

Research Article

# Enhancing Brain MR Image Quality Using CNN With Best Denoising Modality for Improved Diagnosis of Abnormality: An Appraisal

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**Abstract:** Digital medical images acquired from the brain are highly susceptible to noise, which causes significant challenges for radiologists to identify abnormalities in a precise manner. Noise interference hampers both diagnostic accuracy and the interpretation of underlying abnormalities, potentially leading to flawed conclusions. Magnetic Resonance (MR) imaging is the most preferred digital imaging technique for brain abnormality detection. To achieve precise detection, noise-free MR images are essential. Denoising modalities commonly address this issue by reducing unwanted noise while preserving essential image features. However, the effectiveness of denoising methods varies, and achieving an optimal filtered denoised image remains a challenge. This paper undertakes a thorough appraisal of various prominent denoising techniques on two public MR image datasets. The result shows Anisotropic Diffusion Unsharp Masking Filter (ADUM) as the most effective denoising method. A hybrid method that combines a Convolutional Neural Network (CNN) with ADUM filters is proposed to enhance feature extraction and abnormality detection of brain MR images. The performance of these methods is comprehensively evaluated through both qualitative and quantitative measures. The result shows that the proposed method does a better job of reducing noise while keeping edges than other conventional denoising methods, as shown by the examination of the results. This makes it a promising tool for both clinical and research use.

**Keywords:** Brain, Denoising, Magnetic Resonance (MR) Images, Performance Assessment

## Introduction

Brain health issues can have a significant impact on the life of a person. It affects a person's behavior, ability to think and work properly. According to the Mental health statistics of 2024, 13% of the world population live with a brain disorder (Mental Health Statistics, 2025). Many brain disorders share common symptoms such as hallucinations, delusions, disorganized thinking, and incoherent speech (Sobha et al., 2024; Verma et al., 2024a). These disorders are treatable if diagnosed properly. The most commonly preferred digital imaging techniques used for the diagnosis of brain disorders are Magnetic Resonance (MR) imaging and Computed Tomography (CT) scans (Alsadhan, 2023).

In general, MR imaging is often preferred over CT scans because it abstains from ionizing radiation,

safeguarding Deoxyribonucleic Acid (DNA) from harm and mitigating the cancer risk often associated with CT scans and other imaging methods (MRI Basics, 2023.). Using a robust magnetic field and radio frequency pulses, MR images produce intricate visual representations of the internal structures of the human brain (Vijayvargiya et al., 2023). However, MR images frequently contain noises for a variety of reasons that are unavoidable. Major causes of the presence of noise include faulty image sensors, imperfect instruments, issues with the data-collecting process, transmission mistakes, and interference from natural occurrences (Li et al., 2021; Verma et al., 2024b). Automated detection methods employing Deep Learning (DL) methods have shown promising result but presence of noise degrades the visual quality of MR images (Chen et al., 2022). Hence, for accurate identification of any disorder through MR imaging, a preprocessing step is

essential which is to eliminate the presence of noises (Kumar et al., 2024). Denoising is the common preprocessing step for achieving a noise-free image (Chen et al., 2024). The purpose of image denoising is to save the original details of an image while minimizing the amount of random noise it produces (Verma et al., 2025). In order to accomplish the aforementioned goal, an appraisal of different denoising modalities has been done to show which methodology is working better for making MR imaging data noise-free. The result shows Anisotropic Diffusion Unsharp Masking (ADUM) as the most effective method for filtration and contrast enhancement in MR images. This filtration modality is integrated with the DL method, Convolutional Neural Network (CNN) design VGG16, for their ability to deep feature extraction and learn complex data patterns for abnormalities detection (Ilesanmi and Ilesanmi, 2021).

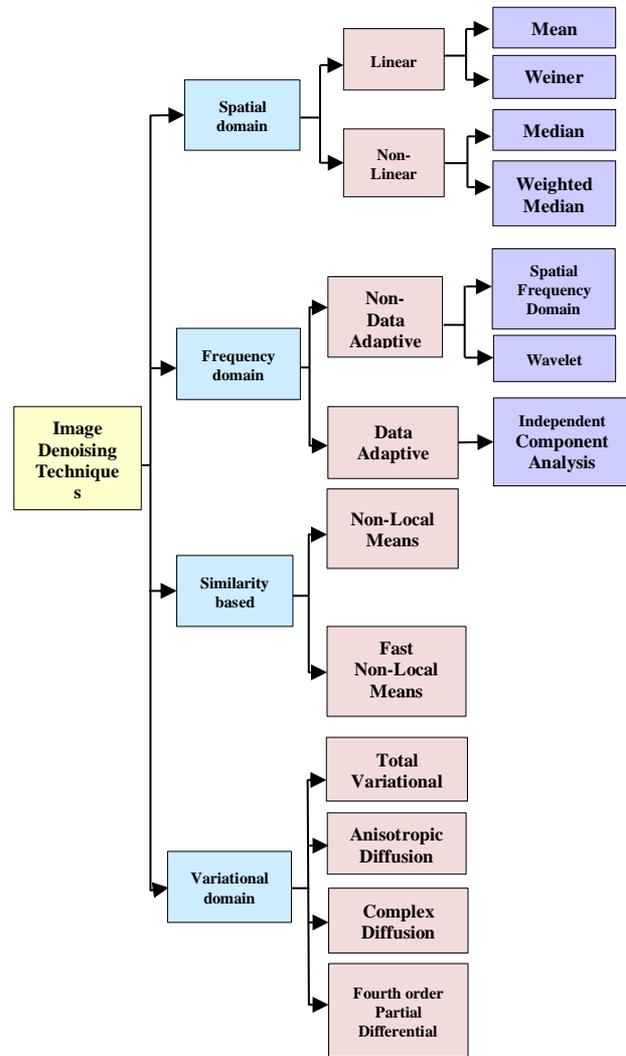
In the medical field, accurate diagnosis and treatment planning of brain disorders heavily depend on the quality of MR images. Denoising enhances the visibility of subtle details and abnormalities, allowing healthcare professionals to make more precise assessments and decisions. It can be especially crucial for early disease detection and monitoring. The primary contributions of this article include:

- Identification and analysis of the most dominating noise within MR images
- Application and assessment of the diverse denoising techniques available for MR image data
- Integration of CNN with ADUM for feature extraction and improved abnormality detection
- Conducting a thorough comparative evaluation, both qualitatively and quantitatively, to determine the efficacy of denoising methods and identify the superior performing approach

### Literature Survey

This section gives a brief overview about various existing denoising techniques to make a noisy MR image noise free. Additionally, these techniques are combined with various enhancement techniques in order to carry out denoising and enhancement simultaneously. Fig. 1 provides a schematic representation of the various denoising techniques. Spatial domain operates directly on image pixels.

