Can Artificial Intelligence Reconstruct Ancient Mosaics?

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ABSTRACT
A large number of ancient mosaics are no longer available to us because they have been destroyed by erosion, earthquakes, looting, or even used as materials in newer construction. To make things worse, among the small fraction of mosaics that have been recovered, many are damaged or incomplete. Therefore, it is of interest to explore how the mosaics may have appeared originally by using virtual reconstruction. This has traditionally been done manually and more recently using computer graphics programs but always by humans. In the last few years, artificial intelligence (AI) has made impressive progress in the generation of images from text descriptions and reference images. State-of-the-art AI tools such as DALL-E2 can generate high-quality images from text prompts and can take a reference image to guide the process. In August 2022, DALL-E2 launched a new feature called outpainting that takes as input an incomplete image and a text prompt and then generates a complete image filling in the missing parts. In this paper, we explore whether this innovative technology can be used to perform virtual reconstruction of mosaics with missing parts. Hence, a set of ancient mosaics have been selected and DALL-E2 has been used to create virtual reconstructions; the results are promising, showing that AI is able to interpret the key features of the mosaics and is able to produce virtual reconstructions that capture the essence of the scene. However, in some cases AI does not reproduce some details or geometric forms or introduces elements that are not consistent with the rest of the mosaic. This suggests that when AI image generation technology matures in the next few years, it could be a valuable tool to create virtual reconstructions of mosaics in the future.

INTRODUCTION

The cultural heritage that we have from ancient civilizations is only partial because many artworks have been lost or damaged due to erosion, earthquakes, looting, or even being used as materials in newer construction, for example. When referring to two-dimensional art pieces, sometimes only fragments of a painting or a mosaic have been recovered. Although mosaics are more resilient to the effects of time than other artworks such as paintings, due to their discontinuous nature and in many cases large size, mosaics are artistic objects prone to incompleteness. The missing parts can be virtually reconstructed based on the fragments available to hypothesize about how the original mosaics may have appeared. Thousands of examples have survived only in a fragmentary state, providing an excellent field for experimentation on image completion and virtual reconstruction.

The reconstruction of artistic works from antiquity was seen for centuries with total naturalness. Until the nineteenth century, there were many collectors who despised works in a fragmentary state to the point of, sometimes, preferring restorations that completed artifacts from insignificant fragments (Haskell and Penny 1981; Miraglia 1994). Famous are examples of the missing legs of the Ercole Farnese at the time of its discovery (Prisco 2007), or that of the lost arm of the Laocoon. Unthinkable as it was to leave the works unfinished, the criteria for completion were entrusted to renowned Renaissance artists, thus conditioning the reception of the models for posterity. At the end of the nineteenth century, in a purely scientific context, the sort of falsification represented by the indiscriminate completion of historical works was under discussion. It was the age of ‘de-restoration’ operations (Fendt, Hermens, and Fiske 2009), consisting of the elimination of the completed parts to restore them to the ‘original’ form at the time of their discovery. However, the visual impact of the reconstructions had become part of the cultural imaginary of each period in its specific form. This explains why each successive alteration, whether towards completion or simplification, is a recurring object of debate (Grossman, Podany, and True 2003). In this context, the possibilities offered by the application of artificial intelligence (AI) seem to introduce new elements to the field of artistic reconstruction hypotheses. AI data analysis lacks the traditional biases of the sectors linked to the study of art history. Exclusively virtual approaches and outputs

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have a less aggressive impact on the visualization than a materially finished object would offer. Therefore, the results may offer greater objectivity and less influence the collective cultural imagination.

Digital image processing techniques play a fundamental role in the preservation of cultural heritage (Stanco, Battiato, and Gallo 2011). In the case of mosaics, orthophotography has been extensively used to obtain digital representations of mosaics both in 2D (Andrews et al. 2005) and 3D (Fregonese et al. 2006). Ground penetrating radar (GPR) has also been used to obtain images parts of the mosaics that are not visible in situ (Calia et al. 2013; Caldeira et al. 2019). More recently, photogrammetry has been used to produce more detailed and accurate images and models of mosaics (Brutto et al. 2015; Caldeira et al. 2019; Fioretti et al. 2019). In all these techniques, many images are processed and combined using different image processing and computer vision software tools. The same trend applies to virtual reconstruction that has been traditionally performed manually and now can be done using advanced image processing tools (Riccio et al. 2015; Monti and Maino 2018; Fazio, Lo Brutto, and Dardanelli 2019). These tools greatly facilitate analyzing mosaics and proposing virtual reconstruction hypotheses, but the process is still human-guided.

