2023 Second International Conference on Advances in Computational Intelligence and Communication (ICACIC) | 979-8-3503-1845-6/23/$31.00 ©2023 IEEE | DOI: 10.1109/ICACIC59454.2023.10435104

A Comprehensive Study on Medical Image Denoising using Convolutional Neural Networks

Ajmal Mohammed
Department of Electronics Engineering
Pondicherry University
Pondicherry, India
ajmalvm@pondiuni.ac.in

Samundiswary Punniakodi
Department of Electronics Engineering
Pondicherry University
Pondicherry, India
sam.dee@pondiuni.ac.in

***Abstract*—Medical images are considered as one of the most important medical data for diagnosis and treatment purposes. For remote consultation and diagnosis, the medical images are frequently transferred using different communication methods. There is a chance of noise degradation of these medical images during transmission. Denoising such medical images is crucial for enhancing the quality and diagnostic precision. The remarkable ability of Convolutional Neural Networks (CNNs) to effectively denoise medical images has attracted considerable interest. This paper discusses various CNN architectures, training strategies, and data augmentation techniques for denoising tasks. In addition, the difficulties and limitations of CNN-based denoising techniques, such as computational complexity and data scarcity, are discussed. In addition, incorporating Generative Adversarial Networks (GANs) and transfer learning for improved denoising performance are discussed. This survey aims to serve as a valuable resource for researchers, clinicians, and developers by fostering a better comprehension of the current state-of-the-art techniques and future directions in medical image denoising using CNNs.**

Keywords—Deep learning, Image denoising, Magnetic resonance imaging, Low-dose CT, Noise

I. INTRODUCTION

Denoising medical images is essential for enhancing the precision and dependability of medical diagnoses and treatments. Various noise sources, such as electronic interference and low radiation doses, can degrade image quality in medical imaging, making it difficult for healthcare professionals to interpret the results precisely. Denoising techniques are vital in addressing these problems by reducing noise while preserving vital anatomical and pathological information. Clear, high-quality images are necessary for accurate diagnosis and treatment planning, as blurry images can lead to misinterpretations, overlooked abnormalities, or unnecessary procedures. Medical image denoising improves image clarity, allowing healthcare providers to detect and analyze subtle details, lesions, and anomalies more accurately. It can enhance the efficacy of numerous medical imaging modalities, such as X-rays, CT scans, MRI, and ultrasound. In addition, denoising contributes to safer and more cost-effective healthcare practices by allowing for lower-dose imaging while maintaining diagnostic quality.

Different approaches were used to remove noise in medical images. Classical methods often include filtering techniques [1] like Gaussian, median, and bilateral filters, which smooth the image but may blur edges. Wavelet-based methods [2] decompose images into multiple scales and remove noise at each scale. Nonlocal means exploiting the similarity between image patches for noise reduction. Different denoising filters are discussed in [3], [4] and comprehensively compare the performance with various image quality parameters.

Machine learning approaches, such as using sparse coding [5] and dictionary learning [6] to represent clean image patches, gained popularity. Principal Component Analysis (PCA) has been used to reduce noise while preserving signal variance. Neural network-based methods, like Autoencoders and CNNs, learn intricate noise patterns and yield state-of-the-art results. GANs leverage a discriminator-generator pair to denoise images.

Deep learning techniques like Variational Autoencoders (VAEs) [7] combine autoencoders with probabilistic models to capture data distribution and remove noise. Transformative approaches like Nonlocal Neural Networks [8] exploit self-similarity, preserving details and reducing noise. In summary, image denoising has evolved from traditional filters to sophisticated learning-based techniques, advancing the field and achieving impressive results.

Due to several key advantages, CNN has proven highly effective in image denoising [9]. First, CNNs can automatically learn complex feature representations from noisy images, enabling them to capture local and global patterns essential for denoising. This adaptability makes CNNs well-suited for various noise types and levels. Second, CNNs excel at hierarchical feature extraction. They employ convolutional layers to progressively abstract and combine features, which helps to distinguish between noise and meaningful image structures. This hierarchical approach enhances the network's ability to remove noise while preserving important details. Third, CNN-based denoising methods [10] can be trained on diverse datasets, allowing them to generalize well to various noise scenarios and image content. Learning from a large dataset empowers CNNs to handle real-world noise [11] and variations effectively.

