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Medical image super-resolution for smart healthcare applications: A comprehensive survey

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ABSTRACT

The digital transformation in healthcare, propelled by the integration of deep learning models and the Internet of Things (IoT), is creating unprecedented opportunities for improving patient care. However, the utilization of low-resolution images, often generated by IoT devices, introduces biases in the deep learning models, thereby affecting the overall clinical decision-making process. While super-resolution techniques have been extensively employed to transform low-resolution images into high-resolution counterparts, the challenge of achieving highly accurate image restoration remains unresolved. This is especially critical in the medical imaging domain, where even minor inaccuracies can lead to significant biases in model training and, consequently, impact clinical outcomes. Although existing surveys have explored various super-resolution methods and their applications across different fields, a comprehensive review emphasizing the accuracy of image restoration in medical imaging and its subsequent influence on deep learning models is notably lacking. This survey seeks to bridge this gap by offering a systematic review of current state-of-the-art models, highlighting the limitations of existing surveys, and underscoring open questions that merit further research. Specifically, we delve into the intricacies of medical image restoration, identify research gaps and unmet challenges in achieving optimal restoration of medical images, and emphasize the crucial role of developing more precise and resilient super-resolution methods to enhance the quality of medical images and, consequently, the performance of deep learning models in healthcare applications. Ultimately, this survey fosters a deeper comprehension of the prevailing challenges and unresolved questions in the field, thus setting the stage for future research efforts focused on refining medical image restoration and, subsequently, boosting the efficacy of deep learning models in healthcare.

1. Introduction

Our Introduction section consists from main topics as:

Super-resolution: An Overview

Definition: Super-resolution is a process of enhancing the spatial resolution of an image.

Significance in Medical Imaging: The importance of high-quality visualization in MRI, CT scans, and the inherent limitations of imaging modalities.

Traditional* vs. *Advanced SR Methods

Interpolation Methods: Traditional methods of enlarging image size and their limitations.

Emergence of Super-Resolution Techniques: How these techniques differ from interpolation and their reliance on discerning patterns in low-resolution images.

Deep Learning and Super-resolution

List of Abbreviations: Super Resolution, SR; Convolution Neural Networks, CNN; Magnetic resonance imaging, MRI; Computed tomography, CT; Positron emission tomography, PET; Compound annual growth rate, CAGR; Vision Transformers, ViT; Generative Adversarial Networks, GAN; High-resolution images, HRI; Low-resolution images, LRI; Super-Resolution Convolutional Neural Networks, SRCNN; Deep Residual Network, DRN; Recurrent Neural Network, RNN; Peak signal-to-noise ratio, PSNR; Structural similarity metric, SSIM; Discrete wavelet transforms, DWT; Multi-contrast Super Resolution, MCSR; Optical coherence tomography, OCT; Mean squared error, MSE; Information entropy, IE; Normalized Root Mean Square Error, NRMSE; Quality Factor, QF; Feature Similarity, FSIM; Universal Quality Index, UQI; Mutual Information, MI; Mean Absolute Error, MAE; Root Mean Square Error, RMSE; Mean Structural Similarity Index, MSSIM; Peak Absolute Error, PAE; Normalized Cross-Correlation, NCC; Ultrasonography, US.

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Deep Neural Networks in SR: How deep learning has influenced the super-resolution domain and the advantages it offers.

Mechanics of Deep Learning-based SR: The two primary stages - feature extraction and reconstruction.

Implications in Smart Healthcare

Benefits of High-resolution Medical Imaging: The advantages of enhanced imagery for radiologists, clinicians, and researchers.

Holistic Aim of Super-resolution: It bolsters diagnostic precision and enlightens healthcare decisions.

Scope of the Survey

A brief overview of what the survey paper will cover: advancements, challenges, applications, and future directions of medical image super-resolution.

Categories of SR Methodologies

An introduction to the broad categories of super-resolution techniques, including Spatial, Transform, Hybrid, Traditional Machine Learning, and Deep Learning approaches.

Super-resolution refers to the process of enhancing the spatial resolution of an image, leading to a higher-quality and more detailed representation. In the realm of medical imaging, such as Magnetic Resonance Imaging (MRI) or Computed Tomography (CT) scans, super-resolution becomes especially pertinent given the necessity for precise visualization of anatomical structures and disease-associated features. Medical images obtained via various imaging modalities often grapple with inherent limitations, including noise, restricted sensor resolution, and hardware constraints. These factors may produce images with reduced spatial resolution, complicating the task of discerning minute details essential for precise diagnosis and treatment planning. Traditional methods for enlarging image size, like interpolation, involve estimating pixel values from their neighbors. Interpolation methods, while straightforward, fail to restore the high-frequency information that is vital in medical images. Super-resolution techniques, contrastingly, utilize advanced algorithms to retrieve finer details and enhance image quality beyond what interpolation can offer. These techniques capitalize on the idea that certain patterns and structures within low-resolution images hint at the high-frequency information found in the original high-resolution counterpart. By discerning and modeling these patterns, super-resolution algorithms strive to predict and amplify absent high-frequency components, yielding a crisper, more detailed image. The advent of deep learning has markedly influenced the super-resolution domain. Deep neural networks, given their ability to learn intricate mappings between low-resolution and high-resolution image pairs from vast datasets, are adept at discerning the relationships between low and high-frequency components. This proficiency empowers them to produce superior-quality super-resolved images from low-resolution sources. Deep learning-based super-resolution typically encompasses two primary stages: feature extraction and reconstruction. The former extracts pertinent features and patterns from the low-resolution input, while the latter stage crafts a high-resolution image using those extracted features. The implications of super-resolution are profound, especially in the realm of smart healthcare. High-resolution medical images furnish more precise information for diagnosis, treatment planning, and surgical procedures. Enhanced imagery can assist radiologists, clinicians, and researchers in pinpointing subtle abnormalities that might remain unnoticed in low-resolution images. At its core, super-resolution revolves around the use of sophisticated algorithms, including deep learning methods, to amplify the resolution of medical images. By reclaiming high-frequency details, super-resolution methods bolster diagnostic precision and foster more enlightened healthcare decisions.

This serves as a foundation for our survey paper, which will probe recent advancements, obstacles, applications, and prospective trajectories of medical image super-resolution within the context of smart healthcare.

In the expansive landscape of SR methodologies, techniques can be categorically divided into Spatial, Transform, Hybrid, Traditional Machine Learning, and Deep Learning approaches.

1.1. Spatial approaches

Super-resolution pertains to the enhancement of an image's spatial resolution, yielding a high-quality and intricate representation. This is paramount in medical imaging, where precise depiction of anatomical structures and disease-associated features is essential. Medical images might sometimes exhibit reduced spatial resolution due to constraints such as noise, sensor limitations, or hardware complications. Conventional methods, such as interpolation—which derives pixel values from adjacent pixels—are rudimentary spatial approaches. The study [1] presents a method to augment the resolution of medical images by leveraging these patterns. Initially, a high-resolution version of the image is constructed using nonlocal interpolation, which draws upon the recurrent patterns inherent in medical images. Subsequently, a technique pinpointing patterns with the least variance is employed to reconstruct this high-resolution image. The process is fine-tuned by continually ensuring that the image aligns with its low-resolution counterpart and by reapplying the pattern-detection method. However, maintaining alignment with the low-resolution version may occasionally introduce artifacts or diminish potential enhancements. [2] proposed to tackle the super-resolution challenges in medical imaging, especially when the degradation kernel is ambiguous or generic based on bilinear interpolation. Med-BSR refines the degradation factors, including blur, noise, and down sampling, making them more reflective of real-world scenarios. A distinctive approach that randomizes the sequence and combination of these degradation factors expands the model's degradation space. [3] method addresses challenges in multi-modal medical image fusion, focusing on balancing computational efficiency and fusion quality while emphasizing high-resolution imaging in clinical settings. The method employs a two-scale decomposition, breaking down the super-resolution image into a base layer and a detail layer. The detail layer undergoes enhancement and information refinement to magnify details and uphold vital features. Meanwhile, the base layer utilizes a Weighted Local Energy Deviation (WLED) rule to maintain the energy information from the original images. Notably, bicubic interpolation-based super-resolution is introduced to MMIF for the first time, enhancing the image's resolution. However, these methods cannot recover the high-frequency information crucial in medical images.

1.2. Transform approaches

In the realm of super-resolution, transform techniques emphasize converting the image from its spatial domain to another using mathematical procedures, such as Fourier, edge-based methods, local self – similarity, special filters (such as Lanczos) or Wavelet transforms [4,5]. The mention of interpolation techniques like nearest-neighbors interpolation and bicubic interpolation also falls within this category as they involve transforming pixel values. [6] delves into the utilization of various medical imaging techniques, like CT, MRI, and ultrasonography, which aid in visualizing internal bodily structures for clinical uses. Focusing on interpolation—a technique to produce new data points from known ones, especially during image transformations—the study introduces and assesses a resampling method using the three-dimensional Lanczos kernel. The method might be optimized for certain resolutions or dimensions and might not scale well for very high or very low resolutions. [7] introduced utilizing a unique generic image called the gradient profile prior. This prior is a parametric descriptor that outlines the shape and sharpness of image gradients. By learning from a vast collection of natural images, this gradient profile prior offers a constraint on image gradients during the transition from a low-resolution to a high-resolution image. The gradient profile prior is learned from a large number of natural images. This might limit the method's effectiveness on images that deviate significantly from the training set, such as medical or astronomical images. [8] the method leverages the BM3D [9] paradigm, capitalizing on the principles of sparsity and the self-similarity of nonlocal patches. Originating from a variational problem framework, the algorithm follows a structure commonly found in iterative back-projection super-resolution techniques, where a high-resolution image is continuously updated based on prior estimations and associated low-resolution error. Iterative back-projection techniques, especially those utilizing BM3D and sparse coding, can be computationally intensive. This might make the method less suitable for real-time applications or processing a large batch of images.

1.3. Hybrid approaches

Hybrid methods in super-resolution are an amalgamation of spatial and transform techniques, leveraging the advantages of both domains. The mention in the content about combining deep learning with traditional super-resolution can be viewed as a hybrid technique. This technique aims to bring together the direct pixel manipulation of spatial methods and the domain transformation of transform techniques for more robust results. [10] introduces a method for single-image SR that relies on self-similarity instead of external data. Traditional SISR methods focus on patch-based techniques, either drawing from large datasets or leveraging similarities within the input image itself. This research innovatively uses vast groups of similar patches from the input image for SISR. It integrates a fresh prior which leads to collaborative filtering of patch groups in a 1D similarity domain, all within an iterative back-projection structure. The use of iterative back-projection can increase computational costs, especially for larger images. This might affect the real-time applicability of the method.

1.4. Traditional machine learning approaches

Traditional machine learning (ML) approaches for super-resolution (SR) in medical imaging primarily revolve around extracting features and learning mappings from low-resolution (LR) to high-resolution (HR) images, while often leveraging the self-similarity inherent in images. Sparse coding is one such method grounded on the principle that images can be represented as a sparse linear combination of basic elements from a dictionary [11]. For SR, separate dictionaries are constructed for both low and high-resolution patches. The representation of a low-resolution patch using the LR dictionary facilitates the reconstruction of its corresponding HR version using the HR dictionary [12]. Another interesting approach is self-exemplar, which utilizes the inherent self-similarities in medical images. The idea is that patches from the same image at different scales can have resemblances [13]. Hence, the low-resolution image itself can serve as a source to find patches similar to the target patch, which are then used for super-resolution. Random forests have also been employed in this domain. They can be trained to predict HR patches directly from LR ones using features that might encompass pixel values, gradients, or textures. The prediction can either be of the HR patch itself or the difference between the LR and HR patches [14].

Manifold learning [15] is a more theoretical approach, operating under the assumption that LR and HR image patches occupy analogous manifolds in their respective spaces. Techniques such as Locally Linear Embedding (LLE) or Isomap can be used to map LR patches to HR patches based on the learned manifold structures. The K-Nearest Neighbors (K-NN) [16] algorithm has been adapted for SR. For each LR patch, its k-nearest neighbors are identified in a database of LR patches, and the corresponding HR patches from this database are utilized to reconstruct the target HR patch.

1.5. Deep learning approaches

The last decade has witnessed a surge in the application of deep learning for super-resolution. Deep neural networks can be trained to understand relationships between low and high-resolution images, enabling the creation of sharper images from low-resolution inputs. Feature extraction and reconstruction are the primary steps in this domain. Feature extraction pertains to capturing essential patterns from the low-resolution image, while reconstruction focuses on generating a high-resolution output using these features. The content provides multiple instances of deep learning applications, such as SRGAN, SRCNN, and other deep learning-based image processing techniques receiving significant attention. Deep learning's potential to enhance diagnostic accuracy in medical imaging, its role in segmentation, denoising, and medical diagnosis, and its challenges are also highlighted.

In recent years, the research community has exhibited significant interest in digital healthcare, as documented by [17] and [18]. Digital healthcare applications often involve processing images of affected human body parts, such as brain tumors or lung cancer, as highlighted by [19]. A notable challenge is that many medical images, for instance, MRI depictions of the brain, typically have low resolution. One intuitive solution to this resolution challenge would be to enhance the resolution of the imaging devices themselves. Nevertheless, in the context of super-resolution, the focus is often on restoring high-frequency details from the existing low-resolution images. The most straightforward approach to boosting image resolution hinges on interpolation techniques, examples of which include nearest-neighbor interpolation, as discussed by [20], and bicubic interpolation, as referenced by [21]. While interpolation methods can increase an image's size, they are not primarily designed to enhance image information. Consequently, they struggle to recover the high-frequency details inherent in the image. Over recent years, deep learning-based super-resolution has seen remarkable advancements. Current trends show that deep learning-oriented image processing techniques are garnering significant attention. Given the pivotal role of medical imaging in diagnosing specific ailments, elevating the resolution of these images stands to markedly improve diagnostic precision and guide effective treatments. Moreover, tasks like automatic recognition and image segmentation can benefit immensely from heightened resolution. However, achieving the desired resolution remains challenging due to constraints related to the imaging environment, system limitations, and inherent issues like noise and blur. While there have been substantial advancements in acquisition technology and the efficacy of optimized reconstruction algorithms over recent decades, super-resolution (SR) techniques offer a solution to address image processing challenges. Various deep learning (DL) methodologies tailored to rectify SR issues in medical images have emerged. Notably, remarkable strides have been achieved in domains like image segmentation as observed by [22], super-resolution [23], medical diagnosis following [24], and denoising as illustrated by [25]. This article endeavors to deliver a comprehensive review of the latest trends in deep learning-driven medical image super-resolution. Predominant research on the SR process can be categorized into two principal phases: feature extraction and reconstruction. Moreover, this review touches on other pivotal themes, including single-contrast SR, multi-contrast SR, the role of super-resolution in healthcare, recent breakthroughs, SR challenges, and metrics for performance evaluation. In conclusion, we highlight several prospective avenues and lingering challenges warranting the community's attention moving forward.

1.6. A brief introduction of medical imaging

In recent years, advances in medical imaging have revolutionized both the healthcare and computer vision sectors. Enhanced diagnostic imaging now offers doctors an unparalleled view of the human body, facilitating precise diagnoses and enabling them to select optimal treatment protocols. These insights are powered by high-definition images capturing both hard and soft tissue structures. Contemporary medical facilities are equipped with a suite of state-of-the-art imaging tools, ranging from MRI and CT to positron emission tomography (PET) and nuclear medicine modalities.

The X-ray, one of the pioneering techniques in medical diagnostic imaging, remains invaluable in diagnosing diseases affecting rigid tissues. As delineated by [26], X-rays are instrumental in identifying skeletal system disorders, such as fractured bones. They are also adept at detecting diseases exclusive to the skeletal system, alongside others like pneumonia, as highlighted by [27], and conditions like pleurisy.

MRI, which harnesses magnetic fields and radio waves, is optimized for imaging the body's soft tissues. It is a go-to modality for identifying conditions affecting internal organs as mentioned by [28], and is adept at spotting muscle ruptures and ligament strains. MRIs are also pivotal in detecting cancers, as referenced by [29], and in diagnosing spinal cord injuries.

CT scans, a sophisticated extension of the X-ray technique, offer cross-sectional, three-dimensional visualizations of the body, aiding in the detection of anomalies across both hard and soft tissues. Using finely focused beams and capturing images from diverse angles, CT delivers intricate visuals that can be analyzed in various dimensions. Its capabilities extend to diagnosing internal injuries, as pointed out by [30], and pinpointing ailments like cancer and cardiac disorders, as referenced by [31] and [32] respectively.

PET is a diagnostic imaging technique that employs radioactive tracers to produce intricate images of the body's internal structures. When introduced into the body, these tracers, or dyes, illuminate the functionality of organs and other body systems as captured by a PET scanner. The modality offers insights into tissue health, blood oxygen levels, and the body's sugar metabolism patterns. As a result, PET scans play a pivotal role in diagnosing a range of conditions including cancer, as highlighted by [33], heart ailments as pointed out by [34], and various neurological disorders.

In scenarios where exposure to ionizing radiation from techniques like CT or PET is deemed risky or unnecessary, or when the expenses associated with MRI are hard to justify, ultrasound (or sonography) emerges as an effective alternative. Utilizing sound waves to produce images, ultrasound is a non-invasive and cost-effective method. While it's most renowned for its use during pregnancy, its applications are vast. As noted by [35], ultrasound imaging is versatile and can be employed for diverse medical procedures, including guiding needle biopsies.

1.7. Market statistics and research trends

According to Fortune Business Insights, the market share of medical imaging will grow at a compound annual growth rate (CAGR) of 5.8% and will reach 56.53 billion USD by 2028 compared to a market share of 37.97 Billion USD in 2021 med [36]. Medical equipment companies are trying to develop low-cost and good-performing medical imaging devices due to the rising prevalence of various diseases (e.g., cancers, chronic and neurological diseases) across the whole world. More specifically, 3D medical imaging devices will play a key role in an increase in the medical imaging market. Among various regions of the world, during the forecast period of 2021–2028, the Asia Pacific region is expected to observe a higher CAGR. Latin America has expected a relatively low growth. On the other hand, a significant increase in the number of publications in the fields of healthcare and super-resolution. Therefore, one can say that super-resolution and digital healthcare can be promising research areas for future work.

1.8. Existing surveys and tutorials

Medical imaging, owing to its critical importance in diagnostics and treatment planning, has been a prolific field for research and innovation. Over the years, many surveys and tutorials have been published, shedding light on different aspects of this domain. This section delves into the existing literature, emphasizing the areas they covered, the gaps they left, and how our survey fills these gaps.

