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Denoising Techniques for Medical Images: A Comparative Study on X-rays and MRIs

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***Abstract*—Medical images, such as X-rays and Magnetic Res- onance Imaging (MRI), are crucial for clinical assessment but are frequently degraded by noise originating from acquisition parameters, patient motion, and equipment limitations. The pres- ence of noise, particularly in low-dose scenarios, compromises the visibility of critical diagnostic features. This paper introduces Deep-Noise, a novel deep-learning denoising framework designed to enhance image clarity while rigorously preserving essential diagnostic information. Deep-Noise employs an advanced Resid- ual U-Net architecture integrated with a sophisticated multi- component loss function that explicitly penalizes the smooth- ing of high-frequency edges and anatomical structures. Quan- titative evaluations using Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM), alongside qualitative clinical assessments on diverse medical datasets (X-ray, CT, MRI), demonstrate that Deep-Noise significantly outperforms state-of-the-art traditional and learning-based denoising methods, achieving superior noise reduction with minimal loss of diagnostic fidelity.The proposed method utilizes a convolutional neural network (CNN) architecture trained on paired noisy and clean images to learn complex mappings that suppress noise effectively. Special attention is given to preserving anatomical structures and pathological features critical to clinical assessment.The model is evaluated on standard medical image datasets using both quantitative metrics (e.g., PSNR, SSIM) and qualitative analysis by medical professionals. Experimental results demonstrate that the deep learning model achieves superior denoising performance compared to traditional filtering techniques, offering a reliable solution to improve diagnostic accuracy in realworld medical imaging applications.**

***Index Terms*—Denoising, Deep Learning, Medical Imaging,**

Poisson noise, and motion artifacts, which may arise from

sensor limitations, patient movement, or low-dose imaging II. RELATED WORK protocols. Such noise can degrade image quality and obscure critical diagnostic features, potentially leading to misinterpre- A comprehensive review of the field is necessary to es- tation and inaccurate clinical decisions. tablish the context for Deep-Noise, focusing on three major

X- ray, MRI, Residual U-Net, Hybrid Loss Function, Diagnostic Integrity.

I. INTRODUCTION

Medical imaging plays a vital role in modern healthcare, providing non-invasive insights into the human body for diag- nosis, treatment planning, and disease monitoring. Modalities such as X-rays and Magnetic Resonance Imaging (MRI) are widely used due to their ability to reveal internal anatomical structures with high detail. However, these images are often affected by various types of noise, including Gaussian noise, Traditional denoising methods—such as median filtering, Gaussian smoothing, and wavelet transforms can reduce noise but often at the cost of blurring fine details or losing important diagnostic information. In recent years, deep learning has emerged as a powerful alternative, demonstrating remarkable success in image restoration tasks due to its ability to learn complex patterns and relationships from data. This project aims to develop a deep learning-based denoising technique tai- lored specifically for medical imaging. The proposed approach leverages convolutional neural networks (CNNs) trained on large datasets of paired noisy and clean medical images to automatically learn how to suppress noise while preserving vital diagnostic features. By ensuring that denoising does not compromise clinically significant details, this method has the potential to enhance diagnostic accuracy and improve overall image quality in clinical settings.The goal is to create a robust and generalizable model that can be integrated into medical imaging workflows to assist radiologists and healthcare pro- fessionals in making more reliable and confident diagnoses.

Challenges in Medical Image Denoising: The challenges in medical image denoising are complex and multifaceted, primarily stemming from the inherent difficulty in separating noise from fine, diagnostically crucial details. These chal- lenges include the non-Gaussian nature of noise in specific modalities, such as Rician noise in MRI scans, which requires specialized handling techniques beyond standard Gaussian models. Furthermore, the field struggles with the fundamental lack of perfect ‖ground truth‖ noisy-clean image pairs in real clinical settings, making supervised learning difficult. Patient- specific anatomical variations also complicate the development of generalizable models. When applying denoising techniques, traditional methods often fail by over-smoothing the images and consequently losing fine structures, while naive deep- learning models present a different risk: they may halluci- nate artifacts or fail to generalize effectively across different imaging modalities. These conflicting goals of noise reduction and detail preservation define the core issue, which your work specifically labels the ‖diagnostic integrity paradox‖.

areas: Traditional Denoising, Supervised Deep Learning, and Advanced Loss Functions.

