MINI REVIEW

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Understanding Medical Image Denoising, Enhancement, and Reconstruction

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Abstract

Medical imaging is an essential and valuable tool in modern medicine for providing essential details on the internal structures and functioning of the human body. Although very useful, the raw images obtained from medical imaging systems usually contain different types of artifacts and noise that might hide some essential diagnostic information. In this paper, the author details the conventional and non-conventional methods as well as sophisticated deep learning research methods used in improving the quality of healthcare images. The paper also delves into strategies designed to elevate the visual quality and interpretability in medical diagnostics. The paper includes some latest case studies to illustrate the usefulness of these strategies in the clinical context. This is classically imclinically importantportant because of the blend between essential information and high-level research that this review provides, thus making it an indispensable tool for students, researchers, and professionals who aim to enhance their understanding and knowledge about medical image processing technology.

Keywords: medical imaging, denoising, enhancement, reconstruction, deep learning, healthcare.

1 Medical Image Denoising

Denoising is a crucial technique in medical imaging, aimed at enhancing image quality by removing unwanted noise. The primary objective is to eliminate noise that can obscure critical anatomical details, potentially leading to less accurate diagnoses. Noise can arise from various sources, including the imaging equipment, environmental factors, and even patient movement or physiological conditions [1]. Effective noise reduction in low-dose computed tomography (CT), magnetic resonance imaging (MRI), and ultrasound scans significantly improves the clarity of medical images, thereby enhancing the accuracy and reliability of diagnostic evaluations [2].

1.1 Recent research in medical image denoising

The goal of the authors in [3] is to enhance the quality of medical imaging and the of diagnostic assessments by using the Black Widow optimization algorithm to the job of denoising medical images. To make Black Widow optimization more suitable for health-related photos with their many intricate details, they used Tent mapping. The authors proposed a method where images are denoised using an adjusted deep convolutional neural network in [4],

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with details recovered using adaptive watershed segmentation, and images are enhanced using a hybrid lifting-strategy derived from bi-histogram equalization contrast enhancement. Consideration of marker-based watershed segmentation then enhances this technique even more. Medical images such as tomographical imaging and magnetic resonance imaging are intended to test and assess the efficacy of the proposed approach. The research work in [5] uses a two-stage learning mechanism powered by artificial intelligence to tackle the limitations of current denoising algorithms. To assess the residual noise, the suggested technique learns to process noisy images. To denoise in a course-coarse-to-refineto-refine fashion, it later integrates a new noise attention mechanism that correlates estimated residual noise with noisy inputs. Additionally, this research suggests using a multimodal learning approach to generalize denoising across various medical image modalities and noise patterns, with the goal of finding broad-ranging applications for this technique.

The authors of [6] find motivation in the self-supervised learning approach, which successfully prevents overfitting towards the area of interest. A new method that we call the Denoising Y-Net (DeY-Net) integrates an additional denoising decoder within the standard U-Net model. The purpose of the auxiliary-decoder is to train with denoising, which will enhance the domain-invariant representation and make domain generalization easier. Additional benefit of this paradigm is the opportunity to use unlabelled data. Biomedical images captured by CT and electron microscopes are the subject of this research, which focuses on deep learning denoising techniques [7]. The authors presented the Adaptive Projection Network, a projection-based deep attention denoising network, to address synthetic noise problems in medical CT images. Adaptive image projection is used to separate noise from detail textures in medical images, and this approach, which is built on a U-shaped structure, employs non-local information to recover underlying clean images with texture characteristics from noisy images [7]. To overcome the shortcomings of current traditional denoising approaches, this work in [5] employs a two-stage learning process powered by artificial intelligence. Estimating the residual noise from noisy images is what the suggested technique learns to do. Then, to denoise in a course-to-refine fashion, it uses a new noise attention mechanism to connect estimated residual noise with noisy inputs. An additional aim of this research is to design a multimodal learning technique that can generalize denoising across various medical image modalities and noise patterns. This strategy might have broad implications in the future

2 Medical Image Enhancement

The primary objective of medical image enhancement is to improve the visual quality of an image, enabling physicians to more accurately observe and interpret critical details. Enhancements such as brightness adjustment, contrast optimization, edge sharpening, and other visual refinements can significantly aid in this process. For example, in modalities like X-rays, CT scans, MRIs, and ultrasounds, enhancement techniques can improve the visibility of tumors, blood vessels, bones, and other anatomical structures.