Various works, such as [37,38], and [39] have surveyed different aspects of healthcare. [37], examined healthcare optimization, discussing recent advancements and identifying open challenges. [38] focused on children's perceptions of healthcare. In their study, they analyzed and compared the children's responses. In a different approach, [39] explored the role of the IoT in enhancing healthcare. Specifically, the authors discussed the various healthcare applications enabled by IoT and open challenges. Conversely, the research by [40] provided an overview of super-resolution and video reconstruction methodologies, while also hinting at potential future directions in the field. [41] in their study, offered a comprehensive review of super-resolution techniques. They delved deep into the nuances of super-resolution, discussing the evaluation of algorithms, the incorporation of color data, the optimization of cost functions, and the intricacies of imaging models and registration algorithms. [42] focused on surveying super-resolution methods, specifically emphasizing the comparison of various super-resolution techniques found in existing literature. [43] offers a thorough review of the latest developments in applying deep learning techniques to medical image super-resolution. The overview also touches upon the challenges and potential trajectories of future research in this domain. However, the review falls short in its evaluation of the studies it incorporates. Specifically, there is an absence of an in-depth assessment of study quality, which could raise questions about the reliability of the review's conclusions. While the authors do make a passing reference to the metrics used in the analyzed studies, a critical appraisal of the methodologies and the limitations of these studies is notably missing. [44] present a detailed review of the latest advancements in using GANs for medical image fusion, encompassing challenges and prospective research directions. The paper underscores the potential of GAN-centric methods in enhancing the quality and precision of medical image fusion, which can subsequently facilitate better diagnosis and treatment of various health conditions. While the paper thoroughly discusses recent research concerning GAN-based medical image fusion, it omits the exploration of other fusion methodologies or techniques. Consequently, the conclusions drawn might not be transferable to different fusion techniques or settings. [45] delve into the potential future trajectories and research avenues within the swiftly progressing domain of transformer models in medical imaging. They tackle both challenges and prospects, aiming to harness these models to transform medical imaging and elevate patient care. Yet, forecasting research trajectories and hurdles is inherently conjectural, so the actual progress in the field may diverge from the authors' projections. [46] examine the seminal innovations, methods, and performance enhancements offered by Vision Transformers (ViT) across diverse medical imaging tasks, including segmentation, classification, and detection. The paper underscores the potential challenges and prospective developments in this emerging arena, spotlighting the importance of ViT-oriented models for bolstering diagnostic precision and aiding clinical judgments. However, the paper's primary focus is on the accuracy and efficiency of ViT models, which somewhat overshadows pivotal concerns like model interpretability, resilience, and broad applicability. Contrary to existing surveys and tutorials such as [37–41], and [42], our study specifically focuses on super-resolution for medical imaging. A comparative analysis is provided in Table 1.

In the realm of digital healthcare, while super-resolution techniques promise significant enhancements to medical imaging, they are not devoid of challenges and limitations. One of the primary challenges faced by these techniques pertains to data variability. Medical imaging data can exhibit vast heterogeneity due to differing modalities, such as MRI, CT, and X-ray, and the specific machine configurations employed across various healthcare settings. Noise amplification, another inherent issue, poses significant challenges. As super-resolution seeks to refine image details, it may inadvertently intensify the noise present in low-resolution images. Such noise amplification could risk obscuring vital diagnostic information, which is critical for accurate medical decision-making. Furthermore, while super-resolution techniques aim to predict or enhance finer image details, there's an ever-present risk of loss of these details, which are of paramount importance in diagnosis.

Table 1
Summary of existing surveys in super-resolution.

Ref	General	SISR	MISR	Medical Imaging	Healthcare	Deep Learning	Datasets	Remarks
[47]	✗	✗	✗	✓	✗	✗	fMRI, MRI, and PETS	A pioneering survey in medical imaging, but lacks recent state-of-the-art deep learning and multi-image SR. Some of the algorithms highlighted here are outdated.
[23]	✗	✓	✗	✓	✗	✓	MRI, CT	This study covers the deep learning-based approaches for medical imaging. However, it considers only MRI and CT.
[48]	✗	✗	✗	✓	✗	✓	MRI, CT	This conference paper covers a very limited.
[49]	✗	✗	✗	✓	✓	✓	Ultrasound Imaging	A very comprehensive review of super-resolution applied to ultra-sound imaging. It lacks the applications of super-resolution in other datasets.
[42]	✓	✓	✓	✗	✗	✓	BSD, Urban 100, DIV2K, Manga109	A very comprehensive survey covering the general scope of super-resolution in wide arrays of applications. The survey is not focused on medical imaging.
[50]	✓	✓	✗	✗	✗	✓	Set14 dataset	This survey focuses on single-image super rosultion-based deep learning methods. While outlining significant contribution, it does not cover the medical imaging aspect.
[51]	✓	✓	✗	✗	✗	✓	Open datasets	This survey elucidates the deep learning-based approaches toward single-image super-resolution. It is not focused on medical imaging.
[52]	✓	✓	✗	✗	✗	✗	DIV2KRK, RealSR, DRealSR, City100 etc	This survey presents a brief overview of single-image super-resolution methods. this survey also does not cover the medical imaging aspect.
[53]	✗	✓	✓	✗	✗	✓	AID, DOTA, UC Merced, etc	This survey focuses on the applications of super-resolution in remote sensing applications.
[54]	✗	✓	✓	✗	✗	✓	CelebA, Helen, FFHQ, 300 W etc.	This is a domain-specific survey covering the impact of super-resolution on face datasets.
Our Survey	✗	✓	✓	✓	✓	✓	CT, MRI, PET, Microscopy, Ultrasound, etc	Our survey presents a comprehensive review of state-of-the-art covering a variety of super-resolution techniques applied to medical imaging of vast categories and presents its impact in next-generation healthcare applications.

Computational demands also present a limitation. High-resolution reconstructions, particularly in 3D imaging modalities, necessitate robust computational resources. This computational overhead can pose barriers in scenarios demanding real-time analysis or in clinical settings with limited computational capacities. Training data limitations further compound the challenge. The efficacy of super-resolution techniques often hinges on the availability of extensive and high-quality training datasets. Acquiring a diverse and representative set of medical images for training purposes remains a perennial challenge due to ethical concerns and data privacy regulations. Even when models are adequately trained, concerns about their generalizability arise, given that a model's performance on one set of medical images might not necessarily extrapolate to images sourced from different devices or demographics.

Moreover, the introduction of imaging artifacts by some super-resolution methods could potentially mislead clinicians. These artificially introduced details might deviate from the true anatomical representation, raising ethical and clinical concerns. While the promise of super-resolution techniques in the domain of medical imaging is undeniable, a judicious acknowledgement of their challenges and limitations is crucial for their optimized and safe application.

In recent advancements of super-resolution methods in medical imaging, several challenges and limitations have been observed. One of the most prominent concerns is the increased computational requirements stemming from the use of multi-head convolutional attention mechanisms with varying kernel sizes [43]. Such computational demands make these methods less apt for real-time applications, particularly on hardware with constrained resources. When delving into the specifics of super-resolution US, another limitation emerges [55]. Due to the utilization of higher frequencies for enhanced resolution, there's a compromise on penetration depth. This can limit the technique's efficacy in imaging deeper or larger breast tissues, potentially hindering its broader applicability. Furthermore, while these methods aspire to refine and highlight essential features in the super-resolved images, they occasionally might exaggerate artifacts and noise from the original low-resolution images. This amplification can compromise diagnostic accuracy, leading to potential misinterpretations. Implementation poses another set of challenges. Integrating the proposed super-resolution techniques into current clinical workflows and imaging systems often necessitates supplementary development and validation efforts. This can hamper the swift adoption of these techniques in practical medical scenarios [56]. When examining the architecture of these super-resolution models, they often demand significant computational power and memory, not just for training but also during inference. This resource intensity might curtail their use in settings with limited computational facilities or in situations that require immediate results. Additionally, the fusion of multiple residual networks in certain models can further exacerbate computational complexity and memory demands, complicating real-time implementations or deployments on devices with limited capabilities [57]. The introduction of multi-attention networks paired with wavelet transforms, although innovative, can obscure the interpretability of the model's internal dynamics. This opacity can hinder the diagnosis and rectification of potential model anomalies. Moreover, the application of GANs in medical image super-resolution isn't free from challenges. Bias in the generated images poses a significant threat, which could mislead clinical decisions [58]. Coupled with GANs' renowned demand for extensive computational resources, their broad use can be restrictive in several medical contexts. Lastly, many of these advanced methods rely heavily on the availability of paired low- and high-resolution images during training. Obtaining such paired datasets can be challenging in specific medical imaging scenarios, posing a bottleneck for the wider adoption of these techniques.

Advancements in super-resolution methods for medical imaging offer promising enhancements, but they come with a suite of challenges and limitations that need to be judiciously addressed for broader clinical adoption. While the aforementioned surveys and tutorials provide valuable insights into SR and its applications, there exist noticeable gaps. Few comprehensive studies intertwine the nuances of SR in medical imaging with the latest deep learning approaches or discuss the integration of IoT in healthcare applications of SR. Furthermore, many surveys lack a systematic investigation of the challenges unique to healthcare applications. In light of this backdrop, our survey seeks to fill these gaps, offering a meticulous exploration of the super-resolution realm, particularly focusing on its applications and challenges in healthcare. By synthesizing information from various sources and introducing fresh perspectives, we aim to provide readers with an updated and holistic understanding of the field.

1.9. Our contributions

Our survey, outlined in Fig. 1, delves into the role of super-resolution and the IoT in medical imaging, aiming to bolster the effective diagnosis of a myriad of diseases. Our key contributions are as follows:

- First, we present an overview of super-resolution from the perspective of medical imaging. Moreover, we clearly discuss in detail the various steps of super-resolution.
- Second, we present the recent advances in super-resolution for medical imaging. Additionally, we rigorously evaluate these recent advances.
- Finally, we found and present various open challenges of enabling super-resolution for medical imaging.

We undertake a comprehensive examination of diverse methodologies pertinent to super-resolution, spanning from foundational techniques to avant-garde innovations. The proposed survey emphasizes the tangible real-world applications of super-resolution based on deep learning models such as SRCNN, DRN, GAN, attention-based models, and RNN, ensuring that the theoretical discussions are anchored in clinical relevance. Beyond presenting recent developments, our narrative adopts a critical evaluative stance. This ensures a deeper understanding of the underpinnings, rationale, and implications of each technique.

Acknowledging the dynamic landscape of technology, our survey is anticipatory, contemplating the likely evolution and potential directions of super-resolution in upcoming years.

By maintaining fidelity to these objectives and ensuring a clear, well-articulated scope, we aspire to furnish a survey that stands as an invaluable resource for scholars, practitioners, and stakeholders in medical imaging.

1.10. Survey systematic investigation

Survey methodology

The main objective of this survey is to provide a comprehensive overview of the current state-of-the-art deep learning-based models for medical image super-resolution. This is a descriptive cross-sectional survey designed to provide a snapshot of the current state of deep learning-based models for medical image super-resolution. The population of this survey includes all published research articles on deep learning-based models for medical image super-resolution. A sample of more than 100 articles published between 2010 and 2023 was selected using a systematic random sampling method. Data were collected through a systematic review of the literature. Articles were identified using a combination of keyword searches and reference list reviews. Data were analyzed using a combination of descriptive statistics and thematic analysis. Descriptive statistics were used to summarize the characteristics of the included studies, and thematic analysis was used to identify common themes and patterns in the findings.

Methodology for literature review on deep learning-based models for medical image super-resolution

The methodology of this literature review is designed to systematically identify, evaluate, and integrate the findings of relevant studies on deep learning-based models for medical image super-resolution. A combination of keywords was used to extract relevant articles. These included terms like "deep learning", "medical image", "super-resolution", "CNN", "GAN", and "MRI". We also performed searches using combined keywords to increase the breadth of our results. To supplement our primary search, we manually examined the reference lists of selected articles, aiming to identify any relevant studies that might have been overlooked in the primary search. To be eligible for inclusion in our review, articles needed to focus specifically on deep learning-based models tailored for medical image super-resolution. We ensured the selected articles were written in English and constituted full-text research articles. Preliminary communications, letters to the editor,

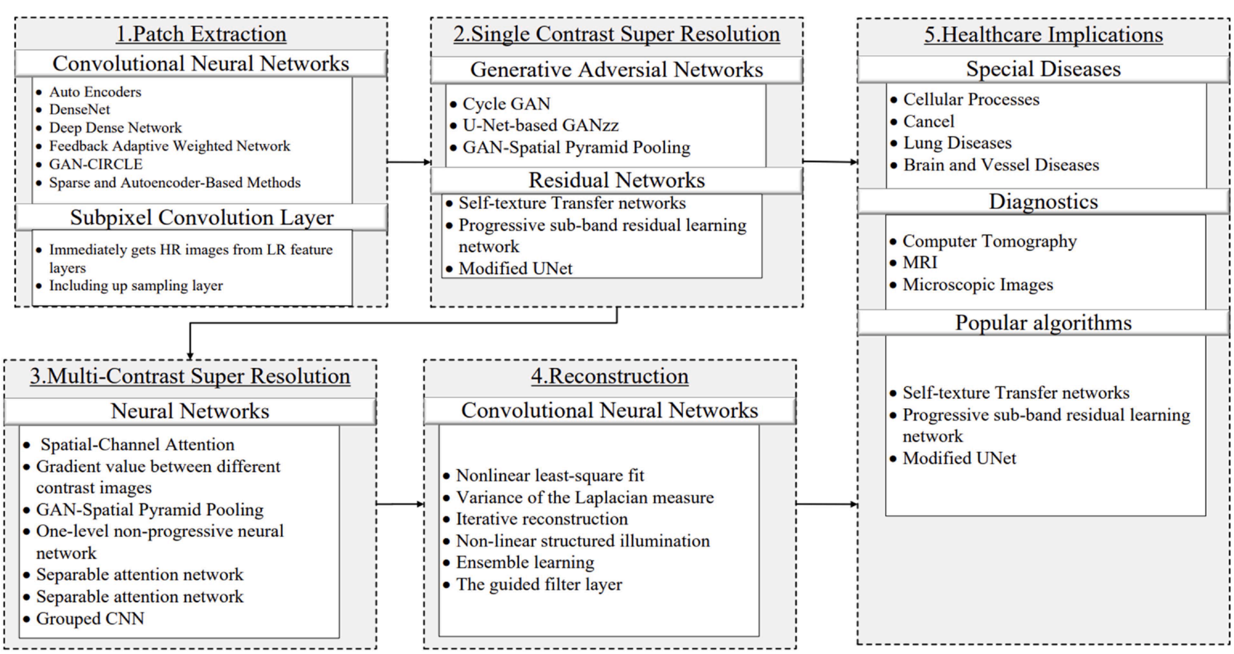

Fig. 1. Proposed Survey Presented state-art medical image super-resolution models and methods.

and review articles were excluded. Additionally, the articles had to present either a novel deep-learning architecture or provide a comprehensive evaluation of existing architectures in the context of medical imaging. Furthermore, we prioritized articles published in peer-reviewed journals or conference proceedings.

On the other hand, studies that did not focus on medical image super-resolution or did not employ deep learning as the primary methodology were excluded. We also excluded duplicate studies, especially those that used the same dataset without introducing a significant variation in methodology. Studies that lacked clarity or did not provide adequate details on their experimental setup were disregarded. In instances where the full-text version of the article was not accessible, we opted to exclude the article from our review. During the data extraction phase, titles and abstracts of the identified articles were initially screened to gage their relevance. Those that failed to meet the basic inclusion criteria were immediately discarded. The shortlisted articles from this initial screening then underwent a comprehensive full-text review. In case of discrepancies regarding their inclusion, we arrived at a resolution through consensus or by consulting a third reviewer when necessary. For every article included in our review, pertinent data points were noted, such as the study's objectives, the deep learning model employed, dataset details, evaluation metrics, and principal findings. Following the extraction, a thematic analysis was undertaken to discern recurrent themes, trends, and patterns in the findings. This allowed us to categorize the articles based on their primary focus, methodology, and contributions.

Our methodological approach was rigorous and structured, aiming to provide readers with an exhaustive and insightful understanding of the current state of deep learning models applied to medical image super-resolution.

Research questions

The main objective of this survey is to provide a comprehensive overview of the current state-of-the-art deep learning-based models for medical image super-resolution. The research questions guiding this survey are:

What is the existing deep learning-based models for medical image super-resolution?

What are the strengths and limitations of each model?

What are the future directions for research in this area?

Search strategy

A systematic search of the literature was conducted using the following electronic databases: PubMed, IEEE Xplore, and Google Scholar. The search terms used were: "medical image", "super-resolution", "deep learning", "SRCNN", "DRN", "GAN", "attention-based models", and "RNN". The search was limited to articles published in English between January 2010 and May 2023.

Inclusion and Exclusion Criteria Studies were included if they were original research articles that used deep learning-based models for medical image super-resolution. Studies were excluded if they did not use deep learning-based models, did not focus on medical images, or were review articles, editorials, or conference abstracts.

Data extraction

Data were extracted from each included study on the following variables: authors, year of publication, study design, type of medical images used, deep learning model used, performance metrics, and key findings.

Quality and Risk of Bias Assessment. The quality and risk of bias of the included studies were assessed using the Quality Assessment of Diagnostic Accuracy Studies (QUADAS-2) tool.

Data synthesis

A narrative synthesis of the findings from the included studies was conducted, organized by the type of deep learning model used.

1.11. Survey organization

The rest of this survey is organized as follows: Section 2 provides a comprehensive foundation of SR followed by SR applications in different domains. Section 5 elucidates recent advances of SR particularly in healthcare applications and covers its applications in different diseases on numerous state-of-the-art public datasets. Section 6 identifies challenges and unaddressed issues of SR in relation to the healthcare domain and Section 7 presents experimental results of several state art models based on medical image super resolution, Section from 8 till 12 concludes this survey including discussion, recommendation parts.

2. Foundations and applications

This section highlights topics such as:

Definition and Objective: Briefly define SR and its primary goal of transforming low-resolution images (LRI) into high-resolution images (HRI).

Techniques and Importance: Discussion on the methodologies, especially deep learning, used for SR and its significance in computer vision.

Diverse Applications: Highlighting the various fields where SR is applied, referencing Fig. 1.

Super-resolution in medical image processing

Role in Medical Imaging: Elucidating the importance of SR in enhancing diagnostic accuracy, treatment planning, and improving patient outcomes.

Challenges with Medical Imaging: Addressing the technical constraints of imaging modalities and the resulting loss of critical information.

Advantages of SR in Medical Imaging: Discuss how SR techniques can overcome challenges and enhance the quality of medical images, along with its implications for patient care.

SR involves the estimation of high-resolution images (HRI) from their low-resolution counterparts (LRI). The primary objective of super-resolution is to transform an LRI input into a detailed HRI output. Numerous methodologies, including deep learning techniques, have been devised to tackle this challenge. SR holds significant importance in the realm of computer vision and has found applications in diverse fields like surveillance, space imaging, and medical image processing. These real-world applications are depicted in Fig. 1. In the realm of medical image processing, super-resolution plays a pivotal role by enhancing diagnostic accuracy, refining treatment planning, and subsequently improving patient outcomes. Owing to technical constraints or concerns about patient safety, medical images like X-rays, CT scans, and MRIs are often acquired at a limited resolution. This can lead to a significant loss of critical information and diminished image quality. By leveraging advanced algorithms, super-resolution techniques have the potential to counteract these constraints, thereby amplifying the resolution of medical images [58]. The end result is a richer and more precise image.

With such enhanced medical imagery, healthcare professionals are better equipped to pinpoint and diagnose conditions, for instance, tumours or anomalous growths, as highlighted by [59]. They can also obtain exact measurements of these anomalies, along with their precise locations. This invaluable information facilitates the formulation of more effective treatment strategies, be it radiation therapy or surgical procedures. Therefore, the value of super-resolution in medical image processing is underscored by its capacity to bolster the fidelity and precision of medical imagery, which, in turn, holds promise for elevating patient care and the efficacy of medical interventions.

2.1. Medical image super resolution

Medical imaging plays an indispensable role in diagnosing and treating a myriad of diseases. However, procuring high-resolution medical images can often be daunting due to challenges such as low resolution, noise, and inherent artifacts. Deep learning-based super-resolution models have surfaced as a compelling solution to these challenges. In this paper, we undertake a comprehensive review of cutting-edge deep learning models tailored for medical image super-resolution. Our discussion encompasses a range of models, from Super-Resolution Convolutional Neural Networks (SRCNN), Deep Residual Networks (DRN), and Generative Adversarial Network (GAN)-based models to attention-driven and Recurrent Neural Network (RNN)-based models. Alongside this, we underscore the advantages and shortcomings inherent to each model. The paper concludes with a forward-looking perspective, delineating potential avenues for future research in this dynamic field.

