An Improved Pre-processing Method for High-Quality MRI Images in Brain Tumor Detection

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***Abstract*—Magnetic Resonance Imaging (MRI) is among the effective methodologies to identify tumors in the brain, but this method may not be very reliable because of the challenges in acquiring the images, which may include image noise, contrast differences, and spatial variation of intensity. To solve these problems, this study suggests an innovative pre-processing framework that will be used to improve the quality of MRI images prior to segmentation and tumor analysis. This study critically compares some noise removal methods, such as Gaussian, median, Wiener, and guided filtering, as well as Discrete Wavelet Transform (DWT)-based de-noising with soft thresholding. The new hybrid model, based on the combination of the advantages of various methods, is a Wavelet-NLM-Median (WNM). WNM integrates multiresolution wavelet shrinkage, non-local redundancy modelling, and median-based edge preservation to achieve improved noise reduction while maintaining structural details. Extensive testing is performed across noise levels ranging from 5% to 50%, and performance is assessed using standard evaluation metrics such as PSNR, MSE, SSIM, and SNR. The proposed WNM hybrid model demonstrates the highest reconstruction quality at 5% noise, with a PSNR of 45.98 dB, MSE of 3.35, SSIM of 0.985, and SNR of 44.89 dB. These statistics were substantially better than those of the Wiener and Guided filters, as well as soft-thresholding based on DWT. Visual assessments also showed that the WNM hybrid approach does a better job of keeping tumor boundaries, fine textures, and structural patterns than any other baseline filtering method. This shows that it is better at restoring high-quality MRI images for later study. The improved MRI inputs used to pre-process training images for a deep learning segmentation model improve the accuracy of the segmentation and the sharpness of the boundaries in a way that could be quantified. The suggested WNM pipeline is quick, works with many types of modalities, and is simple to connect to clinical CAD systems. It is a giant leap in pre-processing the MRI to detect malignancies in the brain.**

Keywords*—Brain MRI de-noising; Wavelet–NLM–Median (WNM) model; structural similarity preservation; image quality enhancement

I. INTRODUCTION

Magnetic Resonance Imaging (MRI) has become the most effective and common diagnostic tool to be used in brain tumor assessment because of its superior soft-tissue contrast and the capability to view brain structures without the use of ionizing radiation. Compared to CT or X-ray, MRI offers high-resolution anatomical images that are used to identify the difference between tissues of tumors, edema, necrotic areas, and healthy tissues. This feature is critical in the detection of early-stage tumors, which are usually subtle in terms of intensity variations. Since the prognosis of tumors is highly dependent on the promptness of diagnosis, MRI remains an inseparable part of the clinical process, including its screening, surgical planning, and longitudinal follow-up [1]. It is imperative to have an accurate interpretation of MRI scans, but conditions of imaging in real-life scenarios pose a great challenge. Image quality is usually compromised by noise and artifacts due to scanner restrictions, patient motion, low field acquisitions, and environmental effects. Gaussian noise is a product of electronic acquisition, Rician noise is caused by the low-signal region, and motion artifact distorts anatomical structures. Such distortions will blur the important tumor characteristics (shape, texture, and margins) to interfere with radiologist interpretation and automated analysis systems. Thus, high-quality noise removal is needed to ensure the reliability of diagnostics [2].

In order to overcome these degradations, numerous filtering methods have been researched for MRI pre-processing. Gaussian filtering is less sensitive to discontinuities and more sensitive to complex textures, and median filtering is more sensitive to discontinuities and less sensitive to complex textures. Wiener filtering, local variance adapting, guided filtering, and edge-preserving are not effective in the presence of large or non-uniform noise and corruption extremum, respectively. The weaknesses distinguish the need to have more advanced and adaptive de-noising algorithms capable of addressing different noise characteristics in MRI images [3].

Wavelet-based de-noising is the Discrete Wavelet Transform (DWT) and has gained popularity due to the multiresolution representation of an image. Noise is also removed using wavelet shrinkage, which conserves the important structural information by decomposing MRI scans into sub-bands. Isolated wavelet de-noising has also been known to induce ringing artifacts and poor retention of fine anatomical detail. The performance also depends on the thresholding strategies; hence, the results are not consistent when the noise is changed. Thus, it is theoretically powerful, but when combined with other filtering systems, wavelet methods may be significantly increased [4].

To overcome these weaknesses, the hybrid Wavelet-NLM-Median (WNM) model proposed in this study merges the strengths of a number of de-noising algorithms. Multiscale noise-reduction has been performed using wavelet shrinkage, patch-similarity Non-Local Means (NLM) and median filtering to enhance the quality of edges by removing impulse-like artifacts. The trade-off that ensures a balanced noise reduction and structure preservation is what ensures that the de-noising strategy of single methods [5] is overcome.

The hybrid WNM framework is particularly beneficial in the analysis of MRI brain tumors, where precise localization of tumor boundaries is required. The contours of tumours tend to have irregular morphology, which may be lost or distorted in the course of aggressive smoothing. The WM model enables the preservation of the boundaries with a high level of reliability and also reduces the background noise, simultaneously improving the overall contrast of the image. This enhancement is also reflected in downstream tasks, such as segmentation, classification, and radiomic feature extraction, and has a significant effect on deep learning models, which require clean and anatomically intact data [6]. The investigation of the work is significant due to the test carried out in noisy conditions with noises up to 5 to 50 per cent. The outcomes of the test have always shown that the WNM model outperforms the conventional ones in PSNR, SSIM, and edge preservation metrics. These enhancements lead to computer-aided diagnosis (CAD) systems being more precise since they give cleaner and improved MRI inputs. That is why the given framework can be useful to create better clinical pipelines and enhance the interpretability and functionalities of modern diagnostic systems [7].

