

## RESEARCH

# Deep image prior inpainting of ancient frescoes in the Mediterranean Alpine arc

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## Abstract

The unprecedented success of image reconstruction approaches based on deep neural networks has revolutionised both the processing and the analysis paradigms in several applied disciplines. In the field of digital humanities, the task of digital reconstruction of ancient frescoes is particularly challenging due to the scarce amount of available training data caused by ageing, wear, tear and retouching over time. To overcome these difficulties, we consider the Deep Image Prior (DIP) inpainting approach which computes appropriate reconstructions by relying on the progressive updating of an untrained convolutional neural network so as to match the reliable piece of information in the image at hand while promoting regularisation elsewhere. In comparison with state-of-the-art approaches (based on variational/PDEs and patch-based methods), DIP-based inpainting reduces artefacts and better adapts to contextual/non-local information, thus providing a valuable and effective tool for art historians. As a case study, we apply such approach to reconstruct missing image contents in a dataset of highly damaged digital images of medieval paintings located into several chapels in the Mediterranean Alpine Arc and provide a detailed description on how visible and invisible (e.g., infrared) information can be integrated for identifying and reconstructing damaged image regions.

**Keywords:** Digital inpainting; Medieval paintings; Deep Image Prior

## 1 Introduction

The synergy between art history, mathematical image analysis and artificial intelligence (AI) is a stimulating meeting point between disciplines to favour the development of new science and to complement historical studies in art and art history. These new tools and methods lead to emerging approach in the comprehension of medieval images as living objects, see, e.g., [1]. In this work we focus on the digital reconstruction of wall paintings of medieval chapels located in the south of the Alpine arc. The wall paintings in this area were produced mainly between the second half of the 15th century and the early 16th century [2]. As part of several restoration campaigns and/or more specific modifications linked to shift of perception and reception of the images depicted in the murals, such paintings have been subject to modifications in later times. Furthermore, the effect of environment and/or the intentional erasure and vandalism caused the disappearance of several imaging data crucial for the understanding of some images and painted texts.

In order to digitally restore the missing/lost image elements made indecipherable by such processes, digital reconstruction approaches and among them, image

inpainting [3], can be applied, see [4, 5, 6] for previous applications in digital humanities contexts. Given the lack of information, the restoration of the original version of the degraded image under consideration is impossible (inpainting is indeed an ill-posed problem lacking uniqueness) so the objectives of inpainting in this context are rather concerned to the reconstruction of a coherent visual experience to the observer, which may help the comprehension and interpretation of damaged images in historic studies.

By combining inpainting with multi-spectral techniques, interesting piece of information can be unveiled, such as the stratification of murals and the evolution of images over time. A careful analysis of the output images may shed light on whether the observed corruptions are involuntary or intentional, thus generally favouring a better understanding of the overall artistic process. In this work, AI and mathematical image processing are applied to historical studies epigraphs and wall paintings painted by minor artists in the south Alpine Arc, where murals present in medieval chapels may have been painted and painted over, modified, and altered. We are interested in particular in the wall paintings signed or attributed to the painters Giovanni Baleison, Giovanni Canavesio, and Tommaso and Matteo Biazaci. They all were active in the last quarter of the 15th century in current France and Italy. Their peculiarity is the frequent use of texts in their painted images. Digital reconstruction obtained by AI can be an incredibly helpful tool to determine both the dates and the authors of each image layer which, compared to major artworks, are still debated. From an historical viewpoint, our objective is to grasp the causes at roots of transformations that may be aesthetic, religious, or ideological. In this way, we think this interdisciplinary project between art history, mathematical image processing and AI, can allow us to chronicle the life of the paintings and better understand their impact and evolution in past societies.

*Contribution.* In this work we propose a Deep Image Prior (DIP) inpainting approach for the digital reconstruction of ancient frescoes in the Mediterranean Alpine Arc. Compared to standard hand-crafted inpainting methodologies requiring either a careful model/parameter tuning, such approach is based on the progressive update of parameters of an untrained convolutional network to generate plausible contents. Compared to supervised deep learning methods relying on often unavailable large datasets of examples, the proposed approach is fully unsupervised and performs reconstruction based only on the available, incomplete, image and on the segmentation of the region to be filled-in. The proposed pipeline is applied directly on the visible image to reconstruct missing contents (image information, text characters) and combined with infrared information for the study of the transformation/retouching process the artworks have been subject to.

*Structure of the paper.* In Section 2 the image dataset used for our study is described and enriched with information on the artistic/historical context. In Section 3 a comprehensive discussion on several inpainting methods is given, covering both model-based and data-driven approaches. In Section 4, the overall pipeline of our approach is described, spanning from the initial treatment and analysis performed on the given image to inpaint till the final inpainted result. Several numerical results are reported in Section 5 where comparisons between inpainting approaches

and combined techniques making use of both visible and invisible (infrared) data are combined, thus showing the potential of the proposed approach to the study of imaging data in digital humanities.

## 2 Dataset description and challenges

The image dataset used in this project has been collected in the online database PA'INT [2] (CEPAM, UCA, FR) which has been collected as part of the PhD thesis of O. Acquier [7]. The database is composed by a large collection of digital images of late medieval wall paintings representing visual scenes and epigraphic items in religious buildings of the south of the Alpine arc. In total, 269 painted monuments have been geolocated of which 75 have been the object of several image acquisition campaigns. As a result, 2600 pictures have been collected and indexed to various details such as the name of the painter(s) (when known), the date(s) of completion as well as a visual descriptions. A total number of 1172 inscriptions have been analysed in [7]. Note that currently PA'INT is in the process of being expanded with images in the infrared and ultraviolet spectral range, which will be analysed and integrated by means of AI tools in a later work. The images in the dataset have been acquired by a modified Nikon D610<sup>[1]</sup> [8], in which a filter that blocks UV and IR has been removed, with the Nikon AF-S NIKKOR 50mm f/1.8G lens. In order to limit the light reception to the desired spectral range, some light filters were used corresponding to a wavelength of 380-780 nm for the visible spectrum and 780-1100 nm for the infrared spectrum. Flashes BOWENS GEMINI 1500 pro as well as lighter and less bulky halogen lamps from CHSOS [9] were used. For the infrared emissions, halogen lamps are placed at approximately 45° of the studied painted surfaces, which were also captured in the visible range for comparisons/data-integration. The interest of IR acquisitions is that they can reveal underwritings and underdrawings if the overpainter layer is IR-transparent and the underpaintings are not. For some references on the use of scientific imaging in digital humanities, we refer to [10, 11].

As a case study, we analysed incomplete and retouched images of wall paintings acquired in three chapels: the chapel *Sainte-Claire*<sup>[2]</sup> in Venanson, France, the sanctuary *Nostra Signora delle Grazie* in Imperia, Italy, and the chapel *San Sebastiano* in Celle di Macra, Italy. The decoration of the Sainte-Claire chapel was painted by Giovanni Baleison in 1481.

