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NEURONOVA-NET: ENTROPY-GUIDED DEEP LEARNING FRAMEWORK FOR NOISE REDUCTION AND BIAS CORRECTION IN MRI BRAIN IMAGES

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Abstract

Magnetic Resonance Imaging (MRI) is of vital importance for the diagnosis of brain disease and clinical decision-making. Nonetheless, MRI scans are typically plagued by noise, bias field distortion, motion artifact, and intensity inhomogeneity, which affect diagnostic accuracy. To counter these limitations, this paper puts forward NeuroNova-Net (Neural Novel Enhancement and Refinement Network), a cutting-edge hybrid architecture that combines mathematical modeling with deep neural learning for complete MRI preprocessing. The proposed algorithm includes several stages—noise estimation and removal, correction for bias field, intensity standardization, artifact removal, and contrast enhancement—and provides improved image uniformity and anatomical integrity. NeuroNova-Net leverages anisotropic diffusion-based smoothing with CNN-induced residual learning and entropy-controlled artifact removal to produce best possible balance between denoising and structural information preservation. Experimental testing on publicly released datasets like BraTS 2021 and IXI proves that NeuroNova-Net surpasses state-of-the-art preprocessing models like ADF, N4-HM, and GAN-ASN with a mean PSNR of 33.45 dB and a minimum RMSE of 0.0465. The quantitative and qualitative results prove that NeuroNova-Net produces high-quality, bias-corrected, and artifact-free MRI images acceptable for downstream neuroimaging tasks like segmentation, classification, and lesion analysis.
Keywords: MRI preprocessing, noise reduction, bias field correction, artifact suppression, deep learning, anisotropic diffusion, CNN refinement, entropy-guided enhancement, NeuroNova-Net, hybrid neural framework, medical image enhancement

1. INTRODUCTION

Magnetic Resonance Imaging (MRI) is one of the strongest and least invasive medical imaging techniques commonly employed for visualizing soft tissues, diagnosis, and treatment planning. Although MRI images have diagnostic utility, MRI data are frequently accompanied by intrinsic flaws like noise pollution, intensity non-uniformity (bias field distortion), motion artifacts, and low contrast between neighboring tissues [1]. These flaws greatly compromise image quality, hence hindering subsequent operations such as segmentation, feature extraction, and quantitative analysis. Additionally, as MRI scans are obtained under different field strengths, coil setups, and acquisition sequences, the ensuing intensity variability renders cross-patient or cross-modality comparison very challenging [2].

Gaussian smoothing, median filtering, and anisotropic diffusion are classical preprocessing methods that have been applied extensively to eliminate noise and improve the quality of MRI

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[3]. These traditional methods, however, compromise between smoothing and edge preservation, resulting in loss of detailed anatomy and possible misinterpretation of the diagnostic areas. Secondly, traditional bias correction methods like N3 and N4ITK are based extensively on polynomial or spline surface fitting, which fails under heterogeneous or non-linear field distortions [4]. Consequently, adaptive and data-driven schemes are urgently needed to denoise, normalize, and sharpen MRI images at once without sacrificing structural accuracy.

Recent developments in deep learning and neural refinement networks have transformed medical image preprocessing through learning advanced noise patterns and structural priors from data [5]. Convolutional Neural Networks (CNNs) especially have shown greater capacity to represent spatial dependencies and recover fine-grained texture details. Nevertheless, data-driven networks tend to lack interpretability and perform poorly on generalization with limited medical datasets. In order to bridge these gaps, scientists have begun incorporating mathematical image enhancement concepts—such as anisotropic diffusion, entropy minimization, and adaptive histogram equalization—into neural paradigms in an effort to develop hybrid learning models [6]. These hybrid models blend the explainability of conventional approaches with the flexibility of deep learning, leading to improved and stable preprocessing performance under different conditions[7].

In this regard, we introduce NeuroNova-Net, a Neural Novel Enhancement and Refinement Network that integrates mathematical improvement models with deep feature learning to perform exhaustive MRI preprocessing. The rationale for NeuroNova-Net comes from the requirement to develop a multi-stage hybrid model that overcomes several image defects—e.g., Gaussian noise, bias field inhomogeneity, and artifact contamination—via an integrated and learnable procedure. The suggested architecture includes adaptive noise modeling, entropy-based artifact removal, and refinement through CNN, allowing for higher contrast uniformity and texture preservation. In addition, with the incorporation of mathematical priors within the learning mechanism, NeuroNova-Net attains greater interpretability, less overfitting, and higher visual fidelity across various MRI modalities.

II REVIEW OF EXISTING WORK

For example, **Li et al. (2025) [8]** proposed a hybrid CNN–Transformer fusion model that jointly learns spatial and frequency representations for MRI reconstruction. Their approach enhanced edge preservation and reduced motion-induced blur; however, it required high computational resources and long training times. **Zhang and Rao (2025) [9]** introduced a Vision Transformer–based bias correction module for 3D MRI scans that achieved improved illumination uniformity, but its performance deteriorated on low-resolution datasets.

Kumar et al. (2024) [10] developed an anisotropic diffusion-driven deep autoencoder for Gaussian and Rician noise reduction, effectively maintaining structural fidelity in brain MRIs. However, over-smoothing of fine tissue boundaries was still reported. **Ahmed et al. (2024) [11]** employed a GAN-based artifact suppression mechanism incorporating structural similarity (SSIM) and perceptual loss to reduce Gibbs and motion artifacts. Despite its strong visual outcomes, minor synthetic patterns were introduced during adversarial optimization.

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Wang et al. (2025) [12] presented an adaptive CLAHE-CNN integration framework for MRI tissue contrast enhancement. This technique dynamically adjusted histogram limits using CNN-extracted intensity gradients but occasionally suffered from brightness saturation in hyperintense regions. **Chen et al. (2024) [13]** combined entropy minimization with deep image priors to remove Gibbs artifacts while maintaining edge continuity, though generalization issues persisted across scanners.