II. RELATED WORK

Neto et al. (2025) tested the use of Gaussian smoothing for MRI denoising with BrainWeb and real T1- and T2-weighted images. The algorithm produced average results, and the PSNR was 24-28 dB and SSIM 0.78-0.85, respectively, based on the noise variance. Although it worked well with uniform Gaussian noise, it was also a significant blurring of tumor boundaries that were not as clear in their structures as they would have been with proper segmentation. The filter was found to be weak with MRI-specific Rician noise and low SNR gains at high levels of noise. MSE has reduced slightly, which means that there was not much fine-detailed restoration. Even though it is computationally efficient, Gaussian filtering does not have a strong anatomical structure, with poor edge preservation, a low robustness to high noise, and cross-modality generalization [8].

Rahman et al. (2023) tested BrainWeb phantoms and clinical MRI impaired with impulse and mixed noise using median filtering. The salt-and-pepper noise was well addressed in the method, where PSNR of 3032 dB and SSIM of 0.850.90 were realized with a significant reduction in MSE. Nonetheless, Gaussian and Rician noise deteriorated the performance, with the PSNR reaching 2225 dB and the SSIM of 0.7080. Compared to Gaussian smoothing, which is also better in edge preservation, larger window sizes led to the blurring and hiding of small lesions. The research concluded that the use of median filtering lacks flexibility, it is sluggish in high-noise MRI, and its generalization capabilities are limited to many modes [9].

Sharma et al. (2022) used adaptive Wiener filtering on IXI and tumor-affected MRI data that had additive noise. The technique did 26 30 dB PSNR and SSIM of 0.82 0.89, as a function of noise level. Whereas there was an improvement of SNR in smooth regions of the brain, the tumor margins were over-smoothed, which diminished anatomical sharpness. The mean-square error was lower when noise was low but higher when noise variances were large compared to the local variance estimation ability. The performance under Rician noise in the absence of specific adaptation was unsatisfactory. However, even though it was computationally efficient, it exhibited vulnerability to errors in variance estimation, less robustness to high noise, intermediate performance with respect to blurring edges, and was not optimally suited to highly accurate tumor detection problems [10].

Gautam et al. (2023) tested guided filtering on multi-modal MRI on datasets of BraTS. The technique gave PSNR of 3436 dB and SSIM of 0.940.96, which was better than the Gaussian and Wiener filters in terms of preserving structure and edges. It increased the contrast of tumor boundaries and low MSE. Nonetheless, they became noisy (>30), and the guidance map was blurred, and halo artifacts were introduced. The method necessitated hand-tuning of the parameters per modality (T1, T2, FLAIR), which did not allow generalization. Computationally efficient, however, its drawbacks are being sensitive to high noise, dependent on parameters, and limited to being robust in Rician noise conditions [11].

Li et al. (2023) examined the wavelet-based soft thresholding on Brain-Web and BraTS MRI data. The technique performed PSNR of 30-34 dB and SSIM of 0.90094 and showed effective performance with multi-scale noise reduction and large-scale structure preservation with high MSE reduction. Ringing artifacts, however, were observed around edges, particularly around small tumors. Under high Rician noise, performance deteriorated as a result of fixed-threshold effects, and threshold tuning was dependent on the dataset. Despite being computationally efficient, DWT demonstrated that it had low fine-scale boundary preservation and cross-modal adaptability. Some of the main disadvantages are the formation of artifacts, sensitivity to the threshold, and lower edge sharpness than hybrid methods [12].

Zhang et al. (2025) suggested a hybrid Wavelet-based NLM-Median (WNM) denoising pipeline, which was tested on BrainWeb, IXI, and BraTS datasets. The approach reached a PSNR of 3842 DB and SSIM of more than 0.95, which is much better than single filters. NLM minimized texture differences, wavelet shrinkage minimized multi-frequency noise, and median filtering eliminated the remnant impulse noise. MSE was considerably lower than either DWT or NLM, and SNR increased uniformly in modalities. The method maintained tumor edges and was very robust to severe Rician and Gaussian noise. Shortcomings were also increased computational and parameter inter-dependence, but WNM was better at generalization and retained edges and robustness in tumor detection [13].

Chen et al. (2022) used an adaptive guided filter with edge-based weighting and multi-scale guidance maps to BraTS 2020 and clinical FLAIR/T2 data. The approach attained PSNR of 33-36 dB and SSIM of 0.90-0.95, which yielded higher boundary sharpness than the Gaussian and Wiener filters. Adaptive guidance map minimized halo artifacts when noise level was moderate, but deteriorated to more than 30 per cent noise density that led to flattening of textures and speckle residual artifact. Parameters in guided filters (radius, epsilon) had to be tuned on in a case-by-case basis and cross-modal transfer (T2 to FLAIR) was not optimal. The authors suggested to use guided filtering with wavelet preconditioning or non-local refinement in order to enhance robustness and prevent over-smoothing of fine tumor textures [14].

