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Comparative Analysis of Classical, Hybrid, and Deep Learning Approaches for MRI Image Denoising under Gaussian and Rician Noise

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Abstract

Magnetic Resonance Imaging (MRI) is a technique used to assess various regions of the body and is useful in medical diagnosis. Because of this, it is important to maintain the clarity of the MRI images that are often degraded by different noises, particularly Gaussian and Rician. In this paper a comprehensive evaluation of different denoising methods for brain MRI images, including classical, hybrid, and deep learning methods is conducted. The methods evaluated include BM3D (Block-Matching and 3D Filtering), PCA (Principal Component Analysis)-based denoising, PCA combined with median filtering, a proposed hybrid approach (combining PCA, median filtering, and bilateral filtering with Rician bias correction), and DnCNN (Denoising Convolutional Neural Network) trained on custom MRI image patches. The metrics used to assess these denoising methods include PSNR (Peak Signal to Noise Ratio), SSIM (Structural Similarity Index), and histogram-based metrics like Bhattacharya distance, intersection, and correlation. In summary, the DnCNN method shows the best results across all noise types and levels, demonstrating high structural preservation. However, the proposed hybrid method also demonstrates competitive results compared to DnCNN and better results in comparison to classical methods like BM3D and PCA-based denoising methods. From this comparison, it can be concluded that while the deep learning-based method is overall the best for denoising, the hybrid method can also be seen as an alternative in cases of limited training resources.

Keywords: Medical Imaging, Patch-Based Processing. Noise Reduction Techniques, Principal Component Analysis (PCA), Median Filtering, Total Variation Denoising, Adaptive Median Filtering, Deep Learning.

1. Introduction

Medical imaging has undergone various transformations in the last few years especially with the growth of digital imaging technology. It is an important field as it can conduct non-invasive diagnosis, treatment planning, and ongoing monitoring. In this context, Magnetic Resonance Imaging (MRI) is a popular imaging technique as it can produce high-resolution, high-contrast images of internal body structures, particularly soft tissues. [1] It is used to obtain

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interior images of various sections of the body, making it possible to detect pathologies such as tumors and degenerative disorders.

The noise produced during the process of generating the MRI image can sometimes degrade the quality of these scans. Noise artifacts degrade image quality by reducing contrast and signal-to-noise ratio (SNR) while also obscuring tiny features, altering the overall visual impression of the image possibly leading to misdiagnosis or treatment delay. There are various factors contributing to this noise including temperature variations, patient movement, device malfunctions, and environmental conditions. In a CT phantom study assessing liver lesions, it was found that the detection sensitivity started dropping as the noise index was increased. [25] This shows that noise may obscure small lesions in MRI images, potentially leading to misdiagnosis. As a result, there is an increasing need for efficient denoising mechanisms that can decrease undesirable noise while retaining crucial anatomical information. [2]

While there are many possible noise types that can affect MRI Images, Gaussian and Rician noise are the most common and problematic. Gaussian noise develops from random fluctuations in electrical signals and manifests as uniform intensity variations across the image. Rician noise, however, is unique to magnitude MRI images and originates from the non-linear translation of the complex-valued MRI data. It introduces a signal-dependent bias, especially in low-intensity regions, and deviates greatly from Gaussian features. [3] Hence, Gaussian and Rician noise are considered for evaluation in this study. Standard denoising methods are found to be inefficient when it comes to effectively removing Rician noise from images without deblurring.

Many conventional denoising methods have been developed previously including Gaussian filtering, median filtering, wavelet-based filtering, etc. While most of these methods are generally effective, they sometimes face a trade-off when it comes to reducing noise in an image and preserving edge details. Excessive smoothing can lead to the destruction of important details in the image, while insufficient smoothing can result in some noise remaining in the image after the process. Additionally, many of these methods are not flexible enough to handle the complex and varying noise patterns in real-world MRI images.

To bridge this gap, numerous approaches have emerged, including PCA (Principal Component Analysis)-based methods, hybrid approaches, and deep learning-based approaches. In this study, a comparison of the effectiveness of five denoising approaches is presented, as follows:

- **BM3D (Block-Matching and 3D Filtering):** This is an advanced traditional method that uses collaborative filtering to group related 2D patches into 3D blocks.
- **PCA-Based Denoising:** A patch-based method that uses Principal Component Analysis (PCA) to lower the number of dimensions and reduce noise. It is extremely effective at removing Gaussian noise from images while maintaining their structure.
- **PCA + Median Filtering:** An improvement over PCA where median filtering is applied as a post-processing step after reconstruction to remove residual speckle and other white noise, thus improving the visual clarity of the image.
- **Proposed Hybrid Method:** This method uses PCA, median filtering, Rician bias correction, and optional bilateral filtering to provide a flexible approach that can

handle both Gaussian and Rician noise while preserving structural and edge details and reducing noise.

- **DnCNN (Denoising Convolutional Neural Network):** It is a denoising network that utilizes deep learning and has been trained on a dataset of MRI patches affected by Gaussian and Rician noise at different levels of intensity. This model has the ability to understand intricate noise patterns and spatial features thereby resulting in high-quality reconstructions of patches and producing good quality denoised images.

A comprehensive evaluation of five denoising methods was conducted on MRI datasets with Gaussian and Rician noise (10%, 20%, 30%) using metrics such as PSNR, SSIM, Bhattacharyya distance, histogram intersection, and correlation coefficient. These findings emphasize the trade-offs involved in the denoising process: while deep learning approaches like DnCNN achieve the highest overall quality, traditional and hybrid techniques still offer practical advantages in terms of interpretability, computational efficiency, and adaptability in specific circumstances. This study provides valuable insights into the trade-offs of different methods, highlighting their clinical and research relevance and guiding the development of robust and versatile denoising strategies for medical imaging.

2. Related Work

Noise reduction in MRI Images has been an important field of research for years and this has led to the creation of different denoising methods. These methods can be categorized into traditional filtering approaches, patch-based statistical methods, model-driven frameworks like BM3D, and newer deep learning techniques. Each method has its own advantages and limitations when it comes to removing Gaussian and Rician noise in MRI images. The effectiveness of some of these methods are discussed in this section.

2.1 Classical Denoising Method

Conventional image denoising methods serve as a foundation for many of the latest noise reduction techniques. Some of the original approaches include Gaussian smoothing, median filtering, and bilateral filtering, each having its own distinct approach to noise reduction.

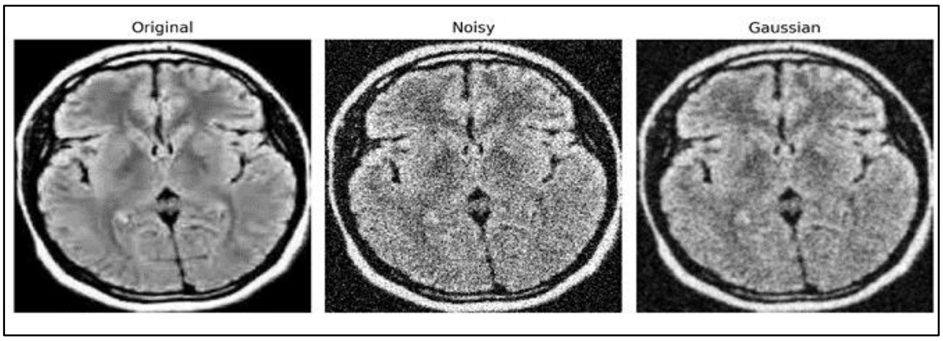


Figure 1. Gaussian Filter Example Image

Gaussian filtering is based on the principle that noise follows a normal distribution and applies a low-pass convolution kernel to process the image and filter the noise. [4] Although this technique is able to successfully suppress high-frequency noise, it tends to blur out the critical anatomical and structural details which becomes a significant challenge in brain MRI images, where subtle variations and boundary definitions are important for accurate medical diagnosis. Figure 1 shows an example of image denoised by Gaussian Filter.