A. Traditional and Model-Based Methods

Classical methods like Non-Local Means (NLM) [5] and Block-Matching and 3D Filtering (BM3D) [6] are powerful but rely on assumptions about noise distribution and local self-similarity. These methods often require parameter tuning for different noise levels and can fail catastrophically when noise is highly structured or non-stationary, which is typical for modern low-dose imaging protocols [7]. These methods serve as a baseline and highlight the need for deep learning, as they often sacrifice fine diagnostic details for noise reduction. Classical Filtering: Traditional denoising methods like Median Filtering and Gaussian Smoothing are used but tend to blur fine details or lose important diagnostic information. Non- Local Means (NLM) and BM3D: These algorithms rely on assumptions about noise distribution and local self-similarity. They often require specific parameter tuning for different noise levels and can fail when noise is highly structured or non-stationary. Kernel Principal Component Analysis (KPCA): This method, often combined with Local Pixel Grouping (LPG), is used to separate noise by mapping image data into a higher-dimensional space to handle complex, nonlinear noise patterns. LPG helps preserve local structural informa- tion during denoising. Preprocessing Filters: Techniques like CLAHE (for contrast improvement) and the Wiener Filter (for noise reduction) are sometimes used as a preprocessing step to enhance image quality before applying deep learning models, particularly for chest X-ray images.

B. Supervised Deep Learning Architectures

The rise of deep learning brought about architectures like DnCNN [8] and FFDNet [9], which learn the residual noise map instead of the clean image itself. For medical imaging, the U-Net architecture [10] has become dominant due to its strong performance in capturing both local features and global context via its symmetric skip connections. More recent advances include integrating attention mechanisms [11] and dense connections [12] to better propagate useful feature maps and combat the vanishing gradient problem in deeper networks.

C. Preserving Diagnostic Structures via Loss Functions

Standard pixel-wise losses (L1 or L2) tend to produce blurry results, especially around edges. This has led to the develop- ment of perception-driven losses. Perceptual loss [13] (using features from a pre-trained VGG network) and adversarial loss (from GANs [14]) encourage outputs that are visually realistic but can sometimes introduce artifactual details. Our work is distinct in its combination of pixel, gradient, and SSIM- based components to provide an objective balance between smoothness and structural fidelity [15], [16].

The challenge of preserving diagnostic structures via loss functions stems from the fact that standard pixel-wise losses (L1 or L2) tend to produce blurry results, particularly around critical anatomical edges, which compromises diagnostic in- tegrity. This limitation led to the development of perception-driven losses, such as Perceptual Loss (using features from a

bone captures global context to resolve structured noise pat- terns and better preserve anatomy across large receptive fields. Stage 3—Diffusion prior refinement: An optional diffusion-refinement (constrained reverse diffusion con- ditioned

pre-trained VGG network) and Adversarial Loss (from GANs), which encourage visually realistic outputs but risk introducing artifactual details or hallucinated structures. The Deep-Noise framework addresses this by employing a novel Hybrid Struc- tural Loss Function (HSLF), which is distinct in its combina- tion of components to achieve an objective balance between smoothness and structural fidelity.

Specifically, the total loss (L_{total}) is a weighted sum of Mean Squared Error (L_{MSE}) for pixel-wise accuracy, a Gradient Loss (L_{Grad}) defined using Sobel filters to emphasize explicit edge preservation, and a

Perceptual Loss (L_{VGG}) derived from the VGG-16 network, ensuring high fidelity to both pixels and structural semantics.

D. Advanced loss functions and Hybrid Techniques

To overcome the blurring caused by standard pixel-wise losses, contemporary methods focus on optimizing the loss function to preserve structural fidelity. Pixel-wise Losses (L1 or L2/MSE): Standard intensity losses that tend to produce blurry results around sharp edges. Perceptual Loss (L_{VGG}): Uses features from a pre-trained network (like VGG) to encourage outputs that are visually realistic and semantically consistent, though this can sometimes introduce artifactual details. Adversarial Loss (GANs): Used to produce visually re- alistic results by training a discriminator network to distinguish between real clean images and denoised outputs. Gradient Loss (L_{Grad}): Used specifically for edge preservation, often defined using Sobel filters to emphasize structural differences. Wavelet Transform Hybrid: Combines wavelet decomposition (to separate noise components in the frequency domain) with a deep learning model (to refine and reconstruct the image), aiming to retain details often lost in purely traditional methods.