They modify themselves based on pixel information in the neighborhood (Juneja et al., 2024). Further, they are classified into linear or nonlinear filters by the way filtration operation is applied to the image (Xiao et al., 2023). The frequency domain operates on the frequency of images. The removal of very high and very low frequency components sharpens the details of the image (Veni and Manjula, 2022). Based on their ability to adjust to image characteristics, we can further classify them into adaptive and non-adaptive frequency domain filters.



**Fig. 1:** Schematic representation of the various denoising techniques

While Adaptive filters fine-tune their characteristics based on local properties of the image, Non-Adaptive frequency domain filters fix denoising parameters on the entire image (Diana Earshia and Sumathi, 2024). Similarity-based image denoising techniques use image redundancy, where similar patterns or structures emerge across regions. This method uses a similar structure in denoising while maintaining edges and texture details (S. Li et al., 2024). Non-Local Means, and Fast Non-Local Means are two kinds of similarity-based image denoising techniques. Non-Local means applies filtration by taking a weighted average pixel of an image globally with maximum detail preservation of the image. However, Fast Non-Local Means minimizes its computational complexity by employing approximations or smaller search spaces (Choi et al., 2019). This led to slight loss of details of the image. Another method of denoising is variational domain-based filtration. This method filters

out images from noise while preserving the edges (Pankaj et al., 2021). Among all the denoising methods, variational domain-based filtration is considered the best denoising method (Barbu, 2013; Yang et al., 2021). They can be further classified into Total Variational (TV), Anisotropic Diffusion (AD), Complex Diffusion (CD), and Fourth order Partial Differential (FPD) filters. The choice of denoising methods depends on the desired trade-off between computational complexity, denoising, and noise reduction.

Dolui et al. (2013) have used the Non-local Means filter (NLM) of similarity-based framework for denoising MR images. The performance of this filtration method has shown a significant improvement in Rician noise statistics over traditional Gaussian-based similarity measures. Yadav et al. (2017) have taken a modified Complex Diffusion-based Non-linear filter [MCDN] for restoration and enhancement of MR images, which is formulated within variational denoising techniques. Here, the data likelihood term is obtained by minimizing the negative log-likelihood of the Rician noise distribution. The filter is introduced as a prior function that will preserve features of images while reducing noise. Rajalakshmi et al. (2018) have done a comparison of some denoising methods and proposed a spatial denoising method that is a wavelet-based weighted median filter (WMF) with brain images for better visualization and diagnostic accuracy. Majeeth and Babu (2019) came up with frequency domain denoising and developed a method by combining the fast-guided filter with the discrete wavelet transform (FGWT) for removal of Gaussian noise. This method yields high-quality output images with balanced edge preservation and computation efficiency. Kumar et al. (2020) have applied denoising with the method known as Anisotropic Diffusion Unsharp-Masking (ADUM), which is an extended version of Perona-Malik model of denoising (Perona and Malik, 1990). This method helps in finding a denoised and contrast-enhanced output image. Sharma and Chaurasia (2021) have proposed NLM method with Non-Subsampled Shearlet Transform (NNSST) for noise reduction and enhancing image quality, making MR scans clearer for clinical analysis and diagnosis. Mahdaoui et al. (2022) have used the total variational method of denoising with Non-Local Self-Similarity (TVNSS) constraint to improve image quality. In addition to denoising, this method gives high quality edge preservation and texture retention. Kumar and Srivastava (2022) have used a reshaped Gabor Filter (GF) for the removal of noise in brain MR images. MR images with varying levels of noise are evaluated with a variety of quantitative assessment metrics. Lee et al. (2023) have used the Median Modified Wiener filter (MMWF) for brain MR image denoising. The quantitative evaluations were obtained in terms of the Coefficient of Variation (COV) and Edge Preservation Index (EPI). This method outperforms specially in edge preservation particularly in noisy image.

Selecting the right filtration method will not only improve image processing but also play a crucial role in achieving accurate medical diagnoses. Nevertheless, the intricate structure of the human brain presents a challenge, as low contrast in MR images makes abnormality detection difficult. After a comparative study of these methodologies, Anisotropic Diffusion Unsharp-Masking is taken as a filtration method for integration with CNN. As AD will help in the smoothing of the image, Unsharp Masking will introduce contrast enhancement, and CNN will enhance feature extraction and improve abnormality detection.

## Materials and Methods

### *Data Collection*

For the identification of noise and comparative study, two brain MR imaging datasets are taken. The brain disorders taken are Schizophrenia and Brain tumor. These two are well-validated MR imaging datasets for neuroimaging. The size of the dataset is sufficient for all kinds of performance analysis. Also, these datasets offer diversity, including MR images that are categorized by age, gender, sample size, etc., all of which contribute to reliable inferences.

### *Dataset 1*

Centre for Biomedical Research Excellence (COBRE) datasets have been taken for comparative analysis (COBRE, 2023). This dataset consists of functional MR images of 72 patients with ages ranging from 18 to 65 years suffering from Schizophrenia. Schizophrenia is an enduring mental disorder that disrupts the cognitive, emotional, and behavioral function of a person (Baghmaleki, 2021). This disease is least known to people, but according to the current report of the World Health Organization (WHO), 50% of people suffering from brain disorders have Schizophrenia (Schizophrenia, 2025).