More recently, the use of AI has been proposed for different tasks related to cultural heritage, for example, to manage cultural data and aid visitors to interpret museums (French and Villaespesa 2019), to classify elements in models of historical buildings using sophisticated decision tree algorithms (Bienvenido-Huertas et al. 2020), or to reconstruct ancient paintings (Wang, Li, and Zou 2019; Zhou et al. 2022). In the case of mosaics, genetic algorithms (Bartoli et al. 2017) and deep learning (Felicetti et al. 2021) have been used to segment mosaics; as AI progresses, it will find new applications in cultural heritage.

One area that has seen tremendous progress in the last few years is AI-based image generation from text. Many text-to-image AI generators are available, such as for example Imagen (Saharia et al. 2022) or Parti (Yu et al. 2022) from Google, Cogview (Ding et al. 2021), Midjourney1 or Stability AI.2 The most famous generator is DALL-E from OpenAI (Ramesh et al. 2021; 2022) that has been, for example, used recently to create the font cover of a well-known magazine.3 These tools take as input a prompt text and optionally a reference image to produce a new image that reflects the description in the text conditioned to the reference image. To do so, the generators have billions of parameters, and huge datasets are used for training. For example, the latest Google generator, Parti, has been trained on several billions of text/image pairs and can have up to 20 billion parameters (Yu et al. 2022). This complexity pays off as the tools provide high-quality images for many text inputs.

In August 2022, DALL-E introduced a new feature called ‘outpainting’ that takes as input an incomplete image and fills in the missing parts.4 This feature could be used for the virtual reconstruction of mosaics. In this paper, we explore for the first time the use of a state-of-the-art AI image generation tool (DALL-E) to perform the virtual reconstruction of ancient mosaics. The rest of the paper is organized as follows. We first describe the tool and procedures used for the virtual reconstructions. Then we study the reconstruction of damaged mosaics by evaluating DALL-E performance on figurative and geometric mosaics. We also take mosaics that are well preserved and artificially remove parts of the image to then perform reconstruction with DALL-E. This enables us to compare the reconstruction against the original image. The results and potential avenues for further research are also discussed and the paper ends with the conclusion about the functionality of DALL-E2 for the virtual reconstruction of incomplete ancient mosaics.

**Virtual reconstruction method**

This section describes the tool and procedures used for AI-based virtual reconstruction. First, the tool is briefly described and then the two procedures used for evaluation are presented.

**Tool**

In all virtual reconstructions, DALL-E, a well-known generative AI tool from OpenAI has been used (Ramesh et al. 2022). It was selected as it is a state-of-the-art tool that can be easily accessed by any user through a web interface5 and it is widely used.

In its default mode, DALL-E takes a text input (known as prompt) and produces several images that represent what is described in the text. A reference image can also be added to the input to guide the generation of the images from the text. This default mode cannot be used for virtual reconstruction; instead, another mode named ‘outpainting’ is used.

In the ‘outpainting’ mode DALL-E takes as input: a text prompt, an image with parts marked as missing, and a window of 1024 by 1024 pixels defining the part of the image on which the missing parts are to be completed by the tool. When the image fits entirely on a 1024 by 1024 pixels window, the virtual reconstruction can be done with a single ‘outpainting’. Instead, when the image is larger, several ‘outpainting’ windows may be needed. The tool only uses the parts of the image within the window to guide the reconstruction. For each run, and differently from the default mode, in ‘outpainting’ a single image is produced. To obtain several alternative completed images, the process must be repeated. Once
generated, the images can be downloaded and include a mark on the bottom right corner.

**Procedures**

Two different procedures were used, one to perform virtual reconstructions of incomplete mosaics and another to emulate damage on well-preserved mosaics and then perform the reconstruction. Both are described next. In all cases, the simple text prompt ‘Roman mosaic’ was used as the text input. The selection of a simple and common text prompt is intended to evaluate the capability of the AI tool to infer from the image with only generic text guidance.

**Virtual reconstruction of incomplete mosaics**

To obtain the virtual reconstructions of incomplete mosaics, the damaged or missing parts are marked to be completed by the tool. Then, depending on the aspect ratio and resolution of the original image, we either adjust its resolution to fit in an ‘outpainting’ window, or perform the reconstruction by running outpainting on several parts of the original image. For each mosaic, several runs were made with similar results and only one of them is presented.

