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From past to present: A tertiary investigation of twenty-four years of image inpainting

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ABSTRACT

Inpainting techniques, rooted in ancient art restoration practices, have become essential tools for digital image editing in modern contexts. Despite their widespread applications across diverse domains, the rapid advance of inpainting methodologies has highlighted the need for comprehensive reviews to document progress and identify areas for deeper investigation. Although there are many works in literature describing the state of the art regarding inpainting methods, algorithms, and technologies, many of them are presented lacking methodological rigor, which compromises the reliability and validity of their conclusions. In light of the wide literature about inpainting, this tertiary review aims to systematically identify their main techniques, recurring challenges, and applications through the perspective of secondary studies, providing a helpful background for new researchers. Our findings are based on an analysis of 45 reviews, where one of the major issues observed was the lack of standardization in the classification of methods, and to address this, we provide a concise and clear classification. Furthermore, we present a summary of the most commonly used metrics and a discussion of the main shortcomings and applications, which extend beyond digital image restoration to include medical imaging, three-dimensional restoration, cultural heritage preservation, and more. While inpainting poses challenges, this review aims to inspire further exploration and advancement in the field by providing a comprehensive overview of inpainting research.

1. Introduction

Inpainting techniques are ancient methods proficient artists employ in restoring damaged paintings and photographs (Fig. 1). In a modern context, where the focus on visual and digital content is becoming increasingly pronounced, these techniques have established themselves as an important image editing tool. Besides, their ability to remove unwanted objects and correct imperfections by filling specific areas in an image turned these methods into an important key, finding applications across diverse domains [1,2].

In the modern context, the evolution of the inpainting technique has taken impressive steps forward, leading to the spread of innovative methodologies. Nevertheless, this rapid expansion also brings forth a crucial need for thorough reviews of these techniques. Reviews play a key role in documenting the progress and diversity of these techniques and identifying areas that demand deeper investigation [3,4].

During a preliminary search on the Scopus platform, we discovered a significant collection of 2794 primary articles related to inpainting, highlighting the vastness of the literature in this area. However, our research revealed only 45 relevant reviews on this topic, many failing to demonstrate methodological rigor.

This absence of a methodological framework can seriously compromise the analysis's integrity. It opens the door to biased interpretations and selective reporting, raising concerns about the reliability and validity of the conclusions drawn from these reviews [4,5]. Therefore, the motivation behind this tertiary study emerges.

Employing a systematic literature review methodology outlined by Kitchenham [5], we established a research protocol with specific research questions to guide our study. These questions were designed to help our main objective of comprehensively understanding the current research landscape, focusing on identifying key approaches, challenges, and practical applications of inpainting techniques.

Despite the extensive primary literature available on the subject and the lack of methodological rigor of many secondary research studies, our investigation aims to comprehensively understand the current state and implications of inpainting research by addressing these research questions. Besides, the absence of tertiary investigations on this topic highlights the relevance of our study.

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Fig. 1. Artistic technique of inpainting applied to Plautilla Nelli's "The Last Supper" painting. Photo: Francesco Cacchiani.
Source: [6].

The main contributions of this paper are:

1. A comprehensive tertiary literature review on inpainting, highlighting their main methods;
2. The enumeration of the most used metrics to evaluate inpainting results; and
3. A discussion on the common challenges and gaps in the current inpainting landscape.

This research begins with an overview of the concepts pertinent to this study (Section 2), followed by a detailed description of the methodology adopted in this research (Section 3). Subsequently, a thorough discussion of the findings obtained from our analysis of the secondary studies collected is provided (Section 4), followed by a reflection on the possible limitations of our research (Section 5). Finally, a conclusive synthesis of the research process is presented (Section 6).

2. Concepts

This section will cover the main concepts discussed in this article regarding inpainting techniques and the principles behind secondary and tertiary reviews.

2.1. Inpainting

The definition of the term inpainting can be simplified as painting inside. It refers to an ancient artistic practice dedicated to restoring paintings [7]. In essence, the main objective of this technique is the harmonious reconstruction of damaged images, preserving the quality and coherence of the painting.

In the digital image process scope, the term inpainting was first addressed by Bertalmio et al. in their article "Image Inpainting" [8]. Applying inpainting techniques in digital images involves filling in pre-existed or generated voids after removing unwanted elements from the image (Fig. 2). Similar to the ancient techniques, there is an agreement regarding the aspiration for an optimal inpainting approach: They must consider the context surrounding the area to be restored and the global context that encompasses the entire image.

To achieve this, the available information in the image is utilized to infer the missing content coherently. This information can be categorized into two aspects: *structural* and *textural*. Structural information pertains to the geometry and details, such as edges and shapes present in the image. Meanwhile, textural information is linked to the patterns and coloration in the image [9].

Considering that one of the primary methods for evaluating inpainting techniques is human observation, structural and textural aspects are crucial elements in the final image [10]. The high visual acuity exhibited by humans in recognizing distortions or inconsistencies in the image underscores the significance of these components in generating coherent and visually pleasant results, where any form of alteration is imperceptible [11].

Various innovative inpainting techniques have been progressively developed in response to this challenge. These techniques encompass various architectures and models, reflecting their practical applications in many fields of study, from creative image manipulation to medical image enhancement [12,13]. A relentless pursuit of excellence has driven these techniques' continuous development and improvement in performance, effectiveness, and applicability in different areas.

2.2. Secondary and tertiary reviews

Secondary studies are comprehensive reviews of existing literature on a particular topic [15]. These studies involve examining and interpreting previously published research findings, often to summarize and critically evaluate the existing knowledge on the subject. With the same objective, tertiary reviews represent a specific category of bibliographic analysis, which, unlike secondary studies, relies on previous literature reviews [16].

In areas with extensive literature, tertiary reviews are valuable for providing a concise and comprehensive overview of the current state of knowledge in a particular area, building on existing reviews [15,17]. Moreover, they can help researchers identify areas of research that require further investigation and highlight advances and challenges in understanding a particular topic [15,18].

In 2004, Kitchenham [5] introduced a systematic process for conducting literature reviews that has become widely used in various disciplines. This method can be applied to either a secondary study, which focuses on presenting the state of the art in a given research topic, or a tertiary study, which also aims to present the state of the art in a topic but through the analysis of secondary studies. Thus, analogous to the rigorous methodologies inherent in systematic literature reviews, a tertiary review entails critically selecting relevant secondary studies and carefully analyzing and synthesizing their key findings [19,20].

The stages of the research process recommended by Kitchenham [5], can be described as follows:

1. *Research questions formulation:* Conversion of information needs into clear and precise research questions to serve as the basis for conducting the systematic review.
2. *Establishment of a search protocol:* Development of a detailed protocol to guide the entire review process. This comprises criteria for including and excluding studies, search strategies, and methods for evaluating the studies found.
3. *Literature search:* Execution of a systematic and comprehensive search in relevant databases using well-defined search terms related to the research questions.

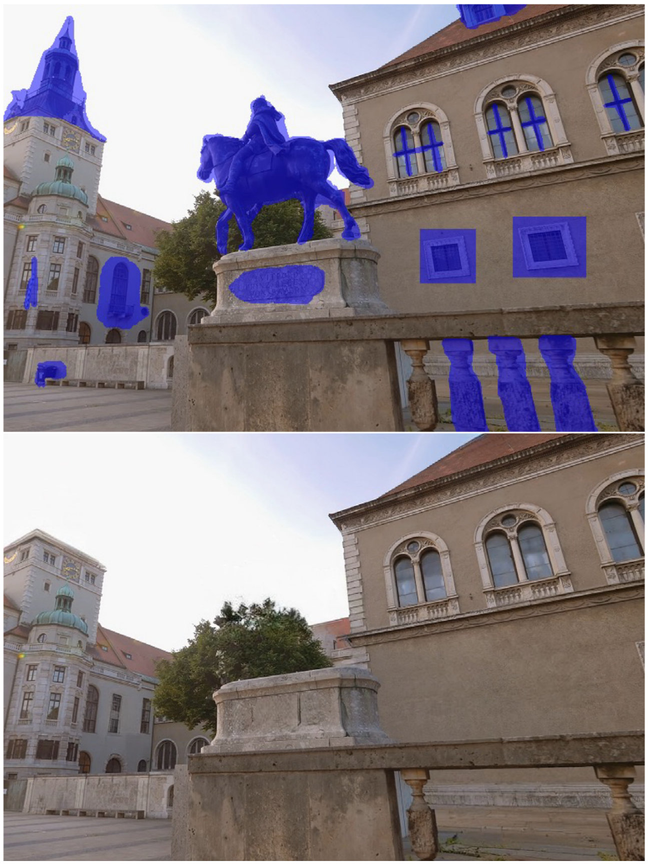

Fig. 2. Digital image inpainting example. The marked structures on the top image where removed in the bottom image.
Source: [14].

4. *Selection of relevant reviews:* Evaluation of the relevance of the studies identified based on the inclusion and exclusion criteria specified in the protocol.
5. *Extraction of relevant data:* Extraction of pertinent data from the included studies using a standardized form, which includes study characteristics and results.
6. *Analysis and synthesis of results:* Critical evaluation of the selected evidence, its validity, relevance, reliability, and finally, interpreting the results in light of the original research questions.

3. Methodology

In this study, we conduct a comprehensive and critical analysis of existing literature reviews on inpainting techniques. This research follows the systematic process outlined by Kitchenham [5], as detailed in Section 2.2, to ensure rigor and coherence throughout the analysis. Each stage of the process will be delineated in the following sections, facilitating transparency and replicability in our research methodology.

3.1. Research questions

Considering the vast amount of primary studies presenting innovative proposals, this research aims to provide a clear background to assist new researchers in the field of inpainting. To achieve this objective, our study systematically identifies and synthesizes the main categories of inpainting techniques, through the perspective of secondary researches. Furthermore, the study explores the key aspects of this topic, including the criteria used to evaluate inpainting techniques, the recurring challenges within the domain, and their main applications.

Based on these considerations, the following research questions and their objectives have been delineated:

RQ1. What are the main inpainting approaches and techniques discussed in existing reviews?
Objective: Identify and categorize the different methodologies and techniques of inpainting presented in the literature reviews.

RQ2. What are the common challenges and gaps in inpainting research highlighted in these reviews?
Objective: Identify recurring problems and gaps that still require further investigation to direct future research.

RQ3. How do these reviews address the performance evaluation of inpainting techniques?
Objective: Understand the criteria and metrics used to evaluate the effectiveness of inpainting techniques, offering insights into the most common evaluation methods and their limitations.