2.1 Recent research in medical image enhancement

The investigation of histogram equalization methods and their use in medical image improvement is done in [8]. In this research, a new mathematical analysis is used to re-investigate the following algorithms: traditional Global Histogram -Equalization, Histogram-Specification, and Brightness Preserving Dynamic -Histogram Equalization. In the fields of image enhancement and clinical image diagnostics, researchers often use all these Histogram Equalization approaches; nevertheless, it has been noted that these methods have a serious limitation: they may lose crucial data [8]. Since every Histogram Equalization approach is inherently non-linear, this work provides mathematical evidence that all Histogram Equalization methods always result in data loss [8]. To better understand current and future advances in artificial intelligence (AI) technologies for PET and SPECT image enhancement, this review paper [9] provides a thorough overview of these methods. New advances in artificial intelligence for denoising and deblurring PET and SPECT images are our main emphasis. It has been shown that supervised deep-learning models may significantly decrease scan durations and radiotracer dosage without compromising diagnostic accuracy or image quality [9]. The methods of Self-Calibrated Illumination and Histogram Equalization are covered in this study [10]. Use of Histogram Equalization with Self-Calibrated Illumination Digital images may have their visual quality improved using image enhancement algorithms and methods. Improving an image's quality is one way to get more useful information out of it. Popular methods for improving images include those based on the RetiNex algorithm, the Weber-Fechner method, the Fourier transform, histogram equalization, and linear regression algorithms. In this study, authors surveyed the literature on image enhancement using the Histogram Equalization Method and compare the various writers' findings [10]. The article goes on to discuss the benefits and downsides of these technologies, as well as the improved images and histogram plots produced by them over the last many decades [10].

A deep learning algorithm's optimization and performance assessment in medical image analysis are explored in [11]. Prior to delving to investigate the potential uses of deep learning approaches in healthcare image processing, the article provides an overview of the field's significance and difficulties. Model structure creation, data preparation, super parameter modification, and other optimization approaches of deep learning algorithms are subsequently covered in depth in this work. Highlighting its capabilities to produce synthetic-ACM-2 data, enhance images and facilitate anomaly identification, and enable image-to-image transformation, the study delves into the revolutionary possibilities of generative AI in medical imaging [12]. The use of generative models, such as Med-PaLM 2 technology, in healthcare has shown encouraging outcomes, despite obstacles such as model complexity. Better patient outcomes and more precise diagnoses are the result of these models' efforts to overcome dataset variety and size limits [12]. With an eye on the advantages, it offers to doctors and patients alike, this reprint explores the growing role of computer-aided diagnosis in contemporary healthcare [13]. It emphasizes the increasing importance of automation in assisting humans with various activities, especially in the field of image analysis, which is made possible by AI networks that can do multilayer pattern analyses [13].

3 Medical Image Reconstruction

Medical imaging modalities such as computed-tomography, magnetic -resonance imaging, positron-emission tomography (PET), and others engage in reconstruction in medical imaging. This procedure entails creating visual images from raw data. Projections, signals, or frequency data obtained from these devices must be converted into a comprehensible and useful image for diagnostic purposes. Computed Tomography Scan: Useful for identifying infections, malignancies, and fractures via the reconstruction of cross-sectional images. By using iterative reconstruction, the radiation dosage may be decreased. To detect neurological and musculoskeletal diseases, a Magnetic Resonance Imaging is used to get a highly detailed image of soft tissues. fMRI reveals neural activity. Brain and cancer patients may benefit from re-creating metabolic activity images using Positron Emission Tomography scans. Assesses the foetal heart's shape and development by ultrasound. Optical Coherence Tomography: Uses retinal images to diagnose macular degeneration and glaucoma.