We undertook an exhaustive review of literature centered on deep learning models tailored for medical image super-resolution. Our study was anchored on research that employed deep neural networks for the enhancement of medical imaging modalities, encompassing MRI, CT, X-rays, and ultrasound scans. In our exploration, we discerned several predominant deep learning models designed for medical image super-resolution, notably SRCNN, DRN, GAN-based models, attention-centric models, and RNN-based models. These advanced models have consistently outperformed conventional interpolation techniques in terms of results. Both SRCNN and DRN deploy convolutional neural networks and residual blocks for feature extraction and the generation of refined high-resolution images. GAN-based models leverage a dual-network setup, encompassing a generator and a discriminator, to yield superior image quality. Attention-driven models introduce an attention mechanism, which purposefully zooms into significant image regions, while RNN-based models adopt a recursive approach to progressively hone the output image.

3. Methods and technologies

This section highlights topics such as:

Medical image super-resolution: deep learning solutions

Challenges in Medical Imaging: Reiterating the need for high-resolution imaging in the medical domain and the prevalent issues.

Deep Learning as a Panacea: Introducing deep learning models as solutions to the challenges in medical imaging.

Scope of the Current Review: Briefly state the purpose and content of the paper.

Deep learning models for SR: A detailed overview of the different models, including:

SRCNN and DRN: Their use of convolutional neural networks and residual blocks.

GAN-Based Models: Highlighting their dual-network setup. And Gan-based vision Transformers models.

Attention-Driven Models: Introducing the attention mechanism's role.

RNN-Based Models: Discussing their recursive approach.

Comparison with Traditional Techniques: How these models outperform conventional interpolation techniques.

Conclusion and Future Directions: Summarize the review's insights and point to potential future avenues in the field.

The demand for HR medical images is increasing exponentially, enabling precise clinical diagnoses and interventions. However, due to various constraints like radiation dose, patient comfort, and scanning time, obtaining HR images can be challenging. Super-resolution techniques have been developed to overcome these constraints and enhance the resolution of acquired LR images. This paragraph discusses the prominent methods and technologies used in the field of medical image super-resolution Figs. 2, 3.

3.1. Convolution neural networks super resolution (SRCNN)

Convolutional neural networks (CNNs) have made significant strides in SR tasks, notably in enhancing medical images. CNNs stand out as potent tools for SR, consistently outperforming traditional SR techniques. In this paper, we provide an in-depth exploration of the application of super-resolution convolutional neural networks (SRCNN) within the realm of medical imaging. We delve into the architecture of SRCNN, its diverse variants, and their influence on various medical imaging modalities, including MRI, CT, and ultrasound. Furthermore, we address the prevailing challenges and prospective avenues in SRCNN-based medical imaging research.

[60] introduced a novel medical image super-resolution technique utilizing a feedback adaptive weighted dense network (FAWDN) to bolster performance. This approach is engineered to enhance the resolution of medical images, ensuring the preservation of diagnostic quality—essential for precise medical diagnosis. The architecture of FAWDN is distinctive, integrating feedback loops and adaptive weighting mechanisms to meticulously capture and retain intricate details in the

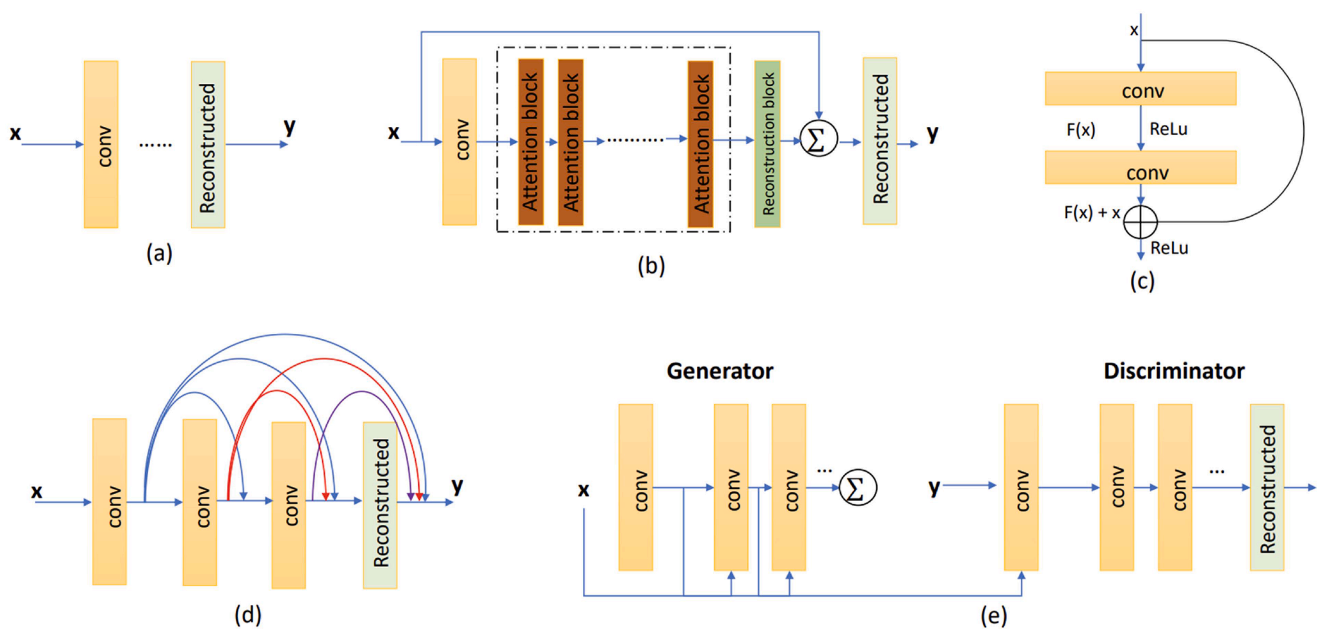

Fig. 2. Deep-learning network structures for single image super-resolution. (a) SRCNN, (b) attention-based network, (c) residual network (d) dense connection-based network, (e) GAN network.

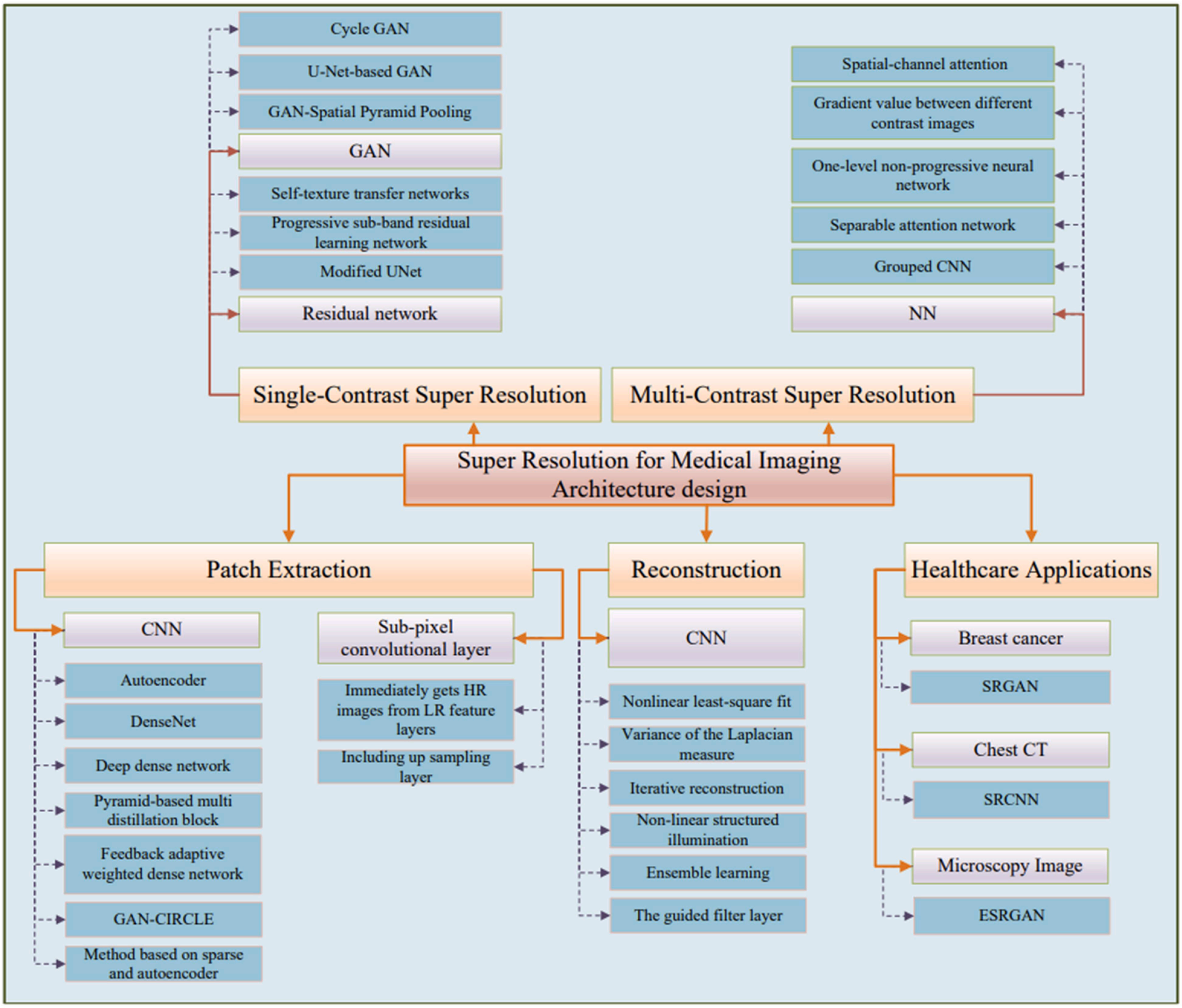

Fig. 3. Overview of methodologies used in this section.

images. During the patch extraction phase, the FAWDN systematically divides input images into smaller, overlapping segments. The innovative inclusion of the hidden section combined with the feedback network—subsequently forwarded to the input section—serves to elevate the low-level features directly, thereby enhancing feature selection. In their work, [61] put forth a method designed to amplify the resolution and quality of medical images, harnessing the power of fuzzy logic, hierarchical fusion, and attention mechanisms embedded within a CNN framework. These advanced integrations enable the model to more adeptly capture and represent high-level features and spatial details from the originating low-resolution medical images. The result? High-resolution images are reconstructed with enhanced precision and clarity, thereby empowering medical professionals with sharper tools for diagnosis and therapeutic strategizing. However, a potential caveat to consider is the augmented computational complexity introduced by the fusion of fuzzy logic, hierarchical fusion, and attention mechanisms into the CNN. This complexity might challenge the model's real-time efficacy in on-the-ground clinical scenarios. [59] introduced the Pyramidal Feature Multidistillation Network (PFMDN), a sophisticated approach that capitalizes on the hierarchical feature structure inherent to CNNs to optimize super-resolution performance. Central to PFMDN are its multiple feature distillation blocks, which facilitate the transmission of high-level semantic insights down to more foundational feature levels. The essence of this approach is to sieve through multi-scale features, streamline these details into condensed representations, and subsequently merge them to produce a high-definition result. In this technique, harvested patches undergo processing within the multi-distillation block, which incorporates the innovative pyramidal convolution mechanism. This convolution strategy, distinct for its employment of filter sets of diverse sizes, is deftly engineered to capture and represent features across varied scales. This multifaceted capture method empowers the network to adeptly discern and recreate high-frequency image details. The end product? Reconstructed imagery that stands out for its crystal-clear clarity and true-to-life fidelity.

[62] introduced a novel approach to SR for anisotropic cardiac MRI images, leveraging the prowess of unsupervised deep learning. A distinguishing feature of this method is its reliance on anisotropic images during training. Utilizing the dense, lower-dimensional latent space produced by an autoencoder, the model is trained to upscale the spatial resolution of these low-definition images. A particularly innovative feature of their approach is the use of two adjacent slice extractions tailored to discern features from the latent space. These slices are then cohesively merged using a method known as a convex combination, thereby improving the accuracy and richness of feature extraction. Perhaps the most remarkable feature of this technique is its unsupervised nature. Instead of relying on pre-existing high-resolution images as

a benchmark or "ground truth" during the training process, the model is conditioned to autonomously generate high-resolution outputs from provided low-resolution inputs. This self-reliant approach empowers the model to grasp and replicate the inherent structure of images, consequently enhancing the fidelity and quality of its super-resolution products.

[63] introduced a unique approach that synergizes multiple convolutional layers, each with distinct kernel sizes, to adeptly capture spatial features in images. This stratagem is further bolstered by a multi-head attention mechanism, which refines the model's capability to zero in on pivotal regions within the image. Such a dexterous fusion of techniques ensures the generation of superior-quality super-resolution medical images. Such images hold the potential to significantly elevate clinical decision-making precision, ultimately leading to enhanced patient care outcomes. However, a noteworthy trade-off is the computational demand of such a sophisticated approach. Incorporating multi-head convolutional attention coupled with diverse kernel sizes invariably escalates computational needs. This could potentially hamper the model's adaptability in real-time scenarios or its seamless deployment on hardware with limited resources. [64], led by Stefanie, introduced a novel approach to ultrasound (US) medical image super-resolution tailored for breast cancer detection. Their method hinges on a nonlinear least-squares fit (LSF) combined with a saturation model. Using the LSF, they constructed the final high-resolution output image, which was determined by the relationships amidst the final coverage data. The core objective of their study was to gage the proficiency of this avant-garde imaging technique, particularly in pinpointing and characterizing breast lesions. They aimed to demonstrate its superior accuracy and spatial resolution when juxtaposed against traditional super-resolution ultrasound (US) methodologies. However, a potential constraint of this technique arises from the elevated frequencies deployed in super-resolution US. These frequencies can curtail the penetration depth, which might constrict the method's efficacy, especially when imaging breast tissues that are positioned deeper or are more voluminous.

[65] put forth a method that fuses the strengths of wavelet transform and deep learning, targeting the precise enhancement of the resolution of CT images, ensuring that crucial features and intricate details are conserved. The process is initiated by decomposing the low-resolution CT images into wavelet coefficients across multiple scales. Subsequently, a deep neural network is trained to ascertain the correlation between the wavelet coefficients of low-resolution and high-resolution images. However, there's a potential pitfall associated with this approach. While the method is designed to meticulously retain critical features in the images that undergo super-resolution, there's a risk of unintentionally accentuating any artifacts or noise that existed in the initial low-resolution images. Such amplification could be detrimental, possibly leading to a decline in diagnostic precision or even causing faulty interpretations. [66] introduced the Self-supervised MOtion-Resistant algorithm, specifically designed to ameliorate the quality and resolution of MRI scans. It aims to mitigate motion artifacts and accentuate intricate details, thereby potentially boosting diagnostic precision. The essence of this method is the self-supervised learning approach, enabling the model to adapt seamlessly across diverse MRI datasets. This adaptation is carried out without the necessity for paired ground-truth images, paving the way for a more robust and universal performance across myriad imaging situations. Yet, there is a subtle challenge attached to this methodology. While the self-supervised model eliminates the need for paired ground-truth images, it might still necessitate some form of supervision or defined constraints to ensure the results are both reliable and precise. This can present a hurdle, especially in situations where such supervisory guidance is either hard to procure or entirely absent. As a result, while the approach offers commendable flexibility, its broad applicability might be constrained by these supervisory prerequisites. [67] introduce a deep learning-based method to reconstruct high-resolution images from lower-resolution inputs. The benefits of such a technique are promising, especially for the domain of medical imaging. However, practical considerations arise when contemplating its adoption in real-world clinical environments. The integration of this method into established clinical workflows and imaging systems could necessitate additional development and validation, potentially impeding its swift adoption.

[68] propose the deep dense network, DDSR, employing a dense connectivity scheme. This densely connected network, rather than having only adjacent layers communicate, facilitates input sharing across all preceding layers. This architecture is designed to enhance the learning of both low-level and high-level features during the feature extraction phase. Such an approach is particularly salient for medical imagery where both macro and micro features are vital for diagnosis. However, dense architectures might introduce additional computational overheads, demanding careful consideration of resource allocation for practical deployment. [69] have harnessed the capabilities of CNNs in the realm of CT imaging. Their approach centers on enabling CNNs to intricately understand and subsequently extract multifaceted features from low-resolution CT scans. The result is the generation of reconstructed high-resolution images that not only augment detail but also mitigate artifacts commonly associated with imaging processes. Despite the promising results, the architecture's performance hinges on the careful selection and optimization of various parameters within the CNN. The number of layers, types of filters, and specific activation functions can greatly influence the output quality, necessitating rigorous experimentation to pinpoint the most effective configuration for specific imaging scenarios. In a somewhat parallel effort, [70] developed a CNN-centric methodology, focusing on the upscaling of low-resolution medical images to higher resolutions. Their approach, rooted in single-image super-resolution, has shown commendable prowess in conserving critical anatomical details and attenuating noise – challenges often faced in medical imaging. Yet, the singular focus on single-image super-resolution could be seen as a limitation. The inherent richness and potential of tapping into multiple images, or gleaning insights from varied imaging modalities, remains unexplored in their model. This untouched avenue could offer even further enhancements in image quality and diagnostic precision. [71] ventured into the domain of MRI, harnessing the capabilities of a sophisticated neural network structure. With foundational training on extensive datasets comprising both low and high-resolution MRI scans, the model showcases its adeptness at transmuting low-resolution images into their high-resolution analogs. This refined output accentuates the visualization of vascular structures, a crucial component in many diagnostic procedures. Nevertheless, the research design carries inherent limitations. A noticeable absence of a control group curtails the establishment of definitive causal links between the intervention and its outcomes, thus introducing a degree of uncertainty regarding the efficacy of the proposed solution. In a related vein, [72] devised a technique rooted in the paradigm of self-texture transfer. The essence of this approach lies in its capability to astutely discern and transpose inherent texture nuances from the input to the output. The resultant super-resolved images exhibit superior quality and precise refocusing, a testament to the model's proficiency. Delving into the specifics of the network's architecture, it comprises a series of components meticulously orchestrated to capture, refocus, and amalgamate the texture, ultimately culminating in a superiorly enhanced image. Nonetheless, every model has its Achilles heel. The case of [72] proposal grapples with images laden with pronounced occlusions or the distortions introduced by motion blur. Such anomalies pose a challenge, often obfuscating the accurate transference of texture details, thus potentially compromising the final image quality.

[73] utilized dictionary training methods for their approach. Central to their technique is the use of an autoencoder, a specific kind of neural network known for feature extraction and dimensionality reduction. Their system is based on the premise that features derived from LR images can represent those from HR counterparts either directly or after an evaluation process. In terms of feature extraction, the method relies

on local features using receptive fields, with the number of filters being equal to the number of local features extracted. The method proposed by [74] is designed to improve the resolution and quality of fundus images. These images play a critical role in the precise diagnosis and tracking of several ocular conditions, including diabetic retinopathy, glaucoma, and age-related macular degeneration. Utilizing sophisticated image processing methods combined with machine learning algorithms, the approach captures diagnostic features. It then uses these features to derive high-resolution images from their low-resolution counterparts. However, a potential limitation is that the technique could be sensitive to noise and artifacts present in the initial images. Such interferences might compromise the quality of the resulting enhanced images. [75], introduced a network formulated to discern both local and global characteristics of the input image. This dual feature detection capability enables the model to yield high-quality super-resolution outcomes. The authors contend that the unique feature extraction technique employed in their approach adeptly captures intricate structures and nuances inherent in medical images, rendering their method, particularly fitting for tasks related to super-resolution in medical imaging.