**Experiments with complete mosaics**

For mosaics that are complete, the procedure is modified to first remove some parts of the image and mark them as to be completed by ‘outpainting’. The parts removed have been selected to illustrate the capabilities of the tool in different scenarios, some with a large part of the mosaic missing and some with smaller parts missing. Once the parts have been artificially removed, the procedure for reconstruction is the same as the first one. For each mosaic, several runs were made with different types of emulated damage, and a representative subset of the results is included in the paper.

**Initial evaluation of AI mosaic virtual reconstruction**

To evaluate the use of AI for virtual reconstruction of ancient mosaics, a set of eight mosaics crafted with the techniques of *opus tesselatum* and *opus vermiculatum* (Henig 1983), has been used. Most of them come from the J. Paul Getty collection and high-quality images of the mosaics are available through the Open Content Program of the Getty Foundation. The rest are taken from the British Museum and the Louvre Museum and are also publicly available. The set includes the most common issues on ancient mosaics such as figurative scenes with humans and animals as well as geometric mosaics with different levels of missing fragments. The results for each mosaic are presented and discussed in the following subsections.

**Mosaic floor with Achilles and Briseis**

The first mosaic represents a scene from Homer’s *Iliad*. In more detail, the mosaic shows Briseis being taken away from Achilles by Talthybios and Eurybates to be given to Agamemnon. The mosaic is thought to come from Antioch (present-day Antakya, Turkey) and to correspond to the 100–300 CE period. From a virtual reconstruction point of view, relevant parts of the image are missing.

The original image and the virtual reconstruction are shown in Figure 1; the AI tool can recreate the scene. However, the reconstructed faces are not well defined and look blurred; moreover, Briseis who appears to be looking left, is reconstructed looking to the front. The herald to her right is reconstructed also with a blurry face and his arm that seems to be holding Briseis is pointing to one of his elbows instead. These deviations in the virtual reconstruction...
can be partly attributed to the AI tool not having the context of the scene represented with such a level of detail. However, in the case of the faces and some of the details, the deviations seem to be genuine limitations of the tool.

**Amazon battle**

The second mosaic depicts the battle of an amazon warrior being seized by her cap by a warrior. It is part of the collection at the Louvre Museum; dated to the second half of the fourth century CE, it was found in the excavations in Antioch as the first mosaic. A large fragment of the right side is missing.

The original image and the virtual reconstruction image are shown in Figure 2. In this case, the AI tool is capable of reconstructing the scene and the result looks convincing. This may occur because the missing part in this mosaic is easier to complete than in the first one; however, even in this mosaic there are weird effects, like adding a fifth leg to the warrior’s horse.

**Alexander mosaic**

The third example is a scene from the Battle of Issus that took place in 333 BCE between Alexander the Great and Darius III of Persia. The mosaic was found in the House of the Faun in Pompeii and is now part of the collection of the National Archaeological Museum in Naples. A significant part of the scene around the figure of Alexander the Great is missing.

The original image and the virtual reconstruction are shown in Figure 3. The tool is capable of interpreting the overall scene, but it seems to miss many details. For example, Alexander the Great is riding a rearing horse but it is reconstructed as a standing horse whose back does not look much like a horse. The recreated warriors are standing while they were more likely to be riding horses as is Alexander. The two seals added also look like a bicycle that a warrior is riding, but this may be a coincidence. In this mosaic, some of these deviations can also be attributed to the lack of context but not identifying the rearing horse seems to be an intrinsic limitation of the AI tool.

**Lion attacking an onager**

The fourth mosaic is a scene of a lion attacking an onager that is part of the Getty collection. The mosaic was found in Tunisia and it is thought to correspond to the 150–200 CE period. Mosaics of animals fighting were popular in the Roman province of Africa that included Tunisia. In this case, only fragments on the borders of the scene are missing.

The original image and the virtual reconstruction are shown in Figure 4. For this mosaic the AI tool is also able to reconstruct the scene. However, there are some inconsistencies. The first is that instead of recreating the partly missing tree on the right side of the mosaic, a type of flying horse is added. On the bottom of the mosaic, the geometric pattern is only partly recreated, and the colors do not follow the sequence of the rest of the mosaic.

**Two male busts**

The fifth mosaic is a panel with two male busts from the fifth century CE and is also part of the Getty collection. In this case, only the central part of the mosaic is present, and the rest is missing.

The original image and the virtual reconstruction are shown in Figure 5. The AI tool is capable of reconstructing the scene; however, as a major part of the mosaic is missing, the virtual reconstruction is just a mere hypothesis of what the mosaic might have looked like as would be the case for a manual reconstruction.

**Head of a Season**

The sixth example is a Byzantine mosaic that shows the head of a Season and is also part of the Getty collection. In this case, only several scattered parts of the mosaic are missing.

