W-LDND: Wavelet-Based Low-Dose to Normal-Dose CT Denoising Method

Afrasama A. Harlapur
School of Computer Science and Engineering
KLE Technological University
Hubballi, India
01fe23bcs428@kletech.ac.in

Shifanaaz Abdulsab Nadaf
School of Computer Science and Engineering
KLE Technological University
Hubballi, India
01fe22bcs013@kletech.ac.in

Aleena A. Sayed
School of Computer Science and Engineering
KLE Technological University
Hubballi, India
01fe23bcs424@kletech.ac.in

Fathma Shekh
School of Computer Science and Engineering
KLE Technological University
Hubballi, India
01fe22bcs005@kletech.ac.in

Shrinivas D Desai
School of Computer Science and Engineering
KLE Technological University
Hubballi, India
sd_desai@kletech.ac.in

Nirmala S R
School of Electronics & Communication Engineering
KLE Technological University
Hubballi, India
nirmala.s@kletech.ac.in

***Abstract*—In clinical examinations and diagnoses, low-dose computed tomography (LDCT) plays a crucial role in minimizing health risks compared to normal-dose computed tomography (NDCT). However, reducing the radiation dose compromises the signal-to-noise ratio, leading to degraded CT image quality. The availability of paired NDCT and LDCT images is essential for academic research. To address this, we propose a method for generating synthetic LDCT images from given NDCT images, followed by denoising using the W-LDND (Wavelet-Based Low Dose to Normal Dose) model with Frequency-Aware Multi-Scale Loss (FAM). The novelty of this research lies in adding region-of-interest (ROI)-specific noise to high-frequency components, which is the primary distinction between LDCT and NDCT. Through experiments, we demonstrate the effectiveness of the proposed method for generating LDCT images from NDCT and validate it using two sample paired NDCT and LDCT images from the literature. We also present the results of denoising using the W-LDND model with FAM**

***Keywords*—Low-dose computed tomography, self-supervised learning, image denoising**

I. INTRODUCTION

Computed tomography (CT) is widely used in medical diagnosis, but increased usage raises concerns about excessive radiation exposure. The ALARA (As Low As Reasonably Achievable) principle is extensively applied to minimize exposure by employing sparse sampling and reducing tube flux. However, reducing the X-ray radiation dose leads to poor-quality images with noticeable noise, which challenges accurate diagnosis. Thus, the development of effective image denoising techniques for CT modalities is a critical need in clinical practice to ensure both patient safety and diagnostic precision.

Recent advancements in deep learning have significantly improved LDCT denoising compared to traditional methods. Supervised denoising techniques, such as CT former and ASCON, learn end-to-end mappings from LDCT to NDCT images. Generative adversarial networks (GANs) have also been employed for LDCT denoising, requiring large amounts of unpaired data.

Despite these advancements, existing methods face challenges, as they require both LDCT and NDCT images, either paired or in large quantities. Due to high costs, privacy concerns, and ethical issues, acquiring such data is often impractical. Therefore, developing self-supervised methods that utilize deep neural networks while minimizing the need for extensive labelled data is essential. Existing self-supervised methods, such as Blind2Unblind, Noise2Sim , Neighbour2Neighbor, and FIRE primarily focus on spatial domain information, overlooking crucial frequency domain details. The primary distinction between LDCT and NDCT images lies in high-frequency components, which are not well explored.

This paper introduces a method for generating LDCT images by applying the Radon transform with a 2° acquisition angle, followed by adding noise modelled from CT images under experimentation. Our W-LDND model contributes two key innovations:

1. Analysing LDCT denoising from a frequency perspective, offering novel insights into optimization.

2. Proposing a frequency-aware multi-scale loss function to enhance the reconstruction network's ability to process high-frequency components effectively.

II. LITERATURE REVIEW

Recent developments in deep learning have significantly advanced low-dose imaging by effectively reducing noise while preserving critical structural details. Several approaches, including Transformers, GANs, U-Net architectures, image fusion, and dictionary learning, have contributed to the field.

Traditional image-domain denoising methods struggle with CT-specific noise patterns, leading to complex streaking artifacts in LDCT due to photon starvation and beam hardening. Existing solutions include:

Table 1: Review and research Gaps from recent contributions

S.No	Author & Publication Year	Proposed Methodology	Result Achieved	Research Gap
1	Zhang et al.	Wavelet-based sparse representation model	Improved subjective and objective quality measures	Manual adjustment limits adaptability to clinical settings
2	Dabov et al.	BM3D (transform-domain collaborative filtering)	Effective on conventional denoising tasks	Struggled with complex noise patterns in medical imaging
3	Guo et al.	Wavelet Packet Transform (WPT) combined with deep learning	Preserved high-frequency details	Needs large datasets, which are difficult to obtain
4	Wang et al.	GAN-based denoising	Produced visually pleasing outcomes	High processing cost and reliance on large datasets
5	Park et al.	Contrastive learning for unpaired image-to-image translation	Improved overall consistency	Poor preservation of fine structural details
6	Zhu et al.	Cycle GAN for cycle-consistent image denoising	Effective for unpaired datasets	Mode collapse and sensitive parameter tuning required
7	Li et al.	Supervised & weakly-supervised methods with anatomical priors	Improved structural preservation	Requires a large number of paired samples
8	Huang et al.	Neighbor2Neighbor (self-supervised, local neighborhood constraints)	Effective in denoising	Over-smoothed fine textures
9	Zhang et al.	Transformer-based models	Strong noise reduction	High computational cost prevents widespread use
10	Xue et al., Patel et al.	GAN-based methods	Strong noise suppression	Training instability, mode collapse issues
11	Huang et al.	Benchmarking studies	Identified generalization gaps	Need for standardized evaluation metrics
12	Li et al.	Deep learning-based denoising	Noteworthy results	High dataset dependency, limited usability in resource-constrained settings
13	Kim et al.	Image fusion for CBCT enhancement	Effective for clinical applications	High computational intensity limits real-time usability
14	Chen et al.	Dictionary learning	Improved structural details	Struggles with extremely noisy data
15	Selig et al., Demir et al.	U-Net architectures for low-dose imaging	Strong benchmark performance	High computational resource requirement, needs validation across noise patterns
16	Fu et al.	TSC-Net (knowledge transfer strategy)	Effective noise reduction	Risk of overfitting on small datasets
17	Wang et al.	Review study on dataset needs	Highlighted need for diverse datasets	Emphasized dataset dependency as a major challenge

Key Research Gaps Identified:

1. High Computational Costs – Many transformer and deep learning models require excessive computational resources.

2. Dataset Dependency – Most methods depend on large, high-quality datasets, limiting their applicability in resource-constrained environments.

3. Generalization Issues – Models perform well on specific datasets but struggle to generalize across different noise patterns.

4. Mode Collapse in GANs – Training stability remains a challenge, affecting the reliability of GAN-based approaches.

5. Over-smoothing & Loss of High-Frequency Details – Many methods fail to preserve crucial fine structural details required for medical diagnosis

III. PROPOSED METHODOLOGY

Balancing image quality and patient safety in CT imaging is crucial. Lower radiation doses result in noisy LDCT images, complicating diagnosis. We propose a method that employs the Radon Transform, Discrete Wavelet Transform (DWT), and Convolutional Autoencoders (CAE) for effective LDCT denoising while preserving clinical details.

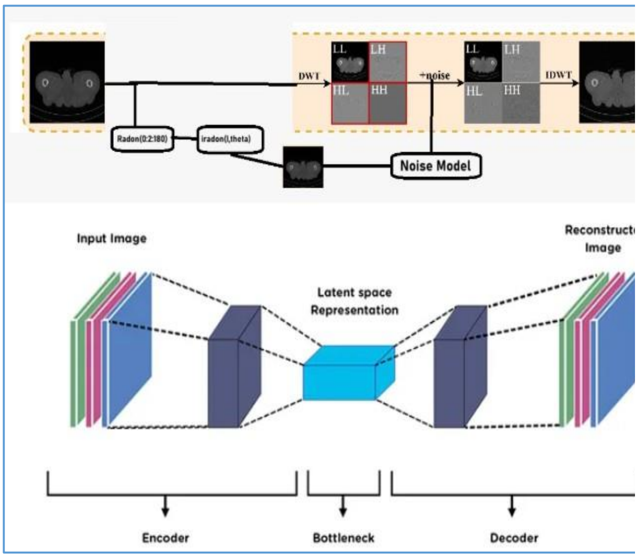


Figure 1: Proposed Model

1. Description of the Proposed System

Imaging with NDCT

NDCT images undergo DWT, decomposing them into sub-band components: LL (low-low), LH (low-high), HL (high-low), and HH (high-high). These components enable selective noise analysis at different resolutions.

Noise Modeling

Noise is added to LH, HL, and HH components while preserving the LL component, which captures the coarse structure. The Inverse Discrete Wavelet Transform (IDWT) reconstructs the noisy LDCT image, used to train the denoising model.

LDCT Image Denoising and Reconstruction

A Convolutional Autoencoder (CAE) is employed:

Encoder: Compresses the noisy LDCT image into a latent space representation.

Bottleneck: Stores learned features of clean NDCT images, focusing on noise removal.

Decoder: Reconstructs the high-quality image, preserving structural and textural fidelity.

The CAE is trained using paired noisy LDCT and clean NDCT images.

Performance Evaluation

The system’s effectiveness is assessed through:

Objective Metrics: PSNR and SSIM.

Subjective Metrics: Clinical evaluation by radiologists.