In the [76], the authors introduced an alternative approach based on a sub-pixel convolution layer, which incorporates additional enhancements to the network architecture via an upsampling layer. In this specific study, the feature extraction method employed is poised to be a pivotal element of the overall reconstruction process. This method is tasked with extracting features or patterns from the low-resolution input image and transmitting them through multiple layers within the neural network. [77] introduced a technique for fusing medical images, a process vital to diagnosis and treatment planning in the medical field. The proposed framework employs a custom-designed CNN architecture capable of efficiently capturing and integrating salient features from multiple input images. It is worth noting that the method's generalizability to diverse imaging modalities or medical conditions may be compromised if the training dataset lacks adequate coverage of these variations. Consequently, fusion performance could be diminished for cases that are either unrepresented or underrepresented. [78] developed a method that combines correlation filters and progressive CNN techniques to generate high-resolution images from low-resolution inputs. The model comprises a series of interleaved convolutional layers and correlation filters, which progressively enhance image resolution. Correlation filters play a crucial role in extracting pertinent information from the low-resolution input, subsequently guiding the progressive CNN to achieve superior high-resolution image reconstruction. However, it is worth noting that the proposed method demands a substantial volume of training data to attain optimal results, a challenge particularly pertinent in the field of medical imaging, where annotated data is often limited in availability. In a related context, [79] have addressed the intricate task of preserving fine structures and upholding high-quality image details while concurrently reducing computational complexity. Their RDN architecture employs residual connections and dense blocks to facilitate effective feature learning and representation. Despite its design to mitigate computational complexity, it still necessitates considerable computational resources for both training and inference, potentially constraining its practical utility in real-time clinical settings.

3.2. Deep residual network (DRN)

Deep Residual Networks (DRN) have been proven to be highly effective for various computer vision tasks, including medical image super-resolution. DRN is a type of deep CNN that employs residual learning to address the vanishing gradient problem, a common issue in deep networks. By incorporating skip connections between layers, DRN can learn residual functions that are more amenable to optimization, allowing for the construction of deeper networks without compromising accuracy. The aforementioned methods and architectures offer efficient solutions for medical image super-resolution using DRN as a foundation. [80] proposed the 3D Deep Densely Connected Neural Network with the goal of enhancing the quality of brain MRI scans by employing a deep learning model to generate high-resolution images from low-resolution input data. The presented architecture incorporates dense connections between layers, facilitating the efficient learning of hierarchical features and promoting improved gradient flow. However, it's important to note that this architecture demands substantial computational resources and memory for both training and inference. This resource-intensive nature may restrict its applicability in settings with limited resources or real-time applications.

[81] presented a method for enhancing the resolution of medical images using multiple improved residual networks. The approach integrates several improved residual network models that collaboratively work to generate high-resolution medical images from low-resolution inputs. By leveraging the strengths of each individual network and incorporating advanced training strategies. Integrating multiple residual networks may increase the computational complexity and memory requirements of the model, making it challenging to implement in real-time or on resource-constrained devices. [82] present an approach for efficient medical lesion image super-resolution using deep residual networks. The proposed method consists of a tailored architecture designed to handle the unique challenges posed by medical lesion images, such as varying textures and noise levels. By employing residual learning blocks and advanced optimization techniques. The architecture and optimization techniques used in the model can be complex, making it difficult to interpret and understand the underlying decision-making process. [83] presented an approach for medical image super-resolution using deep residual neural networks in the shearlet domain. They proposed a framework that combines the advantages of shearlet transforms, which are well-suited for handling multi-scale and directional features in images, with the power of deep residual neural networks for learning complex patterns. The integration of deep residual neural networks and shearlet transforms may lead to increased computational complexity and longer processing times, making it less suitable for real-time applications.

The presented method [84] aims to enhance the quality of low-resolution medical images by reconstructing them into high-resolution versions while preserving essential details and minimizing artifacts. The residual network architecture enables the model to learn and leverage residual information between low and high-resolution images, effectively capturing complex image features. Although the method aims to minimize artifacts, it may still introduce or amplify noise in the reconstructed images, potentially affecting their diagnostic value. [85] presented a method to improve the image quality and resolution of dental CT scans using deep learning-based super-resolution techniques. By leveraging advanced neural networks, the proposed method enhances the clarity and detail of dental CT images, enabling more accurate diagnosis and treatment planning for dental professionals. Implementing the deep learning-based super-resolution method in existing dental CT workflows may require significant changes to software and hardware infrastructure, as well as overcoming potential regulatory hurdles. [86] presented methods to improve the quality and resolution of medical images, making them more reliable for diagnosis and treatment planning. The method incorporates a dense network structure, which enhances feature extraction and image details. Feedback mechanisms and adaptive weighting are employed to optimize the learning process and minimize reconstruction errors. The dense network structure and feedback mechanisms may increase the computational complexity of the model, requiring more processing power and potentially resulting in slower processing times.

[61] presented an approach for enhancing the resolution of cardiac magnetic resonance images using dual U-Net residual networks. The presented method leverages two U-Net architectures in parallel to effectively capture high-frequency details and preserve contextual information. Dual U-Net residual networks are vulnerable to adversarial attacks, where small, carefully crafted perturbations to the input data can lead to incorrect outputs. This vulnerability could have serious

implications in the context of medical imaging. [87] presented a deep learning-based approach for enhancing the resolution of 2D fetal brain MRI scans. The presented method, called Deep Robust Residual Network, leverages the power of residual learning to address the challenges posed by the low resolution and noise in fetal brain MRI. The performance of the above method relies heavily on the quality and quantity of training data. Any bias or inadequacy in the training dataset could negatively impact the network's generalization to unseen cases.

This study [88] presents an approach based on Double Paths Network with Residual Information Distillation, for enhancing the super-resolution of lung CT images. This method leverages a double-path architecture that separately processes high and low-frequency information while maintaining spatial context. The residual information distillation module further refines the reconstructed image by extracting and fusing multi-scale features. Due to the deep architecture and multiple feature maps generated, the presented method has high memory requirements, which constraint for deployment on resource-limited devices. [89] combines the strengths of multi-attention networks and wavelet transforms to improve the super-resolution process. The multi-attention network learns the important features from various imaging modalities, while the wavelet transform aids in capturing both high-frequency details and low-frequency content. The use of a multi-attention network with wavelet transform makes it difficult to interpret the internal workings of the model. This can limit the ability to diagnose and fix any potential issues with the model.

3.3. Generative adversarial network (GAN)

GAN [90] is a type of neural network architecture that consists of two networks, a generator, and a discriminator, that work together to generate realistic synthetic data. In the context of medical image super-resolution, GANs have shown promising results in producing high-resolution medical images from low-resolution input images. Medical images, such as CT scans or MRI images, often require high resolution in order to accurately diagnose and treat medical conditions. However, acquiring high-resolution images can be expensive and time-consuming. GANs can help overcome this challenge by generating high-quality, high-resolution images from low-resolution input images. The generator network in a GAN takes a low-resolution image as input and produces a high-resolution image as output. The discriminator network then evaluates the quality of the generated image and provides feedback to the generator network, which adjusts its parameters to produce a more realistic image. This process continues iteratively until the generator network produces high-quality, high-resolution images that are indistinguishable from real images. One advantage of using GANs for medical image super-resolution is that they can be trained on small datasets, which is particularly useful in the medical domain where data is often scarce. Additionally, GANs can generate diverse images, allowing clinicians to explore a range of possible diagnoses. However, there are also some challenges associated with using GANs in medical image super-resolution. One challenge is the potential for bias in the generated images, which could lead to incorrect diagnoses or treatment plans. Another challenge is the need for large amounts of computational resources, which can be a limitation in some medical settings. To overcome these challenges recent studies presented their own solution for this.

The study proposes a method [91] for medical image super-resolution using Progressive GAN. The model is trained progressively, with each stage generating higher-resolution images than the previous one. While the proposed method shows promising results on various medical image datasets, its generalization ability to unseen data and different medical applications remains to be evaluated. Further research is needed to assess the method's robustness and adaptability in different medical settings. [92] method incorporates a self-attention mechanism, residual blocks, and a perceptual loss function to generate high-resolution medical images from low-resolution inputs. The proposed method relies on the availability of paired low and high-resolution images for training, which may not always be readily available in certain medical imaging applications. In addition, [93] presented an SR method for medical imaging using a relativistic average generative adversarial network, which improves medical images through numerical measures and visual outputs. Feature extraction is applied by a generator consisting of a residual channel attention block that recalibrates the values of certain channels. [94] proposed an innovative approach to enhance the performance of super-resolution generative adversarial networks by incorporating an autoencoder for dimensionality reduction. The proposed method focuses on reducing the computational complexity and memory usage of the model, enabling more efficient and accurate image super-resolution tasks. The autoencoder effectively captures the essential features of the input images and reduces the dimensionality, which in turn allows the GANs to generate higher-quality super-resolved images with reduced resource requirements. The autoencoder may not always produce an ideal latent space representation, which could affect the quality of the generated super-resolved images. Inadequate representation might lead to the loss of essential image features or the introduction of unwanted artifacts.

By utilizing a specifically designed GAN [95] architecture and incorporating domain-specific knowledge, the proposed model achieves superior performance in reconstructing high-resolution images from low-resolution input, while preserving critical diagnostic information. Designing and fine-tuning the GAN architecture requires a deep understanding of the underlying concepts, which may be challenging for non-experts to implement and optimize. [96] introduced an SR of CT images based on a GAN constrained through an identical, residual, and cycle learning ensemble (GAN—CIRCLE). The GAN—CIRCLE model can retain detailed information about the CT images and overcome existing noise. Feature extraction proceeds by utilizing the convolution layer to capture both the global and local image features and all hidden layer outputs concatenated through a skip connection, which helps prevent overfitting and network saturation. The main idea behind the GAN—CIRCLE method is to use a GAN architecture that is constrained by three different loss functions: identical loss, residual loss, and cycle loss. By combining these three loss functions, the GAN—CIRCLE method is able to effectively extract high-resolution features from low-resolution CT images. The proposed model [97] leverages high-resolution representation learning to enhance the quality of low-resolution medical images. By generating more detailed, high-resolution images, the model aims to improve the accuracy and efficacy of medical image analysis, aiding in better diagnosis and treatment planning. The performance of the model is dependent on the quality and diversity of the training data. If the model is trained on a limited dataset, it may not generalize well to different imaging modalities, anatomical structures, or pathological conditions. Another architecture [98], involves three players: a generator, a discriminator, and a reconstructor. The generator creates high-resolution MRI images, while the discriminator assesses whether these images are real or not. The reconstructor, on the other hand, ensures that the generated high-resolution images are consistent with the low-resolution MRI images. The three-player GAN architecture is trained in an adversarial manner, where the generator tries to fool the discriminator, while the reconstructor ensures that the generated images are realistic. The Three-Player GAN requires large amounts of high-resolution MRI images to train effectively. If there is limited availability of such data, the performance of the method can be impacted.

[99] presented an approach, dubbed Super-Resolution of Unsampled Pixels using GAN, which leverages the strengths of GANs to generate high-resolution MRI images from lower-resolution inputs. By training the GAN on a large dataset of MRI scans, the proposed method is able to effectively reconstruct missing details and enhance image quality. The performance of the model may vary across different MRI acquisition protocols, scanner types, or patient populations. Further research is needed to ensure that the method can be effectively applied to a wide

range of clinical scenarios. The proposed method [100] aims to improve the quality and resolution of MR images by leveraging the capabilities of GANs, which consist of a generator and a discriminator network. The proposed model requires large amounts of computational resources and time to train, which may limit applicability in resource-constrained environments or real-time applications. [101] authors aim to enhance the quality and resolution of medical images, such as MRI, CT, and ultrasound scans, which are critical for accurate diagnosis and treatment planning. By leveraging advancements in GANs, the proposed method effectively upscales low-resolution images while preserving important anatomical structures and details. The improved GAN incorporates innovative techniques for better stability, loss function optimization, and image generation quality. The method's performance is sensitive to hyperparameter tuning and architecture design choices, which can affect the overall image quality and stability of the model. [102] presented a novel multi-supervised SRGAN for enhancing the resolution of cytopathological images. This method aims to improve the diagnosis of diseases by providing better-quality images for cytopathologists to analyze. The proposed model, combines the advantages of deep learning-based super-resolution techniques and the adversarial training framework, enabling it to generate high-resolution images with enhanced details and reduced artifacts. The multi-supervised approach integrates multiple loss functions to optimize the training process and achieve superior performance in terms of image quality and diagnostic accuracy.

[103], a medical SR method based on the GAN architecture is proposed, which is improved through adaptive calibration of the function response per channel by expressly structuring the interdependencies among the channels. The image quality of the reconstruction is improved through adaptive calibration of the functional response and a loss of fusion, which can increase the range of low-level features during the training and image reconstruction processes with upward detailed structures for higher scaling factors. [102] employs a channel attention mechanism within the generator and discriminator networks to focus on relevant features, improving the performance of the super-resolution process. The proposed method demonstrates promising results in providing high-quality images for better tumor detection and segmentation in glioma MRI. The method may not perform as well on other MRI datasets or medical imaging modalities, as it has been specifically designed for glioma MRI. In [104], SR for MR images is proposed using ensemble learning based on a deep learning method. The authors applied parallel generative models using previous image feature information as complementary data for the reconstruction step, and the last generative model is used to combine all images through ensemble learning. The next study [105] presented an approach for improving the resolution of brain MR images using fine-perceptive GANs in the wavelet domain. The presented method combines the power of GANs with wavelet transformations to enhance the fine details and structures of brain MR images. By working in the wavelet domain, the method effectively captures and preserves high-frequency information, leading to better super-resolution performance. While the method demonstrates improvements over existing techniques, its practical usefulness in clinical settings is limited if the enhancement does not translate into better diagnostic accuracy or improved patient outcomes.

[106] proposed a GAN-based CapsNet [107] MRI SR method for cancer classification. CapsNet increases the model robustness and power of the generalization to improve the output quality of an SR-utilized MSGGAN. The feature extraction process is applied using DenseNet, where each dense block consists of four layers and the outputs of each layer are connected. However, DenseNet primarily focuses on learning global features across the entire image, which can result in the loss of important spatial information in individual image patches. This can be a challenge when trying to extract fine-grained features from each patch.

3.3.1. Subsection of GAN: recent advances gan models with transformers in medical image super-resolution: a paradigm shift

In recent years, transformer architectures, initially introduced for natural language processing tasks, have significantly impacted the computer vision arena, especially in the area of medical imaging. These architectures, with their unique attention mechanisms, offer the ability to process sequences of data and capture long-range dependencies. Such capabilities are particularly valuable for super-resolution (SR) tasks in medical images. Several transformer-based models have emerged catering specifically to medical image SR. Adapting models like ViTs or integrating local convolutions with global attention mechanisms have shown promising results in preliminary studies. Based on the transformers model [108] presents a comparative analysis of different single-image SR architectures with a focus on the SwinIR Transformer when applied to medical imaging. The primary goal is to enhance the resolution of medical images, thereby ensuring a more detailed understanding of anatomical structures. Traditional architectures like SRGAN, BSRGAN, and RealESRGAN were benchmarked against SwinIR. The study found that the SwinIR Transformer notably outperformed other models, achieving superior peak signal-to-noise ratio (PSNR) and structural similarity metric (SSIM) metrics, making it a promising tool for high-fidelity medical image super-resolution tasks. [109] propose a deep learning strategy, named T-GAN, that integrates Transformer and generative adversarial networks (GANs) for the super-resolution reconstruction of medical images, especially in low-field MRI scans. The introduction of the Transformer mechanism allows for better texture information extraction and enhances focus on essential image regions. The model employs a unique multi-task loss function, combining content loss, adversarial loss, and adversarial feature loss. Comparative evaluations demonstrate that T-GAN outperforms conventional metrics in MRI scans of knees and abdomen by achieving superior texture feature recovery and overall image quality. While the model successfully recovers more texture features, it might overly emphasize them, potentially overshadowing other clinically relevant features.

[110] authors address the challenge of down-sampling MRI super-resolution reconstruction, highlighting the traditional compressed sensing method's limitations. They introduce" SMIR", a novel MRI reconstruction model based on the Swin Transformer. Unlike prevalent convolutional neural network-based methods, SMIR harnesses the power of transformers to achieve superior image reconstruction outcomes. With its dual-module structure focusing on multi-level feature extraction and image reconstruction, the model employs both frequency and spatial domain losses to enhance image detail reconstruction. Comparative analysis with existing traditional and advanced methods demonstrates SMIR's superior performance in MRI super-resolution reconstruction. [111] TransMRSR introduces a two-stage, transformer-based approach for enhancing the resolution of brain MRIs. Combining both local feature extraction via convolutional blocks and global information capture through transformers, this method specifically tackles challenges posed by MRI's low through-plane resolution. To harness more diverse priors, a GAN is incorporated, culminating in superior super-resolution results when compared to standard single-image super-resolution methods. The self-distilled truncation trick further refines the model, minimizing latent space shifts that could arise from the two-stage training process.

The complexity of combining convolutional and transformer blocks, along with a GAN, might make the model susceptible to overfitting, especially if not provided with a diverse and large enough training dataset. In the quest to improve MRI quality under challenges like budget constraints and image degradation, [112] introduces SIFormer. This innovative hybrid framework not only enhances the resolution of under-sampled MR images but also fills in missing sequences. By synergizing the strengths of transformers and convolutional networks, SIFormer captures both global and local image information effectively. Tested against six prominent methods, SIFormer showcased better performance, promising a potential breakthrough in clinical MRI acquisition. [113] introduces AID-SRGAN, an advanced model designed for super-resolution in radiographic images. This approach encompasses a unique medical degradation model, capturing a wider array of degradation elements beyond standard downsampling. Using an attention-driven mechanism, the model adeptly performs denoising and high-resolution radiograph generation. Results indicate its superior performance, with significant improvements over existing methods like SPSR.While the AID-SRGAN shows improvement over SPSR, it may not outperform all other state-of-the-art methods, or its improvements might be marginal in real-world applications.

3.4. Attention-based models

The application of attention-based models in medical image super-resolution generally follows the same principles as in other image super-resolution tasks. The main idea is to use attention mechanisms to focus on specific regions or features of the input image that are most relevant to the task of enhancing the resolution.

[114] method aims to enhance the quality of low-resolution images by reconstructing them into high-resolution versions. The proposed approach leverages deep residual networks and channel attention mechanisms to effectively learn and exploit hierarchical features from the input images. The channel attention mechanism helps to adaptively recalibrate channel-wise feature responses, focusing on important channels and suppressing less relevant ones. This study [115] proposes a novel medical image super-resolution method based on a Dense Blended Attention Network. The method aims to improve the quality and resolution of medical images by leveraging a dense connection structure and a blended attention mechanism. The dense connection structure enables the efficient propagation of features and gradients, while the blended attention mechanism allows the model to focus on important regions and features within the images. The complex nature of the model can make it difficult to interpret the underlying reasons for its decisions. This could be a concern in clinical settings where understanding the rationale behind a model's predictions is crucial for decision-making and trust.

The presented [116] approach for X-Ray images, leverages wavelet transforms to decompose images into different frequency bands, allowing the network to focus on specific frequency components during the super-resolution process. By incorporating attention mechanisms, the model can selectively emphasize important regions and features in the X-ray images. The integration of wavelet transforms and attention mechanisms increases the computational complexity of the model, making it slower and more resource-intensive than simpler super-resolution techniques. The main goal of the model presented [117] is to improve the quality of low-resolution medical images by enhancing their spatial resolution while preserving important details and structures. The proposed method combines multiple attention mechanisms with a feedback loop in order to better capture and exploit hierarchical features from the input images. The combination of multiple attention mechanisms and a feedback loop leads to increased computational complexity, making the network more resource-intensive and slower to train and deploy, especially on large datasets or high-resolution images.