Median filtering is another common method used for eliminating impulse noise, like salt-and-pepper, by replacing each pixel's value with the median of its neighboring pixels' values. This approach is non-linear and maintains edges preservation more effectively compared to Gaussian filtering. [5] Nonetheless, when used to denoise continuous-tone images such as MRI scans, it often distorts delicate textures and reduces subtle low-contrast features, potentially obstructing diagnostic evaluation.

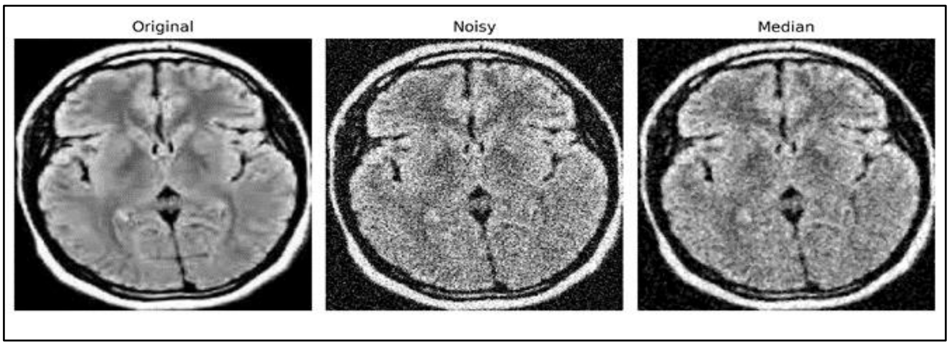


Figure 2. Median Filter Example Image

The bilateral filter reduces noise while preserving the integrity of edges by considering both the spatial position of pixels and their intensity similarities. This filtering method aims to strike a balance between noise reduction and edge preservation by combining spatial and intensity-based weighting. [6] While it is more sensitive to edges compared to Gaussian filtering, bilateral filtering requires careful parameter adjustment and can still lead to smoothing of fine structures when dealing with higher noise levels.

More advanced classical methods like Total Variation Denoising (TVD) have been developed to maintain edge quality while suppressing noise levels. TVD encourages piecewise smoothness by reducing the total variation of the image, making it effective for preserving edges while removing uniform noise. [7]. However, this technique may encounter challenges in environments with high levels of significant noise, often failing to preserve low-contrast or delicate anatomical details that are crucial for medical diagnosis. Figure 3 shows an example of image denoised using the TVD method.

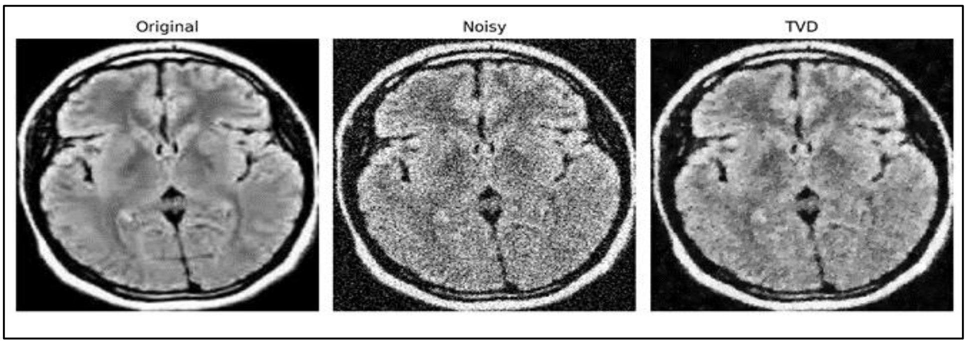


Figure 3. TVD method Example Image

Numerous variations of non-local means (NLM) have been proposed to improve MRI denoising by utilizing structural redundancy. For example, Li et al. (2024) [13] introduced a globally informed NLM approach that utilizes global self-similarity for noise reduction, giving an overall better performance than local patch-based techniques like PRI-NL-PCA. In summary, while traditional denoising methods have proven to be efficient in removing noise, they often fall short of meeting the demands of contemporary medical imaging. Their limited ability to adjust to diverse noise characteristics and maintain anatomical and structural details has led to the pursuit of hybrid and learning-based strategies, which this research intends to investigate and refine.

2.2 Patch - Based and PCA - Based Denoising

Methods based on patch techniques enhance global filtering by making use of the local redundancies found in images. By extracting overlapping patches and recognizing similar patterns [8], these strategies enable more flexible filtering that preserves details. One example of this is Principal Component Analysis (PCA) denoising, which operates under the premise that noise exists within the lower variance components of a set of patches. PCA has demonstrated effectiveness in the reduction of Gaussian noise while maintaining prominent signal structures. However, its performance diminishes when faced with complex noise types like Rician, and it may not completely remove artifacts in uniform areas.

2.3 Model-Based methods: BM3Dand Variants

Block-Matching and 3D Filtering (BM3D) is an advanced denoising method that organizes similar patches into three-dimensional groups and performs collaborative filtering in a transformed domain. [9] It shows remarkable efficacy in managing Gaussian noise and often outperforms earlier patch-based techniques. With its high Peak Signal-to-Noise Ratio (PSNR) and robust structural preservation, BM3D has become a standard for evaluating other denoising approaches. Nevertheless, its performance with Rician noise is not as effective, since it is tailored for additive white Gaussian noise and lacks features to handle signal-dependent bias.

2.4 Rician Noise modeling and Correction

Rician noise, which is characteristic of magnitude MRI images, leads to distortions that are both signal-dependent and non-additive. In contrast to Gaussian noise, Rician noise does not follow a zero-mean distribution and has a greater impact on regions with low intensity. Numerous studies have suggested bias correction strategies to address this issue, often involving statistical models of the Rician distribution or non-local means tailored for the Rician context. [10] These methods strive to eliminate the bias caused during magnitude reconstruction; however, many of them require precise estimation of the noise level and hence can be computationally demanding or sensitive to parameter tuning.

2.5 Deep-Learning Based Denoising

Deep learning techniques have transformed image processing applications, particularly in the area of denoising. In this context, Convolutional Neural Networks (CNNs) have proven to be a strong resource for denoising medical images because they can learn hierarchical features directly from noisy inputs. In contrast to conventional filters that depend on manually created rules, CNNs autonomously retrieve spatial and contextual data to differentiate between noise and significant structures. [17]

DnCNN employs a residual learning approach to estimate noise from an input image and then removes it to produce the denoised result. With training on extensive datasets, DnCNN shows great generalization and outperforms conventional techniques in both visual quality and PSNR values. Recent advancements have adapted DnCNN and comparable architectures to address real-world and multiplicative types of noise. [11] However, most of the pre-trained models assume Gaussian noise and may not perform optimally on MRI-specific noise patterns unless fine-tuned on domain-specific data.