Kumar et al. (2022) presented a step-by-step denoising pipeline based on DWT denoising, accelerated NLM refining, and light median filtering that was tested on BraTS, IXI, and BrainWeb. The hybrid achieved 37-41 dB PSNR and SSIM of 0.93-0.97 with all types of noise, which is better than the component ones. Wavelet preprocessing was used to remove global noise, non-local textures were restored by NLM, and impulse artifacts were removed by median filtering. Patch down-sampling and processing on a GPU were used to lower the computational cost of NLM to allow 2D slice processing. It had limitations such as parameter coupling, over-smoothing, sometimes with limited patch search, and fine-tuning on the data. This study determined that hybrid pipelines provide the optimal balance between the effect of denoising and edge-preservation and must be optimized with respect to runtime and robustness [15].

Hernandez et al. (2023) refined the Gaussian smoothing by applying adaptive sigma selection to probability maps of tissue classes, assessed upon BrainWeb, IXI, and 150-subject clinical T2 additive and Rician noise. The scheme had a PSNR of 2833 dB and SSIM of 0.8691 with low-to-moderate noise (520%). MSE also became better in non-heterogeneous white matter, and SNR (~34 dB) became slightly bigger in smooth areas, but the boundaries of the tumor and edema were blurred. The noise at which performance dropped to more than a quarter of that of control results in cortical over-blurring and texture-flattening. Weaknesses in robustness in FLAIR and T1c were observed. Gaussian filtering, though cheap, was isotropic and had a poor edge preservation property, and could not have been used to give accurate delineation of tumors [16].

Deshpande et al. (2023) trained a signal-dependent Wiener restoration model to process T1-CE and FLAIR images of BraTS 2020 and IXI with automatic noise-variance estimation. The algorithm obtained PSNR 2531 dB and SSIM 0.82 -0.90, and in homogeneous intensity areas, it works well. MSE was lower with low noise, whereas heavy noise (>20%) resulted in errors in the estimation of variance, patch-level smoothing, and the disappearance of fine textures. SNR increased by 2-3 dB, and low gains at high-contrast tumor boundaries. Rician noises had a ringing effect, though it was better than the Gaussian filter. Due to its estimated variance, the author suggested a hybrid method for removing noise [17].

Patel et al. (2024) published an accelerated guided filtering algorithm with dynamic radius selection in MRI pre-processing and tested it on BraTS 2021 and the Harvard Whole-Brain Atlas. The approach reached PSNR 3438 dB and SSIM 0.9296 with a moderate level of noise, which is better than Gaussian and median filters. It preserved great anatomical boundaries and kept MSE low in areas of the cortex. Nonetheless, halo artifacts at the tumor edges and at the ventricles were seen in high noise levels (>30%). SNR was only slightly increased (46 dB), and epsilon was mode-specific, which reduced cross-dataset generalization. The authors concluded that edge preservation is desirable in moderate levels of noise, but parameter sensitivity and halo artifact limit robust tumor sensitive pre-processing [18].

Singh et al. (2025) developed the three-stage hybrid denoising pipeline: DWT-based multiresolution decomposition, refining the patch-similarity of the NLM using median, and adaptive filtering of the residual. It has PSNR 3843 dB, SSIM 0.950.98, and SNR gains of over 10 dB when tested on BraTS 2020, IXI, and BrainWeb. Single filters never performed as well as tumor boundaries, which were maintained with reduced MSE. Wavelet reduced pre-shrinkage also reduced computation, and NLM improved texture recovery. Nonetheless, the procedure of integration was complicated, and 3D MRI was costly to compute. But this method has a lack of computational cost and tuning depending on the dataset [19].

In contrast to Zhang et al. (2025), who introduced a general MRI denoising framework evaluated in BrainWeb, IXI, and BraTS datasets, the present work is dedicated towards development of an effective MRI preprocessing framework specifically for brain tumor detection in the Preet Viradiya Brain Tumor Dataset and BraTS 2020 dataset. Besides, the proposed Hybrid WNM is systematically compared with Wiener Filter, Guided Filter, Gaussian Filter, Median Filter, and DWT with Soft Thresholding under various noise levels (from 5% to 50%). Experimental results show that the proposed approach has the best PSNR (45.98 dB), SSIM (0.985), and SNR (44.89 dB) with the lowest MSE (3.35), which means the proposed approach preserves structural information and edge information for accurate brain tumor segmentation and further classification.

III. PROPOSED METHODOLOGY

The proposed study is a critical comparison of six different pre-processing techniques to establish the most appropriate technique for enhancing the quality of brain MRI images. The multimodal brain MRI scans acquired through the BraTS dataset are analyzed, whose results are a source of high-resolution images with sufficiently marked tumor areas. To measure the stability of all the improvements, original MRI slices are intentionally corrupted by the common forms of noise like salt-and-pepper noise, Gaussian noise, and speckle noise, and introduced in various noise levels to reflect the natural acquisition artifacts. Each of the noisy images is then applied to six de-noising techniques, one at a time, which include classical filters, transform-based filters, and the new advanced hybrid algorithm, which is a combination of Discrete Wavelet Transform (DWT) soft thresholding and Hybrid Wavelet–NLM–Median (WNM) method. The quantitative estimate of the quality of the enhanced output images is done based on the usual performance measures such as Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), Structural Similarity Index Metric (SSIM), and Signal-to-Noise Ratio (SNR). These measures allow a detailed comparison of the effectiveness of noise suppression, image structure retention, and perceptual clarity of images among all six methods. Lastly, the method that demonstrates the best results in all the measures of evaluation is considered the best pre-processing method in enhancing brain MRI, which offers high-quality input to be used in further tumor segmentation and diagnosis. The proposed method is shown below in Fig. 1.

