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CNLNet: Enhancing MRI Brain Image Denoising Using a Convolutional Neural Network with Integrated Non-Local Means Layer

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Abstract: *Magnetic resonance imaging (MRI) is an essential imaging modality for brain, but it is affected by noise which degrades the quality of the images. Traditional methods often fail to maintain the fine details of the image while providing denoising efficiency. Even though deep learning methods perform well, integrating them with traditional approaches for medical image denoising is under explored. In this work, we developed CNLNet, Deep learning(DL) model that combines convolutional neural network (CNN) with Non-local means (NLM) layer for MR brain image denoising. Local feature extraction is done by utilising CNN. NLM layer refines long-range dependencies, delivering better denoising performance. Model was trained on Kaggle MRI brain dataset with varying Gaussian noise of standard deviation 0.1, 0.3, 0.5. Quantitative results of experimentation reveal that CNL Net performs well when compared to the CNN model, traditional median, Wiener, NLM filters in terms of PSNR, SSIM, MSE, MAE. Visual comparison also highlights that CNLNet preserves significant fine details along with noise removal. This approach improves the quality of MRI brain images demonstrating potential for clinical diagnostics applications and offers a more efficient denoising solution compared to conventional methods.*

Keywords: *convolutional neural network; non-local means layer; peak signal-to-noise ratio; medical image denoising; weiner filter.*

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1. Introduction

Image denoising is essential in medical imaging, especially in MRI, as noise may obscure intricate details of brain structures, thereby affecting diagnostic accuracy. Conventional denoising methods, including median filtering, Wiener filtering, and non-local means filtering (Li, Wang & Gao, 2024), have been extensively employed for reducing noise in MRI images (Saxena & Sharma, 2023; Veni & Manjula, 2022; Jayanthi & Sivakumar, 2022). These methods, while effective in some cases, struggle with high noise levels or complex noise patterns, often leading to blurred images or loss of structural details. Additionally, their computational cost can be prohibitive for large-scale image datasets. Moummad et al. (2021) emphasised that conventional denoising methods might inadvertently remove essential features, such as vascular structures, mistaking them for noise. This highlights the necessity for advanced denoising techniques that can effectively distinguish between noise and important image features.

Moreover, traditional denoising algorithms, such as BM3D, have shown promise in improving image quality but may not fully exploit the spatial correlations present in MRI data. Astari, Mulyantoro, & Indrati (2023) demonstrated that grouping similar patches can enhance noise reduction, yet they also noted limitations in the ability of these methods to adapt to varying noise levels and image structures. The use of NLM filtering in conjunction with SENSE parallel imaging reveals that NLM effectively mitigates noise introduced by higher parallel imaging factors, thereby improving overall image quality (Angella, Indrati & Yoshandi, 2023).

Trung et al. (2022) developed DL approaches for low-dose CT image denoising that demonstrated CNN adaptability for various imaging modalities, including MRI. Lyu, Zhang, and Han (2021) introduced DSTnet, a CNN model utilising discrete shearlet transforms, which exhibited enhanced efficacy in image denoising tasks, indicating that integration of advanced mathematical transforms could improve CNN designs. Huber et al. (2021) evaluated a CNN noise reduction method for CT images, demonstrating the potential for cross-modality applications of CNNs in medical imaging. Cheng et al. (2022) focused on denoising diffusion-weighted imaging data using CNNs, illustrating the adaptability of CNN architectures to specific imaging challenges. Gurrola-Ramos, Dalmau, and Alarcón (2021) introduced a Residual Dense U-Net for image denoising, integrating the advantages of U-Net designs with residual learning to attain enhanced denoising performance.

CNN-DMRI, a dedicated CNN model for MRI denoising, emphasises tailored application of CNNs to specific imaging tasks (Tripathi & Bag, 2020). Quantitatively evaluated deep CNN-based denoising techniques for low-dose CT, providing a framework for assessing the performance of denoising algorithms across different imaging modalities (Usui et al., 2021). Comprehensive review of CNN-based denoising methods, identifying challenges and future directions for research in this area (Ilesanmi & Ilesanmi, 2021). Employing CNN with an observer loss function for low-dose CT denoising emphasises how crucial perceptual quality is for denoising algorithms (Han, Shim & Baek, 2021).

CNN's ability to learn to eliminate noise from images while maintaining crucial structural elements has demonstrated impressive outcomes. CNNs are successful, but they frequently have difficulty collecting long-range dependencies in images, which might result in suboptimal performance in certain cases. NLM methods rely on the idea that similar image patches, even if they are far apart in the image, can provide useful information for denoising. To improve the denoising process, Wang et al. (2018) presented concept of non-local neural networks, which combine local picture data with global context. By utilising DL and non-local interactions, this work represented a breakthrough in overcoming the limitations of conventional denoising techniques.

Building on this work, Yue et al. (2018) introduced the concept of compact generalised non-local networks, which aimed to reduce the complexity of non-local operations while maintaining the benefits of long-range pixel relationships. Learning efficient global context representations improved image restoration tasks, including denoising, in these models. Zhang, He,

and Yan (2019) provided LatentGNN, which optimises denoising by learning non-local relations more efficiently utilising latent space representations.

In recent years, a trend toward hierarchical approaches has emerged, where multiple layers of non-local networks are combined to capture different levels of image information. Zhu et al. (2021) and Zhang et al. (2022) explored unifying non-local blocks for neural networks, creating more powerful models that could better capture global dependencies. For complex denoising challenges, including those in medical imaging, the hierarchical technique enables a more detailed comprehension of image structure.

The efficiency of non-local networks has also been a subject of ongoing research. Lecouat, Ponce and Mairal (2020) proposed fully trainable non-local sparse models, which aim to improve both the interpretability and efficiency of non-local methods. This becomes pivotal for applications where computational resources are limited, such as in real-time medical image analysis. By group-sparse convolutional dictionary learning, Janjušević et al. (2023) developed rapid and interpretable non-local neural networks for image denoising, combining non-local means with dictionary learning for improved efficacy. Recent work has also focused on the use of hybrid models for denoising. Xie et al. (2021) employed a non-local regularised deep image prior, which combines traditional image priors with modern neural networks to reduce noise while maintaining image fidelity. Katta et al. (2024), and Song, Xu, and Qin (2024) developed a hybrid CT image noise reduction method combining CNN and Shearlet transform, demonstrating the effectiveness of integrating denoising techniques for improved results.

The advancements in non-local neural networks and hybrid models have paved the way for more accurate and efficient denoising methods for medical images, especially MRI. We focused on improving two important performance metrics: the ratio between the peak signal and noise (PSNR) and the index measuring structural similarity (SSIM). Primary contributions of our research include:

1. We proposed a CNN-based model that incorporates a non-local means layer as an integrated component, leveraging local and non-local information in the image to enhance denoising performance;
2. We evaluated our model on a brain MRI dataset with varying levels of noise, demonstrating its effectiveness in outperforming traditional denoising techniques and standalone CNN models;
3. We provided a comprehensive analysis of results, highlighting the advantages of our approach and discussing its potential applications in medical imaging and beyond.

The remaining paper is organised in the following pattern: Section 2 indicates the materials and planned technique. Section 3 provides experimental results of denoised images and the subsequent discussion. In section 4, the conclusion of the research and future directions are indicated.

