Sparse Feature Aware Noise Removal Technique for Brain Multiple Sclerosis Lesions using Magnetic Resonance Imaging

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***Abstract*—Medical Resonance Imaging (MRI) is non-radioactive-based medical imaging that provides a super-resolution of tissues. However, because of its complex nature using existing Deep Learning-based noise removal (i.e., Denoising) techniques, the reconstruction quality is poor and time-consuming. An extensive study shows very limited work has been done on Brain Multiple Sclerosis (MS) Lesions MRI. Designing an efficient noise removal technique will aid in improving MRI quality; thereby will aid in achieving better segmentation classification performance. In reducing computing time and enhancing image quality (i.e. reduce noise) this paper presents the Sparse Feature Aware Noise Removal (SFANR) technique for Brain MRI using Convolution Neural Network (CNN) architecture. A sparse-aware feature is incorporated into the patch-wise morphology learning model for removing noise in large-scale MRI MS lesion datasets. Experimental results demonstrated that our model SFANR outperforms all other state-of-art noise removal techniques in terms of Peak-Signal-Noise-Ratio (PSNR), Structural Similarity Index Metric (SSIM) with less running time.**

***Keywords*—Convolution neural networks; deep learning; denoising; magnetic resonance imaging; morphology learning; multiple sclerosis; sparse features**

I. Introduction

With the advancement in sensor and computer technologies, medical imaging such as MRI, Positron Emission Tomography (PET), and Computed Tomography (CT) plays a very significant part in diverse diagnostic applications such as treating a serious ailment, radiosurgery, clinical diagnosis [1]. This MRI is used to obtain detailed information on soft tissues, and CT is used to obtain information on implants and bones. This work focuses on Multiple Sclerosis (MS) Lesion brain MRI data. Generally, the multi-contrast MRI provides the radiologists with additional information for studying different pathologies. In [1] demonstrated that for reducing time and redundancy, multi-echo saturation recovery MRI sequences are obtained at different inversion times and echo times to reconstruct a single MRI sequence [1]. Further, different parameter-map (PM) and parameter weighted (PW) contrasts can altogether be reconstructed. The state-of-art reconstruction methodologies employ pixel-wise least-square fitting of motion of macroscopic nuclear magnetization equation for obtaining relaxation parameter (i.e., by summing up all nuclear magnetic moment). Later, the PW contrasts are reconstructed through PMs. However, due to patient motion, over-simplified models, non-linear fitting operations, flow, and partial volume significantly impact the quality of MS lesion brain MRI reconstruction [2]. In particular, the T2-FLAIR (T2-weighted fluid-attenuated inversion recovery) MS lesion brain MRI, low SNR (Signal-to-Noise-Ratio), chemical shift artifacts, and edge-enhancement are seen [3].

The CNNs-based model has attained very good results in medical imaging, especially for CT and MRI. In improving the quality of the image cross-modality between MR/PET [4], [5] and MR/CT [6] has been emphasized. Further, CNN is applied for MRI contrast enchantment. In [7], [8] contrast of T2-weighted MRI is improved using T2-weighted MRI, similarly, in [9] using T1-weighted and T2-weighted the FLAIR MRI is generated, and in [10] using 3T inputs construct 7T high-resolution MRI. All the above-mentioned methods use an encoder-decoder framework using Deep learning Techniques such as ResNets [11] and U-net [12].

In [13] for representing neighborhood features introduced localized network. In [14] the author enhances the texture of the image employed generative adversarial network (GAN). Further, in increasing the sharpness the author in [8] introduced an edge similarity loss function into the generative adversarial network. In [15] reduced the scanning time by combining contrast and under-sampling reconstruction. Additionally, [16] introduce feature structure to resolve unknown contrast problem during image reconstruction [17]. In [18] presented a new noise removal technique through multi-task deep GAN; However, poor correlation among different layers impacts the quality of the feature constructed. In addressing [1] designed an ensemble convolution neural network [19] to obtain high-quality feature sets [20], [21]. However, weights of a convolutional network [22] are updated individually for the entire MRI information; thus, the final reconstructed image exhibit higher noise, poor contrast, and limited sparse feature representation. In [23] addressed the above issues by employing morphology-based [24] feature construction using CNN. The model is efficient in eliminating noise with very good reconstruction quality; however, there exist optimization constraints in obtaining good quality sparse features.