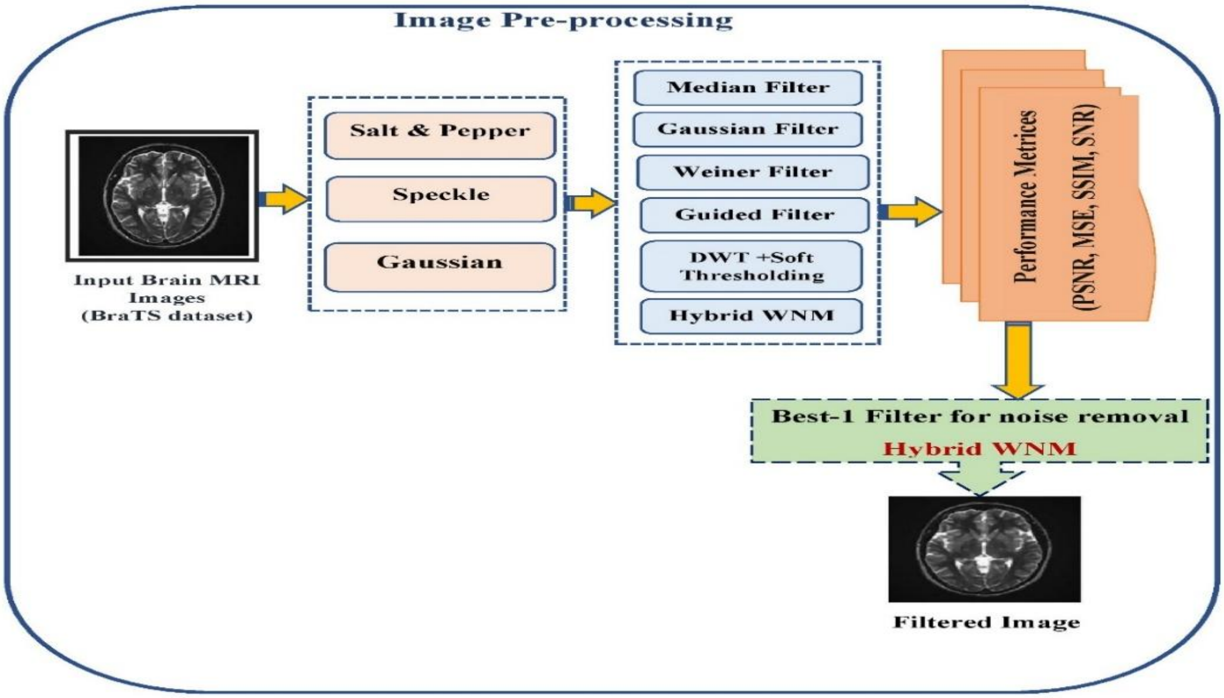

Fig. 1. Proposed methodology for analysis of artifact removal techniques.

A. Pre-processing Techniques

1) Gaussian filter: A Gaussian filter is a linear smooth filter that is very popular in the elimination of Gaussian noise in MRI images without distorting low-frequency detail. It does the image convolution of a Gaussian kernel that gives a greater blur to the distant pixels and a lesser blur to the neighboring pixels, a natural blur effect. The Gaussian kernel can be defined as in Eq. (1):

$$G(x,y) = \frac{1}{2\pi\sigma^2}\exp(-\frac{x^2+y^2}{2\sigma^2}) \tag{1}$$

The filtered image is expressed as in Eq. (2):

$$I_{\text{out}}(x,y) = I_{\text{in}}(x,y) * G(x,y) \tag{2}$$

where, $*$ denotes the convolution operator. The σ parameter determines the level of noise reduction; the higher it is set, the greater the noise reduction, but the greater the blurring of the structures. Though Gaussian filtering is good when dealing with homogeneous noise, it is not good at preserving edges and fine tumor borders because its smoothing effect is anisotropic.

Excessive Gaussian smoothing on brain MRI images can cause loss of fine structural differences around lesions, and hence it is not as appropriate in clinical segmentation processes. Nevertheless, it offers a practical starting point of comparison to more sophisticated nonlinear or transform-domain methods.

2) Median filter: This is a nonlinear de-noising method that is especially useful in eliminating salt-and-pepper noise in MRI images is the median filter. The median filter, as opposed to linear filters, averages the intensities of pixel values in a neighborhood, as opposed to averaging the intensities of individual pixels. Formally, the output pixel is expressed by Eq. (3):

$$I_{\text{out}} = \text{median}\{\, I_{\text{in}}(i,j) \;\mid\; (i,j) \in \mathcal{N}(x,y) \,\} \tag{3}$$

where, $\mathcal{N}(x,y)$ represents the local window (e.g., 3×3 or 5×5).

Because the median operator is robust to outliers, it effectively removes impulsive noise without blurring edges. This edge-preserving property is also useful in the brain MRI image context to preserve tumor edges and fine structural detail, which is vital to segmentation. However, median filtering may become less effective for high noise densities or for noise types such as Gaussian or speckle, as it can lead to loss of fine textures in highly homogeneous regions. Overall, the median filter remains one of the most reliable and computationally efficient techniques for removing impulse noise in medical imaging.