2. Materials and Methods

2.1. Motivation

Magnetic Resonance Imaging plays a crucial role in diagnosing brain disorders, but the presence of noise can deteriorate image quality, affecting clinical diagnostic accuracy. Convolutional neural networks exhibited good image-denoising performance. They focus on local similarity and fail to exploit the non-local redundancy inherent in medical images. Few methods combine the capabilities of NLM and CNNs for denoising images. However, they treat either of these methods as separate stages of preprocessing or post-processing, which limits the efficiency and overall performance of the denoising process. Furthermore, the utilisation of integrated NLM within deep learning frameworks for MRI image denoising remains unexplored. In this work, we focused on addressing this gap by directly incorporating the NLM technique within the CNN framework, aiming to deliver superior denoising performance that balances noise suppression and

the preservation of fine details. Specifically, this approach was done to MR brain images, and this was an unexplored area.

2.2. Methodology

The proposed model is explained in this section. The CNLNet, a CNN-based model integrated with an NLM layer, demonstrates significant improvements in MR brain image denoising. Here, we had initially given a brief description of CNN, nonlocal means denoising, and then the proposed work's details. The conceptual block diagram of the proposed denoising approach is shown in Figure 1.

Convolutional Neural Networks

CNNs are extensively utilised in image denoising because of their capacity to learn spatial hierarchies of features directly from data. CNNs accept noisy images as input and produce corresponding clean images, providing an end-to-end learning framework. The convolutional layers in a CNN extract meaningful features by applying filters across the input, effectively learning patterns that differentiate noise from image details. These filters, refined during training, attenuate noise while maintaining the image's fine structure. Including non-linear activation functions helps CNNs model the complex transformations necessary for efficient noise removal. Superficial layers of the network acquire local characteristics that include edges and textures. Deeper layers get elevated representations essential for distinguishing between noise and content. The output layer reconstructs the denoised image, employing a sigmoid activation function to ensure that pixel values remain within an acceptable range. CNNs learn the denoising process by auto-tuning from data, and this comes with an edge over traditional image restoration tasks. The CNN is used to pull local features from the image of the fine details in specific locations.

Non-Local Means Denoising

NLM denoising is a widely utilised approach that effectively maintains image features during the denoising. The entire noisy image is divided into patches. The new value of each pixel is calculated by taking the weighted average of similar pixels in the surrounding area.

For a noisy image G , the denoised pixel value at location x represented by $G_{nl}(x)$ can be calculated using the equation (1)

$$G_{nl}(x) = \frac{1}{C(x)} \sum_{y \in \Omega} G(y) \cdot \exp \left(- \frac{(\|G(N_x) - G(N_y)\|)^2}{h^2} \right) \quad (1)$$

Where $C(x)$ is the normalisation factor, Ω is the search window, N_x and N_y denote patches centered at pixels x & y , and 'h' corresponds to the smoothing parameter.

Proposed method

In our proposed method, we addressed the limitation of CNN by integrating a non-local block as a layer for considering the global features, inspired by the implementation described in the work "*Non-local Neural Networks*". CNN focuses on extracting local features from the image, capturing fine details in specific areas. Meanwhile, the NLM layer enhances the global features by considering the broader context of the image, helping to refine the overall structure. This combined approach allows for better denoising as the CNN addresses local patterns and the NLM layer smooths out noise while preserving key details across the entire image.

We created the model CNLNet from scratch and also created a basic CNN model for comparative analysis. In this, we used clean images from the publicly available dataset. Gaussian noise was added with a standard deviation(SD) 0.1, 0.3, 0.5 to make the noisy image dataset. The model has been trained with noisy images step by step. Testing has been conducted with testing datasets and also with unseen data. Performance evaluation is conducted for assessing denoised image quality with performance metrics that include SSIM, MSE, PSNR, and MAE.

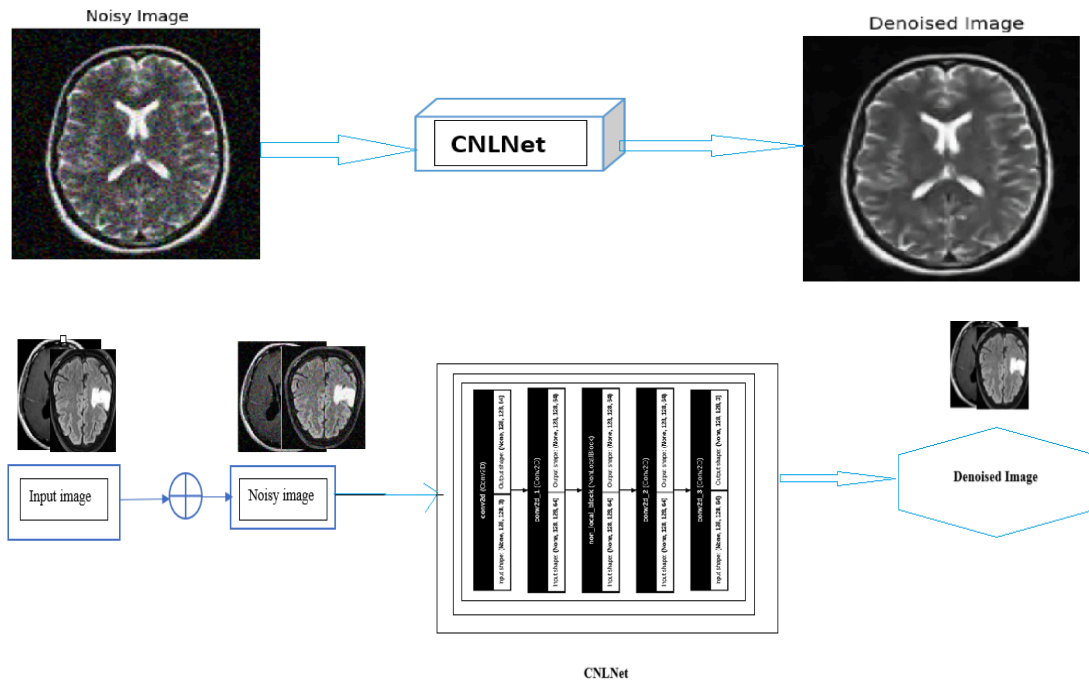


Figure 1. Block diagram of proposed denoising approach

Model Architecture

CNLNet is designed to integrate non-local operations into a convolutional neural network for MRI image denoising. The block diagrammatic representation of the proposed model is given in Figure 2. The model was built from scratch. The details of the architecture are as follows.

1. **Input Layer:** CNLNet accepts noisy MRI images with dimensions $128 \times 128 \times 3$. To enhance stability during training and improve model convergence, the input intensities are normalised to the range $[0, 1]$.
2. **Feature Extraction:** Feature extraction stage comprises 2 convolutional layers, each configured with 64 filters of size $3 \times 3 \times 3$. Both layers utilise the ReLU (Rectified Linear Unit) activation function. This activation function incorporates non-linearity into the model, enabling it to discern intricate patterns within data. Additionally, the ReLU function is computationally beneficial because of its simplicity. The vanishing gradient problem can be resolved by this. This will, in turn, speed up the convergence. The main function of such layers is to extract small-scale patterns like edges, textures, etc, from the input image. Both of these layers produce feature maps that form the basis of the non-local block.
3. **Non-Local Block:** We capture global context through computing self-similarity over the entire feature map using a custom NLM block. This block increases long-range feature dependencies at a mild computational cost. The main innovation in CNLNet is that it embeds a custom Non-Local Block based on Non-local Networks implementation by Xiaolong Wang et al., as described in their work. The mechanism introduced self-similarity across feature maps to capture long-range dependencies in neural networks. How CNLNet operates is described below.