Figure 1 shows the chapel of San Sebastiano and the representation of Hell painted therein by Giovanni Baleison in 1484. The fresco is divided into eight parts, among which seven are dedicated to a particular capital sin, while the last one is Lucifer's den. In this work we will focus in particular on the images of *Lusuria* and *Invidia*, see Figure 2. The scene represented in *Lusuria*, Figure 2a, is ruled by the demon Asmodeus. Its circle welcomes souls prone to lust and carnal pleasures in their earth life. In this scene, green and yellow demons are torturing sinners: a demon is whipping a woman while pulling her hair. Three sinners are seating on a grill fed by a demon, while a group of men and women are burning inside a building. *Invidia*, see

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<sup>[1]</sup>Our digital camera has been modified by EOS FOR ASRTO.

<sup>[2]</sup>Also called chapel of Saint Sebastian because of the representation of the saint.



### 3 Image inpainting via model-based and data-driven methods

The problem of image inpainting consists in filling in missing or damaged parts of an image (representing, e.g., a fresco) using a source of prior information.

In mathematical terms, given an image  $\tilde{x}$  defined on an image domain  $\Omega$  of size  $m \times n$  having an occluded region  $D \subset \Omega$ , the problem is defined in terms of a masking operator  $m \in \{0, 1\}^{m \times n}$  acting point-wise as follows :

$$m_{i,j} = \begin{cases} 1 & \text{if } \tilde{x}_{i,j} \in \Omega \setminus D \\ 0 & \text{if } \tilde{x}_{i,j} \in D . \end{cases} \quad (1)$$

By definition, the mask  $m$  is thus nothing but the characteristic function of the set  $\Omega \setminus D$  and identifies the reliable (i.e., unoccluded) pixels in the observed image.

Most of the classical approaches employed over the last three decades rely on the exploitation of the sole image content in the non-damaged areas of the image, see, e.g., [3, 12, 13, 14] for reference works and reviews. To do so, such methods seek, for an inpainted image  $x$ , to rely on the definition of an energy functional of the form

$$\min_x \lambda \|m \odot (x - \tilde{x})\|^2 + R(x) \quad (2)$$

where the data term forces the reconstructed image to stay close to the available piece of information in  $\tilde{x}$  weighted by  $\lambda > 0$  while  $R(x)$  is a regularisation term favouring, in some suitable way, the propagation of contents within  $D$ . The minimization problem (2) is solved by an iterative optimization method. Given the importance of the choice of such regularisation model, we will refer in the following to this class of approaches as *model-based* approaches.

More recent techniques rely on the shared idea of filling in the incomplete image regions by novel image content generated by neural networks trained on large image datasets [15]. Due to the prominent role played by the data for this class of approaches, we will refer to them as *data-driven* approaches in the following sections. It is important to remark, however, that in the context of digital restoration of ancient artworks these approaches can rarely be applied due to:

- The scarce availability of reference data to be used for training;
- The bias induced by non relevant data during inpainting.

A further approach well-suited to overcome with the aforementioned limitations is the *Deep Image Prior* (DIP) [16]. It can be seen as an hybrid solution between model-based and data-driven schemes, since it exploits a deep neural network to inpaint the image using the sole observation of the damaged image, without any training set. In this paper we will focus on this approach.

In the following paragraphs we review the main available literature on such techniques for digital inpainting, with a particular attention to their application to ancient damaged frescoes and other artworks.

#### 3.1 Inpainting with model-based approaches

Model-based inpainting approaches are particularly suited to reconstruct the image level lines within the damaged region through their propagation by means of

transport [12, 17], diffusion [18, 3, 19] and curvature-driven methods [20], which are typically modelled by a Partial Differential Equation or a variational model, which correspond to a regularisation term  $R$  encoding gradient (such as, e.g., Total Variation-type) or higher-order (e.g., Euler Elastica) information in (2). Being based on the discretisation of differential operators, these approaches are particularly suited to reconstruct small occluded regions such as scratches, text or similar, while they fail in reconstructing more complex (e.g., textural) components. Note that in the context of heritage science, model-based inpainting approaches have been employed for restoring ancient frescoes in several works such as [4, 3, 5].

To deal with more complex image contents, patch-based approaches have been considered in a variety of papers, see, e.g. [21, 22, 23]. There, the main idea thus consists in comparing those patches in terms of a suitable similarity metric which can further take into account rigid transformations and/or patch rescaling. The popularised PatchMatch approach [24] is based on this principle with the advantage of computing correspondence probabilities for each patch, thus weighting the contribution coming from different locations appropriately. Improved versions of PatchMatch have been proposed, e.g., in [25, 26] where such averaging is performed in a non-local manner. Compared to local approaches, patch-based inpainting methods show remarkable performance and, where properly tuned, good reconstruction of both geometric and textured contents. Nonetheless, due to their intrinsic non-convexity, they are often initialisation dependent and are sensitive to the choice of hyperparameters such as, e.g., the patch size. In the context of art restoration, in [6] a combination of a local (as initialisation) and non-local (as main inpainting process) procedure was used for the digital restoration of severely damaged illuminated manuscripts.

An interesting comparison between local/non-local model-based inpainting approaches for the processing of digital images of artworks has been conducted in [27]. Interestingly, the authors therein noted that while manual restoration still seems to lead to the best results, reconstructions obtained by model-based approaches appears often misleading for expert evaluation, while as good as a manual reconstruction for naïve eyes.

### 3.2 Inpainting with data-driven approaches

Data-driven approaches for image inpainting offer an alternative strategy to the conventional method of modelling local regularity through defined energy functionals. Instead, these methods leverage an extensive array of training data and employ neural techniques to estimate mappings from occluded input images to inpainted images. Due to their better deep encoding capabilities, neural approaches are indeed not limited to the modelling of the sole geometric/texture regularities in an image, but they further capture the presence of local/non-local patterns and the semantic meaning of image contents.

An exhaustive review of learning-based approaches for image inpainting is presented in [15]. Upon prior knowledge of the inpainting region, i.e. of the mask operator in (2), data-driven inpainting approaches based on convolutional networks have been designed in [28, 29] and improved in some recent works [30, 31], with the intent to adapt the convolutional operations only to the points providing relevant information.

The performance of data-driven inpainting dramatically improved after the introduction of the generative adversarial network (GAN) architectures in [32]. GANs aim to minimise the distance between ground truth images and reconstructed images not in a point-wise manner, but, rather, in a distributional sense, through the use of two competing networks, the former able to discriminate between ground truth data and samples generated by the latter. Whenever a large number of examples is available, GANs and, more in general, generative approaches, are very effective for inpainting, see, e.g. [29, 33, 34, 35, 36, 37]. Improved approaches perform inpainting by working, rather than at an image level, at the level of feature space, by first reconstructing the geometric content and finally adding finer textures, see for instance [38, 39].

