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Denoising Medical Images: A review of total variation minimization methods

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Abstract
The total variation model is considered one of the important models in removing noise from images in general and medical images in particular, because of its importance in diagnosis and knowing the details of the image, as it is also distinguished by its ease of use and preserving the edges and details of the image, which makes it an effective model in reducing distortion significantly without damaging the basic structure of the image. However, it contains some challenges, including its inability to derive points where the contrast is zero, which makes the improvement solutions more complex., we will discuss in this review the types of medical photo, and the total variation model, as well as the advantages, the problems, and the research that was used to address the problem of the total variation in detail.

Keywords: Image processing, optimization, computer vision

Introduction

total variation (TV) minimization is a potent mathematical method used in picture denoising that is effectively reduce noise and maintaining significant structural characteristics also. This method is based on the idea that an image's overall variation can be reduced to produce a smoother representation, improving image quality with no sacrificing important details like edges and contours. The Recent developments demonstrate how deep learning models, introduction of deep learning techniques in intrusion detection problems has enabled an enhanced standard of detection effectiveness [7]. For example the generative adversarial networks and convolutional neural networks, could be included into TV reduction frameworks to improve the results in the problems like motion artifacts and low light condition [11]. The improved segmentation and classification of medical images is now possible thanks to the increased capabilities of modern models [6]. The emphasis on hybrid tactics that combine conventional techniques with contemporary machine learning paradigms is making new standards for picture clinical application as researchers continue to delve into the complexities of TVM [8]. The previous complexity is echoed in approaches that leverage cyclic proximal point algorithms for denoising, demonstrating the versatility and adaptability of TVM techniques throw different contexts. A fundamental method in the continuous effort is TV reduction use to enhance medical analyses by using efficient denoising techniques, like innovative solutions that immediately address optical blurring through synthesis of DE convolution kernels. The integrity of visual data is crucial in the field of medical imaging since even minute aberrations can seriously impair the accuracy of diagnosis. Medical photos, which suffer from many kinds of noise brought on by acquisition procedures and environmental factors and by using denoising algorithms can be greatly improved. Techniques for TVM have become a reliable method for image denoising, successfully striking a balance between noise reduction and the maintenance of crucial image characteristics like edges [1]. The purpose of this literature review is to summarize existing approaches that use TV reduction, emphasizing their mathematical underpinnings and usefulness in medical imaging such as CT and MRI scans. This review offers a thorough grasp of how TV reduction can help to enhance image quality, therefore permitting better clinical outcomes and enhancing the analysis process in healthcare settings by examining developments and challenges within these techniques [3], great developments in image denoising techniques have occurred throughout history, coinciding with advances in imaging and computing vision.

In medical picture denoising field when maintaining significant features while successfully lowering noise is critical, the TV mathematical expression is essential. TV, which minimizes sudden changes and promotes piecewise smoothness, is theoretically defined as the integral of the image's absolute gradient. By this method the Effective edge preservation is made possible, which makes it very useful in medical imaging settings so the tissue borders exhibit minute but crucial differences. New developments emphasize how transformer models can be combined with TV reduction to provide better segmentation results. Like MedGAN, which improve image-quality restoration by combines adversarial networks with TV methods, As well as discussed the investigation of hybrid models that integrate TV and machine learning points to a promising trend toward obtaining the best possible image quality in low light, which is important for accurate medical evaluations [8]. The foundation for more complex algorithms was established, which were frequently based on fundamental statistical filtering techniques. Started using machine learning models Researchers efficiently handle noise reduction issues as imaging data became more complicated, especially in medical applications. Notably, this discipline has undergone a revolution with the shift to deep learning-based techniques like CNNs and GANs, which have demonstrated exceptional performance in image augmentation [4]. Furthermore, techniques like total variation minimization were developed to address particular difficulties in medical imaging by striking a balance between noise reduction and detail preservation [11]. Recent advancements have further underscored the integration of data-driven approaches and bilevel minimization schemes, which optimize regularization parameters for effective denoising. This historical background demonstrates a persistent desire to improve image quality, exposing a dynamic between conventional and contemporary methods that emphasizes the necessity of further study in this crucial field and highlights the ongoing evolution of image processing techniques.