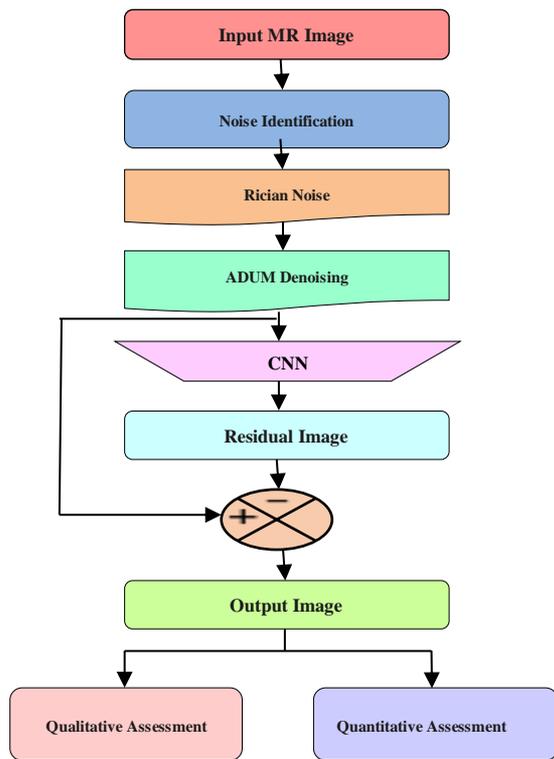
### *Dataset 2*

This is a public dataset that consists of MR images of patients suffering from brain tumor (Brain Tumor MRI Dataset, 2024). The dataset consists of 7022 MR images of the brain which are classified into tumors and no tumors. Brain tumor disease is a kind of neurological disorder in which there is a growth of abnormal cells in brain. Meningiomas, Gliomas, and Pituitary tumors are three types of brain tumor majorly found in human brain (Abdelaziz Ismael et al., 2020).

### *Methodology*

The proposed framework is specially crafted for the identification of dominating noise present during the

acquisition of MR images for serious brain disorders such as Schizophrenia and brain tumors. An extensive comparison of popular denoising techniques has been done using both dataset 1 and dataset 2, respectively. The efficacy of denoising techniques has been evaluated through both qualitative and quantitative measures, such as full-reference and no-reference metrics, along with human visual system assessment. The findings highlight the potential and challenges of each technique in improving the quality and accuracy of digital medical images, particularly in the field of MR images of brain disorders. The best denoising method ADUM is integrated with CNN for enhanced images. Fig. 2 illustrates the framework for the proposed methodology applied on brain MR image datasets. The detailed description of methodology with mathematical expression has been described here.



**Fig. 2:** Framework for the proposed methodology applied on datasets

### Identification of Noise in MR Images

MR images are affected by three primary types of noise: Rician noise, Speckle noise, and Poisson noise (Zeng et al., 2020). Rician noise arises from a combination of the desired signal and intrinsic noise from the patient or scanner, impacting the contrast of the image (Yadav et al., 2016a). Speckle noise, also known as granular noise, results from variations in radiofrequency signals, causing a grainy texture (Kumar and Srivastava,

2022). Poisson noise stems from the randomness in photon or particle counting, affecting low-intensity regions and sparse MR sequences (Saadia and Rashdi, 2018). For analysis of the presence of noise, histogram analysis of a noisy MR image is being done using the curve-fitting method (Günen, 2024). A noisy image typically has a broader and flatter intensity histogram compared to a clean image. Analyzing the shape and spread of the histogram can provide insights into the noise characteristics. Fig. 3(a). displays a sample noisy brain MR image from the dataset, while Fig. 3(b). depicts a histogram plot of the noisy MR image, and Fig. 3(c). represents probability distribution for various noise variations (Hargreaves, 2016). The fact that histogram majorly resembles Rician distribution, concludes that Rician noise is predominant in MR images, with Speckle and Poisson noise also contributing to image degradation.

Noise in MR images can have an adverse effect on the quality of images, which makes it harder for radiologists to diagnose the abnormality accurately. Heat and agitation of electrons produce a form of thermal noise in MR images known as Rician or Rice noise (Yadav et al., 2016a). The presence of noise in MR signals is famously difficult to interpret. Due to the complex nature of Gaussian noise, Rician noise is present in raw MR images. Hence, for accurate identification of any disorder through MR imaging, a preprocessing step is essential, which is to eliminate the presence of noises (Kumar et al., 2024).

Suppose ‘ $I$ ’ be a noise free raw MR image and ‘ $N$ ’ denotes noise present in MR image. It can be represented as:

$$N = N_x + iN_y \quad (1)$$

Where ‘ $N_x$ ’ and ‘ $N_y$ ’ denotes real and imaginary part of noise in MR image.

As zero-mean ‘ $\mu$ ’ uncorrelated Gaussian noise with identical variance ‘ $\sigma^2$ ’, distorts both the real and imaginary parts of the noise in MR image. Thus, their value is given as:

$$N_x \sim \mathcal{N}(\mu_x, \sigma^2), N_y \sim \mathcal{N}(\mu_y, \sigma^2) \quad (2)$$

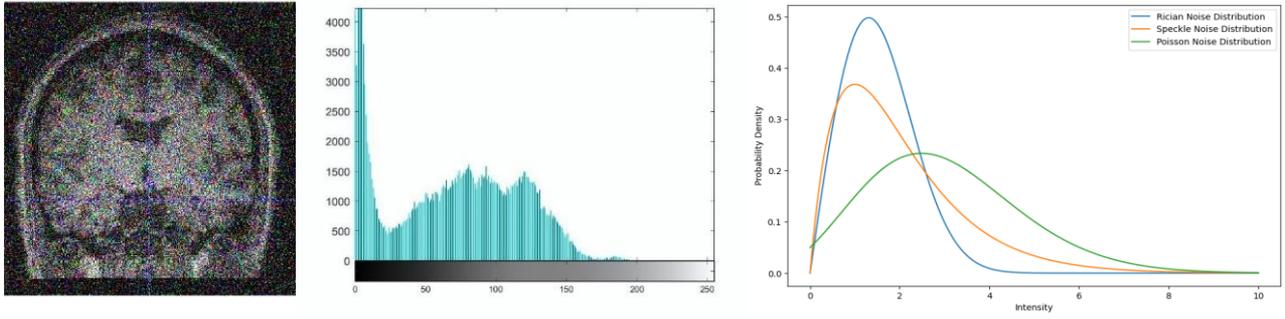
The magnitude value ‘ $M$ ’ of noisy MR image is computed as:

$$M = \sqrt{(I + N_x)^2 + N_y^2} \quad (3)$$

When a signal amplitude exceeds the noise level in MR imaging, the Rician noise model applies.