This [118] paper presents a novel approach called Residual Dense Attention Networks for enhancing the resolution of COVID-19 CT images. The method combines residual learning, dense connections, and attention mechanisms to effectively upscale low-resolution CT scans, providing higher-quality images for improved diagnostics and analysis. The proposed [119] approach combines the strengths of the Swin Transformer, an efficient and powerful vision transformer, with attention mechanisms to effectively learn and exploit local and global contextual information. The model effectively upscales low-resolution CT scans into high-resolution images, improving the quality and accuracy of diagnosis for medical professionals. The presented model inherits the limitations of the Swin Transformer architecture, such as sensitivity to hyperparameter choices, which might affect the model's robustness and performance. The presented [120] method aims to improve the resolution of MRI images while maintaining low computational requirements. The model integrates multi-scale features and bidirectional fusion attention mechanisms to capture both local and global contextual information effectively. The resulting network offers enhanced image quality and better preservation of fine details in MRI scans, making it a promising solution for clinical applications where high-resolution images are essential but computational resources may be limited.

This study [121] presents a model, called MS-DRCA-Net, to enhance the resolution of pulmonary nodule images from low- resolution CT scans. By incorporating a multi-scale architecture, deep residual connections, and channel attention mechanisms, the model effectively captures contextual information for image reconstruction. The joint optimization technique further improves the model's performance. The complex architecture of the MS-DRCA-Net, combined with the joint optimization technique, leads to overfitting, particularly when the available training data is limited or the model is not adequately regularized. The objective of the presented study [122] is to enhance the quality of low-resolution MRI images by reconstructing them into high-resolution images while maintaining accurate details. The presented model combines the strengths of back projection for iterative image refinement, residual learning to capture local and global contextual information, and attention mechanisms for adaptive feature extraction. The presented method [123] focuses on improving the quality and accuracy of low-resolution chest CT scans, which is crucial for better diagnosis and treatment of various lung diseases. The pixel attention mechanism enables the network to adaptively weigh and prioritize the most relevant features within the images. The method faces challenges when processing large images or volumetric data, as the memory and computational requirements could become prohibitive. This necessitates the use of patch-based approaches or other strategies to efficiently process large images.

3.5. Recurrent neural network (RNN)

RNNs can be used for medical image super-resolution tasks, which involve enhancing the resolution of low-quality medical images to produce high-quality images. [124] is a research study that proposes a method for improving the resolution of medical images by leveraging advanced deep-learning techniques. This approach allows for enhanced image quality at any desired scale, enabling more accurate diagnoses and better clinical decision-making. Depending on the complexity of the model and the desired resolution, processing times vary, which is a limitation in time-sensitive clinical settings. The next [125] method combined discrete wavelet transform (DWT) and RNNs to achieve efficient and high-quality compression. DWT was used to decompose the medical images into multi-scale and multi-orientation sub-band images, while RNNs were employed to model the dependencies among the sub-band images and perform the compression. The paper reported significant improvements in compression performance while maintaining image quality compared to traditional methods. However, implementing a combination of DWT and RNNs might increase the computational complexity of the compression process, which concerns resource-limited settings or situations where real-time processing is required. This [126] method addresses the challenge of efficiently reconstructing high-quality MR images from radial k space data, which often results in artifacts and inaccuracies due to the non-Cartesian nature of the sampling. The RNN-based approach leverages the inherent temporal dependencies in the k-space data to model and learn the underlying structure, ultimately producing improved image quality. However, the presented model has high computational complexity, which could lead to longer reconstruction times, making it less suitable for real-time or online applications.

3.6. Single-contrast super resolution

Single-contrast Super Resolution refers to a technique used in the field of image processing, which aims to enhance the resolution of an image without the need for multiple images or additional input data. In essence, the goal is to create a high-resolution image from a single low-resolution input. Single-contrast medical image Super Resolution is a specific application of super-resolution techniques that focuses on enhancing the resolution of medical images obtained from various modalities, such as MRI [127], CT [128], X-ray [129], ultrasound [130], and PET [131]. The goal is to improve the image quality and diagnostic accuracy without increasing the imaging time or radiation exposure to patients Table 2. Based on one or more LR inputs from the same modality, single-contrast SR algorithms attempt to reconstruct an HR representation of the object. Because of their ease of usage, bicubic and bi-spline interpolations are two super-resolution techniques frequently utilized in image SR. However, both methods unavoidably result in blurred and noisy output. The limited SR capability of the interpolation technique can be overcome through the use of deep learning methods, which resolve a large number of issues with a traditional SR method. In this study, we are mainly focusing on learning-based technologies of single contrast (see Sections 3.1,3.2,3.3,3.4,3.5), where algorithms learn the mapping from low-resolution to high-resolution images, which include deep learning techniques such as CNNs and GANs.

3.7. Multi-contrast super resolution

Multi-contrast Super Resolution (MCSR) is a technique used in medical imaging, specifically MRI [176], to enhance the resolution and quality of images. It combines information from multiple image contrasts to generate a high-resolution image with improved tissue contrast and reduced noise. This technique is particularly useful in applications where high-resolution and high-contrast images are crucial for accurate diagnosis or treatment planning. MCSR has shown promising results in improving image quality and resolution in various applications, such as neuroimaging, musculoskeletal imaging, and cardiovascular imaging. In this section we are focusing on MCSR technologies based on deep learning and below we give detailed descriptions of some state-of-the-art methods that represent information about models and their results Table 3.

T1w and T2w are the most frequently acquired multi-contrast images in MRI scans [177]. By contrast, the two inputs of the same object exhibit several edge features. MRI creates images with multiple contrasts and can clearly visualize soft tissue. However, the present SR techniques only use a single contrast or a basic multi-contrast fusion process, neglecting the relationships between various contrasts that are important for enhancing the SR. [184] presented a technique for multi-contrast MRI super-resolution using a Multi-stage Integration Network (MIN). The proposed method aims to enhance the spatial resolution of multi-contrast MRI images by integrating information from multiple low-resolution images and exploiting their inter-modality relationships. The MIN architecture consists of several stages that progressively fuse and refine the high-frequency information from different contrast channels, resulting in a high-resolution output image. The effectiveness of the MIN relies on the assumption that there are strong inter-modality relationships between the different contrast MRI images. If these relationships are weak or absent, the performance of the model could be limited.

Multi-image SR contrast [190,191] is created by utilizing LR images obtained from the same frame with a slightly shifted field of appearance. SR has been proposed for medical images based on a multi-contrast structure and has shown good results in this field. In [178], the authors suggested a model for obtaining richer features from input MR images and reconstructing them as SR MR images. They proposed a multiscale network with a wide-weighted attention structure. To obtain more features, they presented a region-based attention mechanism that

Table 2
Benchmarking of single medical image SR models. The image property index is presented by the structural similarity metric (SSIM) and the peak signal-to-noise ratio (PSNR).

Model	Image type	Training dataset	SSIM	PSNR
[59]	MRI	DIV2K [132]	90%	31.96
MSG Caps GAN [106]	MRI	PROSTATEx [133]	79%	21.09
MFHAN [58]	CT	DIV2K [132], Covid-CT [134]	85.32%	34.53
DNSP [135]	MRI	Brainweb [136](	95%	32.13
GAN framework [104]	MRI	NYU fastMRI [137]	92%	31.35
W-SRCNN [65]	CT	The American Association of Physicists in Medicine (SPIE-AAPM) Lung CT challenge dataset	NA	34.04
DCSRN [80]	MRI	The human connectome project [136]	93.12%	35.05
SRDWT [89]	CT/MRI	DIV2K [132]	94.1%	36.97
GAMA [117]	CT	LDC [138]	98.87%	48.73
SMORE [66]	MRI	NA	95%	38.0
RDAN [118]	CT	T91 [139], BSD500 [11],Set5 [140]	88.8%	31.69
DURN [61]	MRI	Set5 [140]	96%	37.86
Med-SRNet [97]	CT	COVID-19 [134]	89.1%	31.16
SRGAN [141]	MRI	PROSTATEx [133]	66%	21.03
AUTOMAP [142]	MRI	YouTube-8 M [143]	92%	35.4
Deep Attention-based Method [144]	MRI	NA	98%	35.39
GANCNN [92]	MRI/Retinal fundoscopy/Skin cancer	DRIVE(/ [145], ISIC [146], BraTS [147]	95% (MRI)	38.83 (MRI dataset results)
ESRGAN [148]	MRI	DS000113 [149]	94%	26.92
MIASSR [124]	MRI	OASIS-brains [150], BraTS [147], ACDC [151]	95%	36.46
Low field MR images [70]	MRI	fastMRI [137]	95%	35.39
CNN: Subpixel [85]	CT	vivo CBCT [152]	91%	24.50
GAN—CIRCLE [96]	CT	Tibia [153], Abdominal [154]	92.4%	27.25
Three-Player GAN [98]	MRI	Body Datasets [155], Knee dataset [143]	94.3%	36.92
EDSR [101]	CT	DRIVE [145], STARE [156]	99%	38.00
GAN—CIRCLE [157]	CT	NSCLC [158]	85%	28.5
CFIPC [78]	MRI	DRIVE [145]	96.72%	42.20
IDMAN [88]	CT	DeepLesion [159]	94%	34
MRC—Net [52]	CT	CAD-CAP [160]	95.43%	35.58
RRLSRN [87]	MRI	Kirby 21 [161]	98.97%	39.40
CT-SRCNN [162]	CT	CT The Cancer Imaging [163]	92%	32.98
DRIDSR [88]	CT	COVID-CT [134]	83%	31.89
MSBFAN [120]	MRI	IXI [164]	92.66%	31.41
PBPN [89]	CT	BSD500 [11], T91 [139]	96%	37.80
WFSAN [116]	CT	ChinaSet [165]	89%	35.43
SISR [166]	Microscopic Imaging	MaMic [167]	84%	29.62
CESR-GAN [168]	Microscopic Imaging	International Skin Imaging Collaboration [169]	94%	42

(continued on next page)

Table 2 (*continued*)

Model	Image type	Training dataset	SSIM	PSNR
CGAN [102]	MRI	Set5 [140]	88.3%	30.53
WA-SRGAN [170]	Microscopic Imaging	Breast Cancer Histopathological Image [171]	96%	28.74
[172]	MRI	NA	88.61%	35.08
STSRNet [72]	MFP	Refocusing and Super-resolution Dataset for Cytology [173]	95.8%	35.47
PathSRGAN [102]	Cytopathological images	NA	88%	26.92
FP-GAN [105]	MRI	ADNI [174,175]	88.16%	28.30

Table 3
Benchmarking of multi-contrast medical image SR models, where given information about used datasets.

Model	Image Type	Training Dataset	SSIM	PSNR
McMRSR [177]	MRI	fastMRI [137]	90%	33.28
W2AMSB [178]	MRI	IXI [164]	99%	41.72
MGDUN [179]	MRI	IXI [164]	96.37%	35.97
DisC-Di [180]	MRI	IXI [164]	95.51%	31.43
VolumeNet [181]	MRI	Liver Tumor Segmentation [182]	96%	31.61
Based NEDI [183]	MRI	NA	94%	33.89
SANet [184]	MRI	fastMRI [137]	99%	35
MSDT [185]	MRI	fastMRI [137]	61.5%	30.38
MCSR [186]	MRI	IXI [164]	97%	38.51
Gradient-Guided Edge Enhancement [187]	MRI	NAMIC Wiki [188]	96%	34.44
MMHCA [63]	MRI	NA	98%	40.43
INR [64]	MRI	BraTS [147] MSSEG [189]	97%	32.51

extracts the features through a selection process. [179] presented the method Model-Guided Multi-Contrast Deep Unfolding Network (MG-MCDUN) for MRI super-resolution reconstruction. The proposed method aims to improve the spatial resolution of MRI images while preserving fine details and reducing artifacts. The network combines the advantages of model-based and learning-based approaches by leveraging multi-contrast information and unfolding iterative optimization steps. [180] method uses a disentangled conditional diffusion model to enhance the resolution of the MRI scans while preserving the important imaging contrasts. The method aims to improve the accuracy and consistency of MRI super-resolution by addressing the challenges posed by the differences in contrasts between different MRI scans. The diffusion process used in the method may result in the over-smoothing of the images, which can lead to the loss of important features.

[181] presented a parallel constructed network for the SR of 3D MR and CT images. The authors built their model by replacing the convolution layers with lightweight modules, which were constructed using a separable 2D cross-channel convolution. [183] proposed SR for MR brain images based on the local weight similarity (ILWS) among multi-contrast inputs. Multi-contrast input images show the distribution density of the subject, and they largely distribute corresponding structures with various contrasts within the range of relative LR images. The authors of [192] proposed a multi-contrast SR for MR images with a separable attention network, which includes the relationship between the foreground and background and provides rich edge information about the image. [185] presented a model called Multi-Scale Deformable Transformer (MDT) for the task of multi-contrast knee MRI super-resolution. MDT aims to improve the resolution of knee MRI images by leveraging information from multiple contrasts, while simultaneously preserving fine structures and details. The method employs a deformable transformer architecture, which is capable of capturing long-range dependencies and handling spatial variations. This enables the model to effectively learn the relationship between different contrast levels and generate high-resolution images with enhanced quality. The presented model decision-making process can be difficult to interpret, making it challenging to understand the reasoning behind the generated super-resolution images.

In [186], the authors used a generative algorithm to super-sample low-resolution MRI images to establish resulting data with an efficiently higher spatial resolution than the original while retaining structural integrity. [187] introduced a model based on LR image characteristic gradient features to recover the high-frequency details of HR images, utilizing a gradient edge enhancement model to calculate the analogy among input patches with various contrasts. To obtain super-resolved MRI and CT scans [162] applied a multi-modal convolution attention module by extracting useful information from various attention channels. [64] presented a method for improving the resolution of MRI scans using neural networks. The method utilizes multiple contrasts MRI scans and an implicit neural representation to enhance the resolution of the scans, resulting in a more detailed and accurate image. This approach can be used to improve the visualization of small structures and features in MRI scans, which can have important applications in medical imaging and diagnosis. [172] presented a method for improving the resolution of MRI scans using a combination of deep learning and computer vision techniques. The approach uses a transformer-based model to perform multi-scale contextual matching and aggregation to enhance the resolution of the MRI scans. The method is evaluated on multiple datasets and demonstrates improved results compared to traditional super-resolution methods. The model presented in the paper is complex, making it difficult to implement and use in real-world applications.

3.8. Applications of super resolution in healthcare

The integration of SR techniques within the healthcare sector signifies a pivotal transformation, promising enhanced diagnostics and better patient outcomes. This section delves into various applications of SR in healthcare, underscoring the profound impact of this technology.

The successful application of SR in healthcare was demonstrated through an examination and modeling of the collaboration between AI and medical specialists by [193]. In their study, cancer lesions were manually segmented in accordance with the expertise of specialist radiologists, and the performance of the AI models was compared to that of expert radiologists. In the work of [194], a Super-Resolution Generative Adversarial Network (SRGAN) was developed to enhance medical images, specifically utilizing apparent diffusion coefficient (SR-ADC) and enhanced deep SR (EDSR) network images through bicubic interpolation. [162], introduced an SR-based application for chest CT images, achieving image restoration that closely approximated the original ground truth. In the work of [141], they proposed a resolution enhancement application for MR images using a generative network with a preference for upsampling layers over downsampling layers. The authors accomplished this by restoring comprehensive textures based on downsampled images and training a discriminator capable of distinguishing between an SR image and a high-quality source image. In the study conducted by [195], they introduced a multiscale CNN-based image SR application that utilizes weighted least-squares (WLS) optimization. Their framework employs a WLS setup to perform edge-preserving operations that smoothen the image while simultaneously maintaining the edges and enhancing them. This is achieved by striking a better balance between blurring and sharpening. Additionally, they created an SR model by training CNNs using wavelet analysis and incorporated wavelet filters to endow the CNNs with local processing capabilities.

In the work of [52], the authors introduced an SR-based medical diagnosis framework that leverages both local and global image features. Furthermore, they proposed a block for substituting features while establishing a semantic connection between examples and the central intersection of multi-scale information.

In a related study, [170] presented an innovative approach to enhance the diagnosis of age-related macular degeneration (AMD). They achieved this by improving the quality of optical coherence tomography (OCT) images using unsupervised super-resolution techniques based on GANs. Their proposed method involves training a GAN to generate high-resolution OCT images from lower-resolution input images, all without the need for paired ground-truth data. This enhancement in image quality enables better visualization of macular structures, leading to more accurate and reliable AMD diagnoses, potentially benefiting millions of patients worldwide. These super-resolution techniques have found applications in various medical fields like neuroimaging, cardiac imaging, and oncology, enhancing the visualization of fine anatomical structures and pathological changes. However, these techniques also have limitations, including the need for large training datasets, sensitivity to noise, and potential generation of non-existent details.

3.8.1. *Subjective analysis of state art medical image SR applications*

Medical image super-resolution has significantly improved the clarity and details in diagnostic images such as X-rays, CT scans, and MRIs. Enhanced image details can lead to earlier and more accurate diagnoses, especially when diseases have subtle imaging signs. However, there's always the challenge of potentially introducing artifacts, which can mislead clinicians [196]. Consistency in super-resolution performance across various scenarios is pivotal to ensuring trustworthiness in clinical practice [197].

3.8.1.1. The interplay between techniques and disease diagnosis. Medical image super-resolution is not a one-size-fits-all approach. Depending on the disease or clinical requirement, the choice of the SR technique becomes vital. For instance, while GAN-based super-resolution might be exceptional for visual enhancement in oncology imaging, such as the study by [162], the application of SR in neuroimaging might favor architectures like multiscale CNNs, as hinted by the study from [195].

3.8.1.2. Architecture design choices and their relevance. Architectural decisions are instrumental in determining the success of SR applications. For example, the choice by [141] to focus on up-sampling layers over down-sampling layers in their generative network showcases the need to prioritize comprehensive texture restoration, especially for MR images. In contrast, the multiscale CNN-based approach by [195] leverages wavelet analysis, showcasing the importance of local image processing capabilities, especially when the goal is to balance between image blurring and sharpening. Another aspect worth noting is the surge in transformer architectures like TransMRSR [111] in the realm of super-resolution. Their impressive performance metrics highlight the potential benefits of these architectures, like self-attention mechanisms, in capturing intricate image details. However, it is also essential to appreciate the computational implications of these choices.

3.8.1.3. Impact of design choices on clinical applications. The real challenge lies not just in the metric performance but in how these design choices translate to practical clinical settings. For instance, while the SR-ADC and EDSR approach using bicubic interpolation by [194] might showcase significant enhancement in diffusion coefficient images, it's vital to understand its implications in diagnosing conditions like brain tumors or ischemic injuries. Similarly, the method by [52] that synergizes both local and global image features provides a holistic view, which can be especially valuable in a comprehensive clinical analysis, such as tumor staging.

3.8.1.4. Beyond enhancement: risks and trade-offs. While many studies, like those by FAWDN [60] and SRDenseNet [70], show promising results in terms of PSNR and SSIM, there's an inherent risk of over-optimizing for these metrics. In real-world applications, the balance between preserving structural details and achieving high resolution can be delicate. For instance, the disparity in the performance of FAWDN in different scales underlines this challenge. Similarly, while the study by [170] demonstrates significant enhancement in OCT images for AMD diagnosis, real-world validation, especially in diverse patient populations, becomes critical.

SR application in healthcare is multifaceted and highly influenced by the interplay of techniques, architectures, and design decisions. While the summarized performances offer a glimpse into the capabilities of various methods, a deeper analysis, as explored here, sheds light on the nuanced decisions and their broader implications. The ultimate goal remains clear: ensuring these technological advancements directly benefit patient care, diagnosis accuracy, and treatment efficacy.

4. Metrics and dataset

This section highlights topics such as:

Significance of Quantitative Evaluation: The importance of evaluating SR methods, especially in the critical field of medical imaging.

Metrics Overview: Brief intro to the diverse metrics used in SR, referencing Fig. 5.

Need for Datasets: Emphasizing the dependence of medical image SR on high and low-resolution datasets.