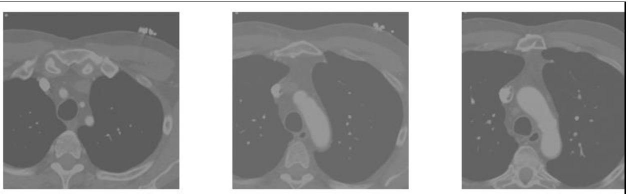
2. Data Set Description

The CTA computed tomography angiography dataset refers to a collection of medical images, mostly chest CT scans used in training and the assessment of machine learning models used in medical image analysis.

The dataset contains about 70 images of LDCT and NDCT that has been used for our proposed work each input image is approximately 630 x 630 JPEG/ jpg image. Since CTA datasets consist of varied images, it allows for training models that could distinguish among many different medical conditions and imaging variations. These datasets are the crucial contributions toward the advancement of the field of medical image analysis and better patient outcomes in general, through AI-driven diagnostics

IV. RESULTS AND DISCUSSIONS

The proposed framework demonstrated significant improvements in the quality of LDCT images. Quantitative evaluation metrics such as SSIM and PSNR highlighted the effectiveness of the denoising process. The framework achieved an average SSIM 8.774, PSNR 34.262, indicating a high degree of similarity between the denoised images and the original high-quality NDCT scans. Similarly, an average of PSNR is 34.262 was observed, confirming the enhancement in image clarity while reducing noise levels.



(I1) (I2) (I3)

Figure 2: Low Dose Cardiac CTA, 150mA

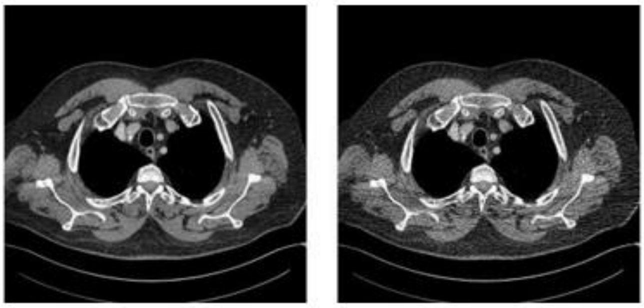
(d1) (d2) (d3)

Figure 3: Denoised LDCT Images

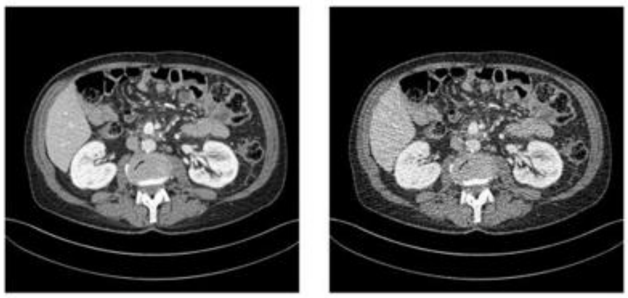
Table 6.1: Average metrics of the Denoised Images

Objective Metrics	Score
SSIM	0.8774
PSNR	34.262
CNR	5.5423
Correlation	0.6253
Chi-Square	0.2212
Intersection	0.6663
Bhattacharyya Distance	0.1437

Additional metrics, including validated the preservation of critical image structures. Qualitative analysis further reinforced these findings, In fig 6.1 with visual comparisons showing a clear reduction in noise and restoration of fine anatomical details. The processed images in fig 6.2 closely resembled the NDCT scans, enabling better diagnostic accuracy. Graphical representations of metric variations during training, such as epoch-wise SSIM improvement, also supported the robustness of the framework. These results collectively underscore the system’s potential for clinical applications, ensuring high-quality imaging while adhering to safety standards by minimizing radiation exposure.



Paired LDCT-NDCT Image1



Paired LDCT-NDCT Image2

Figure 3:Paired LDCT-NDCT Images

The histograms demonstrate that, in contrast to the NDCT image, the Quality-enhanced image has a more uniform distribution of pixel intensities, with a minor tilt towards higher intensities. This implies that while maintaining the original details and texture, the Quality- enhanced image has effectively decreased noise and raised the image's overall brightness. The Quality-enhanced image is architecturally similar to the NDCT image, while there are minor detail variations, according to the comparatively high SSIM and correlation metrics. The two photos appear to have comparable pixel intensity distributions, based on the low Chi-square value; nevertheless, the Quality-enhanced image histogram in fig 6.4 exhibits a more consistent distribution. Additional information on the similarity between the two images may be gleaned from the intersection and Bhattacharyya metrics; a high intersection value suggests that a sizable portion of the pixel intensities are shared, while a low Bhattacharyya value suggests that the distributions are different. All things considered, the analysis indicates that the Quality-enhanced image has effectively preserved the original details and texture while enhancing the NDCT image's brightness and contrast.