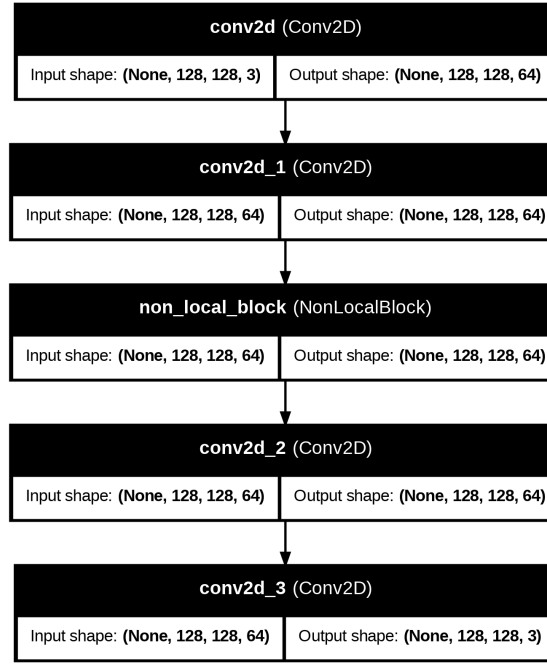


Figure 2. Model architecture of CNLNet

Global Contextual Awareness: Computes global context by evaluating pairwise similarity of all pixels (or regions) within the feature map. It enables the network to learn long-range dependencies and so bypasses locality constraints of traditional convolutions. Softmax Normalisation: It employs the softmax function to normalise the similarity scores to appropriately weigh the contributions of features from different regions.

Feature Aggregation: Each feature is enhanced by aggregating information from globally similar features, weighted by their similarity score. This denoising leverages structural redundancy and repetitive patterns inherent in MRI images and injects this block to improve anatomical fidelity while denoising. The design is relatively computationally efficient such that it can process large images without significant performance overhead.

4. **Feature Refinement:** After enhancement of the features in the NLM block, additional convolutional layers refine it.
5. **Reconstruction Layer:** We denoise the image using a final convolutional layer with 3 filters and sigmoid activation, which reconstructs the denoised image.

2.3. Dataset Preparation

The dataset consists of 3,072 MRI brain images sourced from a publicly accessible Kaggle dataset at <https://www.kaggle.com/datasets/abhranta/brain-tumor-detection-mri>. Images were resized to a uniform resolution of $128 \times 128 \times 3$ and normalised to the range $[0, 1]$ for consistent scaling and improved convergence during training. To construct noisy-clean image pairs, 3 SD of Gaussian noise (0.1, 0.3, and 0.5) were applied. Figure 3 displays sample images of clean and noisy images with SD of 0.1, 0.3, and 0.5, respectively.

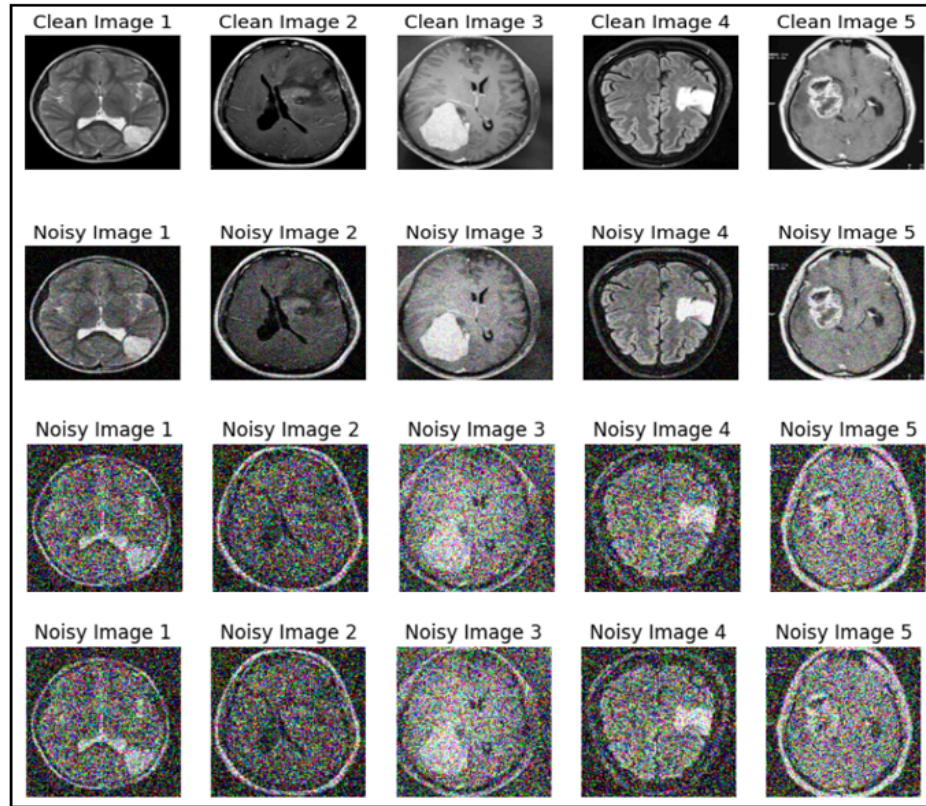


Figure 3. Sample clean and noisy image ($\sigma = 0.1, 0.3, 0.5$)

Unseen datasets, including the IXI dataset and publicly available Kaggle dataset <https://www.kaggle.com/datasets/thomasdubail/brain-tumors-256x256> (consisting of 3096 MR images), were used to evaluate the model's generalisation capabilities.

2.4. Algorithm MRI Brain Image Denoising Using CNLNet

Input: Noisy Brain MR images X_{bnsy}

Output: Denoised Brain MR images X_{bdeno}

1. Initialisation:
Design and configure the CNLNet model architecture from scratch
Initialise the model parameters
Load the dataset D_b
2. Training loop
For each training iteration, **do**
Sample a batch of i noisy MRI images ($X_{bnsy1}, X_{bnsy2}, \dots, X_{bnsyi}$) from the dataset D_b .
Pass X_{bnsy} through the input layer to generate initial feature maps F_0 .
3. Feature extraction
for each convolutional block in the feature extraction stage, **do**
Extract spatial features using $G_{conv} = \text{Conv2D}(G)$
end for
4. Non-local feature enhancement, refinement, and reconstruction
 $G_{NLM} = \text{NonlocalBlock}(G_{conv})$
5. Feature refinement and reconstruction
Pass F_{NLM} through subsequent convolutional layers for feature refinement.
 $F_{REF} = \text{Conv2D}(F_{NLM})$
Generate denoised images X_{bdeno} from the final reconstruction layer
6. Loss calculation
Compute loss (MSE) in Denoised image and the ground truth image.
7. Weight update
Update model's trainable parameters using backpropagation and Adam optimiser to minimise loss.
end for

2.5. Materials

The experimentation was conducted on a varied dataset of MR images, sourced from the publicly accessible Kaggle dataset at <https://www.kaggle.com/datasets/abhranta/brain-tumor-detection-mri>. Unseen datasets, including the IXI dataset and publicly available Kaggle dataset <https://www.kaggle.com/datasets/thomasdubail/brain-tumors-256x256>, were used to evaluate the model's generalisation capabilities. In this paper, 5 MR images are used to represent the experimental reports. Training of the proposed model was sustained on Google Colab, utilising an AP100 GPU for accelerated computation. The specification of the system used was 12th Gen Intel(R)Core(TM)i7 12700 operating at 2.10 GHz, X64-based PC.