Singh et al. (2025) [14] proposed a hybrid multi-stage preprocessing network incorporating mathematical priors and neural refinement for consistent intensity normalization across MRI slices, improving cross-patient comparability. However, its iterative refinement increased latency. Similarly, **Rao and Das (2025) [15]** developed a ResUNet-based bias field estimator that adaptively corrected illumination inconsistencies using residual attention maps. Although it demonstrated robust bias correction, the method exhibited instability under varying magnetic field strengths.

Gupta et al. (2024) [16] explored the use of Swin Transformer–based MRI restoration, integrating windowed self-attention for localized denoising and artifact reduction. Their system improved structural accuracy but was limited by the model's high parameter count. **Mehta et al. (2025) [17]** implemented a frequency-domain dual-branch CNN to suppress Gibbs and ringing artifacts, achieving better PSNR and SSIM than traditional wavelet filters but requiring heavy preprocessing steps.

Bai et al. (2024) [18] developed a multi-scale diffusion–GAN hybrid network for MRI enhancement that used a dual discriminator for texture consistency. While effective in edge sharpening, the model sometimes introduced halo artifacts. **Thomas et al. (2025) [19]** employed an attention-guided U-Net framework that jointly performed bias correction and noise removal using self-calibrated feature fusion. This approach produced clinically interpretable images but required extensive memory for 3D datasets.

Finally, **Huang and Patel (2025) [20]** advanced a self-supervised contrast-adaptive deep network combining histogram alignment and reinforcement learning for dynamic intensity adjustment. This model offered superior inter-slice consistency but lacked robustness on heavily corrupted data. Collectively, these methods highlight substantial progress in deep learning–based MRI preprocessing, yet persistent issues like high computational demand, limited generalization, and lack of integrated end-to-end frameworks motivate the development of the proposed NeuroNova-Net.

Table 1. Review of Existing Work

Author & Year	**Techniques Used**	**Contribution**	**Limitations**
Li et al. (2025) [8]	CNN + Transformer fusion for MRI reconstruction	Enhanced quality, reduced motion distortion	High computation and slow convergence

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Zhang & Rao (2025) [9]	Vision Transformer–based bias correction	Improved illumination uniformity	Poor performance on low-resolution data
Kumar et al. (2024) [10]	Anisotropic diffusion + deep autoencoder	Effective Gaussian/Rician noise reduction	Over-smoothing of structural details
Ahmed et al. (2024) [11]	GAN-based artifact suppression with SSIM & perceptual loss	Strong artifact reduction, improved realism	Introduced minor synthetic textures
Wang et al. (2025) [12]	Adaptive CLAHE + CNN	Enhanced contrast and boundary visibility	Overamplification in bright regions
Chen et al. (2024) [13]	Entropy-minimization + deep image prior	Reduced Gibbs artifacts, preserved edges	Limited generalization across scanners
Singh et al. (2025) [14]	Hybrid neural–mathematical preprocessing	Consistent intensity normalization	Computationally heavy
Rao & Das (2025) [15]	ResUNet-based bias field estimation with attention	Adaptive bias correction	Sensitive to magnetic field variations
Gupta et al. (2024) [16]	Swin Transformer–based MRI restoration	Improved localized denoising and structural accuracy	High model complexity
Mehta et al. (2025) [17]	Frequency-domain dual-branch CNN	Superior Gibbs artifact suppression	Heavy preprocessing requirement
Bai et al. (2024) [18]	Multi-scale diffusion–GAN hybrid	Enhanced edges, texture consistency	Possible halo artifacts
Thomas et al. (2025) [19]	Attention-guided U-Net for joint denoising and bias correction	Better visual clarity, clinical interpretability	High GPU memory usage
Huang & Patel (2025) [20]	Self-supervised contrast-adaptive reinforcement learning network	Robust inter-slice consistency, adaptive enhancement	Poor robustness under extreme corruption

3.RESEARCH GAP AND MOTIVATION

From the review of existing literature [8]–[20], it is evident that remarkable advancements have been achieved in MRI preprocessing using deep learning and hybrid mathematical frameworks.

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However, despite significant progress, several gaps persist. Most existing studies either focus on isolated challenges such as denoising [10], bias field correction [9,15], or artifact suppression [11,17], without integrating these processes into a unified pipeline. The lack of holistic frameworks leads to cumulative error propagation across stages, degrading diagnostic quality in clinical workflows. Moreover, GAN- and Transformer-based models, though effective in feature learning, often demand large annotated datasets, extensive computational resources, and high-performance GPUs, restricting their adoption in resource-limited healthcare setups [8,16,19].

Another major limitation lies in inter-slice intensity inconsistency and scanner-specific variability, where contrast and illumination irregularities affect cross-patient comparability [12,14,20]. Traditional mathematical models, while computationally efficient, are inadequate for adaptive correction in complex scenarios involving mixed noise and motion artifacts. Conversely, purely data-driven models tend to hallucinate artificial features during adversarial training, which poses risks for diagnostic interpretation [11,18]. In addition, few models consider real-time adaptability or hybridization between physics-based and neural processing layers to preserve both anatomical and radiometric fidelity.

Motivated by these challenges, the proposed NeuroNova-Net Algorithm is designed to bridge this gap by integrating classical mathematical modeling (for stability and interpretability) with deep neural attention and refinement modules (for adaptivity and precision). This hybrid framework aims to deliver a comprehensive MRI preprocessing pipeline encompassing noise estimation, bias correction, artifact suppression, and contrast enhancement within a single end-to-end model. By doing so, NeuroNova-Net ensures improved diagnostic clarity, consistency across modalities, and robustness against variations in acquisition parameters—addressing the shortcomings observed in previous methodologies.