RQ4. What are the practical applications of inpainting techniques discussed in these reviews?
Objective: Explore the various practical applications of inpainting techniques, demonstrating how these techniques are applied in real-world contexts and the benefits they offer.

These research questions will guide the following process, allowing for a comprehensive investigation into the inpainting literature.

3.2. Research protocol

To ensure the transparency and reliability of the research, it is necessary to establish a research protocol. A research protocol is a predefined plan that outlines the main strategies and procedures to be followed during the study. This protocol ensures the reproducibility of the process, providing a comprehensive and grounded understanding of the topic under study [5].

Table 1 summarizes the research protocol employed for this study, including important elements used throughout the search, selection, and extraction phases of the research. The subsequent sections will present a systematic and detailed execution of this process and analyze the results obtained following this protocol.

3.3. Search process

The search process was first conducted in November 2023 using the Scopus platform as the primary search source. Scopus is widely recognized for its comprehensive coverage across various disciplines and areas of study, providing researchers with access to a vast and diverse repository of scientific and academic literature [21,22]. Due to its extensive subject coverage, database size, and robust citation search capabilities, Scopus was considered to be the most appropriate option as a primary database for this research.

However, to complement the search, we have decided to include other important databases and redo the search process in May 2024. This strategy aligns with the approach recommended by Gusenbauer and Haddaway [21], which states that a unique search system can be used and classified as primary according to quality criteria such as coverage and database size. Nevertheless, incorporating alternative databases can enhance the evidence base by retrieving additional records [21]. In this context, Scopus was used as the primary resource. At the same time, ScienceDirect, IEEE, and ACM were included as supplementary resources to expand the search scope and ensure comprehensive coverage of the available literature.

The effectiveness of this strategy is validated by the graphical representations in Fig. 3, which demonstrate a higher number of articles retrieved and selected by the Scopus platform compared to other databases. Nonetheless, it is noteworthy that some significant articles were obtained from the supplementary databases, which were not indexed by Scopus.

Table 1
Research protocol.

Research stage	Description
Research Questions	RQ1. What are the main inpainting approaches and techniques discussed in existing reviews? RQ2. What are the common challenges and gaps in inpainting research highlighted in these reviews? RQ3. How do these reviews address the performance evaluation of inpainting techniques? RQ4. What are the practical applications of inpainting techniques discussed in these reviews?
Search Process	*Databases Used:* Scopus (https://www.scopus.com/) IEEE (https://ieeexplore.ieee.org/) ScienceDirect (https://www.sciencedirect.com/) ACM (https://dl.acm.org/)
	Search Type: Article title, abstracts, and keywords
	Search String: (“inpainting”) AND (“review” OR “survey” OR “systematic review” OR “literature review” OR “overview”)
Selection Process	*Inclusion Criteria:* IC1. The article is a literature review specifically on inpainting in images. IC2. The article discusses different inpainting approaches and techniques. IC3. The article details and discusses the performance evaluation of inpainting techniques. IC4. The article addresses the evolution and challenges related to inpainting techniques.
	Exclusion Criteria: EC1. The article is a primary study that does not fall into the category of literature reviews. EC2. The article is not directly related to image inpainting. EC3. The article is not written in English. EC4. The article is a short paper (4 pages or less). EC5. The article is inaccessible.
Extraction Process	*Data extraction form:* Year Review approach Methods explored Metrics analyzed Topic area Main conclusions of the review Main challenges identified by the review

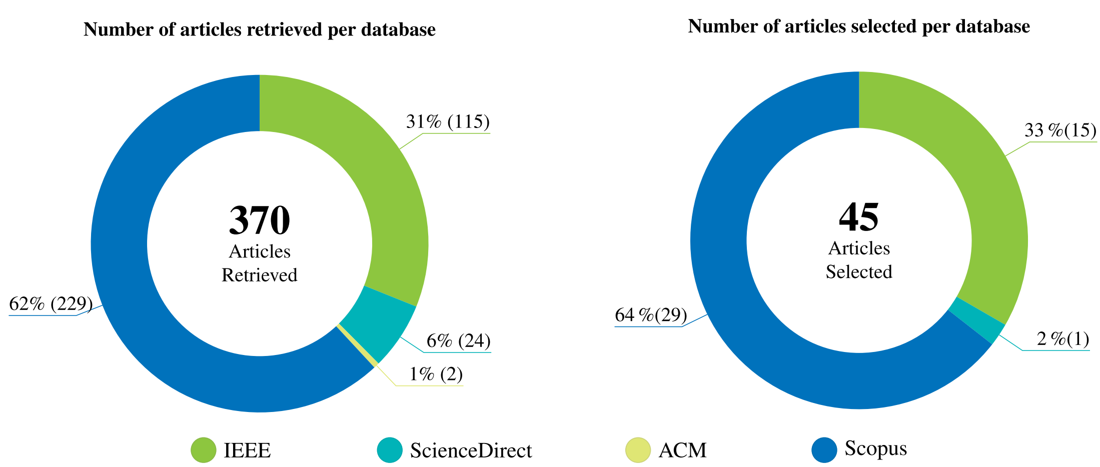

Fig. 3. Distribution of retrieved and selected articles per database.

Once the databases had been selected, experiments were conducted to evaluate the effectiveness of distinct search strings in retrieving relevant results for the current study. Consequently, the following string was selected for the search:

(“inpainting”) AND (“review” OR “survey” OR “systematic review” OR “literature review” OR “overview”)

The string was applied across all four databases selected, and the searches were conducted based on titles, abstracts, and keywords in order to maximize the retrieval of pertinent articles.

3.4. Selection of reviews

After the search, we further refined the retrieved papers to ensure their relevance and consistency with our research objectives. This process was facilitated by using the Parsifal tool. Parsifal has been designed with the express purpose of supporting researchers in conducting systematic reviews. It offers a user-friendly platform for the documentation of the entire research process. This tool provides mechanisms that streamline the search and selection process, ensuring a structured and efficient workflow.

During the planning of the research protocol, the following set of inclusion criteria was established for the current task in accordance with the research questions.

Inclusion criteria

- The article is a literature review specifically on inpainting in images.
- The article discusses different inpainting approaches and techniques.

- The article details and discusses the performance evaluation of inpainting techniques.
- The article addresses the evolution and challenges related to inpainting techniques.

Furthermore, the following set of exclusion criteria was established to ensure the quality of this research.

Exclusion criteria:

- The article is a primary study that does not fall into the category of literature reviews: Ensures that only secondary studies, which synthesize existing research, are included.
- The article is not directly related to image inpainting: Maintains the focus on the specific topic of interest.
- The article is not written in English: Ensures accessibility in language for the research team.
- The article is inaccessible: Ensures that only articles that can be fully reviewed are included.

The entire process of selection can be categorized into three stages: *identification*, *screening*, and *eligibility*. During the identification stage, a deep search is conducted across databases. In this stage, a total of 370 articles were initially retrieved based on their titles, abstracts, and keywords. The first filter was applied in this stage to remove 86 duplicates between databases from the initial pool.

The remaining 284 articles have then proceeded to the screening stage, where each article's abstract was evaluated against the predefined inclusion and exclusion criteria to determine its relevance to the research objectives. During this process, 164 articles were rejected for not being directly related to image inpainting, 44 for being primary studies, 6 for not being written in English, 10 for being short papers and 7 for being inaccessible.

Finally, in the eligibility stage, the 53 articles that passed the previous screening were fully reviewed. Out of these, 45 studies were selected as relevant to the scope of this research. These studies were then subjected to further analysis and extraction of relevant data.

This complete selection and refinement procedure is illustrated in Fig. 4, providing a clear overview of each step in the process. Ok

3.5. Extraction of relevant data

A methodical approach was used to extract the necessary data to effectively address this study's research questions. This step involved a thorough review of the 45 previously selected studies using the following standardized form designed to extract relevant information:

- *Year:* Record the publication year to follow the temporal context of the research.
- *Review approach:* Indicate whether the study is a systematic literature review or not, evaluate if the research protocol is clearly described to ensure transparency, and assess if the search and selection strategies are clearly outlined and reproducible.
- *Methods explored:* Describe the approaches discussed and list the specific inpainting techniques analyzed.
- *Metrics analyzed:* List the main metrics applied to inpainting covered by the review.
- *Topic area:* Identify the main application areas for inpainting techniques as highlighted by the article.
- *Main conclusions of the review:* Summarize the key findings and insights derived from the study.
- *Main challenges identified by the review:* Summarize the major gaps, obstacles, and areas for further investigation highlighted by the study.

This standardized form was employed to ensure consistency and comprehensiveness in data extraction, thereby enabling an effective comparative analysis between different studies. Moreover, applying this structured approach ensures that all relevant information is systematically collected, facilitating the synthesis of results.

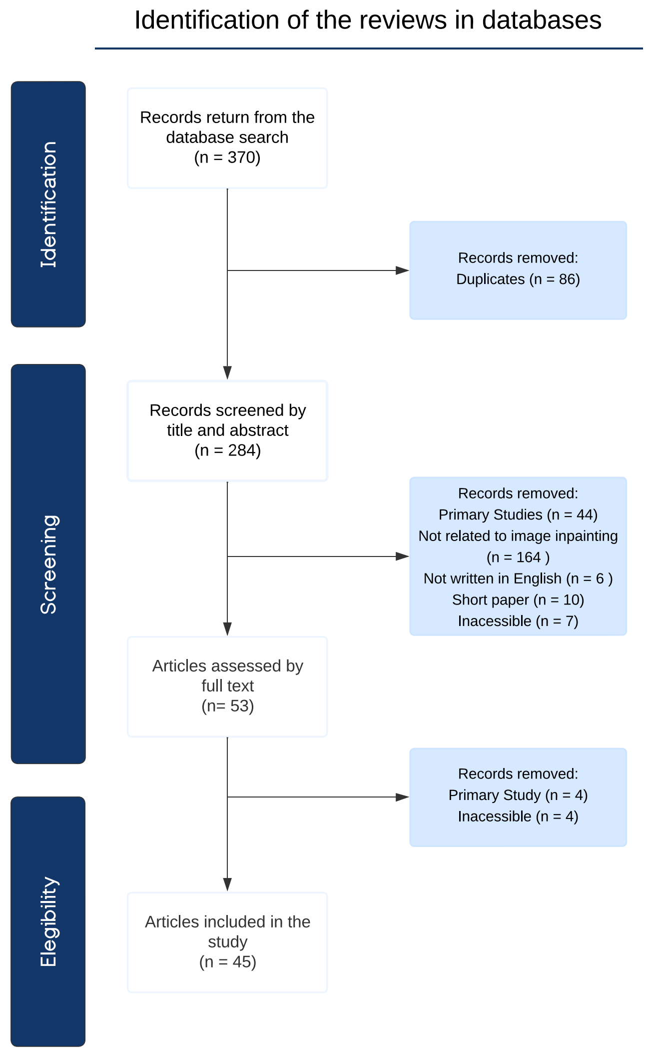

Fig. 4. Diagram of the search process.

