

An Enhanced Pseudocolor-Guided Non-Local Means Approach for Alzheimer's MRI Denoising

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ABSTRACT

Alzheimer's Disease (AD) is a progressive neurodegenerative disease. Magnetic resonance imaging (MRI) is frequently used to investigate brain structure in AD research. MRI images may be corrupted by noise and preprocessing is important for noise suppression while preserving anatomical details and low contrast tissue variations. Non-Local Means (NLM) denoises images by averaging similar patches. Patch similarity based on greyscale may not be sufficient to distinguish subtle patterns in low-contrast regions. In this paper, we propose a pseudocolor-guided Non-Local Means (PC-NLM) framework for brain MRI denoising. The similarity weights are computed by combining the greyscale and pseudocolor patch distances with a convex combination. The denoised intensities are reconstructed from the original greyscale image. The method was validated on sagittal slice 66 from 50 subjects of the Open Access Series of Imaging Studies (OASIS) dataset with synthetic Gaussian noise of variance 0.01, 0.02 and 0.03. PC-NLM yielded a higher peak signal-to-noise ratio (PSNR) than conventional NLM (22.244 dB vs 21.773 dB), a higher structural similarity index (SSIM; 0.253 vs 0.236) and a lower mean squared error (MSE; 0.005965 vs 0.006648) for a noise variance of 0.03. PC-NLM achieved the highest PSNR and MSE for the reported noise levels among the methods considered, while median filtering achieved the highest SSIM. The results show that pseudocolor guidance can improve the performance of denoising by PSNR and MSE compared to conventional Non-Local Means (NLM) under the tested conditions, while median filtering can achieve a higher SSIM.

Keywords: Alzheimer's disease, Brain MRI, Image denoising, Medical image preprocessing, Non-local means.

1. INTRODUCTION

Alzheimer's disease (AD) is a progressive neurodegenerative disease that gradually deteriorates cognitive functions from moderate impairment of memory to severe loss of

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daily functioning (**Li et al., 2022**). There is no cure for the disease, but early diagnosis may delay symptoms. Therefore, early diagnosis by MRI is important to control the effects while enhancing the quality of life in later stages. MRI is an extensively utilised non-invasive imaging modality that registers the brain structures and provides detailed images of soft tissue anatomy and affected areas by AD (**Rehman et al., 2024**). Subtle anatomical variations can be obscured by acquisition noise, hardware artefacts, and motion disturbances that often degrade MRI images, reducing diagnostic reliability (**Aamir et al., 2025**). Therefore, appropriate preprocessing is required to enhance the image quality while maintaining diagnostically relevant structures. There are many denoising methods and the Non-Local Means (NLM) algorithm has received much attention in medical imaging (**Kim, 2024**). NLM denoises by using the redundancy and similarity in an image by working on similar patches. NLM differs from traditional local filters that operate in a local window by calculating weighted averaging of pixels based on similarity of patches, thus achieving effective noise reduction while preserving edges and fine structural details.

Traditional NLM uses similarity based on greyscale intensity, which often fails to recognise subtle structural variations in low-contrast MRI regions (**Saini et al., 2025**). Medical imaging often employs pseudocolor techniques to increase contrast and to aid visualisation. Pseudocoloring can reveal patterns and boundaries that are difficult to see in grey-scale images. Pseudocoloring is the mapping of intensities to colour spaces. Pseudocolor is primarily used for visualisation, but it may also be useful for similarity estimation in denoising, which is an area that has not been explored much (**Thulasimani et al., 2024**). Thus, a pseudocolor-guided NLM preprocessing framework for AD brain MRI analysis is proposed. This approach enhances the patch similarity estimation process in the NLM process by considering pseudocolor information, and denoising is applied only to the original greyscale MRI image (**Lee et al., 2022**). This separation guarantees the structural fidelity of the MRI and avoids artificial colour artefacts. The patch selection stage is augmented with pseudocolor guidance to enhance low-contrast regions and to enhance the quality of preprocessed MRI images for subsequent AD analysis. The primary outcome is the introduction of a dual-domain similarity measure that fuses greyscale and pseudocolor representations (**Alabduljabbar et al., 2025**) to improve the discrimination of structurally similar patches in low contrast regions. A further important contribution is the disentanglement of standard guiding and reconstruction, where pseudocolor information is only utilised for the similarity calculation, while the final denoising is performed strictly on the original greyscale image, thus maintaining anatomical reliability (**Singh et al., 2024**). The proposed framework also preserves the simplicity of the conventional NLM algorithm with negligible computational overhead. The experimental results demonstrate that this approach can achieve better noise mitigation and better structure retention, and it can be used as a pre-processing method for subsequent tasks (segmentation and classification, etc.) in AD studies.