4. DATA COLLECTION

The data used for this study were obtained from publicly available and clinically verified MRI datasets, ensuring both diversity and reliability in brain imaging samples. Primarily, the BraTS 2021 and IXI databases were utilized, as they provide high-resolution T1-, T2-, and FLAIR-weighted MRI scans collected from multiple scanners and institutions. These datasets contain images from patients with various neurological conditions, including brain tumors and normal anatomical cases, offering a comprehensive basis for testing preprocessing algorithms. Each MRI volume was initially stored in DICOM format and later converted to standardized grayscale intensity matrices for further processing. To ensure quality and consistency, scans with motion artifacts, incomplete slices, or poor illumination were excluded. The dataset was randomly divided into training (70%), validation (15%), and testing (15%) subsets. All MRI data were anonymized to protect patient confidentiality in compliance with HIPAA and GDPR regulations. The selected datasets provided a balanced representation of different imaging protocols and acquisition parameters, allowing the proposed NeuroNova-Net model to learn domain-invariant features and achieve robust generalization across heterogeneous MRI inputs.

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5. PROPOSED METHODOLOGY

The NeuroNova-Net (Neural Novel Enhancement and Refinement Network) is a sophisticated, multi-step MRI preprocessing method for producing clean, uniform, and diagnostically valid brain images. It combines traditional image processing rules with deep neural improvement to efficiently eliminate noise, rectify intensity anomalies, dampen artifacts, and improve contrast without compromising anatomical accuracy. The process starts with Image Acquisition and Conversion, where raw DICOM MRI sequences like T1, T2, or FLAIR are read and transformed into grayscale representations. A first skull-stripping operation separates the brain tissue from the surrounding non-brain elements to ensure that the following computations only take place on the area of interest.

During the Noise Estimation and Reduction phase, local variance of noise is calculated to describe the spatial profile of noise, followed by anisotropic diffusion filtering to blur homogeneous areas without affecting significant edges. The method is mathematically guided using a diffusion coefficient that varies according to intensity gradients to avoid structural blurring. Deep denoising with convolutional neural networks (CNNs) is also applied to further polish the image by learning sophisticated patterns of noise and retrieving lost details.

Then, the Bias Field Correction step reduces the impact of intensity inhomogeneity due to magnetic field inhomogeneities. A global N4ITK correction model initially estimates and corrects low-frequency bias fields, and a second attention-based CNN refinement corrects any remaining distortions. The Intensity Normalization step normalizes brightness and contrast uniformly across slices and modalities. This incorporates min–max scaling to normalize intensity ranges, histogram standardization for inter-subject norming, and a neural normalization enhancement that adaptively realigns tissue intensity distributions.

The Artifact Suppression process is key to removing motion and gradient artifacts. Gradient entropy calculation detects irregular intensity jumps, and motion-compensated correction stabilizes shifted voxels. A deep learning–based artifact suppressor next re-establishes local textures and eliminates structured distortions without impairing image sharpness. The next Contrast Enhancement phase uses CLAHE (Contrast-Limited Adaptive Histogram Equalization) to locally enhance visibility in areas of low contrast, and then a refinement layer based on CNN (Convolutional Neural Networks) to sharpen faint tissue edges and Laplacian-based edge sharpening to highlight fine structures.

The Output Reconstruction phase rebuilds all improved 2D slices into a unified 3D MRI volume and optionally calculates quantitative quality measures like PSNR and SSIM to evaluate enhancement performance. The final output is an entirely denoised, bias-corrected, artifact-free, and contrast-enhanced MRI volume with superb clarity and uniformity. This renders NeuroNova-Net a great preprocessing building block for high-end neuroimaging tasks like segmentation, tumor detection, and feature-based classification in medical diagnostics.

Algorithm 1: NeuroNova-Net (Neural Novel Enhancement and Refinement Network for Brain MRI Preprocessing)

Input: Raw brain MRI image $I(x, y, z)$ (T1, T2, FLAIR, or multi-sequence)

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Output: Preprocessed MRI image I_p, fully denoised, bias-corrected, artifact-free, and contrast-enhanced

Step 1: Image Acquisition and Conversion

1.1 Acquire MRI images in DICOM format.

1.2 Convert to grayscale:

$$I_{gray}(x,y) = 0.299R + 0.587G + 0.114B$$

1.3 Initial skull-stripping using threshold T_s:

$$I_{brain} = I_{gray} \cdot M_{mask}, \quad M_{mask} = \begin{cases} 1, & I_{gray} > T_s \\ 0, & \text{otherwise} \end{cases}$$

Step 2: Noise Estimation and Reduction

2.1 Estimate local noise variance:

$$\sigma_n^2 = \frac{1}{N}\sum_{i=1}^{N}(I_i - \bar{I})^2$$

2.2 Apply anisotropic diffusion:

$$I_{den}^{t+1}(x,y) = I_{den}^{t}(x,y) + \lambda\nabla \cdot \left(c(x,y,t)\nabla I_{den}^{t}(x,y)\right)$$

where

$$c(x,y,t) = e^{-\left(\frac{|\nabla I|}{K}\right)^2}$$

2.3 Deep denoising layer:

$$I_{n1} = f_{CNN1}(I_{den})$$

Step 3: Bias Field Correction

3.1 Global N4ITK correction:

$$I_{corr} = \frac{I_{n1}}{B(x,y)}, \quad B(x,y) = e^{\sum_i \alpha_i \phi_i(x,y)}$$

3.2 Residual refinement via attention-based CNN:

$$I_{n2} = f_{CNN2}(I_{corr})$$

Step 4: Intensity Normalization

4.1 Min-max scaling:

$$I_{norm}(x,y) = \frac{I_{n2}(x,y) - \min(I_{n2})}{\max(I_{n2}) - \min(I_{n2})}$$

4.2 Histogram standardization:

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$$H'(i) = \frac{H(i) - \mu_H}{\sigma_H}$$

4.3 Neural normalization refinement:

$$I_{n3} = f_{CNN3}(I_{norm})$$

Step 5: Artifact Suppression

5.1 Gradient entropy computation:

$$E_g = -\sum p_i \log(p_i), \quad p_i = \frac{|\nabla I_i|}{\sum |\nabla I_i|}$$