3.6. Analysis and synthesis of the results

At this stage, an in-depth analysis of the data collected from the selected reviews was conducted. The objective was to recognize any recurring patterns, significant trends, and pertinent insights that would address the research questions. The results of each review's data extraction and analysis were detailed and organized in tables, providing an overview of the findings. The next section will present these results in further detail.

4. Results and discussions

This section presents a discussion of the results found throughout the research. Initially, the discussion is organized into a descriptive data analysis, followed by an overview of the content surveyed, answering the research questions.

4.1. Descriptive analysis

The selected publication covers a period of 17 years, ranging from 2007 to 2024. Notably, most of these publications, totaling 30 out of 45, were published from 2020 to 2024. This concentration of reviews in the latter period suggests a rapid acceleration in research activity and a growing interest in inpainting techniques. Also, it can probably be associated with the emergence and advancement of deep learning-based techniques. Until 2020, the primary focus of research was on traditional methods. Since then, the attention of the reviews has been shifted towards deep learning-based techniques, reflecting the significant impact of this approach in the field.

Regarding the methodology adopted by the reviews, among the 45 publications, only one outlines a search process strategy. The article authored by Susan and Subashini [23], describes a search strategy, but the methodology adopted does not fully conform to the methodological rigor advocated by Kitchenham [5], once the research protocol is not well-established, making it difficult to reproduce. This observation highlights a potential deficiency in the consistency of the review methodologies employed across the sampled publications. It raises the need for greater attention to methodological rigor within the area.

Overall, the analysis revealed various inpainting categories discussed in the selected reviews. This diversity proved to be a significant challenge during the research. Although some underlying classification patterns were discernible, it is important to note that many of these classifications exhibited considerable variations among them. Besides, the taxonomy associated with these categories also demonstrated a vast heterogeneity. This suggests a lack of consensus or uniform standards in how methods are described, evaluated, and categorized in the reviewed literature. Such variability can lead to difficulties in directly comparing studies and generalizing results.

One main purpose of reviews is gathering and analyzing different techniques within a specific domain, providing a synthesis that facilitates understanding and evaluation for future researchers. A consistent taxonomy and categorization play a crucial role in this context, providing a structured framework for comparing the investigated strategies.

For this reason, as part of our research process, we endeavored to establish a concise classification system with a standardized taxonomy. To achieve this, we conducted a thorough analysis of the reviews, considering the diverse classification systems employed by each review and examining the primary studies cited within each category. The objective was to identify overlaps among these classifications and spot common categories, aiming to effectively group and standardize the mentioned techniques.

As a result, we have presented the classification outlined in Fig. 5. Following our analysis, we can classify these techniques into two main categories: *traditional techniques* and *deep learning-based techniques*. The traditional techniques include diffusion-based, exemplar-based, texture synthesis-based, sparsity-based, and hybrid methods. On the other hand, deep learning-based techniques encompass models based on Convolutional Neural Networks (CNN), Generative Adversarial Networks (GANs), and Transformers Networks.

It seems reasonable to summarize inpainting techniques into traditional and deep learning-based, as this division has already been adopted in various reviews and because it effectively encapsulates different approaches under different underlying principles. Traditional techniques rely on classical image processing and mathematical models, while deep learning-based techniques rely on neural network architectures and machine learning.

In addition, we have compiled Table 2 to indicate where each method is discussed in the reviewed literature, guiding readers to more detailed information sources. Furthermore, Table 3 presents each review's exact taxonomy and categorization, offering a comprehensive overview of how these techniques are classified across the literature. In brief, with this process and these collective resources, we aim to clarify and facilitate the understanding and comparison of different inpainting methods for future research in the field.

Only twelve publications have thoroughly examined the predominant metrics in inpainting, as can be seen in the results of the data extraction process presented in Table 3.

Concerning the application of inpainting techniques, most publications focus their investigations on the general application in digital image restoration. However, numerous studies also delve into diverse fields. For instance, Susan and Subashini [23] concentrated their research on medical applications. At the same time, Yatnalli et al. [39] focused on the inpainting applicability of inpainting to communication engineering, and Basu et al. [58] investigate the usefulness of digital inpainting in cultural heritage restoration. This broad scope underscores the versatility and applicability of inpainting methodologies across various domains, highlighting their relevance beyond traditional image processing contexts.

4.2. Answering the research questions

After a thorough analysis of the reviews compiled and based on the information gathered in the previous stages, we addressed the research questions established at the beginning of this study.

RQ1. What are the main inpainting approaches and techniques discussed in existing reviews?

The analysis of the selected reviews provided a broad overview of inpainting techniques. However, as highlighted in the descriptive analysis, a concern arising from evaluating these studies is the lack of a clear taxonomic and hierarchical standard. This issue can be relevant, as it hinders the organization and understanding of the different approaches presented.

Regarding this, we had to conduct a thorough analysis to identify a way to group and standardize the techniques to address this research question. After the analysis, we basically summarized the techniques mentioned by the reviews in two classes: *traditional techniques* and *deep learning-based techniques*.

Essentially, traditional inpainting techniques are based on iterative algorithms aimed at reproducing structures and textures coherently within the empty spaces of the image. They are robust methods for filling simple images and addressing small regions, such as cracks and small holes, without the need for training on datasets. However, for more complex images, such as those with a lot of texture or large gaps, inpainting becomes more challenging [27,40,59]. The main traditional inpainting methods addressed by the reviews include:

- *Diffusion-based methods:* As the term implies, diffusion-based approaches are grounded in principles of information diffusion to reconstruct missing regions [9,45,47]. These inpainting techniques commonly involve the application of Partial Differential Equations (PDEs) for the diffusion process, which allow for the gradual propagation of information from the surrounding areas into the void [9,49]. In general, these techniques are good for filling small gaps and correcting minor imperfections, but they may struggle with more complex images that have significant texture variations or larger missing regions [45,46,64].
- *Exemplar-based methods:* The exemplar-based models belong to a class of inpainting techniques that adopt an iterative approach that combines structure and texture synthesis [30,36]. These methods search for patches or pixels in the image that resemble those around the damaged region. The patches selected through this process are then replicated within the empty region, gradually completing the image [9,65]. The replication of patches ensures the maintenance of structural and textural coherence in these methods [47]. However, the iterative search and matching process can be computationally expensive; besides, it may struggle to find suitable patches, generating artifacts [9,36].
- *Texture-synthesis-based methods:* These methods employ texture synthesis algorithms to achieve natural appearing inpainted images [59]. To accomplish this, these algorithms analyze the damaged area's texture characteristics and replicate similar patterns to fill the gaps cohesively [14,58]. Overall, these methods are effective for handling complex patterns, but they may fail to synthesize highly structural textures [27,47].

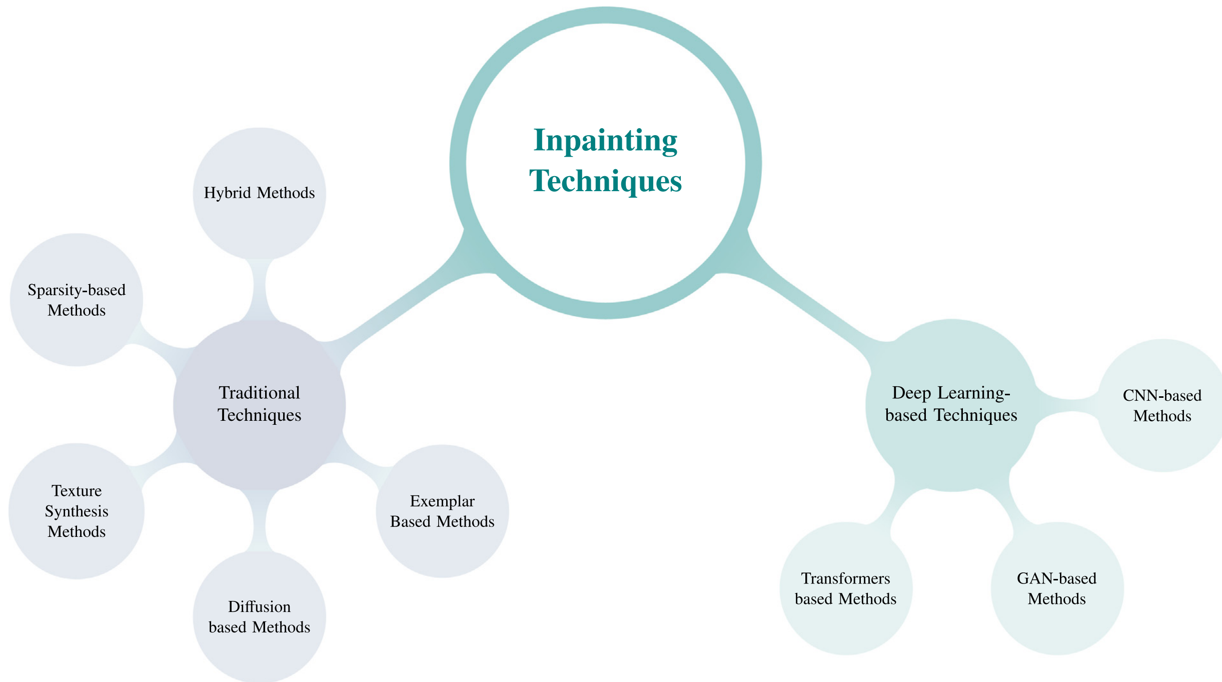

Fig. 5. Inpainting techniques classification.

- *Sparsity-based methods:* Sparse-based inpainting methods aim to leverage the sparse nature of image representations to reconstruct missing areas [47]. Widely employed in signal processing techniques, they are grounded in the notion that many natural signals, including images, can be efficiently represented using a small number of significant components [66]. In inpainting methods, the fundamental concept resides in the mutual sparsity representations shared by both the known and unknown regions of an image [36,47]. As a result, when transform equations are applied to these representations, the damaged areas can be restored [49]. These methods are effective for reconstructing images after compression or transmission, but they rely on the assumption that the data can be represented sparsely [29,47], so any deviation in the image can lead to artifacts.
- *Hybrid methods:* Essentially, hybrid methods often involve integrating traditional inpainting techniques [9]. These methods aim to exploit each approach's strengths to achieve more accurate and visually appealing results [36]. This strategy is generally more effective than others, although it can significantly increase the computational cost [9].

