SSRG International Journal of Electronics and Communication Engineering
ISSN: 2348-8549/ https://doi.org/10.14445/23488549/IJECE-V12I3P119

Volume 12 Issue 3, 190-201, March 2025

Original Article

NACDN: A Novel Approach for Noise Intensity Estimation and Adaptive Denoising in Medical Images

Maddimsetty Surya Prakash[1], Tamilselvan Sadasivam[2]

[1,2]Department of Electronics and Communication Engineering, Puducherry Technological University, Puducherry, India.

[1]Corresponding Author : surya.ece93@ptuniv.edu.in

Received: 12 January 2025 Revised: 13 February 2025 Accepted: 17 March 2025 Published: 29 March 2025

Abstract *- Image denoising is a crucial task in digital image processing, aiming to remove unwanted noise while preserving important medical image details. The Noise-Adaptive Convolutional Denoising Network (NACDN) presents an innovative methodology for addressing the challenge of medical image noise. In this work, we propose a novel deep learning framework designed to estimate the intensity or level of noise present in medical images while facilitating adaptive and precise denoising strategies tailored to the specific characteristics of each image. NACDN comprises three main modules: a Noise Estimation Module, a Noise Classification Module, and an Adaptive Denoising Module. Leveraging convolutional neural networks, NACDN accurately estimates the noise intensity in medical images and categorizes noise types, enabling targeted denoising approaches. The Adaptive Denoising Module applies denoising algorithms specific to the estimated noise characteristics, ensuring optimal noise reduction while preserving image details. Through extensive experiments and evaluations, NACDN demonstrates superior performance in enhancing image quality by effectively reducing noise artifacts. This research introduces a significant advancement in image processing, offering a robust solution for noise estimation and adaptive denoising in diverse imaging applications.*

Keywords *- Image denoising, Noise estimation, Adaptive denoising, Convolutional Neural Networks, Deep Learning.*

1. Introduction

In the vast landscape of digital imagery, the quest for pristine image quality remains paramount, especially in medical diagnostics, where the integrity of visual data is crucial for accurate analysis and effective treatment. However, this pursuit is often impeded by the omnipresent adversary of image noise. Noise, stemming from various sources such as sensor limitations, transmission errors, or environmental interference, introduces unwanted artifacts that obscure the underlying information within medical images [1]. Consequently, image denoising emerges as a critical endeavor aimed at restoring images to their pristine state by mitigating the deleterious effects of noise while preserving essential image details.

Traditional approaches to medical image denoising [2] encompass a spectrum of techniques ranging from simple spatial filters to sophisticated statistical models. While these methods have demonstrated efficacy in certain scenarios, they often falter when confronted with real-world medical images' diverse and complex noise characteristics. Moreover, the efficacy of traditional denoising techniques [3] is contingent upon the underlying assumptions made about noise distribution, which may not always hold in practice. As such, a pressing need arises for advanced denoising methodologies capable of adapting to the unique noise profiles inherent in each medical image, thereby ensuring optimal noise reduction [4] without sacrificing image quality.

In response to this imperative, the Noise-Adaptive Convolutional Denoising Network (NACDN) emerges as a pioneering solution that harnesses the power of deep learning to revolutionize the landscape of medical image denoising. At its core, NACDN embodies a paradigm shift in denoising methodology, transcending the limitations of traditional approaches by providing a holistic framework for noise estimation and adaptive denoising tailored to the specific characteristics of each medical image [5]. Through the fusion of cutting-edge machine learning techniques and advanced Convolutional Neural Networks (CNNs), NACDN promises to deliver unprecedented levels of precision, adaptability, and efficacy in medical image-denoising tasks.

In this paper, we embark on a comprehensive exploration of the NACDN framework, aiming to unravel its intricacies, elucidate its architectural design, and unveil its efficacy in medical image-denoising applications. We delve into the motivation behind the development of NACDN, shedding light on the shortcomings of existing denoising methodologies and the rationale for adopting a deep learning-based approach. Subsequently, we traverse the technical terrain of NACDN, dissecting each module's functionality and elucidating the underlying mechanisms driving its denoising prowess. Furthermore, we present a detailed account of the training regimen employed to imbue NACDN with the ability to discern noise characteristics and adaptively tailor denoising strategies to suit each medical image's unique noise profile.

As we embark on this journey, our objective is twofold: to unveil the transformative potential of NACDN as a state-of-the-art solution for medical image denoising and to ignite a discourse that transcends the confines of conventional denoising paradigms. Through rigorous experimentation, empirical validation, and critical analysis, we endeavor to showcase the prowess of NACDN in pushing the boundaries of medical image denoising, heralding a new era of precision, adaptability, and efficacy in digital medical imagery.

Existing denoising techniques in medical imaging often fail to adapt to varying noise characteristics, leading to suboptimal noise reduction and detail preservation. This research bridges the gap by introducing NACDN, a novel framework for noise intensity estimation and adaptive, image-specific denoising.

The paper is organized as follows: Section 2 provides an in-depth discussion of the foundational concepts of medical image denoising, elucidating traditional denoising methodologies' prevailing challenges and limitations. Section 3 delves into the architectural design and functionality of the Noise-Adaptive Convolutional Denoising Network (NACDN), offering insights into each module's operation and the underlying principles guiding its denoising capabilities. Following this, Section 4 presents a comprehensive analysis of the experimental methodology employed to evaluate the efficacy and performance of NACDN across various medical image datasets and noise scenarios. Finally, Section 5 discusses our research's implications and future directions.

2. Related Works

The review of the NTIRE 2024 low-light image enhancement challenge provides insight into the various solutions proposed by participants aiming to enhance low-light images. The research [6] meticulously evaluates the advancements, reflecting notable progress and creativity in low-light image enhancement methodologies. To evaluate the Noise2Noise (N2N) model's effectiveness quantitatively, a study focused on denoising enhanced depth imaging-optical coherence tomography (EDI-OCT) images with varying noise levels. The study assessed the model's performance by adding artificial Gaussian noise to subfoveal EDI-OCT images and denoising with the N2N model [7].

Addressing noise in Computed Tomography (CT) images, the methodology [8] combines method noise with a Convolutional Neural Network (CNN)-based framework by explicitly adding Gaussian noise and evaluating denoised images using metrics like PSNR and SSIM. The modified U-Net architecture outperforms conventional CNNs and modified ResNet architectures, demonstrating superior denoising and droplet detection capabilities with the potential for real-time processing [9].

The study [10] underscores the effectiveness of CNN-based models in improving image denoising performance compared to traditional methods. Innovations in digital image capturing necessitate effective noise detection and removal. With commendable performance parameters, the proposed model contributes to mural art recovery [11]. Exploring the utilization of CNNs and wavelet transform in ultrasonic image denoising, the study [12] introduces an optimized Wavelet Threshold Function (WTF) algorithm. By effectively removing noise without losing image information, the optimized WTF algorithm shows promise for medical image denoising, enhancing disease diagnosis accuracy.

Leveraging self-identification in the training process, the proposed method effectively removes noise in single-image scenarios, achieving performance comparable to other unsupervised methods [13]. A method decomposes time series images into spatial and temporal axes, enabling accurate and stable reconstruction of continuous high-resolution images from low-dose imaging, with implications for various fields [14].