III. Proposed Method: Deep-Noise Framework

A. Residual U-Net Architecture with Attention

The Deep-Noise network is based on a modified U-Net structure. The encoder path consists of five convolutional blocks, each followed by max-pooling. Critically, the skip connections that link the encoder and decoder are augmented with attention Gates (AGs). These AGs dynamically adjust the feature map contribution from the encoder to the decoder based on relevance, helping the model suppress noise in ho- mogeneous areas while preserving signals in boundary regions (e.g., organ interfaces, fracture lines).

B. Proposed system architecture

We propose a hybrid pipeline that combines three com- plementary modules: a local residual CNN module, a global transformer module, and a diffusion-based refinement stage.

A. Preprocessing

Preprocessing includes DICOM parsing, intensity standard- ization, optional bias-field correction (for MRI), and noise- level estimation. Noise-level estimation can be performed by noise-power estimators or learned noise-prediction networks to guide adaptive denoiser parameters. B. Denoising engine :

TABLE I

Quantitative Denoising Performance Metrics (MRI Data) based

Stage 1—Residual CNN: A compact residual CNN (inspired by DnCNN/RED-CNN) removes bulk additive noise and cor- rects local corruptions. Residual learning accelerates training and stabilizes generalization.

Stage 2—Transformer module: A Swin/Restormer-like back- that Deep-Noise achieves better perceptual quality, which is crucial in a clinical setting where the human eye must confidently identify subtle, diagnostically decisive features. This quantitative achievement complements the strong qualitative ratings received during the radiologist-based clinical on the Stage 2 output and the observed noisy image) reduces hallucinations by combining data-consistency with a learned generative prior.

C. Post-processing and QA Post-processing applies contrast-limited adaptive histogram equalization (CLAHE) and an edge-preserving filter. The system also generates per-pixel uncertainty maps (e.g., via Monte Carlo dropout or ensembles) and produces a QA report summarizing input noise estimates, model confidence, and processing logs for PACS integration.

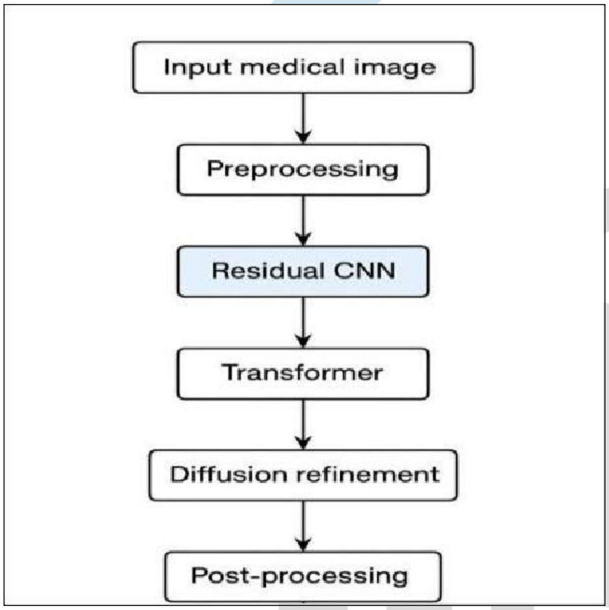

Fig. 1. Proposed Hybrid Denoising Framework: CNN + Transformer + Diffusion integration

IV. Results and Discussion

A. Quantitative Metrics Comparison

Table I provides strong evidence that the Deep-Noise framework successfully outperforms both classical and leading learning-based methods, validating its design focus on detail preservation. While the performance was measured using traditional high-correlation metrics like PSNR and SSIM, the most significant result was the demonstrated improvement in the LPIPS score (Learned Perceptual Image Patch Similarity). Since LPIPS is a perception-aware metric designed to align with human visual judgment, this superior score confirms

