Medical Image Inpainting based on Generative Adversarial Networks: A Review

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Abstract. Inpainting is the process of recovering images between pixels to reconstruct the damaged or defective parts of the image without any visual change to the rest of the image. Although image inpainting has been around for several years, its popularity has been increasing due to advances in image processing techniques. The combination of improved image processing tools and the flexibility of digital image editing has led to the emergence of inpainting with deep learning, one such Generative Adversarial Networks (GANs). For that reason, in this paper we perform a comprehensive literature review of GANs related to inpainting in medical image. In addition, the Boolean method was used to collect information in a range between 2018 and 2023. The search was performed through relevant databases such as Scopus, Google Scholar and PubMed. A total of 32 articles were obtained which have been separated by different categories to be analyzed in a better way.

Keywords: Inpaiting · GANs · Medical images · Deep Learning · Computer vision.

1 Introduction

Image processing is a task that has become increasingly important because the information contained in the images is relevant to the objective of the analysis [44]. Inpaiting is the process of reconstructing a damaged or altered image so that it is not detectable by an ordinary observer. This process depends on various factors including damage, distortions, objects superimposed on the image, etc [8]. For example, image restoration involves removing unwanted details from an image. Image encoding and transmission programs recover missing blocks, in other words, pixels. Traditional inpainting techniques include diffusion-based methods and patch-based methods [14]. On one hand, diffusion-based methods are based on the idea of propagating information from neighboring pixels to fill gaps in the image. On the other hand, patch-based methods focus on using information from similar patches or regions in the image to fill in missing areas [1] [33].

In recent years, the implementation of technologies based on deep learning has been very successful for this task [38]. That is why inpainting has become more relevant in computer vision tasks including: removal of unwanted objects, image reconstruction, restoration of old images, among others. Within these techniques, one that has gained great relevance is the use of Generative Adversarial Networks (GANs) for the task of image inpainting. GANs are a type of neural network architecture consisting of two main components: the generator and the discriminator [10]. GANs are capable of generating visually coherent and realistic content that can be used to fill in missing areas in an image. The GAN generator learns to synthesize information that matches the distribution of the input data and can generate believable pixels to fill in missing regions.

On the other hand, the inpainting task has multiple applications. One of these is the inpainting of medical images [28] [32]. Medical images may contain artifacts and noise that make interpretation and analysis by doctors and specialists difficult. This may be due to technical problems, involuntary movements of the patient, or the quality of the imaging machinery used. For this reason, inpainting task can be useful to remove those objects that are not relevant for medical analysis [36]. In contrast, medical images may have missing areas for the same reasons mentioned above. However, inpainting has also proved to be a favorable option to fill in these missing or deteriorated areas in a realistic and coherent way. These inpainting applications contribute to improving the quality and usability of medical imaging, providing more accurate diagnosis and advancing medical research. Due to the large amount of information available on this topic, the present paper proposes a review of scientific articles. This research is based on analyzing the advances that have been made in the period 2019 - 2023 on inpainting in medical images using GANs. Additionally, the present work is based on answering the following research question: What are the inpainting techniques in medical imaging based on GANs being used?

2 Related Works

2.1 Image Inpatinting

Inpainting is a technique used in image processing and computer vision to restore or fill in missing or damaged areas in an image. The main objective of inpainting is to remove unwanted elements or imperfections in an image and replace them realistically with visually coherent information. According to Guillermot *et al.* [11], this field of research has been very useful and achieved by numerous applications like restoring images from scratches or text overlays, loss concealment in a context of impaired image transmission, object removal in a context of editing, or disocclusion in image-based rendering (IBR) of viewpoints different from those captured by the cameras. Also, Jam *et al.* [14] notes that in the context of computer vision, inpainting is based on interpolating neighboring pixels to reconstruct the damaged portion of an image. This is done by using the information learned from entire portions of the image and filling in unknown regions.