In recent years, Denoising Diffusion Probabilistic Models (DDPM) [40] emerged with comparable and possibly overall greater inpainting performance. DDPMs are able to achieve optimal results in generative tasks without the impairment typical of GAN models, such as adversarial learning instabilities and high computational cost [41]. A recent effort in inpainting with diffusion models reported impressive results [42] by conditioning the reverse diffusion process with mask information. Other recent examples of neural data-driven inpainting techniques include [43, 44, 45, 46].

The main limitation of data-driven approaches for inpainting is that in order to generate suitable image content these techniques require the availability of large datasets of relevant and high-quality data for training. As a consequence, they can rarely be applied to the problem of digital restoration of images of fragmentary frescoes, for which, very often, very little training data from the same author is available.

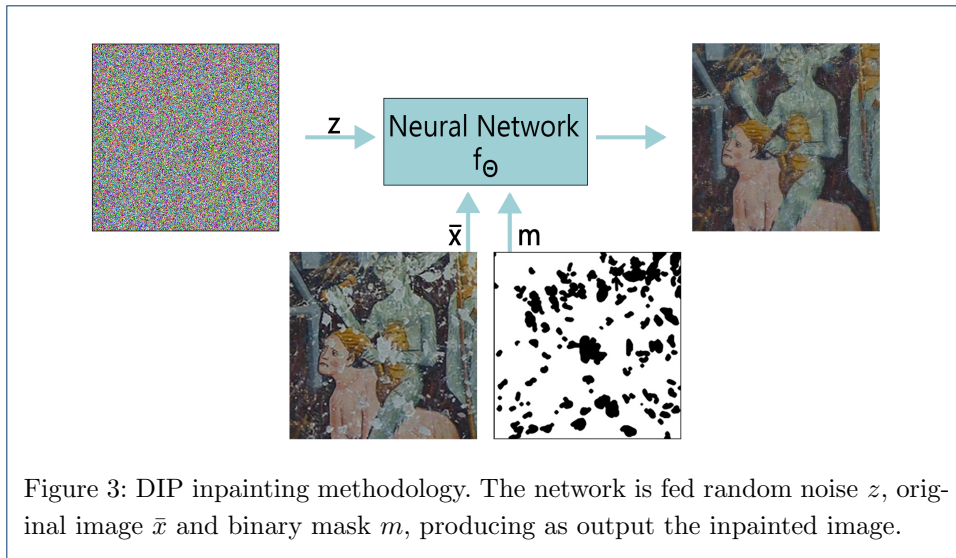
### 3.3 Inpainting with the Deep Image Prior approach

To overcome the poor quality results and the sensitivity to parameters of model-based inpainting methods as well as the requirement of large datasets of data-driven approaches, we consider in this work a hybrid scheme, popularised in [16] under the name of Deep Image Prior. This technique pioneers the use of *low-level image statistics* extracted from the network structure itself, enabling its use in inpainting applications. The key concept behind DIP is that, by using an expressive architecture, it is possible to obtain an accurate inpainted image without the need of a training set.

In Figure 3 we graphically represent how DIP works for the inpainting problem at hand. In particular, we show that the neural network takes as input an image  $z$  randomly sampled from a uniform distribution with a variable number of channels and it also considers the damaged image  $\bar{x}$  and its corresponding mask  $m$  and gives as output the inpainted image. More details on the network architecture will be given in section 4. Denoting by  $f_{\Theta}(\cdot)$  the image reconstructed by the neural network, depending on the vector of neural networks parameters  $\Theta$  the DIP solves the following minimization problem:

$$\hat{\Theta} \in \operatorname{argmin}_{\Theta} \mathcal{L}_{\theta}(z) := \|m \odot (f_{\Theta}(z) - \bar{x})\|^2, \quad (3)$$

For the inpainting problem considered here, the task is to enforce the optimal network parameters  $\hat{\Theta}$  to generate an output image  $x = f_{\hat{\Theta}}(z)$  which matches  $\bar{x}$  outside



$D$  and fills contents in  $\Omega \setminus D$ . Numerically, this problem can be solved by standard iterative optimisation algorithms such as gradient descent with back-propagation. Being (3) a non-convex optimisation problem, different initializations for  $\Theta$  may lead to different results. Note that, unlike in traditional methods, DIP enforces regularisation in an implicit manner, i.e. in terms of the network structure, but early stopping of iterations is necessary to avoid noisy inpainting.

We remark that the minimization in (3) determines the network weights as it is common in training procedures. but it must be solved for each image independently

We remark that DIP computes the neural network weights by solving the minimization problem (3) for each processed image. Hence its computational cost is more similar to the one of model-based methods than to data-driven approaches, where the parameters are computed only once with a much more expensive training phase.

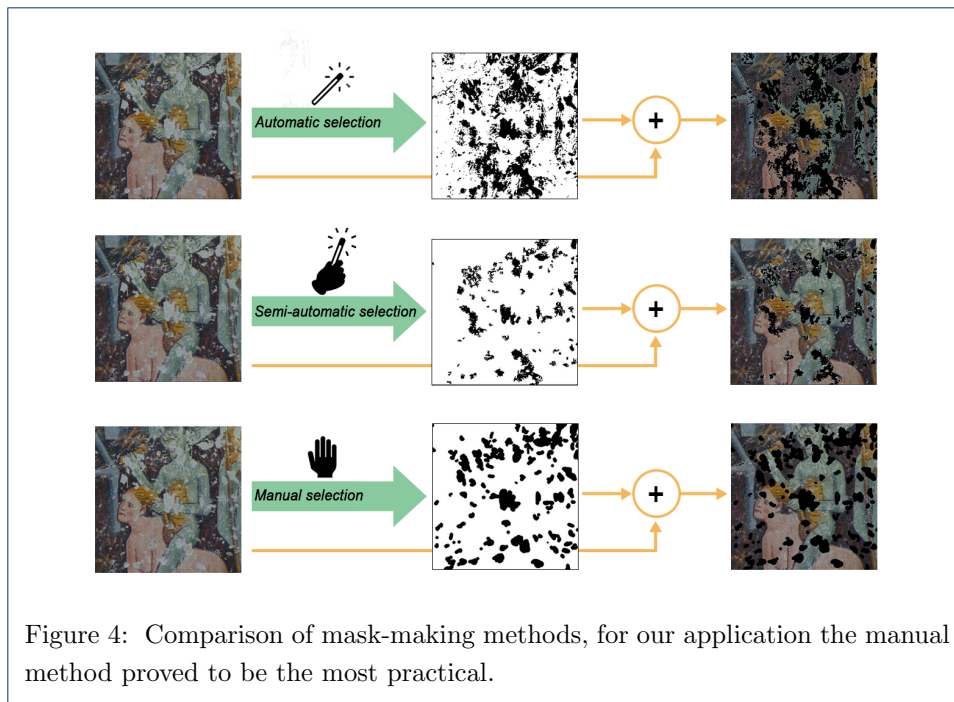
## 4 Experimental setup

The proposed inpainting workflow consists of three distinct steps. First, given an RGB to inpaint, we perform a basic pre-processing (i.e., resizing) to give it as an input to the DIP model, see Section 4.1. Next, a masking operator identifying the region to inpaint has to be defined, see Section 4.2. Lastly, both the input and the mask images are given as an input to the the DIP network whose weights are then optimised to produce the desired inpainting result, see Section 4.3. During the mask selection step, we highlight that the masking image can be extracted by infrared (or other non-visible) data. This is discussed separately in Section 5.2.