In addressing the research problem, this paper presents sparse feature-aware noise removal technique for MS lesion MRI data. The patch-wise CNN framework can extract features in a parallel manner aiding in reducing training overheads.

Further, the SFANR model can remove different types of noise such as Rician, Gaussian, and Speckle more efficiently through the adoption of the morphological-based feature construction mechanism adopted in SFANR. The proposed noise removal technique helps in reducing redundant features and computation overheads; thus, significantly SFANR improves PSNR and SSIM.

The significance of SFANR is described below:

- The work presented a CNN-based noise removal technique using sparsity-aware morphological features.
- No prior work has considered denoising the brain MS lesions MRI.
- The SFANR achieves much higher PSNR and SSIM in comparison with existing denoising methodologies.
- The model achieves very less running time in comparison with other noise removal methodologies.

The rest of the manuscript is arranged as described. In Section II, the literature survey is discussed. In Section III, the proposed sparse feature aware noise removal technique for MS lesion Brain MRI is presented. In Section IV, the outcome i.e., MS lesion brain MRI reconstruction quality achieved using proposed SFANR and existing noise removal models is studied. In Section V, the significance of SFANR is concluded and future enhancement of the SFANR model is given.

II. Literature Survey

This section presents a survey of various noise removal techniques presented in recent times for brain MS lesions MRI. In [1], the author presented a fully-connected CNN-based denoising method by optimizing the loss layer. The three-dimensional CNN and residual network are merged for extracting multi-dimensional features. Finally, ensemble feature extraction along two models constructed by varying noise levels. The model is efficient in eliminating Gaussian-like noise.

In [17], the author designed a deep learning model through multi-task learning for extracting association among spatial and relaxation features. The model utilizes association mapping among different T2-weighted MRI with varying contrast for enhancing the reconstruction quality such as low SNR (Signal-to-Noise-Ratio), chemical shift artifacts, and edge-enhancement are seen [3] as shown in Fig. 1. Similarly, [18] designed a denoising model using GAN by extracting features from Multi-Contrast MRI.

In [20], the author designed a denoising method using end-to-end residual CNN. The image is reconstructed using a loss function employing mean square error to optimize the feature extraction process. In [21] an autonomous CNN-based model has been employed for removing noise in Diffusion tensor MRI data. The model denoising accuracies are not dependent on high SNR MRI input. Similarly, [22] presented a new noise removal technique that works with a single-subject dataset encompassing with low-noise of voxel-by-voxel Diffusion tensor MRI sequence by employing one-dimensional CNN and deep learning models.

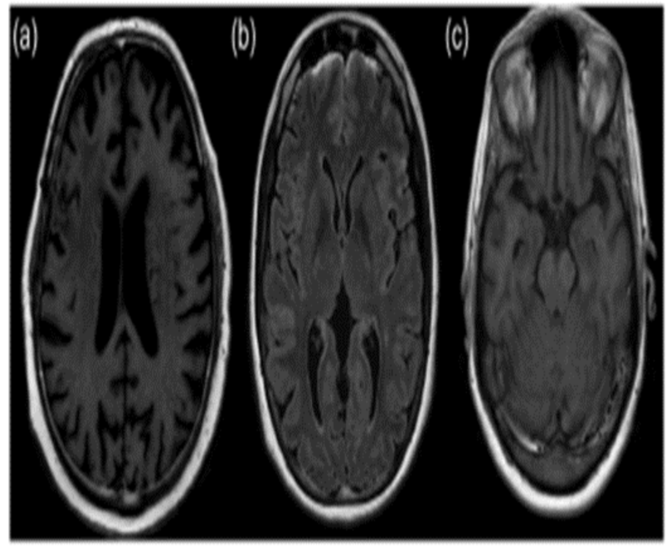


Fig. 1. Low-quality Reconstruction Outcome Obtained using Standard Noise Removal Technique (a): T1-FLAIR (b): T2-FLAIR (c): T1-weighted [1].

