validation studies are presented.

- Rationale: Transparency and evidence-based demonstrations of AI capabilities can alleviate concerns and highlight the benefits of these technologies, leading to greater acceptance.

Method

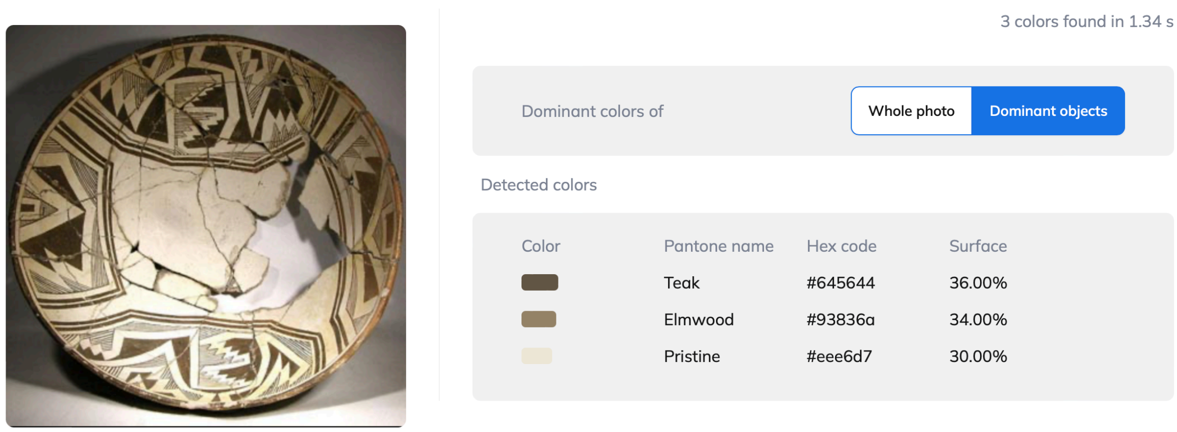
In general, there are two specific approaches to finding a texture-generating visual. The first method is to generate a new texture by resampling either pixels [3] or whole patches [4] of the original texture. To determine the most effective approach for achieving the project's goal, I explored several pattern recognition and texture synthesis applications currently available on the market. This involved testing their capabilities, analyzing their performance, and comparing their results concerning historical artefact restoration needs. By evaluating these findings, I plan to use the insights gained to guide the development of a specialized pattern recognition GAN. This GAN will be specifically designed to handle the complex textures and intricate patterns found in historical artefacts, ensuring the restoration process is as accurate and authentic as possible.

4.1 Current In-Market Applications

4.1.1 Ximilar AI

Looking closely at Ximilar AI [8], this platform has different tools supporting computer vision.

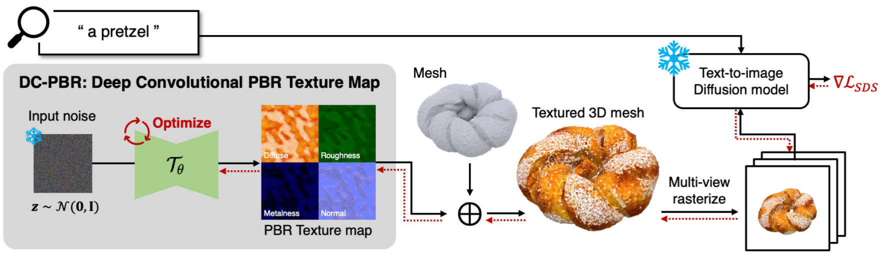
Figure 1: Ximilar AI colour detection tool



I used the colour detector to test how successful the algorithm is in detecting colour patterns, which I found satisfying. The colour detection feature will be needed while developing my tool to double-check the output when compared to the input colours.