### 4.1 Image pre-processing

The RGB images in the available dataset have different resolutions and have different quality. Some of them were taken for documentation purposes and are, generally, low quality. On the other hand, some were taken with high-resolution cameras for the visualisation of fine details. This makes the image dataset not homogeneous,





which could be indeed a complication as the architecture neural networks for image reconstruction is typically fine-tuned typically for inputs of specific size and quality.

As discussed below in Section 4.3, the neural network considered in this work runs on square images, for which reason we chose a common image size of  $512 \times 512$  pixels and used these rescaled data for inpainting. Note that the DIP approach considered requires indeed the whole occluded image as an input. The use of the proposed approach on (overlapping) image patches was therefore not considered in this work but could represent indeed an interesting direction of future research.

#### 4.2 Mask detection

Computing the pixels in the input image that have to be inpainted is nothing but a binary image segmentation problem which can be handled separately by means of any available segmentation routine. Such procedure can be approached in different ways, depending on both how much automation one aims to implement and on how relevant the intervention of the restoration professional is. We describe in the following sections three techniques for mask detection falling into the category of automatic, semi-automatic and manual approaches. We stress that other approaches (based, e.g., on the use of deep learning based routines) could alternatively be used.

For several RGB images in the PA'INT dataset under consideration, an effective segmentation was not possible due to difficulties in detecting the damaged areas. A valid tool to overcome this issue is the use of infrared (IR) imaging data, which is able to uncover *overpaints*, damages and previous restorations. The inpainting procedure can then be implemented either on the RGB image itself or possibly on the IR image, as schematically reported in Figure 5 and discussed in the following section.

*Automatic mask selection.* For automatic mask selection we refer to a method where an algorithm takes as input a color, corresponding to the tone of the damaged areas, and automatically select all the pixels of that colour (within a defined tolerance) in the entire image. For our results the threshold was defined on the composite of all three colour channels using GIMP [47]. Such procedure works effectively if the damaged areas have considerably distinguishable characteristics with respect to the preserved content, and if this property is consistent throughout the image. If that is not the case and/or too much noise is present in the input data, precision may suffer.

We found that this techniques was not precise enough for our purposes: additional pixels belonging to the undamaged areas were indeed wrongly detected, see, e.g., Figure 4.

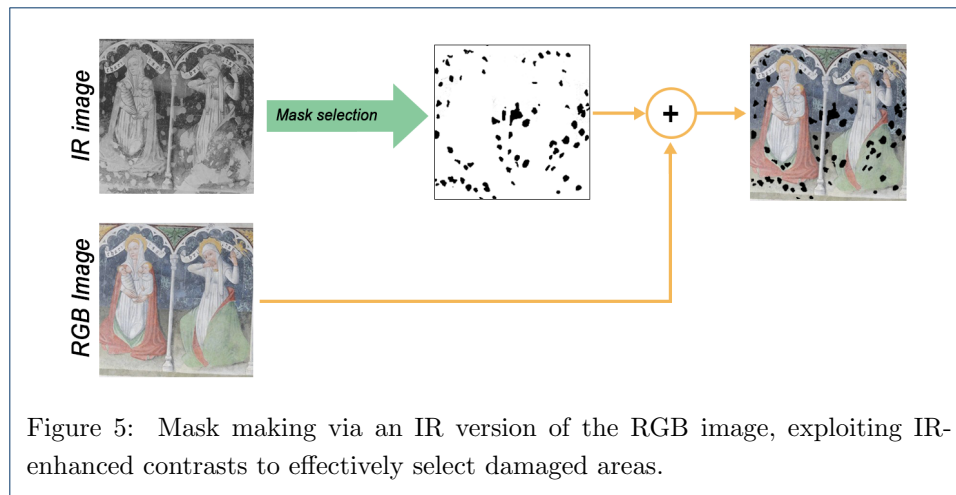
*Semi-automatic mask selection.* To prevent the mask from including pixels of the selected colour but not belonging to damages areas, we propose the semi-automatic mask creation. Unlike to the previous approach, it is done not only by providing a colour and a threshold, but also manually selecting one seed pixel for each connected region of the mask. Each region of the mask is then automatically detected by region growing from the selected pixel. Differently from the automatic technique, this approach allows for a better localization of large damages, but the seed selection may become challenging and potentially imprecise for small regions, as visible in Figure 4.

*Manual mask selection.* The manual mask selection process involves an expert user utilizing a paint tool to select the damaged areas. This technique is highly effective as it ensures complete coverage of the damage and allows for a customized selection. By employing this method, we are able to address the problem of not fully covering the border areas and at the same not extending the mask excessively into the preserved image, as it usually happened with the previous selection methods. In fact, leaving portions of the edges of the damages areas outside the mask, produces discontinuities in the restored images, with a detrimental impact on the quality of the inpainting process. In our experimental setting, it proved to be the most effective approach in generating the highest quality masks. However, manual mask selection may become impractical due to the considerable amount of manual work involved.

### 4.3 DIP architecture

The network architecture used for the DIP reconstruction procedure in Figure 3 is represented in Figure 6.

The "hourglass" structure consists of convolutional downsampling and bilinear upsampling with filter stride equal to 2, whereas the non-linearity considered is a LeakyReLU. In more detail, downsampling is achieved via strides and convolution or via max pooling and downsampling with Lanczos kernel. For the upsampling, the two most common approaches are bilinear upsampling and nearest neighbours upsampling. Regarding convolutional filters, we tested both filters with the same size and a progressively increasing number for both the encoder and decoder. The



size of the filters define the sensitivity of the convoluted network to different scales of features. In our experiments, we kept the filter size at  $3 \times 3$  for all the convolutional layers and we finally chose the reflection padding for ore local coherent results in the corner areas. As shown in Figure 6, we used skip connections, which are direct links between different parts of the convoluted network, allowing information flow not only within the architectural structure but also outside of it, which allows an alternative gradient back-propagation path. This technique proved to be one of the most effective tools in improving the performance of convoluted networks, see, e.g., [48, 49]. Input and output images are of the same size, i.e.  $512 \times 512$  pixels. The input image is generally drawn from a multi-variate uniform noise distribution with values in  $[0, 1]$ . The performance of the model is significantly impacted by the selection of the optimiser. After evaluating various options, we ultimately decided to use RMSProp (Root Mean Square Propagation) by PyTorch, which exhibited robustness against artefacts. Optimisation was run for 3000 iterations with a learning rate of size 0.01.