The original image and the virtual reconstruction are shown in Figure 6. In this mosaic, it appears that the AI tool is capable of reconstructing the scene convincingly, since only small parts of the mosaic are missing, making the reconstruction easier.

**Floor with animals**

The two last mosaics are represented by mostly geometric forms rather than figurative scenes. The first one is also part of the Getty collection and is a floor with geometric forms and small figures of animals. In this case only a small part of the mosaic is missing. The original image and the virtual reconstruction are shown in Figure 7. The AI tool is capable of reconstructing the scene, interpreting the symmetry and recreating the missing part accordingly. However, it should be noted that it inserts a black triangle to reconstruct a small missing part at the top of the mosaic which does not seem plausible.

**Thurston floor**

The last mosaic is a pavement with geometric forms that is part of the collection of the British Museum and a large part of the mosaic is missing. When discovered, this mosaic floor had its central roundel showing a large figure of Bacchus (see Figure 3 on page 67 in Ling 2007). The heads in the corners probably
represent the seasons. The incomplete inscription has not been fully deciphered; it might refer to the owner of the villa (Henig and Soffe 1993): Quintus, Natalius, Natalinus and Bodeni.

The original image and the virtual reconstruction are shown in Figure 8. The AI tool is capable of reconstructing the main geometric forms, but this time the colors used are slightly different from the rest of the mosaic. Instead, the tool does not recreate the central figure of Bacchus, present in the original mosaic (Ling 2007); this can be in part attributed to the lack of context, but it is also true that it was common to have figurative scenes in the middle of the mosaics and the tool does not recreate any figure.

Emulation of mosaic reconstruction

Instead of a damaged mosaic, an interesting observation is that to evaluate the AI capabilities for virtual reconstruction, we can also start from a well-preserved mosaic and then remove parts of the image to test the ability of the AI to perform virtual reconstruction. This allows evaluating damages on any arbitrary parts of the mosaic as well as comparing with the original image to assess the quality of the virtual reconstruction. In particular, in addition to the visual comparison, we use the structural similarity index measure (SSIM) to quantitatively assess the quality of the reconstruction. The SSIM is one of the most popular metrics to estimate the similarity of images (Wang et al. 2004). Hence, a smaller set of four additional mosaics from the Getty collection have been used; as described in the following sections, we also present the results and analysis of the AI virtual reconstructions.

Combat between Dares and Entellus

The first mosaic is a scene of the fight between Dares and Entellus; this mosaic was part of a larger floor of
a villa in southern France and dated between 175–200 CE. This fight is part of a passage from Virgil’s *Aeneid* in which Aeneas honored the anniversary of his father’s death by holding elaborate funeral games, including a boxing match. This match pitted the Trojan Dares against the local Sicilian champion Entel-lus. The image has been altered by removing a large part of the warriors, and also part of a corner.

The original image, the editing with the modifications introduced artificially, and the AI reconstructed image are shown in Figure 9. The AI tool is capable of reconstructing the scene correctly but puts clothes on the warriors that were originally naked. This may be due to the protection mechanisms that image generation tools typically have to avoid explicit content such as nudity. Another mistake is that the warrior on the right is depicted front facing, instead of rear facing. In terms of SSIM, a value of 95.53% is obtained when comparing the original and the modified images. The SSIM value increases to 97.88% after the reconstruction with the tool recovering 52.56% of the initial loss.

**Birds**

The second mosaic depicts two birds. It comes from Rome and is dated in the third or fourth century CE. In this case the damage is localized on several small parts of the mosaic including the two birds themselves.

The original image, the editing with the damage introduced artificially, and the AI reconstructed image are shown in Figure 10. The AI tool is capable of reconstructing the scene correctly, but it fails to reconstruct the branches at the bottom of the mosaic. The AI tool considers the missing parts of the crossed branches, below the birds, as a discontinuity in a curve; it reconstructs the entire mosaic as in the
Gestalt principle of closure, in which incomplete elements, with interruptions or gaps, tend to be mentally reconstructed (Koffka 2013). This has been observed in some AI image classification systems that to some extent tend to follow the Gestalt principles (Amanatiadis, Kaburlasos, and Kosmatopoulos 2018).

In terms of SSIM, a value of 98.33% is obtained when comparing the original and the modified images. The SSIM value increases to 99.22% after the reconstruction with DALL-E recovering 53.29% of the initial loss, so similar to the first mosaic.

**Mosaic floor with head of Medusa**

The third mosaic is a floor with geometric shapes and the head of a Medusa in the center, from about 115–150 CE in Rome. Extensive damage has been made to the bottom-right part of the mosaic.