In [23] a denoising model is presented to remove Rician noise from MRI using a sparse dictionary learning mechanism. The dictionary is constructed leveraging Maximum posterior combined using noisy MRI. Similarly, [24] used morphological features to address the impact of noise due to non-uniform illumination. Further, employed principal component analysis retains detailed features such as textures, smooth edges, etc. during RGB to grey conversion. The extracted features are trained using CNN. However, poor feature correlation during training significantly impacts noise removal accuracies.

An extensive survey shows exploiting sparse features and morphology construction, and CNN aided in improving noise removal performance; however, existing models are not efficient in adaptively removing different noises such as speckle, Rician, and Gaussian. In addressing the limitation in the next section, a novel methodology namely the sparse feature aware noise removal technique has been presented.

III. Proposed Methodology

The proposed methodology for efficiently removing noise from brain MS lesions MRI is given. The proposed methodology employs a convolution neural network for eliminating noise in brain MS lesions MRI. A sparse feature-aware noise removal technique using CNNs improve the quality of MS lesion MRI data. The proposed methodology is composed of three stages morphology construction stage, aggregating sparsity-aware features into the patch-wise morphology stage, and validating the quality of image reconstructed image. First, in the morphological construction stage, a different sparsity feature-aware layer is created by sub-dividing the input MRI (i.e., each MRI is segmented into multiple patches; then, those patches are given as input to the SFANR-CNN model). The outcome i.e., sparse feature weight variance among different layers is used during the training process for the construction of morphology structure. In the subsequent stage, the sparsity-aware feature is used for the creation of morphology, and the information is trained with CNN and later used during the testing stage for removing noise from MS lesion MRI data; thus, aiding in improving the quality of reconstructed MS lesion MRI images. In our work, the quality of noise removal technique is validated using Peak-Signal-to-Noise-Ratio (PSNR) and Structural Similarity Index Metric (SSIM). A significant amount of work has been done for removing noise in MRI datasets. Nonetheless, the standard noise removal methodologies exhibit poor performance due to issues like large dataset size, time consumption, high slew rate, large power absorption, and temporal dimension. The aforementioned issues are addressed through the construction of sparsity feature-aware CNN architecture using patch-wise morphological learning for designing an effective noise removal model with good processing efficiency.

A. Convolution Neural Network

The CNN is widely used for removing noise from MRI and CT [19], [20]. The CNN-based noise removal techniques [21], [22], provide an effective way of eliminating a different kind of noise [23] from MRI and improving its reconstruction quality [24], [25], and enhancing segmentation [26], [27] and classification outcomes as well [28], [29]. The CNN employs a hierarchical learning mechanism where a feed-forward network is used for the extraction of different features and a hidden layer is used to optimize the feature learning weights. However, in this work sparsity-aware feature using CNN is modeled as shown in Fig. 2 shows removing noise from brain MS lesion MRI data. The proposed SFANR-CNN adopts a patch-wise morphological learning mechanism using prior information; thus, is very fast and efficient in removing a different kind of noise present in brain MS lesion MRI.

B. Noise Removal Framework

This section presents a framework for removing noise from brain MS lesion MRI as shown in Fig. 2. Initially, the brain MS lesion MRIs are segmented into different patches. Later, the segmented brain MS lesion MRI is given as input to SFANR-CNN for extraction of sparsity-aware features. The sparsity-aware feature weights are optimized during the training process for the construction of morphology. Later, during the testing process, the constructed morphology is used for removing noise from brain MS lesion MRI. The quality of reconstructed brain MS lesion MRI using SFANR-CNN is measured in terms of PSNR and SSIM.

C. Patch-wise Learning Model

Patch-wise morphological learning technique is presented for eliminating noise from MS lesion MRI data. Let noise k be aggregated to the input brain MS lesion MRI patch signal i,

$$\mathbb{Y} = i + k, \tag{1}$$

where the value of parameter k is generally set in the range of 8 and 12. Here, the patch-wise noise removal method is established considering the patch size of $m \times m$. The noise in MS lesion MRI data is individually removed from all the patches, and later MRI is reconstructed through the integration of entire patches within a frame; later, using the averaging function, the overlapped patches are optimized. In this work, the size of Morphology $\mathbb{D}$ is set to $m^2 \times n$ where n is greater than m^2.