2.6. Performance Metrics

Mean Square Error (MSE): It is commonly used in the performance evaluation of denoising techniques. MSE is the measure of the average of the squared difference between corresponding pixels in a clear image and the respective pixel value in the denoised image. A higher value indicates that the performance is low. The MSE is calculated using the expression (2). In this equation the pixel value of a clear image is denoted by 'I(i, j)', and 'I_{denoised}(i, j)' represents a denoised image.

$$MSE = \frac{1}{MN} \sum_{i=1}^{nN} \sum_{j=1}^N (\bar{I}(i, j) - I_{denoised}(i, j))^2 \quad (2)$$

Here, I(i, j) is the original pixel value, and $I_{denoised}(i, j)$ is the corresponding denoised pixel value.

Structural Similarity Index (SSIM): the measure quantifies similarity between two images based on brightness, structure, & contrast attributes. This metric is often utilised for denoising evaluation because it assesses perceptual image quality. The maximum value that can be obtained for structural similarity is one.

Mean Absolute Error (MAE): For evaluating the similarity of the noisy and denoised images. The lower the MAE, the higher the similarity between the clean and the denoised version of the image and vice-versa. It is calculated by the equation (3)

$$MAE = \frac{1}{N} \sum_{i=1}^N (I_{org}(xi, yi) - I_{den}(xi, yi)) \quad (3)$$

I_{org} and I_{den} denote pixel value at the x_i, y_i of the clean image and the Denoised image, respectively. N represents the total number of pixels

Peak Signal-to-Noise Ratio (PSNR): Most frequently utilised metrics for assessing denoising methods. It measures the ratio between the maximum possible signal value and the noise level. It is obtained by the equation (4).

$$PSNR = 10 \log_{10}((MAX_I)^2 / MSE) \quad (4)$$

In this equation, the highest possible value of the pixel is denoted by MAX_I . The higher the PSNR, the better the denoising performance. MSE corresponds to mean squared error.

2.7. Training and Testing

The denoising model has been trained and then tested on 7371 clean images and their noisy counterparts. Clean images have been exposed to Gaussian noise, with SDs of 0.1, 0.3, and 0.5. The dataset has been divided into 615 images (20%) for testing and 2457 images (80%) for training for each noise level. The model has been trained separately for each noise level over thirty epochs with

batch size of 10. This was done using noisy images as inputs and clean images as targets. The Adam optimiser with MSE loss function has been employed. A validation split of twenty percent during training ensured monitoring to prevent overfitting. Testing was conducted on the held-out 615 images for each noise level.

The model was tested with unseen data from additional publicly available Kaggle datasets and the benchmark IXI dataset. The result was evaluated using SSIM, PSNR, and MSE. Training loss for the model CNLNet while training with clean and noisy pairs, of noisy image sets with a standard deviation of 0.1 Gaussian noise, is shown in Figure 4(a). The graph showing training and validation loss for a noisy set with 0.3 is shown in Figure 4(b).

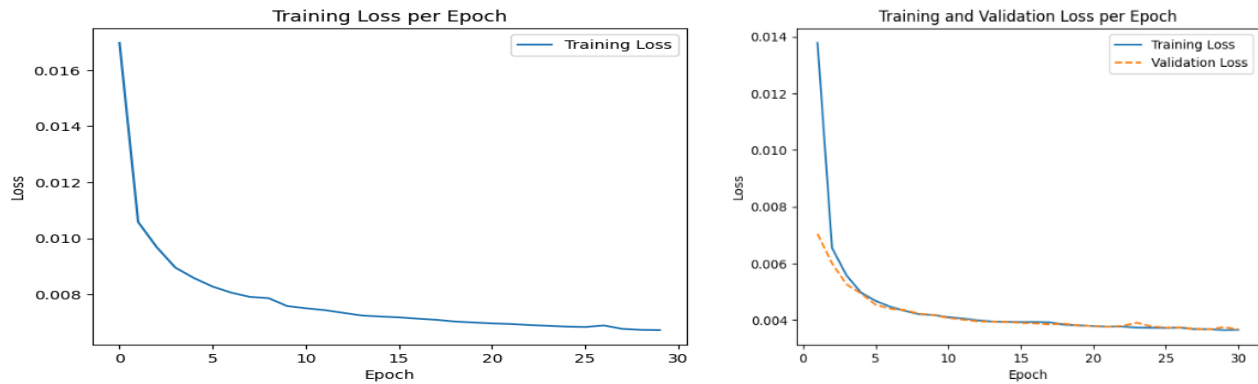


Figure 4. (a) Training loss, (b) Training and validation loss curve

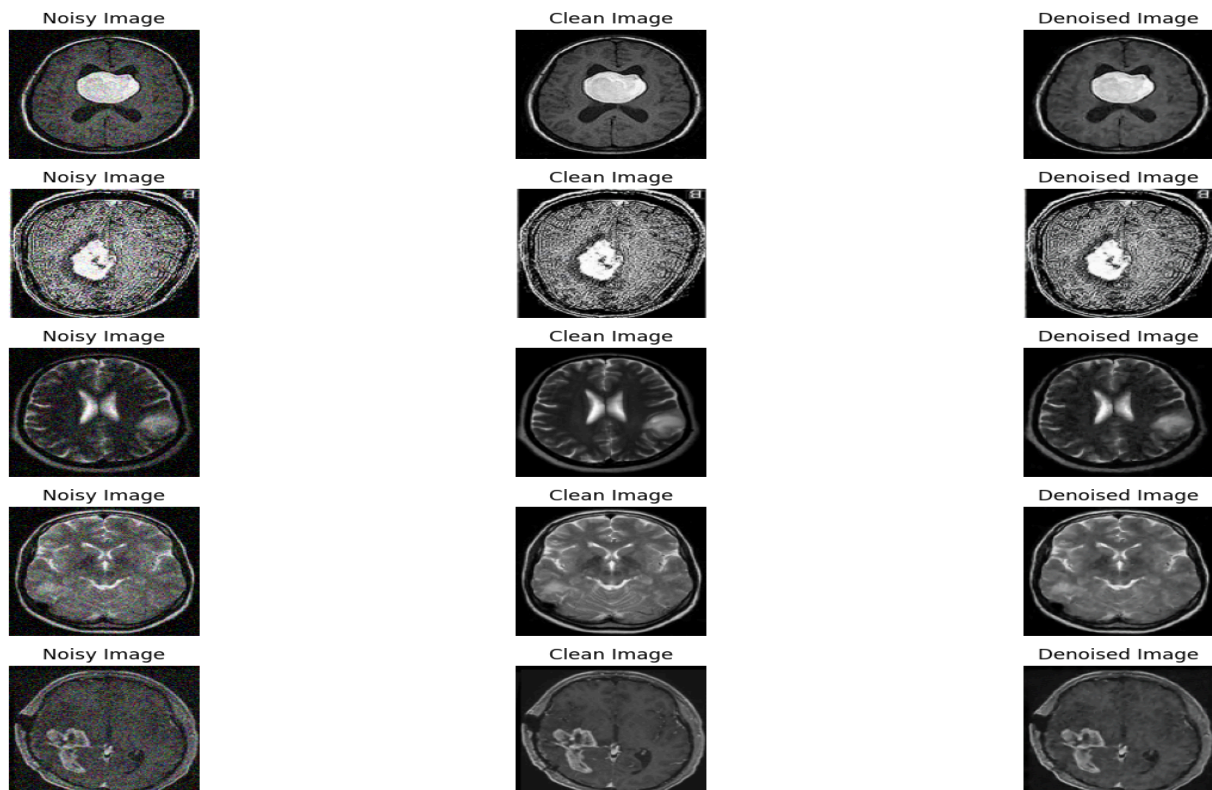


Figure 5. Denoised images of five samples from the testing dataset for $\sigma = 0.1$