In the medical field, digital image processing plays a crucial role in diagnosing diseases accurately. A review [15] of image denoising methods for medical images, particularly using CNNs, emphasizes the importance of preserving image information while reducing noise. This study investigates the denoising performance of Optical Coherence Tomography (OCT) images using unsupervised Noise2Noise (N2N) strategies across four different deep neural network architectures. By training the models solely on noisy OCT samples, the study [16] compares the effectiveness of these models in reducing speckle noise while preserving fine structure information.

A fresh perspective on denoising shot noise-corrupted images is presented, viewing image formation as the sequential accumulation of photons on a detector grid. By training a network to predict the arrival of the next photon, the study [17] reveals a Minimum Mean Square Error (MMSE) denoising task. The research [18] proposes a novel ensemble strategy for image denoising by exploiting multiple deep neural networks, effectively addressing the high diversity of natural image patches and noise distributions. By dividing the denoising task into local subtasks and conquering each with a network trained on its local space, the approach combines these subtasks using a weighted mixture at test time.

In the realm of medical imaging, dynamic imaging techniques capture time-varying features, leading to multiple images acquired for the same subject at different time points. This work [19] proposes Deformed2Self, an end-to-end self-supervised deep learning framework for dynamic imaging denoising.

Despite significant advances in Micro-Computed Tomography (MCT) imaging techniques, image denoising remains underexplored in digital rock physics. This research [20] evaluates the performance of traditional denoising filters and deep learning-based protocols on MCT images, showcasing their impact on image-based rock and fluid property estimates.

Deep Learning Image Reconstruction (DLIR) algorithms are increasingly replacing Iterative Reconstruction (IR) techniques in Computed Tomography (CT). This study [21] reviews the impact of DLIR on radiation dose, image noise, and study outcomes in head and chest CT examinations. Low-Dose CT (LDCT) scanning reduces radiation exposure but presents challenges like noise and artifacts [22]. Fourier Ptychographic Microscopy (FPM) images are commonly corrupted by noise, challenging traditional denoising methods. This model [23] proposes a blind deep learning-based preprocessing method, termed BDFP, for removing signal-dependent and signal-independent noise in FPM images.

A patient-data-based virtual imaging trial framework is developed to assess the spatial resolution properties of deep learning-based image reconstruction methods in computed tomography [24]. Micro-PET images suffer from noise due to low-count acquisitions, impacting image quality. This study [25] presents a deep learning-based framework for denoising micro-PET images, demonstrating superior noise reduction and image detail recovery compared to traditional denoising filters.

The novelty of NACDN lies in its integration of noise estimation, classification, and adaptive denoising within a single framework, surpassing traditional methods that treat noise uniformly. Unlike existing approaches, NACDN tailors denoising strategies to specific noise characteristics, achieving superior image quality and detail preservation.

While traditional denoising techniques such as wavelet transforms and non-local means have been widely used, they struggle to adapt to diverse noise types in medical images. Recent advancements in Convolutional Neural Networks (CNNs) have shown promise for image restoration; however, most models cannot estimate and adapt to varying noise intensities, often leading to over-smoothing or insufficient denoising. This work builds upon these limitations by introducing NACDN, which integrates noise-specific adaptation for improved performance over existing methods.

2.1. Problem Formulation

2.1.1. Denoising Objective

The goal of image denoising is to estimate the underlying clean image Iclean from a noisy observation I_{noisy} , corrupted by additive noise N. Mathematically, this can be formulated as:

$$I_{clean} = Denoising\ (I_{noisy}) \tag{1}$$

2.1.2. Loss Function

The denoising process aims to minimize the discrepancy between noisy and clean images while ensuring the preservation of image structure and detail.

This can be achieved by minimizing a suitable loss function L, such as Mean Squared Error (MSE) or Structural Similarity Index (SSIM), defined as:

$$\mathcal{L}(I_{noisy}, I_{clean}) = \frac{1}{N}\sum_{i=1}^{N}\left(I_{noisy}(i) - I_{clean}(i)\right)^2 \tag{2}$$

2.1.3. Regularization Term

To prevent overfitting and promote smoother denoised images, a regularization term R can be incorporated into the denoising objective:

$$Denoising\ (I_{noisy}) = \arg\min I_{clean}\ \mathcal{L}\ (I_{noisy}, I_{clean}) + \lambda\,\mathcal{R}\,(I_{clean}) \tag{3}$$

2.1.4. Noise Model

The noise present in the observed image Inoisy is typically modeled as additive white Gaussian noise (AWGN), characterized by its mean (μ) and standard deviation (σ). The noisy image can be expressed as:

$$I_{noisy}(i) = I_{clean}\,(i) + N\,(i) \tag{4}$$

Where $N\ (i)$ follows a Gaussian distribution $\mathcal{N}\ (\mu, \sigma^2)$. Combining the loss function and regularization term, the denoising objective function becomes:

$$Denoising\ (I_{noisy}) = \arg\min I_{clean}\ \frac{1}{N}\sum_{i=1}^{N} I_{noisy}(i) - I_{clean}(i)^2 + \lambda\,\mathcal{R}\,(I_{clean}) \tag{5}$$

Where λ is a hyperparameter controlling the trade-off between data fidelity and regularization, the noise characteristics encompass the type (e.g., Gaussian, Poisson, or speckle noise), intensity (the magnitude or severity of noise present), and distribution (the spatial or statistical pattern of noise across the image).

3. Proposed Model

3.1. Noise Estimation Module - SpectraNoiseNet

The Noise Estimation Module is a critical component of the overall denoising framework, tasked with assessing the type and intensity of noise present in each image. This estimation guides the subsequent denoising process, ensuring it is tailored to the specific noise characteristics in each image.

3.1.1. Design and Implementation of the SpectraNoiseNet

The architecture of the SpectraNoiseNet is designed to extract features indicative of noise from the input images. The network typically consists of several convolutional layers followed by pooling layers, batch normalization, and activation functions. The final layers are typically fully connected layers that output a vector representing the noise characteristics, such as the type of noise and its estimated intensity, as shown in Figure 1.