Inpainting techniques based on deep learning present a promising approach that has been widely used lately. These methods harness the power of deep neural networks to learn high-level representations of images, allowing for a deeper understanding of visual content [47,50]. In contrast to conventional techniques, deep learning-based models are trained on extensive image datasets, enabling them to reproduce a wide variety of textures and structures during the inpainting process [40,47]. Based on the techniques addressed by the reviews, this approach can be divided into the following methods:

- *Convolutional Neural Networks-based methods:* Convolutional Neural Networks (CNNs) are a type of architecture composed of multiple convolutional layers that employ filters to extract relevant features from input data through convolutions [14]. CNNs demonstrate an exceptional ability to understand spatial dependencies within images, enabling them to reconstruct missing or damaged areas with coherent visual content effectively. This results from their capacity to capture intricate patterns and semantic information, allowing accurate and contextually relevant inpainting results, even in challenging scenarios [47,49].
- *Generative Adversarial Networks-based methods:* Generative Adversarial Networks (GANs) are a class of unsupervised learning introduced by Goodfellow et al. in 2014 [67]. In brief, this technique was developed to generate high-quality synthetic data by extracting patterns and features from an unlabeled dataset [67,68]. The architecture of a GAN is characterized by two neural networks: the *generator network* and the *discriminator network*. The first produces convincing synthetic data, whereas the second distinguishes the real and fake data. The training of this model is done competitively. While the generator attempts to create realistic fake data to deceive the discriminator, the latter tries to improve its judgment ability [68]. This architecture has been widely used, particularly for solving inpainting problems.
- *Transformer-based methods:* Transformers are recent neural network architectures originally developed for natural language processing. One prominent aspect that sets these networks apart is their innovative structure, which introduces a mechanism called "self-attention". This mechanism enables the model to selectively focus on different parts of a sequential input. Thus, these networks acquire the ability to comprehend dependencies between spatially distant elements. As a result, they outperform traditional neural network models in various tasks that involve complex and extensive sequential data processing [69]. Although initially designed for natural language processing, Transformers networks have quickly become relevant in other fields, including image processing [70,71]. Their ability to learn the context between significantly distant pixels in an image has made them attractive for solving inpainting problems [14,72].

In brief, we can categorize the main inpainting approaches and techniques into traditional and deep learning-based categories. It is important to emphasize that this categorization was carefully constructed based on an extensive analysis of the selected reviews. This concise categorization is intended to facilitate comprehension of the main inpainting techniques present in the literature, given the absence of standardization in their classification systems. For readers seeking

Table 2
Summary of inpainting methods. We use - to indicate when inpainting techniques are not classified clearly.

Study			Method							
			Traditional					Deep learning		
Author	Year	Ref.	Diffusion	Exemplar	Texture synthesis	Sparsity	Hybrid	CNN	GAN	Transformer
Tauber et al.	2007	[24]	✓	✓	✓					
Ravi et al.	2013	[25]	✓	✓	✓	✓	✓			
Guillemot and Le Meur	2014	[9]	✓	✓			✓			
Vreja and Brad	2014	[26]	✓	✓	✓		✓			
Zarif et al.	2015	[27]	✓	✓	✓	✓	✓			
Buyssens et al.	2015	[28]	✓	✓	✓	✓				
Liu and Shu	2015	[29]	✓	✓	✓	✓				
Salman et al.	2015	[30]	✓	✓	✓					
Pushpalwar and Bhandari	2016	[31]	✓		✓		✓			
Narmadha et al.	2017	[32]	–	–	–	–	–	–	–	–
Rasaily and Dutta	2017	[33]	–	–	–	–	–	–	–	–
Ali et al.	2017	[34]	–	–	–	–	–	–	–	–
Lakshmanan and Gomathi	2017	[35]	✓	✓	✓	✓	✓			
Qureshi et al.	2017	[36]	✓	✓		✓	✓			
Ahire and Deshpande	2018	[37]	–	–	–	–	–	–	–	–
Atapour-Abarghouei and Breckon	2018	[38]	–	–	–	–	–	–	–	–
Yatnalli et al.	2020	[39]	✓	✓	✓					
Elharouss et al.	2020	[40]	✓	✓				✓	✓	
Barbu	2020	[41]	✓							
Mehra et al.	2020	[42]	–	–	–	–	–	–	–	–
Kadian and Khadanga	2020	[43]	✓	✓	✓		✓	✓		
Patil and Patil	2020	[44]	✓	✓	✓	✓		✓		
Rojas et al.	2020	[45]	✓	✓				✓	✓	
Al-Jaberi and Hameed	2020	[46]	✓							
Jam et al.	2021	[47]	✓	✓	✓	✓	✓	✓	✓	
Yap et al.	2021	[48]	–	–	–	–	–	–	–	–
Sreelakshmy and Binsu	2021	[49]	✓	✓		✓	✓	✓	✓	
Qin et al.	2021	[50]	✓	✓				✓	✓	
Liu et al.	2022	[51]		✓				✓	✓	
Shylaja and Kumar	2022	[52]	✓	✓		✓	✓	✓	✓	
Shah et al.	2022	[53]	✓	✓	✓	✓		✓	✓	
Sun et al.	2022	[54]	✓		✓				✓	
Dong and Hua	2022	[55]	–	–	–	–	–	–	–	–
Parida et al.	2023	[56]	–	–	–	–	–	–	–	–
Haritha and Prajith	2023	[57]						✓	✓	
Basu et al.	2023	[58]	✓	✓	✓		✓	✓	✓	
Li et al.	2023	[59]	✓	✓	✓			✓	✓	
Susan and Subashini	2023	[23]	✓	✓	✓	✓	✓	✓	✓	
Xiang et al.	2023	[1]						✓	✓	✓
Zhang et al.	2023	[2]						✓	✓	
Shobi and Dhanaseelan	2023	[60]	✓	✓	✓		✓	✓	✓	
Patil and Bendre	2023	[61]	–	–	–	–	–	–	–	–
Xu et al.	2023	[62]						✓	✓	✓
Quan et al.	2024	[63]						✓	✓	✓
Barglazan et al.	2024	[64]	✓	✓					✓	✓

more detailed information about each technique, Table 2 provides an overview of the techniques discussed in the reviews.

RQ2. What are the common challenges and gaps in inpainting research highlighted in these reviews?

Table 4 presents the main conclusions and challenges of inpainting raised by the secondary studies analyzed. It makes it evident that many of these challenges persist over time. For example, one of the main challenges raised by the reviews is the difficulty in dealing with large-scale and complex artifacts within an image. Many traditional inpainting methods struggle to reconstruct regions containing large gaps or highly irregular textures. However, this challenge persists with the advent of deep learning models. This is due to their reliance on local and contextual information, which can result in inaccurate outcomes or visible artifacts around object edges.

Related to this, another significant challenge in inpainting is preserving images' semantic and structural content. Ensuring that the remaining content remains coherent without noticeable distortions is crucial. This task requires a deep understanding of the semantics of the image and the ability to preserve important features, such as textures and objects, without compromising the visual integrity of the scene.

Fig. 6 illustrates these problems. Large gaps pose a significant challenge for inpainting models, as it hinders their ability to comprehend the overall semantic context of the image. With these gaps covering a substantial portion of the image, it is common for the inpainting process to generate artifacts, compromising the quality of the final result.

With the emergence of deep learning-based techniques, significant progress has been made in mitigating this problem. However, these advancements have also raised new concerns or highlighted existing ones. The main issue with these techniques is related to computational cost. These models typically demand considerable computational resources, posing practical constraints for the users.

In addition, these models have notable difficulty when it comes to handling high-resolution images. This presents a significant challenge that needs to be explored and addressed, especially in a context where

Table 3
Summary of the research protocol results.

Study description	Classification system	Analyzed metrics
Tauber et al. (2007) [24] *Review Approach:* Non-systematic *Topic Area:* Digital image inpainting applied to 3D reconstruction	*Structural methods:* - Diffusion - Bounded variation and Total Variation - PDEs - Fluid Flow - High Order PDEs *Textural methods* *Combined Structural and Textural methods*	
Ravi et al. (2013) [25] *Review Approach:* Non-systematic *Topic Area:* Digital image inpainting	*Texture synthesis and block applying methods:* - Pixel synthesis - Texture Synthesis - Multi-Resolution - Multi-scale Pyramids Decomposition - Block Replicating *PDE-based methods* *Exemplar and Search based methods* *Pixel-based methods* - Patch priority using structure sparsity - Structure Sparsity *Hybrid methods*	
Guillemot and Le Meur (2014) [9] *Review Approach:* Non-systematic *Topic Area:* Digital image inpainting	*Diffusion-based methods:* - PDE models - Variational based models *Exemplar-based methods* *Hybrid based methods* *Global methods*	
Vreja and Brad (2014) [26] *Review Approach:* Non-systematic *Topic Area:* Digital image inpainting	*PDE-based methods* *Semiautomatic methods* *Texture synthesis-based methods* *Methods based on templates* *Hybrid methods*	
Buyssens et al. (2014) [28] *Review Approach:* Non-systematic *Topic Area:* Digital image inpainting	*Geometry-based methods* *Sparsity-based methods* *Texture synthesis-based methods* *Exemplar-based methods:* - Greedy approaches - Hybrid approaches - Energy approaches	
Liu and Shu (2015) [29] *Review Approach:* Non-systematic *Topic Area:* Digital image inpainting	*Structure methods:* - PDE methods - Exemplar based methods *Sparse-representation methods* *Texture-based methods*	
Zarif et al. (2015) [27] *Review Approach:* Non-systematic *Topic Area:* Digital image inpainting	*Structure-based methods:* - PDE and Variational-based models - Convolutional-based models - Wavelet-based models *Texture-based methods:* - Statistical-based models - Pixel-based models - Patch-based models *Hybrid methods:* - Decomposition-based models - Exemplar-based models *Multiple source images*	
Salman et al. (2015) [30] *Review Approach:* Non-systematic *Topic Area:* Digital image inpainting	*PDE-based methods* *Texture synthesis-based methods* *Exemplar-based methods*	

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Table 3 (*continued*).