4.1.2 Paint-in

Figure 2: Paint-in overall pipeline

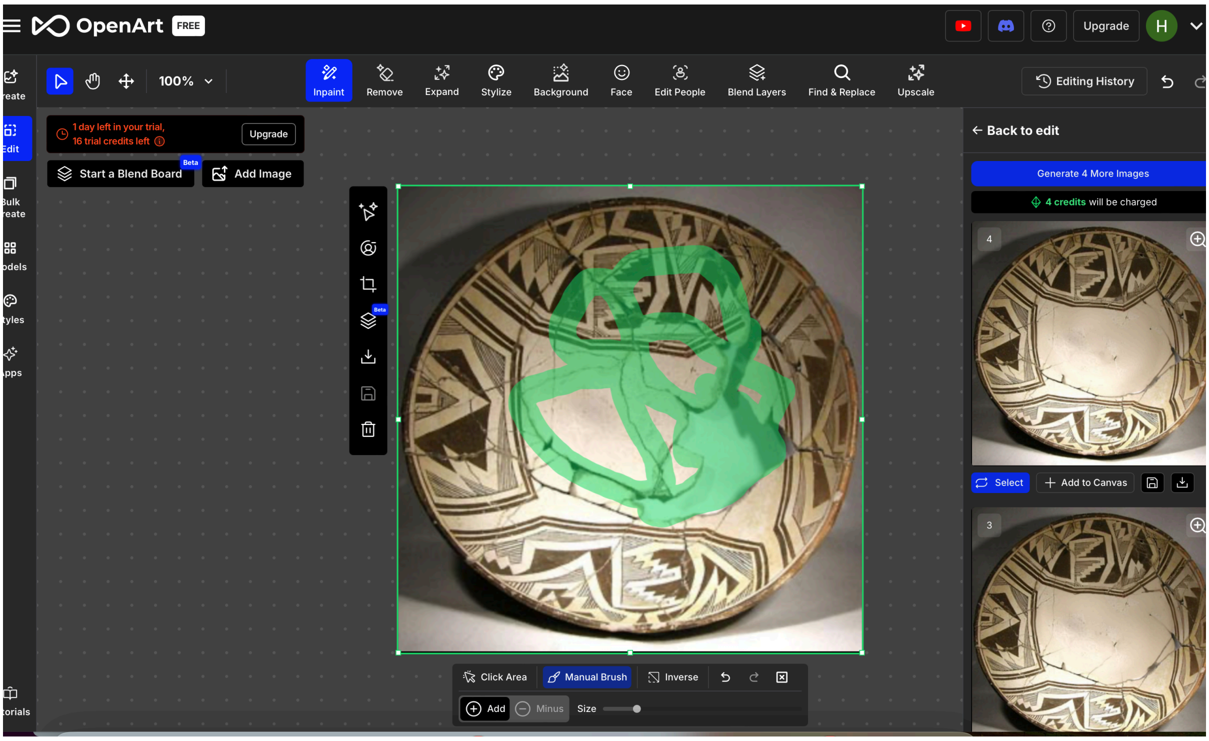


Additionally, reviewing exploratory code papers has provided me with a deeper understanding of the technical aspects, offering a broader perspective compared to simply using AI service platforms. According to research which also belongs to the figure above [7], a high-fidelity texture map synthesis tool called Paint-it has been developed for 3D meshes using neural re-parameterized texture optimization. While this tool appears highly successful, my experience with it was limited because the tool relies on its image dataset, preventing me from uploading my visuals for testing.

However, I did get the chance to experiment with its features, and I found the colour adaptation particularly satisfying, with realistic shadows and textures. Despite its strengths, the tool is primarily designed for use in the gaming industry, generating visuals from 3D meshes. This feature, though useful for gaming, is not aligned with my needs, as I am developing a tool for artefact restoration that requires a different approach.

4.1.3 OpenArt AI

Figure 3: Brush tool used to highlight requested ares to generate

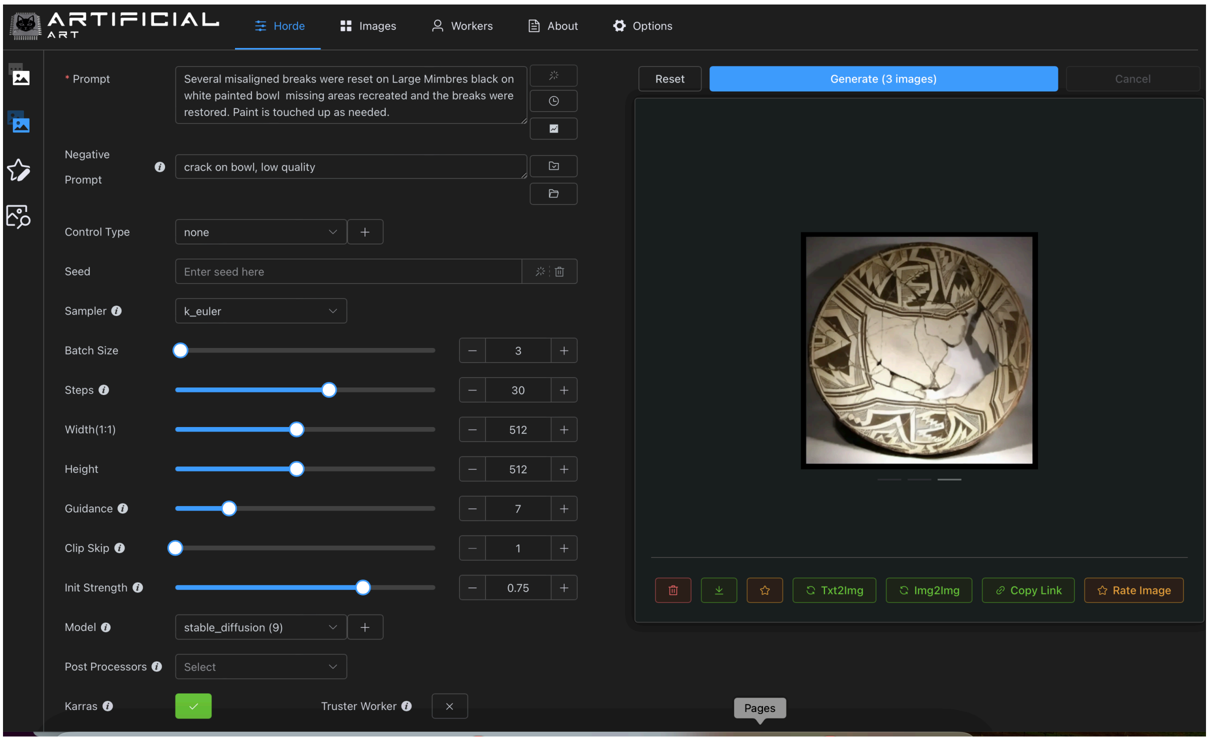


While exploring user interfaces that incorporate AI-based texture synthesis features, I came across OpenArt AI [10], which delivered highly impressive results. One of the standout aspects of OpenArt AI is that it's free to use, and its interface is both user-friendly and packed with a range of useful features. Among the features I frequently utilised were the positive and negative prompts, a brush tool that allowed me to focus on specific areas of the image, and a feature extraction bar that analysed the current image to enhance the output.