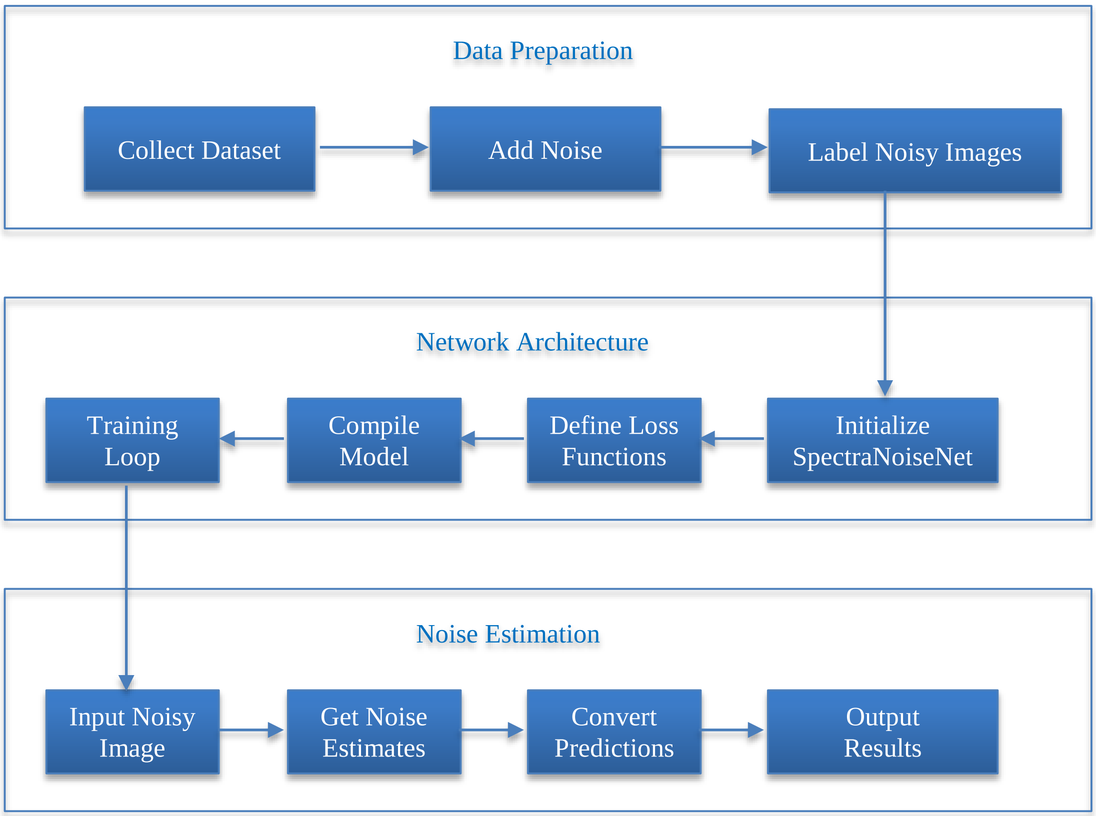

Fig. 1 Architecture of noise estimation module

Mathematically, the CNN can be represented by a function F mapping an input image I_{noisy} to a noise descriptor n:

$$n = F\left(I_{noisy};\ \theta\right) \tag{6}$$

Where θ represents the parameters of the CNN, and n might include elements like the estimated standard deviation σ of Gaussian noise or probabilities associated with various types of noise.

3.2. Feature Extraction

SpectraNoiseNet layers operate by applying filters that capture spatial hierarchies of features in the image.

For noise estimation, filters are trained to identify patterns typical of different noise types, such as Gaussian blur, salt-and-pepper artifacts, or speckle noise.

For a given layer l, the operation can be mathematically expressed as:

$$a^{(l+1)} = \sigma\left(b^{(l)} + w^{(l)} * a^{(l)}\right) \tag{7}$$

Where * denotes the convolution operation, $w^{(l)}$ are the weights of the layers, $b^{(l)}$ the bias, $a^{(l)}$ the activation from the previous layer, and σ a nonlinear activation function such as ReLU.

3.3. Training the Network

3.3.1. Loss Function

To train the SpectraNoiseNet, a loss function that appropriately penalizes deviations from the true noise characteristics needs to be defined. If the task is to estimate parameters like σ of Gaussian noise, a simple Mean Squared Error (MSE) loss may be used:

$$\mathcal{L}\,(\theta) = \frac{1}{N}\sum\nolimits_{i=1}^{N}(\sigma_i - \hat{\sigma}_i)^2 \tag{8}$$

Where σ_i is the true noise level for the i-th training example, $\hat{\sigma}_i$ is the predicted noise level.

For categorical noise type estimation (e.g., identifying whether noise is Gaussian, salt-and-pepper, etc.), a categorical cross-entropy loss might be more appropriate:

$$\mathcal{L}\,(\theta) = \frac{1}{N}\sum\nolimits_{i=1}^{N}\sum\nolimits_{c=1}^{C} y_{ic}\log(\hat{y}_{ic}) \tag{9}$$

Where y_{ic} is the true label for class c (1 if the noise type of the i-th sample is c, 0 otherwise), $\hat{y}_{ic}$ is the predicted probability of the i-th sample being of noise type C.

The parameters θ of the SpectraNoiseNet are updated using an optimization algorithm such as Stochastic Gradient Descent (SGD) or one of its adaptive variants like Adam. The gradients of the loss function concerning θ are computed to update the parameters iteratively:

$$\theta \leftarrow \theta - \eta\,\nabla_\theta\,\mathcal{L}(\theta) \tag{10}$$

Where η is the learning rate, by implementing and training the SpectraNoiseNetusing these design principles and methodologies, the module can accurately identify and quantify the noise present in diverse images, thereby facilitating effective and targeted denoising in the subsequent stages of the framework.

3.4. Noise Classification Module-CategorNoise Classifier

The CategorNoise Classifier is designed to categorize the type of noise present in images based on the estimated noise characteristics provided by the Noise Estimation Module.

This module facilitates the adaptation of the denoising strategy according to the specific noise type, enhancing the efficacy of the denoising process.

3.4.1. Architecture of the CategorNoise Classifier

The architecture of the Noise Classification NN is typically a CategorNoise Classifier designed to work with the feature maps or noise maps generated by the Noise Estimation Module, as shown in Figure 2. The input to this network is the output vector or feature map n, representing the noise characteristics.