2.2 Image Inpanting with Generative Adversarial Networks (GANs)

One of the inpainting techniques that has gained more relevance is the use of Generative Adversarial Networks (GANs). Jiang *et al.* [15] propose a method based on a generator, a global discriminator and a local discriminator. In addition, they used a Wasserstein GAN loss to ensure the stability of the training. With these parameters they achieve an improvement in the predictive performance of the generator and obtain more realistic images. The proposed technique proved favorable for image denoising. Other implementation proposal is given by Yuan *et al.* [46] who propose the implementation of Patch-generative adversarial networks (GANs). This structure is based on a generator, a multiscale discriminator and an edge processing function. This allows the extraction of holistic features from the damaged or incomplete image. This new approach takes into account information from reconstruction loss, edges, global and local aspects. This new method proved to learn the details of the image more carefully and restore them in a more realistic way. In the same way, Chen *et al.* [5] propose a progressive inpainting method based on Deep Convolutional Neural Network (DCGAN). This method is based on a gradual inference process since it starts with a low resolution image until a high resolution image is achieved through iterative processes. They use the backpropagation of the most suitable input and send it to the generator to repair the damaged image. As a result, clear images are obtained by gradual refinement of details.

3 Methodology

For this study, a search was conducted to identify scientific articles on using Generative Adversarial Networks (GANs) in inpainting in medical imaging. The search was performed in recognized databases, including Scopus, Google Scholar, and PubMed using the Boolean method [6]. The Boolean method allows to improve the efficiency and accuracy of searches in online search engines. In this manner, the keywords used for the search included «inpainting», «GANs», «medical images», «MRI», «CT», and «X-Ray» and. Additionally, it is important to note that the study focused on articles published between January 2019 and June 2023. In the end, a comprehensive set of 32 articles specifically addressing the application of GANs for inpainting in medical images was obtained.

4 Results

Regarding the production of articles about the use of GANs for inpainting on medical images, the publications made in 2019 correspond to 15.63% ($n = 5$) of the total. In 2020, there is a slight increase with respect to the previous year representing 18.75% ($n = 6$) of the articles. In 2021, the same amount of articles as in 2019 is obtained, and its percentage corresponds to 15.63 % ($n = 5$). Particularly in 2022, it is observed that the number of published articles is much higher than in the previous three years; this results in a percentage of 37.5% ($n = 12$). Finally, in 2023, 12.5% ($n = 4$) of the total percentage was reached. The statistics show that the years 2019 and 2023 correspond to those with the lowest and highest number of scientific publications within the analyzed period, respectively. Nonetheless, it is important to mention that as of the current date of completion of this article, only half of 2023 has elapsed, which directly impacts the number of articles found for this specific year. Currently, there is a growing trend towards the use of Deep Learning (DL), specifically GANs for various applications, in this case, for inpainting in medical images, which is reflected in the data for 2022. For this reason, it would be expected that by the end of the year, the number of articles published will be much higher. Figure 1 shows a line chart with the aforementioned information.