Evolution of the Field: Discuss how advancements in the field owe to computer vision breakthroughs and quality datasets.

Common Datasets in SR: An introduction to datasets prevalent in the SR research, referencing Table 4 and Fig. 4.

Introduction to Datasets: Understanding the importance of varied datasets in SR research.

Understanding Metrics: An introduction to the diverse metrics employed for evaluating SR algorithms.

SR methods, especially in medical imaging, must be quantitatively evaluated to ensure their effectiveness, reliability, and safety. This section explores the commonly used metrics (see Fig. 5) for assessing the performance of SR techniques and highlights standard datasets in the field.

4.1. *Datasets*

The field of medical image SR is reliant on high and low-resolution image datasets. Significant developments in this subject can be attributed to improvements in computer vision and the availability of top-notch training datasets. This section presented medical image datasets and descriptions that are mostly used in SR research as shown in Table 4 and Fig. 4.

4.2. *Standard datasets*

Super-resolution research has been significantly bolstered by the availability of robust and diverse datasets. Among these, the Set5 [140] and Set14 [200] datasets have gained traction for their concise collection of images that span portraits to urban scenes. Similarly, the BSD100 dataset [139], which originates from the broader BSD300, offers a rich array of images, making it a popular choice for benchmarking.

For those researchers interested in intricate details and unique textures, the Manga109 dataset [201] is unparalleled. Comprising high-resolution images from Japanese comic books or manga presents a unique challenge for super-resolution algorithms. Meanwhile, the DIV2K dataset [132], though relatively newer, has emerged as a staple in SR research with its vast collection of 1000 high-quality images. The Urban100 dataset [202], with its focus on urban scenes, brings forth the challenge of retaining intricate architectural and structural details in super-resolution tasks. When it comes to facial recognition or tasks specific to human faces, the CelebA dataset [203], brimming with over

Table 4
The brief description of popular medical image datasets for SR.

Dataset Name	Brief description	Image Type	Default task	Created Year
COVID-CT [134]	The publicly available dataset COVID-CT includes 463 non-COVID-19 CTs in addition to 349 COVID-19 CT pictures from 216 patients.	CT	COVID-19 diagnosis models based on AI	2020
PROSTATEx [133]	The SPIE-AAPM-NCI Prostate MR Classification Challenge, also known as the PROSTATEx Challenge, was organized in connection with the 2017 SPIE Medical Imaging Symposium and focused on quantitative image analysis techniques for the diagnostic classification of clinically relevant prostate malignancies.	MRI	For prostate cancer diagnosis	2017
OASIS-brain [150]	The Open Access Series of Imaging Studies (OASIS), which aims to make neuroimaging datasets freely accessible to the scientific community, recently released OASIS-3 and OASIS-4.	MRI	Clinically diagnosed with very mild to moderate Alzheimer's disease.	2007
ADNI [174]	The Alzheimer's Disease Neuroimaging Initiative (ADNI) seeks to enhance clinical trials for Alzheimer's disease prevention and therapy (AD). In order to investigate patients with AD, a dataset integrates knowledge and resources from the public and commercial sectors.	MRI	The ADNI Alzheimer's Disease diagnosis has had an international influence in two ways: first, by creating a set of defined protocols that enable the comparison of results from various centers; and second, by adopting a data-sharing policy that makes all of the data openly available to qualified researchers throughout the world	2004
IXI [164]	Nearly 600 MR images of healthy, normal patients make up the IXI Dataset. Each subject's MR image acquisition protocol includes diffusion-weighted images, MRA images, T1, T2, and PD-weighted images with 15 directions.	MRI	Brain disease diagnosing. Utilizing 1.5T and 3T scanners, the data was gathered at three different hospitals in London	2010
LSMRI [198]	This data collection includes 515 patients with symptomatic back pain and their anonymized clinical MRI study, or series of scans. There may be one or more MRI studies connected to each patient's data.	MRI	Spine disease diagnosing. Our dataset consists of 48,345 MRI slices in total. The majority of the slices have a 320 × 320 pixel image resolution, although there are slices from three investigations that have a 320 × 310 pixel resolution.	2019
MRNet [199]	The 1,370 knee MRI tests conducted at Stanford University Medical Center make up the MRNet dataset. 1,104 abnormal exams the total were found in the sample, with 319 ACL tears, and 508 meniscal tears. The 1,370 knee MRI tests conducted at Stanford University Medical Center make up the MRNet dataset. 1,104 abnormal exams the total were found in the sample, with 319 ACL tears, and 508 meniscal.	MRI	Acute and chronic pain, follow-up or preoperative evaluation, and injury/trauma were the most frequent reasons for knee MRI exams in this dataset.	2012

200,000 celebrity images, has been the go-to choose for many.

For researchers exploring video super-resolution, the Vid4 dataset [204] with its varied motion patterns serves as an excellent resource. Additionally, while the COCO dataset [205] was primarily designed for various other computer vision tasks, its extensive collection of labeled images across 80 categories has seen it being adapted for super-resolution tasks by subsets.

Incorporating insights from these standard super-resolution datasets can provide valuable perspective and benchmarking standards for medical image super-resolution research. It's vital to acknowledge the foundational role these datasets have played in the evolution of super-resolution models, as they offer a rich tapestry of challenges and scenarios, driving models to achieve excellence [206].

4.3. Calculation metrics in medical SR

Various metrics are used to evaluate the performance of super-resolution algorithms. Here in our study, we presented some commonly used ones.

The PSNR is frequently used to assess image quality. This is particularly based on the context of SR reconstruction and denoising. The PSNR is calculated as follows:

$$PSNR = 10 * log_{10}\left(\frac{(2^n - 1)^2}{MSE}\right) \tag{1}$$

Here, the mean squared error (MSE) is a loss function. When the PSNR is higher, the MSE decreases, and the SR result is closer to the actual data. Therefore, the quality of the reconstructed images is

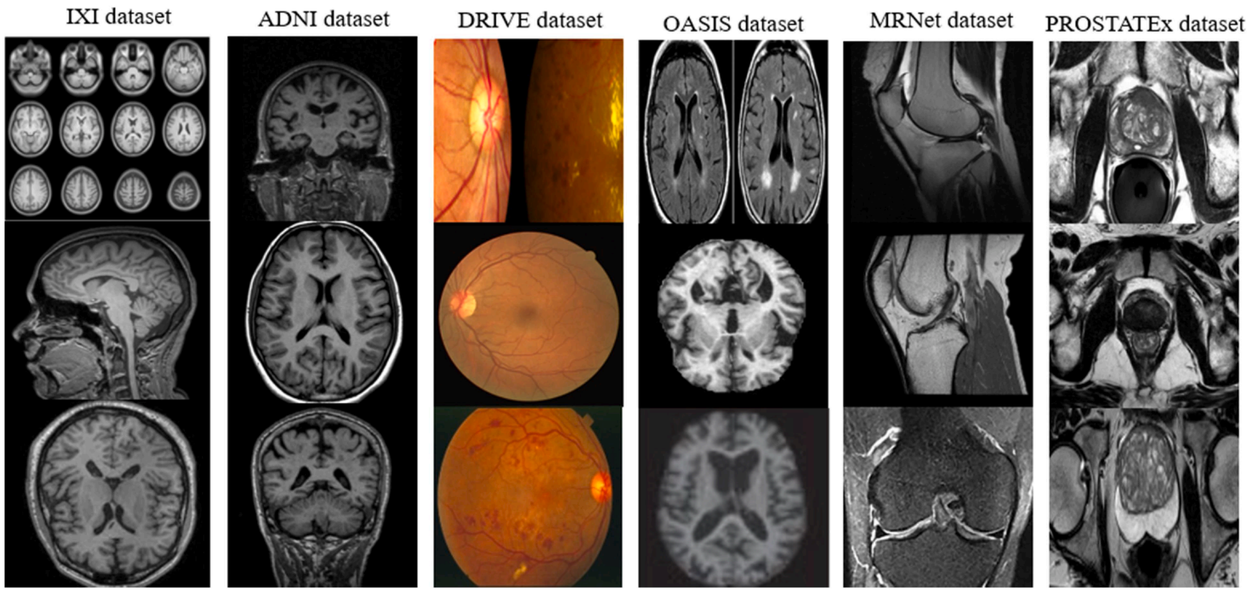

Fig. 4. Medical image SR datasets.

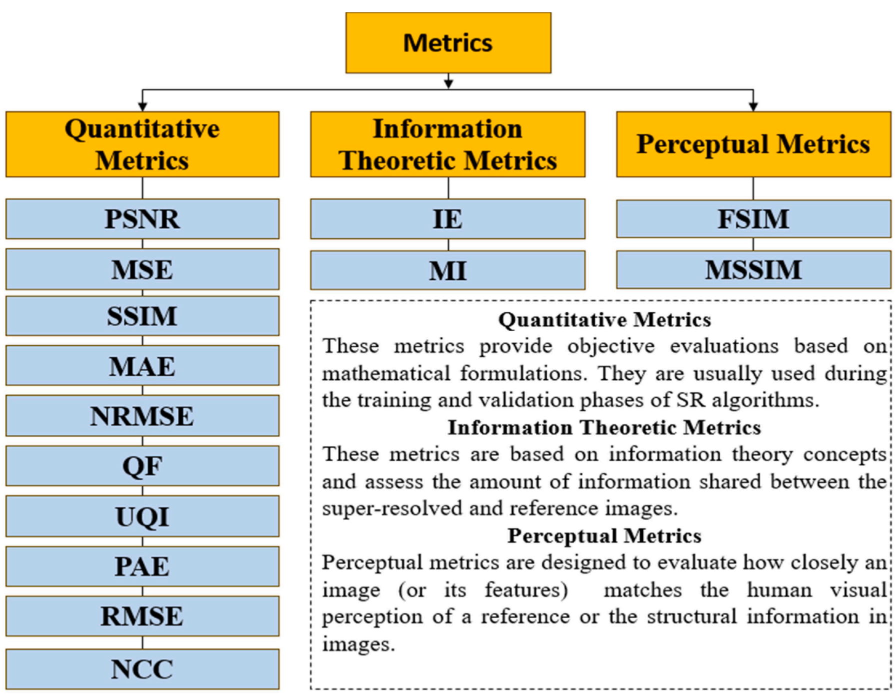

Fig. 5. Overview of commonly using metrics in medical image processing.

enhanced by decreasing the loss function.

The quantitative evaluation metric described below is information entropy (IE), which does not require a reference HR image, and measures the amount of information present in an image. To determine whether the features are adequately maintained during the reconstruction process, the IE of a reconstructed image is measured. The IE is calculated as follows:

$$IE = -\sum_{i=0}^{L-1} p(i) log_2 p(i) \tag{2}$$

where L is the dynamic range of the intensity values, and p(i) indicates the likelihood that each pixel has a signal intensity of i. The more information an image includes, the higher the image quality and the larger the IE.

The SSIM is the final criterion. According to the SSIM, the observed changes in structural information are regarded as image deterioration. The similarity between the two images is determined by comparing the SR image with the ground truth. An ideal correspondence between the two images is indicated by a mean SSIM value close to unity. The SSIM is calculated as follows:

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_x\sigma_y + C_2)}{(\mu_2^x + \mu_2^y + C_1)(\sigma_2^x + \sigma_2^y + C_2)} \tag{3}$$

where x and y refer to the average signal intensities in the original image and the reconstruction, respectively. The standard deviations of the associated images are represented by x and y, where $k_1 = 0.01$, $k_2 =$

0.03, and L is the dynamic range of the pixel values $C_1 = (k_1 L)^2$ and $C_2 = (k_2 L)^2$ Wang et al. (2004). According to this concept, a high SSIM value denotes a high degree of image integrity and vice-versa.

Normalized Root Mean Square Error (NRMSE) is a frequently used measure that enables the comparison of errors between different tests. It is calculated as the root mean square error normalized by the range of values:

$$NRMSE = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}}{y_{max} - y_{min}} \tag{4}$$

where n is the total number of samples. y_i is the actual value for the i^{th} sample. $\hat{y}_i$ is the predicted value for the i^{th} sample. y_{max} is the maximum observed value. y_{min} is the minimum observed value.

Quality Factor (QF) takes into account both the error (difference between the reconstructed and original image) and the smoothness of the reconstructed image:

$$QF = \alpha \text{ x } PSNR + (1 - \alpha) \text{ x } S \tag{5}$$

Where PSNR is the Peak Signal-to-Noise Ratio of the image, S is a measure of the smoothness of the image. α is a weighting factor that balances the two metrics.

Feature Similarity (FSIM) considers two main features when comparing two images: phase congruency, which is a natural image feature that captures the structural information of the image, and gradient magnitude, which represents the contrast information:

$$FSIM = \frac{1}{N}\sum_{i=1}^{N}[S_l(x_i, y_i) * S_c(x_i, y_i) * S_s(x_i, y_i)] \tag{6}$$

In this equation, N is the total number of pixels, x_i and y_i are the corresponding pixels in the two images being compared, S_l is the luminance similarity measure, S_c is the contrast similarity measure, S_s is the structural similarity measure.

Universal Quality Index (UQI) is a quantitative measurement that calculates the similarity between the reference image and the processed image. The best value is 1 and the worst value is −1:

$$UQI(x, y) = \frac{4\sigma_{xy}\mu_x\mu_y}{\left(\sigma_x^2 + \sigma_y^2\right)\left(\mu_x^2 + \mu_y^2\right)} \tag{7}$$

where x and y are the images being compared, μ_x and μ_y are the mean intensities of images x and y, respectively. σ_x^2 and σ_y^2 are the variances of images x and y, respectively, σ_{xy} is the covariance of x and y. The UQI value falls in the range [−1, 1], with 1 indicating a perfect match between the images.

Mutual Information (MI) is an excellent method for medical image alignment because it provides a robust measure of image similarity, capable of handling intensity variations and changes in image content:

$$MI(X, Y) = \sum_{y\in Y}\sum_{x\in X} p(x, y) log\left(\frac{p(x, y)}{p(x)p(y)}\right) \tag{8}$$

here X and Y are the pixel intensities in the two images being compared, *p(x, y)* is the joint probability distribution function of X and Y. *p(x)* and *p (y)* are the marginal probability distribution functions of X and Y, respectively.

Mean Absolute Error (MAE) computes the average absolute difference between corresponding pixels in the original and super-resolved medical images. The MAE provides a measure of the average discrepancy between the pixel values of the two images. A lower MAE indicates better image similarity and higher quality:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|x_i - y_i| \tag{9}$$

where N is the total number of pixels in the images being compared, x_i and y_i are the pixel values of the original and super-resolved images at position *i*, respectively.

Root Mean Square Error (RMSE) calculates the square root of the average squared differences between corresponding pixels in the original and super-resolved images. RMSE calculates the square root of the average squared differences between corresponding pixel values in the original and super-resolved images. It provides a measure of the overall discrepancy between the images:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - y_i)^2} \tag{10}$$

where N is the total number of pixels in the images being compared, x_i represents the pixel value of the original image at position i and y_i represents the pixel value of the super-resolved image at position *i.*

Mean Structural Similarity Index (MSSIM) is an extension of SSIM that calculates the structural similarity index across multiple windows in an image, providing a global assessment. MSSIM calculates the average Structural Similarity Index across multiple windows or regions in the images, providing a global assessment of image quality based on structural similarities:

$$MSSIM = \frac{1}{N}\sum_{i=1}^{N} SSIM(x_i, y_i) \tag{11}$$

here N is the total number of windows or regions in the images being compared, x_i represents a window or region in the original image at position *i and* y_i represents the corresponding window or region in the super-resolved image at position *i.*

Peak Absolute Error (PAE) measures the maximum absolute pixel difference between the original and super-resolved images. PAE calculates the maximum absolute difference between corresponding pixel values in the original and super-resolved images, providing a measure of the most significant discrepancy between the two images:

$$PAE = \max_i |x_i - y_i| \tag{12}$$

where *i* represents the pixel position in the images being compared, x_i represents the pixel value of the original image at position *i,* and y_i represents the pixel value of the super-resolved image at position *i.*

Normalized Cross-Correlation (NCC) measures the similarity between the super-resolved and original images using cross-correlation, accommodating brightness variations. NCC computes the normalized cross-correlation between corresponding pixel values in the original and super-resolved images. It measures the similarity between the two images while accommodating variations in brightness:

$$NCC = \frac{\sum_{i=1}^{N}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{N}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{N}(y_i - \bar{y})^2}} \tag{13}$$

N is the total number of pixels in the images being compared, x_i represents the pixel value of the original image at position *i*, and y_i represents the pixel value of the super-resolved image at position *i*.

5. Advancements in disease prognostication leveraging medical super-resolution

This section highlights topics such as:

Redefining Physical Imaging: The growth of SR in studying cellular structures at nanoscale levels.

Techniques and Achievements: Prominent advancements in SR microscopy, focusing on structured illumination microscopy and multi-scale deep learning.

Future Avenues and Challenges: The hurdles ahead and the ongoing research towards better integration and model efficiency.

SR and Early Cancer Detection: The profound impact of SR techniques on early cancer diagnosis.

Technological Strides: Various studies and methodologies, such as GANs for lung cancer CT images, MR signal motion compensation, and multi-network methods for breast cancer detection.

Challenges and Future Outlook: The challenges impeding the adoption of SR in cancer research and the potential areas for growth.

Revolutionizing Lung Disease Diagnosis: The role of SR in enhancing the detection process of pulmonary nodules.

Technical Advancements: Studies and techniques dedicated to SR enhancement for respiratory conditions, including COVID-19 detection and pulmonology disease visualization.

Opportunities and Limitations: The potential of SR in disease progression tracking and the barriers to its widespread clinical usage.

Advancing Neurological Imaging: The importance of non-invasive techniques and SR's promise in the field.

Technological Innovations: Key advancements in SR applications for brain anomalies, Alzheimer's disease detection, and other neurovascular conditions.

Emerging Trends and Prospects: An overview of the latest SR methodologies in brain imaging and the potential of these techniques in the future.

In this section, we outline recent advances in SR towards various healthcare applications such as cancer, brain, and lung disease imaging. The SR of medical images is a significant area of image analysis. Many computer-vision applications have used image SR techniques extensively. The success of deep learning techniques in image SR has drawn the focus of an increasing number of researchers in recent years. In terms of network architecture, network structure, and training techniques, this paper provides a brief overview of the impact of recent deep-learning-based approaches to the medical imaging of diseases. An overview of the recent advances in SR is shown in Fig. 6.

5.1. SR insights into cellular processes

SR techniques have made remarkable strides in physical imaging, significantly impacting the accuracy and speed of diagnostic processes. They have become indispensable tools for studying cellular structures and dynamics at the nanoscale level. In the realm of SR microscopy image analysis, significant advancements have been made, promising more detailed visualizations from LR images, as demonstrated by [207]. Structured illumination microscopy image SR, developed by [208] using a deep Fourier channel attention network, has led to substantial improvements in content and image reconstruction, particularly for images with low signal-to-noise ratios. Furthermore, a multiscale deep learning-based CNN method, as presented by [166], has achieved success in enhancing the resolution of LR microscopic images. They employ a residual learning scheme to discern differences between paired images and effectively insert lost details from an LR image into an HR image. While significant advancements have been made in SR methods, challenges persist. These include the requirement for extensive training data and the risk of overfitting. Addressing these challenges is an ongoing focus of research, with efforts aimed at developing more efficient models and techniques. Furthermore, the integration of SR methods with other imaging techniques, such as electron microscopy and fluorescence microscopy, holds the potential to offer a comprehensive view of cellular processes.