The early diagnosis of AD is especially challenging, particularly during the mild cognitive impairment (MCI) phase, where symptoms are subtle and vary between patients (**El-Sappagh et al., 2022**). MRI has become an important tool in AD research, as it provides detailed structural information on the brain. It can now be detected at an early stage by means of automatic and quantitative analysis of MRI scans using computational image analysis. Structural MRI is widely used for early detection of AD (**Hu et al., 2023**). Findings suggest that MCI is associated with grey matter atrophy in regions like the hippocampus and entorhinal cortex, changes that are strongly associated with memory decline (**Jobin et al.,**



2023). In addition, the National Institute on Ageing and the Alzheimer's Association have emphasised the necessity of neuroimaging biomarkers for the diagnosis of AD (**Albert et al., 2011**). These findings together underscore the utility of MRI based analysis in AD research and diagnosis. Therefore, pre-processing of MRI images is the key to reliable diagnosis. The quality of the MRI data directly affects the performance of the automated diagnostic systems. Recent studies show that pre-processing has a great impact on the accuracy of deep learning (DL) models for Alzheimer's detection (**Cho et al., 2023**), and many neuroimaging studies compared different pre-processing pipelines (**Shukla et al., 2022**). In particular, it has been demonstrated that the precise classification of different Alzheimer's stages from MRI images has a significant clinical importance when coupled with metaheuristic optimisation methods, such as the Snake Optimisation Algorithm (SOA), leading to enhanced performance results (**Riyadh Adnan et al., 2025**). These studies suggest that the choice of pre-processing methods can significantly affect the accuracy and generalisation ability of conventional ML models (**Lamoglia et al., 2025**). Likewise, fMRI studies indicate that the final results may be affected by the order and choice of pre-processing steps (**Gargouri et al., 2016**). These findings together emphasise the need for efficient and well-designed pre-processing for MRI based diagnosis of Alzheimer's disease. Noise reduction is one of the key pre-processing steps. Noise can be acquired during the acquisition or due to the environmental disturbances which degrades the quality of the image and further affects the analysis (**Hussain and Hyeon, 2024**).

A traditional denoising method is median filtering which is usually applied to remove single structure noise and to preserve the image integrity (**Chalghoumi and Smiti, 2022**). Advanced hybrid filtering methods such as ROFTV Fast ICA, adaptive hybrid median bilateral filtering and trilateral filtering are used to deal with complex noise types and to improve the quality of MR images (**Jesline and Albert, 2021; Kumar and Guhan, 2025; Chang et al., 2018**). Frequency domain filtering techniques also have been successful in maintaining important image features (**Veni and Manjula, 2022**). There are many ways to denoise medical images. Among them, the Non-Local Means (NLM) algorithm has been studied extensively (**Li et al., 2024**). It has the advantage of using a standard redundancy by comparing similar patches across the image. Unlike conventional local filters, NLM searches for similar neighbourhood patches and calculates a weighted mean of intensities. It is very effective in noise removal while preserving edges and fine structural details. Based on reviews, NLM is an effective MRI denoising method for brain scans (**Heo et al., 2020**). Conventional metrics may have difficulty distinguishing significant anatomical structures from noise in low variance areas, where intensity information alone is not sufficient to capture subtle tissue alterations that are important for detecting AD. So, the choice of a bad patch can result in a bad denoising. Hybrid NLM methods have been proposed by combining NLM with DWT (**Pillai and Anoop, 2025**) or PSO to optimise the parameters. Variants like the Anisotropic Weighted KS NLM enable different patch weights to better preserve structure (**Kanoun et al., 2020**).