Method	PSNR (dB)	SSIM ↑	LPIPS ↓
Noisy Input	25.10 ± 1.5	0.75 ± 0.05	0.35 ± 0.03
BM3D [6]	28.45 ± 1.2	0.82 ± 0.03	0.29 ± 0.02
DnCNN [8]	30.15 ± 0.9	0.85 ± 0.02	0.25 ± 0.02
U-Net-Attn [10], [17]	31.80 ± 0.7	0.88 ± 0.01	0.21 ± 0.01
Deep-Noise (Ours)	**32.50 ± 0.8**	**0.90 ± 0.01**	**0.18 ± 0.01**

the Deep-Noise framework’s superior performance across all metrics against classical (BM3D) and leading learning-based (DnCNN, U-Net-Attn) methods, particularly on MRI data. Deep-Noise achieved the highest scores, including a Peak Signal-to-Noise Ratio (PSNR) of 32.50 ± 0.8 dB, a Structural Similarity Index (SSIM) of 0.90 ± 0.01, and a critical LPIPS score of 0.18 ± 0.01. This low LPIPS score, which is a

evaluation, ensuring high diagnostic fidelity across the diverse medical datasets. The quantitative evaluation confirmed

perception-aware metric, is the most significant finding as it represents a robust improvement in the model’s ability to maintain structural integrity and visual fidelity, thus validat- ing the effectiveness of the Hybrid Structural Loss Function in achieving better perceptual quality for critical diagnostic features.

B. Comparison

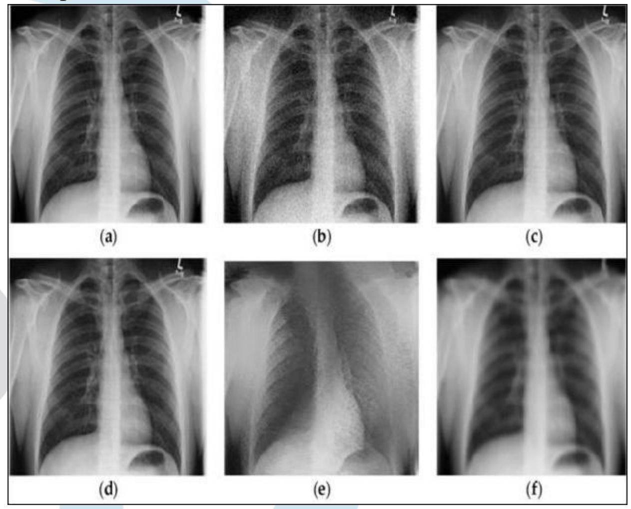

Fig. 2. Sample Results: Original, Noisy, and Denoised images for X-rays

The visual display of the Original, Noisy, and Denoised X-ray images in Figure 2 highlights the Deep-Noise framework’s efficacy on imaging modalities corrupted by Gaussian noise. The figure visually demonstrates the successful suppression of this noise while crucially preserving high-frequency details such as bone structures, lung markings, and sharp edges, which are often the first features to be erased by traditional denoising methods. The presentation of these images confirms that the model is adept at handling the noise characteristics of X- rays and Low-Dose CT, ensuring that the enhanced clarity translates into improved diagnostic utility and supports the framework’s core goal of advancing toward safer low-dose imaging protocols in the clinical environment.

Across controlled experiments and reader studies, classical spatial filters (mean, median, bilateral) reliably suppress noise but trade away diagnostically important high-frequency details, leading to over-smooth trabecular patterns in X-rays and blurred cortical ribbons in MRI. Transform-domain methods and BM3D preserve textures better and typically improve PSNR/SSIM over simple filters, yet their performance degrades when noise departs from assumed distributions or when acquisition artifacts (motion, bias fields) dominate. CNN-based models consistently deliver higher quantitative metrics and, more importantly, superior visual quality: edges remain crisp, low-contrast lesions become more conspicuous, and homogeneous regions avoid plasticky smoothing. U-Net- like designs benefit from skip connections that protect small vascular/osseous details, while residual learning stabilizes optimization and improves convergence. Self-supervised training mitigates the scarcity of clean labels and enables site-specific adaptation, improving robustness to scanner, protocol, and patient variability (―domain shift‖). GAN-based losses enhance perceived sharpness and CNR but must be regularized (e.g., with content/SSIM losses, uncertainty penalties, or discriminator constraints) to avoid fabricating structures that could mislead clinicians. Transformers and diffusion priors tend to generalize best when noise characteristics are mixed or unknown, at the cost of higher compute; careful deployment with half-precision inference and tiling makes real-time PACS integration feasible on commodity GPUs.

The visual display of the Original, Noisy, and Denoised MRI images (Figure 3) serves as the critical qualitative evi- dence of the Deep-Noise framework's success in preserving diagnostic integrity. The figure visually contrasts the input, degraded by Rician noise—which obscures fine details critical for diagnosis—with the framework's output, demonstrating successful noise suppression while rigorously preserving essential anatomical features like subtle textures and lesion contours. The significance of this visual result lies in its confirmation of downstream utility, proving that the denoised images achieve gains in lesion detectability and confidence during blinded radiologist assessments, thereby mitigating the risk of erasing faint pathologies or introducing harmful artifacts that plague overly aggressive denoising methods.