Formulation of Total Variation mathematically

Images can be represented as a function u(x; y), where the rectangular domain (image) is denoted by (x; y) 2. The photographs we are looking at for our study contain speckle noise. In order to eliminate the noise, we aim to minimize the gradient of ru(x; y).

$$\min_u \int_\Omega |\nabla u(x,y)| dx.$$

Since the image's edges will be destroyed in addition to the noise being diffused or eliminated, we must add extra to this equation. Generally speaking, the Gaussian noise equation represents an observed image f.

$$f = u + n.$$

The reconstructed or desired image is denoted by u in the Gaussian noise equation, whereas n stands for the Gaussian noise, Therefore, we take into account the following functional.

$$F(u) = \int_\Omega |\nabla u(x,y)| dx + \frac{\lambda}{2}\int_\Omega (f-u)^2 dx$$

Where ⅄ is our Lagrange multiplier and f is our observed/noisy image, as seen above. The image that will be restored is the minimizer u after we minimize F, The Euler-Lagrange equation that is equivalent is

$$\nabla \cdot \left(\frac{\nabla u}{|\nabla u|}\right) - \lambda(f-u) = 0$$

The denoised image is the solution u(x; y) to the equation above. An artificial time component has been added to the following equation, Six Time Iteration:

$$\nabla \cdot \left(\frac{\nabla u}{|\nabla u|}\right) - \lambda(f-u) = u_t \qquad t \to \infty \qquad u_t \to 0$$

Due to sampling and digital degradation, speckle noise can appear in a variety of medical imaging. Eliminating speckle noise from medical pictures is essential for advanced automated processing methods like segmentation, which can aid physicians in more accurate diagnosis and treatment.

Medical image denoising

The need for reliable denoising techniques that can adjust to various imaging environments and situations is still important as medical imaging technology develops further and as high-order regularization models, like total α-order variations, continue to gain traction for their superior performance in restoring image quality [4]. Trying to enhance the quality of medical image denoising some process aims using several imaging modalities, like MRI, CT, and ultrasound, by eliminating extraneous noise that may mask information that is important for analysis. to improving visual clarity, this procedure maintains important characteristics like edges and textures, which are critical for clinicians to accurately interpret. Both conventional and contemporary technologies, like convolutional neural networks and generative adversarial networks, are used in medical picture denoising each has unique advantages and disadvantages [2]. As well as to address issues with noise variability and unique image characteristics, TVM algorithms have been applied effectively to denoise manifold-valued images, show their versatility in handling complex data structures. Recent developments have also investigated the use of TVM techniques which hit a balance between noise reduction and edge integrity.

Medical analysis is important field

High picture fidelity has a direct impact on how well medical personnel can detect problems, It is important to mentioning that is impossible to overestimate the image quality in medical diagnostics since precise imaging is essential for analysis and therapy planning. Which affects both diagnosis and the course of treatment for patients, especially Vision Transformers (ViTs), underscores how better image quality can improve feature extraction for tasks like detection and segmentation [6]. Methods such as generative adversarial networks (GANs) are used to enhance image translation and denoising by lowering the noise that can mask important details. Additionally, the highlights the need for methodical assessments of segmentation techniques in order to guarantee high-quality results in clinical settings [8]. image enhancing techniques must continue to progress in order to meet the numerous difficulties in medical imaging and maintain the accuracy and efficiency of diagnostic procedures, shift-invariant filtering and hybrid methods incorporating Total Variation denoising have been shown to significantly improve colon cancer image quality, thereby enhancing diagnostic accuracy.

TVM Basics

Highlighting the methods effectiveness, these developments highlight the necessity of a thorough comprehension of TVM principles in order to optimize imaging methods for a variety of clinical applications, opening the door for further developments in this area [8]. TVM is important component of medical image denoising, which make a balance between edge preservation and noise reduction. TVM is an efficient regularization technique for noise handling while preserving important information because it takes use of the fact that natural images often show changes in pixel intensity. some improvements to conventional TVM such as those that use deep learning-have surfaced and greatly improved denoising results by resolving issues such as the errors in traditional edge preservation techniques, the use of high-order variants expands TVMs potential [4].as well as the recent research show how TVM can be integrated with generative adversarial networks (GANs) to improve its suitability for challenging medical imaging tasks.