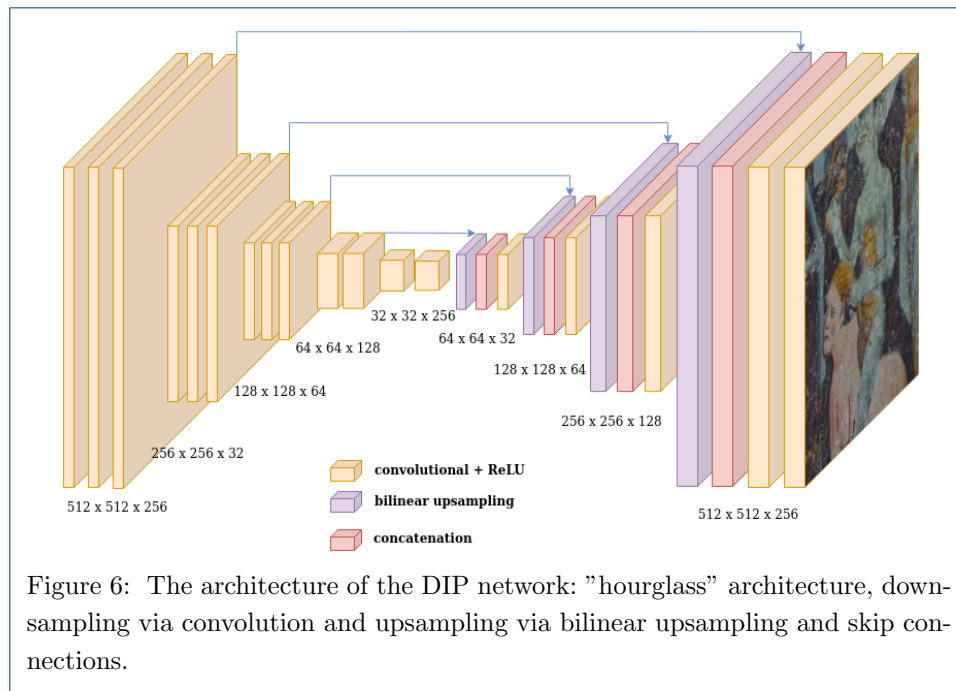
## 5 Results

In this section we show the results of the proposed DIP inpainting techniques applied to some images from PA'INT dataset described in Section 2.

### 5.1 Comparison between model-based/patch-based methods and DIP

In Figures 7 and 8 we report a comparison between the reconstructions obtained by different inpainting methods tested on the *Invidia* and *Lusuria* frescoes in Figure 2, respectively. In particular, we compare the inpainting results obtained by running the TV inpainting model [50], a PDE-based approached based on Navier-Stokes equations [51], the exemplar patch-based method [25, 26] and the proposed DIP approach. Note that fully data-driven approaches for image inpainting (see, e.g., [15]) cannot be applied here as they rely on the use of lot of training data (from the same painter, chapel...) that can hardly be obtained in digital humanities.

The TV inpainting result is reported in Figure 10b: we note that, as it is well-known, TV regularisation cannot connect well level lines over large inpainting regions, resulting in a blurred reconstruction within the largest areas. Figure 10c

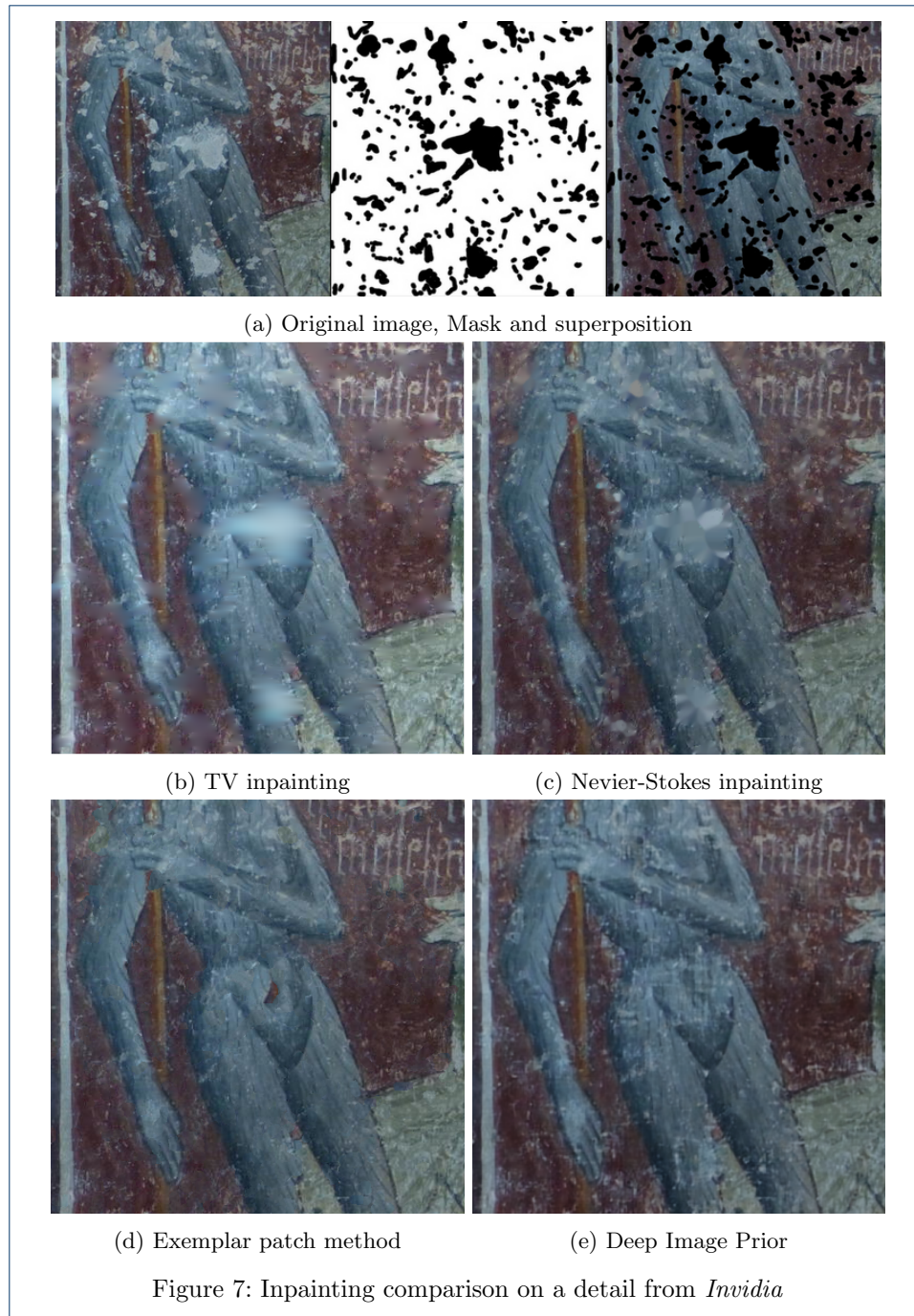


shows the results obtained by applying the Nevier-Stokes inpainting algorithm in [51] which show evident reconstruction artefacts. The image obtained by the non-local patch-based method, Figure 7d, is far better, although we notice the appearance of a ghosting artefact in correspondence of the large inpainting area. This is probably due to the choice of the patch size, which is a crucial parameter to tune whose choice is often tedious. The DIP inpainting result is reported in Figure 7e: compared to the other results, it appears to produce the most visually satisfying reconstruction, with no reconstruction artefacts.