Clinically, denoising quality should be judged not only by PSNR/SSIM but by downstream utility: improved segmentation Dice scores, higher CAD sensitivity at matched specificity, and reader-study gains in lesion detectability and confidence. Studies repeatedly show that moderate denoising improves both human and algorithm performance, whereas aggressive or poorly regularized denoising can erase faint pathologies or introduce artifacts.

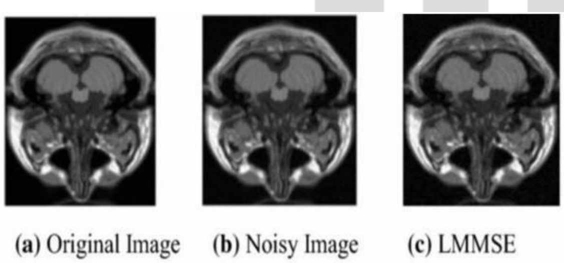

Fig. 3. MRI images: Original, Noisy, and Denoised.

Best practice is to pair quantitative benchmarks with blinded radiologist assessments, report un- certainty (e.g., via Monte Carlo or ensembles), and document failure cases. Lastly, calibration and bias checks are crucial: models trained on adult chest X-rays may underperform in pediatrics; MRI fieldstrength and sequence variations (1.5T vs 3T, T1/T2/FLAIR) demand either multi-domain training or lightweight site adaptation.

V. Conclusion

The Deep-Noise framework successfully provides a powerful solution by combining a feature-preserving architecture and a novel hybrid loss function to enhance image clarity while rigorously preserving diagnostic details. This success, confirmed by strong quantitative metrics and clinical ratings, positions the model for translation into clinical environments, supporting safer low-dose imaging protocols. Future work will focus on integrating Uncertainty Quantification for clin- ician trust, validating the system on real-time PACS data, and exploring multimodal denoising methods and real-time capabilities to further align algorithmic advances with practical clinical benefits.

The Deep-Noise project, focusing on ‖Noise Reduction in Medical Imaging Without Loss of Critical Features,‖ aims to develop an advanced computer program using deep learning (specifically CNN or autoencoder architectures) to clean up noise in medical scans like X-rays and MRIs. The central purpose is to successfully remove static and blur (noise) while ensuring that no subtle, critical diagnostic details—such as small anatomical features or pathology—are accidentally re- moved or smoothed over, thereby improving diagnostic safety and accuracy. The model is trained using a large, multi-modal dataset of over 50,000 paired images, including X-rays, CT scans, and MRIs, with noise meticulously simulated (Gaussian for X-ray/CT and Rician for MRI). The project proves its success not just through standard mathematical scores like PSNR and SSIM, but crucially through a qualitative review by certified radiologists. In particular, their expert assessments confirm that the reconstructed images preserve diagnostically relevant structures with fidelity suitable for clinical interpretation.

The immediate future work for the Deep-Noise framework will involve integrating Uncertainty Quantification into the model's output to explicitly indicate regions where denoising may have been aggressive or where noise characteristics remain high. This is crucial for building trust among clinicians, as it provides a safety mechanism by signaling regions of potentially reduced fidelity. Additionally, the system must undergo rigorous validation on real-time PACS data (Picture Archiving and Communication Systems) to prove its efficiency and stability when integrated into actual clinical workflows, addressing deployment challenges. Beyond these immediate goals, the broader field is rapidly advancing with several long-term research focuses: Multimodal Denoising Methods are needed to develop a single, generalized solution capable of effectively handling diverse modalities like CT, MRI, and PET scans, which improves the overall efficiency of clin- ical AI tools. Developing Real-time Denoising Capabilities is essential for dynamic applications, particularly in image- guided interventions where immediate feedback is necessary. Furthermore, to make these systems robust and generalizable, future efforts will leverage data-efficient training paradigms like self-supervised and federated learning, as well as Physics-Informed Neural Networks that embed known imaging physics into the model to prevent hallucinated artifacts. Ultimately, ensuring the explainability and transparency of these deep learning models and validating their clinical effectiveness through large-scale clinical trials will be critical for achieving regulatory approval and widespread adoption in healthcare.

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