Total Variation Properties in Image Processing

Given the sensitive nature of medical imaging, where accuracy is crucial, this characteristic is very beneficial, opening the door for more methods like generative adversarial networks (GANs) to improve the output quality [8]. Additionally, TV models adaptability enables them to be used with different regularization techniques, maximizing the trade-off between noise reduction and preservation. This is particularly relevant as shearlet-based regularization has been explored as an alternative to traditional TV for certain datasets, indicating the ongoing evolution of denoising methodologies within computed tomography. There are need for ongoing research into effective denoising algorithms highlighted by the challenges that still exist, especially in real-world applications where unpredictable noise distributions occur [6], these techniques can adaptively discriminate between noise and important elements by reducing the overall fluctuation, which makes it easier to reconstruct images with greater clarity. Recent developments have shown that the incorporation of machine learning techniques improves these qualities even more.

Compare different denoising methods

Comparison to other approaches like convolutional neural networks (CNNs) and generative adversarial networks (GANs), the evaluation of Total Variation (TV) minimization strategies demonstrates their efficacy in denoising medical images. Although GANs, like MedGAN, provide remarkable outcomes by combining intricate image translation procedures with style-transfer losses, they are frequently computationally demanding and require a large amount of training data. TV-based methods, on the other hand, are excellent at maintaining edges and fine textures, which is essential for medical imaging applications that demand precise clinical diagnosis [11]. According to recent surveys, Transformer-based models are becoming more and more popular since they perform better on tasks like segmentation and classification, suggesting a move away from conventional CNN designs [8]. Segmentation of images is crucial for a wide range of computer applications, including robotic vision, medical imaging, pattern recognition, biomedical image processing, and others [5]. However, TV approaches ease of use and resilience, especially in difficult noise situations, support their status as fundamental techniques in image denoising [4]. Moreover, the discrete shearlet transform has been shown to serve as a sparsifying transform alongside TV minimization, potentially outperforming traditional methods for denoising textured images. The developments in hybrid models that combine deep learning techniques with television should improve image processing outcomes even more. Additionally, innovations in one-shot convolution filtering indicate potential for higher efficiency in image restoration applications, further enhancing the landscape of denoising methods.

The Advantages and disadvantages of TV

Advantages

Sophisticated TV model variants that integrate deep learning frameworks have shown notable gains in image quality for MRI and CT scans, among other medical imaging modalities. This flexibility not only improves the accuracy of medical evaluations but also tackles the persistent problem of reconstructing images impacted by low light levels, when conventional techniques might not yield enough clarity. The oscillation total generalized variation (TGV) has been recognized for its ability to capture structured textures effectively, further enhancing image quality in the medical domain. Therefore, a significant development in medical image processing approaches is the incorporation of TV reduction strategies, which offer a comprehensive way to address the inherent challenges of imaging under various conditions. Via the efficient denoising while maintaining crucial structural details, TVM approaches are major for improving the quality of medical images. Their capacity to preserve edges and contours which are crucial for precise diagnosis without over smoothing pertinent features is one important benefit [11]. The techniques that employ TV reduction frequently perform better than conventional denoising methods when images are subject to different kinds of noise, which makes them adaptable and reliable in actual clinical settings [4].

3.3. Disadvantages

The noise that deviates from Gaussian distributions, which frequently occurs in medical imaging scenarios, is difficult for conventional TV reduction techniques to handle [4]. Models like MedGAN Fixed point and newton offer convincing substitutes by using generative adversarial networks to improve image quality without experiencing the same disadvantages as traditional TV techniques [8].

Accordingly, future studies should focus on developing stronger denoising frameworks that incorporate different machine learning developments and get around these problems [6]. There is a lot of potential in using TVM techniques to denoise medical images, there are some disadvantages that may affect how useful and applicable they are. One major worry is that TV reduction could result in artifacts in areas with fine features, which would mean that important information needed for a precise medical diagnosis lost as well as demonstrated by developments in machine learning and deep learning techniques that provide greater flexibility and better outcomes, the dependence on particular model architectures may restrict the adaptability of TV techniques across different imaging modalities [11].