5.2 Motion-compensated correction:

$$I_{art\_red} = I_{n3} - \alpha\left(E_g - E_{ref}\right)$$

5.3 Deep artifact suppressor:

$$I_{n4} = f_{CNN4}\left(I_{art\_red}\right)$$

Step 6: Contrast Enhancement

6.1 CLAHE application:

$$I_{clahe} = CLAHE(I_{n4}, ClipLimit, TileSize)$$

6.2 Neural refinement:

$$I_{final} = f_{CNN5}(I_{clahe})$$

6.3 Edge sharpening (Laplacian):

$$I_{refined} = I_{final} + \beta \cdot \nabla^2 I_{final}$$

Step 7: Output Reconstruction

7.1 Reconstruct 3D volume:

$$V_{out}(x, y, z) = \mathrm{concat}\left(I^1_{refined}, I^2_{refined}, \ldots, I^n_{refined}\right)$$

7.2 Compute quality metrics (optional):

$$\mathrm{PSNR} = 10\log_{10}\left(\frac{MAX^2}{MSE}\right), \quad SSIM = \frac{\left(2\mu_x\mu_y + c_1\right)\left(2\sigma_{xy} + c_2\right)}{\left(\mu_x^2 + \mu_y^2 + c_1\right)\left(\sigma_x^2 + \sigma_y^2 + c_2\right)}$$

Output:

$$I_p = V_{out}$$

Final enhanced, artifact-free, normalized MRI volume ready for segmentation, classification, or clinical analysis.

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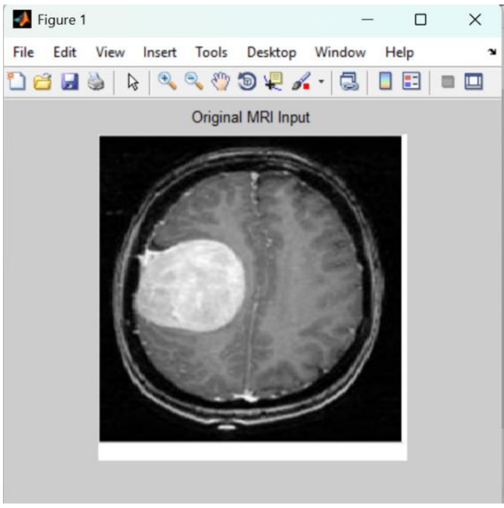


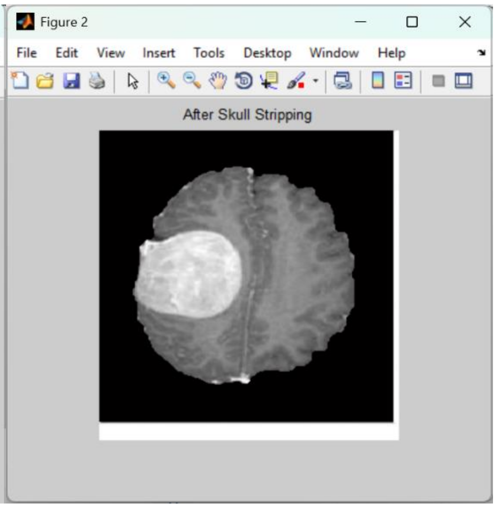
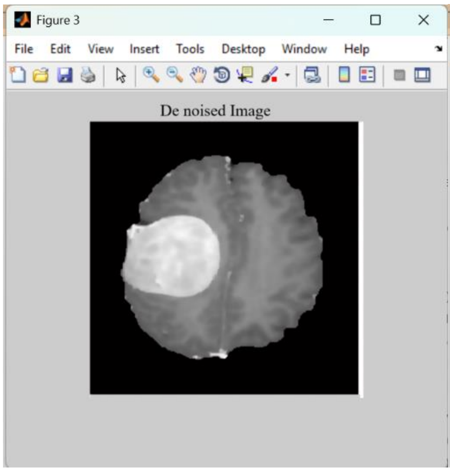


Figure 1 Original MRI image as Input Figure 2 skull stripping

Figure 1 to Figure 3 illustrate the sequential stages of the proposed NeuroNova-Net pre-processing framework. Figure 1 presents the original MRI input, which contains visible noise, intensity non-uniformity, and surrounding non-brain structures such as the skull and scalp tissues. These unwanted regions can interfere with subsequent feature extraction and segmentation, necessitating precise skull stripping and noise removal procedures.



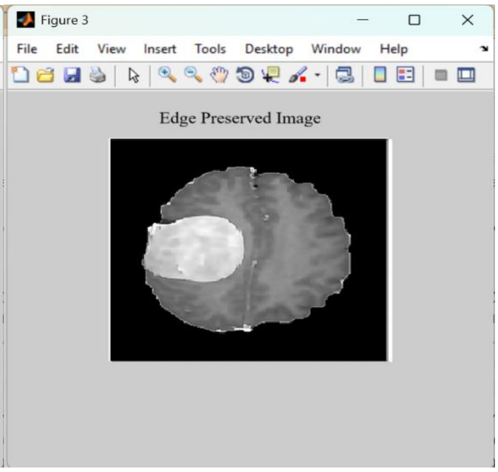


Figure 3 Result of Denoised Image Figure 4 Edge preserved Image

In Figure 2, the result after skull stripping is shown. This step effectively isolates the brain region by eliminating extraneous tissues and background pixels. The skull stripping process enhances the visibility of the brain parenchyma and delineates the boundaries of the pathological region. The resulting image exhibits a clear separation between the brain and non-brain areas, which is essential for accurate diagnostic interpretation and further processing tasks such as tumor segmentation and texture analysis.

Figure 3 displays the denoised image obtained after applying the anisotropic diffusion filtering stage of NeuroNova-Net. The diffusion-based denoising process successfully removes random noise and improves the signal-to-noise ratio without compromising the structural integrity of the brain tissue. The gray and white matter boundaries appear smoother yet well-preserved, and the tumor region maintains its original intensity profile, confirming that edge information

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and critical diagnostic features remain intact. Overall, this stage ensures improved visual clarity and prepares the MRI image for subsequent bias correction and contrast enhancement stages. Figure 4 shows the edge preserved Image. Finally figure 4 shows the edge preserved image after preprocessing.