The Rician noise distribution in MR images is mathematically formulated as (Yadav et al., 2017):

$$p(I/M) = \frac{M}{\sigma^2} e^{-\left(\frac{M^2 + I^2}{2\sigma^2}\right)} J_0\left(\frac{IM}{\sigma^2}\right) \quad (4)$$



**Fig. 3:** (a) Input noisy MR images, (b) Histogram analysis of MR image, (c) Noise distribution

Where ‘ $I$ ’ denotes the noise free image and ‘ $M$ ’ denotes magnitude of noisy MR image, ‘ $\sigma^2$ ’ is Rician noise variance, and ‘ $J_0$ ’ is zero order modified Bessel’s function.

With the presence of Rician noise, it can be hard to tell the difference between low-intensity region and noise, especially in places where signs are weak. Signal and noise magnitude affects Rician noise distribution. When a signal amplitude exceeds the noise level in MR imaging, the Rician noise model applies.

For high SNR region,  $\gg \sigma$  :

$$M \approx I + \mathcal{N}(0, \sigma^2) \quad (5)$$

Here, generally ‘ $M$ ’ follows noise distribution centered at ‘ $I$ ’ similar to Gaussian distribution.

For low SNR region,  $\sim 0$  :

$$M \sim Rice(0, \sigma) \quad (6)$$

Here, ‘ $M$ ’ follows Rice or Rician distribution with non-zero mean even if ‘ $I = 0$ ’.

Measurements of signal intensity are reduced due to Rician noise, particularly in low-SNR areas. It affects diagnostic interpretation by introducing a positive bias in low-intensity areas.

The mathematical expression for the proposed methodology is given as:

Suppose ‘ $I_N$ ’ denotes noisy MR image given as input, then output obtained after passing through ADUM filter is given as:

$$I_{ADUM}(i, j) = I_N(i, j) + \lambda \cdot \nabla \cdot (c(i, j, t) \cdot \nabla I_N(i, j)) \quad (7)$$

Where ‘ $\lambda$ ’ is the diffusion rate, ‘ $\nabla$ ’ is gradient operator, ‘ $c(i, j, t)$ ’ is the conduction coefficient that controls the sensitivity of the edges:

$$c(i, j, t) = \frac{1}{1 + (\frac{\nabla I}{k})^2} \quad (8)$$

After passing through CNN, the image obtained is a residual image ‘ $I_R$ ’ whose value can be written as:

$$I_R(i, j) = CNN(I_{ADUM}(i, j)) \quad (9)$$

Finally, the noise free output image ‘ $I$ ’ obtained is given as:

$$I(i, j) = I_{ADUM}(i, j) - I_R(i, j) \quad (10)$$

$$I(i, j) = I_{ADUM}(i, j) - CNN(I_{ADUM}(i, j)) \quad (11)$$

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**Algorithm 1:** Pseudo code for the proposed method:

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**Input:** Read noisy input image  $I_N(i, j)$ .

**Output:** Denoised MR Image  $I(i, j)$ .

Identification of dominant Rician noise.

Compute a noise-free image using the Rician probability distribution for each pixel  $(i, j)$  in the image.

#Apply Anisotropic Diffusion Unsharp Masking (ADUMF)

def ADUM( $I_N, \lambda, n, k$ )

# Initialize the image for the diffusion process

For  $t = 1$  to number of iterations ‘ $n$ ’:

$I_{ADUM} = I_N$ . Copy ()

# Compute the gradient of the image

gradient = compute gradient( $I_N$ )

# Calculate conduction coefficient

conduction =  $1 / (1 + \exp(-(\text{abs}(\text{gradient}) / K) ** 2))$

# Update the image using the diffusion equation

$I_{ADUM} = I_N + \lambda * \text{divergence}(\text{conduction} * \text{gradient})$

return  $I_{ADUM}$

# CNN-based Denoising

def CNN\_denoise( $I_{ADUM}, \text{model}$ ):

# pre-trained CNN model to predict residual noise

$I_R = \text{model.predict}(I_{ADUM})$

return  $I_R$

# Hybrid Denoising Framework

def hybrid\_denoising( $I_N, \lambda, n, k, \text{model}$ )

# Final denoised output image

$I = I_{ADUM} - I_R$

return  $I$

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### Performance Assessment

Image performance assessment refers to the process of assessing the quality of an image processing methodology. It is an essential step in evaluating the overall quality of the processed image. The

comprehensive full reference performance interpretation, the performance of the human visual system, and the interpretation of images with no reference are all done for the purpose of evaluating the existing denoising techniques (Ohashi et al., 2023; Ortiz-Jaramillo et al., 2016).

### Full Reference Image Performance Interpretation

The objective of this interpretation is to assess the degree to which the processed images correspond to the qualities and attributes of an ideal reference image. The parameters taken are:

- Mean Square Error (MSE) - It is a representation of the typical variation that occurs between each pixel throughout the entire image (Kumar et al., 2022). The expected value should be low
- Peak Signal to Noise ratio (PSNR) – It is used in conjunction with the mean square error, which determines the most likely value of the noisy image input (Kumar and Srivastava, 2022). It is expressed in decibel (dB) and the expected value should be high
- Root Mean Square Error (RMSE) - It is one of the most common metrics used to evaluate the precision of an image prediction (Verma et al., 2024a). The expected value should be low

### Human Visual System Performance Interpretation

The goal of this interpretation is to make sure that denoise images are not visually exquisite but also good enough for correct diagnosis. The parameters taken are:

- Structural Similarity (SSIM) index - To evaluate how similar two images are to one another, SSIM is employed (Tang et al., 2020). The expected value should be high.
- Multi-scale Structural Similarity (MS-SSIM) Index - MS-SSIM is an improved version of SSIM that compares images based on their structural similarity at a number of different image scale (Wang et al., 2004). The expected value should be high.