Existing deep learning and transform domain techniques such as BM3D and DnCNN have also shown good performance for medical image denoising (**Chaudhary et al., 2023**). BM3D relies on the cooperative filtering in the transform domain, whereas DnCNN utilises the convolutional neural networks for learning the noise patterns from the training data (**Begum and Selvaraj, 2023**). These methods are good at removing noise but DL methods generally need large dataset and high computational power. Conversely, the proposed framework aims to improve the similarity estimation in the traditional NLM while keeping



the computational cost low and the anatomical accuracy unchanged. Thus, selecting an appropriate noise reduction method is crucial for reliable MRI analysis. Most of the existing NLM based methods only use the greyscale intensity information to compute the patch similarity, which is a limitation in Alzheimer's MRI. To deal with this, recent studies have explored the integration of additional information, such as multi modal or multi contrast data (**Ghosh and Jayanthi, 2022; Polinati et al., 2021**). Pseudocolor visualisation techniques are commonly used to increase contrast in medical imaging. It can enhance patterns and boundaries that are not as clear in greyscale images. Pseudocolor separates near greyscale structures and aids in extracting features by mapping intensity values to colour spaces (**Semary, 2018**). Pseudocolor is primarily used for visualisation, but it may also be useful to guide similarity estimation for denoising, an avenue not explored widely. Therefore, this paper proposes a pseudocolor guided NLM preprocessing framework for AD brain MRI. The framework exploits pseudocolor guidance in the patch similarity estimation, while the denoising is performed on the original greyscale MRI so as to preserve the morphological fidelity and avoid artificial artefacts. Thus, noise suppression is enhanced in low contrast regions, and the quality of preprocessed MRI images for AD studies is improved. It overcomes the limitations of intensity-only similarity, and achieves structural refinement without introducing artificial colour distortions, by preserving greyscale reconstruction while applying pseudocolor for guidance. To assess the denoising performance, we used widely adopted metrics, e.g., PSNR and SSIM (**Wang et al., 2004**). This work aims at improving patch similarity estimation in Non-Local Means denoising of brain MRI by fusing greyscale and pseudocolor patch distances while limiting the averaging to the original greyscale image, and quantifying the ensuing gains over conventional NLM, median filtering and Gaussian filtering on OASIS slices under synthetic Gaussian noise. The contributions are: (i) a dual-domain similarity measure, (ii) separating guidance and reconstruction, and (iii) an evaluation on three noise levels and 50 subjects.

2. METHODOLOGY

Redundancy in images is used by the Non-Local Means (NLM), a famous denoising algorithm. Rather than relying on local neighbourhoods, this is achieved by averaging similar patches. (**Buades et al., 2005**) originally formulated the weight calculation and reconstruction process based on the similarity of the patches. In NLM, patches are usually compared by the squared Euclidean distance and the denoised pixel intensity is estimated by weighted average of neighbouring pixels. Gaussian smoothing is commonly used as a pre-processing step to stabilise intensity variations prior to similarity estimation. In image processing, Gaussian filtering is a standard low pass technique to reduce random fluctuations and preserve structural details (**Gonzalez et al., 2008**). These classic formulations are the theoretical basis of our work. We then propose a new extension of NLM with the use of pseudocolor guidance on the patch similarity estimation while still keeping the greyscale reconstruction.

3. PROPOSED WORK

In this paper, we propose a pseudocolor-guided NLM framework for Alzheimer's MRI preprocessing. The key idea is to separate guidance and denoising: pseudocolor information is used only for patch similarity estimation, while the denoising operation is performed only on the original greyscale MRI image as shown in **Fig. 1**.