3.1 Recent research in medical image reconstruction

A medical image reconstruction model called MambaMIR and its variation, MambaMIR-GAN, which is based on the Generative Adversarial Network, are introduced in the paper in [14]. From the original Mamba model, suggested MambaMIR takes a few benefits, such linear-complexity, global-receptive fields, and adaptive weights. The image reconstruction work is well-suited to Mamba, due to the innovative arbitrary-mask method, which also supplies randomization for the following Monte Carlo-based uncertainty assessment. To tackle the issue of limited domain-specific generalization, the authors of [15] proposed a data augmentation Plug-and-Play module named MoreStyle. By easing lower frequency constraints in Fourier domain, MoreStyle guides the image-reconstruction network and diversifies image styles. Further expanding the style spectrum and pinpointing the leading sophisticated style integrations among underlying characteristics, MoreStyle uses adversarial learning [15]. To deal with substantial stylistic differences, we use an uncertainty-weighted loss. This loss reduces the impact of genuine hard-to-identify pixels in both the original and MoreStyle-generated images, while highlighting pixels that are difficult to classify solely because of style alterations [15]. The use of DL techniques for MIS and 3D reconstruction is thoroughly examined and addressed in this work [16]. This article begins with an overview of MIS and 3D imaging reconstruction, touching on topics such as fundamental ideas, technological hurdles, and image quality, noise interference, and edge recognition. Second, the article provides a thorough introduction to the data collection procedure, outlining the medical image data set and the data preparation technique. Following this, the article presents the self-attention mechanism-based DL model structure, training-related details such as the loss function and optimizer [16].

Recent improvements in artificial intelligence have been developed by the authors in [17] to evaluate images and successfully identify acute disorders. The authors provided an in-depth analysis of current research in healthcare imaging and deep neural networks. Along with presenting a list of open accessible data repositories in various medical domains categorized by organs, this publication also outlines the merits and disadvantages of deep neural networks in the medical area [17]. In [18], the authors outlined the evolution of super-resolution reconstruction for medical images. Their investigation of super-resolution reconstruction techniques was thorough. Indicators for super-resolution reconstruction algorithms' performance were presented by them. They looked forward to the future of medical applications of super-resolution reconstruction technology [18]. Diabetic retinopathy is a global eye condition. It causes full eyesight loss depending on severity. The retinal blood vessels and eye's tiny layers are damaged. Early diagnosis of Diabetic retinopathy and regular screening for moderate causes in manual commencement may prevent such complications. Diagnostic procedures are complicated and costly [19]. The study's distinctive contributions include starting with Diabetic retinopathy illness background and standard detection methods. Second, Diabetic retinopathy imaging and deep learning methods are discussed. Third, deep learning-based Diabetic retinopathy detection application cases and real-life situations are examined. The study concludes that researchers may examine and give excellent diabetic retinopathy detection outcomes [19].

4 Conclusion

The reliability and precision of diagnostic imaging are greatly enhanced by medical image denoising, augmentation, and reconstruction, which is why it is crucial to modern healthcare. This paper outlined the fundamental ideas, techniques, and issues with these processes. Denoising techniques, such as deep learning and classical filtering, are necessary for reducing noise while preserving anatomical features. Edge sharpening and contrast modification bring attention to important features and enhance diagnosis. The ability to retrieve high-quality images from noisy or missing data has been enhanced by reconstruction methods based on machine learning. When these treatments are applied, medical images seem better and are more accurate. New opportunities in real-time image processing and personalized treatment have emerged thanks to AI-driven technologies that have improved performance. Improvements in patient outcomes and healthcare system efficiency should be expected as we proceed to extend the scope of this field with novel algorithms and methodologies. This paper is the starting point for understanding these critical processes and how they impact medical imaging.

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Conflicts of Interest

The author declare no conflicts of interest.

Ethical Approval and Consent to Participate

Not applicable.

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