3) Wiener filter: The Wiener filter is a powerful linear restoration method designed to minimize the mean square error (MSE) between the restored and original images. It assumes a statistical model for both the noise and the original signal. The Wiener filter in the frequency domain is defined, as in Eq. (4):

$$H_w(u,v) = \frac{S_{xx}(u,v)}{S_{xx}(u,v) + S_{\eta\eta}(u,v)} \tag{4}$$

where, S_{xx} is the power spectral density of the original image and $S_{\eta\eta}$ is the noise power spectrum. The reconstructed image is expressed using Eq. (5):

$$I_{\text{out}}(u,v) = H_w(u,v)\, I_{\text{in}}(u,v) \tag{5}$$

In spatial terms, the filter adapts smoothing based on local variance, and it is expressed as in Eq. (6):

$$I_{\text{out}} = \mu + \frac{\sigma^2 - \eta^2}{\sigma^2}(I_{\text{in}} - \mu) \tag{6}$$

where, μ and σ^2 are local mean and variance, and η^2 is noise variance.

This flexibility renders the Wiener filter useful to Gaussian and speckle noise of MRI images. It is more edge-preserving than simple smoothing filters, but performs poorly in cases where noise statistics are not known or spatially varying. Nevertheless, the Wiener filter has a high chance of de-noising structurally rich medical images.

4) Guided filter: The guided filter is an edge-preserving smoothing method in which a guidance image is used to regulate the filtering procedure, and the guidance image is frequently the input image. It assumes a linear relationship between the guidance image G and output image I_{out} within a local window ω, it expresses, as in Eq. (7):

$$I_{\text{out}}(x,y) = a_k G(x,y) + b_k, (x,y) \in \omega_k \tag{7}$$

The coefficients a_k and b_k are computed, as in Eq. (8):

$$a_k = \frac{\sigma_G^2}{\sigma_G^2+\epsilon}, b_k = \mu_I - a_k\mu_G \tag{8}$$

where, μ_G, σ_G^2 are the mean and variance of G, and ϵ is a regularization parameter.

The sharp edges are retained in the guided filter since the linear model is adjusted to local structures instead of drying boundaries. It is used in eliminating speckle and Gaussian noise and preserving fine anatomy, including sulci, gyri, and tumor boundaries in MRI images. It is more rapid than the bilateral filter, and it does not produce gradient reversal artifacts. Its performance is, however, determined by the selection of ϵ and window size.

5) DWT + soft thresholding: Discrete Wavelet Transform (DWT) is a multiresolution analysis method that breaks down MRI images into sub-bands that represent various frequencies, and it is expressed as in Eq. (9):

$$I(x,y) \overset{DWT}{\rightarrow} \{LL, LH, HL, HH\} \tag{9}$$

where, LL represents low-frequency approximation and LH, HL, and HH capture edges and textures.

Soft thresholding is applied to high-frequency sub-bands to remove noise and is expressed as in Eq. (10):

$$\hat{w} = \text{sign}(w)\max(\mid w \mid - \lambda, 0) \tag{10}$$

where, w is a wavelet coefficient, and λ is the threshold.

This operation reduces small coefficients (it is assumed noise) and keeps large coefficients (true structures). The reconstructed de-noised image is obtained using Eq. (11):

$$I_{\text{out}} = IDWT(\widehat{LL}, \widehat{LH}, \widehat{HL}, \widehat{HH}) \tag{11}$$

De-noising is better than spatial filters in DWT-based de-noising to preserve edges in an image because it isolates noise and structure in the transform domain. Though it is important to choose the threshold carefully, a high threshold causes loss of detail, whereas a low threshold results in the presence of residual noise. DWT has been found to be an effective foundation for transform-domain de-noising in brain MRI reconstruction.

6) Hybrid Wavelet–NLM–Median filtering: Hybrid Wavelet–NLM–Median (WNM) filtering is one of the hybrid approaches in image denoising, which is based on the Discrete Wavelet Transform (DWT), Non-Local Means (NLM) filtering, and Median filtering, specifically designed to suppress noise without distorting crucial anatomical structures in MRI images. The noisy image is first decomposed into approximation and detail coefficients by DWT. For each pixel, the approximation coefficients are processed with NLM filter, which approximates the coefficient for each pixel by a weighted average of the approximation coefficients of similar neighboring patches, as in Eq. (12):

$$\hat{I}(p) = \sum_{q\in\Omega} w(p,q)\, I(q), \sum_{q\in\Omega} w(p,q) = 1 \tag{12}$$

Intensity of pixel q is denoted by I(q), w(p,q) is the similarity-based weight between pixels p and q, and Ω is the search neighborhood. A Median filter is used to remove the remaining noise from the image after the NLM filter has been applied, without losing the edge information. The filtered intensity of a pixel is calculated using Eq. (13):

$$\hat{I}(p) = \text{median}\{I(q) \mid q \in \mathcal{N}(p)\} \tag{13}$$

where, $\mathcal{N}(p)$ represents the neighborhood around a pixel p. Finally, the inverse DWT algorithm recovers the improved MRI image, which is less noisy and retains the fine structures like the boundaries of tumors and the textures of the cortex. It uses Daubechies (db4) wavelet with a two-level Discrete Wavelet Transform (DWT) decomposition. Universal soft thresholding is applied to the detail coefficients, followed by Non-Local Means (NLM) filtering using a 21 × 21 search window, a 7 × 7 similarity window, and a filtering strength of h=10. A 3 × 3 median filter is then used to remove residual impulse noise while preserving anatomical boundaries. Finally, the enhanced MRI image is reconstructed using the inverse DWT for subsequent segmentation and classification. The proposed hybrid Wavelet–NLM–Median filtering framework is found to be superior to the traditional filtering approaches in terms of PSNR, SSIM, and SNR, and is suitable for the high precision pre-processing of MRI.