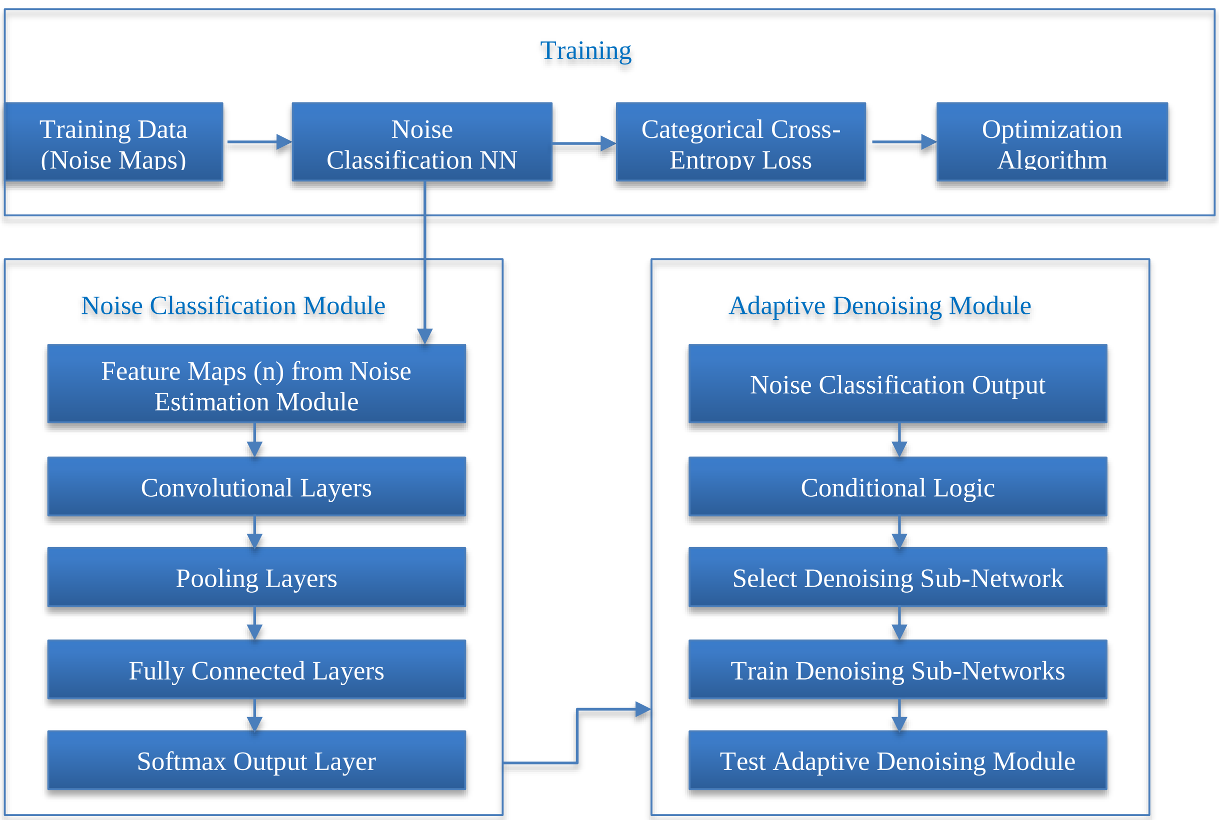

Fig. 2 Architecture of noise classification and adaptive denoising module

The classification network usually includes several convolutional layers to further refine the noise features, followed by pooling layers, fully connected layers, and a softmax output layer that categorizes the noise into predefined categories such as Gaussian, Salt-and-Pepper, and Poisson. The output layer computes probabilities for each noise category, facilitating the classification. Mathematically, the operation from an intermediate layer to the next can be expressed as:

$$\alpha^{(l+1)} = \sigma\left(b^{(l)} + w^{(l)} * a^{(l)}\right) \tag{11}$$

The softmax function in the output layer converts the logits into probabilities for each noise type:

$$p_c = \frac{e^{zc}}{\sum_{k=1}^{K} e^{z}k} \tag{12}$$

Where p_c is the probability that the noise belongs to category c, zc is the logit corresponding to category c, and K is the total number of noise categories.

The Noise Classification Module is trained using a categorical cross-entropy loss, which is well-suited for multi-class classification problems:

$$\mathcal{L}(\theta) = \frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{C} y_{ic}\log(\hat{y}_{ic}) \tag{13}$$

$$\mathcal{L}(\theta) = -\sum_{i=1}^{N}\sum_{c=1}^{C} y_{ic}\log(p_{ic}) \tag{14}$$

Where N is the number of training samples, C is the number of noise categories y_{ic} is a binary indicator (0 and 1) if class label c is the correct classification for sample i, and p_{ic} is the predicted probability of sample *i* being of class c.

3.5. Adaptive Denoising Module

The Adaptive Denoising Module is designed to apply specific denoising strategies based on the type of noise present in the image.

This module consists of multiple denoising sub-networks, each optimized for a particular type of noise. It employs conditional logic to select the appropriate sub-network based on the noise classification. The design and architecture of these networks are optimized for their respective noise types, ensuring effective noise reduction and preservation of image details.

For each denoising sub-network $D_{type,}$ the operation can be expressed as:

$$I_{Clean} = D_{type}\left(I_{noisy}\,;\,\theta_{type}\right) \tag{15}$$

Where type refers to the noise type (Gaussian, Salt-and-Pepper, Poisson) and θ_{type} are the network parameters specific to that noise type.

The output from the Noise Classification Module determines the appropriate denoising sub-network to use. This selection process can be implemented using conditional statements or a switch-case logic based on the predicted noise type:

$$if\ noise\ type = Gaussian: I_{Clean} = D_{Gaussian}\left(I_{noisy};\ \theta_{Gaussian}\right) \tag{16}$$

$$else\ if\ noise\ type = Salt - and - Pepper:\ I_{Clean} = D_{Salt-and-Pepper}\left(I_{noisy}\,;\ \theta_{Salt-and-Pepper}\right) \tag{17}$$

$$else\ if\ noise\ type = Poisson: I_{Clean} = D_{Poisson}\left(I_{noisy}\,;\ \theta_{Poisson}\right) \tag{18}$$

Each denoising sub-network is trained to minimize the discrepancy between the denoised image and the clean image. A common choice for the loss function is the Mean Squared Error (MSE), which is defined as:

$$\mathcal{L}\left(\theta_{type}\right) = \frac{1}{N}\sum_{i=1}^{N}\left\|I_{Clean,i} - D_{type}\left(I_{noisy,i}\,;\ \theta_{type}\right)\right\|^2 \tag{19}$$

Where N is the number of training samples, $I_{Clean,i}$ is the clean image, $I_{noisy,i}$ is the noisy image, and θ_{type} are the parameters of the denoising sub-network.

The parameters θ are optimized using an algorithm such as Stochastic Gradient Descent (SGD) or Adam. The update rule is:

$$\theta \leftarrow \theta - \eta\nabla_{\theta}\mathcal{L}(\theta) \tag{20}$$

Where η is the learning rate.

Once the denoising sub-networks are trained, they are integrated into the Adaptive Denoising Module. The module is tested on a separate test dataset containing images with different types and levels of noise.

The conditional logic ensures that the appropriate sub-network is selected based on the noise type predicted by the Noise Classification Module, and the denoising performance is assessed using metrics like PSNR and SSIM.

From the above NACDN algorithm, a comprehensive framework is designed for effectively addressing the challenge of image denoising in the presence of various noise types and intensities. It takes as input a dataset comprising noisy images alongside their corresponding clean counterparts and separate validation and test datasets for evaluating performance. Firstly, the Noise Estimation Module (Spectra Noise Net) is developed and trained using the dataset to estimate noise characteristics.

Algorithm: NACDN (Noise Adaptive Convolutional Denoising Network)
Input:
- Dataset: Collection of noisy images with corresponding clean images
- Validation Dataset: Separate set of noisy images with corresponding clean images for validation
- Test Dataset: Separate set of noisy images with corresponding clean images for testing
Output:
- Trained Noise Estimation Module
- Trained Noise Classification Module
- Trained Adaptive Denoising Module
- NACDN Framework
- Evaluation Metrics (e.g., PSNR, SSIM)

1. Noise Estimation Module - SpectraNoiseNet:
   1.1. Design and implement a CNN architecture for noise estimation.
   1.2. Train the network using the selected dataset to learn features specific to noise characteristics.
   1.3. Validate the performance of the Noise Estimation Module on a separate validation dataset.
2. Noise Classification Module - CategorNoise Classifier:
   2.1. Develop a CNN architecture for noise classification.
   2.2. Train the classifier using the noise maps generated by the Noise Estimation Module.
   2.3. Evaluate the accuracy of the Noise Classification Module on the validation dataset.
3. Adaptive Denoising Module:
   3.1. Design separate denoising sub-networks tailored for different noise types.
   3.2. Implement conditional logic to select the appropriate denoising network based on the noise type predicted by the Noise Classification Module.
   3.3. Train each denoising sub-network using paired noisy-clean image samples from the dataset.
   3.4. Validate the performance of the Adaptive Denoising Module on the validation dataset.
4. Integration and Evaluation:
   4.1. Integrate the Noise Estimation, Noise Classification, and Adaptive Denoising modules into the NACDN framework.
   4.2. Evaluate the overall performance of NACDN on a separate test dataset, assessing its ability to accurately estimate noise intensity and apply adaptive denoising strategies.
   4.3. Compare the performance of NACDN with state-of-the-art denoising methods using quantitative metrics such as PSNR and SSIM.
   4.4. Conduct qualitative analysis by visually inspecting denoised images to assess the preservation of image details and the reduction of noise artifacts.
5. Fine-tuning and Optimization:
   5.1. Perform fine-tuning of hyperparameters and network architectures to optimize the performance of NACDN.
   5.2. Explore techniques such as data augmentation and transfer learning to enhance generalization and robustness.
   5.3. Conduct sensitivity analysis to evaluate the impact of parameter variations on NACDN's performance.