Study description	Classification system	Analyzed metrics
Pushpalwar and Bhandari (2016) [31] *Review Approach:* Non-systematic *Topic Area:* Digital image inpainting applied to 3D reconstruction	*Structural methods* *Texture methods* *Hybrid methods*	
Narmadha et al. (2017) [32] *Review Approach:* Non-systematic *Topic Area:* Digital image inpainting	*The article does not propose a taxonomy.* *It only discusses the main inpainting techniques.*	
Rasaily and Dutta (2017) [33] *Review Approach:* Non-systematic *Topic Area:* Digital image inpainting	*The article does not propose a taxonomy.* *It only discusses the main inpainting techniques.*	
Ali et al. (2017) [34] *Review Approach:* Non-systematic *Topic Area:* Digital image inpainting applied to remote sensing images	*The article does not propose a taxonomy.* *It only discusses the main inpainting techniques* *and their main application to remote sensing images.*	
Qureshi et al. (2017) [36] *Review Approach:* Non-systematic *Topic Area:* Inpainting evaluation metrics	*Exemplar-based methods* *Sparsity-based methods* *PDE methods* *Hybrid methods*	PWIIQ ASVS VisCoM DN GD BorSal StructBorSal
Lakshmanan and Gomathi (2017) [35] *Review Approach:* Non-systematic *Topic Area:* Digital image inpainting applied to remote sensing images	*Exemplar-based methods* *Structure-based methods* *Texture-based methods:* - Statistical - Pixel-based - Patch-based *Diffusion-based methods* - PDE type - Variational type *Wavelet transform-based methods* *Discrete Cosine transform-based methods* *Semi-automatic and fast methods* *Hybrid methods*	
Ahire and Deshpande (2018) [37] *Review Approach:* Non-systematic *Topic Area:* Digital image inpainting applied to 3D reconstruction	*The article does not propose a taxonomy.* *It only discusses about the main inpainting techniques* *used to handle occlusions in-depth images.*	
Atapour-Abarghouei and Breckon (2018) [38] *Review Approach:* Non-systematic *Topic Area:* Digital image inpainting applied to 3D reconstruction	*The article does not propose a taxonomy for inpainting.* *It only proposes a classification system to* *depth image completion strategies.*	
Yatnalli et al. (2020) [39] *Review Approach:* Non-systematic *Topic Area:* Digital image inpainting applied to wireless communication	*PDE methods* *Texture synthesis and Exemplar-based methods*	
Elharouss et al. (2020) [40] *Review Approach:* Non-systematic *Topic Area:* Digital image inpainting	*Sequential-based methods:* - Patch-based models - Diffusion-based models *CNN-based methods* *GAN-based methods*	

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Table 3 (*continued*).

Study description	Classification system	Analyzed metrics
Barbu (2020) [41] *Review Approach:* Non-systematic *Topic Area:* Digital image inpainting	*Nonlinear diffusion-based methods:* - Variational models - Non-variational models *Reaction–diffusion equation-based models* *Fluid dynamics equation-based models* *Curvature-driven diffusion-based models* *Cahn–Hilliard equation-based models*	
Mehra et al. (2020) [42] *Review Approach:* Non-systematic *Topic Area:* Digital image inpainting	*The article does not propose a taxonomy.* *It only discusses the main inpainting techniques.*	MSE PSNR SSIM
Kadian and Khadanga (2020) [43] *Review Approach:* Non-systematic *Topic Area:* Digital image inpainting applied to UAV images	*Diffusion-based methods* *Texture Synthesis and exemplar-based methods* *Hybrid methods* *CNN-based methods*	PWIIQ DN BorSal ASVS GD VisCoM
Patil and Patil (2020) [44] *Review Approach:* Non-systematic *Topic Area:* Digital image inpainting	*Bregman-based methods* *Patch scale-based methods* *Markov random field-based methods* *Wavelet transform-based methods* *PDE-based methods* *TV-based methods* *Gaussian-based methods* *Neural networks-based methods*	
Rojas et al. (2020) [45] *Review Approach:* Non-systematic *Topic Area:* Digital image inpainting	*Traditional methods:* - Diffusion-based techniques - Patch-based techniques - Convolution Filter-based techniques *Deep learning based methods*	PSNR SSIM
Jam et al. (2021) [47] *Review Approach:* Non-systematic *Topic Area:* Digital image inpainting	*Traditional methods:* - Exemplar-based texture-synthesis models - Exemplar-based structure-synthesis models - Diffusion-based models - Sparse Representation models - Hybrid models *Deep learning methods:* - CNN models - GAN models	MAE MSError PSNR SSIM
Yap et al. (2021) [48] *Review Approach:* Non-systematic *Topic Area:* Digital image inpainting applied to facial wrinkles	*The article does not propose a taxonomy for inpainting.* *It only proposes a classification system to* *facial wrinkles completion strategies.*	
Sreelakshmy and Binsu (2021) [49] *Review Approach:* Non-systematic *Topic Area:* Digital image inpainting	*Introspective methods:* - Diffusion-based models - Exemplar-based models - Sparsity-based models - Hybrid models *Extrospective methods:* - Search-based models - Learning-based models - User-guided inpainting models	MAE MSE PSNR SSIM TV IS FID

(*continued on next page*)

the quality of produced images has been consistently improving, and the popularity of image editing has been on the rise.

Furthermore, there are also significant gaps in the evaluation and performance metrics of inpainting. Measuring the quality and effectiveness of inpainting methods objectively and accurately is fundamental to advancing research in this area. However, the absence of standardized metrics and evaluation benchmarks can make comparing different approaches and identifying superior methods difficult.

RQ3. How do these reviews address performance evaluation of inpainting techniques?

Performance evaluations in the field of inpainting play a crucial role in objectively assessing and comparing different techniques and algorithms. To carry out these evaluations, various metrics are used to measure the quality and effectiveness of inpainting methods. Although not all of the selected reviews included a metric survey (only 12 out of 45), those that did explore a range of metrics, such as:

Table 3 (*continued*).

Study description	Classification system	Analyzed metrics
Qin et al. (2021) [50] *Review Approach:* Non-systematic *Topic Area:* Digital image inpainting	*Traditional methods:* - Diffusion based methods - Patch-based methods *Deep learning-based methods (Single stage):* - Single result models - Pluralistic result models *Deep learning-based methods (Progressive):* - Low-resolution models - High-resolution models *Prior Knowledge-based methods:* - Contour edge guided models - Generative prior guided models	
Al-Jaberi and Hameed (2021) [46] *Review Approach:* Non-systematic *Topic Area:* Digital image inpainting	*Variational methods:* - Total Variational model - Fourth order Total variation model - Curvature of driven diffusion model - Mumford–Shah model - Euler-Elastica and Curvature-Based - Mumford–Shah–Euler Model - Modified Cahn–Hilliard Model *PDE methods:* - Isotropic Diffusion - Harmonic Extension Model - Navier–Stokes Equation - Transport Method	
Shylaja and Kumar (2022) [52] *Review Approach:* Non-systematic *Topic Area:* Digital image inpainting	*Traditional methods:* - Exemplar-based texture synthesis - Exemplar-based structure synthesis - Diffusion-based methods - Sparse representation methods - Hybrid methods *Deep Learning methods:* - CNN based models - GAN models	
Liu et al. (2022) [51] *Review Approach:* Non-systematic *Topic Area:* Digital image inpainting applied to forensic technology	*Image synthesis methods* *Deep learning methods:* - CNN-based models - Structure-based GAN models - Loss function-based GAN models	
Shah et al. (2022) [53] *Review Approach:* Non-systematic *Topic Area:* Digital image inpainting	*Traditional methods* *Deep learning methods*	PSNR SSIM
Sun et al. (2022) [54] *Review Approach:* Non-systematic *Topic Area:* Digital image inpainting	*Conventional methods:* - Texture-based methods - Diffusion-based methods *Deep learning methods*	MAE PSNR SSIM
Dong and Hua (2022) [55] *Review Approach:* Non-systematic *Topic Area:* Digital image inpainting	*The article does not propose a taxonomy.* *It only discusses the main inpainting techniques.*	
Parida et al. (2023) [56] *Review Approach:* Non-systematic *Topic Area:* Digital image inpainting	*The article does not propose a taxonomy.* *It only discusses the main inpainting techniques.*	

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- *Mean Absolute Error (MAE):* MAE is a common metric used to quantify the mean absolute discrepancy between the intensity values of pixels in the inpainted regions and the corresponding values in the original regions of the image [42,47].
- *Mean Squared Error (MSE):* This metric is calculated by averaging the squared differences between the values of the real pixels and the values of the inpainted pixels in all reconstructed regions [47]. The lower the MSE value, the more similar the

Table 3 (*continued*).

Study description	Classification system	Analyzed metrics
Basu et al. (2023) [58] *Review Approach:* Non-systematic *Topic Area:* Digital image inpainting applied to cultural heritage artifacts reconstruction	*Traditional methods:* - Diffusion-based models - Texture synthesis-based models - Exemplar-based models - Hybrid models *Deep learning methods:* - CNN-based models - GAN-based models	
Li et al. (2023) [59] *Review Approach:* Non-systematic *Topic Area:* Digital image inpainting	*Traditional methods:* - Structure-based models - Texture synthesis-based models *Deep learning methods:* - Single-stage models - Multi-stage models - Priori condition-guided models	PSNR SSIM LPIPS
Susan and Subashini (2023) [23] *Review Approach:* Non-systematic. Only presents a search strategy *Topic Area:* Digital image inpainting applied to medical images	*Traditional methods (CNN-based):* - Patch-based texture - Exemplar-based Structure Synthesis - Diffusion Based Method - Sparse Representation - Hybrid Method *Supervised methods (CNN-based):* - Partial CNN models - Bilateral CNN models - Gated CNN models - U-net CNN models - Dilated CNN models *Unsupervised (GAN-based) methods:* - Simple GAN models - Patch GAN models - Nested GAN models	
Xiang et al. (2023) [1] *Review Approach:* Non-systematic *Topic Area:* Digital image inpainting	*Progressive methods:* - Coarse-to-fine models - Part-to-full models - Low-to-high-resolution models - Structure-to-content models - Mask-to-image models *Structural information guided methods:* - Edge guided models - Segmentation guided models - Landmark guided models - Voxel guided models - Gradient guided models *Attention-based methods:* - Contextual attention-based models - Attention transfer-based models - Cross attention-based models - Patch swap-based models - Transformer-based models *Convolution aware-based methods:* - Partial convolution models - Gated convolution models - Bidirectional convolution models - Region-wise convolution models *Pluralistic methods:* - GAN-based models - Variational-based models - Transformer-based models *Autoencoder network-based methods:* - CNN-based models - FCN-based models - U-net-based models *Variational Autoencoder network-based methods* *GAN-inversion network-based methods*	MSE PSNR SSIM LPIPS IS FID

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Table 3 (*continued*).