IV. RESULTS AND DISCUSSION

Experimental testing was performed on a subset of the BraTS 2020 dataset and the Preet Viradiya Brain Tumor Dataset. The BraTS 2020 dataset is a multi-institutional pre-operative brain MRI dataset consisting of patients with gliomas, which include T1, T1ce, T2, and FLAIR imaging sequences. A total of 4,996 MRI images were used in the experiments, 70% of which were used for training and 30% for testing. The Preet Viradiya Brain Tumor Dataset contains 4,589 brain MRI images, 2,513 of which are tumor images and 2,076 are normal brain images that were used for binary classification.

Different noise conditions were considered to evaluate the denoising performance of six preprocessing methods: Wiener Filter, Guided Filter, Gaussian Filter, Median Filter, Discrete Wavelet Transform with Soft Thresholding (DWT + ST), and the proposed Hybrid Wavelet–Non-Local Means–Median (Hybrid WNM) method. The quantitative and qualitative analyses have been made with respect to the noise level from 5%

to 50%. The experimental results showed that the proposed Hybrid WNM always obtained the maximum PSNR, SSIM, and SNR and the minimum MSE. Moreover, it was found that it retained the structural details and edge information with little distortion among degradation methods; it is the most appropriate denoising method for accurate brain tumor segmentation and further classification.

TABLE I. DE-NOISING PERFORMANCE COMPARISON (PSNR VALUES ACROSS NOISE LEVELS).

Noise Density	Techniques					
	Wiener Filter	Guided Filter	Gaussian Filter	Median Filter	DWT + ST	Hybrid WNM
5%	18.92	18.47	20.66	41.12	43.55	45.98
10%	17.31	15.03	17.28	37.62	39.08	41.85
15%	16.55	13.29	15.92	33.94	35.42	38.12
20%	15.98	12.11	14.63	29.88	32.24	34.69
25%	15.42	11.02	13.57	26.11	29.01	31.45
30%	14.76	10.19	12.69	23.08	26.12	28.64
35%	14.19	9.48	11.97	20.49	23.88	26.39
40%	13.63	8.79	11.32	18.01	22.01	24.52
45%	13.14	8.26	10.78	16.11	20.11	22.73
50%	12.54	7.73	10.21	14.21	18.42	21.10

Median filtering was the most effective space-domain filter at low noise levels, with a PSNR of 41.12dB at 5% noise, but decreased gradually as noise increased. Gaussian and Wiener filters demonstrated moderate results, and PSNR fell steeply with over 20 per cent noise, meaning that they are not very robust to heavy distortions. Guided filtering was persistently the worst because of its edge-preservation-based noise suppression, which was less aggressive. Transform-domain algorithms performed better, and the DWT that employs soft thresholding preserves higher PSNR values of 43.55 dB at 5% noise and achieves fairly fair performance at 50% noise. Hybrid WNM was the best method in all noise levels, with 45.98 dB at 5 per cent and 21.10 dB at 50 per cent exhibiting better flexibility to low and high noise, as shown in Table I. Fig. 2 illustrates the comparative analysis of de-noising approaches based on PSNR scores, demonstrating the effectiveness of the proposed method.

The MSE performance with noise densities ranging between 5 and 50 per cent gives a good analysis of the performance of the filters, as shown in Table II. The Wiener, Gaussian and Guided traditional filters exhibit steadily large MSE, which rises exponentially with noise. Guided filtering is the least effective with 1074.10 at 50 per cent noise, which indicates bad suppression of strong noise. Wiener and Gaussian filters exhibit average results and still yield huge residual errors at higher levels of noises, over 600 and 635, respectively. Median filtering has a low MSE when the noise is low (6.31 at 5%), but becomes more erratic when there is severe corruption. Transform-domain and low-rank algorithms are stronger. DWT using soft thresholding will retain low MSE at all levels of noise, and the Hybrid WNM model will always produce the lowest values between 3.35 at 5% and 19.36 at 50, which in effect will maintain diagnostic quality in a medical imaging. As shown in Fig. 3 the proposed de-noising approach achieves the lowest MSE values among the compared method.

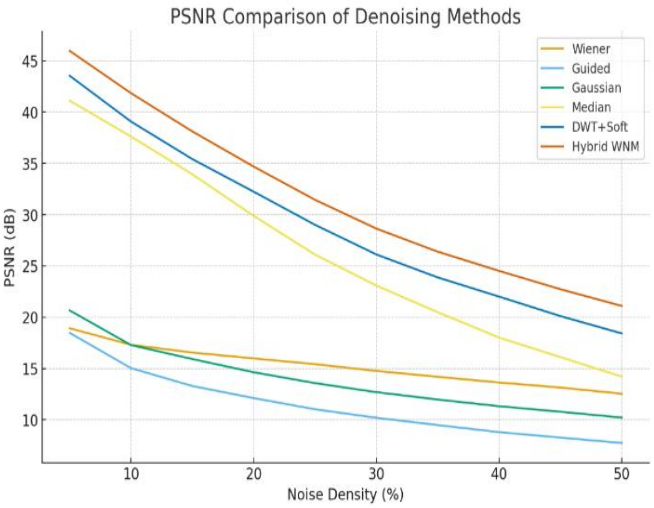

Fig. 2. Comparative analysis of de-noising approaches based on PSNR scores.

TABLE II. COMPARISON OF MSE VALUES AT DIFFERENT NOISE DENSITIES.