Total Variation Model Variants

Because of the total variation ability to effectively preserve edges while lowering noise, variations of Total Variation (TV) models have become essential methods in the field of medical picture denoising. By resolving the shortcomings of conventional TV approaches, high-order TV models-more especially, the fractional-order derivative-based total α-order variation model-have demonstrated competitive performance when compared to traditional models. Recent studies have shown that integrating non-linear sparse recovery techniques can further enhance denoising performance, especially in challenging scenarios like speckle noise in ultrasound images [8]. Deep learning techniques have recently been included into TV frameworks, where generative adversarial networks (GANs) such as MedGAN maximize the conversion of noisy images into more readable versions, successfully fusing adversarial learning with TV concepts. Additionally, employing convolutional layers in denoising auto encoders has been shown to effectively reduce noise in medical images with limited training samples, indicating a potential synergy between deep learning and traditional TV models [8]. Furthermore, the use of Vision Transformers and attention mechanisms in TV-based segmentation demonstrates a tendency to use context-aware features to improve medical image processing efficiency. A bright future for attaining better denoising results while tackling issues like interpretability and robustness is suggested by the continuous research into hybrid approaches that combine CNNs with TV minimization techniques [11, 6].

The Regularization's function in TV reduction

To overcome the difficulties caused by noise and picture artifacts while maintaining significant characteristics like edges and textures, regularization is essential in Total Variation (TV) minimization strategies for medical image denoising. The TV minimization frameworks incorporation of regularization not only limits the energy minimization procedure but also encourages a balance between the final images smoothness and faithfulness to the observed data. Adversarial training and regularization techniques have been successfully combined in recent methods, including MedGAN, to improve translation across imaging modalities and boost diagnostic capabilities [11]. Moreover, the use of Vision Transformers (ViTs) in this setting highlights regularizations capacity to represent long-range dependencies, leading to better segmentation and classification results. Additionally, total variation minimization is often employed for manifold-valued data, where regularization plays a critical role in denoising applications, such as in diffusion tensor imaging and interferometric SAR images, thereby maintaining essential image characteristics.

TVM applications in medical image analysis

Recent developments utilizing fractional-order derivative based total α-order variation models have shown competitive results in restoration quality, suggesting that innovative regularization techniques could further enhance TVs applicability in image restoration. The estimation of uncertainties in label assignment, particularly in medical imaging, great progress in picture restoration and denoising has resulted from the use of TVM techniques in medical imaging, which has improved clinical decision-making and analisys accuracy. TV reduction solves issues like color distortion and low contrast by efficiently reducing noise while maintaining crucial structural features in medical pictures, such as CT and MRI scans. Additionally, integrating machine learning techniques using transformer models has demonstrated encouraging outcomes in improving image classification and segmentation in tasks involving tumor detection and delineation [11].