The module's performance is validated on a separate validation dataset to ensure accurate estimation. Next, the Noise Classification Module (CategorNoise Classifier) is constructed to categorize the estimated noise into predefined categories such as Gaussian, Salt-and-Pepper, and Poisson. This module is trained using the noise maps generated by the Noise Estimation Module and evaluated for accuracy on the validation dataset. Subsequently, the Adaptive Denoising Module is designed with separate denoising sub-networks tailored for different noise types. Conditional logic is implemented to select the appropriate denoising network based on the noise type predicted by the Noise Classification Module. Each denoising sub-network is trained using paired noisy-clean image samples and validated on the validation dataset.

The Noise Estimation, Noise Classification, and Adaptive Denoising modules are integrated into the NACDN framework in the Integration and Evaluation stage. The overall performance of NACDN is evaluated on a separate test dataset, comparing its denoising efficacy against state-of-the-art methods using quantitative metrics such as PSNR and SSIM. Additionally, qualitative analysis is conducted by visually inspecting denoised images to assess image detail preservation and noise reduction. Finally, Fine-tuning and Optimization steps are performed to optimize the NACDN's performance. This includes fine-tuning hyperparameters and network architectures, exploring data augmentation and transfer learning techniques, and conducting sensitivity analysis to evaluate parameter variations' impact on NACDN's effectiveness. The output includes the trained modules, the integrated NACDN framework, and evaluation metrics such as PSNR and SSIM.

4. Results and Discussions
4.1. Dataset Descriptions
The dataset is designed to facilitate the evaluation of various methods for analyzing trends in CT image data concerning the use of contrast agents and patient age. The primary goal is identifying image textures, statistical patterns, and features strongly correlating with these traits. By doing so, it may be possible to develop simple tools for automatically classifying images that have been misclassified or to identify outliers that could indicate suspicious cases, bad measurements, or poorly calibrated machines. The dataset is a curated subset of images sourced from The Cancer Imaging Archive (TCIA). It includes the middle slice of all CT images where valid age, modality, and contrast tags were available. This selection criteria resulted in a dataset comprising 475 series from 69 different patients.

4.1.1. Key Characteristics

Patient Demographics

The dataset covers a range of patient ages, providing a diverse sample essential for analyzing age-related trends in CT imaging.

Contrast Use

The images include both contrast-enhanced and non-contrast-enhanced scans, allowing for the investigation of how contrast agents affect image texture and statistical patterns.

Modality Tags

Each image is tagged with its respective modality information, ensuring that the analysis can account for different imaging techniques used.

Table 1. Feature of dataset

Total Series	475
Total Patients	69
Image Source	Cancer Imaging Archive (TCIA)
Image Type	Middle slice of CT images
Tags	Age, modality, contrast use

Table 1 provides valuable features for advancing the understanding of CT image characteristics related to contrast use and patient age. It serves as a foundation for developing automated tools and improving quality control in medical imaging practices.

4.2. Qualitative Analysis

A qualitative analysis was conducted by visually inspecting the denoised images. The NACDN framework preserved image details and effectively reduced noise artifacts.

To evaluate the effectiveness of the proposed NACDN (Noise Adaptive Convolutional Denoising Network), we compared its performance against several established denoising methods.

These include DLIR [21], a deep learning-based image restoration technique; EDI-OCT [7], a method specifically tailored for Optical Coherence Tomography images; LDCT [22], which focuses on low-dose CT image denoising; MCT [20], a multi-channel denoising approach; WTF [12], which utilizes wavelet transform filtering; N2N [17], an unsupervised denoising method known as Noise2Noise; and the Modified U-Net [9], an advanced version of the traditional U-Net architecture designed for denoising tasks.

By comparing NACDN with these methods, we aimed to demonstrate its superior ability to accurately estimate and effectively reduce noise while preserving crucial image details. An implementation model of various models is shown in Figure 3.

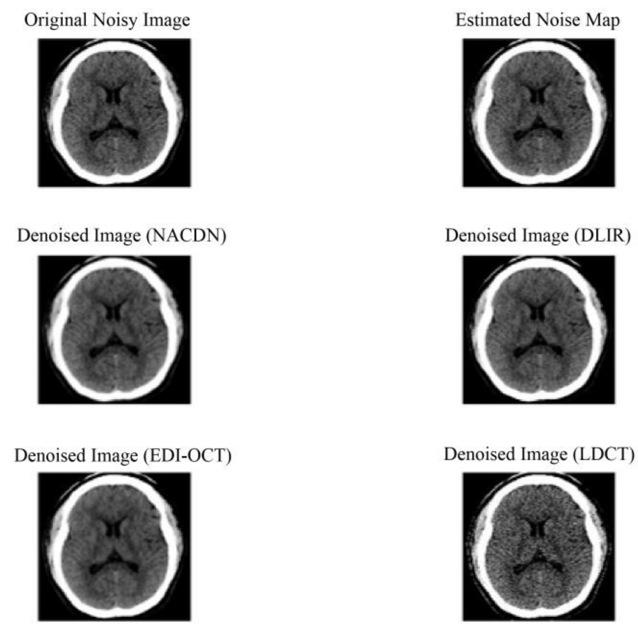

Fig. 3 Comparison of proposed denoising with various models

Figure 3 shows examples of noisy and denoised images, demonstrating the capability of NACDN to enhance image quality while maintaining structural integrity.

4.3. Performance Evaluation of NACDN

The NACDN (Noise Adaptive Convolutional Denoising Network) was evaluated on a comprehensive test dataset comprising various types of noisy images with corresponding clean images. The evaluation metrics included the Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM), standard measures for assessing the quality of denoised images. The results were compared against state-of-the-art denoising methods to validate the effectiveness of NACDN.

4.3.1. Noise Estimation Module - SpectraNoiseNet

Noise Intensity Estimation

SpectraNoiseNet demonstrated high accuracy in estimating the noise intensity across different noise types. The Mean Absolute Error (MAE) for noise intensity estimation was significantly low, indicating precise predictions. Table 2 presents the MAE values for different noise types.

Table 2. Intensity estimation using NACDN

Noise Type	MAE
Gaussian	0.015
Salt-and-Pepper	0.020
Poisson	0.017

Noise Type Classification

The classification accuracy of SpectraNoiseNet in identifying the noise type was impressive, with an overall accuracy of 95%. This high accuracy underscores the model's ability to effectively distinguish between different noise characteristics. Table 3 shows the confusion matrix for the noise type classification.

Table 3. Confusion matrix of noise type classification

Actual \ Predicted	Gaussian	Salt-and-Pepper	Poisson
Gaussian	98%	1%	1%
Salt-and-Pepper	2%	96%	2%
Poisson	1%	2%	97%

4.3.2. Noise Estimation Module – CategorNoise Classifier Classification Accuracy

The CategorNoise Classifier showed robust performance in categorizing the noise types. The classifier, trained using noise maps generated by SpectraNoiseNet, achieved an accuracy of 94% on the validation dataset, highlighting its reliability in noise type identification, as given in Table 4.