Study description	Classification system	Analyzed metrics
Zhang et al. (2023) [2] *Review Approach:* Non-systematic *Topic Area:* Digital image inpainting	*CNN-based methods:* - U-net-based models - FCN-based models *GAN-based methods:* - Context-encoder models - Conditional GAN models - Deep convolutional GAN models - Wasserstein GAN models - Patch-based GAN models	
Haritha and Prajith (2023) [57] *Review Approach:* Non-systematic *Topic Area:* Digital image inpainting	*CNN-based methods:* - Encoder-Decoder model - Fully Convolutional Network - U-net *GAN-based methods*	
Shobi and Dhanaseelan (2023) [60] *Review Approach:* Non-systematic *Topic Area:* Digital image inpainting	*Traditional methods:* - Image restoration techniques - Texture synthesis-based techniques - Hybrid exemplar-based techniques - Patch priority-based techniques - Exemplar-based techniques - Modified Exemplar-based techniques - Wavelet transform-based techniques - Semi-automatic and fast techniques *Deep Learning-based methods*	
Patil and Bendre (2023) [61] *Review Approach:* Non-systematic *Topic Area:* Digital image inpainting	*The article does not propose a taxonomy.* *It only discusses the main inpainting techniques.*	
Xu et al. (2023) [62] *Review Approach:* Non-systematic *Topic Area:* Digital image inpainting	*Classification according to component optimization:* - Convolution method - Dilated Convolution - Partial Convolution - Gated Convolution - Attention Mechanism *Classification according to network structure:* - Multi-stage network - Single-stage network - Diffusion Models *Classification according to training method:* - Different Masking techniques - Diverse inpainting	FID MSError PSNR SSIM
Quan et al. (2024) [63] *Review Approach:* Non-systematic *Topic Area:* Digital image inpainting	*Deterministic image inpainting methods (Single-stage):* - Mask-aware design - Attention Mechanism - Multi-scale aggregation - Transform domain - Encoder–decoder connection - Deep prior guidance *Deterministic image inpainting methods (Two-stage):* - Coarse-to-fine methods - Structure-then-texture methods *Progressive methods* *Stochastic methods:* - Variational autoencoder methods - GAN-based methods - Flow-based methods - MLM-based methods - Diffusion-based methods	MAE MSError PSNR SSIM MS-SSIM FID LPIPS P/U-IDS
Barglazan et al. (2024) [63] *Review Approach:* Non-systematic *Topic Area:* Digital image inpainting applied to forensic technology	*Diffusion-based or PDE-based methods* *Exemplar-based or Patch-based methods* *Progressive methods* *Machine Learning-based methods:* - GAN-based models - Transformers models - Diffusion-based models	

Table 4
Main conclusions and challenges in image inpainting research.

Study reference	Main conclusions	Main challenges
Tauber et al. (2007) [24]	- The integration of digital inpainting with image-based rendering techniques has the potential to significantly enhance the quality of generated images. Although, there are no current methods that effectively integrate inpainting functionality with the extraction of depth surfaces in 3D images	
Ravi et l. (2013) [25]	- Diffusion-based methods are more effective for small areas - Texture synthesis methods are more suitable for large areas, but may cause distortions at the edges - Exemplar-based methods are good for propagating linear structures and textures, but it struggles with curved structures - Hybrid methods are only effective on structurally and texturally simple images	- Size of image gaps - Handle with complex texture and structures - High computational cost
Guillemot and Le Meur (2014) [9]	- Diffusion-based models effectively complete straight lines, curves, and small regions but struggle with large areas - Exemplar-based models are better at filling large texture areas but present a high computational cost - The assessment of restored image quality is subjective due to the absence of quantitative metrics and a ground truth	- Size of image gaps - Computational costs
Vreja and Brad (2014) [26]	- PDE-based methods fail to reconstruct textures - Texture synthesis methods are efficient but struggle with highly structured textures	- Reconstruct complex textures - High time cost - Requires complex formulation
Zarif et al. (2015) [27]	- Exemplar-based methods successful in handling large damaged regions by combining structure and texture information - Common drawbacks include blurred results from diffusion processes, difficulty in recovering fine details, and limitations in handling large regions	- Depth ambiguity - Reconstruct complex structures - High time cost - Lack of quality assessments
Buyssens et al. (2015) [28]	- Regarding the focus of the article on Exemplar-based methods, the author highlights that no algorithm is superior, it all face the same issues - The filling process in Exemplar-based methods follows a priority order, and any changes to this order or patch size cause significant differences - Hybrid techniques are interesting but separating structure and texture remains a challenge - The authors propose three improvements: Use tensors with structural information to select the best candidate pixels for filling; enhance the patch search method; and improve patch blending to avoid artifacts	- Reconstruct complex structures - High time cost
Liu and Shu (2015) [29]	- PDE methods exhibit better structure continuity across the void - Exemplar-based methods may introduce artifacts due to patch similarity search across the image - The authors emphasizes that the choice of algorithm heavily depends on the application context, and suggests that optimal results can be achieved by combining variational and exemplar-based methods	- Size of image gaps - High computational cost - Reliance on information available in the rest of the image
Salman et al. (2015) [30]	- Exemplar-based methods are effective for filling images regarding both structures and textures. However, any error in the beginning can propagate through the iterative process - The key in Exemplar-based methods relies in the selection process and filling order of the best patches - The authors recommend as future work the reduce of processing time by adjusting the algorithm's search space, and combine gradient-based and non-gradient-based exemplar techniques	- High time cost - Common propagation of artifacts
Pushpalwar and Bhandari (2016) [31]	- Structural inpainting techniques are complex but good at preserving structures - Texture-based techniques can handle large areas but fail to preserve structures - Hybrid methods overcome these limitations but are complex and costly - There are no suitable method for filling large areas in depth maps and significant progress in the area is still needed	- High time cost - Handle with complex texture and structures
Narmadha et al. (2017) [32]	- Overall, inpainting techniques can provide restored images in good quality restoration at the cost of time and computational resources - Mostly of the techniques are effective for small gaps but struggle with large missing areas	- High computational cost - Size of image gaps - Handle with complex texture and structures
Ali et al. (2017) [34]	- Exemplar-based techniques are effective for small gaps and simple backgrounds, otherwise the quality results decreases and processing time increases - Modified Exemplar-based techniques, in turn, perform well in both cases with lower processing time	- High time cost - Size of image gaps
Qureshi et al. (2017) [36]	- Need for new metrics as current ones rely on original images, which may not always be available or suitable	- Size of image gaps - Lack of standardized datasets specifically designed for inpainting
Lakshmanan and Gomathi (2017) [35]	- Non-local inpainting techniques are the most suitable for satellite image restoration but often yield unsatisfactory results - Current inpainting algorithms are more suitable for natural images. However there is a need exists for an efficient method to handle satellite image	- Size of image gaps - High time cost

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Table 4 (*continued*).

Study reference	Main conclusions	Main challenges
Ahire and Deshpand (2018) [37]	- Inpainting and rendering techniques integration, is still at an early stage, especially for filling disocclusions	- Handle with complex texture and structures - High time cost
Atapour-Abarghouei and breckon (2018) [38]	- The selection of an appropriate technique depends on a number of factors, including the desired output quality, the input requirements, the algorithmic complexity, the processing speed, and the specific user needs	- High computational cost
Yatnalli et al. (2020) [39]	- Inpainting techniques can assist in image compression by enabling more compact representations and reducing the amount of information required for transmission or storage	- Size of image gaps - Reconstruct complex textures
Elharouss et al. (2020) [40]	- Deep learning methods are slow to train and require high-performance machines, although they have shown promising results - There is no single technique capable of addressing all types of image distortion. Each type of damage requires a specific treatment technique	- Size and complexity of image gaps - Lack of standardized dataset - High computational cost
Barbu (2020) [41]	- Nonlinear diffusion-based models offer a faster and more effective solution for inpainting, despite potential limitations with complex image structures	- High time cost - Reconstruct complex textures and structures
Mehra et al. (2020) [42]	- The combination of structural and textural image inpainting techniques produces better results, but it increases the complexity - The current focus of inpainting is on developing new techniques for high-resolution images that are more efficient and have reduced computational costs	- High computational cost - Reconstruct complex textures and structures
Kadian and Khadanga (2020) [43]	- Most methods are effective for small areas, but they struggle to handle large disappearing areas and curved sequences - Subjective assessment methods are the most accurate for evaluating image inpainting. However, they are laborious, time-consuming, and require a large number of observers	- Size of image gaps - Handle with noises
Patil and Patil (2020) [44]	- Further development is needed to effectively inpaint larger regions while preserving image quality	- Preserve image quality - Reconstruct complex textures and structures
Rojas et al. (2020) [45]	- None of the traditional techniques are able to generate new objects or produce semantically consistent results - Diffusion-based techniques are effective for small missing areas but cause blurs and increase processing time for larger areas - Patch-based techniques perform better in large missing regions but rely on low-level features and cannot generate new objects or complex structures - Deep learning techniques address many issues by providing deeper semantic understanding and the ability to generate new objects, maintaining local and global consistence. However, efforts are needed to reduce training time and computational resources	- High computational cost - Necessity of post-processing - Size and complexity of image gaps
Jam et al. (2021) [47]	- Traditional methods are effective in numerous cases but struggle to capture high-level semantics and maintain globally consistent structures, particularly in complex mask regions like faces or objects with non-repetitive structures - Although deep learning techniques have shown promising results in inpainting, they often demand high computational resources and may still face challenges in achieving high-quality final images	- Size of image gaps - High computational cost - Lack of standardized evaluation system and dataset - Reproducibility of the models
Yap et al. (2021) [48]	- While deep learning methods for image inpainting have rapidly improved, they currently lack dedicated applications for facial wrinkle inpainting	- High computational cost - Unrealistic results
Sreelakshmy and Binsu (2021) [49]	- Improved evaluation metrics are essential as current ones often fail to detect artifacts in the inpainted image - Efforts to establish standardized evaluation metrics and datasets for inpainting techniques are necessary	- Lack of adequate metrics - Lack of standardized datasets and metrics
Qin et al. (2021) [50]	- CNN-based methods are widely used for inpainting, although some models attempt to improve by combining other techniques - Incorporating prior knowledge into the framework enhances inference, especially in scenarios with complex structures and textures	- Size of image gaps - Handle with high-resolution images - Reconstruct complex textures - Training stability
Al-jaberi and Hameed (2021) [46]	- All PDE-based methods encounter challenges in recovering large, highly textured damaged areas - The authors propose the use of PDE methods using nonlinear diffusion to recover destroyed regions while preserving discontinuities, combined with extended wavelet transform to enhance edges	- Size of image gap - High time cost - Handle with complex texture
Liu et al. (2022) [51]	- Image synthesis methods offer quick and stable results with few images but struggle to extract high-level features - Deep learning methods can extract high-level image features, achieving higher quality. However, they require a large amount of data and have a high computational cost	- Preserve image quality - High computational cost - Training stability
Shylaja and Kumar (2022) [52]	- Deep learning methods excel in quality and speed, surpassing traditional methods - The authors suggests further efforts in extreme image inpainting and the development of simpler, and more efficient techniques	- Handle with complex textures - Size and complexity of image gaps - Handle with high-resolution images