Furthermore, CNN architectures can be tailored for specific denoising tasks, incorporating techniques like skip connections, residual learning, and attention mechanisms. These adaptations enhance the model's performance by facilitating the propagation of helpful information and suppressing noise. Lastly, the parallel processing capabilities of CNNs enable efficient training and inference, making them practical for real-time or near-real-time denoising applications. Due to these advantages, CNNs are considered a leading approach for image denoising, yielding impressive results across a spectrum of noise reduction challenges.

In this paper, various CNN models for medical image denoising [12]-[25] are analyzed with the databases employed, types of images utilized, and the quality of the denoised medical images.

The remaining sections in this paper are organized as follows.In Section. II, various CNN medical image denoising techniques were examined, and the literature is summarised in Section. III.

II. LITERATURE REVIEW

This section explains the recent research works in the field of medical image denoising using different CNN models. Elhoseny and Shankar [12] have presented an innovative method for improving the quality of medical images for more precise measurements. The authors integrate the optimal bilateral filter with CNN-based denoising. As a preprocessing step, the optimal bilateral filter reduces noise while effectively preserving key image features and edges. Afterward, a CNN is utilized to refine the denoised images by leveraging its ability to learn intricate data patterns and structures. This synergistic approach improves the overall image quality and increases the accuracy of subsequent medical measurements, making it a promising method for advancing diagnostic and analytical duties in medical imaging.

Kokil and Sudharson [13] use deep learning techniques, specifically a Residual Learning Network (RLN) that has been pretrained, to address the widespread issue of speckle noise in clinical ultrasound images. It utilizes CNN to learn and eliminate speckle-noise patterns effectively. The RLN can learn residual features, enabling the network to capture and remove noise from ultrasound images while preserving the underlying structures. RLN has trained on a large dataset of clinical ultrasound images with ground truth annotations to optimize the despeckling process. The results indicate that this deep learning approach considerably improves image quality for clinical applications, making it a promising technique for enhancing the diagnostic utility of ultrasound imaging.

Tripathi and Bag [14] proposed a novel CNN method for Denoising MRI scans (CNN-DMRI). By training on a diverse dataset of MRI scans, the CNN-DMRI model learns to distinguish between noise and actual anatomical structures, producing denoised images with enhanced clarity. This advancement holds promise in improving the diagnostic accuracy of MRI scans, aiding medical professionals in obtaining more precise and reliable images for accurate interpretation and diagnosis.

The method [15] employs a Progressive Learning Network Strategy (PNLS) architecture, which is comprised of multiple interconnected neural modules. These modules are designed to capture and improve the underlying statistical distributions of MRI data. The denoising procedure unfolds progressively across these modules, allowing for the incremental refinement and reduction of image noise. In addition, the PNLS integrates a module for distribution estimation that aids in modeling the complex noise patterns present in MRI scans, allowing for improved noise reduction performance. By exploiting the inherent data distributions and iteratively refining image representations, this method achieves superior denoising results in MRI images, potentially improving the accuracy of medical diagnoses and image quality for clinical applications.

Tianxu et al. [16] propose another CNN architecture based on an Unsupervised Generative Adversarial Network (UGAN) for denoising MRI images. The proposed UGAN implements unsupervised denoising of medical images from beginning to end. The generator in UGAN receives a set of noisy medical images and generates comparative denoised false images. At the same time, the discriminator accepts real and fake samples and attempts to distinguish between them.