2.6 Hybrid and Adaptive Denoising Techniques

Recent research has explored hybrid filtering methods that combine the benefits of different techniques to overcome the shortcomings of single methods. For example, merging PCA with median filtering has been proposed as a way to effectively diminish both global and local noise variations. Other hybrid approaches integrate deep learning with statistical preprocessing, allowing networks to concentrate on learning the residuals from inputs that have been partially denoised. These methods seek to find a balance between obtaining successful denoising results and maintaining important details, especially in fields like medical imaging.

2.7 Summary and Research Gap

Previous works rely on classical filters like BM3D, Mean, Median, and PCA. Classical filters are modeled for Additive White Gaussian Noise (AWGN), which does not consider Rician Noises. Rician noise is signal-dependent, demonstrating poor performance in MRI denoising. It also introduces bias in low intensity regions, which cannot be corrected by classical filters. Classical filters apply a fixed operation for the whole image and do not adapt to local image statistics. There are only a handful of studies that provide an extensive comparison under both Gaussian and Rician noise scenarios, specifically focused on MRI brain images. Additionally, there has been limited research comparing hybrid PCA-based approaches to advanced deep learning models like DnCNN and traditional benchmarks such as BM3D within a systematic and uniform framework.

The present work addresses this gap by:

- Training a DnCNN model on MRI-specific patches.
- Designing a hybrid approach that integrates PCA, median filtering, and optional Rician correction.
- Evaluating all methods using quantitative metrics like PSNR, SSIM, and histogram-based metrics (Bhattacharyya, Intersection, Correlation).
- Comparing the performance of Gaussian and Rician noise under multiple noise levels (10%, 20%, 30%).

3. Proposed Work

The methods used in this work to denoise brain MRI images are explained in this section. This category includes deep learning techniques like DnCNN, BM3D, and methods like principal component analysis (PCA) and median filtering. Since hybrid approaches may yield better results, a hybrid solution is described for Rician noise. To ensure consistency, comparable datasets and metrics are used to evaluate the methods.

Let I_{clean} be the clean MRI image, I_{noisy} be the corrupted image affected by either Gaussian or Rician noise. The goal of image denoising is to $I_{denoised} \approx I_{clean}$ such that the noise is suppressed while preserving structural details.

3.1 Image Processing

Before using any algorithms on the images, it is advised that they normalization, it's a good practice. Prior to being normalized to the range [0,1], the images are first converted to grayscale. This ensures numerical consistency throughout the calculations and simplifies the processing pipeline.

Normalization is applied as follows to image I:

$$I_{norm(x,y)} = \frac{I(x,y)}{255} \tag{1}$$

Normalizing provides a uniform range of pixel values which enhances the effectiveness of subsequent statistical and filtering processes.

3.2 Patch Based PCA Filtering

Principal Component Analysis (PCA) is a popular statistical method used to eliminate noise in an image by lowering its dimensionality, making it particularly efficient in tasks involving image denoising. In most cases, noise is found the in low variance directions and PCA has the capability of separating this noise from dominant signal structures. By converting image patches into a reduced-dimensional subspace, PCA successfully suppresses noise elements while preserving key features and anatomical details. [12] PCA is developed around the idea that information in an image can be represented in fewer pixels. The additional unnecessary noise pixels can be filtered out without causing any loss of structural details.

Patch Extraction

The core of the denoising process is based on patch-wise PCA filtering. Initially, the input images are converted to equal sized square patches (typically 8 × 8) with a predefined stride to allow overlap.

For a normalized image I of size $H \times W$, overlapping patches size $p \times p$ are extracted as:

$$Pij = I(i{:}\ k, j{:}\ l) \tag{2}$$

Here, i and j denote the row and column index and k and l are taken as k = $i + p - 1$, l = $j + p - 1$.These are used to show how the i and j values vary over the image in steps of the chosen stride. Each patch P_{ij} is flattened into a vector and collected into a matrix $X \in R^{m \times n}$ where m is the number of patches and $n = p^2$ is the number of pixels in each patch.

PCA Transformation

PCA is used to project the patch data into a lower-dimensional subspace that captures the most significant variance in the data. The steps are:

- **Mean Centering:** For a given dataset *X* with *m* samples, the mean of each feature can be computed as:

$$\mu_j = \frac{1}{m} \sum_{i=1}^{m} X_{ij} \tag{3}$$

Here, j = 1,2,3……n. where n is the number of features.

The mean-centered data is then:

$$X' = X - \mu \tag{4}$$

- **Covariance Matrix:** Compute the covariance matrix *C* of the mean-centered data:

$$C = \frac{1}{m-1} X'^T X' \tag{5}$$

- **Eigen Decomposition:** Compute the eigenvalues λ and eigenvectors *V* of *C*:

$$CV = \lambda V \tag{6}$$

Eigenvectors define the principal components, while eigenvalues represent the variance contributed by each component.

- **Projection and reconstruction:** Let V_k be the matrix of top *k* eigenvectors that preserve 95% of the variance. The data is transformed and reconstructed as:

$$X_{PCA} = X' \; V_k^T \; V_k + \mu \tag{7}$$

This suppresses noise (captured in lower-variance components) while preserving structural details.

Patch Aggregation

The grouping of clean patches created by the PCA reconstruction process is known as patch aggregation. Data is gathered to create the final denoised image. Overlapping patches result in multiple reconstructions of a pixel. The intensity of a pixel is determined by the weighted average of the overlapped patches. The image reconstruction is smooth because the patch aggregation process creates a smooth transition between the overlapping patches.

In most situations, principal component analysis-based denoising is a reliable method that offers significant advantages. It achieves this by separating the noise's random particles from the image's intrinsic structure in the direction of greater variance. PCA does not require previous modeling or training because it is unsupervised and can adapt to local features. [14] PCA is a popular choice for denoising because of its interpretability, computational efficiency, and general versatility for the majority of real-world problems, even though it isn't always superior to more sophisticated options like deep learning models.

Median Filtering

By using median filtering, denoising is achieved by replacing each pixel's value with the median value extracted from the surrounding pixels. While trying to reduce noise, linear filters like the Gaussian filter have a propensity to smooth out edges. By using the median filter, which can denoise an image while preserving its edges and structural components, this can be prevented. [16] As a result, it is a perfect addition to PCA.

For a pixel *I(x,y)*, a median filter over a *3× 3* neighborhood is defined as:

$$I'(x,y) = median\{I(i,j)|(i,j) \in N(x,y) \quad (8)$$

where $N(x,y)$ denotes the neighborhood centered at (x,y). This step effectively removes isolated noise particles without blurring edges.

The two primary objectives of using a median filter after PCA are to:

- Remove extra noise that PCA might have missed
- Offer structural refinement to enhance local uniformity in consistent regions of images without sacrificing edges.

When these two techniques are combined, a visually cohesive denoising solution that can strike a balance between removing noise and preserving fine details is produced.

3.3 Hybrid Denoising Framework

One or two traditional techniques are insufficient to reduce complex noise patterns in MRI images, primarily those resulting from Rician noise. Patch-based PCA denoising, median filtering, Rician bias correction, and, if preferred, bilateral filtering and histogram matching are all combined in this hybrid approach to improve visual and structural quality. Figure 4 illustrates how the methodology flows.

- PCA patch-based denoising
- Median filtering
- Rician bias correction (for Rician noise)

Since Rician noise is signal-dependent, conventional denoising techniques like PCA and median filtering may leave some noise particles behind after the process is finished, especially in low-intensity regions of magnitude MRI images. This is addressed by performing a Rician bias correction step, which restores the underlying signal's statistical expectation.