The resolution of the generated images was unexpectedly high, the textures produced were highly realistic and detailed also the adaptation of the generated image to the prompt was very high. I liked the brush tool which gave clarity to the input prompt by highlighting the specific area. Based on this experience, I would aim to design a similar interface in the future, specifically tailored to the restoration and adaptation of historical artefacts.

4.1.4 Artificial Art

Figure 4: Hyperparameters of Artificial Art



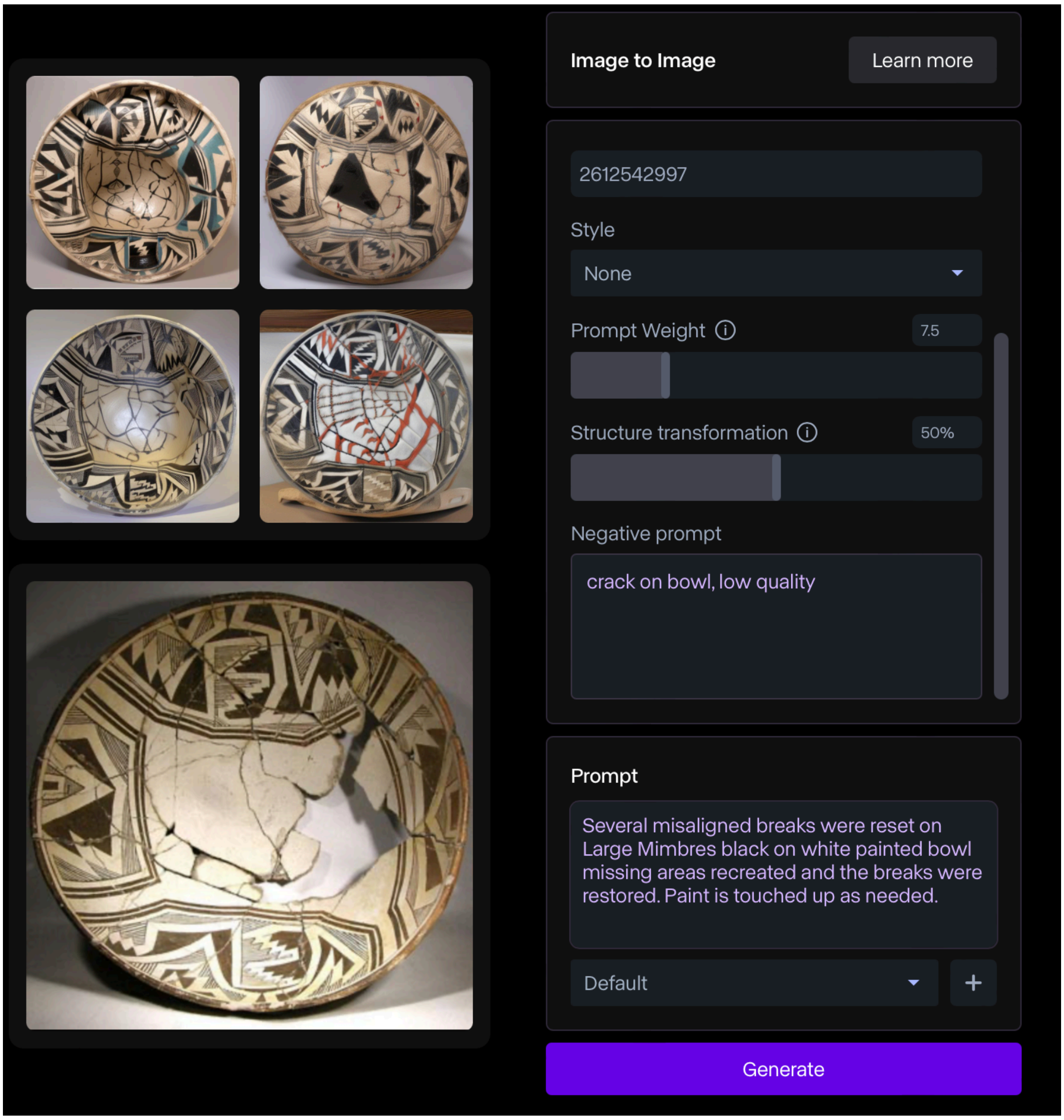
The Artificial Art [9] tool is an interface for generating images using the Stable Diffusion AI model. It offers users a wide range of customisable parameters and settings to control the image generation process. These include options like prompt inputs, negative prompts, sampling methods, and various numerical adjustments such as batch size, steps, and guidance strength.