The original image, the editing with the damage introduced artificially, and the AI reconstructed image are shown in Figure 11. The AI tool is capable of extrapolating the complex geometric shapes from other parts of the mosaic and produces an almost perfect reconstruction. However, the kylix on the bottom right corner is slightly different from the other three while it should be exactly the same. Looking at the SSIM, a value of 91.45% is obtained when comparing the original and the modified images. The SSIM value increases to 95.56% after the reconstruction with DALL-E recovering 48.16% of the initial loss which is consistent with the previous results.

**Mosaic floor with Orpheus and the animals**

The last mosaic is a floor with Orpheus and the animals and the four seasons in the corners from around 150–200 CE that was found in France. Damage has been introduced at selective locations across the mosaic.

The original image, the editing with the damage introduced artificially, and the AI reconstructed image are shown in Figure 12. The AI tool is capable...
of reconstructing the scene correctly with good quality except for minor defects on the round decorative border and small geometric forms. Looking at the SSIM, a value of 97.22% is obtained when comparing the original and the modified images. The SSIM value increases to 98.93% after the reconstruction with DALL-E recovering 61.76% of the initial loss.

**Analysis and discussion**

The evaluation conducted on different mosaics in the previous sections (either originally damaged, or with simulated damage), shows that DALL-E is capable of approximately interpreting the main elements present on the scene and performing a virtual reconstruction. This applies to scenes that contain people and animals or to those with geometric forms and designs. However, the virtual reconstructions of the mosaics that are artificially damaged show several mistakes. In those cases, the tool is still far from the quality of a good manual reconstruction. However, the AI tool has been trained with a huge amount of data and its proposals for virtual reconstructions can complement those of human experts. This suggests that a potential use of these tools would be to assist humans to explore virtual reconstructions, rapidly trying many different solutions using the AI tool to then focus on a few that can be refined manually. The worst performance is obtained when recreating faces and in the presence of nudity (this is due to DALL-E policies on the contents of images). For geometric shapes, the performance seems to be better, but DALL-E has some limitations on color recreation and for some of the forms, especially when they are small. The tool also has limitations when having to reconstruct large missing parts for which the style and type of mosaic provide fundamental information. Even with these limitations, the performance of
DALL-E is overall noteworthy if we take into consideration that the evaluation has been done on the beta version of the outpainting feature using a very generic text prompt.

Further work is needed to better understand the capabilities of current AI tools to perform virtual reconstructions of mosaics. One direction is to explore whether additional guidance in the text prompt would improve the results by trying more specific text inputs for each mosaic. Another interesting experiment would be to explore the removal of parts from complete mosaics using predefined patterns for all of them and automating the test and computation of the similarity index to obtain a larger and more systematic set of results. This would have to be done using an application programming interface to access the AI tool to achieve automation. The use of a quantitative similarity metric and automated texting would enable the exploration of a larger number of damage patterns and mosaics. This can be used to explore, for example, the ability of the tool when reconstructing small holes (interpolation) in the mosaic versus completing or extending borders (extrapolation) for which less context information is available. Finally, this work has focused on DALL-E2; it would also be of interest to assess the performance of other tools that have recently added the outpainting feature.

Looking forward to the future, we should expect major improvements in AI tool performance for mosaic reconstruction. DALL-E has continually implemented improvements with a second release of the tool and the addition of features such as outpainting in less than two years. The same applies to other companies developing similar tools, like Google with Imagen that was shortly followed by Parti, or MidJourney that has released several versions of its tool. With the race to improve technology continuing and accelerating, we can only expect performance to improve. As this happens, AI image generators may become a valuable tool for the preservation of cultural heritage and will likely find new uses for virtual reconstruction of cultural heritage beyond mosaics.

The performance of the AI tools for image generation and virtual reconstruction will almost certainly improve as larger data sets and models are used and better algorithms are designed; new tools and updated versions of existing tools are being developed and introduced in the commercial market. These advancements will apply to nearly all types of images as this technology becomes ubiquitous in the coming years. However, specific improvements for mosaic reconstruction (and more generally for the reconstruction of art) can also be made; for example, a tailored AI tool can be trained only with mosaics and related images and texts for a tool that can
interpret and reconstruct the details of the mosaics and also make it consistently with the commonly used patterns in the type of mosaic being reconstructed. The ranges of colors could also be used for training. For example, there are mosaics with a generally more restricted palette which are made only with natural stones, while others, formed by mixtures of ceramics or tinted glasses, have much more variegated colors.