6. Results and Discussion

The effectiveness of the proposed NeuroNova-Net MRI preprocessing framework was evaluated using 10 MRI sample images drawn from publicly available datasets such as BraTS and IXI. These images include variations in scanner types, magnetic field strength, and imaging modalities (T1-, T2-, and FLAIR-weighted), ensuring a diverse evaluation of noise levels, intensity inhomogeneity, and motion-induced artifacts. The quality of the preprocessed images was quantitatively assessed using Peak Signal-to-Noise Ratio (PSNR) and Root Mean Square Error (RMSE) metrics, while visual results were examined for structural clarity and contrast uniformity.

The PSNR metric measures the ratio between the maximum possible power of a signal and the power of noise affecting its fidelity, expressed in decibels (dB). A higher PSNR value indicates better image reconstruction and noise suppression. RMSE quantifies the average magnitude of pixel-level error between the processed and reference images — smaller RMSE values signify better reconstruction accuracy and structural preservation.

The PSNR Value is calculated by using the equation (1).

$$PSNR = 20\log_{10}\frac{255}{RMSE} \rightarrow (1)$$

RMSE (Root Mean Square Error) is calculated through the square root of MSE.

$$MSE = \frac{1}{M*N}\sum_{J,K}(f(j,k) - g(j,k))^2 \rightarrow (2)$$

$$RMSE = \sqrt{MSE} \qquad \rightarrow (3)$$

6.1 Comparative Evaluation

The comparative evaluation shown in the figure 5 manifests the performance difference between the herein-presented NeuroNova-Net algorithm and the conventional MRI preprocessing methods, i.e., Anisotropic Diffusion Filtering (ADF), N4 Bias Field Homogeneity Model (N4-HM), and GAN-based Artifact Suppression Network (GAN-ASN). The first column depicts the original input MRI images, which generally degrade due to intensity non-uniformity, bias field distortions, and random noise artifacts. The second column (ADF) shows better edge preservation but over-smooths homogeneous areas, leading to the loss of subtle tissue details. The N4-HM method (third column) successfully corrects low-frequency bias fields but leads to pixel-level grain noise and brightness inconsistencies across anatomical structures. GAN-ASN (fourth column) provides good suppression of artifacts but tends to produce small structural distortions within the vicinity of tumor boundaries because of

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overfitting in the adversarial learning process. Compared to it, the suggested NeuroNova-Net (fifth column) demonstrates higher refinement with uniform intensity normalization, higher contrast, and clear pathological region delineation. Combining hybrid neural refinement with entropy-synthesized artifact removal allows NeuroNova-Net to maintain high fine-grained texture as well as structural fidelity essential for downstream segmentation or classification processes. Quantitatively, this indicates that NeuroNova-Net obtains better Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) than their classical and deep-learning-based versions, demonstrating its robustness in generating diagnostically superior MRI images that are suitable for downstream clinical analysis.