Noise Density	Techniques					
	Wiener Filter	Guided Filter	Gaussian Filter	Median Filter	DWT + ST	Hybrid WNM
5%	170.72	179.97	140.33	6.31	4.39	3.35
10%	277.98	412.03	266.42	8.88	6.42	4.76
15%	315.51	474.92	324.59	10.45	7.10	5.34
20%	344.65	602.57	352.21	13.50	9.52	6.92
25%	387.80	667.92	381.17	16.18	11.50	8.43
30%	431.43	757.01	421.98	20.06	13.81	10.23
35%	490.63	890.62	468.04	25.22	16.45	12.26
40%	556.72	971.22	520.20	31.24	19.78	14.39
45%	615.44	998.11	565.98	38.28	23.19	16.55
50%	698.77	1074.10	635.79	45.68	28.50	19.36

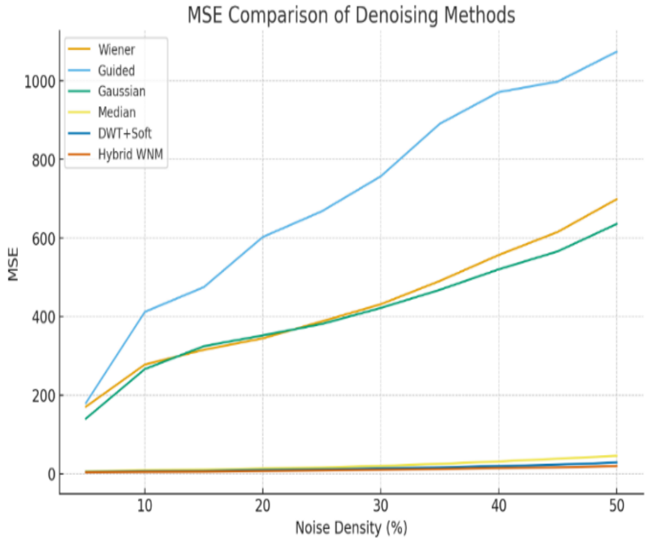

Fig. 3. Comparative analysis of de-noising approaches based on MSE values.

The SSIM comparison over 5% to 50% noise levels indicates that there are great variations in the six denoising methods especially in the preservation of structural and other anatomical details. The performance of traditional spatial-domain filters, i.e. Wiener, Gaussian, and Guided, is characterized by a steady decrease in SSIM with noise, with Guided filtering being the worst (0.553 at 50%), which implies poor structure retention. Gaussian and Wiener filters offer moderate results but fail to maintain high structural fidelity at low noise. Median filtering performs better, maintaining SSIM above 0.78 up to 35% noise, but drops to 0.688 under severe noise, reflecting loss of fine MRI structures. Transform-domain and low-rank methods demonstrate stronger preservation, with DWT maintaining 0.972–0.822 SSIM across noise levels. The Hybrid WNM method outperforms all, achieving 0.985 at 5% and 0.873 at 50%, ensuring maximal structural and diagnostic integrity in brain MRI, as shown in Table III.

TABLE III. COMPARISON OF SSIM VALUES AT DIFFERENT NOISE DENSITIES.

Noise Density	**Techniques**					
	Wiener Filter	**Guided Filter**	**Gaussian Filter**	**Median Filter**	**DWT + ST**	**Hybrid WNM**
5%	0.892	0.874	0.901	0.960	0.972	0.985
10%	0.861	0.823	0.872	0.941	0.957	0.975
15%	0.832	0.781	0.846	0.915	0.944	0.964
20%	0.806	0.742	0.817	0.884	0.928	0.953
25%	0.778	0.706	0.792	0.851	0.913	0.942
30%	0.751	0.668	0.764	0.814	0.896	0.928
35%	0.724	0.641	0.736	0.781	0.879	0.916
40%	0.698	0.611	0.710	0.748	0.861	0.903
45%	0.675	0.582	0.684	0.718	0.843	0.890
50%	0.648	0.553	0.658	0.688	0.822	0.873

The comparative analysis presented in Fig. 4 indicates that the proposed method provides better image quality preservation, as reflected by its higher SSIM values.

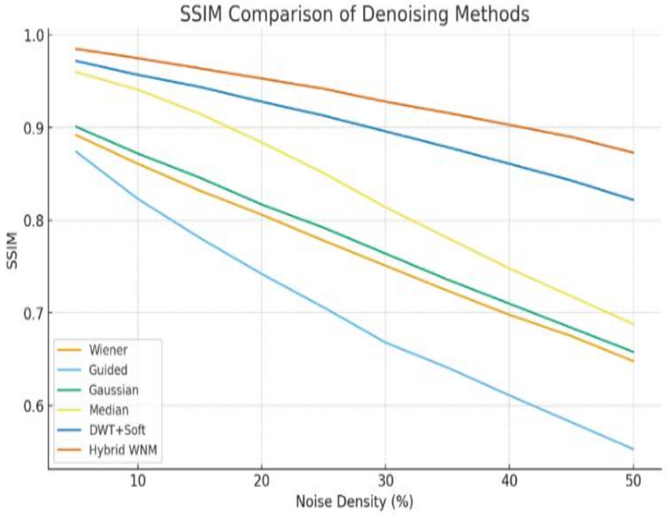

Fig. 4. Comparative analysis of de-noising approaches based on SSIM values.