A more subtle potential benefit of these tailored AI tools is that existing general tools seem to add a patina of time to the reconstruction. This is probably linked to the tools being trained with old images that show mosaics that have endured the passing of time. This also reveals the need to handle variables such as time that are beyond geometry and iconography. Taking the argument further, a central paving mosaic does not have the same wear as a lateral one; also a mosaic that has suffered an ‘accident’ such as a fire or an earthquake does not have the same surface-distorting patina as a similar one ‘preserved’ by different layers of earth. These variables can lead to errors in recreations as encountered and commented on with the analyzed images (and this does not depend on the good work of the original authors). By developing tailored AI tools, we could train the system only with images that have not suffered degradation to improve the quality of the recreations or even not only reconstructing the missing parts but removing the effects of the time on the entire mosaic. Similarly, it would be interesting for future AI tools to provide an indication of their confidence in the reconstruction.

**Figure 8.** Thruxton floor: original (top), virtual reconstruction (bottom).

**Figure 9.** Combat Between Dares and Entellus: original (top), simulated damage (middle), virtual reconstruction (bottom).
(such as AI classifiers when performing classification). This would help to better interpret and use the AI generated images.

Another interesting topic for future research is to explore new applications of AI based virtual reconstruction for cultural heritage. A third dimension could also be considered in these new avenues of research because the possibilities in the fields of architecture and sculpture are wide-ranging. Some candidates could be not only damaged artifacts but also (intended or not) unfinished ones, such as the slaves by Michelangelo or his Pietà Rondanini or known incomplete architecture such as the Greek Temple of Segesta or the Malatesta Temple of Rimini.

**Conclusion and future work**

In this paper, we have for the first time proposed and evaluated the use of artificial intelligence (AI) for virtual reconstruction of damaged ancient mosaics. The results show that state-of-the-art AI tools such as DALL-E are capable of producing plausible reconstructions of damaged mosaics. The current tool still has many limitations that result in reconstructions still far from the level of a manual reconstruction. However, it is expected that performance of the AI tools will
improve dramatically in the next few years, opening new paths to explore virtual reconstructions of mosaics. Looking further into the future, AI tools could be used to address challenges in other areas of cultural heritage such as the virtual reconstruction of three-dimensional objects (like sculptures and buildings) and the exploration of the completion of unfinished work. As AI image generation technology keeps improving in the coming years, we expect it to be a key enabler for innovation in cultural heritage research.

Figure 12. Mosaic floor with Orpheus and the animals: original (top), simulated damage (middle), virtual reconstruction (bottom).

Notes

1. Available at www.midjourney.com.
2. Available at https://stability.ai/blog/stable-diffusion-announcement.
3. Available at www.cosmopolitan.com/lifestyle/a40314356/dall-e-2-artificial-intelligence-cover/.
4. https://openai.com/blog/dall-e-introducing-outpainting/.
5. Note that other tools like MidJourney were only accessible through Discord.
6. https://www.getty.edu/projects/open-content-program/.
7. Further details as well as the image with different resolutions are available at https://www.getty.edu/art/collection/object/103SPQ.
8. Further details as well as the image with different resolutions are available at https://es.wikipedia.org/wiki/Archivo:Amazonomachy_Antioch_Louvre_Ma3457.jpg.
9. Further details as well as the image with different resolutions are available at https://commons.wikimedia.org/wiki/File:Battle_of_Issus_mosaic_-_Museo_Archeologico_Nazionale_-_Naples_2013-05-16_16-25-06_BW.jpg.
10. Further details as well as the image with different resolutions are available at https://www.getty.edu/art/collection/object/103SYF.
11. Further details as well as the image with different resolutions are available at https://www.getty.edu/art/collection/object/105Y74.
12. Further details as well as the image with different resolutions are available at https://www.getty.edu/art/collection/object/105X9N.
13. Further details as well as the image with different resolutions are available at https://www.getty.edu/art/collection/object/103SQ4.
14. Further details as well as the image are available at https://www.britishmuseum.org/collection/image/105193001.
15. Further details as well as the image with different resolutions are available at https://www.getty.edu/art/collection/object/103SQM.
16. Further details as well as the image with different resolutions are available at https://www.getty.edu/art/collection/object/105X9J.
17. Further details as well as the image with different resolutions are available at https://www.getty.edu/art/collection/object/103SQK.
18. Further details as well as the image with different resolutions are available at https://www.getty.edu/art/collection/object/103QSM.