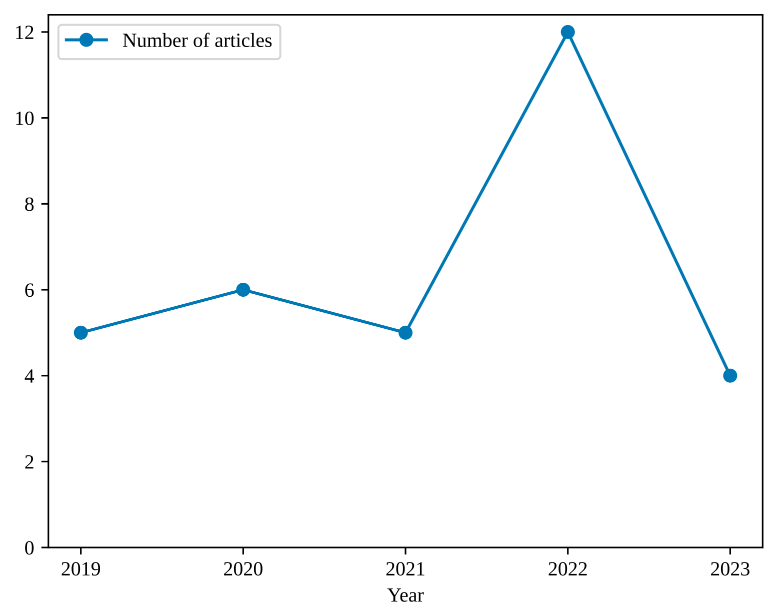

Fig. 1: Articles published per year between 2019–2023

Table 1 summarizes the bibliography sorted in descending order according to publication date. In addition, the author, object of study, method used, and results and conclusions of each scientific article are shown.

Table 1: Scientific articles related to the use of GANs in medical image inpainting

Study	Objective	Method	Results/Conclusions
Chen *et al.* (2023) [4]	Inpainting 2D ovarian tumor ultrasound images	Mask-guided generative adversarial network (MGGAN)	Make the texture and structure. Boundaries smoother. Highest scores in LPIPS, FID, and SSIM
Valat *et al.* (2023) [37]	Inpainting sinograms	Pix2pix Generative Adversarial Network and DCGAN	Model that infers a substantial number of consecutive missing acquisitions
Xie *et al.* (2023) [42]	Inpaint the truncated areas of CT images.	GANs with gated convolution (GatedConv)	GatedConv could directly and effectively inpaint incomplete CT images
Liang *et al.* (2023) [24]	Restore colon tissue pathological images	Multi-scale self-attention generative adversarial network (MSSA GAN)	Improved RMSE, PSNR and SSIM of the restored images
Xie *et al.* (2022) [40]	Limited-angle CT reconstruction based on sinogram inpainting	Sinogram Inpainting GAN (SI-GAN), and Artifact Removal GAN (AR-GAN)	Reconstruction with only [0, 90] of limited sinogram projection data
Yang *et al.* (2022) [43]	Inpainting of simulated bi-planar X-Ray images for 3D spine structures	Modified the X2CT-GAN with ResNet into a new 2D to 3D-GAN	Better performance during training, indistinct disc spaces, blunting borders of transverse processes, and blunting border of spinous processes
Xie *et al.* (2022) [41]	Inpaint the metal artifact region in MRI images	GAN with gated convolution (GC) and contextual attention(CA)	GatedConv could directly and effectively inpaint the incomplete MRI images generated by masks

Table 1: *(continued)*

Lin *et al.* (2022) [25]	Generate face acne lesion labeled images for boosting downstream diagnostics in an automated way	Class-Guided PG-GAN (CGPG-GAN)	The method can improve the performance of downstream diagnosis remarkably
Preedanan *et al.* (2022) [31]	Creating synthetic images based on stone and non-stone mask inputs	the MultiResUnet model using original stone and proposed synthetic samples.	This model increases the detection of stones with synthetic images
Zhao *et al.* (2022) [49]	Synthesize traumatic brain injury (TBI) scans with paired brain label maps.	TBI-GAN with label inpainting	Results show that can produce sufficient synthesized TBI images with high quality and valid label maps
Zhang *et al.* (2022) [48]	Restoring low-dose CT imaging with limited-angle imaging	Traditional GAN a generator network and a discriminator network	This work proves that the limited-angle CT imaging technique can be used to reduce the CT radiation dose
Fagereng *et al.* (2022) [9]	Early identification of a polyp in the lower gas-trointestinal (GI) tract	PolypConnect pipeline	The polyp segmentation model trained using synthetic data, and real data shows a 5.1% improvement of mean intersection over union (mIOU)
Madesta *et al.* (2022) [26]	Restore correct anatomical information of areas affected by artifacts	Detection of common interpolation (INT) and double structure (DS) artifacts	Highlight the potential of DL-based inpainting for restoration of artifact-affected 4D CT data
Daher *et al.* (2022) [7]	Inpaint the hidden anatomy under specularities inferring its appearance from neighbouring frames	Temporal GAN (TGAN)	The results show a positive effect of specular highlight inpainting on these tasks in a novel comprehensive analysis