Similar considerations can be made for the inpainted images in Figure 8. The restoration detail of the text inside the zoom is particularly interesting. Reliable inpainting approaches should indeed avoid any major modifications to image contents so as to guarantee a reliable, or even improved, interpretation of the artwork. In this respect, we observe that while local and non-local methods may alter the image content, the DIP network better preserves the desired text information with higher level of precision. To empirically verify this assumption we provide in Figure 9 a comparison between DIP and patch-based method for the restoration of the textual character "a" cropped from a San Sebastiano's fresco for large artificial mask. Results show that DIP reconstruct the letter successfully and without gaps, unlike the competing method. Analogously, in Figure 10 we provide a comparison of inpainting methods on a portion of damaged text from Venanson, where we observe that a more consistent text reconstruction is obtained by the DIP method.

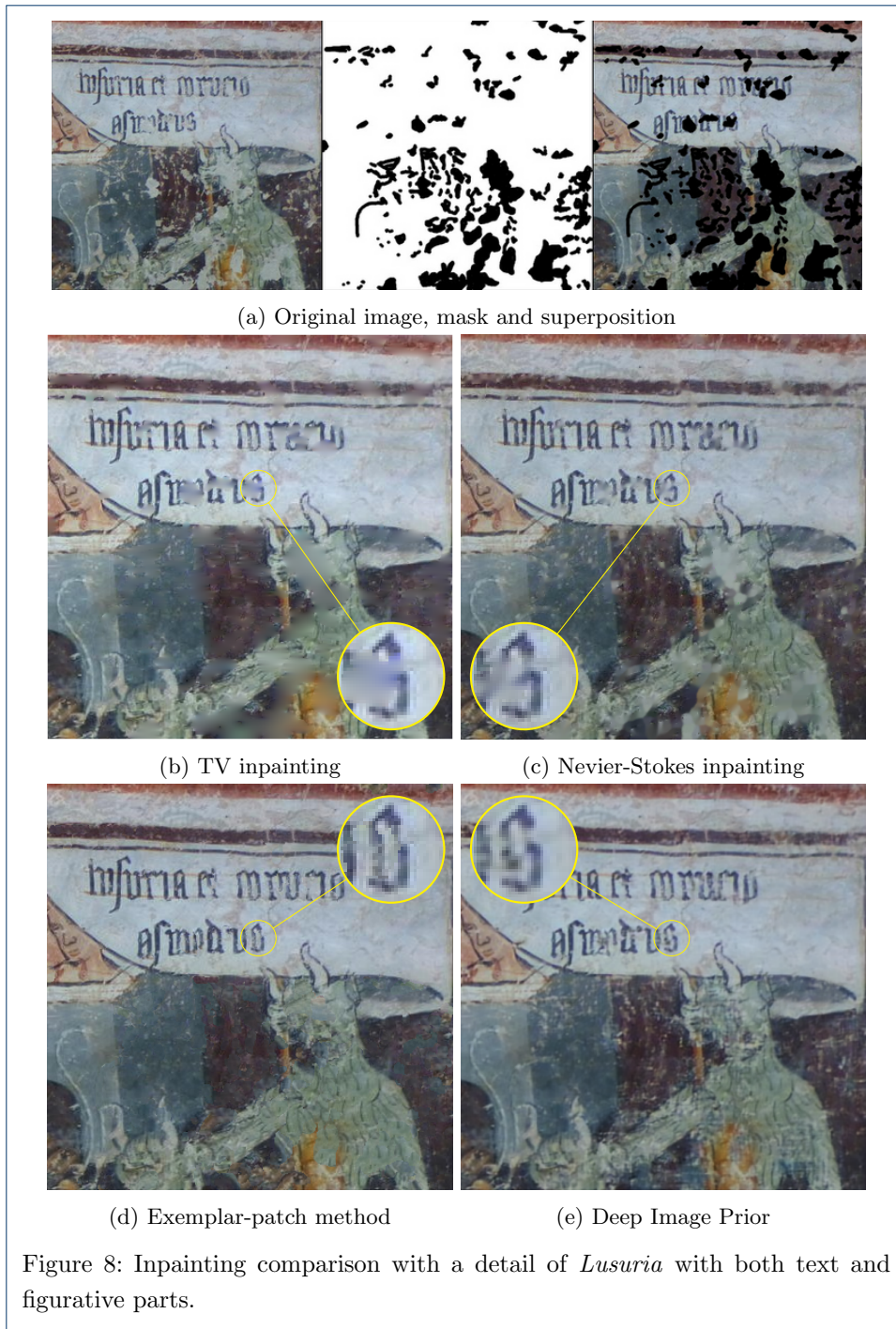
## 5.2 Inpainting based on IR images

When an infrared (IR) image of a fresco is available, it may allow the discovery of under-drawings and under-writings not easily discernible within the visible spectrum, i.e. on the RGB image. In Figure 11 we exploit such property by creating the