If I_d is the denoised image and σ is the estimated noise standard deviation, the bias-corrected image is computed as:

$$I_{corrected}(x,y) = \sqrt{\max(I_d\ (x,y)^2 - \sigma^2, 0)} \quad (9)$$

This correction is derived from the statistical expectation of Rician-distributed signals.

The upward bias caused by magnitude reconstruction can be handled by this. The square root formulation ensures that only physically meaningful (non-negative) intensities are retained after bias removal.

Noise level σ is estimated from the difference between the original noisy image I_n and the denoised image I_d:

$$\sigma = \mathrm{std}(I_{noisy} - I_{denoised}) \tag{10}$$

This step is critical in recovering accurate signal representation, especially in low-SNR regions where Rician bias has the greatest impact.

Bilateral Filtering

Bilateral filters allow for both smoothing and edge preservation because they consider both spatial proximity and intensity similarity, unlike traditional linear filters. This produces an easily interpretable denoised image, which is particularly helpful in medical imaging domains like brain MRI, where edge integrity and soft tissue clarity are essential. This can be considered an optional post-processing technique to improve the visual quality of the denoised image.

The bilateral filter for a pixel *I(x,y)* is given as:

$$I_{bilateral}(x,y) = \frac{1}{W_p}\sum_{(i,j)\in N} I(i,j) \cdot fs(\| (i,j) - (x,y) \|) \cdot fr(| I(i,j) - I(x,y) |) \tag{11}$$

where:

- fs is the spatial kernel (e.g., Gaussian with respect to distance).
- fr is the range kernel (e.g., Gaussian with respect to intensity difference).
- W_p is a normalization factor.

Histogram Matching

Histogram matching involves contrasting the denoised image's intensity distribution with a reference image, which is typically a template or a version of the image without noise. For the denoised image's cumulative distribution function (CDF) to closely resemble the reference image's CDF, it is adjusted. Histogram matching is helpful in standardizing contrast and intensity levels across different images. To address the intensity variations that occur during the denoising and bias correction processes, the transformation ensures that the statistical properties of the noise-reduced image match those of high-quality images [19]. This can be viewed as an additional post-processing option.

This combined approach utilizes the advantages of each of the current methods. PCA aids in the following processes: bilateral filtering to enhance perceptual quality; median filtering to selectively reduce impulsive noise; Rician bias correction to recover low-intensity values; and histogram matching to normalize contrast. All of these elements work together to create a strong denoising mechanism designed to control the complex noise patterns in MRI data, guaranteeing better visual clarity and ultimately a more accurate diagnosis.

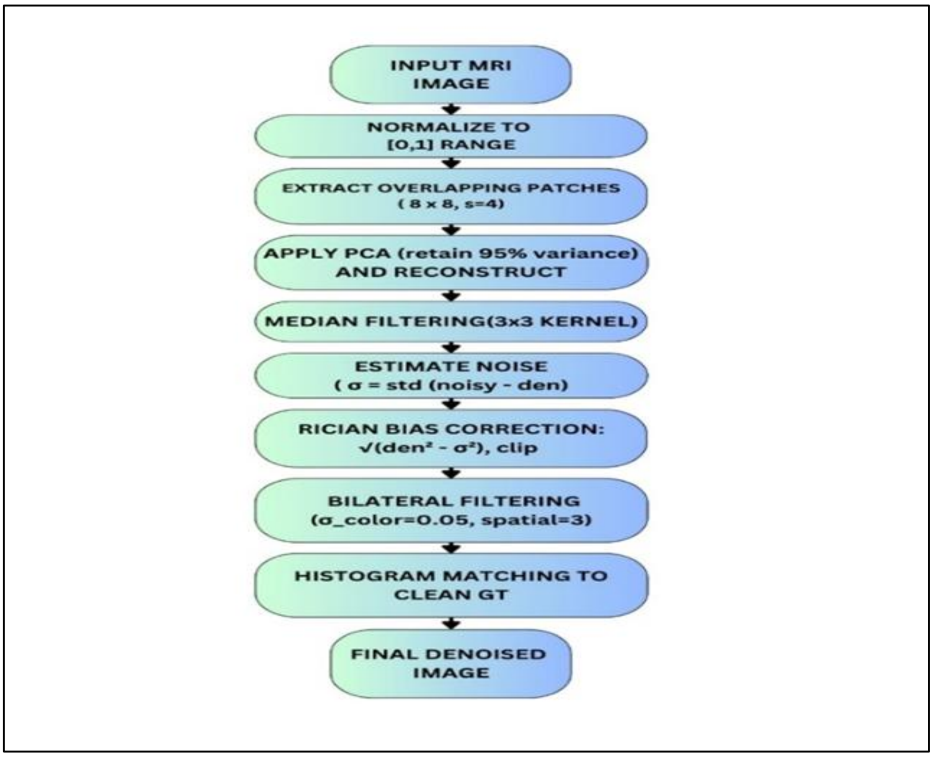


Figure 4. Hybrid Method Workflow

3.4 BM3D Denoising

Block-Matching and 3D filtering, or BM3D, is an image denoising technique with high acclaim for its ability to suppress a wide range of noise effectively while also maintaining complex textures and fine details. Its rationale is that in a natural or medical image, many sites contain similar patches or patterns. These patches are clustered by BM3D, which exploits the ensuing redundancy.

There are some significant steps in the BM3D process:

- Grouping analogous 2D patches into 3D blocks.
- Performing a 3D transform (such as DCT or wavelet).
- Applying coefficient shrinkage (thresholding).
- Executing the inverse transform and merging the results.

Let Y be the 3D group of noisy patches:

$$Y_{denoised} = T^{-1}\,(Shrink(T(Y))) \tag{12}$$

Where Y is the 3D stack of similar noisy patches, T denotes the 3D transform, $Shrink$ represents the thresholding function, and T^{-1} is the inverse transform.

The BM3D can efficiently handle the denoising of Gaussian-impacted images. Its collaborative and non-local characteristics enable it to provide optimal denoising performance with texture preservation and edge crispness.

Moreover, the BM3D method is non-parametric, which implies that it does not need to adjust parameters or undergo any form of extensive prior training. [15] However, BM3D is not ideal for handling non-Gaussian noise like Rician, which is commonly found in MRI scans. Since it is designed for Gaussian noise, its thresholds and similarity measures fail to consider the signal-dependent, non-zero mean distribution of Rician, leading to frequent residual artifacts or over-smoothing, especially in low-intensity regions.

3.5 DnCNN (Denoising Convolutional Neural Network)

DnCNN (Denoising Convolutional Neural Network) is one of the most widely used deep convolutional neural networks. It utilizes residual learning to predict the noise and clean it from the noise-corrupted images and has been shown to perform well in eliminating both Gaussian and Rician noise. Rather than trying to predict the clean image, it tries to predict the expected noise and subtracts the same from the image to yield a denoised outcome. The residual learning strategy utilized in DnCNN enhances the training effectiveness since it enables the network to learn the complex noise patterns, particularly in clinical images such as MRI where the features of the noise may vary in different regions. The architecture diagram is illustrated in Figure 5.

Architecture Details:

The network architecture comprises 17 convolutional layers. Details of the architecture are explained in Table 1.

- The first layer performs a convolution with 64 filters of size 3×3, followed by a ReLU activation.
- The intermediate 15 layers each consist of convolutional layers with 64 filters of size 3×3, followed by Batch Normalization and ReLU activations.
- The final layer is a convolutional layer with a single output channel (for grayscale images) and no activation, yielding the predicted noise. More details are provided in Table 1.