Despite the tool's extensive customisation options, the generated result fell short of expectations. The output image did not closely resemble or even accurately represent the intended concept described in the prompt. I found it unsatisfactory due to no change made even though I changed several features while generating. However, it does produce results in txt2img generations.

This disappointing outcome suggests that this project path may not be appropriate to use Stable Diffusion model since the expected outcome must be belonging to a base image. The inability to produce high-quality, accurate results, even with detailed inputs and existing image guidance, indicates that this particular implementation or interface might not be well-suited for leveraging Stable Diffusion's potential in image generation tasks.

4.1.5 RunwayML

Figure: 5 images generated through RunwayML



This interface offers slightly fewer feature selection options than other tools, but it's well-suited for users who have an average AI background. The output was quite satisfactory by the matching input form, especially when compared to the Artificial Art UI. The input image closely matched the output, though the only drawback was that the colours and the pattern that was supposed to be replaced instead of the crack didn't align perfectly. However, the pattern on the third image was very close to the original.

4.2 Phases of Method

4.2.1 Data Collection

The first phase in developing a pattern recognition system for texture synthesis and completion models in architectural restoration is data collection, identified as images in this study. This process requires gathering a substantial and diverse dataset of architectural elements, including damaged and incomplete textures from various periods, materials, and architectural styles. The dataset should ideally consist of high-resolution images of both intact and damaged architectural surfaces to ensure the model can learn the textures' intricate details and structural patterns. However, to make more solid comparisons across AI tools and manual restoration, the default image uploaded to current tools will be the input image from Artifax Restoration Services, given on the side [5]:

Figure 6: Mimbres bowl before restoration

For this research, a collection of digital images from historical buildings, ruins, and artefacts will be sourced from repositories, museums, and restoration projects. The dataset must be extensive enough to capture the variability in architectural textures—whether stone, wood, marble, or fresco. Additionally, any data collected must be of high quality to ensure the model has reliable information to detect patterns. This step ensures that the system can generalise well across different restoration scenarios, avoiding patterns too specific to one subset of the data.

Figure 7 : Mimbres bowl after manual restoration

4.2.2 Feature Selection

In the feature selection stage, the key attributes of architectural textures that are crucial for accurate restoration are identified after the application evaluation. For a specific development of an AI-based architectural restoration tool, these will include:

- Colour distribution: Different materials and surfaces have unique colour palettes that must be reconstructed accordingly.
- Edge and structural details: Architectural textures often involve fine details, such as carvings or engravings, which are important for historical accuracy.
- Texture granularity and pattern repetition: The surface texture, whether smooth, rough, or patterned, must be reconstructed to match the original artefact.
- High resolution: The outcome quality must fit with the input image quality.

Highlighting the important points of artefact restoration, these features will be the main categories in selecting the appropriate GAN so the selection must provide significant value to the restoration process. The goal is to restore architectural elements such as cracks, erosion patterns, and weathering marks to ensure the AI system can generate plausible reconstructions of the missing portions.

4.2.3 Model Selection

The model selection phase involves choosing the most suitable model for the problem at hand. Several approaches are evaluated, including:

- Statistical Models: These might be used to understand the distribution of textures and predict missing segments based on known portions. They offer simplicity but may not handle complex textures effectively.

- Neural Models (GANs): As seen in the Markovian Generative Adversarial Networks (MGANs), neural models can handle complex, large-scale texture synthesis tasks and generate high-quality outputs in real-time. SGANs can be employed here due to their ability to learn and replicate intricate patterns, making them suitable for architectural restoration, which requires detailed and realistic texture generation.

- Hybrid Models: In some cases, combining neural models with traditional statistical approaches or patch-based synthesis (as seen in the Weighted Similarity-Confidence Laplacian Synthesis model) can yield superior results for specific tasks like edge reconstruction or colour matching.

- Stable Diffusion: Stable Diffusion is a deep learning model primarily used for generating detailed images from text descriptions. It works by gradually transforming random noise into a coherent image, making it useful for generating high-quality textures and patterns. However, for this project, Stable Diffusion did not meet the expectations as it focuses more on text-to-image generation, which is not fully aligned with the specific need for detailed texture restoration and synthesis from existing image data.

I have chosen to adapt Spatial Generative Adversarial Networks (SGAN) from the paper "SGAN: Spatial GenerativeAdversarial Networks" [12] to this specific project because of its ability to generate and complete high-resolution spatial images. In architectural restoration, where capturing spatial dependencies between textures and structures is critical, SGAN excels by preserving local and global texture coherence. SGAN's architecture is ideal for image completion tasks, as it ensures that the generated textures fit seamlessly into the surrounding architectural patterns, delivering realistic restorations for large-scale surfaces. The chosen model for this project will be based on a GANs model due to its ability to generate intricate and realistic textures, particularly in tasks that require high-quality outputs like architectural restoration. While I prefer to incorporate features such as real-time processing and more computationally intensive methods for high-resolution texture completion, these will be left for future phases depending on the complexity of the current algorithm and resource constraints.