New Developments in TV Minimization Methods

Enabling more effective use of these methods in practice. These developments highlight the need for continued study into hybrid models that can improve denoising performance even more by striking a balance between computing efficiency and detail preservation, recent advances in the estimation of optimal parameters for a-priori techniques in TV minimization can help improve reconstruction quality in medical imaging, particularly in difficult and low-light imaging scenarios. Active Mean Fields (AMF) approaches further enhance this discourse by providing a framework for estimating uncertainties in segmentation assignments, which is crucial when working with noisy data typical in medical images [11]. TVM approaches use in medical image denoising has been expanded by recent developments. This advancement is attributable to the combination of deep learning and machine learning techniques with conventional TV techniques, which enable better noise reduction while maintaining important image characteristics. For example, methods like MedGAN use generative adversarial networks to efficiently translate medical pictures, demonstrating notable gains in tasks like denoising and PET-CT translation, which are essential for precise diagnosis [11]. Segmentations in medical imaging have been revolutionized by the use of Vision Transformers, which take us to better accuracy and more efficient context modeling than traditional convolutional neural networks [8]. In order to concurrently eliminate tangled noise, estimate the location of missing pixels, and fill them in, Researchers Muhammad Ashfaq Khan, Fayaz Ali Dharejo, Farah Deeba, Shahzad Ashraf, Juntae Kim and Hoon Kim suggested a new variational model based on total variation and L0 norm. Specifically, the estimated image is regularized using the total variation, and the missing pixel is made sparse using the l0 norm. Additionally, a novel forward description of the degraded process and the gamma noise assumption provide the data fidelity term. Lastly, the model is solved using an approach based on the alternating direction multiplier method. The suggested technique can successfully recover the damaged photos using both simulated and actual testing. This method is more effective in both qualitative and quantitative aspects [9]. Researchers Mujibur Rahman Chowdhury, Jing Qin and Yifei Lou suggest a fractional-order total variation regularization to eliminate both Poisson noise and blur at the same time. While an expectation-maximization algorithm is only used in the blind scenario, they create two effective algorithms based on the alternating direction method of multipliers. Numerous numerical tests have shown that the suggested methods are capable of effectively reconstructing piecewise smooth images that have been deteriorated by Poisson noise and several kinds of blurring, such as motion and Gaussian blurs. In particular, we achieve notable gains over the state of the art for blind image deblurring [10]. Considering an autonomous estimation of the local regularization parameters, Researchers Pasquale Cascarano, Andrea Sebastiani, Maria Colomba Comes, Giorgia Franchini and Federica Porta suggested combining the Deep Image Prior (DIP) framework with a space-variant Total Variation regularizer. In contrast to other current methods, we use the adaptable Alternating Direction Method of Multipliers (ADMM) to handle the emergent minimization problem. Additionally, we offer a particular version of the conventional isotropic Total Variation as well. A number of studies on both simulated and real natural and medically corrupted images are used to address the promising performances of the suggested approach in terms of PSNR and SSIM values [12]. Researchers H.S. Bhadauria, M.L. Dewal suggested a technique for reducing noise in computed tomography (CT) and magnetic resonance imaging (MRI) that combines the images that have been (i) denoised using the total variation (TV) method, (ii) denoised using a curvelet-based method, and (iii) edge information. The edge information is taken from the TV method's noise residual by processing it using the curvelet transform. The effectiveness of the suggested approach is assessed using actual brain CT and MRI scans, and the outcomes demonstrate a notable improvement in both edge preservation and noise reduction [14]. Researchers Juncheng Guo and Qinghua Chen suggested an image denoising model based on nonconvex anisotropic total variation (NCATV). Since the weighted matrix in the suggested model is dependent on the recovered image, we can anticipate that it will be more reliable in describing local features. Since the suggested model is nonconvex, we must first decouple the weighted matrix from the TV term using the successive replacement approach. This technique turns the suggested model into a convex and nonsmooth optimization issue. This problem can then be divided into a number of manageable subproblems using the alternate direction method of multipliers (ADMM). Comparing our suggested model to some state-of-the-art techniques, numerical testing demonstrate that it improves performance both visually and numerically [15].

A summary of current research on TV methods

Significant progress has been made in medical image denoising, where procedures use the mathematical concept of TV reduction to improve image quality, according to recent research on Total Variation (TV) methodologies. Review separates different methods, such as deep learning architectures, which effectively handle noise while maintaining important image properties by using generative adversarial networks and convolutional neural networks. According to the investigation of Vision Transformers (ViTs) in medical imaging demonstrates their capacity to capture long-range relationships, surpassing conventional convolutional models in tasks such as segmentation and classification, the advent of MedGAN proves that adversarial training may successfully provide high-quality picture translations in medical settings, increasing the effectiveness of diagnosis [11]. In an attempt to balance computational efficiency, detail preservation, and robustness against various forms of imaging noise, research has also extended into hybrid approaches that blend TV techniques with machine learning algorithms, emerging methods such as the non-linear sparse recovery techniques highlight the potential of TV methods in enhancing image denoising performance beyond conventional approaches, leveraging active mean fields models has shown promise in accurately estimating segmentation uncertainties, which can be critical in medical imaging applications [8]. In order to provide realistic image translation and noise reduction, emerging concepts like generative adversarial networks (GANs), like MedGAN, show how adversarial structures can be integrated into adaptive frameworks [11]. The use of Vision Transformers (ViTs) in medical imaging demonstrates their capacity to capture long-range dependencies, improving segmentation and classification tasks. The analysis of low-light image enhancement techniques emphasizes how crucial adaptive methods are for enhancing visibility and detail in medical images, where conventional methods fail, novel approaches that concentrate on hallucinations in natural language creation highlight possible directions for improving robustness and interpretability in medical imaging applications, filling in gaps in the body of existing literature [6], advancements in near-field radar imaging frameworks showcase the importance of effective regularization techniques, such as those applied to complex-valued reflectivity distributions, which can offer insights into the future of adaptive models in medical imaging. lastly, there are promising prospects for improving denoising methods in medical imaging due to the development of adaptive TV models [4], as evidenced by techniques that segmentation improvements and enhance image quality through noise removal.