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References

Alterio, L., G. Russo, and F. Silvestri. 2017. “Seismic Vulnerability Reduction for Historical Buildings with Non-Invasive Subsoil Treatments: The Case Study of the Mosaics Palace at Herculaneum.” *International Journal of Architectural Heritage* 11 (3): 382–398. https://doi.org/10.1080/15583058.2016.1238969.

Amanatiadis, A., V. G. Kaburlasos, and E. B. Kosmatopoulos. 2018. “Understanding Deep Convolutio

onal Networks Through Gestalt Theory.” *2018 IEEE International Conference on Imaging Systems and Techniques (IST)*, 1–6. https://doi.org/10.1109/IST.2018.8577159.

Andrews, D., N. Beckett, M. Clowes, and S. Tovey. 2005. *“A Comparison of Rectified Photography and Orthophotography as Applied to Historic Floors—with Particular Reference to Croughton Roman Villa.”* *CIPA, XX*, Torino, Italy 1: 77–81.

Bartoli, A., G. Fenu, E. Medvet, F. A. Pellegrino, and N. Timeus. 2017. “Segmentation of Mosaic Images Based on Deformable Models Using Genetic Algorithms.” *In Smart Objects and Technologies for Social Good*, edited by O. Gaggi, P. Manzoni, C. Palazzi, A. Bujari, and J. M. Marquez-Barja, 233–242. Cham: Springer International Publishing.

Bienvenido-Huertas, D., J. E. Nieto-Julián, J. J. Moyano, J. M. Macías-Bernal, and J. Castro. 2020. “Implementing Artificial Intelligence in H-BIM Using the J48 Algorithm to Manage Historic Buildings” *International Journal of Architectural Heritage* 14 (8): 1148–1160. https://doi.org/10.1080/15583058.2019.1589602.

Brutto, M. L., A. Garraffa, L. Pellegrino, and B. di Natale. 2015. “3 D Mosaic Documentation Using Close Range Photogrammetry.” In *Proceedings of the 1st International Conference on Metrology for Archaeology*, Benevento, Italy, 22–23.

Caldeira, B., R. Oliveira, M. Teresa Teixidó, J. Borges, H. Renato, A. Carneiro, and J. Pena. 2019. “Studying the Construction of Floor Mosaics in the Roman Villa of Pišões (Portugal) Using Noninvasive Methods: High-Resolution 3D GPR and Photogrammetry.” *Remote Sensing* 11: 1882. https://doi.org/10.3390/rs11161882.

Calia, A., M. Lettieri, G. Leucci, L. Matera, R. Persico, and M. Sileo. 2013. *“The Mosaic of the Crypt of St Nicholas in Bari (Italy): Integrated GPR and Laboratory Diagnostic Study.”* *Journal of Archaeological Science* 40 (12): 4162–4169. https://www.sciencedirect.com/science/article/pii/S0305440313002082. https://doi.org/10.1016/j.jas.2013.06.005.

Ding, M., Z. Yang, W. Hong, W. Zheng, C. Zhou, D. Yin, J. Lin, et al. 2021. “CogView: Mastering Text-to-Image Generation via Transformers.” https://arxiv.org/abs/2105.13290.

Fazio, L., M. Lo Brutto, and G. Dardanelli. 2019. “Survey and Virtual Reconstruction of Ancient Roman Floors in an Archaeological Context.” *ISPRS – International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences* XLII-2/W11: 511–518. https://doi.org/10.5194/isprs-archives-XLII-2-W11-511-2019.

Felicetti, A., M. Paolanti, P. Zingaretti, R. Pierdicca, and E. S. Malinvernì. 2021. “Mo. Se.: Mosaic Image Segmentation Based on Deep Cascading Learning.” *Virtual Archaeology Review* 12 (24): 25–38. https://doi.org/10.4995/var.2021.14179.

Fendt, A., E. Hermens, and T. Fiske. 2009. *Restoration or de-Restoration? Two Different Concepts of Presenting the Authentic Condition of Ancient Sculptures in the Collection of Classical Antiquities in 19th-Century Berlin*. London: Archetype Publications.

Fioretti, G., P. Acquafredda, S. Calò, M. Cinelli, G. Germanò, A. Laera, and A. Moccia. 2019. “Study and Conservation of the St. Nicola’s Basilica Mosaics (Bari, Italy) by Photogrammetric Survey: Mapping of Polychrome Marbles, Decorative Patterns and Past Restorations.” *Studies in Conservation* 65: 1–13. https://doi.org/10.1080/00393630.2019.1614270.

Fregonese, L., C. Monti, G. Monti, and L. Taffurelli. 2006. “The St Mark’s Basilica Pavement: The Digital Orthophoto 3D Realisation to the Real Scale 1:1 for the Modelling and the Conservative Restoration.” *Innovations in 3D Geo Information Systems*, 683–693. https://doi.org/10.1007/978-3-540-36998-1_52.