### No Reference Image Performance Interpretation

No reference metrics are quantitative performance measure that are used to evaluate the performance of output MR image without taking any reference or ground truth image. In brain MR images, no reference image performance interprets how well noise is reduced, structures and contrast are kept, artifacts are avoided, and total image quality is maintained for detection of abnormalities. Due to no dependency on reference images, evaluation of these parameters is easy for real world applications. The parameters taken are:

- Discrete Entropy (DE) - Image storage space requirements can be quantified using discrete entropy.
- When the entropy is high enough, a more detailed representation of the image is produced (Krbcova and Kukal, 2017). The expected value should be low
- Perception-based Image Quality Evaluator (PIQE) - It inversely affects image perception. High score values suggest low perceptual quality, whereas low scores indicate high (Pandey et al., 2020)
- The mathematical formulation of these quantitative parameters is explained in Table 1
- In addition to these parameters, a robust statistical validation has been done that uses the probability value (p-values) with PSNR and SSIM as its parameters. It is a level of marginal significance within the hypothesis testing that represents the likelihood of obtaining the observed data.  $p\text{-value} \leq 0.05$ , is considered statistically significant as probability of finding true method is 0.95 (1.00 – 0.05). This shows the method has 95% confidence interval (Andrade, 2019; Greenland et al., 2016)

After integration of deep learning framework with the denoising methods, Perceptual Loss (PL) function has been introduced.

**Table 1:** Mathematical formulation of quantitative assessment parameters

	$MSE = \frac{1}{m \times n} \sum_{i=1}^{m-1} \sum_{j=1}^{n-1} (M - I)^2$
Full Reference Image Performance Interpretation	<p>where ‘<math>M</math>’ is the noisy MR image, ‘<math>I</math>’ is the filtered processed image.</p> $MSE = \frac{1}{m \times n} \sum_{i=1}^{m-1} \sum_{j=1}^{n-1} (M - I)^2$ <p>where ‘<math>L</math>’ is possible pixel range of image.</p> $RMSE = \sqrt{MSE}$
Human Visual System Performance Interpretation	$SSIM = \frac{(2\mu_M\mu_I + C_1)(2\sigma_{MI} + C_2)}{(\mu_M^2 + \mu_I^2 + C_1)(\sigma_M^2 + \sigma_I^2 + C_2)}$ <p>where ‘<math>\mu</math>’ denotes mean of image and ‘<math>\sigma</math>’ denotes variance of image ‘<math>C_1</math>’ and ‘<math>C_2</math>’ are taken to prevent the resulting instability.</p> $MSSSIM = \frac{(2\mu_M\mu_I + C_1)}{(\mu_M^2 + \mu_I^2 + C_1)} \prod_{0}^{L-1} \frac{(2\sigma_{MI} + C_2)}{(\sigma_M^2 + \sigma_I^2 + C_2)}$
No Reference Image Performance Interpretation	$DE = - \sum_{i=0}^{L-1} I \log_2 I$

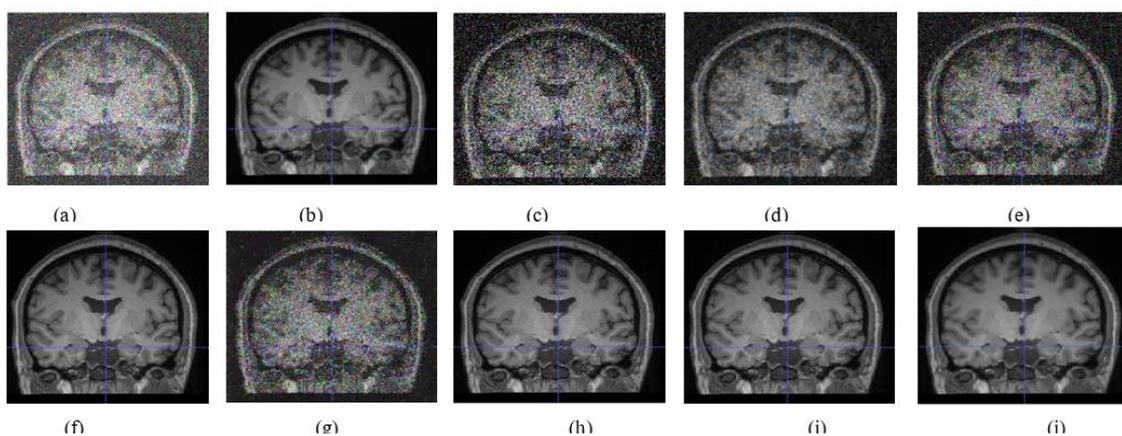
In order to make model predictions that are more in line with human predictions, a PL is commonly used loss function (Yang et al., 2017) This loss function estimates some aspect of human perception. It uses the distance between deep features acquired from a neural network to calculate the error between two images. Unlike MSE, which measures pixel-wise differences losing important structural details, the PL measures how similar the output and input images are to the human vision (Lin et al., 2024). The value of PL for each denoising methodology is calculated through the integration of CNN for dataset 1 and dataset 2. The low value of PL indicates a high level of feature similarity for the output image with respect to the input image. This signifies that the generated output image will gaze very natural and visually close to the reference image (Wu et al., 2020).

## Results and Discussion

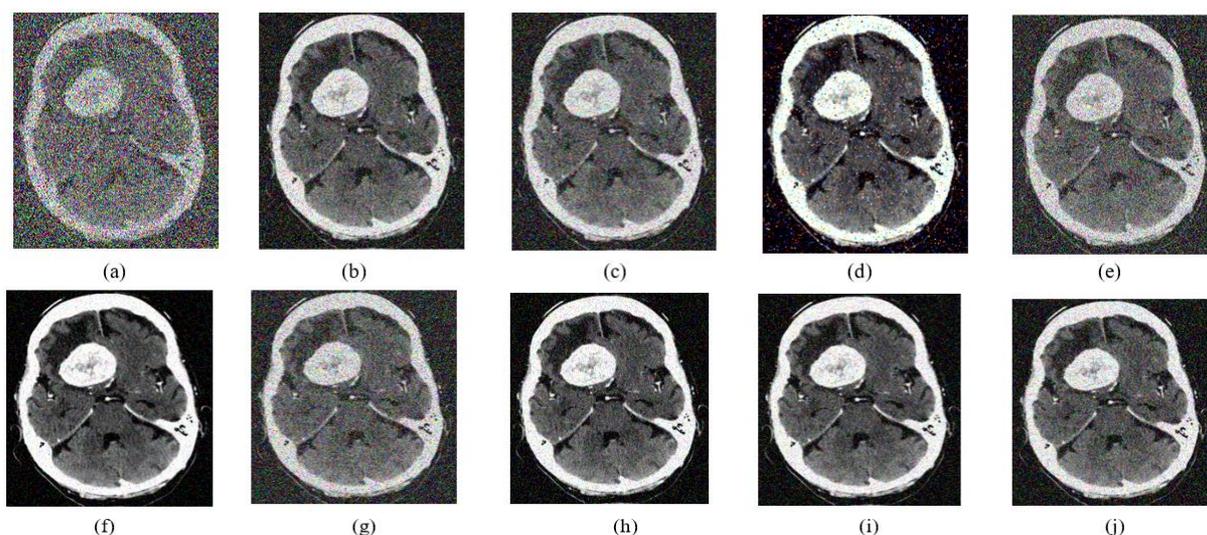
In this section, qualitative and quantitative analysis of the results that were achieved through the application of the existing denoising techniques are carried out. All of the analyses of the results are performed on the two public brain image MR datasets.