Table 1: *(continued)*

Kim *et al.* (2022) [19]	Inpainting the L/R markers in chest radiographs	EfficientDet for detection and GAN for inpainting	Better score of area under the curves (AUCs) and accuracies, as well as an improvement in the Grad-CAM
Kearney *et al.* (2022) [17]	Dental inpainting algorithm using generative adversarial networks (GANs)	GANs coupled with partial convolutions to predict out-of-view anatomy and enhance clinical attachment level (CAL)	Improved clinical attachment level (CAL) prediction accuracy compared to non-inpainting algorithms
Magister & Arandjelović (2021) [27]	Create realistic retinal images for teaching through automatic machine learning-driven inpainting	Wasserstein GAN (WGAN) with a semantic image inpainting algorithm	Outperform the artist's impression of the retina in some areas
Wang *et al.* (2021) [39]	CT reconstruction of pleural and cranial cavity slices	Complementary-sinogram-inpainting generative adversarial networks (CSI-GAN)	Reduced RMSE, increased PSNR, and improved structural similarity (SSIM)
Ketola *et al.* (2021) [18]	Artifact-free images from interior CT angiography	Double GAN (DGAN)	Increased RMSE, SSIM and increment of the reconstruction area by 10% and 20%
Huang *et al.* (2021) [13]	Super-resolving to handle multiple degradations	HLH-GAN, (high-to-low (H-L) GAN together with a low to-high (L-H) GAN) in a cyclic pipeline	The method outperforms many existing superresolution and inpainting approaches, especially on brain MRI data
Zhang *et al.* (2021) [47]	Method for synthesizing lesions in brain CT images using a combination of shape imitation and image inpainting techniques	GAN for cross-modality synthesis from CT to PET for improved automated lesion detection	The results show that the proposed method outperforms other state-of-the-art methods in terms of lesion detection accuracy

Table 1: *(continued)*

Hsieh *et al.* (2020) [12]	Image inpainting was integrated to generate the delicate details of the lung part	Boundary Equilibrium Generative Adversarial Networks (BEGAN)	Increase the amount of high-resolution medical images for future applications
Armanious *et al.* (2020) [2]	Introduce a new framework for the inpainting of medical modalities with local distortions	ipA-MedGAN	A superior performance of ipA-MedGAN for the inpainting of brain MR images with respect to other approaches
Yu *et al.* (2020) [45]	Novel two-stage GAN for medical image inpainting composed of the multimodal guided network and the fine inpainting network	Generative adversarial network via multi-modal guidance (MMG-GAN)	The method outperforms other state-of-the-art methods in terms of PSNR, SSIM, and l1 measures on Thyroid Ultrasound Image (TUI) and TN-SCUI2020 datasets
Pepe *et al.* (2020) [30]	Reconstruct the aorta before the formation of a dissection by performing 3D inpainting with a two-stage GAN	3D inpainting method based on a two-stage GAN	The suggested 3D inpainting approach performs considerably better than the state-of-the-art 2D counterpart
Rikarnto *et al.* (2020) [34]	Improved method for semantic image inpainting using deep generative models	Modification to the prior term in the inpainting technique to achieve a more balanced contribution to the total cost	Faster than classical PDE-based techniques, and its running time was almost independent of the size of the missing area
Sun *et al.* (2020) [35]	Computer vision to address fundamental medical image analysis problems of segmentation and classification	ANT-GAN for translating a medical image containing lesions into a corresponding image via color correction	The proposed ANT-GAN model was able to remove lesions from medical images and generate corresponding healthy-looking images