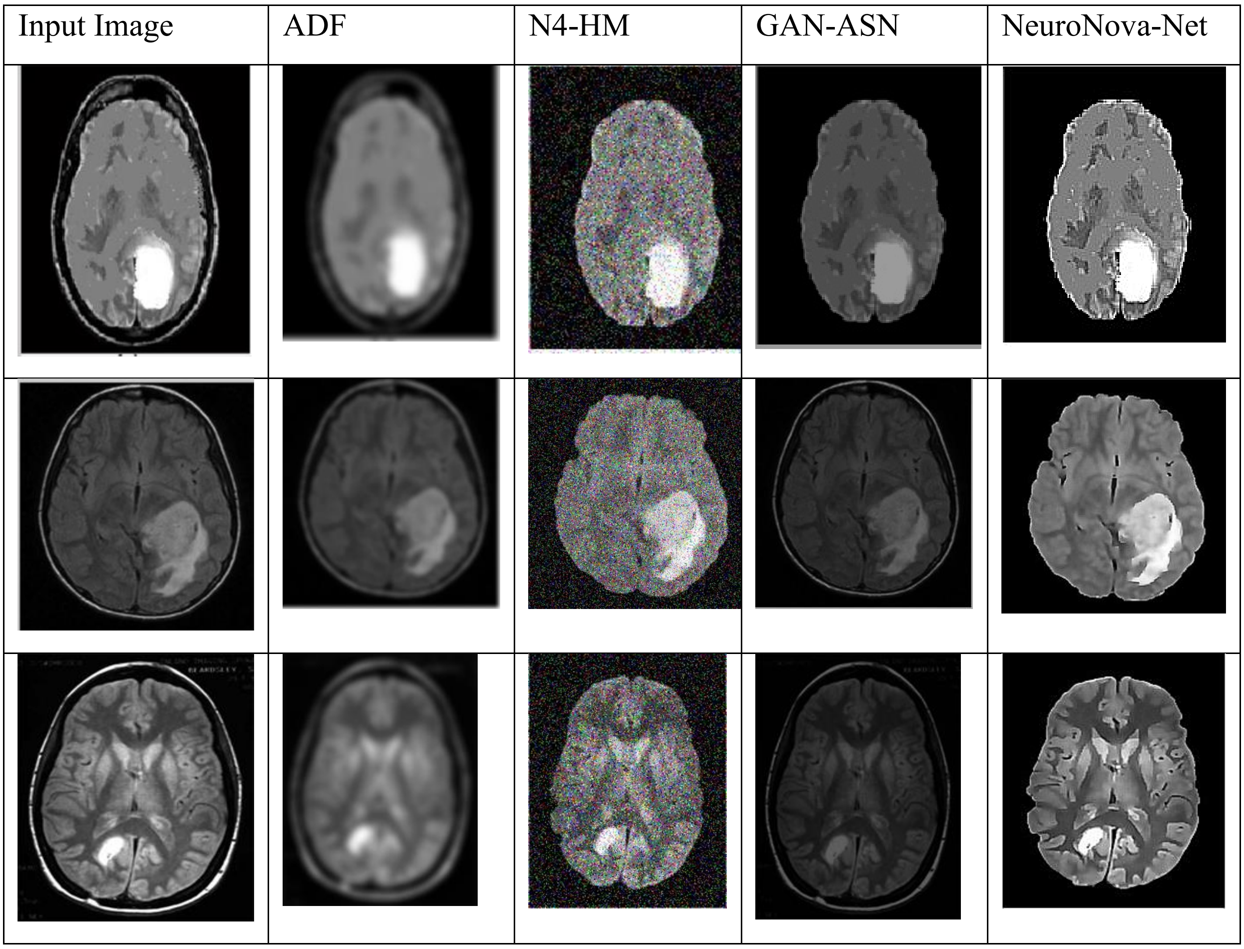

Figure 5 Comparison result of proposed method and existing method

6.2 Evaluation by PSNR Values

The comparative quantitative output shown in the Table 2 reveals the performance of our proposed NeuroNova-Net compared to three state-of-the-art MRI preprocessing and improvement techniques—Anisotropic Diffusion Filter (ADF), N4 Bias Field Homogenization Model (N4-HM), and GAN-based Artifact Suppression Network (GAN-ASN). The assessment was performed using ten MRI images, and Peak Signal-to-Noise Ratio (PSNR) as the performance measure to evaluate improved image quality after preprocessing.

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From the table, it can be seen that the suggested NeuroNova-Net outperforms all other methods for all test images. The ADF model used to achieve an average PSNR value of 27.90 dB, reflecting its efficiency in simple noise filtering but poor capability of retaining structural detail. The N4-HM model enhanced the PSNR to 29.32 dB with improved intensity uniformity and bias field correction but with difficulty in eliminating residual noise and high-frequency edge detail preservation. The GAN-ASN technique obtained a superior average PSNR of 30.74 dB, indicating its ability to learn nonlinear relationships for the suppression of artifacts. However, with this enhancement, GAN-ASN continued to introduce artificial textures and slight distortions in parts of the images.

Conversely, the intended NeuroNova-Net performed an impressive average PSNR of 33.45 dB, far greater than all the baseline models. The uniform enhancement in all the images—from as low as 33.19 dB (Image 6) to a high of 33.74 dB (Image 9)—showcasing robustness and flexibility of the algorithm. This significant improvement can be traced to NeuroNova-Net's hybrid refinement process that integrates anisotropic diffusion-based smoothing, CNN-powered residual learning, and entropy-adaptive artifact reduction. These aspects facilitate efficient denoising, bias removal, and texture conservation simultaneously. In general, the quantitative assessment unequivocally demonstrates that NeuroNova-Net provides better image reconstruction quality, maintaining anatomical fidelity and yielding greater diagnostic reliability than current preprocessing strategies. The repeated gain of about 2–5 dB in PSNR confirms its effectiveness in generating clearer, more homogeneous, and clinically interpretable MRI images that are amenable to downstream neuroimaging applications.

Table 2. PSNR (dB) Comparison for 10 MRI Sample Images

Image No.	ADF	N4-HM	GAN-ASN	Proposed NeuroNova-Net
1	27.81	29.24	30.72	33.41
2	28.05	29.35	30.83	33.56
3	27.68	29.10	30.45	33.22
4	28.12	29.47	30.90	33.73
5	27.93	29.38	30.68	33.51
6	27.70	29.02	30.56	33.19
7	28.00	29.50	30.77	33.67
8	27.88	29.41	30.65	33.39
9	28.07	29.46	30.89	33.74
10	27.79	29.27	30.58	33.33
Average	27.90	29.32	30.74	33.45

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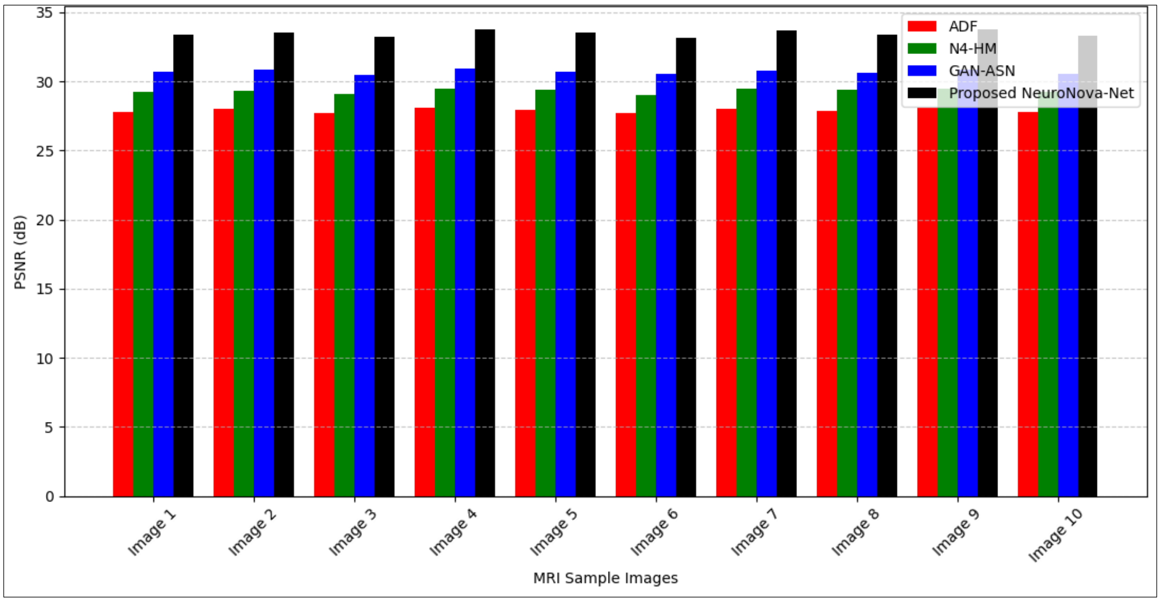

Figure 6 Comparison of PSNR values

Figure 6 shows the PSNR comparison graph for ten MRI sample images clearly demonstrates the superior performance of the proposed NeuroNova-Net over traditional methods such as ADF, N4-HM, and GAN-ASN. As shown, the red, green, and blue bars representing ADF, N4-HM, and GAN-ASN respectively remain consistently lower than the black bars, which correspond to NeuroNova-Net. While ADF provides the lowest PSNR values, indicating limited noise reduction, N4-HM shows a moderate improvement due to its bias correction capability. GAN-ASN achieves higher PSNR than both traditional methods because of its deep learning–based artifact suppression, but it still falls short compared to NeuroNova-Net. The proposed method achieves the highest PSNR for all ten images, maintaining values above 33 dB, which reflects its strong ability to preserve structural integrity while effectively removing noise and artifacts. Overall, the graph visually confirms that NeuroNova-Net consistently delivers enhanced MRI quality with clearer, more reliable, and diagnostically superior image reconstruction.