### Qualitative Analysis

Qualitative analysis has been conducted using MR images for both the brain MR image datasets, with the underlying rationale being the potential presence of anomalies, micro calcifications, or specific masses in the patient population. The sample image taken is of 20% Rician noise, Speckle noise, and Poisson noise distribution. Figs. 4-5 presents visual representation the obtained result images from various denoising methods for dataset 1 and dataset 2, respectively.



**Fig. 4:** Obtained output images from various denoising methods: (a) Sample noisy MR image (b) NLM, (c) MCDN, (d) WMF, (e) FGWT, (f) ADUM, (g) NNSST, (h) TVNSS, (i) GF, and (j) MMWF



**Fig. 5:** Obtained output images from various denoising methods: (a) Sample noisy MR image (b) NLM, (c) MCDN, (d) WMF, (e) FGWT, (f) ADUM, (g) NNSST, (h) TVNSS, (i) GF, and (j) MMWF

A comprehensive survey involving a diverse group of individuals with expertise in medical imaging, including radiologists, clinicians, and imaging scientists, was conducted about the output images from two different datasets that had been denoised using different methods. They were asked to scrutinize the best output images from all these filtered images. The majority of individuals voted for Anisotropic Diffusion Unsharp Masking followed by Total Variational method of denoising with Non-Local Self-Similarity (TVNSS) and Median Modified Wiener filter (MMWF). Also, as per doctors from the medical department at the National Institute of Technology Patna, India, Anisotropic Diffusion Unsharp Masking will provide clearer and better MR images with more detailed

abnormalities, which will help in accurately finding disorders.

*Quantitative Analysis*

Quantitative assessment consists of various reference, non-reference, and human visual parameters needed for performance analysis of different denoising methodologies. The purpose of collecting data is to analyze it quantitatively, utilizing tools such as numbers and statistics. The parameters taken are already discussed in the performance assessment section. Tables 2 and 3 depict a comparative quantitative assessment value of various MR image denoising modalities on dataset 1 and dataset 2, respectively.

**Table 2:** Variation of reference parameter, human visual reference parameters, and no reference parameters for dataset 1

Methods	Performance Assessment Parameters							
	PSNR	MSE	RMSE	SSIM	MS-SSIM	DE	PIQE	PL
NLM (Dolui et al., 2013)	21.52	0.56	0.67	0.54	0.88	6.84	18.33	8.42
MCDN (Yadav et al., 2016b)	24.93	0.64	0.79	0.62	0.85	5.61	21.74	7.57
WMF (Rajalakshmi et al., 2018)	20.43	0.58	0.76	0.69	0.77	3.53	29.51	7.12
FGWT (Majeeth and Babu, 2019)	25.45	0.61	0.81	0.79	0.81	6.97	46.18	7.44
ADUM (Kumar et al., 2020)	39.46	0.43	0.65	0.87	0.91	7.84	48.32	6.89
NNSST (Sharma and Chaurasia, 2021)	32.51	0.49	0.69	0.55	0.65	5.84	37.57	8.37
TVNSS (Mahdaoui et al., 2022)	34.64	0.47	0.72	0.67	0.73	6.23	41.12	8.59
GF (Kumar and Srivastava, 2022)	30.52	0.57	0.75	0.71	0.84	5.31	32.16	7.46
MMWF (Lee et al., 2023)	36.43	0.66	0.76	0.42	0.77	3.63	35.64	6.97

**Table 3:** Variation of reference parameter, human visual reference parameters, and no reference parameters for dataset 2

Methods	Performance Assessment Parameters							
	PSNR	MSE	RMSE	SSIM	MS-SSIM	DE	PIQE	PL
NLM (Dolui et al., 2013)	20.74	0.54	0.73	0.34	0.62	4.64	20.48	13.77
MCDN (Yadav et al., 2016b)	25.43	0.45	0.67	0.46	0.51	4.49	24.65	15.35
WMF (Rajalakshmi et al., 2018)	21.64	0.49	0.71	0.54	0.57	3.42	32.87	13.83
FGWT (Majeeth and Babu, 2019)	27.12	0.47	0.68	0.59	0.68	4.98	43.41	17.32
ADUM (Kumar et al., 2020)	42.53	0.31	0.56	0.77	0.85	3.21	47.19	12.76
NNSST (Sharma & Chaurasia, 2021)	34.82	0.39	0.62	0.65	0.67	5.04	38.35	13.53
TVNSS (Mahdaoui et al., 2022)	35.97	0.41	0.64	0.51	0.53	3.89	31.76	14.61
GF (Kumar and Srivastava, 2022)	33.39	0.52	0.72	0.43	0.58	4.37	33.92	12.97
MMWF (Lee et al., 2023)	37.32	0.36	0.68	0.56	0.62	3.96	37.48	15.38