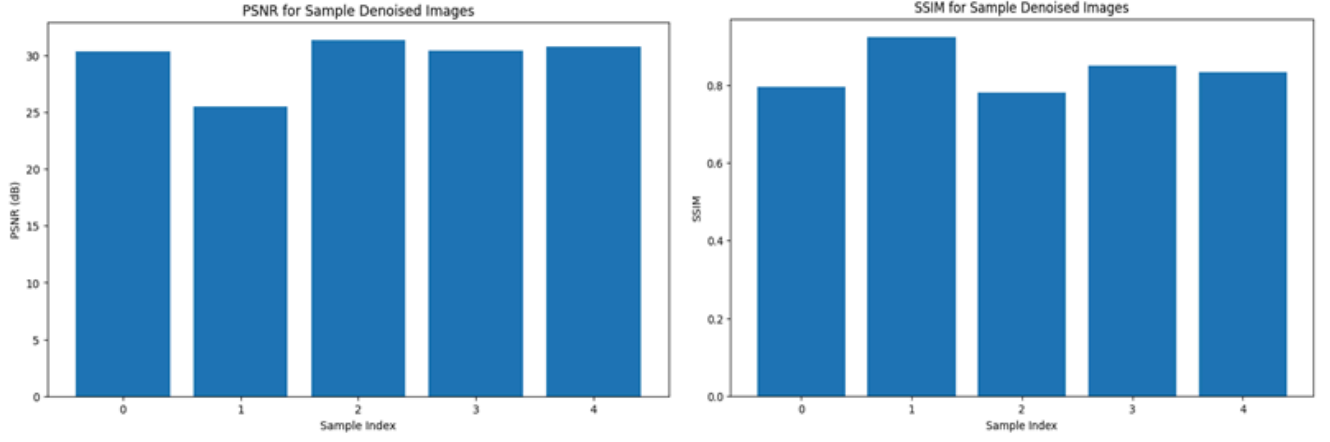


Figure 6. PSNR and SSIM of the denoised five sample images from the testing dataset for $\sigma = 0.1$

Denoised images of the five sample pictures are shown in Figure 5. Its corresponding PSNR and SSIM are illustrated in Figure 6. Distribution of PSNR and MSE for the entire dataset is shown in Figures 7 and 8.

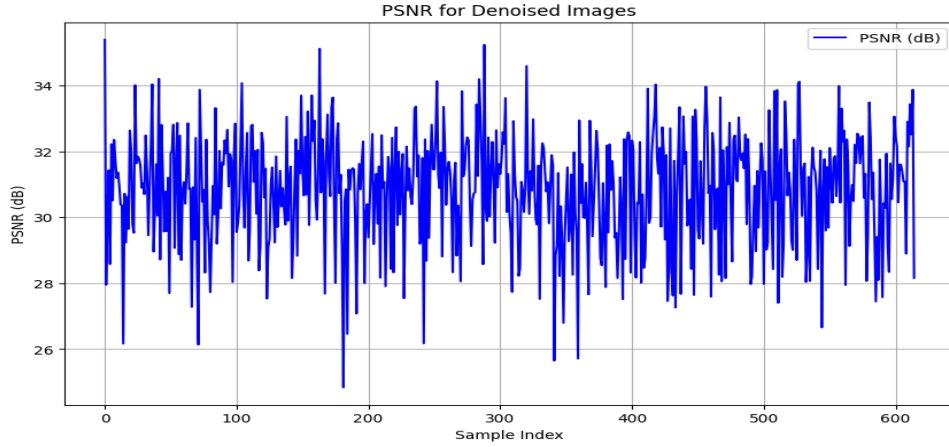


Figure 7. PSNR for the denoised image of the testing data set for 0.1 noise

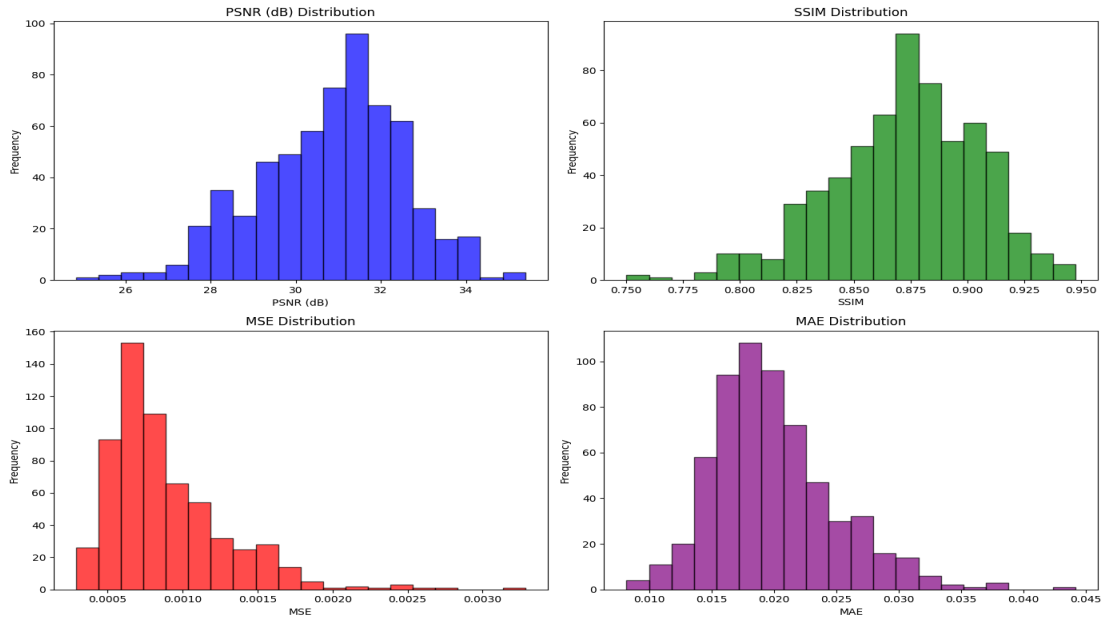


Figure 8. Distribution of PSNR, SSIM, MSE, and MAE for the testing data set for 0.1 noise

4. Results and Discussion

We had trained and tested the CNLNet model for denoising the noisy brain MR images with Gaussian noise 0.1, 0.3, and 0.5, respectively. We had conducted the training of the model for thirty epochs and a batch size of ten in all cases. This selection was made after conducting two groups of hyperparameter settings on the 0.1 Gaussian noise dataset.

Hyperparameter Setting. We had done model training and testing for (50, 32) and (30, 10) epoch and batch size combinations.