4.2.4 Learning

Spatial Generative Adversarial Networks (SGAN) is a variation of GANs designed to handle tasks involving spatial data, such as image completion, inpainting, and texture synthesis. Unlike traditional GANs, SGANs incorporate spatial constraints into the generative process, ensuring the generated outputs maintain local and global coherence. This makes them particularly effective for large-scale image restoration tasks, where the continuity of patterns and textures across space is crucial.

In architectural restoration, SGANs excel by modelling the spatial relationships between architectural textures and structures, making them ideal for reconstructing missing or damaged surfaces. The spatial constraints embedded within SGANs enable them to generate highly plausible and coherent textures that seamlessly integrate with surrounding undamaged areas, making them perfect for applications where visual consistency and historical accuracy are paramount.

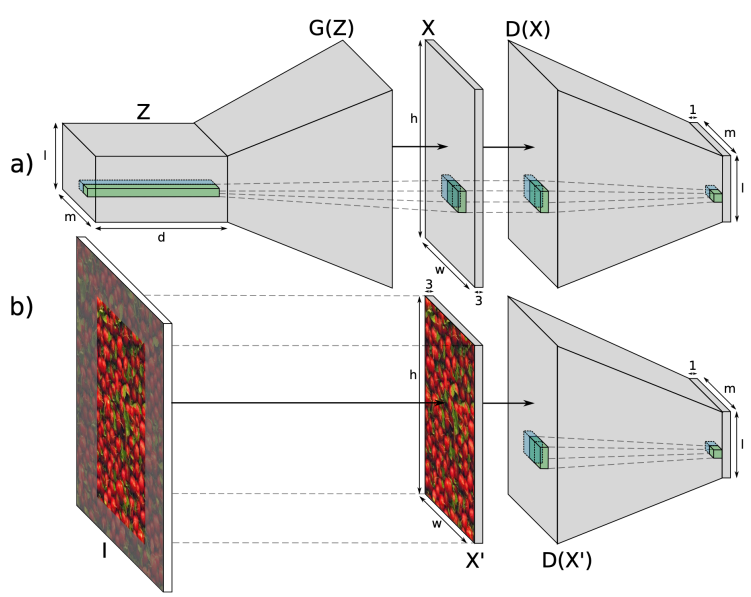
SGANs utilize both adversarial loss (to ensure realism) and spatial constraints (to maintain structure), thus offering superior performance in completing architectural textures compared to models that focus only on pixel-based synthesis. This approach helps in producing restorations that are both visually coherent and structurally plausible, critical for large-scale surface restoration in architectural projects. To sum up, SGAN is designed for generating large, coherent, high-resolution textures, making it a powerful tool for this architectural restoration tool, where spatial consistency and texture fidelity are crucial.

Adopting the SGAN model to the project, there will be four steps: Image Preprocessing, GAN Architecture, Texture Sampling and Training Loop, Data Loading, respectively. In the first step, where image preprocessing is handled, the loaded artefact image is prepared for texture synthesis. Next, the GAN architecture is regenerated to learn and apply the texture synthesis through generators and discriminators. The third step is to establish a logic to sample textures, train the GAN and synthesise textures. The main goal of this learning is to learn textures and apply them to the artefact images. The last step is where data is loaded to produce an outcome by loading patches from the artefact texture to feed into GAN for training.

4.3 The SGAN Model

The Spatial Generative Adversarial Network (SGAN) builds upon the foundational concept of GANs by learning a generator (G) and discriminator (D). The generator takes a random tensor $(Z \in R^{l \times m \times d})$, sampled from a simple prior distribution, and maps it to an image $(X \in R^{h \times w \times 3})$ in the image data space. The discriminator outputs a probability map indicating whether the generated image patches are real or synthetic.

Figure 8: Demonstration of the model from research paper



In traditional GANs, *(Z)* is a single vector, whereas in SGAN, *(Z)* is spatially structured, meaning it contains more dimensions corresponding to the spatial information of the image. Each small "slice" of *(Z)*, denoted *z*λU, is independently sampled, maintaining spatial coherence across the image. The generator is fully convolutional, allowing it to manipulate and adapt spatial dimensions without modifying its weights. This means a network trained on smaller images can generate larger ones without losing texture fidelity.

Relating SGAN to the project, both the generator and discriminator networks are convolutional, making it a design to perform texture synthesis on historical artefact images. The generator *(G)* creates the texture and structure of an artefact image by learning from the spatial arrangement of features in *(Z)*. The discriminator *(D)* assesses whether small patches of the image are real textures or generated. The adversarial process allows *(G)* to learn and improve, generating increasingly realistic images by optimising the spatial patches. Lastly, the loss calculation is used to calculate the loss for both the generator and the discriminator, proving the algorithm's accuracy.

Key Aspects:

- Spatial Consistency: The model captures local and global spatial dependencies, crucial for texture synthesis in architectural restoration. This is particularly important when reconstructing large surfaces where textures must be spatially coherent.

- Translation Invariance: The generated textures are translation-invariant, meaning the generator produces consistent textures across different image areas. This ensures the generated textures can seamlessly blend into the real architectural surfaces.