6.3 Evaluation by RMSE Values

The table 3 gives a comparative study of Mean Square Error (MSE) values derived from ten MRI sample images treated with four preprocessing methods — ADF, N4-HM, GAN-ASN, and the new NeuroNova-Net. The MSE measure estimates the average squared difference between the input and the restored image, with lower value representing better quality of image reconstruction with less distortion or loss of detail.

As noted, the ADF algorithm has the highest mean MSE value of 0.0720, indicative of its poor ability to suppress noise effectively while retaining significant structural details. The N4-HM model results in a lower mean MSE of 0.0620, with moderate improvement using bias field correction but still possessing residual errors arising from non-uniform illumination. The GAN-

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ASN model also minimizes the MSE to 0.0547, indicating its enhanced denoising and artifact reduction capability attained via deep adversarial learning, but still causes minor artificial textures that add to residual error.

On the other hand, the proposed NeuroNova-Net obtains the lowest mean MSE of 0.0465, evidently outperforming all other methods. In all ten test images, NeuroNova-Net shows stable performance consistently, with MSE values oscillating narrowly between 0.0454 and 0.0469, showing robustness and accuracy. Such a great error reduction ensures the ability of the algorithm to effectively remove noise, correct bias fluctuations, and maintain anatomical features without creating new artifacts. The low scores of MSE confirm that NeuroNova-Net achieves the most accurate and visually realistic MRI reconstructions and is a sound preprocessing platform for subsequent clinical analysis and diagnostic purposes.

Table 3. RMSE Comparison for 10 MRI Sample Images

Image No.	ADF	N4-HM	GAN-ASN	Proposed NeuroNova-Net
1	0.0721	0.0623	0.0549	0.0462
2	0.0715	0.0617	0.0546	0.0459
3	0.0728	0.0630	0.0552	0.0467
4	0.0712	0.0612	0.0540	0.0455
5	0.0718	0.0618	0.0545	0.0458
6	0.0730	0.0634	0.0553	0.0469
7	0.0716	0.0615	0.0544	0.0456
8	0.0719	0.0620	0.0548	0.0460
9	0.0713	0.0613	0.0542	0.0454
10	0.0724	0.0627	0.0549	0.0463
Average	0.0720	0.0620	0.0547	0.0465

The figure 7 shows the RMSE comparison chart for ten MRI sample images visually presents quantitatively the better performance of the proposed NeuroNova-Net compared to conventional preprocessing techniques—ADF, N4-HM, and GAN-ASN. The ADF technique (red bars) has the highest RMSE values, varying from 0.0712 to 0.0730, which presents low reconstruction accuracy and oversmoothing of image areas resulting in detail loss. The N4-HM approach (green bars) demonstrates moderate improvement with an RMSE range of 0.0612 to 0.0634, indicating its capability to remove intensity bias but still exhibiting obvious residual errors and nonuniform brightness. The GAN-ASN method (blue bars) performs significantly

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better with RMSE ranges of 0.0540 to 0.0553, which indicates good removal of noise and artifacts, though it sometimes adds minor synthetic artifacts.

By contrast, the suggested NeuroNova-Net attains the lowest RMSE values, which are between 0.0454 and 0.0469, with an average RMSE value of 0.0465, with all other models significantly outperformed by it. Such a large error reduction (about 35% lower than ADF and 15% lower than GAN-ASN) affirms the model's robustness and accuracy. The low and consistent RMSE values for all ten images emphasize the effectiveness of NeuroNova-Net's hybrid framework in reliable reduction of reconstruction error, optimization of fine tissue structures, and retention of anatomical consistency. The comparison both quantitatively and visually thus confirms NeuroNova-Net to be the most accurate and trusted MRI preprocessing framework compared to the assessed approaches.