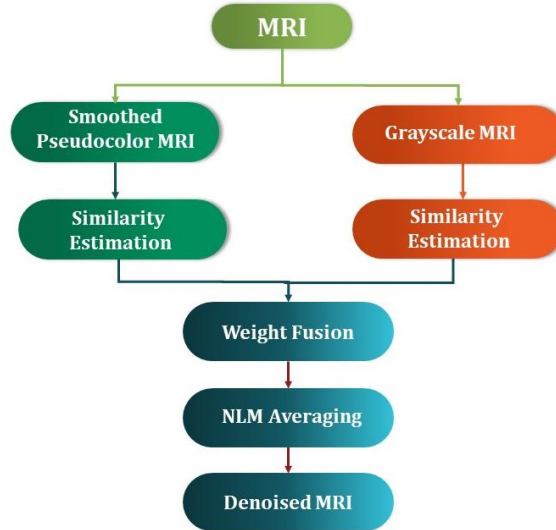


Figure 1. Diagram of Proposed Methodology

3.1 Guidance Image

Let I be the noisy grayscale MRI image. To help stabilize the variation in intensity levels before applying the pseudocolor map, a lightly smoothed version of I , I_s , is extracted using a low-pass filter:

$$I_s = I * G \quad (1)$$

Where G is a small Gaussian or weighted averaging kernel. A Gaussian smoothing filter with a standard deviation of one pixel was used to generate the guidance image prior to pseudocolor mapping. This step minimizes the effect of random fluctuation due to noise while preserving the structures of anatomy. The smoothed (subsampling) image I_s is transformed into a pseudocolor image I_c by a contrast-enhancing colormap. This pseudocolor image is only used for patch similarity estimation and is not used for the denoising averaging.

3.2 Patch-Based Similarity Estimation

For each pixel location i , let P_i denote a square grayscale patch of size $P \times P$ centered at i in the original image I . Let P_i^c denote the pseudocolor patch extracted from I_c . Candidate pixels j are systematically selected from all pixel locations within the finite search window Ω centered around the reference pixel i . This ensures that similarity estimation considers all possible neighbors in the local region, rather than random sampling.

3.2.1 Grayscale Patch Distance

The grayscale similarity between patches P_i and P_j is calculated using the squared Euclidean distance:

$$d_{gs}(P_i, P_j) = \|P_i - P_j\|^2 \quad (2)$$

This measures intensity-based structural similarity among patches in the original MRI image.



3.2.2 Pseudocolor Patch Distance

To improve discrimination in low-contrast regions, a pseudocolor-based patch distance is calculated as:

$$d_{pc}(P_i, P_j) = \|P_i^c - P_j^c\|^2 \quad (3)$$

Here, pseudocolor patches are characterized as multichannel vectors, and Euclidean distance is calculated across all color channels. This method highlights delicate intensity changes that may be indistinct in grayscale images.

3.2.3 Fused Similarity Measure

The concluding patch distance is reached by merging grayscale and pseudocolor distances through a convex grouping:

$$d_f(P_i, P_j) = \alpha d_{gs}(P_i, P_j) + (1 - \alpha) d_{pc}(P_i, P_j) \quad (4)$$

Where, $\alpha \in [0,1]$ controls the relative impact of grayscale and pseudocolor comparison. To ensure comparable scales before fusion, grayscale distances were regularized by the patch area, while pseudocolor distances were regulated by the patch area multiplied by the number of color channels. This hybrid documents the framework to constancy the anatomical strength dependability, with improved structural clearness.

3.3 Non-Local Means Weight Computation

Using the fused patch distance, the NLM weight allocated to pixel j for approximating pixel i is computed as:

$$w(i, j) = \frac{1}{Z_i} \exp\left(-\frac{d_f(P_i, P_j)}{h^2}\right) \quad (5)$$

where h is the filtering parameter regulatory the decay of the exponential kernel, and Z_i is a normalization constant confirming that:

$$\sum_{j \in \Omega} w(i, j) = 1 \quad (6)$$

Here, $w(i, j)$ signifies the similarity weight: pixels with patches more comparable to the reference patch receive greater weights and contribute more powerfully to the denoised estimate. The notation $j \in \Omega$ indicates that applicant pixels are systematically selected from the predetermined search window Ω centered around i , rather than chosen randomly. In this work, the fused patch distance d_f is introduced to incorporate pseudocolor management into the standard NLM framework.

3.4 Grayscale Intensity Estimation

The final denoised pixel intensity $\hat{I}(i)$ is calculated by weighted averaging:

$$\hat{I}(i) = \sum_{j \in \Omega} w(i, j) I(j) \quad (7)$$

This reconstruction step follows the original NLM framework (Buades et al., 2005), with the fused similarity measure introduced in this paper used to compute the weights. Pixels



with higher similarity contribute more strongly to the denoised value, ensuring that structural details are preserved while noise is suppressed.