- Ergodic and Strong Mixing Properties: The network's design ensures that different patches of the generated image are independent, meaning they can be treated as separate sections while maintaining coherence. This property helps in generating continuous textures over large areas without repeating patterns, which is ideal for restoring architectural surfaces.

- Scalability: Since SGAN uses convolutional layers and avoids fully connected layers, it can scale up from small patches to larger image sizes, making it highly adaptable for various restoration tasks, such as texture reconstruction over large architectural facades or complex patterns in ancient ruins.

Optimization Parameters:

Learning Rate	0.0002	The learning rate for Adam optimiser
B1	0.5	Beta1 value for Adam optimiser
l2_fac	1E-08	L2 weight regularisation factor to prevent overfitting
epoch_count	100	number of epochs to train the model
K	1	number of discriminator updates for each generator update
batch_size	25	number of images preprocessed per batch
epoch_iters	batch_size x 100	Number of steps inside one epoch

4.4 Limitations

Throughout the methodology phase, I carefully evaluated a range of AI-based texture synthesis and pattern recognition tools to understand their features and capabilities. However, I encountered several significant limitations.

Firstly, many of the tools I wanted to explore were not available for free trials. This restricted my ability to test and compare their functionalities directly, particularly for those tools that were highly recommended for their effectiveness. Without access to these trials, it was challenging to determine which tools would be most suitable for my specific needs.

Secondly, I noticed a lack of tools specifically tailored for historical artefact restoration. Most of the available software focused on architectural applications, which prioritize different types of textures and restoration methods. This mismatch means that while these tools may excel in their respective areas, they do not adequately address the unique requirements of restoring historical artefacts, such as preserving authenticity and intricate details. This gap in the market underscores the necessity for developing specialized tools that cater specifically to the challenges of historical restoration.

Results

5.1 The Architecture of Code

To implement texture synthesis on historical artefacts, I forked code from a published SGAN model from 7 years ago and adopted it to project expectations[11]. Then, I regenerated the code, fixed some issues, and updated it, creating a solution tailored for this project. Combining aspects of GAN-based texture synthesis and image manipulation allows the algorithm to synthesise textures and apply them to historical artefact images. The code can be found in GitHub link [11].

Here's the plan:

1. Image Preprocessing: Convert images to the appropriate tensor format for processing.
2. Texture Sampling & Generation: Use a GAN-based architecture to generate or manipulate texture images. I will regenerate the GAN architecture code and the necessary functions to implement this.
3. Texture Synthesis: Apply the synthesized texture to a given image of an artefact.
4. Output: Save and visualize the results to see the quality of the texture synthesis.

Code Outline:

1. Image Preprocessing: Convert images to tensors and preprocess them for the model.
2. GAN Architecture: A simple SGAN (Spatial GAN) will be used to learn textures and apply texture synthesis to the image.
3. Texture Application: Overlay or blend the synthesized textures with artefact images.

Some results obtained are as follows:

Figure 9: Input - Output - Original image comparison

I found the results of the first phase to be satisfactory, though the overall accuracy was average. While the colours in the output were close to those of the input, they didn't match as precisely as I had hoped. I believe this discrepancy is due to the learning rate and the number of training epochs being set too low. By adjusting and fine-tuning these parameters in the next phases, I expect to achieve better colour alignment and improve both the accuracy and plausibility of the final results. This fine-tuning should enhance the model's ability to produce outputs that more closely match the original input.

The initial comparison of AI tools provided a valuable foundation for the study. The results were promising, suggesting that with better fine-tuning, the outputs could become more consistent. I found the crack completion in the second output particularly satisfying because the tool effectively selected and distributed the darkest colour across the entire patch, creating a realistic result. However, in the last output, the pattern generated was significantly different from the original input. This indicates that the fine-tuning parameters used were not well-suited for pattern completion, and adjustments will be needed to improve alignment with the desired output.

Discussion

The results from the first phase of this study indicate that the model's performance, while satisfactory, leaves room for improvement. The overall accuracy was moderate, with colour alignment between the input and output being close but not as precise as expected. This mismatch is likely due to hyperparameter settings for the learning rate and the number of training epochs. As these parameters were set too low, the model's ability to accurately capture and replicate the input details was hindered. In the next phases, I plan to fine-tune these parameters, which should lead to improved colour matching and overall accuracy, making the output more plausible and closely aligned with the input.

The initial comparison of different AI tools served as a crucial step in determining the model's potential. The results from this phase were encouraging, particularly in terms of consistency. In one case, the model completed a crack by selecting and distributing a dark colour across the entire patch, creating a realistic and visually coherent outcome. However, the final output produced a pattern that was entirely different from the proposed input. This indicates that the current fine-tuning parameters do not fully support pattern completion tasks, suggesting that further adjustments are necessary to enhance the model's capacity for pattern recognition and replication. Moving forward, refining these aspects will be key to achieving higher fidelity and more accurate outputs.

The reluctance of stakeholders to adopt this AI-based texture synthesis model for artefact restoration could stem from concerns about authenticity and the potential loss of cultural integrity. Historians and conservators may fear that AI-generated reconstructions might distort historical truths or obscure the role of human expertise. However, stakeholders may adopt it for its ability to improve efficiency and reduce costs while handling large restoration tasks with consistency and precision.