Table 1: *(continued)*

Li *et al.* (2019) [22]	Restore missing sinogram data to suppress the singularity of the truncated sinogram for ultra-limited-angle reconstruction.	Sinogram-inpainting-GAN (SI-GAN)	The proposed method performed well in reducing the serious artifacts caused by ultra-limited-angle scanning.
Armanious *et al.* (2019) [3]	Inpainting 2D medical images in general	Generative Adversarial Network (GAN) two patch-based	The proposed framework outperformed other techniques in terms of quantitative metrics such as Universal Quality Index (UQI)
Li *et al.* (2019) [23]	Obtain high-quality CT image reconstruction results for the ultra-limited-angle problem	Deep learning-based approach that combines a sinogram inpainting GAN (SI-GAN) with simultaneous algebraic reconstruction technique-total variation (SART-TV)	The estimated sinograms by SI-GAN were more realistic than those by the patch-GAN method
Li *et al.* (2019) [21]	To present a novel approach for blind image inpainting to remove cross symbols of thyroid ultrasound images	The Py-GAN consists of a generator with a pyramid structure and a global discriminator.	Higher quality inpainting results than existing works for blind image inpainting to remove cross symbols of thyroid ultrasound images
Miao *et al.* (2019) [29]	To propose a practical method for restoring CT images of spinal tumors	V-Net for 2D spinal image segmentation, Faster R-CNN for lesion detection, and WGAN-GP for image inpainting.	Good performance in semantic segmentation of vertebral bodies and lesion detection of spinal neoplasm using the proposed method

Among the articles included in the study, a total of five categories were identified considering the type of medical image used to perform inpainting. Thus, the defined categories are *X-Ray*, *computed tomography* (CT), *ultrasound images*, *magnetic resonance imaging* (MRI), and *others*, which includes various types of images not included in the groups previously mentioned. It is important to mention that some articles do not focus solely on one type of image but obtain results in medical images of various categories. Thus, the 18.75% ($n = 6$) of the articles applied inpainting techniques to X-Ray images ([37] [24] [19] [43] [31] [17]). A 50% ($n = 16$) of the total used CT ([40] [39] [18] [41] [22] [30] [42] [3] [26] [48] [9] [12] [29] [47] [23] [35]). Additionally, the 9.38% ($n = 3$) used ultrasound images ([4] [45] [21]). The studies that use MRI represent 15.63% ($n = 5$) ([2] [3] [13] [49] [35]). Finally, 12.5% ($n = 4$) of the articles use diverse types of medical images. Such is the case of the studies by Magister & Arandjelović [27], Lin et al. [25], Siavelis et al. [34], and Daher et al. [7] which used retinal, facial, laparoscopic, and endoscopic images, respectively. Figure 2 visually shows this information.