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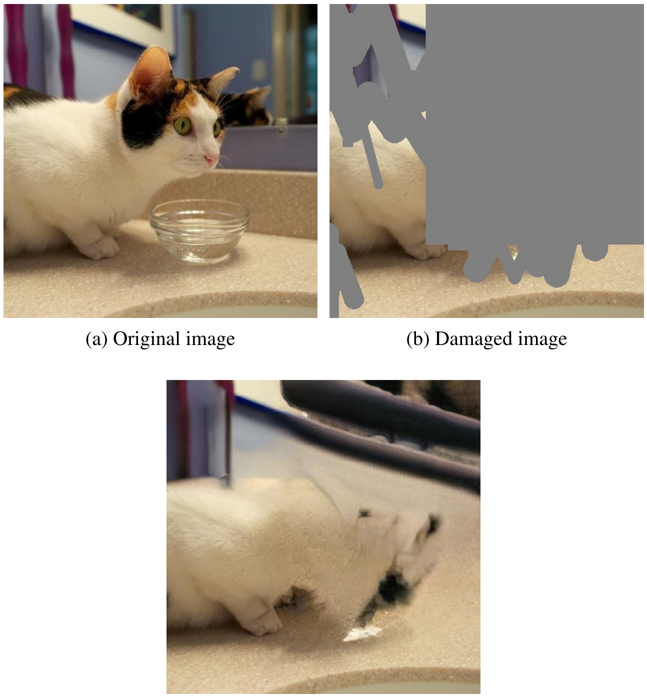
Table 4 (*continued*).

Study reference	Main conclusions	Main challenges
Shah et al. (2022) [53]	- Traditional methods are effective for small gaps but unable to generate information that is not present in the rest of the image, leading to inconsistencies - Deep learning-based models can address this issue but require large amounts of data and time - Further improvements are needed especially in result accuracy and training time	- High computational cost - Size and complexity of image gaps
Sun et al. (2022) [54]	- GAN-based models exhibit higher quality and performance compared to CNN-based models - The authors have indicated that the capture of important information across the image remains a primary focus for improvement, and that the construction of an end-to-end inpainting model is necessary	- Limited capacity of learn important features and context - Handle with complex texture and structures
Dong and Hua (2022) [55]	- Changes in convolutions operations and network structure can contribute to generating high-resolution images - Considering contextual information can make inpainting more coherent - GANs-based methods are not perfect to solve the inpainting problem	- Limited capacity of learn important features and context - Handle with complex texture and structures
Parida et al. (2023) [56]	- Further analysis has shown that working in a low-dimensional latent space yields better performance - Despite advancements, inpainting remains a complex problem, as all techniques still have limitations	- High computational cost - Generalization problems - Handle with complex texture and structures
Basu et al. (2023) [58]	- Inpainting techniques have great importance in the reconstruction and restoration of heritage buildings - It is necessary to develop efficient techniques, especially for the restoration of cultural heritage	- Requirement of large datasets for training - High computational cost
Li et al. (2023) [59]	- Integrating prior knowledge with deep learning frameworks can significantly improve inpainting performance	- Handle with high-resolution images - Reconstruct complex textures and structures - High computational cost
Susan and Subashini (2023) [23]	- It is necessary to develop inpainting methods that can achieve high-quality results with smaller datasets and shorter training processes - Although inpainting methods can be useful in removing artifacts from medical images, there are few methods specifically designed for this purpose	- Necessity of post-processing - High computational cost
Xiang et al. (2023) [1]	- Current inpainting methods are more efficient on simple, low-resolution images with small voids - It is necessary to explore the development of learning techniques capable of training on small datasets - It is necessary to establish protocols for evaluating and to compare fairly across different inpainting models	- Size of image gaps - High computational cost - Lack of standardized datasets and metrics - Reproducibility of the models
Zhang et al. (2023) [2]	- Traditional evaluation metrics such as PSNR and SSIM may not fully reflect the quality of generated images, while human perception significantly influences the assessment. - New techniques should focus on investing in two-stage networks, multi-scale attention mechanisms, and iterative filling processes to enhance restoration quality	- Handle with high-resolution images - Reconstruct complex textures and structures - High computational cost - Lack of precise evaluation metrics
Haritha and Prajith (2023) [57]	- CNN-based methods are effective but have high processing times even for small regions and are ineffective for larger areas - GAN-based techniques yield better results but struggle with generalization and have limitations such as preserving semantic contexts of the image - The authors highlights the need for developing deep learning methodologies capable of handling images with multiple voids and varying sizes while maintaining semantic and textural content	- Limited capacity of learn important features and context - High computational cost - Size and complexity of image gaps
Shobi and Dhanaseelan (2023) [60]	- Despite their development and generally good results, inpainting methods still have limitations - There is a need for development of algorithms that are more efficient, with reduced processing time, and capable of generating high-quality and precise images	- Handle with high-resolution images - High computational cost
Patil and Bendre (2023) [61]	- The authors propose that the implementation of a hybrid model, combining filtering techniques and inpainting techniques is a way to solve the problems related to both cases	
Xu et al. (2023) [62]	- The authors propose that future research should focus on developing lighter models with adaptive learning, incorporating multimodal fusion techniques, and addressing the challenges on handling high-resolution and extensively damaged images	- Preserve image quality - High computational cost - Size of image gaps
Quan et al. (2024) [63]	- Among the deep learning techniques, diffusion models show the highest potential, despite long inference times - In current models, the image filling process is uncontrolled. A promising research direction is developing models that allow user guidance on content filling within images	- Reproduction of artefacts - Generalization problems - Size and Complexity of image gaps - High computational cost
Barglazan et al. (2024) [64]	- Inpainting advancements pose a significant challenge for forgery detection technologies - The main challenges in forgery detection algorithms include the size of filled areas (smaller areas are more challenging to identify), visual similarity with the rest of the image, high computational cost, and presence of false positives	- Lack of datasets specially for forgery detection



(a) Original image (b) Damaged image

(c) Inpainted result

Fig. 6. Inpainted image revealing the challenge posed by large gaps in the image. *Source:* [14].

pixel intensities are between the reconstructed and original regions [47].

- *Peak Signal-to-Noise Ratio (PSNR):* It is a widely used metric for evaluating the quality of inpainting [49]. It quantifies the relationship between the maximum signal intensity in an image and the noise introduced during the reconstruction process [47]. The higher the PSNR value, the lower the noise level in the reconstructed image compared to the original signal, indicating better reconstruction quality.
- *Structural Similarity Index (SSIM):* It measures the structural similarity between the reconstructed and original images. It considers three main factors: *luminance*, *contrast*, and *structural similarity*, which, once combined, generate a local structural index [47,59]. The closer the SSIM value is to 1, the greater the structural similarity between the images, indicating a more accurate and faithful reconstruction.
- *Multi-Scale Structural Similarity Index (MS-SSIM):* It is an extension of SSIM that measures similarity at multiple scales, capturing structural and luminance features at different scales [63].
- *Perceptual Weighted Image Inpainting Quality (PWIIQ):* Evaluation metric that incorporates perceptual aspects when analyzing image reconstruction quality. It considers human visual sensitivity to different types of distortions, such as texture loss, edge discontinuities, or color discrepancies, and assigns corresponding perceptual weights to these distortions [36].
- *Fréchet Inception Distance (FID):* It is based on a technique that uses the Fréchet distance, a measure of dissimilarity between two distributions of points in a feature space, commonly applied to features extracted from a pre-trained convolutional neural network [49]. A lower FID score indicates greater similarity between the feature distributions of the real and generated images, suggesting a more realistic reconstruction in the context of inpainting.
- *Total Variation (TV):* Quantifies the amount of change or detail present in an image, calculated as the sum of absolute differences between neighboring pixels [49]. Minimizing total variation during the inpainting process aims to preserve important structures and edges in the image while reducing noise and unwanted artifacts. Therefore, TV is employed as a penalty term in the loss function during the optimization of the inpainting model, ensuring that the resulting reconstruction is smooth and aesthetically pleasing without compromising the structural fidelity of the original image [49].
- *Inception Score (IS):* Based on the classification of images by a pre-trained convolutional neural network, IS aims to quantify the confidence and coherence of class predictions on inpainted images, as well as the diversity of the generated images [1]. Higher IS scores indicate that the generated images have higher class quality and greater diversity [1,49].
- *Learned Perceptual Image Patch Similarity (LPIPS):* This metric assesses the perceptual similarity between two images using deep features extracted by a trained convolutional neural network [1]. Lower LPIPS scores indicate greater perceptual similarity between the images, suggesting a more accurate reconstruction [59].
- *Paired/unpaired inception discriminative score (P/U-IDS):* The metric uses a pre-trained Inception Network to compute the distance between the feature distributions of the original images and the generated images [63].
- *Average Squared Visual Salience (ASVS):* calculates the average of squared visual saliency values in the restored areas [36]. Visual saliency refers to a region's ability to attract the observer's visual attention. Therefore, the higher the ASVS value, the greater the visual saliency of the filled regions, potentially indicating areas that are reconstructed in a more visually prominent manner [36].
- *Visual Coherence Metric (VisCoM):* Quantifies the structural similarity between the filled regions and their surroundings, considering aspects such as texture, color, and pixel patterns [36]. Therefore, the higher the value of VisCoM, the greater the visual coherence of the filled regions, indicating a more harmonious and integrated reconstruction with the original image.
- *Degree of Noticeability (DN):* A metric that assesses how noticeable the filled regions are in a reconstructed image compared to the undamaged areas [36]. It quantifies the difference between visual characteristics such as texture, color, and contrast in the filled and original regions [36]. A higher DN value indicates more noticeable restored areas, suggesting potential visual artifacts or visible discrepancies.
- *Gaze Density (GD):* Based on the analysis of human eye movements while viewing reconstructed images, GD allows the identification of areas that attract more visual attention, considering the remarkable sensitivity of the human gaze to perceive distortions and inconsistencies in the image [36]. Therefore, filled images with distortions attract more attention than images without artifacts [36].
- *Border Saliency-based measure (BorSal):* It analyzes the difference in the saliency map between the original and restored pixels at the edge of the damaged area [36,43]. Typically, higher preservation of edge saliency indicates a more precise reconstruction of the original image's structural characteristics, while a decrease in edge saliency may indicate visible artifacts or distortions in the restored regions.
- *Structural Border Saliency-based measure (StructBorSal):* Same approach as BorSal, but by analyzing the preservation of structure with the saliency maps, StructBorSal provides a more comprehensive assessment of the structural fidelity of the restoration [36].