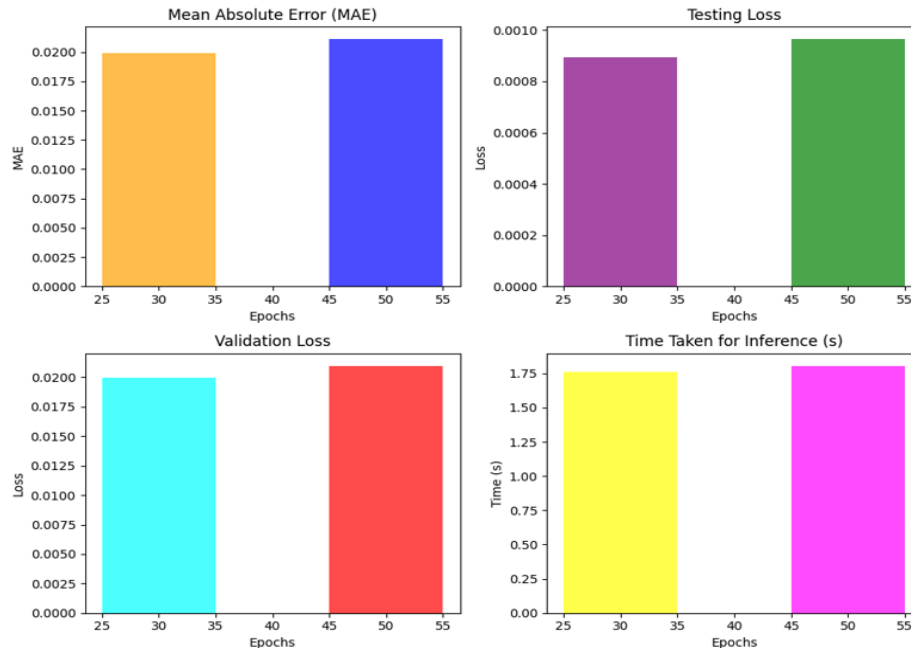


Figure 9. Performance comparison for hyperparameter setting

Considering it generates lower testing loss (0.000895), validation loss (0.0199836), and MAE (0.0199) than 50 epochs with a 32 batch size while keeping the same inference time per step (79 ms) and slightly faster overall inference, the selection of 30 epochs with a 10 batch size is justified. It avoids overfitting and is computationally more efficient, balancing accuracy and resource usage effectively. Performance comparison for hyperparameter tuning is illustrated in Figure 9.

Integrating Non-Local Means in CNN. The integration of the Non-Local Means (NLM) layer within a Convolutional Neural Network (CNN) in CNLNet is based on well-established theoretical principles. CNNs are highly effective at capturing local spatial features, making them powerful tools for extracting fine details in images. However, standard CNNs struggle to capture long-range dependencies, which are crucial for medical image denoising, where noise patterns often exhibit global correlations. In contrast, NLM-based approaches utilise self-similarity to capture information from distant, yet structurally similar, regions within the image. By incorporating an NLM layer directly within the CNN framework, CNLNet enhances both local and global feature extraction, leading to superior noise suppression without losing important anatomical structures. This design builds upon the principles introduced in Non-Local Neural Networks (Wang et al., 2018) and extends their applicability to MRI brain image denoising. Our results demonstrate that this synergy significantly improves PSNR and SSIM compared to traditional filtering methods and standalone CNN models.

Comparison with Different Methods. We have compared the proposed method's performance with other existing denoising methods, including Median, Wiener, NLM, and CNN. Gaussian noise was added to the image.

Table 1. Comparison of Evaluation Metrics of the Proposed Model with Other Methods

Method	PSNR	SSIM	MSE
Median	22.42	0.4839	0.0057
Wiener Filter	27.50	0.5500	0.0040
Non-Local Means Denoising filter	30.27	0.6532	0.0025
CNN	28.48	0.5966	0.0014
CNLNet	35.38	0.9416	0.0002

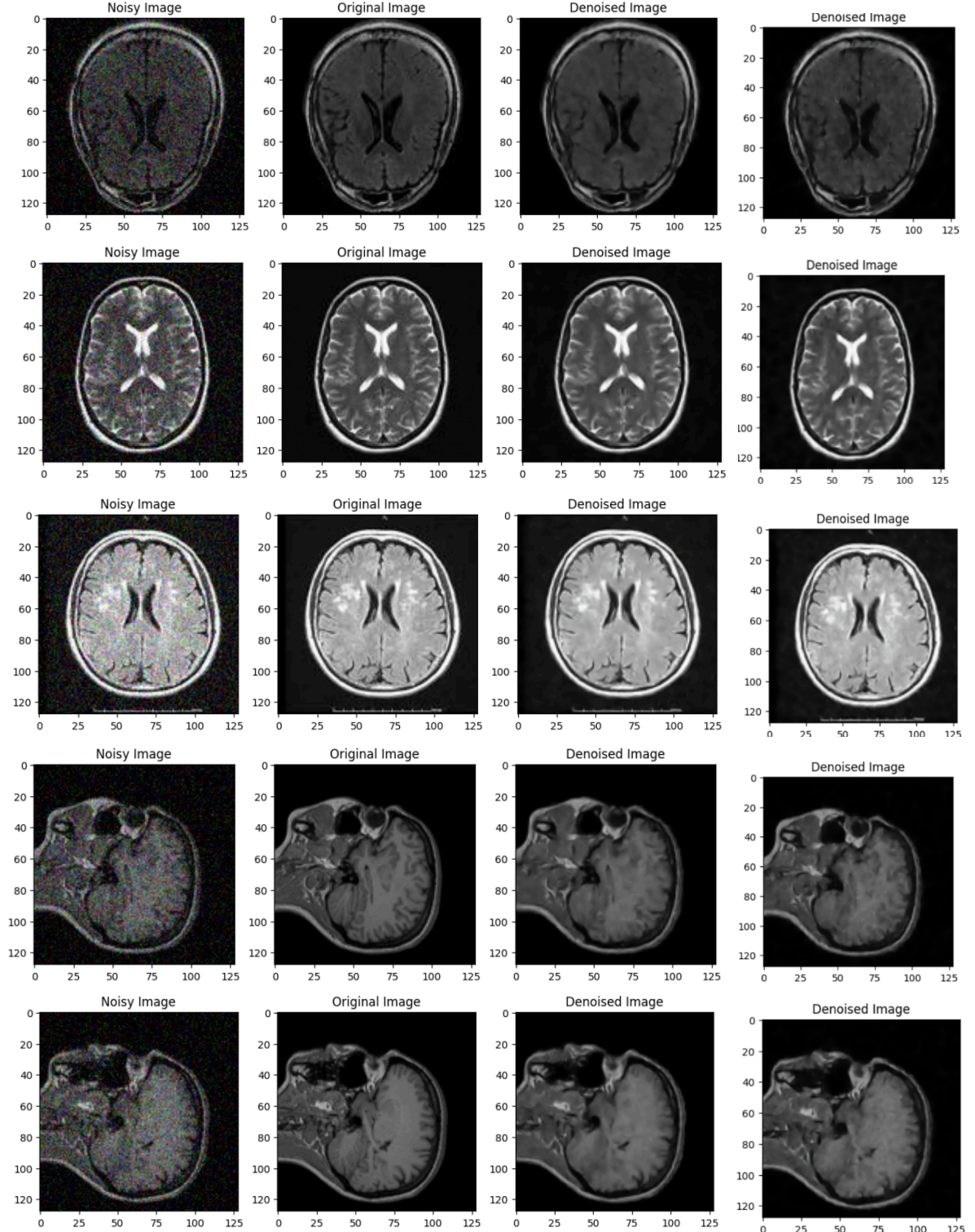


Figure 10. Denoising of images with noise of standard deviation 0.1; (a) noisy version, (b) clean image, (c) Denoised output image of CNLNet (d) Denoised output image of CNN

From the experimentation, it was evident that the denoising result obtained for CNLNet was the best value. Table 1 shows the values of performance metrics obtained while denoising the noisy image having a standard deviation of 0.1. Here, the result obtained for only one image is given.