French, A., and E. Villaespesa. 2019. “AI, Visitor Experience, and Museum Operations: A Closer Look at the Possible.” In *Humanizing the Digital: Proceedings from the MCN 2018 Conference*, 101–113. Museums Computer Network. https://www.researchgate.net/publication/333852865_AI_Visitor_Experience_and_Museum_Operations_A_Closer_Look_at_the_Possible.

Grossman, J. B., J. C. Podany, and M. True. 2003. *History of the Restoration of Ancient Stone Sculptures*. Los Angeles: Getty Publications.

Haskell, F., and N. Penny. 1981. *Taste and the Antique: The Lure of Classical Sculpture*, 1500–1900. New Haven: Yale University Press.

Henig, M. 1983. A *Handbook of Roman art: A Survey of the Visual Arts of the Roman World*. Oxford: Phaidon.

Henig, M., and G. Soffe. 1993. “The Thruxton Roman Villa and Its Mosaic Pavement.” *Journal of the British Archaeological Association* 146 (1): 1–28. https://doi.org/10.1179/jba.1993.146.1.1.

Koffka, K. 2013. *Principles of Gestalt psychology*. London: Routledge.

Ling, R. 2007. “Inscriptions on Romano-British Mosaics and Wall-Paintings.” *Britannia* 38: 63–91. https://doi.org/10.3815/000000007784016395.

Miraglia, L. 1994. “Piranesi’s Vasi, Candelabri Reinterpreted.” *Visual Resources* 10 (3): 221–233. https://doi.org/10.1080/01973762.1994.9658289.

Monti, M., and G. Maino. 2018. “Non-Metric Digital Reconstruction of Roman Mosaics Excavated in the City of Ravenna (Italy).” *Virtual Archaeology Review* 9 (19): 66–75. https://ojs.upv.es/index.php/var/article/view/7227. https://doi.org/10.4995/var.2018.7227.

Prisco, G. 2007. “La più bella cosa di cristianità’: i restauri alla collezione Farnese di scultura, in C. Gasparri (a cura di), Le Sculture Farnese. Storia e documenti, Napoli 2007, pp. 81–133.”

Ramesh, A., P. Dharval, A. Nichol, C. Chu, and M. Chen. 2022. “Hierarchical Text-Conditional Image Generation with CLIP Latents.” *https://arxiv.org/abs/2204.06125.*

Ramesh, A., M. Pavlov, G. Goh, S. Gray, C. Voss, A. Radford, M. Chen, and I. Sutskever. 2021. “Zero-Shot Text-to-Image Generation.” *https://arxiv.org/abs/2102.12092.*

Riccio, D., S. Caggiano, M. D. Marsico, R. Distasi, and M. Nappi. 2015. “MOSAIC+: Tools to Assist Virtual Restoration.” 08.
Saharia, C., W. Chan, S. Saxena, L. Li, J. Whang, E. Denton, S. K. S. Ghasemipour, et al. 2022. Photorealistic Text-to-Image Diffusion Models with Deep Language Understanding. "https://arxiv.org/abs/2205.11487.

Stanco, F., S. Battiato, and G. Gallo. 2011. “Digital Imaging for Cultural Heritage Preservation.” Analysis, Restoration, and Reconstruction of Ancient Artworks. Boca Raton: CRC Press. https://doi.org/10.1201/b11049

Wang, Z., A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli. 2004. “Image Quality Assessment: From Error Visibility to Structural Similarity.” IEEE Transactions on Image Processing 13 (4): 600–612. https://doi.org/10.1109/TIP.2003.819861

Wang, H., Q. Li, and Q. Zou. 2019. “Inpainting of Dunhuang Murals by Sparsely Modeling the Texture Similarity and Structure Continuity.” Journal on Computing and Cultural Heritage 12 (3): 1–21. https://dl.acm.org/doi/10.1145/3280790

Yu, J., Y. Xu, J. Y. Koh, T. Luong, G. Baid, Z. Wang, V. Vasudevan, et al. 2022. “Scaling Autoregressive Models for Content-Rich Text-to-Image Generation.” https://arxiv.org/abs/2206.10789.

Zhou, Z., X. Liu, J. Shang, J. Huang, Z. Li, and H. Jia. 2022. “Inpainting Digital Dunhuang Murals with Structure-Guided Deep Network.” Journal on Computing and Cultural Heritage. Just Accepted, https://doi.org/10.1145/3532867.