In practice, this proposed model can indeed be used for certain restoration tasks, particularly in repetitive or large-scale texture replication, such as wall surfaces or less intricate architectural details. For more complex, culturally sensitive tasks, AI should complement rather than replace human expertise. A proposal for moving forward could involve developing hybrid approaches that combine AI with human guidance, using AI to handle repetitive tasks while allowing experts to focus on intricate, high-importance restorations. This balanced approach could bridge the gap between AI capabilities and the needs of stakeholders, making the technology more widely accepted.

I have gained valuable experience in comparing various models and selecting the one that best fits the project's goals. This model selection process was the most challenging part since it formed the foundation of the entire project. I also learned to adjust hyperparameters, such as the learning rate and number of epochs, to find a balanced setting that works well for different cases, whether it involves crack completion or pattern restoration. However, in future phases, I plan to implement a recognition algorithm specifically designed to identify the structure of the artefact, such as pattern or texture completion. This algorithm would allow for more accurate results by using customized hyperparameters tailored to each specific restoration task. Additionally, applying advanced pre-processing techniques, such as edge detection to highlight key features or colour correction to ensure more accurate outputs, would improve the overall results.

Incorporating a feedback mechanism to evaluate the model's performance would be another critical development. By continuously analyzing the outputs and adjusting the parameters based on performance, the model would be able to learn from its errors and gradually generate more accurate and realistic outputs over time. This approach would lead to a more refined and precise restoration process.

To sum up, this research reveals that AI-based texture synthesis models have a significant impact on the accuracy of reconstructing historical artefacts, often surpassing traditional methods by offering more precise and detailed reconstructions. These models excel in replicating intricate textures, ensuring the structural coherence of the restored areas. However, the historical plausibility of AI-generated reconstructions remains a critical factor, with mixed results depending on the dataset and model used. While AI can replicate physical textures, ensuring cultural and historical accuracy still requires human expertise. The perception of AI among stakeholders varies: while AI is seen as a valuable tool for efficiency and precision, historians and conservators may express concerns about the potential loss of authenticity, whereas the public's acceptance tends to depend on the transparency of the process and the visibility of AI's role in restoration. As project phases continue to evolve, balancing its potential with ethical and cultural considerations will be key to achieving wider acceptance and success in artefact restoration.

Ethical Concerns

Ethical concerns surrounding the use of the adapted Spatial Generative Adversarial Networks (SGANs) in architectural restoration and image synthesis revolve around issues of authenticity, transparency, and cultural sensitivity. Authenticity becomes a challenge when AI-generated restorations risk altering the original cultural or historical value of an artefact or structure. There's also the potential for loss of human expertise in the restoration process, raising concerns about over-reliance on AI and devaluation of traditional craftsmanship. Transparency is crucial, as AI-generated restorations should be clearly distinguished from original elements to prevent misleading future historians, researchers, or the public. Furthermore, AI models may unintentionally introduce bias by replicating patterns that reflect modern or inaccurate interpretations of ancient designs, potentially distorting cultural heritage. Thus, balancing AI capabilities with human oversight and ethical guidelines is essential to preserve historical integrity.

Conclusions

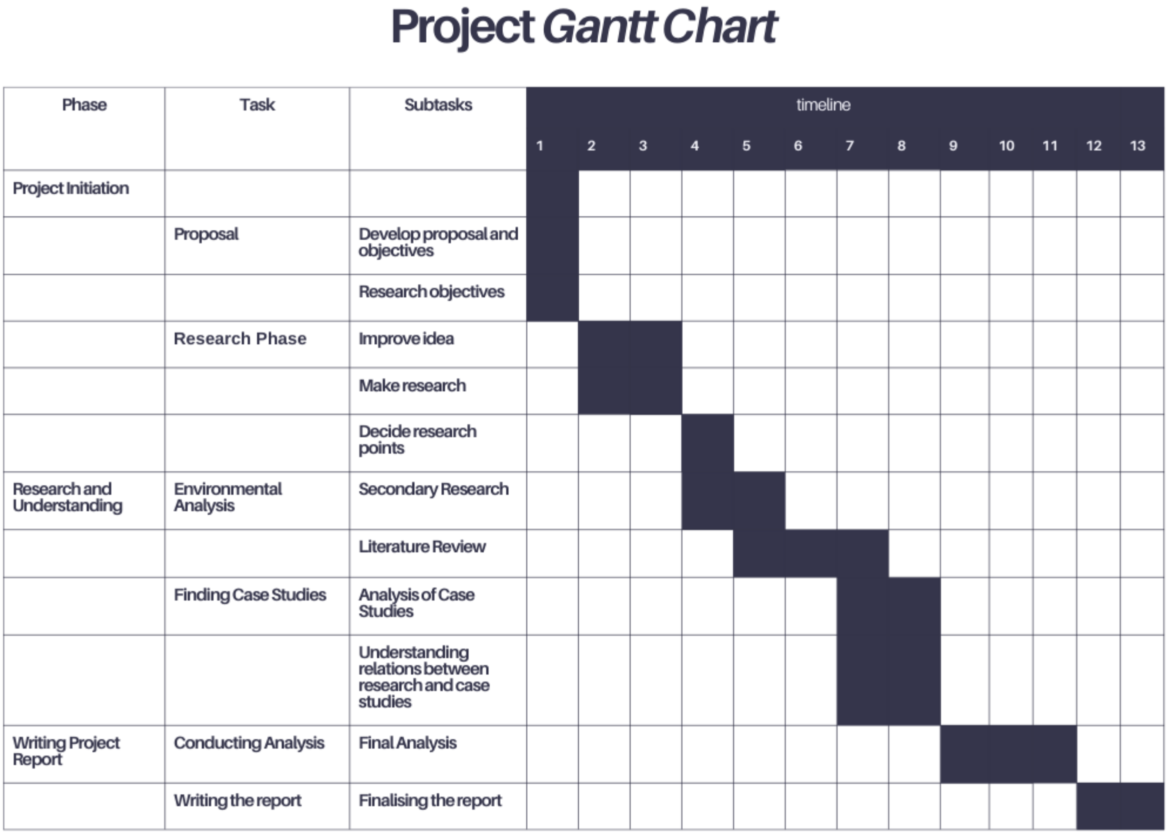
The results from the first phase of this study provided valuable insights but also highlighted areas for improvement that differed from the initial expectations. While the overall performance of the model was satisfactory, it became apparent that accuracy, particularly in terms of colour alignment between input and output, was not as precise as anticipated. This discrepancy likely stemmed from suboptimal settings in the hyperparameters, including the learning rate and the number of training epochs. These parameters were set too low, limiting the model's ability to effectively capture and replicate fine details from the input data. This mismatch between input and output textures indicates the need for more aggressive fine-tuning of these parameters to achieve the desired level of precision.