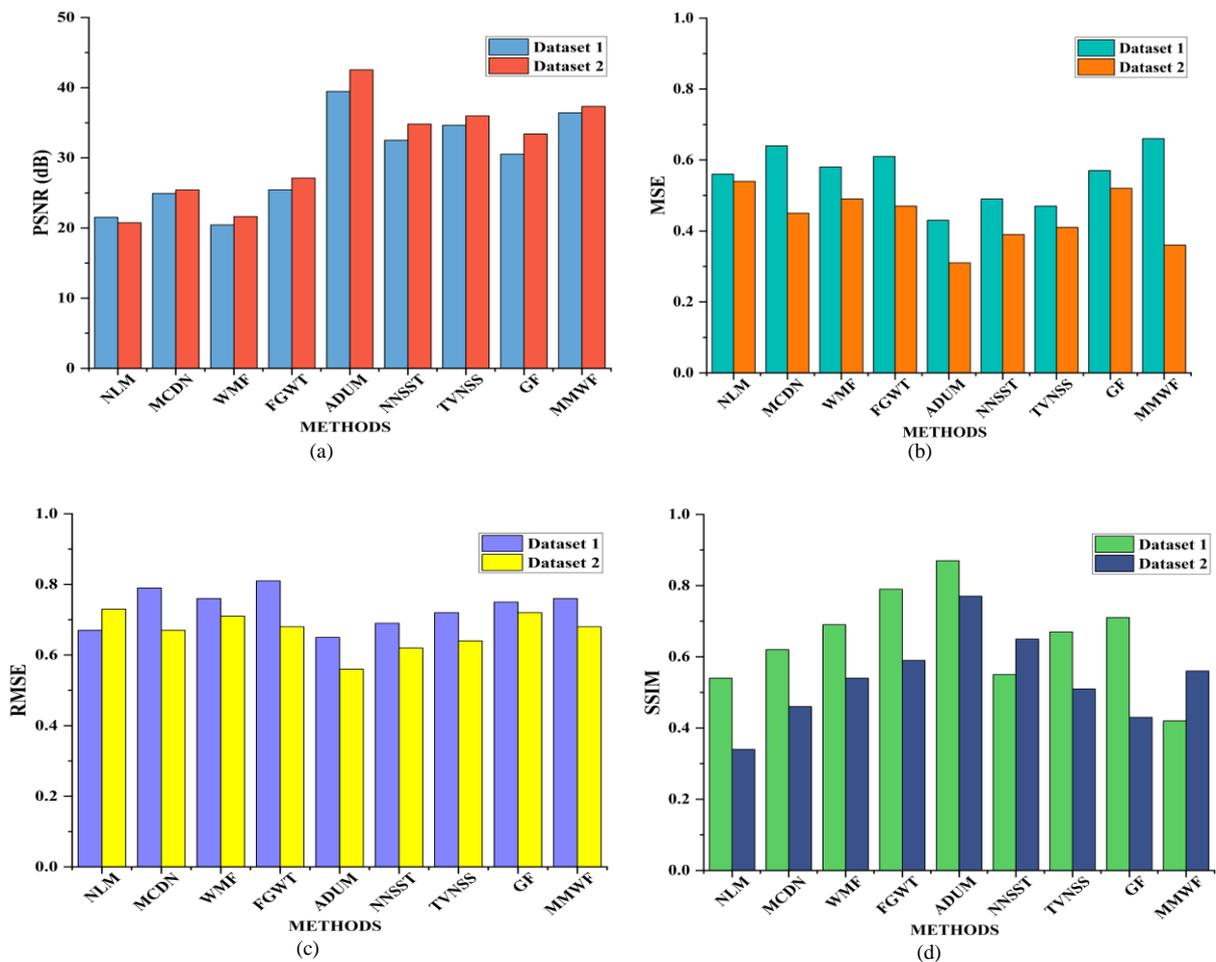
The performance assessment of various denoising techniques based on a range of parameters provides valuable insights into their effectiveness in improving

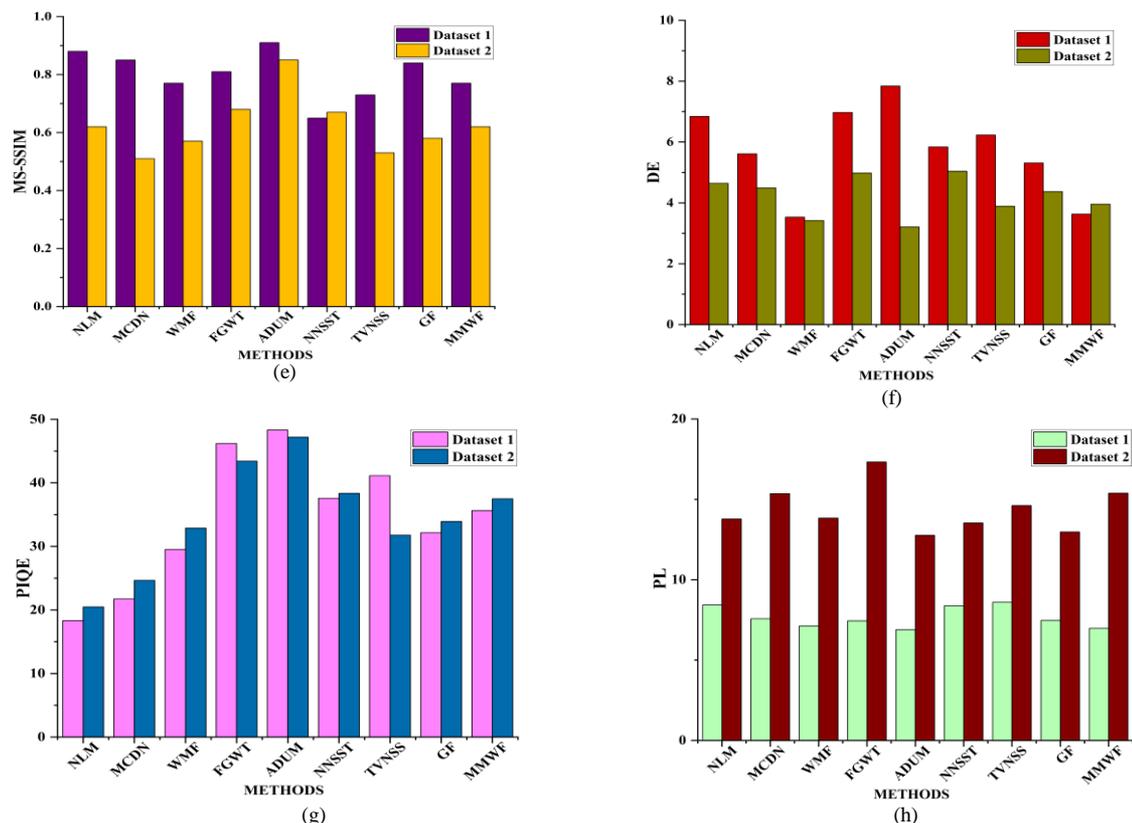
the quality of brain MR images. The best values are highlighted with bold letters. Among the evaluated methods, ADUM emerges as the most optimum