Gu et al. [17] provide an innovative deep-learning methodology to denoise low-dose CT scans. The method suggested in this study is grounded on the CycleGAN framework, a robust unsupervised learning approach that enables the translation of pictures across two distinct domains. Nevertheless, the initial CycleGAN framework necessitates utilizing two generators based on deep neural networks. This characteristic can provide challenges regarding processing resources and the training process. In order to tackle this matter, the proposed approach employs a solitary switchable generator. The generator incorporates Adaptive Instance Normalization (AdaIN) layers, enabling it to seamlessly transition between two operational modes: a low-dose to routine-dose mode and a routine-dose to low-dose mode. This facilitates the training process of the generator, enhancing its efficiency and stability. Additionally, it enables the examination of the intermediate denoising level. The experimental findings from an analysis conducted on a publicly available dataset of low-dose CT scans demonstrate that the suggested methodology performs better than prior CycleGAN techniques, although employing almost half the number of parameters. The approach under consideration additionally offers adjustable denoising capabilities that could benefit a healthcare setting.

Cammarasana et al. [18] proposed a denoising algorithm for ultrasound images. In this technique, the algorithm tries to replicate the available denoising technique by training a neural network. After comparing several cutting-edge denoising algorithms, Weighted Nuclear Norm Minimization (WNNM) possesses high accuracy, preservation of anatomical features, and enhancement of edges. WNNM acts as a backbone network for tuned variant of WNNM (tuned-WNNM), improving the image quality and extending its applicability to ultrasound images.

Two techniques are proposed by Zhang et al. [19] to enhance the quality of medical ultrasound images. The first technique, Dual Image (DI), is an unsupervised learning approach for denoising medical ultrasound images. DI does not require clear medical ultrasound images for training, but instead employs CT images and noise patches extracted from medical ultrasound images. DI first decomposes the medical ultrasound image into noise and clear components. A patch-based denoising network eliminates the noise component, and the clean component is restored using a structural enhancement block. The second technique is Segmenting On Ultrasound Image (SOUI), an extension of the SOLOv2 instance segmentation framework for medical ultrasound images. SOUI enhances SOLOv2's performance by introducing two new modules: the Double Feature Pyramid Network (DFPN) and the mask fusion branch. DFPN enhances the communication and fusion of various feature layers, whereas the mask fusion branch helps to improve segmentation outcomes by fusing the predictions from different instances. Extensive experiments on real-world medical ultrasound images demonstrate that the proposed techniques can considerably enhance the quality of medical ultrasound images and the efficiency of instance segmentation.

Wang et al. [20] propose a novel unpaired learning framework, Self-Supervised Guided Knowledge Distillation (SGKD). Two phases comprise the SGKD framework. During the first stage, a self-supervised cycle network generates two groups of paired training data from unpaired Low Dose CT (LDCT) and Noise-free CT (NCT) images. The cycle network produces the first group of paired data, while the second group is produced by horizontally rotating the NCT images. In the second stage, a knowledge distillation strategy is employed to enhance the denoising performance of the SGKD framework. In particular, a student network is trained to imitate the output of an instructor network, which was pre-trained on the paired data generated in the first stage. It has been demonstrated that the SGKD framework effectively denoises unpaired LDCT images and performs better than state-of-the-art methods.

TABLE I COMPARISON OF CNN DENOISING METHODS

References	CNN name	Noise type & noise level	Image type	Advantages	Disadvantages
[12]	Bilateral, CNN	Salt & pepper noise, 40%	Medical Image	Excellent edge maintenance and effective noise elimination.	Need a great deal of processing capacity and are difficult to set up.
[13]	Pretrained RLN	Speckle noise, 10%	Ultrasound images	Reduces network degradation without learning identity mapping.	Increases network complexity and depends largely on batch normalization
[14]	CNN-DMARI	Rician noise, 19%	MRI images	Reducing the size of feature maps yields a positive outcome. Reduces the vanishing gradient issues for residual blocks.	Network configuration requires much processing capacity and is difficult to implement.
[15]	PNLS	Rician noise, 19%	MRI images	Reduces vanishing gradient issues and generates an effective noise-removal network.	Requires more interference time and generates a high test error
[16]	UGAN	Mixed noise,9%	MRI images	Effectively retain edge information with denoising.	Training-intensive and produces space complexity
[17]	AdaIN	Mixed noise, 10%	Low-dose CT	Switchable CycleGAN for efficient unsupervised low-dose CT images.	Training-intensive and model is validated for CT images.
[18]	Deeplearning	General noise, 30%	Ultrasound images	Generic approach and general blocks were used for denoising	Clinical and industrial validation has to be completed
[19]	DFPN	General noise, 20%	Medical images	Model has the ability to do segmentation and denoising.	Need huge amount dataset for training
[20]	SGKD	General noise, 30%	Low-dose CT	Effectively learning filtering tasks can reduce computation time.	Application to a large dataset may result in low precision.
[21]	FAL	Mixed noise, 50%	CT images	Sample quicker and more easily for CT images.	More evaluation required by using other medical image modalities.
[22]	DudeNet	Gaussian noise, 50%	Chest Xray	Shows good noise removing capability for Xray images with different noise levels.	Need a great deal of computing capacity
[23]	Autoencoder	General noise, 30%	Retinal images	Multilabel retinal image classification along with denoising.	Require improvement in adversarial learning.
[24]	CNN	General noise. 30%	Medical images	CNN model provides image denoising and artifact removal	Requires a large amount computational resource.
[25]	GAN-CNN	General medical noise, 25%	CT images	Even with a low-dose CT image, it is possible to make an accurate diagnosis.	Proper tuning of hyperparameters of the GAN is essential.