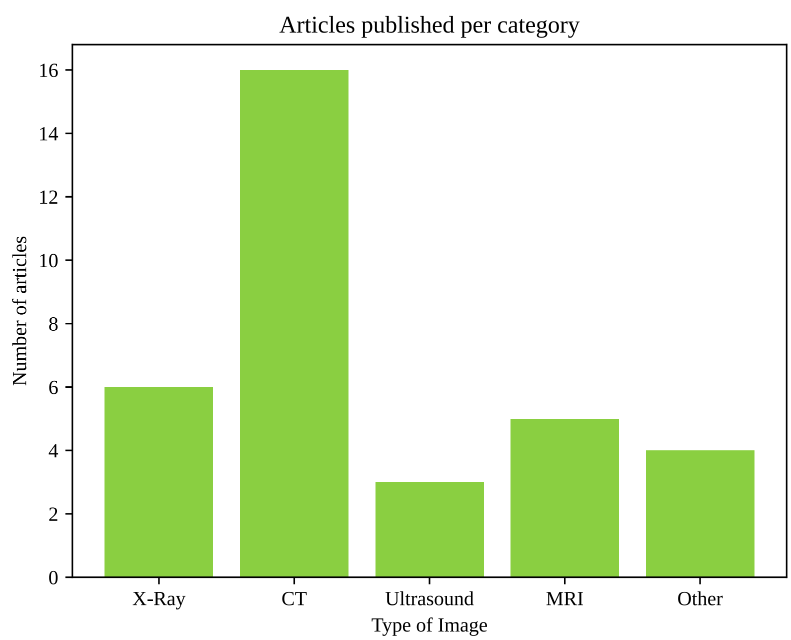

Fig. 2: Articles published per category

From the selected articles, another categorization can be carried out based on the region or part of the human body from which the medical image was extracted. In this way, studies were identified that apply inpainting using GANs on X-Ray and CT images of chest [37] [19] [43] [48] [39]; Lung CT [24] [39] [22] [26] [12]; CT of the head [48], MRI and CT of the brain [2] [3] [13] [49] [47] [23] and CT of the cranial cavity [39] [22]; CT of heart [18] [30]; MRI of teeth regions [41] [17]; thyroid ultrasound [45] [21], and different types of images of different parts of the digestive system such as X-Rays of the colon [24], esophagus [42] and the Lower Gastrointestinal tract CT [9], and stomach and intestines endoscopies [7]. Some articles also perform inpainting on images of other body parts, such as ovarian X-Ray [4], retinal [27] and facial images [25], urinary system, [31] spinal cord CT [29], and gallbladder laparoscopy images [34].

5 Discussion and Conclusion

The methods of inpainting with GANs have been the subject of interest by researchers from different areas. As demonstrated by the results, which indicates an increase in published scientific articles, having its highest point until the completion of this review in the year 2022. This is due to the fact that the GANs are capable of reproducing pixel distributions, generating images realistic looking and learn exact verification metrics [16]. In addition, GANs offer flexibility in terms of customization and adaptability to different medical imaging modalities, such as MRI, CT or ultrasound imaging. It has been shown that these networks can be trained and tuned specifically for each medical study modality, which is important in addressing the particular challenges of each type of medical image. Added to that, inpainting techniques that are beneficial for deep learning purposes.

Due to the rare nature of some diseases, medical images often suffer from imbalance or distortion, which is why different types of X-Ray, CT, Ultrasound, MRI and other images were taken into account for the review. Identifying CT as the most recurrent type of image (n=16) for this review. This indicates the great importance of CT images in the development of inpainting with GANs, since CT imaging is a fast, painless and detailed procedure [20]. On the other hand, among the most relevant areas of the body, images of the head-cranial-brain (10), those related to the lungs (5), those related to the chest (4), among other images, were obtained. This reflects the importance of these areas of the body which care is required to examine and treat. These also prove to be the most relevant diseases in the latest research related to GANs for the inpainting task. In the same way, it indicates conditions in vital organs that expose the patient to death [20]. For this reason, great detail is required in the generation of images with inpainting and GANs.

In conclusion, the reconstruction of medical images based on deep learning and applying inpainting techniques, especially the one studied in this article, GANs, has become a topic of important research. GANs have demonstrated their ability to reconstruct realistic, high-quality images, which is crucial in medical applications where image accuracy and precision are essential. Thus, it has been demonstrated throughout this research that GANs can learn to reconstruct the missing areas of an image in a coherent way with the general context and the visual characteristics of the rest of the image. The ability to inpainitng with GANs to reconstruct data distributions opens up the possibility of detecting abnormal cases in real data sets [14]. Also, the ability of GANs to reconstruct damaged or missing areas in medical images has the potential to improve diagnosis, treatment planning and medical research. New deep learning approaches and methods are expected to emerge in the coming years in order to boost their development. Finally, this study can be used as a reference source on issues related to inpainting techniques for medical images based on GANs. and have recent knowledge about applications in this area.

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