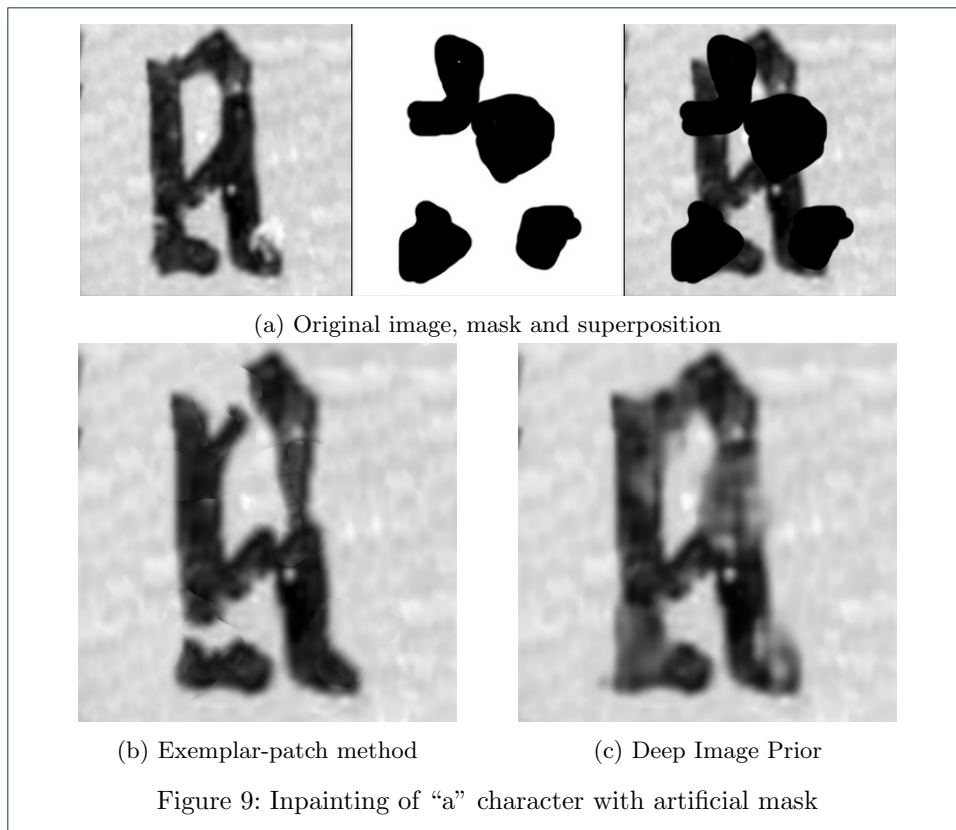


mask of these regions using the IR image (Figure 12d). The mask is subsequently super-imposed to the original fresco, where the damaged areas are harder to detect. DIP inpainting can there be applied so as to obtain the inpainted image shown in Figure 12d. In such inpainting result the background looks more coherent to the remaining part of the fresco, thus providing probably a more faithful image of how the original fresco looked like before retouches.

Interestingly, in the Derision of Christ painted by Pietro Guido da Ranzo in the sanctuary Nostra Signora delle Grazie, Imperia, between 1524 and 1540, the IR data



revealed ancient text appearing severely faded in the colour image (see Figures 12d and 12c). After selecting the inpainting mask on the IR picture, in this example we used it to inpaint directly the IR image and combine together the inpainted IR channel with the G and B channels of the visible image so as to get image 12d where text appear more visible and interpretable.



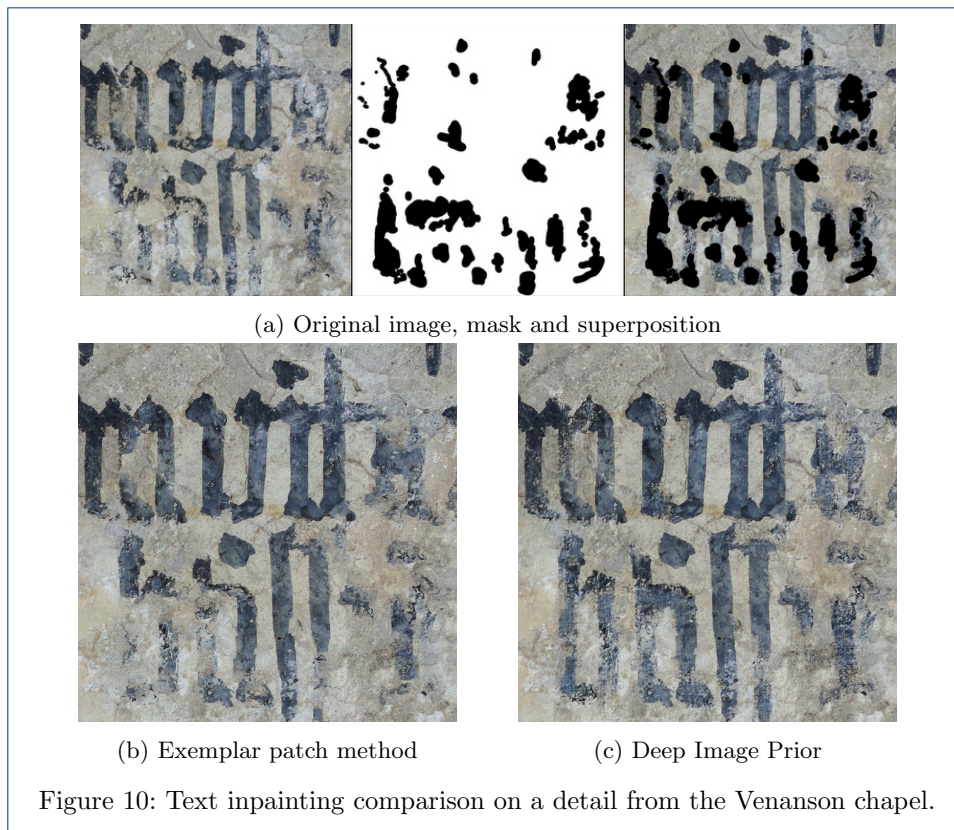
## 6 Discussion and outlook

In digital imaging, bringing back to light hidden and/or destroyed piece of information in ancient frescoes using techniques in the realm of variational methods and deep learning is often a very challenging task. The lack of reference data and the poor quality of both the fresco and of its digital representation often make hopeless the use of both standard approaches based on local reconstruction techniques and complex learning architectures relying on lots of training data.

In particular, in the study of medieval images, inpainting plays a crucial role by facilitating the general comprehension of heavily altered frescoes and digitally retrieving lost materials for the completion of painted objects and texts. This technique is particularly valuable in addressing the challenges posed by destruction, ancient restorations, and modifications that have resulted in the loss of data, limiting our full perception of medieval murals.

In this paper, we consider the problem of image and text inpainting for images acquired in the Mediterranean Alpine arc (dataset PA’INT) and corrupted by severe degradations. Our objective is to investigate the actions taken toward painted images and their causes, which sometimes emerge in a different context from the period of the artworks’ creation.

For such challenging dataset, we validate the use of flexible Deep Image Prior Inpainting as a hybrid technique relying on the expressivity of (an untrained) neural network and on its interpretability as a non-convex variational approach based on iterative regularisation. By using as a training image the sole given data, improved reconstructions are obtained in the occluded/damaged areas. In comparison with



classical approaches, the results computed show less artefacts and favour better interpretability of the data by art historians.

Furthermore, when combined with additional infrared data, the proposed techniques integrate and restore image contents effectively thus providing useful piece of information for subsequent analysis.

Through this interdisciplinary project combining art history, mathematical image processing, and AI, we aim to better understand the historical data and later interventions on medieval images. By doing so, we hope to chronicle the life of the paintings and gain insights into their impact and evolution within past societies.