Figure 10 (c) demonstrates denoised images of the proposed model during the testing phase of the model with noisy data of 0.1, while Figure (d) displays the CNN model. The CNLNet model outperformed all other methods due to the inclusion of the NLM block along with CNN layers. The qualitative visual analysis was performed by zooming into specific areas of the original and denoised versions of CNLNet and CNN. Here, 800% of zooming of a specific area is done. It is noted that the visual quality of CNLNet crosses the CNN. The image of the zoomed part of the original, denoised CNLNet, and CNN are presented in Figure 11.

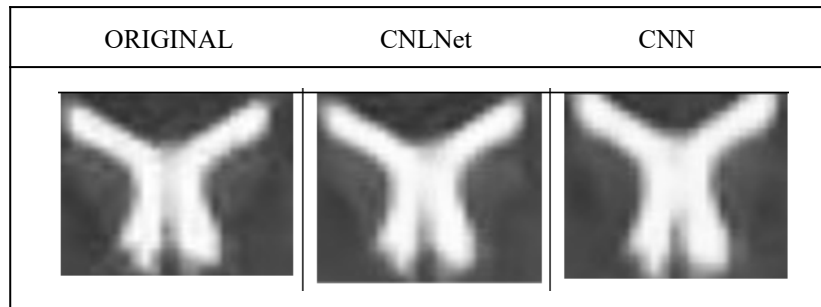


Figure 11. Zoomed version of the original image, denoised using CNLNet, CNN for 0.1 noisy image

Table 2. Performance of the model for CNLNet with different Gaussian noises

Noise of $\sigma=0.1$				
Image	Technique	PSNR	SSIM	MSE
Image1	CNN	31.3199	0.8217	0.0007
	CNLNet	32.1255	0.8739	0.0006
Image2	CNN	30.7498	0.8842	0.0008
	CNLNet	31.2369	0.9079	0.0008
Image 3	CNN	29.3958	0.8521	0.0011
	CNLNet	30.0640	0.8531	0.0010
Image 4	CNN	32.0378	0.8166	0.0006
	CNLNet	32.3904	0.8899	0.0006
Image 5	CNN	31.6955	0.8163	0.0007
	CNLNet	32.1826	0.8852	0.0006
Noise of $\sigma=0.3$				
Image	Technique	PSNR	SSIM	MSE
Image1	CNN	25.6789	0.6062	0.0027
	CNLNet	26.0908	0.6946	0.0025
Image2	CNN	24.9494	0.7146	0.0032
	CNLNet	25.4450	0.7869	0.0029
Image 3	CNN	23.5197	0.6638	0.0044
	CNLNet	24.0060	0.7150	0.0040
Image 4	CNN	26.3034	0.5710	0.0023
	CNLNet	26.4476	0.7475	0.0023
Image 5	CNN	26.1539	0.5744	0.0024
	CNLNet	26.3904	0.7330	0.0023
Noise of $\sigma=0.5$				
Image	Technique	PSNR	SSIM	MSE
Image1	CNN	25.6394	0.4834	0.0027
	CNLNet	22.9469	0.4605	0.0051
Image2	CNN	19.4438	0.4307	0.0114
	CNLNet	22.3944	0.6755	0.0058
Image 3	CNN	22.7995	0.4746	0.0052
	CNLNet	21.3611	0.6211	0.0073
Image 4	CNN	22.1658	0.6403	0.0061
	CNLNet	23.8024	0.5619	0.0042
Image 5	CNN	19.9271	0.5319	0.0102
	CNLNet	23.8292	0.5753	0.0041

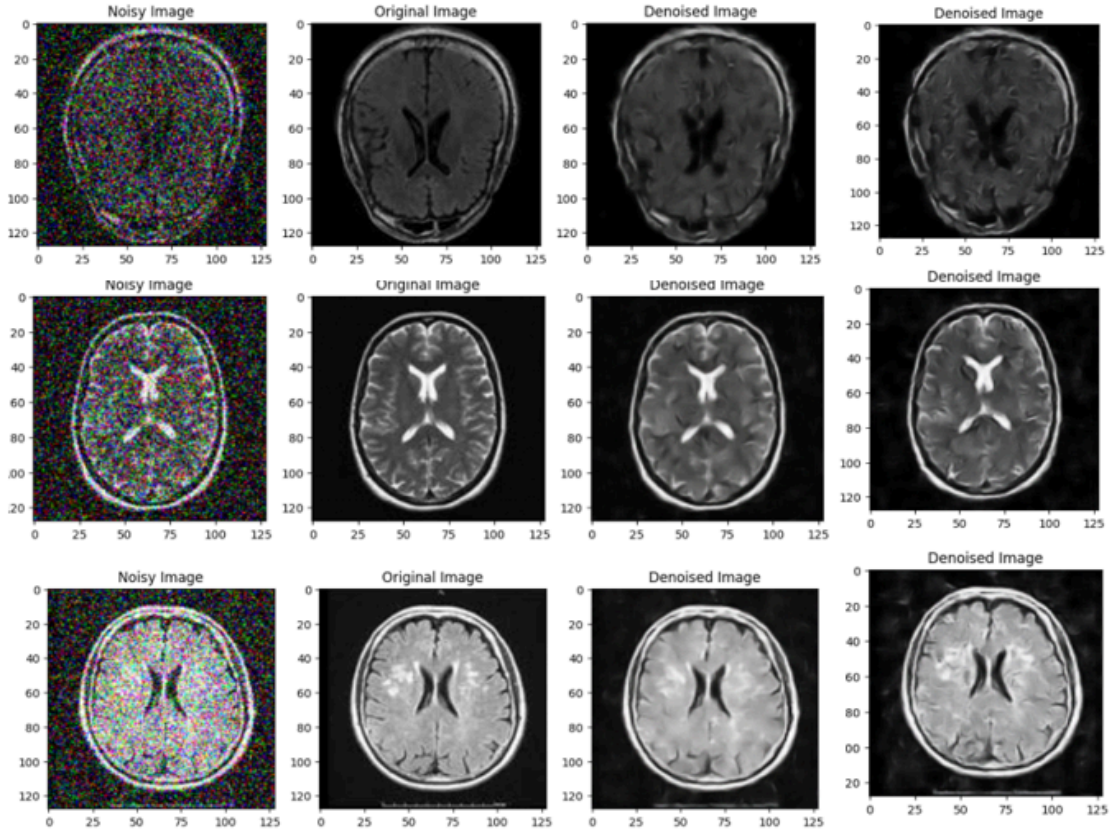


Figure 12. Denoising of images with noise of standard deviation 0.3; (a) noisy version, (b) clean image, (c) Denoised output image of CNLNet (d) Denoised output image of CNN