Table 3 presents the results of the research extraction data process, including the metrics covered by each review, offering a reference for readers interested in exploring these metrics.

PSNR and its variation, the SSIM, are the most commonly reported metrics in the reviews. Additionally, MSE and RMSE have also been frequently reported in the literature. While these metrics are widely used in image processing and provide a quantitative measure of the fidelity of the reconstructed image compared to the original, they may not fully capture human visual perception [36].

To overcome this limitation, some performance evaluations include perceptual evaluations, where humans assess the inpainting results. This can be done through subjective evaluation studies, in which participants are asked to rate the quality of the reconstructed images based on criteria such as realism, naturalness, and visual integrity. The high visual acuity humans exhibit in recognizing distortions or inconsistencies in the image highlights their ability to evaluate inpainting results. Therefore, it is the most effective tool for producing coherent and visually pleasant results where any form of alteration is imperceptible. However, this type of evaluation may be time-consuming and must be done under controlled conditions to eliminate subjectivity [36,43].

Among the reviews analyzed, the article authored by Qureshi et al. [36] offers a detailed and comprehensive analysis focused exclusively on the evaluation of metrics used for inpainting. In this review, the authors conduct a performance evaluation, investigating the consistency of various metrics compared to human visual perception. Among the techniques evaluated, ASVS and DN showed the least correlation with human perception, while GDin, BorSal, StructBorSal, and VisCOM demonstrated better correlation, indicating their potential for evaluating inpainting techniques [36].

Furthermore, the authors do not include PSNR and MSE in their evaluation, stating that these metrics rarely correlate with human perception [36]. This is mostly because PSNR and MSE are heavily influenced by small pixel intensity changes and do not account for structural information, which is crucial for human visual assessment.

Another problem highlighted in the reviews is the reliance of most metrics on the original image for comparison, once inpainting is frequently employed when the original image is either corrupted or unavailable [36,62]. Besides, the performance of the metrics is significantly related to the inpainting model and the type of damage present in the image, exhibiting better performance in the case of small damage regions [36].

In summary, despite the widespread use of these metrics, evaluating inpainting performance remains a complex challenge due to the subjective nature of visual perception. Besides, no automated metrics can exactly match the precision of human analysis, which is the main objective of their use. Therefore, a holistic approach that combines objective metrics and perceptual evaluations is often employed to comprehensively understand the performance of inpainting methods in various contexts and applications.

RQ4. What are the practical applications of inpainting techniques discussed in these reviews?

Initially focused on light retouching, such as correcting scratches and removing unwanted text, inpainting techniques were mainly used to restore old photographs and to correct small defects in digital images. With the growing demand for editing software that offers more advanced functionalities, inpainting techniques have evolved to the extent that they permit the removal of entire objects from an image and the automatic filling of the removed areas with content visually consistent with the rest of the image scene.

The reviews indicate that the most frequently covered applications are those related to digital image restoration and retouching. Nevertheless, as these techniques evolve, inpainting has become a valuable tool not only for the common users but also for professionals interested in:

Medical Images: In medicine, inpainting can fill in missing or damaged areas on diagnostic images such as Computed Tomography (CT) or Magnetic Resonance Imaging (MRI) scans [23]. For instance, it can be used to remove specular reflections in cervical cancer images or even facilitate the 3D reconstruction of brain MRIs [2,23]. Applying inpainting techniques can allow for more accurate and detailed analysis by medical professionals, leading to more reliable diagnoses. Among the selected articles, Susan and Subashini's [23] review focuses on the application of deep learning-based inpainting models to medical images, providing a comprehensive overview of the main advantages and disadvantages of these methods in the medical field. Moreover, Zhang et al. [2] briefly summarize inpainting applications in medicine and present some models developed for these purposes.

Forensic Technology: In the forensic context, inpainting can be used to restore crucial information in damaged or low-quality surveillance footage, helping to investigate crimes and identify evidence [62]. However, there are significant concerns about the potential misuse of these techniques. As the advances in inpainting technologies produce convincingly real images, they can ease the forgery of documents and images, making it difficult to distinguish between authentic and fake. Therefore, the forensic field is constantly evolving, developing methods for detecting forgeries that keep pace with the advances of inpainting techniques [51,64]. Regarding the reviews analyzed, Barglazan et al. [64] and Liu et al. [51] present an extensive and comprehensive overview of the main inpainting techniques and the inpainting forgery detection mechanisms designed in the forensic field.

Conservation and Restoration of Art and Cultural Heritage: The term "inpainting" originated from the manual artistic reconstruction techniques commonly employed by museums to repair damaged paintings [7]. With the introduction of digital inpainting techniques, new possibilities in this field have opened up, allowing the seamless reconstruction of damages on artworks by predicting an appearance similar to the original. This is very helpful, mainly in situations where the manual restoration could compromise the integrity of the artwork [58]. In addition to paintings, digital inpainting is employed to restore old photographs, historical documents, and deteriorated films, eliminating stains and scratches and reconstructing texts to restore clarity and original details [56]. In this manner, inpainting techniques can significantly contribute to preserving and conserving historical and cultural heritage. In their article, Basu et al. [58] explore different digital restoration methods that can be applied to preserve cultural heritage, including inpainting techniques. Additionally, Xu et al. [62] and Xiang et al. [1] provide a brief explanation of the main problems in this field and discuss some inpainting techniques designed to address them.

Three-Dimensional and Depth Map Reconstruction: With the increasing use of 3d sensing systems, techniques of 3D reconstruction and depth map generation have found diverse applications, such as in the construction of autonomous vehicles or in the development of virtual and augmented reality environments. Inpainting techniques can be applied to generate more precise 3D images by filling gaps that are commonly caused by incomplete scans and occlusions produced during the data acquisition [24,31]. Among the reviews selected, Atapour-Abarghouei and Breckon [38] provide a comprehensive review of scene depth completion techniques, including inpainting methods. Furthermore, Tauber et al. [24] propose a review focused on disocclusion in image-based rendering using inpainting techniques, while Ahire and Deshpande [37] offer a review of inpainting techniques applicable to depth image-based rendering. Pushpalwar and Bhandari [31] present a review of inpainting techniques for 2D images and depth maps. Additionally, Mehra et al. [42], Guillemot and Le Meur [9] and Zhang et al. [2] provide a brief overview of the issues related to disocclusion in 3D images and the application of inpainting algorithms.

Remote Sensing: In remote sensing, inpainting can correct flaws in satellite images caused by sensor failures, clouds, shadows, or other factors that obstruct the view of the Earth's surface [1,2]. This process improves data quality and enhances the accuracy and usefulness of satellite images across various applications. For instance, in environmental monitoring, inpainting helps recover areas obscured by clouds or acquisition errors, facilitating continuous analysis of land use changes and environmental phenomena [35]. In this scenario, Lakshmanan and Gomathi [35] and Ali [34] provide surveys and evaluations of different inpainting techniques applicable to remote sensing images. Kadian and Khadanga [43] review the main inpainting techniques and their applicability to UAV images. At the same time, Xu [62], Xiang [1], and Zhang [2] provide a short introduction to the primary issues in remote sensing images and the main techniques to deal with them.

Data Loss Recovery: With the increasing popularity of streaming services and the rising volume of data transmitted over networks, data packet loss has become a common issue. During image compression and transmission, this issue results in corrupted images, and the application of inpainting techniques can restore this lost data, ensuring the visual integrity of the transmitted images [9]. The article presented by Yatnalli et al. [39] presents a review focused on problems caused by wireless communication, highlighting the effectiveness of inpainting techniques in mitigating these issues. Quan et al. [63] introduces problems related to image compression and discusses some inpainting techniques used to address these problems. In their respective works, Mehra et al. [42] and Guillemot and Le Meur [9] offer brief insights into the main challenges associated with packet loss in image and video transmissions.

The applications covered by the reviews analyzed demonstrate the versatility and importance of inpainting techniques in various fields.

5. Limitations of this study

In this study, we used Scopus as the primary database for the research process and included IEEE, ScienceDirect, and ACM as secondary databases to expand our coverage. Despite our efforts to ensure broad coverage, relevant studies in other databases may have been omitted. Additionally, our search string was designed to retrieve as many reviews as possible. However, some studies might not have been captured because they used terminologies different from those we employed.

Another important issue was the inaccessibility of some returned articles. The search process was conducted with the support of the Capes Periodicals Portal, which provides free access to various academic publications, but not for all of them.

Finally, during the study, we discovered that many of the reviews lacked sufficient information, and the content's organization made it difficult to extract and analyze the necessary information. In some cases, crucial information, especially regarding the categories of inpainting, was not explicitly stated in the paper, and we had to infer this information from the context. Despite our intensive efforts to be consistent and precise during the data extraction, following well-defined protocols to ensure data accuracy, the possibility of some information being overlooked remains.

6. Conclusion

This is the first tertiary review dedicated to analyzing image inpainting reviews. After examining the existing research on the topic, the critical issues observed are (i) the lack of a systematic approach and (ii) the lack of a standardized classification system for inpainting methods. These issues present a significant challenge in comparative assessments and compromise the study's reliability. Therefore, this highlights a significant gap in the methodological rigor of inpainting and suggests an opportunity to improve the clarity and transparency of review processes in the field.

Throughout this study, it is evident that many analyzed papers focus on using inpainting as a digital image processing tool, including restoring damaged images, removing unwanted objects, and filling in missing areas. However, it is interesting that inpainting has a broader spectrum of potential applications beyond digital image restoration. For instance, it can be used to inpaint medical images, restore videos, and remove artifacts in historical documents, among other possibilities.

Despite its versatility, inpainting remains a significant challenge. Recreating coherent and realistic information is complex, requiring ongoing research and innovation. Fortunately, the continuous emergence of new techniques, especially deep learning-based ones, offers promising solutions for addressing these challenges and achieving increasingly compelling results.

In this context, recognizing that the primary goal of reviews is to provide a clear and broader understanding of a subject, we hope to offer a comprehensive overview of the current state of inpainting research through this review, shedding light on areas for further exploration and inspiring future advancements.

CRediT authorship contribution statement

Iany Macedo Barcelos: Writing – original draft, Validation, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Taís Bruno Rabelo:** Writing – review & editing, Visualization. **Flavia Bernardini:** Writing – review & editing, Visualization, Supervision. **Rodrigo Salvador Monteiro:** Writing – review & editing, Visualization, Supervision, Project administration. **Leandro Augusto Frata Fernandes:** Writing – review & editing, Visualization, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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