5.2. Advancements in cancer detection

Recent advances in SR techniques have created new opportunities for improving the diagnosis and treatment of cancer. HR images obtained through SR can significantly enhance the early detection and diagnosis of cancer. These techniques also improve treatment planning by providing higher-resolution images, allowing for precise delineation of tumor boundaries. This is particularly crucial in radiotherapy planning, where accurate targeting is essential. SR-enhanced imaging supports the monitoring of tumor progression or regression during and after treatment. This capability enables more timely adjustments to treatment plans, ultimately leading to improved patient outcomes. [157] focused on SR of lung cancer CT images using GAN methodology. They integrated spatial pyramid pooling and a GAN model for patch-focused training. [142] proposed SR for lung cancer disease detection, reconstructing images based on MR signal motion compensation and golden-angle radial acquisition. MR slices were encoded into a

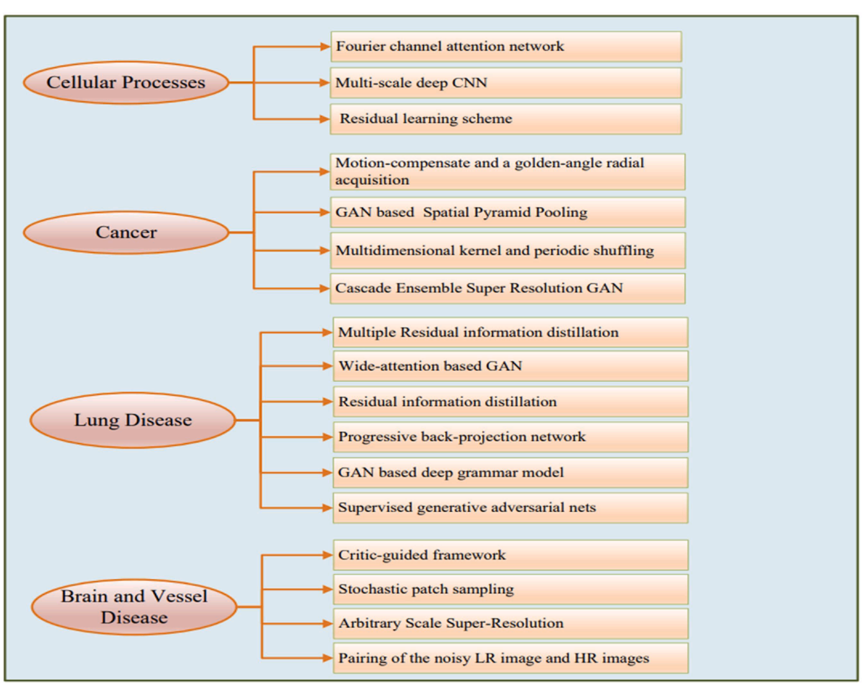

Fig. 6. Overview of SR methods for the special disease.

golden-angle radial trajectory and features using motion-encoded k-space. [209] applied image SR to breast cancer ultrasound. Their approach consists of two main networks: feature extraction and upsampling. To obtain deep multi-scale features, the feature extraction network employs skip connections. Extracted features are then passed to the sub-pixel convolution layer for upsampling, achieving HR output through a shuffling operation with a multi-dimensional kernel. An SR approach was introduced for the reconstruction of skin cancer images by [168]. They employed GAN in combination with cascade ensemble methods. Their method aims to capture more detailed features by utilizing aggregated residual transformation blocks within the network. Additionally, they incorporated a GMSD-based loss function to assess the accuracy of the generated image. In another context, [210] addressed the issue of decreasing resolution in medical image lesion diagnosis. They proposed SR multiscale networks that leverage both global and local features for the reconstruction process. [170] proposed an SR approach for breast histopathology cancer images. In this approach, the author extracted focused features, and the upsampling process involved the use of a generative model with a self-attention layer and widening residual blocks. To address the challenge of SR in cervical cancer screening and reduce processing time, [102] introduced a new pathology GAN-based progressive multi-supervised SR model. In their work, the authors presented a multi-supervised super-resolution model based on a two-stage generator, where the first stage is built upon the U-Net model.

While SR techniques hold great promise in cancer research, they also come with several challenges and limitations. These encompass the risk of introducing artificial details, the substantial demand for extensive training data, the computational complexity of the algorithms, and the difficulty in validation due to the scarcity of ground truth high-resolution images. Future research efforts should be directed toward developing more robust and efficient SR algorithms tailored to the nuances of cancer imaging. Moreover, the integration of multi-modal medical imaging data holds the potential for enhancing the accuracy and utility of SR techniques in oncology, extending beyond image enhancement to areas such as surgical planning and personalized medicine. Furthermore, it is essential to address ethical and regulatory considerations related to the application of these techniques in clinical practice. This includes ensuring patient privacy, data security, and compliance with healthcare regulations.

5.3. Respiratory disorder prognostication

Medical imaging plays a pivotal role in diagnosing and managing lung diseases. In recent years, the quality of these images has seen remarkable improvement thanks to the application of super-resolution techniques, increasingly driven by deep learning methodologies. Particularly noteworthy is the impact on the detection of pulmonary nodules, a crucial factor in early lung cancer diagnosis. SR techniques have significantly enhanced the accuracy of this process. Recent studies have illustrated the effectiveness of SR-enhanced CT scans in detecting even the smallest nodules, enabling early and more precise diagnoses.

To enhance the accuracy of COVID-19 detection from images, [88] employed SR techniques, utilizing a double-path approach to capture both low- and high-frequency features. Their method incorporates multiple residual information distillation steps to obtain high-frequency features, facilitating the recovery of HR images.

In another study, [89] presented an SR module for CT-based COVID-19 images. Their design incorporates two residual blocks and an attention module to extract deep features, which are then progressively upsampled to reconstruct the HR output at different scale factors. Additionally, SR techniques were applied to CT lung images for early-stage pulmonary nodule detection by [211]. The authors introduced a generative model featuring functional semantic graph construction that employs tree-based instructions to generate HR images.

Chest X-ray image SR, as demonstrated by [138], utilizes conditional GANs with spectral normalization. This approach has been instrumental in the classification of pulmonological diseases, as GANs enable precise reconstruction while preserving pathological invariance. In [212], a method for chest X-ray lesion image SR reconstruction is introduced. This method is based on a recursive neural network, addressing concerns related to poor detail extraction and lengthy training times in SR reconstruction processes. Furthermore, [116] presented SR for pulmonology disease detection using chest images. Their approach relies on a lightweight wavelet frequency separation attention network. A dedicated wavelet network is designed with a specific path for approximating wavelet subband frequencies to predict wavelet coefficients.

The integration of SR techniques into lung disease diagnosis holds promise for enhancing both detection and disease progression tracking. However, the widespread clinical adoption of these techniques remains limited due to factors such as computational costs and the necessity for extensive validation. In the realm of neurodegenerative diseases, such as Alzheimer's and Parkinson's, SR techniques have played a pivotal role. They have significantly improved the resolution of MRI images, thereby enhancing the visualization of brain structures and contributing to early diagnosis efforts.

5.4. Unveiling neurovascular complexities: super-resolution in brain and vessel disease detection

The increasing prevalence of non-invasive imaging techniques for detecting and monitoring neurological and vascular diseases has spurred the need for the development of advanced image-processing algorithms. SR methods, with their capacity to deliver improved image resolution and clarity, hold promising capabilities in these domains.

In the detection and analysis of brain anomalies using vessel images, [144] employed paired MRI LR and HR images, introducing applications for reconstruction and upsampling. These applications utilizing SR images exhibit higher accuracy compared to those obtained from interpolated images, making them strong candidates for clinical research. Additionally, [148] presented an SR-GAN application for brain MRI images, particularly in the context of Alzheimer's disease detection. Their proposed method is trained using two techniques: the training process is augmented by increasing the dataset size through stochastic patch sampling, and artifacts are mitigated using two input HR images and the generated images

In the context of Alzheimer's disease detection in brain images, [135] introduced another SR method based on paired prior information to obtain HR output images. For arbitrary-scale SR of brain MRI images, [124] proposed a generative model incorporating coupled meta-learning, effectively reducing the number of model parameters compared to existing methods. [213] presented an SR method for augmentation using GANs, generating synthetic images to expand the training dataset. In another approach, [70] employed a DenseNet architecture to pair noisy LR and HR images for SR MR brain image reconstruction.

The application of SR techniques to medical images, particularly in the context of brain and vascular diseases, has yielded significant enhancements in image resolution and clarity. These improvements have, in turn, advanced diagnostic and treatment capabilities in these critical domains. As AI and machine learning technologies continue to evolve, we anticipate even greater gains in the accuracy and efficiency of these techniques.

6. Challenges

This section highlights topics such as:

SR Insights into Cellular Processes

The role of SR in physical imaging.

Advancements in SR microscopy image analysis.

Challenges and future potential.

Advancements in Cancer Detection

The importance of HR images in early cancer detection and treatment.

Notable methodologies are applied in different types of cancer imaging.

Limitations and future directions in cancer research.

Respiratory Disorder Prognostication

Role of SR in diagnosing and managing lung diseases.

Techniques in enhancing COVID-19 detection.

Application of SR techniques for early-stage pulmonary nodule detection.

Unveiling Neurovascular Complexities: Super-Resolution in Brain and Vessel Disease Detection

Significance of non-invasive imaging techniques.

Role of SR in detecting brain anomalies and Alzheimer's disease detection.

Challenges:

Challenges Associated with Stereo Imaging, applying SR Techniques to Ultrasound Imaging, obstacles in Adopting Unsupervised Super-Resolution for Clinical Imaging, Extremely Dense Imaging, CNN Models, Generative Models, Robustness to Noise and Artifacts, dealing with Motion, Transfer Learning Challenges, Multiscale SR.

In this section, a detailed analysis of the challenges and unaddressed issues in SR is presented (see Fig. 7). This section sheds light on the prominent hurdles that the community faces in realizing the full potential of super-resolution methods in healthcare applications.

6.1. Challenges associated with stereo imaging

An understanding of medical imaging is essential for effective disease diagnosis. In healthcare applications, there has been a recent shift towards stereo imaging techniques, with notable examples including stereo endoscopy and stereomicroscope. Stereo imaging involves the creation of three-dimensional (3D) images by manipulating signals within a 180-degree stereo field. The introduction of stereo imaging has revolutionized the diagnostic process in healthcare. However, challenges arise when the image disparity exceeds the receptive fields, leading to lower-quality images that require techniques like SR for enhancement. While recent advances in single-image SR and deep learning-based SR have made significant strides in medical imaging, they often face difficulties when applied to stereo imaging. The NTIRE, a standard baseline for single-image SR, has also underscored the challenges of stereo-image SR. In response, a 2022 challenge was initiated to address the optimization of single-image SR methods for typical stereo images.

6.2. Challenges in applying super-resolution techniques to ultrasound imaging

A significant number of studies have leveraged ultrasound imaging for in vivo investigations of the human vascular system. SR techniques play a crucial role in enhancing the depth and detail of these images, surpassing the capabilities of other state-of-the-art methods. However, the application of SR in ultrasound imaging remains limited, with many potential applications yet to be explored. Notable examples of SR in ultrasound imaging include its use in oncology and neurology imaging by [49], kidney imaging by [214], and lower-limb imaging for diabetes analysis by [215]. However, SR in ultrasound imaging is still in its early stages, and various challenges remain unexplored. For instance, determining the accuracy of a high-resolution output image is constrained by factors such as observed vessel characteristics, diameter, and velocimetry after image reconstruction, as highlighted by [49]. Similarly, challenges related to insufficient information for microscopy localization, inaccuracies in velocimetry, and incomplete motion information are pressing issues within ultrasound imaging. While some studies, such as those conducted by [216], have examined the reconstruction of 3D images, the accurate acquisition of all channels remains challenging, making this a promising area for future SR research.

6.3. Obstacles in adopting unsupervised super-resolution for clinical imaging

One of the major obstacles in smart healthcare applications is the acquisition and labeling of data required for supervised machine learning. In the case of SR, the process demands a pairing of high- and low-resolution images to effectively estimate the quality of new images with a known downsampling rate. However, in many instances, imaging devices primarily produce low-resolution images. Hence, the need for unsupervised SR techniques becomes paramount in such scenarios. While there have been prior attempts to enhance the resolution of individual images using unsupervised learning techniques, the application of these techniques to multiple images still lags significantly behind the current state-of-the-art approaches. For example, methods like zero-shot, as demonstrated by [217], work well when the image possesses sufficient depth for downsampling. However, for images that are

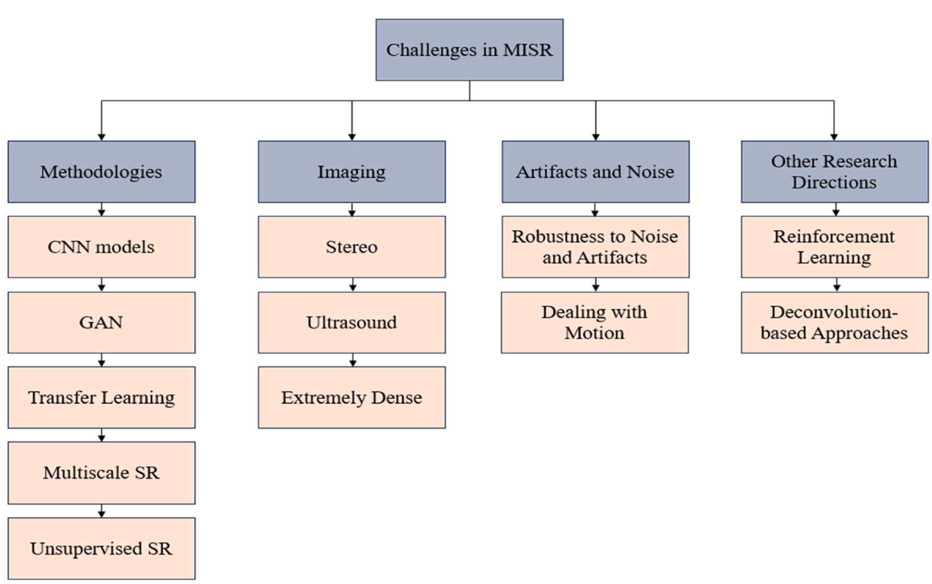

Fig. 7. Overview of challenges in medical image SR.

inherently low-resolution to begin with, such techniques prove ineffective.

6.4. Extremely dense imaging

In medical imaging, image acquisition devices often capture images at a high density, aiming to capture fine details. For example, the prediction of breast cancer requires mammograms with extremely high-density images to examine each tissue closely. Current SR techniques typically operate with a maximum patch extraction size of 32 pixels × 32 pixels, which is relatively limited in terms of available studies. Consequently, for scenarios like the aforementioned breast cancer prediction, a much higher SR rate is necessary, demanding further attention. While notable studies have applied SR to high-density mammogram images ([187]; [64]), their approach to SR rate selection remains arbitrary, highlighting the need for standardization, as noted by these authors. Some noteworthy attempts (e.g., [218,219]) have explored higher SR rates to extract finer details in medical images. However, challenges such as accuracy and processing time remain significant hurdles to establishing a standard rate. For instance, in their work, [218] employed high-resolution 128-pixel × 128-pixel images for standard ultrasound localization. Nevertheless, the study highlighted challenges related to GPU acceleration and real-time optimization required to extract such minute details.

6.5. CNN models

Advanced CNN architectures, especially deep networks, require significant computational power. This demand is not only for training but also for inference, making it challenging to deploy in real-time applications or on edge devices with limited computational resources [220]. CNN-based models focus on end-to-end mapping from low-resolution to high-resolution images, potentially overlooking the rich intermediate features that can be critical for image recovery. Intermediate features can provide a more detailed understanding of the underlying structures, which is crucial for medical images [221].

6.6. Generative models

GANs, have ushered in a new era of capabilities within the realm of SR, particularly for medical imaging. The synergistic model architecture of GANs, involving a generator striving to upscale images and a discriminator evaluating the quality of the generated images, offers an innovative approach to the enhancement of image resolution. However, the deployment of GAN-based models for medical image SR has brought forth certain intricate challenges that become paramount given the delicate nature of medical imaging.

One of the foremost issues that looms is that of mode collapse. This phenomenon sees the generator start to yield strikingly similar outputs for diverse inputs. In the context of medical imaging, the implications of such an occurrence could be detrimental. Overlooking critical details or anomalies in the upscaled images can lead to misdiagnoses, thereby affecting patient care. Training stability, or rather the lack thereof, further compounds the intricacies of using GANs [157]. Achieving a harmonious equilibrium in training GANs can often be a tumultuous journey, particularly when the loss functions are not meticulously defined or balanced. The fallout from such instability is the generator's propensity to craft unrealistic images. Within the sensitive landscape of medical imaging, the generation of images that are not an accurate representation of the underlying anatomy can lead to diagnostic errors [222]. The risk of over-enhancement is another challenge that cannot be overlooked. The prowess of GANs in amplifying image details, while commendable, can sometimes be their Achilles' heel. There exists a tangible risk where the model may overemphasize or exaggerate certain features that aren't inherently present in the actual high-resolution image. Such over-enhancements can introduce artifacts or, even worse, paint benign structures as pathological, leading clinicians down an erroneous path [223].

6.7. Robustness to noise and artifacts

Medical images can often contain noise or artifacts from the imaging process. SR methods should be robust to these to avoid amplifying or introducing new artifacts. Robustness to noise and artifacts is a pivotal challenge in medical image processing. Given the high stakes involved in medical decisions, it's vital that algorithms can reliably interpret images even in the presence of such impediments. Simple and computationally efficient methods for SR can be beneficial for real-time applications due to their speed [224]. However, when trying to upscale images by significant factors, these methods can often introduce visual artifacts [225].

6.8. Dealing with motion

Especially in modalities like MRI, CT, and ultrasound images, motion that comes due to patient movement, cardiac activity, or respiration can introduce inconsistencies in images [226]. SR techniques need to account for and correct these inconsistencies. Iterative optimization algorithms often face challenges, especially in high-dimensional spaces such as those encountered in medical imaging [227].

6.9. Transfer learning challenges

The application of transfer learning to medical image super-resolution offers an enticing avenue, capitalizing on the rich feature representation learned from large and diverse datasets like ImageNet. However, its implementation in the realm of medical imaging isn't devoid of challenges. One of the most pronounced challenges is the domain gap. The inherent nature of medical images diverges significantly from that of natural images. Medical images, whether they are MRIs, CT scans, or X-rays, capture unique underlying physiological phenomena. These images might present various contrasts, modalities, and structures that are atypical in natural images. Consequently, a model pre-trained on natural images might find it initially challenging to grapple with the distinct properties of medical imagery. Compounding the issue is the data distribution mismatch. The pixel value distributions, contrasts, and intricate features of medical images can vary vastly from natural images. Thus, ensuring that the early layers of a pre-trained model remain pertinent and beneficial for the medical super-resolution task becomes a critical aspect. However, with medical datasets often being limited in size due to privacy concerns and data acquisition constraints, the risk of overfitting looms large. This limited data availability leads us to another conundrum of fine-tuning difficulties. When only a limited set of high-resolution medical images is accessible, the question arises: Which layers of the model should be fine-tuned, and which ones should be frozen? An incorrect decision here can lead to the model memorizing the training data, rather than genuinely learning the nuances of medical image SR [216].

Additionally, there's the issue of model complexity and computational overhead. Models pre-trained on extensive datasets like ImageNet [228] are often characterized by their depth and might entail substantial computational resources. In scenarios where such complexity is not warranted, employing these models can lead to unnecessary computational costs and inefficiencies. Lastly, a pivotal concern is featuring relevance. While the initial layers of a pre-trained model capture generic features, their direct applicability to medical images remains questionable. It becomes essential to ascertain that these features don't detract from the super-resolution task but rather augment it.