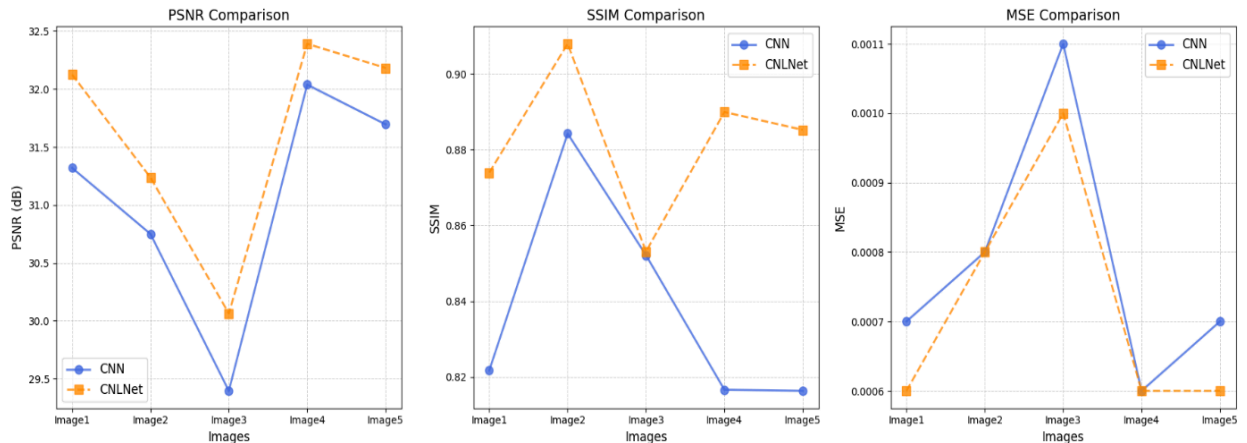


Figure 13. Comparative analysis of the denoising performance of CNN and CNLNet for unseen images

Table 2 displays CNN model results in addition to the model's performance for CNLNet with various Gaussian noises. A comparison of CNN and CNLNet's denoising performance employing three essential metrics, PSNR, SSIM, and MSE, is illustrated in Figure 13. The evaluation was conducted on five test images (Image1 to Image5) at various noise levels (0.1, 0.3, and 0.5). PSNR values, indicative of image quality, reveal that higher PSNR corresponds to more accurate recovery of the original image. Notably, CNLNet consistently outperforms CNN, particularly at lower noise levels of 0.1, with the most pronounced improvement observed in Image1. In terms of SSIM, which quantifies structural similarity within denoised and original images, CNLNet demonstrates superior performance in preserving the image structure, with significant gains observed in Image2 and Image4. Furthermore, the MSE metric, which measures error within the denoised image and the original, indicates that CNLNet generally achieves lower MSE values compared to CNN, indicating

more efficient noise reduction, particularly in Image3 and Image5. These results collectively suggest that CNLNet provides more effective denoising, particularly in maintaining image quality and reducing noise, thereby establishing it as a promising approach for image denoising tasks.

Statistical Analysis

At noise levels of $\sigma = 0.1$ and 0.3 , statistical analysis revealed significant differences in denoising performance between CNN and CNLNet. Specifically, CNLNet demonstrated superior performance in PSNR and SSIM, with t-statistics of -7.0661 ($p=0.0021$) and -3.1763 ($p=0.0337$) for $\sigma = 0.1$ and -5.0514 ($p=0.0072$) and -4.4427 ($p=0.0113$) for $\sigma = 0.3$, respectively. MSE results also indicated a trend toward better performance by CNLNet, although the differences were not always statistically significant. However, at $\sigma = 0.5$, insignificant differences were observed between the two methods, with t-statistics for PSNR, SSIM, and MSE showing values close to zero and p-values above 0.05 . These findings suggest that CNLNet is more effective at lower noise levels.

Ablation Study

An ablation study was done for different epochs and batch combinations. The results were furnished in Table 3. Model's performance has been evaluated in ablation research utilising various combinations of batch size and epoch. The model demonstrated consistent performance with a 32-batch size and 50 epochs, commencing with high PSNR and SSIM, then changing partially in subsequent epochs. The configuration of 10 epochs and a batch size of five provided the highest initial performance but degraded over time. The thirty epochs and batch size of ten setting achieved the best balance, with the highest initial PSNR and SSIM, maintaining solid performance throughout the training. The study highlights that while fewer epochs and smaller batch sizes improve computational efficiency, higher epochs and larger sizes yield better denoising performance.

Table 3. Epoch vs. batch size of test images with Gaussian noise of $\sigma=0.1$

No of Epoch	Batch size	Model inference time	MAE	Testing loss	Test Validation Loss	Time taken for inference (s)
50	32	79 ms/step	0.0211	0.000965	0.0209743	1.8052034
30	10	79ms/step	0.0199	0.000895	0.0199836	1.759787
10	5	77ms/step	0.0214	0.000985	0.021482	1.687043
Epoch, Batch size /Method	PSNR, SSIM, MSE, MAE					
(50, 32)/CNN	Sample Index	PSNR (dB)	SSIM	MSE	MAE	Average PSNR (dB): 30.47 Average SSIM: 0.8615 Average MSE: 0.000966 Average MAE: 0.020974
	0	31.703994	0.908590	0.000675	0.017326	
	1	28.231540	0.838793	0.001503	0.028248	
	2	28.185158	0.840362	0.001519	0.025347	
	3	30.956187	0.893308	0.000802	0.019025	
(30, 10)/CNLNet	Sample Index	PSNR (dB)	SSIM	MSE	MAE	Average PSNR (dB): 30.83 Average SSIM: 0.8724 Average MSE: 0.000894 Average MAE: 0.019969
	0	35.389726	0.941660	0.000289	0.008169	
	1	27.950277	0.877368	0.001603	0.026753	
	2	29.904705	0.830245	0.001022	0.021738	
	3	31.428249	0.901050	0.000720	0.018793	
(10, 5)/CNLNet	0	34.633663	0.864301	0.000344	0.010404	Average PSNR (dB): 30.39 Average SSIM: 0.8510 Average MSE: 0.000986 Average MAE: 0.021483
	1	27.462936	0.842161	0.001794	0.028701	
	2	29.770952	0.820032	0.001054	0.022713	
	3	30.952843	0.880083	0.000803	0.020358	

Future Scope and Limitations

This study primarily focused on denoising with Gaussian noise, which serves as a standard benchmark in MRI denoising research. However, real-world MRI noise presents more complex challenges. External validation was performed using unseen datasets (IXI and another Kaggle dataset). In future work, we will include testing the model on real noisy MRI datasets to assess its performance under more realistic conditions. Comparison with more advanced deep learning models will also be included as future work. Additionally, clinical validation involving an evaluation of the clinical impact of the proposed model was not within the scope of this study. Such validation and application to a specific task would enhance the clinical relevance of the model, and we consider it a valuable research direction to assess the model's practical applicability in medical settings.

4. Conclusion

In this work, we proposed CNLNet, a novel DL-based model that combines an NLM layer with a CNN layer to improve the denoising of MRI brain images. The hybrid design is used here, which combines the contextual awareness of the NLM with the feature extraction and learning capabilities of the CNNs. As proven by our tested outcomes, we see that CNLNet, in comparison with Gaussian filtering, median filtering, standalone CNNs, and NLM, is superior concerning PSNR and SSIM. This model effectively removes noise while preserving the essential components of the medical image. Future work will explore applying the model to a clinical application to substantiate the practical relevance of the model. Furthermore, we will aim to extend this architecture to handle multimodal brain imaging data and optimise the network for real-time deployment in medical imaging systems.

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