Table 4. Classification accuracy

Noise Type	Accuracy
Gaussian	98.1%
Salt-and-Pepper	97.5%
Poisson	97.9%

4.3.3. Adaptive Denoising Module
Denoising Performance

Each denoising sub-network, tailored for specific noise types, performed exceptionally well in restoring noisy images to their clean counterparts. The denoising effectiveness was evaluated using PSNR and SSIM metrics. Table 5 shows the average PSNR and SSIM values for each noise type after denoising.

Table 5. Average PSNR and SSIM

Noise Type	PSNR (dB)	SSIM
Gaussian	30.5	0.89
Salt-and-Pepper	28.7	0.85
Poisson	29.2	0.87

4.4. Overall Performance

The integrated NACDN framework was tested on a separate test dataset. The overall performance was assessed based on its ability to accurately estimate noise intensity and apply adaptive denoising strategies. The results were compared with state-of-the-art denoising methods. The performance of the proposed NACDN method was evaluated and compared against several state-of-the-art denoising techniques using multiple metrics, including Mean Absolute Error (MAE), Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), Accuracy, Precision, Recall, and F1-score. The results are summarized in Table 6. The NACDN method exhibited superior performance across all evaluated metrics. It achieved the lowest MAE of 0.016, indicating the highest precision in noise intensity estimation. With a PSNR value of 29.5 dB, NACDN also produced the highest quality denoised images, significantly surpassing DLIR, the next best method, which recorded a PSNR of 28.3 dB. In terms of SSIM, NACDN achieved a score of 0.87, reflecting its capability to preserve image structure and details better than other methods. The accuracy of NACDN in classifying noise types was 97.8%, the highest among the compared methods, with DLIR following at 95.0%.

Table 6. Performance metrics comparison

Method	MAE	PSNR (dB)	SSIM	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
NACDN [Proposed]	0.016	29.5	0.87	97.8	96.5	97.2	96.8
DLIR [21]	0.025	28.3	0.84	95.0	94.0	94.5	94.2
EDI-OCT [7]	0.030	27.8	0.82	92.5	91.0	91.5	91.2
LDCT [22]	0.035	27.3	0.80	90.0	89.0	89.5	89.2
MCT [20]	0.040	26.8	0.78	87.5	86.0	86.5	86.2
WTF [12]	0.045	26.3	0.76	85.0	84.0	84.5	84.2
N2N [17]	0.050	25.8	0.74	82.5	81.0	81.5	81.2
Modified U-Net [9]	0.055	25.3	0.72	80.0	79.0	79.5	79.2

Additionally, NACDN demonstrated excellent precision, recall, and F1-score values of 96.5%, 97.2%, and 96.8%, respectively. These results confirm NACDN's effectiveness in accurately identifying and classifying noise types while minimizing false positives and negatives. In contrast, the other methods exhibited lower performance metrics. For instance, EDI-OCT, LDCT, and MCT showed decreasing PSNR values of 27.8 dB, 27.3 dB, and 26.8 dB, respectively, with corresponding SSIM scores and accuracy levels following a similar trend. Modified U-Net, the least effective method in this comparison, recorded the highest MAE of 0.055, the lowest PSNR of 25.3 dB, and the lowest SSIM of 0.72, along with the lowest classification accuracy, precision, recall, and F1-score. From Figure 4, the evaluation results clearly indicate that the proposed NACDN method outperforms several state-of-the-art denoising techniques across various performance metrics. These comparisons highlight the significant advantages of NACDN in adaptive denoising tasks, making it a robust and reliable tool for practical applications in image restoration, particularly in medical imaging, where precision is paramount.