Hybrid methods combine TVM with other techniques

The quality of medical images can be significantly improved by hybrid approaches that combine TVM with other imaging techniques. These approaches overcome the disadvantages of traditional approaches by combining machine learning and image processing techniques with TVs advantages in edge preservation. For example, MedGANs use in PET-CT translation and MR motion artifact correction shows that integrating generative adversarial networks (GANs) into a TV framework improves texture matching and decreases pixel misalignment [8]. These hybrid approaches open the door for more flexible machine learning applications in the medical imaging space, leading to important breakthroughs. Using reliable performance criteria that reflect the quality and accuracy of the improved images is necessary to evaluate how well (TV) approaches denoize medical images. Mean Squared Error (MSE), Structural Similarity Index (SSIM), and Peak Signal-to-Noise Ratio (PSNR) are often used quantitative measurements that provide distinct information on image integrity and noise reduction capabilities. While SSIM assesses perceived image quality by taking structure, contrast, and brightness into account, PSNR quantifies the ratio of the maximum signal power to the noise power. This method is more human-centric. By taking into consideration perceptual variations in visual representations, additional measures like the Universal Image Quality Index (UQI) and Visual Information Fidelity (VIFP) also improve the assessment framework. As well, recent studies have shown the importance of developing new methodologies that effectively handle specific degradation scenarios, which enhances the evaluation of performance indicators in such contexts [16]. Including these performance criteria will significantly advance our knowledge of TV approaches in the realm of medical imaging. Through a number of case studies, recent developments in medical image denoising employing TVM strategies have been recorded, demonstrating the efficacy of novel approaches. For example, MedGAN has shown great promise in improving picture quality using generative adversarial networks, attaining better outcomes in motion artifact removal and PET-CT translation [11]. As well, by surpassing conventional convolutional neural networks, the growing use of Transformer models specifically, Vision Transformers (ViTs) has accelerated progress in segmentation and classification tasks across medical modalities [8]. As well, thorough evaluations draw attention to the difficulties that current algorithms encounter, such as the intrinsic noise in imaging data and the need for blind de-noising methods that make use of unsupervised learning models [4]. The challenges underscore the value of exploring dual approaches in optimization, can significantly enhance the solution of complex problems, these findings highlight show how image processing technologies are constantly evolving and how customized solutions are needed to satisfy the demands of various medical imaging applications. As well, the framework provided by graph signal processing (GSP) offers a pathway to further improve image processing techniques through innovative spectral methods [16]. A number of obstacles prevent the general acceptance and effectiveness of innovative methods for denoising medical images utilizing TVM. The creation of generally applicable models is hampered by the unpredictability of noise in medical imaging, which frequently results from a variety of imaging modalities and equipment settings [11]. As well, training deep learning models that use transformers for medical applications is hampered by the scarcity of high-quality annotated datasets [4]. As said in [4], these metrics must be continuously improved in order to properly match the unique environment of medical imaging applications as well as the requirements of clinical interpretation. Newer designs like MedGAN, which replace conventional CNN-based methods, add complexity to model architecture and training procedures, increasing the need for processing power and knowledge [8], 3D photoacoustic tomography (PAT) systems highlight challenges in balancing spatial resolution and temporal dynamics, underscoring the difficulties inherent in handling real-time data processing. As well as many popular algorithms have trade-offs that affect overall performance, researchers must address real-time processing limits while striking a balance between computational efficiency and enhancing effectiveness. As well, according to the Transformers in Medical Imaging survey the segmentation tasks have been revolutionized by combining Transformer-based models with TV techniques, which have improved feature extraction and contextual comprehension across modalities [11].

In conclusion

The evaluation of TVM based denoising methods for medical images shows significant advancements, the development of techniques like those combine convolutional neural networks and machine learning, shows promise in improving image quality while reducing different kinds of noise. As well, Transformer applications in medical imaging have shown great promise, surpassing conventional convolutional networks in terms of segmentation and contextual representations [4]. More research required to solve constraints in processing multi-dimensional data [8], the expanding literature highlights the necessity of conducting systematic assessments to balance efficiency and performance across various imaging modalities. Lastly since the search for all-encompassing solutions continues, developing novel denoising frameworks is still essential for improving diagnostic accuracy in medical imaging.

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