Additionally, while the texture synthesis and pattern completion were mostly consistent, the model faced challenges with more complex pattern replication tasks. For instance, when tasked with completing a crack or filling in a missing segment, the model successfully distributed colour in a way that looked visually coherent, yet it produced patterns that were sometimes entirely different from the expected input. This issue suggests that the current setup of pattern completion algorithms within the model does not fully support tasks that require intricate detail reproduction. As a result, further model refinement is necessary, specifically focusing on improving its ability to accurately recognize and replicate complex patterns found in architectural surfaces. Looking back, several changes could improve future phases of the project. Firstly, hyperparameter optimization should be a more central focus in the early stages of the training process. The learning rate and the number of epochs can significantly influence how well the model learns from the data, and by setting these parameters too low initially, the model underperformed in terms of accuracy. A higher learning rate, combined with more extensive training epochs, would likely result in better colour alignment and sharper texture synthesis. Furthermore, the initial comparison of various AI tools highlighted the strengths and weaknesses of each, providing a crucial foundation for selecting the right model for the project's goals. However, the model selection process posed unexpected challenges, particularly when balancing between different approaches like Generative Adversarial Networks (GANs) and Convolutional Neural Networks (CNNs). In hindsight, combining these two approaches might yield better results by utilizing the strengths of each architecture: the pattern recognition ability of CNNs and the generative capabilities of GANs. A hybrid model could offer better overall performance, especially in tasks requiring both texture synthesis and pattern completion.

If I were to repeat this phase of the project, I would also incorporate a more dynamic feedback mechanism. Currently, the model does not have an integrated system to learn from its outputs. Implementing a feedback loop would allow for continuous evaluation and refinement, where the model could adjust its performance based on real-time assessments of the generated outputs. By analyzing errors and adjusting parameters based on performance during the restoration process, the model could gradually improve its accuracy, producing more realistic and historically plausible outputs. In future iterations, advanced pre-processing techniques should be applied to the input data to ensure better results. For example, edge detection algorithms could be used to highlight key structural features in architectural textures before the model begins the completion process. This would allow the model to focus on the most important aspects of the texture, improving both accuracy and realism. Additionally, colour correction techniques could help ensure that the colour distribution between input and output matches more closely, addressing one of the key areas where the current model fell short.

In conclusion, while the results from the first phase of the study were encouraging, they did not fully meet the initial expectations in terms of colour alignment and pattern replication. Key improvements, such as hyperparameter fine-tuning, the introduction of a recognition algorithm tailored to architectural textures, and the use of pre-processing techniques, would significantly enhance the model's performance in future phases. By incorporating these adjustments, I expect that the model will achieve higher levels of accuracy and plausibility in the restoration of historical artefacts, ultimately leading to more realistic and culturally sensitive reconstructions.

Appendices


Project Gantt Chart
Phase
Task
Subtasks
timeline
1
2
3
4
5
6
7
8
9
10
11
12
13
Project Initiation
Proposal
Develop proposal and objectives
Research objectives
Research Phase
Improve idea
Make research
Decide research points
Research and Understanding
Environmental Analysis
Secondary Research
Literature Review
Finding Case Studies
Analysis of Case Studies
Understanding relations between research and case studies
Writing Project Report
Conducting Analysis
Final Analysis
Writing the report
Finalising the report

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