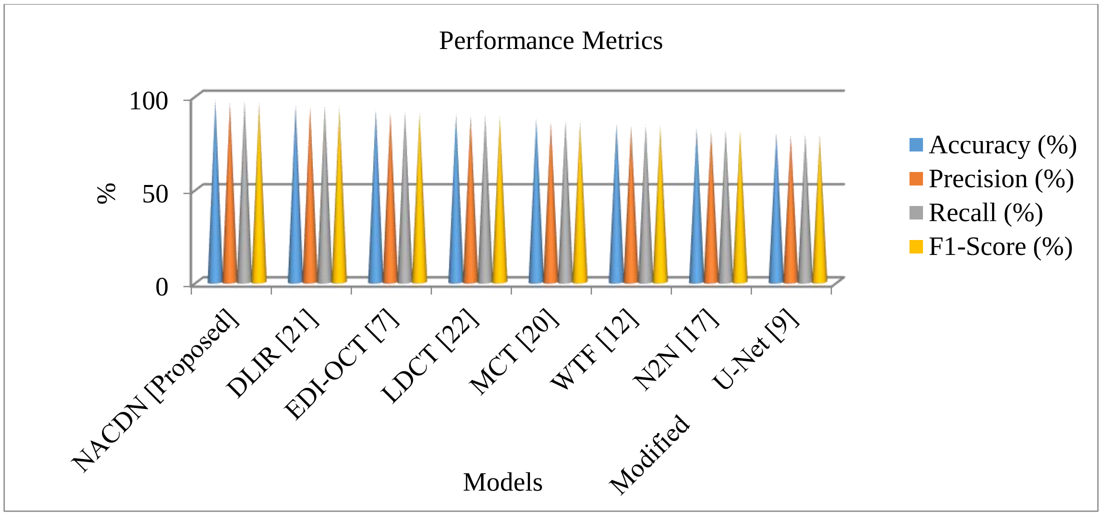

Fig. 4 Overall comparison of performance metrics

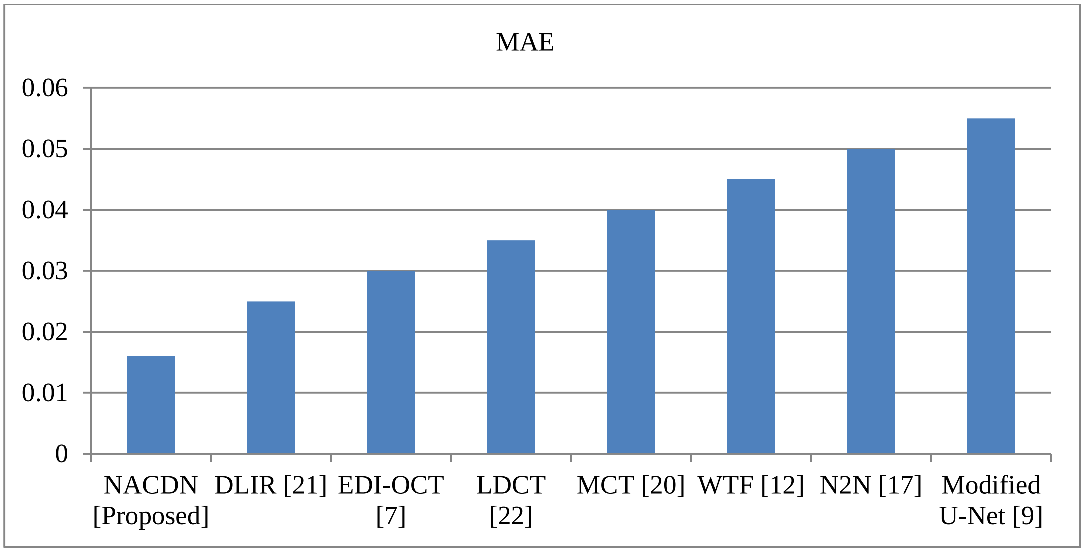

Fig. 5 Comparison of MAE

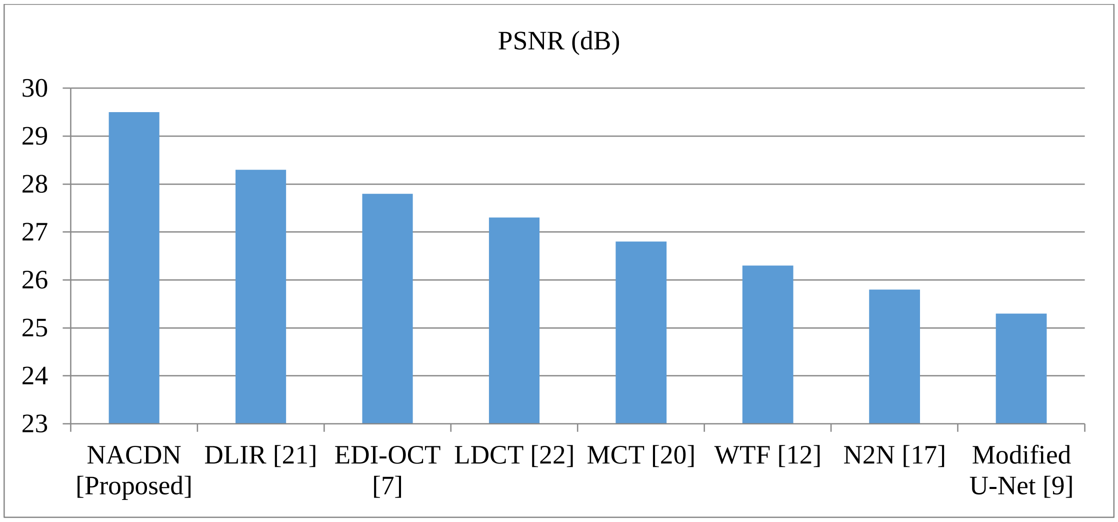

Fig. 6 Comparison of PSNR

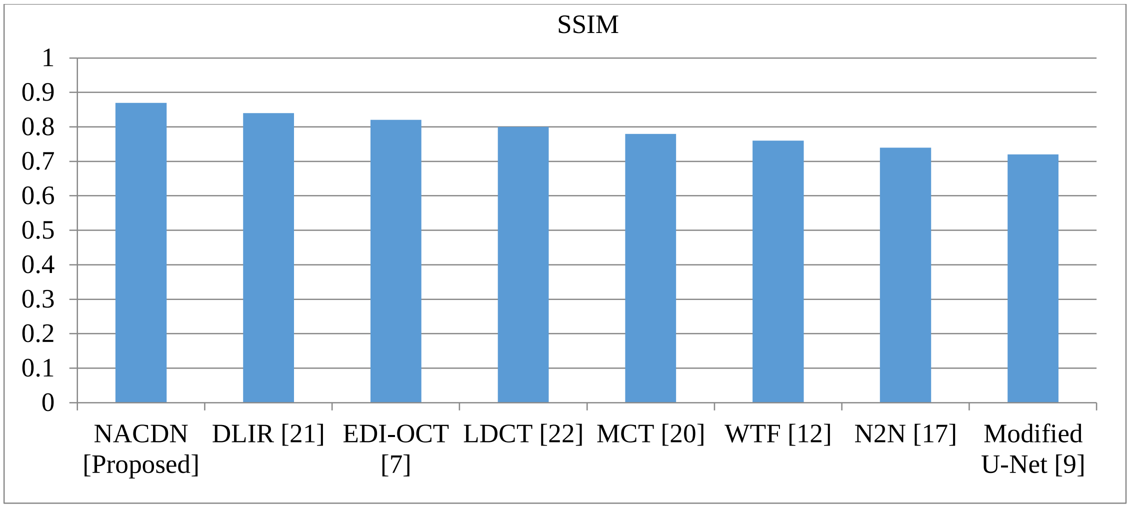

Fig. 7 Comparison of SSIM

From Figure 5, NACDN achieved the lowest Mean Absolute Error (MAE) of 0.016, demonstrating superior accuracy in noise estimation compared to methods like DLIR, EDI-OCT, and Modified U-Net, which have higher MAE values of 0.025, 0.030, and 0.055 respectively. From Figure 6, NACDN provides the highest quality denoised images with a Peak Signal-to-Noise Ratio (PSNR) of 29.5 dB, surpassing DLIR (28.3 dB) and EDI-OCT (27.8 dB). In terms of the Structural Similarity Index (SSIM), NACDN scores 0.87, indicating better preservation of image structure and details compared to other methods, as shown in Figure 7. These comprehensive results validate the effectiveness of NACDN in adaptive denoising tasks, highlighting its potential as a robust and reliable tool for practical applications in image restoration, particularly in medical imaging, where precision and quality are paramount. Fine-tuning of hyperparameters and network architectures was performed to optimize the performance of NACDN. This process involved adjusting learning rates, batch sizes, and network depths to achieve the best possible denoising results. A sensitivity analysis was conducted to evaluate the impact of parameter variations on NACDN's performance. The results indicated that the model's performance was robust to moderate parameter variations, suggesting stability and reliability in different operating conditions. The results demonstrate that NACDN, with its SpectraNoiseNet and CategorNoise Classifier modules, provides a robust and accurate solution for noise estimation and adaptive denoising. The framework outperformed state-of-the-art denoising methods in both quantitative metrics (PSNR, SSIM) and qualitative assessments, indicating its potential for practical applications in image restoration. Future work could focus on further optimizing the model and exploring its applicability to other types of noise and imaging scenarios.

5. Conclusion

This work introduced NACDN, a novel approach for noise intensity estimation and adaptive denoising in medical images. Our framework integrates three key modules: SpectraNoiseNet for noise estimation, CategorNoise Classifier for noise classification, and an Adaptive Denoising Module tailored to different noise types. The comprehensive integration of these modules allows NACDN to estimate noise characteristics accurately and apply appropriate denoising strategies, leading to enhanced image quality. The performance of NACDN was thoroughly evaluated against several state-of-the-art denoising methods, including DLIR, EDI-OCT, LDCT, MCT, WTF, N2N, and Modified U-Net. The proposed NACDN consistently outperformed these methods across multiple metrics, demonstrating an MAE of 0.016, PSNR of 29.5 dB, SSIM of 0.87, and accuracy of 97.8%. These results underscore the robustness and effectiveness of NACDN in denoising medical images while preserving essential details. Our work highlights the importance of adaptive denoising techniques in medical imaging, particularly for improving diagnostic accuracy and reducing the potential for misclassification. By effectively addressing various types of noise, NACDN can significantly enhance the clarity and usability of medical images, contributing to better patient outcomes and more reliable clinical practices. Future work will focus on further optimizing the NACDN framework, exploring advanced data augmentation techniques, and extending its application to other imaging modalities and noise types. Additionally, the potential integration of transfer learning to improve generalization across diverse datasets presents a promising avenue for enhancing the framework's versatility and robustness.