technique, exhibiting better results across multiple metrics. Remarkably, ADUM achieves the highest PSNR and SSIM values, indicating its ability to preserve image details and structural information while reducing noise interference. Low MSE values show accurate prediction and closeness to input data. Moreover, ADUM demonstrates comparable performance in terms of MS-SSIM and PIQE, highlighting its efficacy in enhancing both local and global image features. However, for DE only, dataset 2 is giving the best value in comparison to other methodologies, but overall ADUM is the only method showing the best value in the majority of parameters for both datasets. Also, the value of perceptual loss for dataset 1 and dataset 2 for ADUM are coming out to be 6.89 and 12.76, respectively. The PL value obtained with ADUM is less than all other PL values obtained through the integration of CNN with methodologies. A low PL value means the output image features are very similar to the input image. This means that the obtained output MR image will look very natural and similar to the original image. In addition to this, for dataset 1, the p-values for PSNR and SSIM are coming out to be 0.008 and 0.0011, respectively. For dataset 2,

the p-values are 0.002 and 0.007 for PSNR and SSIM, respectively.

These values are  $<0.005$ , showing output is statistically significant. It is observed in Tables 2-3 that a few other methods exhibit comparatively lower scores across most evaluation parameters, suggesting limited effectiveness in achieving significant noise reduction without compromising image quality. Among all, it can be concluded integrating CNN and ADUM shows a lot of promise for making it easier to diagnose brain disorders by making images clearer and more accurate. Apart from numerical superiority, ADUM achieves superior computation efficiency as it eliminates complex global operations such as non-local patch searches and wavelet transforms. It parallelizes local computations, reduces unnecessary post-processing steps, memory, and parameters, and does not require expensive training datasets. This improves computing efficiency, making this method a great real-time denoising solution for medical imaging. Fig. 6 illustrates the comparative histogram plot of the quantitative assessment parameter values obtained with different denoising techniques that are shown in Table 3.





**Fig. 6:** Comparative quantitative analysis of different denoising techniques in terms of performance assessment parameters: (a) PSNR, (b) MSE, (c) RMSE, (d) SSIM, (e) MS-SSIM, (f) DE, (g) PIQE, and (h) PL

### Discussion

The evaluation of denoising techniques for brain MR images presented in this study highlights both the advancements achieved and the ongoing challenges in enhancing the diagnostic precision of neurological disorders. Our findings demonstrate the effectiveness of Anisotropic Diffusion Unsharp-Masking (ADUM) with CNN in significantly reducing noise interference while preserving essential image features, surpassing other existing methods. The obtained results suggest that this method holds promise for improving the reliability of brain abnormality diagnosis, crucial for accurate prognosis and treatment planning in neurological healthcare. An important part of this study is evaluating the results using both qualitative and quantitative measures. Through these evaluation approaches, the performance of those methods can be understood from different perspectives. The noise-free MR images obtained after denoising are important for accurate result interpretation and improving the diagnostic accuracy of brain disorders. Further, it is important to think about how these methods of denoising will work in real clinical situations. Denoising enhances the quality of MR images, leading to more reliable diagnoses and minimizing the risk of misinterpretation. Things like computational

difficulty are reduced, aiding in better disease monitoring and prognostic prediction. The denoising method optimizes diagnostic quality with a reduced scan processing time. Not only does this lessen the discomfort that patients experience, but it also improves imaging efficiency in extremely busy radiology departments. Apart from accuracy and efficiency, denoised images also contribute to the safety of patients. Once the good-quality denoised MR image quality is obtained, there is no need for further scanning for abnormality diagnosis, leading to the safety of the body from harmful radio waves. Also, non-repetition of MR imaging reduces additional costs for multiple scans. Enhanced patient experience can be achieved by the utilization of shorter and more efficient imaging sessions, particularly for patients who are claustrophobic, elderly, or pediatric and who may have difficulty with extended scans. In general, developments in techniques for lowering noise in MR images could make both the clinical workflow and the quality of care for patients better in the field of neuroimaging.

### Conclusion and Future Aspects

Many brain diseases can only be diagnosed and predicted with the help of MR images. Getting rid of noise in an MR image is a key part of making brain abnormality

detection more accurate and reliable. Reducing the noise present in MR scans is important for enhancing anatomical structures and minor abnormalities. Not only does this process of denoising make it easier to see small details, but it also makes diagnostic tools more accurate, which are used to find and explain brain problems. This manuscript examines the effectiveness of various denoising modalities in enhancing MR images using two brain MR image datasets. The experimental results are evaluated using both qualitative and quantitative methods to give a full assessment of the different denoising methods while maintaining the structural details of the input MR images. These analyses have identified ADUM as the optimal method for denoising and contrast enhancement. A hybrid model has been designed by integrating ADUM with CNN that significantly improves feature extraction and abnormality detection. The results show that the proposed methodology enhances abnormality diagnosis while preserving the structural details of the input image, making it a valuable tool for medical application.

Even though ADUM has shown promising results, getting the best denoised MR image is still a challenge. More research in this area is necessary to enhance MR imaging's ability to diagnose abnormalities related to brain healthcare. To build on these results, more research could look into using deep learning algorithms like Generative Adversarial Networks (GANs) or transformer-based models to improve feature extraction and denoising performance based on specific brain imaging characteristics found in MR images of people with brain disorders. Further optimization of CNN architecture can be done to enhance model efficiency and generalizability across different MR image datasets. Also, real-time clinical validation with medical professionals and radiologists is essential to practical deployment, verifying that the proposed technology meets medical diagnostic standards.

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## Author's Contributions

**Kavery Verma:** Formal analysis, writing original draft, software.

**Subodh Srivastava:** Writing review and edited, supervision, visualization, validation.

**Ritesh Kumar Mishra:** Writing review and editing, supervision, visualization, validation. This section should

state the contributions made by each author in the preparation, development and publication of this manuscript.

## Ethics

The authors confirm that this manuscript has not been published elsewhere and we have no ethical issues.

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