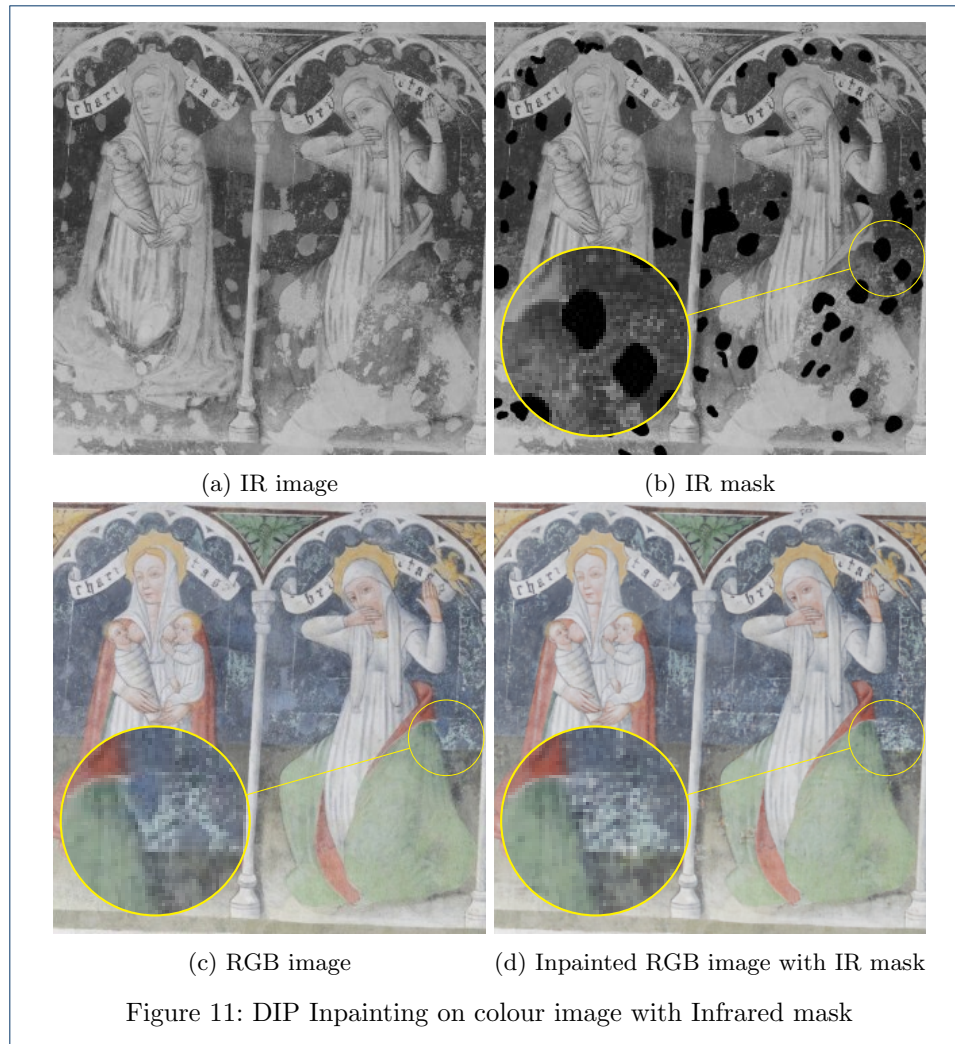
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#### Abbreviations

- DIP: Deep Image Prior
- PDE: Partial Differential Equation
- AI: Artificial Intelligence
- DDPM: Denoising Diffusion Probabilistic Models
- GAN: Generative Adversarial Network
- RMSProp: Root Mean Square Propagation
- TV: Total Variation
- IR: InfraRed





#### Availability of data and materials

The datasets analysed during the current study are available in the PA'INT [52] repository. The source code used for DIP inpainting is openly accessible in a dedicated GitHub repository [53].

#### Competing interests

The authors declare that they have no competing interests.

#### Authors' contributions

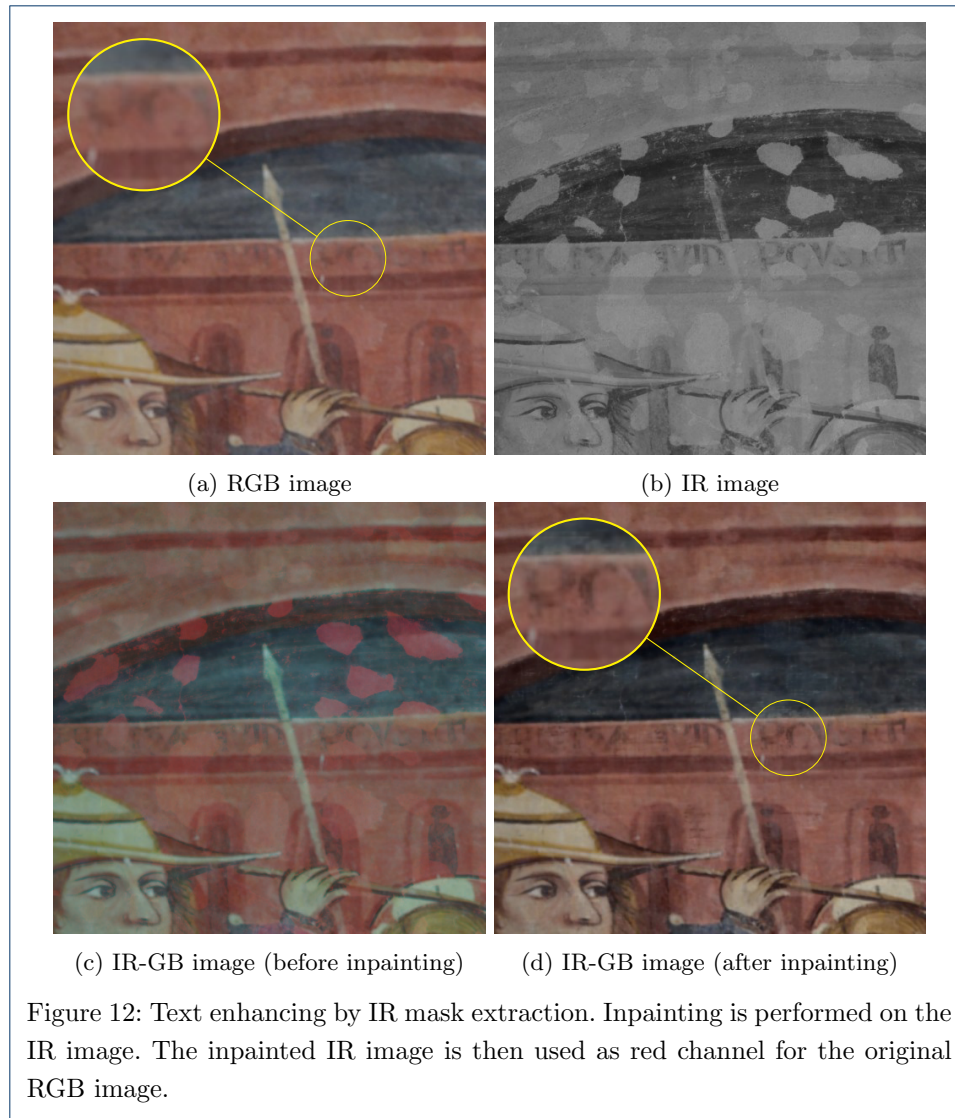
OA and PS collected the data. FM developed the computational methods and processed the data. FM, PS, EM and LC analysed the results. PS, RMD provided the historical and artistic background for the project. PS, FM, EM, ELP and LC wrote the manuscript.

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