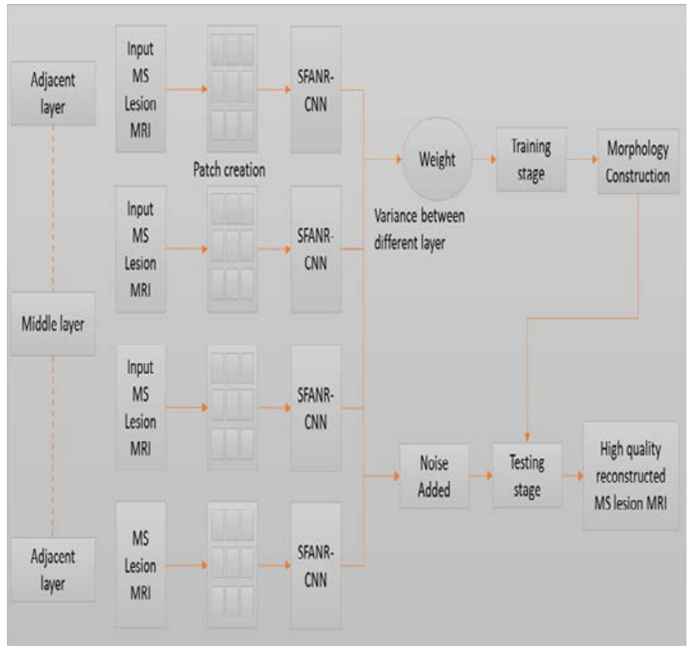


Fig. 2. Architecture of Sparse Feature aware Noise Removal (SFANR) Technique.

D. Sparse Feature Aware Patch-wise Learning Model

In a patch-wise morphology construction-based noise removal mechanism the atomic element [28] is used as the basis function. A sparsity-aware linear noise removal mechanism is used to remove the noise within entire patches constructed from brain MS lesion MRI data. The additive white Gaussian noise error is minimized through the following mathematical representation.

$$\min\|\alpha\|_0 \; s.t. \|\mathbb{D}_\alpha - \mathbb{Y}\|_2 \leq \in, \tag{2}$$

where $\mathbb{Y}$ represents brain MS lesion MRI patch with the presence of noise, l_0 defines a pseudo normalization parameter that is used for estimating $\|\cdot\|$, and $\in$ defines pre-defined. Using l_0 the sparsity-aware feature can be optimized at the cost of convex normalization problem. The parameter $\in$ is optimized for approximating the normalization error $\|\mathbb{D}_\alpha - \mathbb{Y}\|_2$ through its variance. Then, using a sliding window the quality of denoised brain MS lesion MRI can be enhanced; similarly, the optimization of overlapping patches is done by employing averaging function as defined.

$$\mathbb{D} \leftarrow \eta \triangle \frac{\triangle\|i-\mathbb{D}_\alpha\|_2}{\Delta\mathbb{D}}, \tag{3}$$

where η defines a parameter of the sliding window. Using the below equation the minimization of overlapping patches is done.

$$\min\|i - \mathbb{D}_\alpha\|_2 \; s.t. -1 \leq \alpha \leq 1, \tag{4}$$

Here, we evaluate the pixel mean of different patch sizes of $m \times k$, where m and k are hyper-parameters and $\bar{i}$ denotes local mean estimates for an image.

$$\bar{i} = \mathbb{F}\{i\} = \mathbb{F}\{\mathbb{Y} - k\} = \mathbb{F}\{\mathbb{Y}\} - \mathbb{F}\{k\} = \mathbb{F}\{\mathbb{Y}\} = \overline{\mathbb{Y}}, \tag{5}$$

where $\mathbb{F}$ is function to obtain pixel mean $\overline{\mathbb{Y}}$,. We estimate that the actual input image is corrupted using Rician, Speckle, and Additive White Gaussian noise and which can be described using equation (6).