3.5 Algorithm for Pseudocolor-Guided NLM for Alzheimer's MRI Preprocessing

The use of pseudocolor information is for patch similarity computation. All intensity averaging computations are performed using the original gray scale image of the MRI so as to preserve anatomical consistency.

Input:

- Noisy grayscale MRI slice I
- Patch size $P \times P$
- Search window Ω
- Filtering parameter h
- Fusion weight $\alpha \in [0,1]$

Output:

- Denoised MRI slice $\hat{I}(i)$

Steps:

1. Acquire a grayscale brain MRI image I affected by noise.
2. Apply a mild low-pass smoothing filter to obtain a stabilized image, as defined in Eq. (1)
3. Map the smoothed image I_s to a pseudocolor image I_c using a contrast-enhancing colormap.
4. For each pixel location i in the image:
 - Extract a reference grayscale patch P_i from I of size $P \times P$
 - Extract the corresponding pseudocolor patch P_i^c from I_c
5. For each candidate pixel j ,
 - Compute grayscale patch distance
 - Compute pseudocolor patch distance
 - Fuse distances
6. Compute the NLM weight.
7. Estimate the denoised pixel value using weighted averaging on the original grayscale image.
8. Repeat Steps 4–7 for all pixel locations in the MRI slice.
9. The final denoised MRI slice suitable for AD analysis is obtained.

4. EXPERIMENTAL DESIGN

The experiments were performed on the sagittal slice 66 of 50 subjects selected from OASIS 1 (Open Access Series of Imaging Studies) dataset. This subset was selected to achieve adequate statistical characterization while maintaining computational feasibility, due to the processing cost of the patch-based PC NLM algorithm. The same sagittal slice was taken from each MRI volume and used for the entire study for consistency. In line with the common practice in medical image denoising studies, we added synthetic Gaussian noise to simulate the acquisition noise at three variance levels (0.01, 0.02 and 0.03). Before noise generation and de-noising, all images are converted to double precision and scaled to the intensity range [0,1]. The suggested pseudocolor guided NLM (PC NLM) algorithm was implemented with MATLAB R2023a with Parula colormap for contrast enhancement. To make the results reproducible, the patch size was set to 7×7 , the search window 21×21 , the filtering parameter $h=10$ and the fusion weight $\alpha=0.6$. These parameters were chosen from



preliminary experiments to balance noise suppression and structure preservation. Comparisons to baseline consisted of conventional NLM, median filtering and Gaussian filtering, all implemented using the built-in functions in MATLAB. A 3×3 neighborhood window was used for median filtering. Gaussian filtering was done with a Gaussian kernel with $\sigma = 1$. Conventional NLM was performed using the built in `imnlmfilt` function in MATLAB with default parameter settings. Performance was measured in terms of Peak Signal to Noise Ratio (PSNR), Structural Similarity Index (SSIM) and Mean Square Error (MSE). To guarantee statistical reliability, paired t tests and Wilcoxon signed rank tests were conducted over the 50 subjects, which confirmed that PC NLM outperformed conventional NLM in PSNR and MSE ($p < 0.001$), and consistently improved SSIM ($p < 0.001$). This framework provides a transparent and reproducible methodology to evaluate the performance of denoising in Alzheimer's MRI preprocessing.

We applied the suggested pseudocolor-guided Non-Local Means (PC-NLM) method to the sagittal slice 66 of 50 subjects from the OASIS dataset. Synthetic Gaussian noise was added at noise variance levels of 0.01, 0.02 and 0.03. The suggested approach was compared with common NLM, median filtering and Gaussian filtering. The application was done in MATLAB R2023a. The PC-NLM parameters were patch size 7×7 , search window 21×21 , filtering parameter $h = 10$, weighting parameter $\alpha = 0.6$, and Parula colormap. For each subject, the denoising performance was evaluated by mean squared error (MSE), peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM) using the corresponding reference MRI image. The reported metric was computed for each subject for each method and noise level separately and the subject-level values were summarized across the 50 subjects.