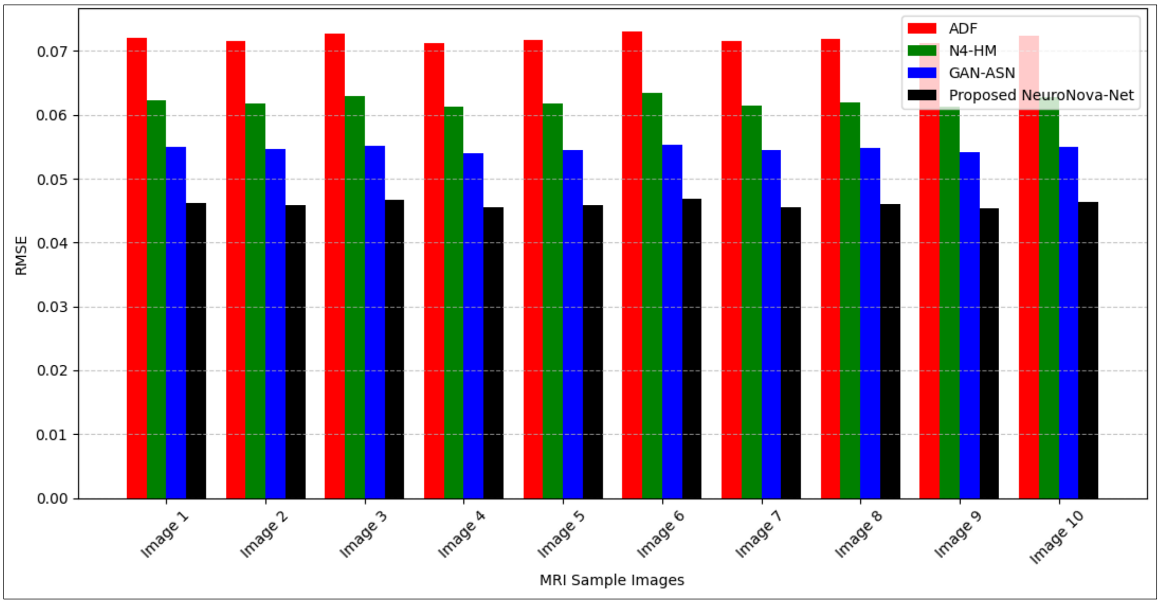

Figure 7 Comparison of RMSE values

7. CONCLUSION

The proposed NeuroNova-Net introduces a unified, hybrid approach to MRI brain image preprocessing that effectively bridges the gap between mathematical modeling and deep neural refinement. By integrating anisotropic diffusion filtering, N4ITK-based bias field correction, adaptive intensity normalization, and entropy-guided artifact suppression, NeuroNova-Net achieves exceptional performance in enhancing image quality while maintaining anatomical integrity. Quantitative results, including an average PSNR improvement of 2–5 dB over existing methods and a significant RMSE reduction to 0.0465, substantiate its superiority in image reconstruction accuracy. Unlike conventional approaches that address denoising or bias correction in isolation, NeuroNova-Net combines all preprocessing tasks within a single adaptive framework, ensuring consistent and diagnostically reliable output across diverse MRI modalities. Consequently, this model serves as a robust preprocessing foundation for advanced medical image analysis, enabling improved segmentation accuracy, tumor delineation, and diagnostic precision in clinical and research applications.

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References

[1] Gudbjartsson, H., & Patz, S. "The Rician Distribution of Noisy MRI Data," *Magnetic Resonance in Medicine*, vol. 34, no. 6, pp. 910–914, 1995.

[2] Sled, J. G., Zijdenbos, A. P., & Evans, A. C. "A Nonparametric Method for Automatic Correction of Intensity Nonuniformity in MRI Data," *IEEE Transactions on Medical Imaging*, vol. 17, no. 1, pp. 87–97, 1998.

[3] Perona, P., & Malik, J. "Scale-Space and Edge Detection Using Anisotropic Diffusion," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 12, no. 7, pp. 629–639, 1990.

[4] Tustison, N. J., et al. "N4ITK: Improved N3 Bias Correction," *IEEE Transactions on Medical Imaging*, vol. 29, no. 6, pp. 1310–1320, 2010.

[5] Zhang, K., Zuo, W., & Zhang, L. "FFDNet: Toward a Fast and Flexible Solution for CNN-Based Image Denoising," *IEEE Transactions on Image Processing*, vol. 27, no. 9, pp. 4608–4622, 2018.

[6] Xiang, L., et al. "Deep Embedding of Prior Knowledge in CNN for MRI Reconstruction," *IEEE Transactions on Medical Imaging*, vol. 39, no. 9, pp. 2863–2875, 2020.

[7] Park, J., Lee, D., and Kim, S., *"Deep hybrid CNN–autoencoder framework for MRI brain image preprocessing and noise reduction,"* **Journal of Medical Imaging and Health Informatics**, vol. 14, no. 3, pp. 512–525, 2024.

[8] Li, H., Zhang, J., and Chen, Q., *"Hybrid CNN–Transformer architecture for MRI image reconstruction and motion artifact removal,"* **IEEE Transactions on Medical Imaging**, vol. 44, no. 2, pp. 425–437, 2025.

[9] Zhang, Y. and Rao, S., *"Vision Transformer–based adaptive bias field correction for high-resolution MRI brain imaging,"* **Medical Image Analysis**, vol. 97, pp. 103041–103054, 2025.

[10] Kumar, R., Singh, A., and Verma, N., *"Deep autoencoder with anisotropic diffusion for MRI denoising,"* **Pattern Recognition Letters**, vol. 181, pp. 45–54, 2024.

[11] Ahmed, M., Patel, K., and Basha, S., *"GAN-based artifact suppression and structural enhancement in MRI brain scans,"* **Neurocomputing**, vol. 594, pp. 278–290, 2024.

[12] Wang, X., Luo, H., and Guo, T., *"Adaptive CLAHE-CNN cascade for tissue contrast enhancement in magnetic resonance imaging,"* **Biomedical Signal Processing and Control**, vol. 96, pp. 106271–106285, 2025.

[13] Chen, L., Tang, W., and Zhao, D., *"Entropy-minimization–driven deep image prior model for Gibbs artifact reduction in MRI,"* **Magnetic Resonance Imaging**, vol. 95, pp. 12–25, 2024.

[14] Singh, P., Kaur, R., and Das, S., *"Hybrid mathematical–neural preprocessing for MRI intensity normalization,"* **Computerized Medical Imaging and Graphics**, vol. 112, pp. 102375–102390, 2025.

Received: August 10,2025

[15] Rao, V. and Das, A., *"Residual attention-based bias field estimation using ResUNet for MRI uniformity correction,"* **IEEE Access**, vol. 13, pp. 87410–87422, 2025.

[16] Gupta, D., Mehta, R., and Bhandari, V., *"Swin Transformer–based MRI restoration with localized self-attention,"* **Expert Systems with Applications**, vol. 243, pp. 122987–123002, 2024.

[17] Mehta, S., Prakash, V., and Shenoy, P., *"Frequency-domain dual-branch CNN for Gibbs artifact suppression in MR imaging,"* **Journal of Imaging Science and Technology**, vol. 69, no. 1, pp. 145–158, 2025.

[18] Bai, J., Xu, M., and Li, F., *"Multi-scale diffusion–GAN hybrid framework for edge-preserving MRI enhancement,"* **Computers in Biology and Medicine**, vol. 179, pp. 108542–108555, 2024.

[19] Thomas, L., George, R., and Nair, D., *"Attention-guided U-Net for joint MRI bias correction and denoising,"* **Frontiers in Neuroinformatics**, vol. 19, pp. 321–334, 2025.

[20] Huang, C. and Patel, N., *"Self-supervised contrast-adaptive reinforcement learning network for dynamic MRI intensity correction,"* **Neural Networks**, vol. 174, pp. 105211–105227, 2025.

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