This structure is designed to maintain the input image dimensions through same padding. The network output, which estimates the noise $F_\theta\ (I_{noisy})$, is subtracted from the noisy input to obtain the denoised image.

$$I_{denoised} = I_{noisy} - F_\theta\ (I_{noisy}) \tag{13}$$

Where F_θ is the trained model.

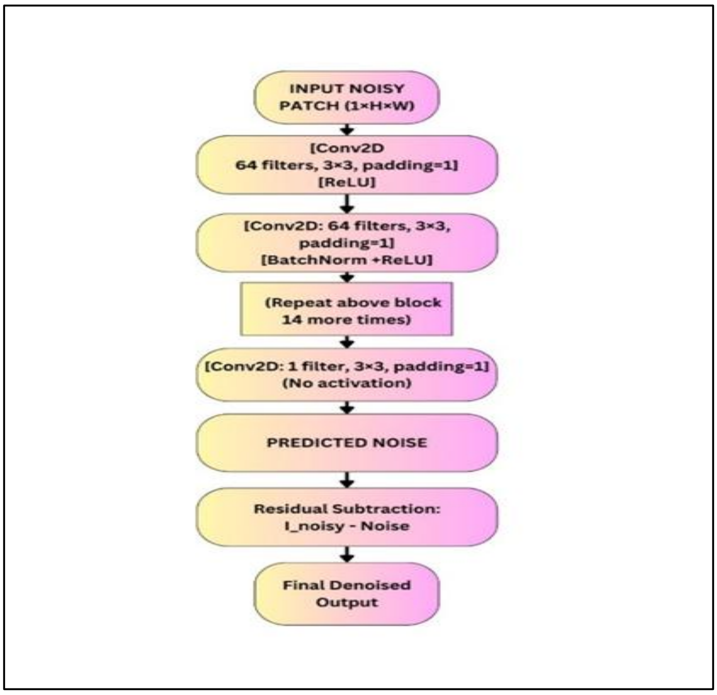


Figure 5. DnCNN Architecture

To improve the DnCNN model's generalization to domain-specific artifacts, it was retrained using MRI-specific patches that had synthetically injected Gaussian and Rician noise. While many new deep learning techniques, such as UNet, GANs, and Transformer-based models, may yield better results, DnCNN is used in this study because it is less complicated than GAN or Transformer-based models while still producing powerful denoising results. Because DnCNN is frequently used in the literature for benchmarking, the outcomes are comparable to earlier research.

Table.1 Layer-Wise Configuration of the DnCNN Model used in this Study

Layer	Layer Type	Filter Size	No of Filters	Activation	Batch Normalization	Purpose
1	Convolution	3 × 3	64	ReLU	No	Feature extraction
2-16	Convolution	3 × 3	64	ReLU	No	Deep representation
17	Convolution	3 × 3	1	None	No	Noise estimation

4. Experimental Setup

To evaluate the effectiveness of various denoising methods for MRI images corrupted with different types and levels of noise, a structured dataset was prepared and a controlled testing framework was implemented.

4.1 Dataset preparation

A total of 27 clean brain MRI images were collected from an open-source data science platform Kaggle. These high-quality, noise-free images served as the ground truth reference for both training and evaluation. The dataset was chosen for its diversity in anatomical structures and consistency in resolution, making it suitable for denoising tasks.

To simulate realistic noise conditions commonly encountered in MRI, two types of noise were artificially introduced:

- Gaussian noise (additive white noise, modeled using a normal distribution)
- Rician noise (signal-dependent noise typical in MRI magnitude images)

Each noise type was applied at three different noise intensity levels: 10%, 20%, and 30%. Thus, the training dataset consisted of a total of 162 noisy images. The Gaussian and Rician affected images modeled the fundamental characteristics of hospital MRI images. Real hospital MRI images include additional complexities like hardware artifacts patient motion, physiological noise, and magnetic field inhomogeneity, which could not be simulated in this study. Therefore, the experiment on the inclusion of synthetic noise is an approximation, not a perfect match.

4.2 Patch Extraction for DnCNN Training

To train the DnCNN model, each of the 162 noisy images was divided into small overlapping patches of size 40×40 pixels using a sliding window approach. Training the dataset took almost 36 hours on a CPU only system for 10epochs. This process resulted in 10,584 training patches, which were used to train a noise-specific version of the DnCNN denoising model. These patches capture a variety of structural patterns and noise characteristics across different intensities and types.

4.3 Test Set Preparation

For objective evaluation, an independent test set was curated (as seen in Table 2). It consists of 7 clean MRI images, each corrupted with the same two noise types (Gaussian and Rician) at three levels (10%, 20%, 30%), resulting in 6 test subsets, each containing 7 images thus resulting in 42 testing images. These noisy test images were not part of the training set and were used to evaluate the generalization ability of the denoising algorithms. While 42 images may seem like a small number for testing, several similar studies, such as those conducted by Olesen et al. [26][27] have used limited dataset and still achieved comprehensive results. The current set is sufficient for initial study and evaluation however for clinical-level assurance, larger-scale validation on multi-center datasets will be needed.

These test images were denoised using:

- The trained DnCNN model
- The proposed hybrid approach (PCA + Median + optional Rician bias correction)

- Two additional ablation setups:
  - PCA only
  - PCA + Median
- A benchmark state-of-the-art method: BM3D.

Table .2 Test Set Images Details

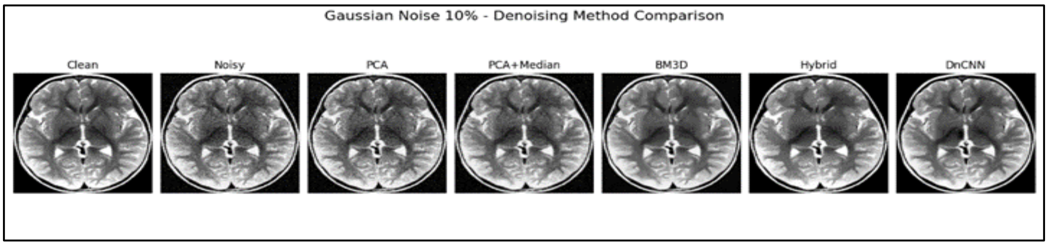
Noise Type	Noise Level	No. of Images
Gaussian	10%,20%,30%	21(7 each)
Rician	10%,20%,30%	21(7 each)

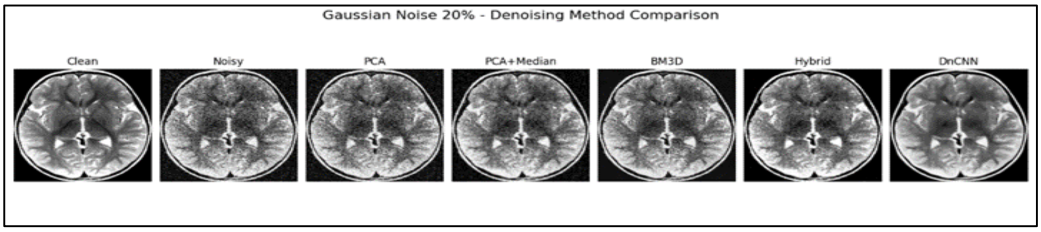
While the training process for the dataset took long hours, the testing process only requires few seconds to produce the results. All the experiments were conducted on a system equipped with an Intel 12th Generation Core i5-12450H CPU (8 cores, 12 threads) and 16 GB of RAM, running Windows 11. The implementation was carried out in Python (with libraries including NumPy, OpenCV, Scikit-learn, and TensorFlow) using the PyCharm IDE.