$$\log q(\mathbb{Y}|i) = \frac{1}{2\sigma^2}\sum_{r,n}\left(\mathbb{Y}_{r,n} - i_{r,n}\right)^2, \quad (6)$$

Here, the indexes r and n represent all positions of an MS lesion MRI data.

$$\min_\beta \mathcal{P} = \mathbb{F}\left\{\left(i - \bar{i} - \beta\left(\mathbb{Y} - \bar{i}\right)\right)\right\}, \quad (7)$$

where β is a decision factor that defines if β is close to 1 then the MS lesion MRI data will be noisy type $\mathbb{Y}$ and if β is near to 0 then it is the de-noised image $\bar{i}$. Equation (7) demonstrates the minimization of squared error.

Patch-wise morphology learning is constructed encompassing distinctive sparse-aware features for both noiseless and noisy brain MS lesion MRI datasets. The patch-wise morphology learning methodology is very efficient in solving the complexity of optimization of sparsity feature construction; thus, improving brain MS lesion MRI reconstruction outcomes. The morphology construction is extremely fast which takes about 20% time and reaming time it takes for training the model for removing noise from brain MS lesion MRI. No heuristic knowledge is required for the construction of morphology; thus, one can learn sparse feature-based morphologies more adaptively. The constructed morphology is later used during the testing process to obtain a very good denoised brain MS lesion MRI.

E. *Training Patch-wise Learning Model for Removing Noise in MRI*

Designing an efficient training model aid in detecting a different kind of noise and improves the brain MS lesion MRI reconstruction quality. However, the brain MS lesion MRI is extremely large and complex; thus, is time-consuming for performing the training process. In this work, the training time is reduced by adopting parallel execution of patch-wise morphology construction. The parameter selection for training is set as a random process where parameter estimation is carried out considering different patches and noise types. The small normalization vectors can be optimized easily where the regularization parameter is optimized using pre-training. Using CNN variance among different layers to optimize weight and morphology is constructed. The training efficiency for removing noise from brain MS lesion MRI is measured using PSNR and SSIM.

F. *The Testing Patch-wise Learning Model for Removing Noise in MRI*

In the testing for removing noise from brain MS lesion MRI in this work the noise is detected patch-wise. Further, in avoiding the over-fitting problem the patch-wide weight variance is minimized. The morphology constructed during the training stage is used during the testing process for reducing noise in brain MS lesion MRI.

$$\hat{i} = \bar{i} + \frac{\left(\mathbb{F}\{(\mathbb{Y}-\mathbb{Y})^2\}-\sigma^2\right)\left(\mathbb{Y}-\bar{i}\right)}{\mathbb{F}\left\{\left(\mathbb{Y}-\overline{\mathbb{Y}}\right)^2\right\}}, \quad (8)$$

where σ defines the level of noise present in brain MS lesion MRI and the Eq. (8) defines noise removed MS lesion dataset mathematical representation. The testing process encompasses the estimation of $\bar{i}$ and $\mathbb{F}\left\{\left(\mathbb{Y} - \overline{\mathbb{Y}}\right)^2\right\}$. The effectiveness of estimation of $\bar{i}$ is enhanced through reduction of noise from brain MS lesion MRI using patch-wise morphology information with a patch size of $m \times k$. The model aids in minimizing sparse error and overhead reduction. The improved probability distribution function using logarithm for removing noise in brain MS lesion MRI is given as.

$$i^{(t+1)} = i^{(t)} + \eta\left[\sum_{r=1}^{K} N_r^- * \psi_r\left(N_r * i^{(t)}\right) + \frac{\lambda}{\sigma^2}\left(\mathbb{Y} - i^{(t)}\right)\right] \quad (9)$$

where η defines step size estimation, convolution is defined by $*$ sign, and N_r^- describes the central pixel. To bring trade-off among likelihood and prior λ is used. The outcome of λ depends according to the presence of noise level σ. The experiment conducted in the next section shows the proposed SFANR-CNN is effective in removing a different kind of noise and enhancing the quality of brain MS lesion MRI in terms of PSNR and SSIM.