6.10. Multiscale SR

In the evolving landscape of medical imaging, the introduction and subsequent adoption of multiscale models have marked a significant leap in the realm of SR. These models, by virtue of their design, attempt to assimilate information across different scales, thereby aiming to retrieve a synthesis of both the macroscopic and microscopic features inherent in medical images. Through this approach, the promise is a more nuanced and detailed super-resolved image that captures the intricacies of underlying anatomical structures. However, the marriage of multiscale modeling with medical image SR is not without its challenges.

A primary concern arises from the very strength of multiscale models—their ability to process varied scales of an image. While this is instrumental in capturing a diverse range of details, it also demands a comprehensive contextual understanding of the image. Medical images are not mere visual data they encapsulate a plethora of physiological and pathological information. Ensuring that features derived from various scales align coherently in the super-resolved image while maintaining their clinical relevance can be an arduous task [229]. Moreover, the juxtaposition of features from different scales introduces the potential for conflicts in the final super-resolved image. For instance, while enhancing the finer details, there is a risk of overshadowing or distorting broader structures that are equally vital for clinical interpretation. Achieving a harmonious balance between these scales without introducing artifacts or inconsistencies remains a formidable challenge [229]. Furthermore, multiscale models often demand significant computational resources. The need to process and integrate information from multiple scales escalates the computational overhead. Given the urgency and real-time demands of many medical scenarios, such as surgeries or emergency diagnostics, the feasibility of deploying multiscale SR models becomes a point of contention.

Each of these challenges represents an opportunity for future research and development in the field of medical image super-resolution. By conscientiously highlighting these challenges and limitations, this survey underscores the importance of continual research, collaboration, and innovation in the domain. As we champion the strides made, we also emphasize the path ahead, marked by both promise and intricate challenges.

6.11. Other research directions

Apart from the above challenges, the current trend in the literature has led to the use of semi-supervised and reinforcement-learning-based methods to compensate for the requirement of massive sets of medical images. Reinforcement-based methods generally require much less data and are therefore not limited to the acquisition of massive medical data. However, the downside of such approaches is the optimization time of the policy, and in some situations, despite an appropriate design, the policy does not converge, which in turn makes these approaches unusable. Some studies have been based on reinforcement learning to partially solve a process in SR, such as a blur kernel [59] and the selection of the best action from existing supervised models [230]. The positive side of both these approaches is lightheartedness and faster response compared to supervised approaches; however, they work on a partial process of SR, and thus involving a pure reinforcement learning solution is still a massive gap in the current form of state-of-the-art approaches.

Another popular method that has received significant attention in recent years is the deconvolution technique for the SR of microscopic image data. The deconvolution works best for sparse data such as structured illumination microscopy and fluorescent microscopy. Similar to reinforcement learning, these methods are lightweight and fast [231]. Moreover, in contrast to deep learning-based content-dependent approaches, deconvolution-based approaches are content-agnostic, which further avoids the limitation of the acquisition of high-resolution images. However, deconvolution-based models require information about the prior image to model the SR image. The current state-of-the-art approaches have witnessed an application in microscopy and ultrasound imaging [232], where the information is sparse; however, if such faster techniques can be applied to highly dense medical images, such as mammograms, it would be a valuable addition to state-of-the-art techniques. The summary of the unaddressed challenges and research directions are mentioned in Table 5.

While significant advancements have been made in medical image super-resolution, challenges remain. Future research should focus on developing more robust and interpretable SR models, incorporating domain-specific knowledge, and addressing the issues of noise and over-enhancement. In addition, the integration of these SR techniques into the clinical workflow will require careful validation to ensure the reliability and safety of the super-resolved images.

7. Experimental analysis

In this section we focused on experimental details of several state art methods in medical SR. We implemented this section-based IXI MRI brain dataset [164] for SR Table 6. This dataset includes a significant number of MRI scans from a diverse range of subjects, allowing for comprehensive testing of super-resolution algorithms, especially for enhancing the details in neuroimaging. We compared the performance of state-of-the-art SR methods based on two primary metrics: PSNR and SSIM. Both PSNR and SSIM give us insights into the quality of the

Table 5
Summary of the unaddressed problems and future directions.

Challenges	Medical images	Application area	Research direction
Stereo Imaging	Stereo endoscopy and stereomicroscope	Endoscopy, Microscopy	Improved Acquisition Techniques, Advanced Visualization Tools
Ultrasound Imagining	Vascular Data	Oncology, Neurology, Kidney, Diabetes	3D reconstruction Accurate velocimetry Incomplete Motion
Unsupervised Learning	general data	tumor detection, cancer detection	Multiple image unsupervised learning
Extremely Dense	Ultrasound data, Mammogram	Breast cancer prediction, Tumour prediction	Real-time optimization, Higher rates accuracy
Reinforcement Learning	Applied to all	Blind super-resolution	Time optimization, policy model, evaluation model
Deconvolution	Sparse Microscopic data, filament structure data, DNA imaging, Ultrasound data	Fluorescence microscopy, structured illumination microscopy	3D Resolution of microscopic data, Content-agnostic super resolution, Model of the prior for deconvolution
CNN	Applied to all	Clinical healthcare based on AI	AI based smart healthcare
GAN	Applied to all	AI based image regenerator	Reconstruction medical images, creating syntactic datasets
Motion	MRI/CT/Ultrasound	Healthcare applications	Image correction
Transfer Learning	Applied to all	Architectural Innovations, Domain Adaptation	Enhancing Scans, Data Augmentation, Fine-tuning
Multiscale SR	Applied to all	Enhanced Disease Diagnosis, Improved Treatment Planning	Functional MRI, Diffusion Tensor Imaging, Structural Analysis

Table 6
Experimental analysis of state art models of medical image SR.

Model	Scale	PSNR	SSIM	Scale	PSNR	SSIM
SRCNN [233]	x2	36.20	81.43	x4	28.42	78.28
FAWDN [60]		43.30	98.50		33.23	90.36
PFMDN [59]		35.84	91.87		29.63	87.28
MHCA [63]		45.20	96.50		32.65	94.86
W-SRCNN [65]		25.62	89.62		19.99	76.84
SRDenseNet [70]		45.68	98.70		36.20	92.32
CFIPC [78]		46.81	95.21		38.42	91.02
MRDN [79]		37.80	96.60		31.69	88.86
MIRN [81]		32.64	92.12		29.21	88.62
DURN [61]		31.99	92.00		28.45	78.99
RRLSRN [87]		38.67	98.52		31.25	88.92
DRIDSR [88]		36.99	91.99		31.89	83.54
Multimodal-Boost [89]		37.52	93.58		30.27	89.34
SRGAN [234]		28.49	81.85		30.68	86.89
GAN-MSR [92]		38.85	94.17		32.42	89.53
GAN—CIRCLE [96]		28.69	79.63		32.25	89.12
Med-SRNet [97]		45.89	99.20		33.84	89.87
FP-GANs [105]		28.23	91.99		26.32	89.85
SwinIR [108]		36.56	90.84		34.99	85.48
T-GAN [109]		35.12	94.26		31.28	90.51
TransMRSR [111]		43.68	97.61		36.37	98.50
SIFormer [112]		39.74	95.22		33.50	97.99
AID-SRGAN [113]		33.28	94.00		30.52	89.65
WFSAN [116]		35.62	93.26		29.85	89.27
GAMA [117]		43.05	98.56		32.89	90.52
RDAN [118]		36.16	94.28		31.48	85.62
STAN [119]		35.21	94.89		31.24	84.99
MSBFAN [120]		33.56	90.99		30.42	91.89
DisC-Dif [180]		37.61	98.52		31.42	95.99

reconstructed high-resolution images in comparison to the original high-resolution images. For instance, models like FAWDN [60] and MHCA [63] exhibited higher PSNR values, hinting at better image detail restoration. However, performance variability was evident across different SR methods. While some models showed superior performance in terms of PSNR and SSIM, there's a catch. High computational complexity, seen in models like FAWDN [60], might render them impractical for real-time applications. Moreover, despite their impressive metrics on the IXI dataset [164], some models may not generalize well to other datasets, underscoring the importance of multi-dataset validation.

CFIPC [78] stands out for its performance in scale x2 with the highest PSNR of 46.81. However, when it comes to SSIM at the same scale, Med-SRNet [97] dominates with a remarkable score of 99.20. SRDenseNet [70] also makes a strong appearance with competitive scores in both PSNR and SSIM. When examining the scale x4, TransMRSR [111] emerges as a frontrunner, demonstrating exceptional performance in both PSNR and SSIM. It's worth noting how this model outperforms even the established benchmark, SRCNN, which offers a decent PSNR of 36.20 and SSIM of 81.43 for scale x2 but sees a performance drop at scale x4. Several models surpass SRCNN's performance, underlining the rapid advancements in medical image super-resolution techniques. Among them, CFIPC [78] and SRDenseNet [70] exhibit particularly strong performances, which highlight the efficacy of their underlying architectures. Interestingly, recent transformer architectures, specifically tailored for image processing, are making a mark in the super-resolution domain. SwinIR[104], T-GAN [109], TransMRSR [107], and SIFormer are prime examples. In particular, TransMRSR [107] leads the pack, excelling in both PSNR and SSIM metrics. Furthermore, FAWDN offers a fascinating case. While it boasts an impressive SSIM at scale x2, its PSNR at scale x4 is comparatively lower. This disparity underscores the challenges in striking a balance between preserving structural similarities and achieving a high peak signal-to-noise ratio. On the topic of specialized models, STAN, which synergizes the capabilities of the Swin transformer with attention mechanisms, yields commendable results specifically for CT imaging. Additionally, models like WFSAN [116] and AID-SRGAN [113] adopt distinctive approaches, focusing on specific types of medical imaging such as chest X-rays and radiographs. A higher SSIM value indicates that a method preserves structural details better, which is of paramount importance in medical imaging. Though high PSNR values signify good image quality, in a practical medical setting, a high SSIM could be more indicative of the model's usefulness. Beyond metrics, the clinical validation of these techniques is paramount. What medical practitioners, such as radiologists, perceive these enhanced images and their subsequent impact on diagnosis or treatment decisions should be a core evaluation criterion. In the pursuit of enhancing resolution, there's a potential pitfall: some methods could introduce artifacts or distort specific features, which can be counterproductive in medical diagnostics.

The field of medical image super-resolution is witnessing rapid advancements with various architectures, ranging from convolutional networks to transformers, all striving to achieve better clarity and precision in medical images.

8. Discussion

This comprehensive survey aimed to provide an extensive overview of the current state-of-the-art deep learning-based models for medical image super-resolution, with a particular focus on their application in smart healthcare. We reviewed various models, including SRCNN, DRN, GAN-based models, attention-based models, and RNN-based models, and discussed their strengths and limitations. Additionally, we highlighted several challenges and unaddressed issues in the field, such as noise handling, integration with other imaging modalities, maintaining clinical features, clinical validation, and hardware constraints.

Our review revealed that deep learning-based models, particularly those based on GANs and attention mechanisms, have shown significant promise in enhancing the resolution of medical images, outperforming traditional interpolation methods. These models have been successfully applied to various types of medical images, including MRI, CT, X-ray, and ultrasound scans, and have the potential to revolutionize the diagnostic process by enabling more precise clinical diagnoses and interventions.

However, we also identified several critical challenges that need to be addressed to facilitate the widespread adoption of these techniques in clinical practice. Firstly, developing models that can handle different types of noise and produce clean, high-resolution images is a significant challenge. Secondly, integrating these models with different imaging modalities and ensuring that they maintain all clinically relevant details is crucial. Thirdly, these models need to be clinically validated to ensure their reliability and safety. Lastly, navigating the regulatory landscape and obtaining the necessary approvals for clinical use is a complex and time-consuming process.

Additionally, we noted that there is a lack of standardization in the selection of super-resolution rates, and the accuracy and time consumption of higher rate extractions are still challenges toward the realization of a standard rate. The integration of super-resolution techniques into the clinical workflow will require careful validation to ensure the reliability and safety of the super-resolved images. Moreover, the optimization time of the policy in reinforcement learning-based methods and the requirement of prior image information in deconvolution-based models are notable limitations that need to be addressed. While semi-supervised and reinforcement learning-based methods have been proposed to compensate for the requirement of massive sets of medical images, these approaches have their own set of challenges, such as the optimization time of the policy and the non-convergence of the policy in some situations. Additionally, the application of faster techniques like deconvolution to highly dense medical images, such as mammograms, remains an unexplored area that warrants further investigation.

9. Future directions

The potential pathways for advancement in the field of medical image super-resolution are numerous and exciting. The continuous progress in deep learning algorithms and increasing computational capabilities suggest that super-resolution models will soon become indispensable tools in the diagnostic and treatment planning arsenal. These models hold the promise of drastically enhancing the quality of medical images, thereby facilitating more accurate diagnoses and more precise interventions. Additionally, the capacity to generate high-resolution images from existing low-resolution ones could minimize the necessity for additional scans, consequently reducing radiation exposure and enhancing patient comfort. Furthermore, as the availability of data expands and models become more sophisticated, it is anticipated that super-resolution models will be equipped to manage a broader range of imaging modalities and clinical applications. This will pave the way for the creation of personalized and patient-specific models that can deliver more precise and clinically pertinent outcomes.

9.1. Tackling specific challenges in medical image super-resolution

As we stand on the cusp of advancements in medical image super-resolution, certain pressing challenges demand our attention. The road to an optimized future in this field may seem daunting, but with meticulous strategies, it is achievable [19].

Data scarcity and diversity have long plagued the realm of medical imaging. The efficacy of deep learning models hinges on vast and varied datasets, but acquiring such data sets, especially high-resolution ones, remains an uphill task in medical domains [206]. To circumvent this, the use of synthetic datasets and data augmentation techniques appears promising. By deploying generative models to simulate medical images, we can amass a larger pool for model training. Additionally, the realm of transfer learning offers potential avenues [216]. Here, models that have been trained on expansive natural image datasets can be fine-tuned with the limited medical data available, facilitating better performance without the need for massive medical datasets [56].

Another challenge that emerges is model generalization across different imaging modalities. There is a lingering concern that models trained on a specific modality, such as MRI, might falter when presented with another, like CT scans [40]. A future direction to ensure robustness across modalities is to focus on creating modality-agnostic architectures. A strategy worth exploring is multi-task learning, where models are trained across multiple imaging types. This simultaneous training can equip the model to identify shared features and intricacies across various modalities, ensuring consistent performance.

Computational overhead is a concern, especially when real-time applications are considered. Surgeries and immediate diagnostics demand swift super-resolution without image quality being compromised [15]. This necessitates the exploration of lightweight model architectures, with mobile-optimized neural networks being a prime candidate. Moreover, hardware accelerators, including FPGAs and custom ASICs tailored for super-resolution tasks, might hold the key to facilitating real-time processing without delays.

The medical community becomes increasingly reliant on AI-augmented images, and the interpretability of models is paramount. Clinicians need to understand the underlying decision-making processes of these models to trust their outputs fully. To this end, integrating techniques like attention mechanisms can be instrumental. These mechanisms can illuminate regions in the image crucial for the super-resolution process, offering clinicians insights into what the model perceives as important. Training models to generate explanations alongside super-resolved images can further bridge the trust gap and facilitate more widespread adoption of these advanced technologies in clinical settings.

10. Prospective

The outlook for medical image super-resolution in the realm of smart healthcare applications is incredibly promising. Advances in deep learning and computational capabilities indicate that super-resolution models are on track to become a fundamental component of the diagnostic and treatment planning process. These models are poised to substantially enhance the quality of medical images, thereby enabling more accurate diagnoses and more precise interventions. Additionally, the capability to generate high-resolution images from existing low-resolution ones could eliminate the need for additional scans, thereby reducing radiation exposure and improving patient comfort.

Moreover, as the availability of data increases and models become more sophisticated, it is expected that super-resolution models will be capable of handling a wider range of imaging modalities and clinical applications. This will facilitate the development of personalized and patient-specific models that can provide more accurate and clinically relevant results.

11. Recommendations

In order to fully harness the potential of medical image super-resolution in smart healthcare applications, several key recommendations about the critical need for standardization in the selection of super-resolution rates and the validation of models. This includes developing standardized datasets and evaluation metrics that can be used to objectively compare the performance of different models. Encouraging collaboration between researchers, clinicians, and industry partners is essential to accelerate the development and implementation of super-resolution models. This includes sharing of data, expertise, and resources. Furthermore, it is important to rigorously validate the models in real-world clinical settings to ensure their reliability and safety. This includes conducting clinical trials and studies to assess the impact of super-resolution models on diagnostic accuracy and patient outcomes.

Additionally, efforts should be made to develop models that are computationally efficient and can be easily integrated into existing clinical workflows. This includes optimizing the models for different hardware platforms and developing user-friendly interfaces.

Lastly, it is important to address the ethical and legal considerations associated with the use of super-resolution models, such as data privacy, informed consent, and liability. Developing clear guidelines and policies for the responsible use of these models is crucial to ensure their widespread adoption and success. The future of medical image super-resolution in smart healthcare applications looks incredibly bright. By addressing these key challenges and harnessing the power of deep learning and computational advances, we can develop models that significantly improve the quality of medical images, enhance diagnostic accuracy, and ultimately lead to better patient outcomes.

12. Conclusion

In the era of digital healthcare transformation, the need for high-resolution medical images is more pressing than ever. Deep learning models, in synergy with medical imaging, have the potential to redefine diagnostic accuracy and precision. Nonetheless, the challenge of creating clear, high-resolution images from low-quality outputs remains. Our analysis of contemporary techniques and state-of-the-art models offers insights into the current capabilities and limitations of super-resolution in medical imaging. While models like SRCNN, VDSR, and SRGAN have shown promise, there remains room for optimization and adaptation specific to medical nuances.

The intertwining of deep learning with medical imaging has already started to redefine healthcare applications, especially with the rise of smart hospitals. As the next-generation healthcare transformation accelerates, it's crucial that the medical community, together with AI researchers, focuses on enhancing these models further. Ensuring clarity, accuracy, and reliability in medical images is not just a technical challenge; it's imperative for patient care.

Our journey through this paper underlined the critical importance of high-resolution medical images, especially given the propensity of low-resolution images, often captured by IoT devices, to introduce biases into deep learning models. Such biases, when unchecked, have the potential to severely skew clinical decisions, ultimately affecting patient care.

We delved into the world of super-resolution techniques, which, though employed extensively, still grapple with the challenge of achieving impeccable image restoration. In the realm of medical imaging, where precision is paramount, slight inaccuracies can significantly influence model training, which in turn has cascading impacts on clinical outcomes. Through our comprehensive review, we unearthed the limitations of existing methods and the notable absence of a targeted examination of the accuracy of image restoration in medical imaging. By examining the state-of-the-art models and their inherent challenges, we aimed to highlight the indispensable role of accurate and robust super-resolution methods in medical image enhancement. Such enhancements are pivotal not just for the immediate diagnostic process but also for bolstering the overall efficacy of deep learning models in healthcare applications. In hindsight, our survey provides a roadmap, charting both the accomplishments and the yet-to-be-explored avenues in the field of medical image restoration. As we move forward, it is evident that optimizing medical image restoration is not just a technological goal but a critical need for advancing healthcare outcomes. We remain hopeful that future research, spurred by the challenges and questions highlighted in this survey, will drive innovations that will further bridge the gap between medical imaging and its optimal utilization in deep learning.

CRediT authorship contribution statement

Sabina Umirzakova: Methodology, Software, Validation, Writing – original draft. **Shabir Ahmad:** Formal analysis, Resources, Data curation, Writing – review & editing. **Latif U. Khan:** Project administration, Writing – review & editing. **Taegkeun Whangbo:** Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Taegkeun Whangbo reports administrative support, article publishing charges, statistical analysis, and writing assistance were provided by Gachon University. Taegkeun Whangbo reports a relationship with Gachon University that includes: consulting or advisory, employment, funding grants, and paid expert testimony. Taegkeun Whangbo has patent None pending to Assignee. 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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