5. Results and Discussions

In this section the quantitative and qualitative metrics used to evaluate the resultant denoised brain MRI images obtained across the different noise types (Gaussian and Rician) and at intensities (10%, 20%, 30%) are discussed. The comparison is between classical denoising methods like BM3D, PCA, and PCA with median filtering along with our proposed hybrid method and deep learning method (DnCNN). The performance metrics used for evaluation include PSNR (Peak Signal-to-Noise Ratio), SSIM (Structural Similarity Index) and histogram-based metrics like Bhattacharya distance, intersection and correlation.

To achieve a comprehensive analysis, the average results of the denoised images for all the testing images across the different quantitative metrics are considered. To analyze the quality of the images, the resultant denoised images for all the methods for one brain MRI testing image are shown. The visual comparison can be seen in Figure 6.





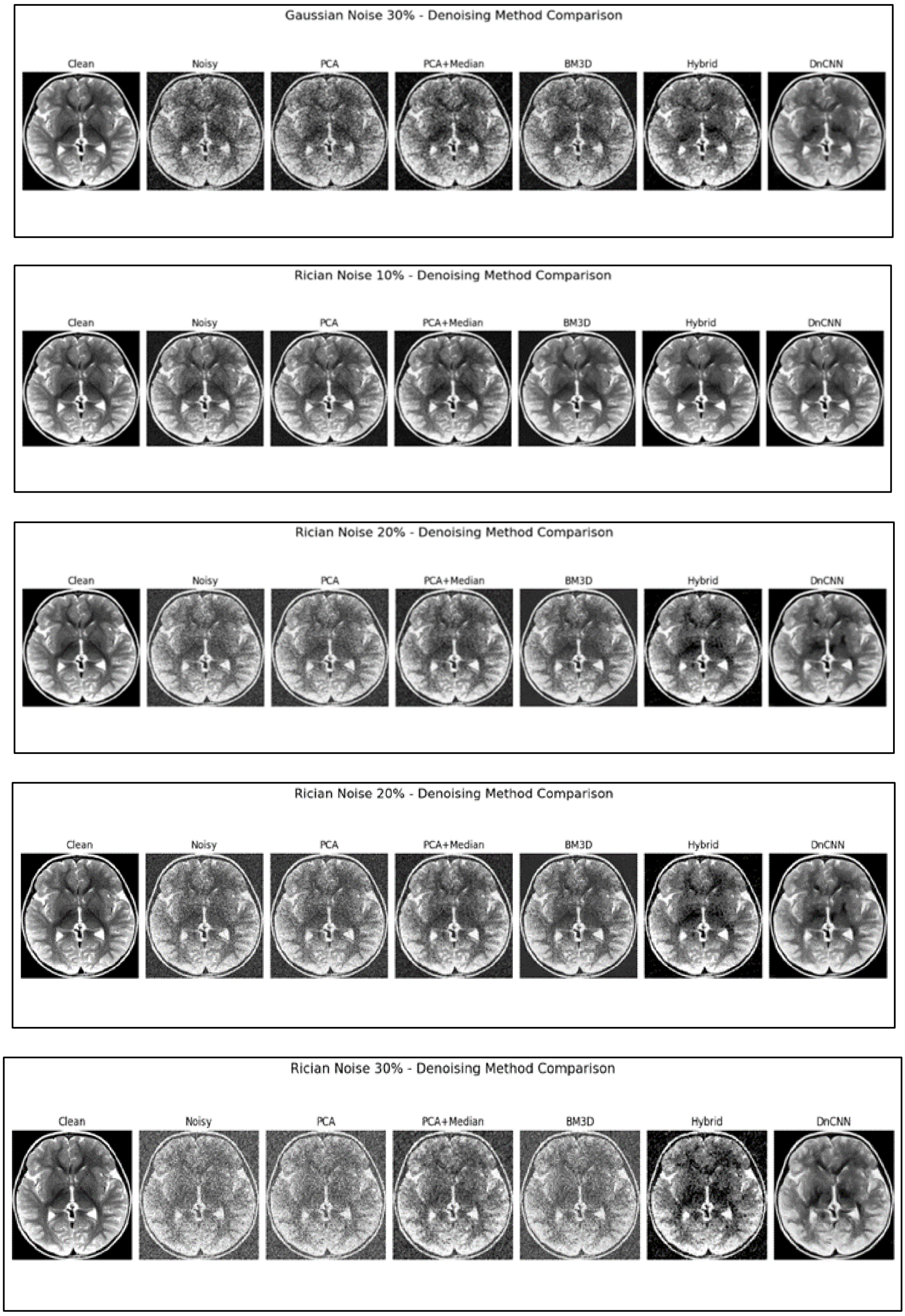


Figure.6 Resultant Denoised Brain MRI Images across Different Noise Types and Intensities

Quantitative Assessment (PSNR and SSIM Metrics)

To objectively measure how well the suggested methods as well as classic methods work, two well-known image quality measurements, Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM) are used.

Peak Signal-To-Noise Ratio (PSNR)

PSNR is a logarithmic metric used to evaluate the original image (meaning the maximum signal power) against the discrepancy between the original and altered image in order to measure the strength of the original images in comparison to the unwanted noise that reduces its fidelity. PSNR can be calculated using the formula:

$$\text{PSNR} = 10log_{10}(R^2/\text{MSE}) \tag{14}$$

Here, R represents the maximum possible pixel value of the image (255 for 8-bit images) and MSE stands for Mean Squared Error which can be calculated as:

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(I(i) - K(i))^2 \tag{15}$$

Here:

- I stands for original image
- K stands for denoised image
- N stands for the total number of pixels

Structural Similarity Index (SSIM)

SSIM is a quantitative metric used to measure the loss of image quality of the resultant denoised image compared to the original image after undergoing various processing steps. It gives a more accurate assessment of how much closer the denoised image is to the original image in comparison to PSNR. PSNR only considers pixel-wise differences, while SSIM compares similar patterns between images and judges if it has better edge and structural preservation. [18] The SSIM results can be found using the following formula:

$$SSIM(I,K) = (2\mu_I\mu_K + C_1)(2\sigma_{IK} + C_2)/(\mu_I^2 + \mu_K^2 + C_1)(\sigma_I^2 + \sigma_K^2 + C_2) \tag{16}$$

Where:

- μ_I and μ_K are the average pixel values of the original and denoised images, respectively.
- σ_I^2 and σ_K^2 represents the variances of the original and denoised images.
- σ_{IK} denotes the covariance between the original and denoised images.
- C_1 and C_2 are small stabilizing constants used to prevent division errors.

Histogram-Based Similarity Metrics

In image processing, histograms indicate how pixel intensities are distributed and how they can be used to classify objects based on colours. When comparing two photos side by side, such as a denoised image and its clean reference image, the histograms can tell us how well the overall intensity distribution is maintained throughout the denoising process. [20]

The histogram metrics considered for analysis are as follows:

Bhattacharyya Distance

It measures the similarity between two probability distributions. A lower Bhattacharyya distance implies greater similarity.

Let $H_1(i)$ and $H_2(i)$ be the normalized histogram values (probabilities) of the original and denoised images, respectively, for intensity bin i:

$$D_B(H_1, H_2) = -\ln\left(\sum_{i=1}^{N} \sqrt{H_1(i).H_2(i)} + \epsilon\right) \quad (17)$$

Here N stands for the number of histogram bins (usually taken as 256 for grayscale images) and ϵ is taken as a small constant (e.g., 1× 10^{-1}) to avoid log (0).