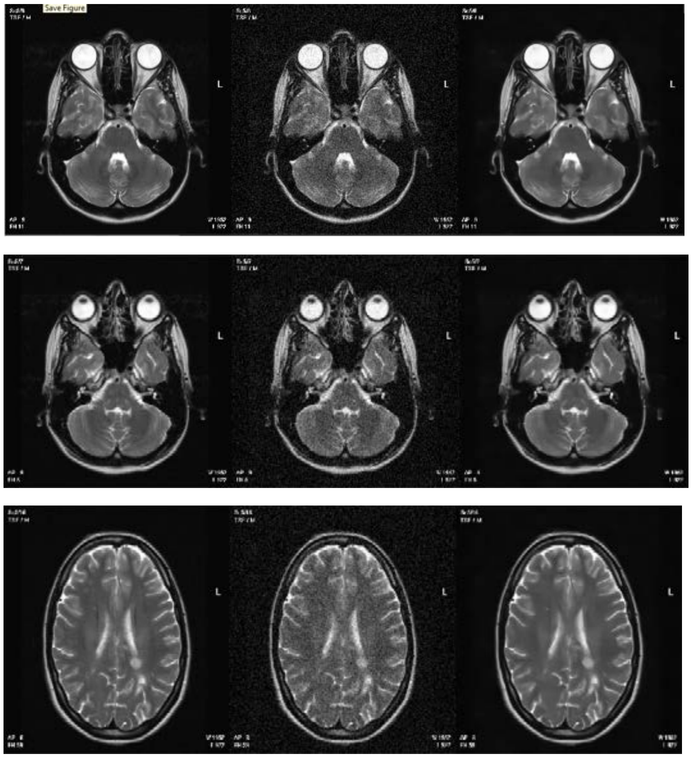
IV. Simulation Analysis and Results

This section studies the performance efficiency of the proposed SFANR technique and existing noise removal techniques [1], [17]. This work uses brain MS lesion MRI data used in [30] which is very similar to brain MRI used [1], [17]. In this work noise such as Speckle, Gaussian, and Rician is added to the brain MS lesion MRI. The performance of different noise removal techniques is measured in terms of PSNR and SSIM. The PSNR and SSIM are computed using the equation defined in [1]. The experiment is conducted on Windows 10 operating system running an I-5 quad-core processor with 16 GB RAM equipped with a dedicated 4GB CUDA GPU. Fig. 3 shows the input, MRI with noise, and reconstructed MS lesion brain MRI using the SFANR technique.

The graphical representation of PSNR is shown in Fig. 4. The graphical representation of SSIM is shown in Fig. 5. A higher value indicates better performance; thus, the SFANR achieves much better outcomes than existing methods, namely, a U-NET [1], Multi-Task Deep Learning (MTDL) [1], Deep Parallel Ensemble Denoising (DPED) [17]. Thus, are very efficient in removing Gaussian, Speckle, and Rician noise from MS lesion MRI.

The Table I shows the computation outcome achieved using proposed SFANR over existing noise removal methods such as DPED [1], Morphology learning CNN (ML-CNN) [24], and noise removal using dictionary learning (NRDL) [1]. The SFANR achieves much lesser running time than other existing methodologies; thus, are very efficient.

The Table II shows the SSIM and PSNR performance achieved using SFANR considering different noise. No prior work has considered such evaluation.



Original MS lesion MRI | Noise added MS Lesion MRI | Noise Removed MS lesion MRI

Fig. 3. The Outcome was achieved using the SFANR-CNN Model.

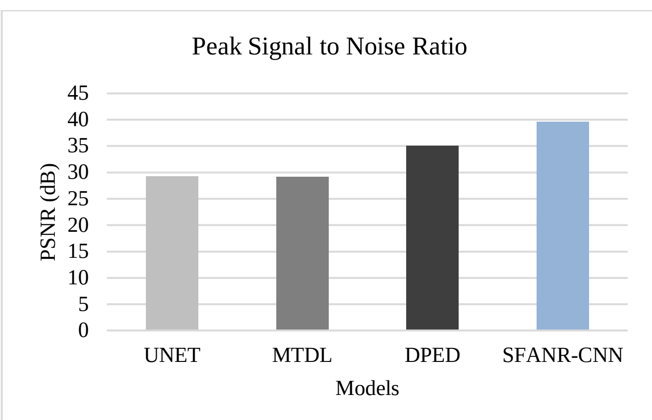


Fig. 4. PSNR achieved using SFANR-CNN and other Noise Removal Technique.