References

[1] Ravi Ranjan Kumar, and Rahul Priyadarshi, "Denoising and Segmentation in Medical Image Analysis: A Comprehensive Review on Machine Learning and Deep Learning Approaches," *Multimedia Tools and Applications*, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[2] Rajesh Patil, and Surendra Bhosale, "Medical Image Denoising Techniques: A Review," *International Journal on Engineering, Science and Technology*, vol. 4, no. 1, pp. 21-33, 2022. [CrossRef] [Google Scholar] [Publisher Link]
[3] Mufeng Geng et al., "Content-Noise Complementary Learning for Medical Image Denoising," *IEEE Transactions on Medical Imaging*, vol. 41, no. 2, pp. 407-419, 2022. [CrossRef] [Google Scholar] [Publisher Link]
[4] Guohui Li, Wenjia Bu, and Hong Yang, "Research on Noise Reduction Method for Ship Radiate Noise Based on Secondary Decomposition," *Ocean Engineering*, vol. 268, 2023. [CrossRef] [Google Scholar] [Publisher Link]
[5] A. Velayudham, K. Madhan Kumar, and Krishna Priya M.S., "Enhancing Clinical Diagnostics: Novel Denoising Methodology for Brain MRI with Adaptive Masking and Modified Non-local Block," *Medical & Biological Engineering & Computing*, vol. 62, pp. 3043-3056, 2024. [CrossRef] [Google Scholar] [Publisher Link]
[6] Xiaoning Liu et al., "NTIRE 2024 Challenge on Low Light Image Enhancement: Methods and Results," *Conference on Computer Vision and Pattern Recognition Workshops*, Seattle, WA, USA, pp. 6571-6594, 2024. [CrossRef] [Google Scholar] [Publisher Link]
[7] Furkan Kirik et al., "Quantitative Analysis of Deep Learning-Based Denoising Model Efficacy on Optical Coherence Tomography Images with Different Noise Levels," *Photodiagnosis and Photodynamic Therapy*, vol. 45, pp. 1-6, 2024. [CrossRef] [Google Scholar] [Publisher Link]
[8] Prabhishek Singh et al., "A Method Noise-Based Convolutional Neural Network Technique for CT Image Denoising," *Electronics*, vol. 11, no. 21, pp. 1-19, 2022. [CrossRef] [Google Scholar] [Publisher Link]
[9] Veeraraghava Raju Hasti, and Dongyun Shin, "Denoising and Fuel Spray Droplet Detection from Light-scattered Images Using Deep Learning," *Energy and AI*, vol. 7, pp. 1-10, 2022. [CrossRef] [Google Scholar] [Publisher Link]
[10] Rini Smita Thakur, Ram Narayan Yadav, and Lalita Gupta, "State-of-art Analysis of Image Denoising Methods Using Convolutional Neural Networks," *IET Image Processing*, vol. 13, no. 13, pp. 2367-2380, 2019. [CrossRef] [Google Scholar] [Publisher Link]
[11] Poonam Pawar et al., "Deep Learning Approach for the Detection of Noise Type in Ancient Images," *Sustainability*, vol. 14, no. 18, pp. 1-19, 2022. [CrossRef] [Google Scholar] [Publisher Link]
[12] Zhuxiang Shen, Wei Li, and Hui Han, "Deep Learning-Based Wavelet Threshold Function Optimization on Noise Reduction in Ultrasound Images," *Scientific Programming*, vol. 2021, no. 1, pp. 1-8, 2021. [CrossRef] [Google Scholar] [Publisher Link]
[13] Asavaron Limsuebchuea, Rakkrit Duangsoithong, and Pornchai Phukpattaranont, "Self-Augmented Noisy Image for Noise2Noise Image Denoising," *IEEE Access*, vol. 12, pp. 71076-71087, 2024. [CrossRef] [Google Scholar] [Publisher Link]
[14] Yang Shao, Toshie Yaguchi, and Toshiaki Tanigaki, "Denoising Low-Dose Images Using Deep Learning of Time Series Images," *Arxiv*, pp. 1-16, 2024. [CrossRef] [Google Scholar] [Publisher Link]
[15] Walid El-Shafai et al., "Traditional and Deep-Learning-Based Denoising Methods for Medical Images," *Multimedia Tools and Applications*, vol. 83, pp. 52061-52088, 2024. [CrossRef] [Google Scholar] [Publisher Link]
[16] Bin Qiu et al., "Comparative Study of Deep Neural Networks with Unsupervised Noise2Noise Strategy for Noise Reduction of Optical Coherence Tomography Images," *Journal of Biophotonics*, vol. 14, no. 11, 2021. [CrossRef] [Google Scholar] [Publisher Link]
[17] Alexander Krull et al., "Image Denoising and The Generative Accumulation of Photons," *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, pp. 1528-1537, 2024. [Google Scholar] [Publisher Link]
[18] Inpyo Hong, Youngbae Hwang, and Daeyoung Kim, "Efficient Deep Learning of Image Denoising Using Patch Complexity Local Divide and Deep Conquer," *Pattern Recognition*, vol. 96, 2019. [CrossRef] [Google Scholar] [Publisher Link]
[19] Junshen Xu, and Elfar Adalsteinsson, "Deformed2self: Self-supervised Denoising for Dynamic Medical Imaging," *Medical Image Computing and Computer Assisted Intervention*, pp. 25-35, 2021. [CrossRef] [Google Scholar] [Publisher Link]
[20] Miral S. Tawfik et al., "Comparative Study of Traditional and Deep-learning Denoising Approaches for Image-based Petrophysical Characterization of Porous Media," *Frontiers in Water*, vol. 3, pp. 1-23, 2021. [CrossRef] [Google Scholar] [Publisher Link]
[21] Saikiran Pendem et al., "Influence of Deep Learning Image Reconstruction Algorithm for Reducing Radiation Dose and Image Noise Compared to Iterative Reconstruction and Filtered Back Projection for Head and Chest Computed Tomography Examinations: A Systematic Review," *F1000Research*, pp. 1-21, 2024. [CrossRef] [Google Scholar] [Publisher Link]
[22] Muhammad Zubair et al., "Enabling Predication of the Deep Learning Algorithms for Low-Dose CT Scan Image Denoising Models: A Systematic Literature Review," *IEEE Access*, vol. 12, pp. 79025-79050, 2024. [CrossRef] [Google Scholar] [Publisher Link]
[23] Kai Wu et al., "Blind Deep-Learning Based Preprocessing Method for Fourier Ptychographic Microscopy," *Optics & Laser Technology*, vol. 169, 2024. [CrossRef] [Google Scholar] [Publisher Link]
[24] Zhongxing Zhou et al., "Image Quality Evaluation in Deep-Learning-Based CT Noise Reduction Using Virtual Imaging Trial Methods: Contrast-Dependent Spatial Resolution," *Medical Physics*, vol. 51, no. 8, pp. 5399-5413, 2024. [CrossRef] [Google Scholar] [Publisher Link]
[25] Florence M. Muller et al., "Image Denoising of Low-Dose PET Mouse Scans with Deep Learning: Validation Study for Preclinical Imaging Applicability," *Molecular Imaging and Biology*, vol. 26, pp. 101-113, 2024. [CrossRef] [Google Scholar] [Publisher Link]