Interpretation:

- $D_B = 0$. Perfect match
- Higher values indicate more dissimilarity.

Histogram Intersection

It quantifies the amount of overlap between two histograms. Higher intersection values imply greater similarity.

$$Intersection(H_1, H_2) = \sum_{i=1}^{N} \min(H_1(i), H_2(i)) \quad (18)$$

Interpretation:

- Maximum possible value is 1 which signifies perfect overlap
- The closer it is to 1, the more similar the two histograms are.

Correlation Coefficient

Measures the linear correlation between two histograms. It compares how intensity values trend between the two distributions.

$$Corr(H_1, H_2) = \frac{\sum_{i=1}^{N}(H_1(i) - \overline{H_1})(H_2(i) - \overline{H_2})}{\sqrt{(\sum_{i=1}^{N}(H_1(i) - \overline{H_1})^2.(\sum_{i=1}^{N}(H_2(i) - \overline{H_2})^2}} \quad (19)$$

Where $\overline{H_1}$ and $\overline{H_2}$ are used to represent the mean values of histogram.

- Correlation close to 1 indicates a strong positive similarity
- A value near 0 implies no correlation

The results of the denoised images using the above-mentioned metrics are shown in Table 3 to 8.

Table 3. Gaussian Noise 10% Results

Denoising Approach	PSNR	SSIM	Bhattacharya	Intersection	Correlation
PCA Method	23.89	0.5986	-2.1716	6.2181	0.7829
PCA + Median Method	27.17	0.7318	-2.1204	5.7236	0.2477
BM3D Method	26.21	0.7901	0.3844	5.2915	0.1068
Hybrid Method	27.77	0.8409	-1.8531	6.0650	0.9955
DnCNN Method	28.89	0.8669	0.0912	5.7076	0.9881

Table 4. Gaussian Noise 20% Results

Denoising Approach	PSNR	SSIM	Bhattacharya	Intersection	Correlation
PCA Method	16.05	0.3189	-2.1250	6.1547	0.9038
PCA + Median Method	22.03	0.5379	-2.1651	5.7626	0.2485
BM3D Method	17.95	0.3907	0.4045	5.1427	-0.0033
Hybrid Method	23.16	0.6569	-1.8531	6.0651	0.9955
DnCNN Method	26.09	0.7953	0.1222	6.3430	0.9698

Table 5. Gaussian Noise 30% Results

Denoising Approach	PSNR	SSIM	Bhattacharya	Intersection	Correlation
PCA Method	12.70	0.2107	-2.0363	5.7155	0.8621
PCA + Median Method	18.84	0.4116	-2.1844	5.7912	0.2591
BM3D Method	13.13	0.2195	0.3587	5.3975	0.0970
Hybrid Method	21.76	0.4919	-1.8532	6.0650	0.9955
DnCNN Method	24.07	0.7073	0.1635	6.2181	0.9097

Table 6. Rician Noise 10% Results

Denoising Approach	PSNR	SSIM	Bhattacharya	Intersection	Correlation
PCA Method	21.49	0.5675	-2.1279	5.5057	0.0929
PCA + Median Method	23.35	0.7031	-2.0373	5.2630	0.1038
BM3D Method	24.12	0.7606	0.4368	4.9346	0.0822
Hybrid Method	27.39	0.8210	-1.8531	6.0650	0.9955
DnCNN Method	28.79	0.8620	0.0729	6.3174	0.9933

Table 7. Rician Noise 20% Results

Denoising Approach	PSNR	SSIM	Bhattacharya	Intersection	Correlation
PCA Method	14.25	0.2914	-2.1377	5.4490	0.0151
PCA + Median Method	17.14	0.4936	-2.0603	5.0983	0.0878
BM3D Method	15.84	0.3804	0.4403	4.7707	0.0186
Hybrid Method	22.66	0.5541	-1.8531	6.0650	0.9955
DnCNN Method	25.28	0.7615	0.1250	6.3777	0.9800

Table 8. Rician Noise 30% Results

Denoising Approach	PSNR	SSIM	Bhattacharya	Intersection	Correlation
PCA Method	10.79	0.1784	-2.0819	5.3119	0.0006
PCA + Median Method	13.29	0.3543	-2.0234	4.6982	0.0651
BM3D Method	11.23	0.1973	0.4074	5.1449	-0.0155
Hybrid Method	19.13	0.3647	-1.8531	6.0650	0.9955
DnCNN Method	22.74	0.6799	0.1582	6.0434	0.9782

In this study, the effectiveness of different denoising methods for brain MRI images affected by Gaussian and Rician noise at different intensities (10%, 20%, 30%) was analysed with the help of quantitative metrics like PSNR, SSIM, and histogram metrics such as

Bhattacharya distance, intersection, and correlation. These multi-faceted metrics provide a thorough analysis of the important characteristics of a denoised image, which include edge and texture preservation, noise reduction, and artifact reduction. The primary objective is to demonstrate whether these methods can preserve important anatomical structures while removing noise, which is critical for effective medical diagnosis. Doctors rely on visual interpretability, lesion clarity, and diagnostic confidence, which PSNR/SSIM cannot fully capture. Radiologist-based assessments of diagnostic performance are necessary to establish doctor-level trust. The scores used in this study are helpful for technical benchmarking, but by themselves, they do not guarantee that images are clinically trustworthy

BM3D demonstrated strong denoising performance under low noise conditions. However, as the noise level started to increase, it began to distort the finer details in the image, resulting in lower PSNR and SSIM values. Similarly, other classic methods like PCA and PCA + Median filter were also found to be efficient under lower noise conditions, but their performance degraded with increasing noise.

6. Future Work

Future work can include integrating deep learning models like SwinIR, which have the ability to learn complicated noise patterns from large-scale annotated MRI datasets, allowing for flexible and context-aware denoising with improved performance in mixed noise environments. [21]. Recent works, such as Shou et al. (2023) [24], have shown that transformer-based models give better performance than standard CNNs in denoising 3D arterial spin labelling (ASL) MRI. Other fields where future work can be done include 3D volumetrics which involve extending the framework from 2D splicing to a 3D volumetric framework. This can help preserve the spatial continuity between slices, which is useful for accurate medical diagnosis, as it provides consistent anatomical structure preservation in multi-planar reconstructions and can perform better volumetric analysis. [22] Future work can also include real-time optimization and deployment as well as cross-modality and generalization methods. By evaluating the technique across multiple MRI modalities, such as T1-weighted, T2-weighted, and FLAIR, as well as across different scanner manufacturers and field strengths the robustness and flexibility of the framework can be improved and used for broader medical applications. [23].

7. Conclusion

Compared to the classical denoising methods based on PCA, the proposed hybrid approach has yielded better results across all metrics. It efficiently reduces residual noise and maintains edge preservation for low- to medium-level noise images, thus making it ideal for low-noise clinical settings. The hybrid method is practical for real-life use. It can run efficiently on a CPU, and while it has more steps compared to classical filters, it balances performance and practicality. However, the performance of the hybrid method starts degrading at higher levels of noise, specifically at Rician 30% and Gaussian 30%. On the other hand, DnCNN consistently provides clean and detailed outputs even in severe noise conditions. Its ability to deliver strong denoising even at higher levels makes it the most stable approach of all and most suitable for real-world and medical applications. The results are consistent for the hybrid approach with a slight decrease in the 30% range, while DnCNN provides the highest PSNR and SSIM values.