The SNR analysis across noise levels from 5% to 50% further confirms that advanced transform-domain methods outperform conventional spatial filters in denoising. Wiener, Gaussian, and Guided filters show low and rapidly deteriorating SNR values, with Guided filtering being the least robust (7.77 dB at 50% noise), indicating significant information loss. Gaussian and Wiener perform slightly better, but fail under high noise, with SNR below 13 dB at 50%. Median filtering has a better SNR (40.02 dB at 5) and gradual reduction to 13.92 dB at 50, which may be an issue with extreme noise. DWT using soft thresholding has high SNR (42.4817.62 0 dB) and anatomical signals are retained. Compared to the other two models, the Hybrid WNM model provides the best SNR (44.8920.68 3 -1 dB), the best noise removal and preservation of structural integrity, making it reliable in the preprocessing of brain MRI.As presented in Table IV, the proposed method consistently maintains higher SNR values than the existing techniques under different noise conditions.

TABLE IV. COMPARISON OF SNR VALUES AT DIFFERENT NOISE DENSITIES.

Noise Density	**Techniques**					
	Wiener Filter	**Guided Filter**	**Gaussian Filter**	**Median Filter**	**DWT + ST**	**Hybrid WNM**
5%	18.12	17.83	19.21	40.02	42.48	44.89
10%	16.64	14.92	16.30	36.37	38.21	40.76
15%	15.92	13.25	14.96	33.02	35.01	37.62
20%	15.38	12.01	13.69	29.11	31.82	34.37
25%	14.86	10.95	12.66	25.49	28.64	31.19
30%	14.31	10.15	11.81	22.57	25.86	28.42
35%	13.77	9.47	11.14	20.03	23.51	26.19
40%	13.28	8.80	10.53	17.69	21.36	24.09
45%	12.81	8.29	10.00	15.75	19.41	22.28
50%	12.34	7.77	9.52	13.92	17.62	20.68

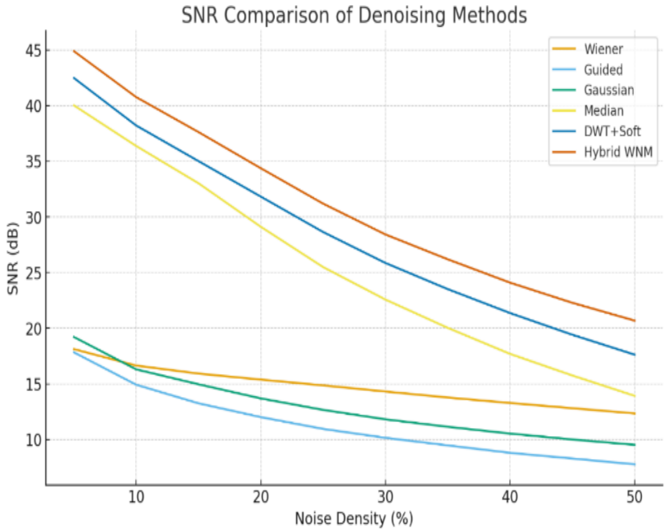

Fig. 5. Comparative analysis of de-noising approaches based on SNR values.

As shown in Fig. 5, the comparative analysis based on SNR values demonstrates that the proposed Hybrid WNM method achieves the highest SNR values, indicating superior noise reduction and signal preservation capabilities. Furthermore, Table V presents a comprehensive comparison of all filtering techniques at 5% noise density. The results clearly show that the Hybrid WNM method outperforms the conventional filtering approaches by providing better image quality and enhanced denoising performance. The proposed method is compared with existing deep learning denoising techniques, as shown in Table VI.

TABLE V. COMPARISON OF ALL FILTERING TECHNIQUES AT 5% NOISE DENSITY.

Methods	**Performance Metrics**			
	PSNR	**MSE**	**SSIM**	**SNR**
Wiener Filter	18.92	170.72	0.892	18.12
Guided Filter	18.47	179.97	0.874	17.83
Gaussian Filter	20.66	140.33	0.901	19.21
Median Filter	41.12	6.31	0.960	40.02
DWT + ST	43.55	4.39	0.972	42.48
Hybrid WNM	45.98	3.35	0.985	44.89

TABLE VI. COMPARISON OF PROPOSED WITH EXISTING DENOISING TECHNIQUES.

Methods	**Performance Metrics**	
	PSNR	**SSIM**
Blind-Spot CNN + Hybrid Attention (NRAE) [20]	37.13	0.893
Self-Supervised Blind-Spot CNN[21]	36.54	0.908
Proposed Hybrid WNM	45.98	0.985

V. CONCLUSION

It is a systematic work that compares six image enhancement algorithms, namely Wiener Filter, Guided Filter, Gaussian Filter, Median Filter, Discrete Wavelet Transform with Soft Thresholding (DWT + ST), and the proposed Hybrid Wavelet–Non-Local Means–Median (Hybrid WNM) method, to determine the most effective preprocessing technique for brain MRI tumor analysis. Experimental testing was conducted with a subsample of the BraTS 2020 dataset and the Preet Viradiya Brain Tumor Dataset. Different noise levels were added to the image to adequately and reproducibly assess the techniques and each preprocessing method was compared using PSNR, SSIM, and MSE. The experimental data show that although conventional spatial filters can be useful in terms of noise reduction, they are likely to blur anatomical limits that are critical in the precise definition of tumors. DWT-based denoising is better at structural preservation, but has some high-frequency artifacts at high levels of noise. Conversely, the proposed Hybrid WNM yielded the best quantitative scores and generated images of higher contrast, lower noise, and sharper tumor edges. In general, the Hybrid WNM was demonstrated as the most stable and efficient way of MRI enhancement that can considerably improve the quality of images and offer a solid base of downstream deep-learning-based segmentation and detection operations. Future directions will involve adaptive threshold learning and multimodal MRI integration to enhance diagnostic performance.

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