TABLE I. COMPUTATION TIME STUDY

Methodology	Running time (seconds)
NRDL [23], 2019	143.97
DPED [1] 2021	3.11
ML-CNN [24], 2022	11.3
SFANR	2.98

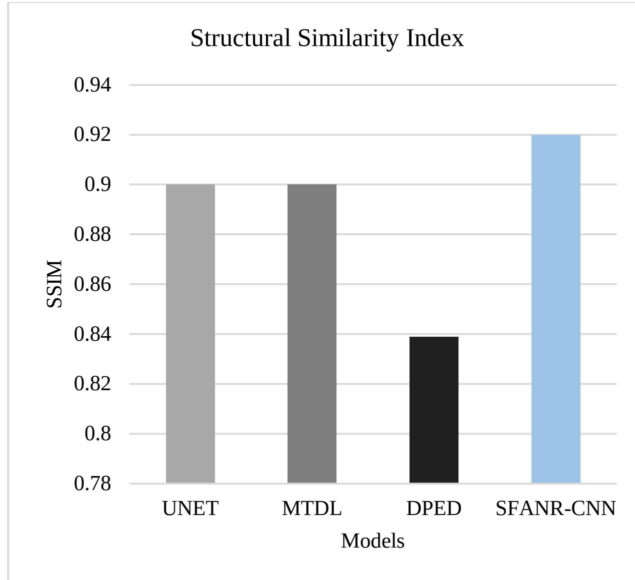


Fig. 5. SSIM achieved using SFANR-CNN and other Noise Removal Technique.

TABLE II. NOISE STUDY OF SFANR

Methodology	PSNR (dB)	SSIM
Speckle	37.34	0.901
Gaussian	39.63	0.925
Rician	38.54	0.903

The Table III shows comparative study of proposed SFANR with other methodologies. The table shows no prior work have worked on detecting and removing noise for brain MS lesion MRI. Then, each method is modeled to remove only one particular noise; however, SFANR are trained with multiple noise type such as Rician, Speckle, and Gaussian; thus, are adaptive to remove different noise.

TABLE III. COMPARATIVE ANALYSIS

Methodology	Method	Noise Type	Metrics	MS Lesion MRI
Jian et al., [23], 2019	Dictionary learning	Rician	SSIM, PSNR, & time	No
Aetesam et al., [1], 2021	Parallel Ensemble Denoising	Gaussian-Impulse	SSIM, PSNR, &running time	No
Wang et al., [17], 2020	Multi-task deep learning model	Gaussian	HFEN, SSIM, & PSNR	No
Bhutto et al., [24], 2022	Morphology learning and CNN	Background noise	SNR & time	No
SFANR	Sparse-morphology using CNN	Rician, Speckle, and Gaussian	SSIM, PSNR, running time	Yes

V. Conclusion

MRI is a widely used detection technique; however, image detection is a complex and time-consuming procedure as data is not clear because of its noisy nature. Therefore, we have implemented a sparsity-based noise removal technique using CNN architecture for the high-quality reconstruction of thermal and ultrasound images with improved time efficiency. In our model SFANR-CNN, we implemented a patch-wise morphology learning algorithm by producing morphology while training for efficient denoising for various types of noises. We have used various parameters to define the high quality of our reconstructed MS lesion MRI namely PSNR and SSIM. Experimental outcomes show that our model SFANR-CNN outperforms all other state-of-art-algorithms in terms of PSNR and SSIM. Our model produces high PSNR results of 39.63 dB which is much higher than any other algorithm. Similarly, SSIM outcomes are 0.92 using our model SFANR-CNN. Alongside, a running time of 2.98 seconds is attained for removing noise. These results demonstrate the superiority of our model SFANR-CNN.

Future work would consider evaluating performance by introducing a different kind of noise. Designing a better noise removal technique will aid in detecting and segmenting MS lesions more efficiently which in the future will be considered.

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