Atal [21] presents a novel CNN-based Optimal Deep Vectorial Variation (ODVV) filter for medical image denoising. The ODVV filter consists of three modules: a module for identifying erratic pixel maps, a module for removing noise, and a module for pixel enhancement. The module for identifying noisy pixel maps uses a deep CNN to recognize noisy pixels in the input image. The noise removal module uses the Feedback Artificial Lion (FAL) optimization algorithm to eradicate noise from noisy pixels. The pixel enhancement module employs the vectorial total variation norm to enhance the denoised image. Lena and medical CT images were utilized to evaluate the ODVV filter. The ODVV filter outperformed other state-of-the-art methods in terms of Peak Signal-to-Noise Ratio (PSNR), Second-Derivative-like Measure of Enhancement (SDME), Structural Index Similarity (SSIM), and Edge Preserve Index (EPI).

For medical image denoising, Sahu et al. [22] proposed a Dual Deep convolutional neural Network (DudeNet). The four components of DudeNet are a feature extraction block with a sparse mechanism, an enhancement block, a compression block, and a reconstruction block. The block for feature extraction extracts features from a chaotic image using convolutional neural networks. Afterward, the enhancement block employs residual learning to improve the features further. The compression block decreases the number of network parameters in order to accelerate the training process. The reconstruction block then reconstructs the denoised image using the compressed image features. The DudeNet is evaluated using chest X-ray images with additive white Gaussian noise. Comparing DudeNet to several other cutting-edge denoising techniques, they discovered that DudeNet had the most remarkable performance in terms of PSNR and SSIM.

Chai et al. [23] propose a novel deep-learning model for multi-label medical image classification. Four components comprise the model: a label predictor, a component for mining frequent patterns, a denoiser, and a discriminator. The label predictor consists of a collection of binary classifiers to generate initial predicted labels for each image. The frequent pattern mining component identifies frequently co-occurring labels and uses this data to correlate the binary classifiers' predictions. The denoiser is an adversarial-based denoising autoencoder used to eliminate image noise. The discriminator is a binary classifier that differentiates between genuine and artificial images. The entire model is trained by minimizing the loss of the label predictor, the frequent pattern mining component, the denoiser, and the discriminator. The model was evaluated on the MICCAI 2018 Colonoscopy Image Analysis Challenge dataset and obtained state-of-the-art results.

Choi et al. [24] introduce a novel technique for reducing helical artifacts in medical imaging through image segmentation and CNN denoising. By utilizing the inherent structure of helical scans, the method first performs precise image segmentation to identify artifact-affected regions. Subsequently, a CNN-based denoising process is applied to these areas, eliminating artifacts while preserving clinical information. This innovative approach showcases significant improvements in image quality, enhancing diagnostic accuracy and aiding medical professionals in making more informed decisions. The proposed method demonstrates a promising advancement in artifact reduction, addressing a critical challenge in medical imaging with a data-driven solution.