The proposed methods are computationally efficient classical and hybrid filters run within seconds per slice on CPUs, and the deep learning model, DnCNN, delivers near real-time inference once trained, making them suitable for hospital use without workflow delays. Overall, the study and analysis conclude that while there is no single method that can be considered optimal for all conditions, the integration of different strategies, like the proposed hybrid method, provides a powerful foundation for robust denoising. A flexible and adaptive denoising pipeline, capable of switching between classical and deep learning methods, would be most useful for real-time MRI preprocessing systems.

References

[1] Andria, Gregorio, Filippo Attivissimo, and Anna Maria Lucia Lanzolla. "A statistical approach for MR and CT images comparison." Measurement 46, no. 1 (2013): 57-65.

[2] Dr. Y. MaryReeja," Comparative Analysis of Noise Reduction Techniques for Brain MRI Image", J. Electrical Systems 20-10s (2024): 6068-6077

[3] Gudbjartsson, Hákon, and Samuel Patz. "The Rician distribution of noisy MRI data." Magnetic resonance in medicine 34, no. 6 (1995): 910-914.

[4] Sriani, S., Ilka Zufria, and Mhd Syahnan. "Improved Digital Image Quality Using the Gaussian Filter Method." IJISTECH (International Journal of Information System and Technology) 5, no. 5 (2022): 556-563.

[5] George, Ginu, Rinoy Mathew Oommen, Shani Shelly, Stephie Sara Philipose, and Ann Mary Varghese. "A survey on various median filtering techniques for removal of impulse noise from digital image." In 2018 conference on emerging devices and smart systems (ICEDSS), IEEE, (2018): 235-238.

[6] Kaur, Bobbinpreet, Ayush Dogra, and Bhawna Goyal. "Comparative analysis of bilateral filter and its variants for magnetic resonance imaging." The Open Neuroimaging Journal 13, no. 1 (2020).

[7] Komoto, Yuki, Jiho Ryu, and Masateru Taniguchi. "Total variation denoising-based method of identifying the states of single molecules in break junction data." Discover Nano 19, no. 1 (2024): 20.

[8] Alkinani, Monagi H., and Mahmoud R. El-Sakka. "Patch-based models and algorithms for image denoising: a comparative review between patch-based images denoising methods for additive noise reduction." EURASIP journal on image and video processing 2017, no. 1 (2017): 58.

[9] Li, YingJiang, Jiangwei Zhang, and Maoning Wang. "Improved BM3D denoising method." IET Image Processing 11, no. 12 (2017): 1197-1204.

[10] Phan, Tran Dang Khoa. "A spatially variant high-order variational model for Rician noise removal." PeerJ Computer Science 9 (2023): e1579.

[11] Wang, Wenjing. "An improved denoising model for convolutional neural network." In Journal of Physics: Conference Series, vol. 1982, no. 1, p. 012169. IOP Publishing, 2021.

[12] Mudrova, M., and Aleš Procházka. "Principal component analysis in image processing." In Proceedings of the MATLAB technical computing conference, Prague, (2005): 1-4.

[13] Li, Shiao, Fei Wang, and Song Gao. "New non-local mean methods for MRI denoising based on global self-similarity between values." Computers in Biology and Medicine 174 (2024): 108450.

[14] Henriques, Rafael Neto, Andrada Ianuş, Lisa Novello, Jorge Jovicich, Sune N. Jespersen, and Noam Shemesh. "Efficient PCA denoising of spatially correlated redundant MRI data." Imaging Neuroscience 1 (2023): 1-26.

[15] Han, Trong-Thanh, Hinh Nguyen Van, and Phat Nguyen Huu. "Denoising Method for MRI Images Using Modified BM3D Filter with Complex Network and Artificial Neural Networks." Journal of Electrical and Computer Engineering 2024, no. 1 (2024): 2606485.

[16] Wang, Yuan-Bin, and Hai-Long Huang. "Image denoising based on adaptive sector rotation median filter." In Journal of Physics: Conference Series, vol. 1769, no. 1, p. 012056. IOP Publishing, 2021.

[17] Zhang, Qi, Jingyu Xiao, Chunwei Tian, Jerry Chun-Wei Lin, and Shichao Zhang. "A robust deformed convolutional neural network (CNN) for image denoising." CAAI Transactions on Intelligence Technology 8, no. 2 (2023): 331-342.

[18] Sara, Umme, Morium Akter, and Mohammad Shorif Uddin. "Image quality assessment through FSIM, SSIM, MSE and PSNR—a comparative study." Journal of Computer and Communications 7, no. 3 (2019): 8-18.

[19] Bottenus, Nick, Brett C. Byram, and Dongwoon Hyun. "Histogram matching for visual ultrasound image comparison." IEEE transactions on ultrasonics, ferroelectrics, and frequency control 68, no. 5 (2020): 1487-1495.

[20] Forero, Manuel G., Carlos Arias-Rubio, and Brigete Tatiana González. "Analytical comparison of histogram distance measures." In Iberoamerican Congress on Pattern Recognition, Cham: Springer International Publishing, (2018): 81-90.

[21] Liang, Jian, Pengxu Chen, and Mian Wu. "Research on an image denoising algorithm based on deep network learning." In Journal of Physics: Conference Series, vol. 1802, no. 3, p. 032112. IOP Publishing, 2021.

[22] Zhao, Shutian, Fan Xiao, James F. Griffith, Ruokun Li, and Weitian Chen. "Denoising of volumetric magnetic resonance imaging using multi-channel three-dimensional convolutional neural network with applications on fast spin echo acquisitions." Quantitative Imaging in Medicine and Surgery 14, no. 9 (2024): 6517.

[23] Meyer, Maria Ines, Ezequiel de la Rosa, Nuno Barros, Roberto Paolella, Koen Van Leemput, and Diana M. Sima. "An augmentation strategy to mimic multi-scanner variability in MRI." In 2021 IEEE 18th International Symposium on Biomedical Imaging (ISBI), IEEE, (2021): 1196-1200.

[24] Shou, Qinyang, Chenyang Zhao, Xingfeng Shao, Kay Jann, Hosung Kim, Karl G. Helmer, Hanzhang Lu, and Danny JJ Wang. "Transformer-based deep learning denoising of single and multi-delay 3D arterial spin labeling." Magnetic resonance in medicine 91, no. 2 (2024): 803-818.

[25] Kanal, Kalpana M., Jonathan H. Chung, Jin Wang, Puneet Bhargava, Jennifer R. Kohr, William P. Shuman, and Brent K. Stewart. "Image noise and liver lesion detection with MDCT: a phantom study." American Journal of Roentgenology 197, no. 2 (2011): 437-

441.

[26] Olesen, O. F., et al. (2022). Evaluation of MRI denoising techniques using BrainWeb simulated datasets. BrainWeb. https://doi.org/10.3389/frai.2021.642731.

[27] Yang, Haibo, Shengjie Zhang, Xiaoyang Han, Botao Zhao, Yan Ren, Yaru Sheng, and Xiao-Yong Zhang. "Denoising of 3D MR images using a voxel-wise hybrid residual MLP-CNN model to improve small lesion diagnostic confidence." In International Conference on Medical Image Computing and Computer-Assisted Intervention, Cham: Springer Nature Switzerland, (2022): 292-302.