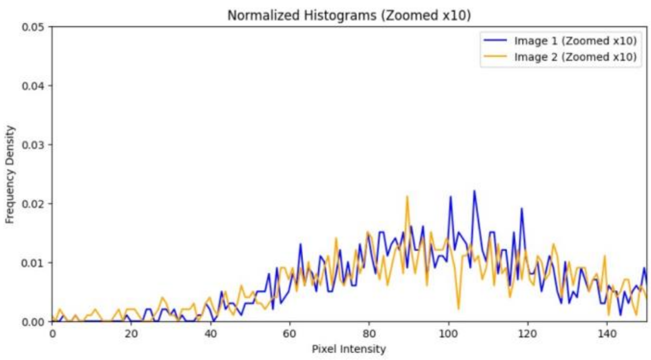


Figure 5: Histogram for NDCT and Quality Enhanced Image

The image 6.4 shows a comparison of two images using their normalized histograms, which represent the frequency of each pixel intensity value. The histograms are zoomed in by a factor of 10 for better visualization, suggesting that the differences between the two images are subtle. The blue line represents LDCT image, while the orange line represents NDCT Image, and the two histograms are quite similar, but some differences exist, especially in the high pixel intensity range. The "Metrics" box provides additional information to compare the two images quantitatively, including the SSIM, Correlation, Chi-Square, Intersection, and Bhattacharyya values. These metrics suggest a moderate level of similarity between the two images, with the SSIM value of 0.6773 indicating a moderate level of similarity, and the correlation value of 0.9326 suggesting a very strong positive correlation. The Chi-Square value of 1.0915 and the Bhattacharyya value of 0.1469 also indicate a moderate level of similarity, with significant overlap between the two distributions.

Table 6.2:Comparission between LDCT and generated LDCT Images

Image Pair	LDCT	Generated LDCT Images
SSIM	0.715	0.6773
Correlation	0.9526	0.9326
Chi-Square	1.3232	1.0915
Intersection	2.5632	2.5908
Bhattacharya Distance	0.1418	0.1469

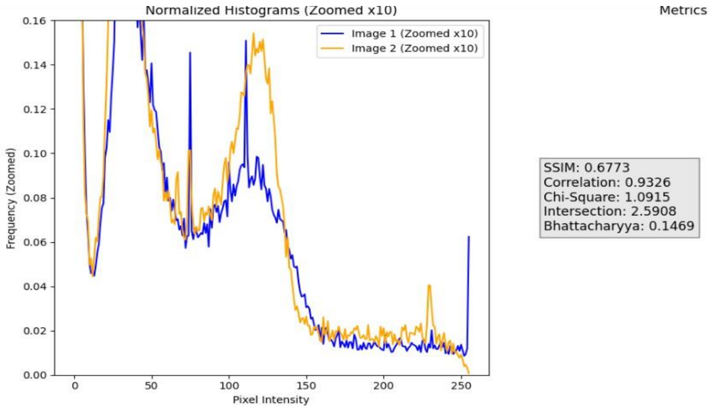


Figure 6: Histogram for NDCT-LDCT 2

V. CONCLUSIONS AND FUTURE SCOPE

The developed system for enhancing LDCT images successfully addresses the challenge of balancing noise reduction with the preservation of diagnostic quality. By employing advanced techniques like Radon Transform, Discrete Wavelet Transform, and Convolutional Autoencoders, the framework achieved high-performance metrics, making it a reliable solution for low-dose imaging scenarios. This methodology aligns with the ALARA principle, promoting safer diagnostic practices without compromising image fidelity. It is analytically difficult to correct the effect of dose reduction on image quality Despite its success, the framework faces certain limitations, such as dependency on high-quality datasets and the need for optimization for real-time deployment in resource-constrained environments. Future work could focus on extending the system to other imaging modalities, incorporating more robust noise models, and improving computational efficiency. Overall, this study highlights the potential of deep learning to revolutionize medical imaging by enabling safer and more accurate diagnostics.

Numerous prospects for further study and advancement are presented by the suggested framework for improving LDCT images. It can be applied to other imaging modalities where maintaining image quality and reducing noise are crucial, like MRI, PET, and X-rays. The smooth integration into clinical operations will be made possible by optimizing computational efficiency for real-time deployment. The resilience and generalizability of the system can be improved by increasing dataset variety and creating sophisticated noise models to replicate various imaging situations. The framework's noise reduction and feature preservation can be further enhanced by combining it with methods like transformers or GANs feature preservation can be further enhanced, by combining it with techniques like transformers or GANs, the features in the improved image become indistinguishable from those in a ground truth version. Furthermore, the technology will be used in environments with restricted resources thanks to lightweight models for low-power devices. The system's adoption and practical utility can be guaranteed by clinical studies and intuitive user interfaces. The framework will develop into a complete solution for safer and more precise medical imaging as a result of these developments.

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