Lee et al. [25] propose a novel technique for enhancing CT images using GANs. GANs leverage a dual neural network setup to generate realistic images by pitting a generator against a discriminator. GANs are tailored to denoise CT scans while preserving edge features crucial for accurate medical diagnosis. Radiomic feature reproducibility analysis ensures that the denoising process does not compromise essential diagnostic information. This integration of GANs and radiomic analysis presents a promising approach to improve CT image quality while maintaining clinical utility.

Table I summarizes the different medical image denoising CNN models. Table I discusses the CNN model name, associated noise type and maximum noise level tested, image type, and advantages and disadvantages of each model. From Table I, it is evident that CNN has replaced all other denoising techniques for different medical imaging modalities. Performance evaluation of each CNN model is graphically represented in Fig 1. Each model in the reference provides a minimum PSNR of 25 dB and SSIM of 66% at different noise levels. PSNR and SSIM value shows that the denoised medical image has better quality and can be used for further processing.

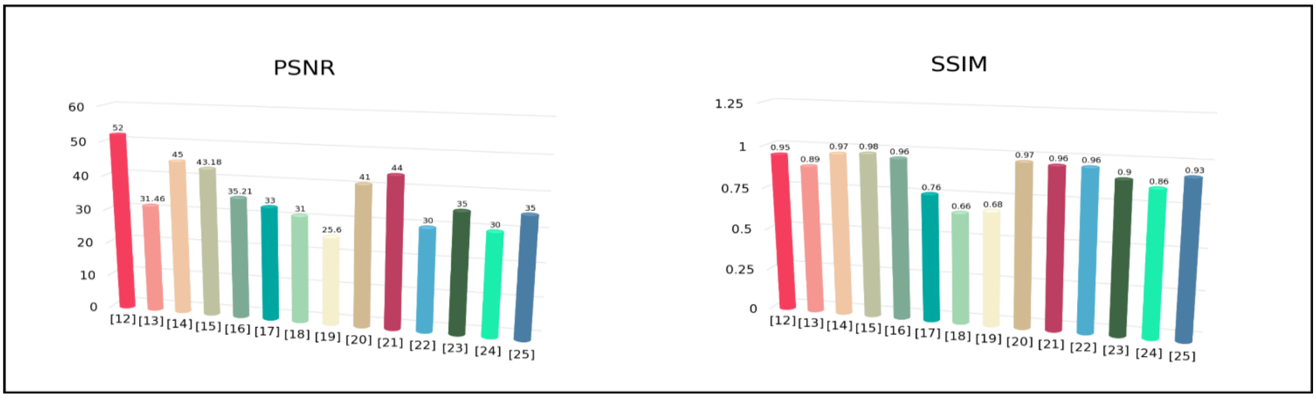

Fig. 1. PSNR and SSIM values of different€ denoising CNN models

This paper evaluates the different CNN techniques for medical image denoising, highlighting their advancements and contributions. The survey emphasizes the transition from conventional image-denoising techniques to deep learning-based solutions, demonstrating how CNNs capture complex noise patterns effectively. Incorporating spatial patterns within the architecture of CNN can facilitate a transition from traditional approaches to the utilization of deep learning methodologies. In contrast to prevailing notions that CNN are opaque, utilizing feature visualization techniques offers a reliable means of eliminating all types and different levels of noise. Nevertheless, the primary obstacle that persists is the significant demand for computational resources in terms of time and space. Overall, the paper provides an exhaustive overview of contemporary CNN-based denoising techniques, highlighting their strengths and weaknesses.

III. Conclusion

CNN-based medical image denoising demonstrates the remarkable potential of deep learning techniques for enhancing image quality. CNN-based denoising techniques have demonstrated promising results in reducing noise artifacts, enhancing image clarity, and aiding medical personnel in making more precise diagnoses. The versatility of CNN architectures and the availability of large datasets pave the way for advancement in the field. However, obstacles such as the need for robust training data, the interpretability of CNN architectures, and the availability of large datasets pave the way for advancement in this field. However, obstacles such as the need for robust training data, interpretability of deep models, and computational requirements persist, necessitating ongoing research efforts to refine and optimize CNN-based medical image denoising techniques for clinical applications.

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