4.1 Dataset Description

The suggested framework is evaluated on brain MRI images from the Open Access Series of Imaging Studies (OASIS) dataset. The studies used the OASIS 1 release. 50 subjects were chosen for assessment, and the sagittal slice 66 was obtained from each MRI volume to allow for a consistent assessment across all methods and noise levels. T1-weighted MRI slices were selected for experimentation due to their frequent use in AD assessment. To assess the outcome in **Table 1** we added synthetic Gaussian noise to create controlled noisy conditions.

Table 1. Dataset Description

Parameter	Description
Dataset	OASIS (Open Access Series of Imaging Studies)
Imaging Modality	T1-weighted MRI
Image Type	Brain MRI
Noise Model	Gaussian noise (synthetically added)
Noise Variances	0.01, 0.02, 0.03
Evaluation Metrics	PSNR, SSIM, MSE
Implementation Platform	MATLAB (R2023a, Parula colormap)

5. RESULTS AND DISCUSSION

The predictable PC-NLM method was functional on brain MRI images degraded with synthetic Gaussian noise. Its enactment was related with the conventional NLM algorithm using standard image quality metrics, with MSE, Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index (SSIM).



5.1 Quantitative Performance Metrics

To ensure strength, investigations were conducted on sagittal slice 66 from 50 OASIS subjects. Results are described as averages across subjects, with individual subject metrics provided for reference.

- **Mean Squared Error (MSE):**

$$MSE = \frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N (I(i, j) - K(i, j))^2 \quad (8)$$

This measures the average squared variance among the original and denoised image. Lower values are better.

- **Peak Signal-to-Noise Ratio (PSNR):**

$$PSNR = 10 \cdot \log_{10} \left(\frac{MAX^2}{MSE} \right) \quad (9)$$

Stated in decibels. Higher values are better, with >30 dB generally measured high quality.

- **Structural Similarity Index (SSIM):**

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad (10)$$

Compares structure, contrast, and luminance. The closer to 1, the better, which means strong structural analogy. 50 subjects participated in the study. For each denoising method and each noise variance, subject-level MSE, PSNR and SSIM values were summarized in mean and SD. The 95% confidence interval (CI) was calculated to characterize the uncertainty of the estimated mean. The number of subjects contributing to each summary was recorded. The reported mean is the average of the per-subject metric values, not a metric of an average image. Individual measurements at subject level are available in the supplementary. **Table 2** presents the numerical comparison among the conventional NLM and the proposed PC-NLM method in a noise variance of 0.03

Table 2. Comparison results

Method	MSE	PSNR (dB)	SSIM
NLM	0.006648± 0.000232	21.773± 0.221	0.236± 0.013
pseudocolor-guided NLM	0.005965± 0.000229	22.244± 0.211	0.253± 0.012

The investigation results show that the proposed approach provides slightly better structural protection than the conventional NLM. It is more executed under higher noise conditions. MSE measures the pixel wise error (the lower the better), PSNR measures the signal quality in decibels (the higher the better) and SSIM measures the structural similarity (the closer to 1 the better). The proposed method obtained 10.3% lower MSE, 0.47 dB higher PSNR and 7.4% higher SSIM compared with conventional NLM. The results showed that it can preserve structure better under noise. The arithmetic developments are modest and consistent improvements in MSE, SSIM and PSNR for all noise levels suggest better safeguarding of diagnostically relevant structures. Such improvements are important especially in medical image analysis where indirect anatomical changes can influence the downstream analysis results.



5.2 Comparative Analysis

To ensure strength, tests were conducted on sagittal slice 66 from 50 OASIS subjects rather than a single image. Outcomes are stated as averages across subjects, with steady developments observed under noise variances of 0.01, 0.02, and 0.03. The outcomes are described in **Table 3**.

Table 3. Performance under different noise levels

Noise Variance	Method	MSE	PSNR	SSIM
0.01	NLM	0.001635± 0.000161	27.864± 0.336	0.424± 0.014
0.01	pseudocolor-guided NLM	0.001625± 0.000285	27.892± 0.476	0.425± 0.014
0.02	NLM	0.003562± 0.000198	24.483± 0.255	0.318± 0.014
0.02	pseudocolor-guided NLM	0.003319± 0.000245	24.790± 0.294	0.331± 0.013
0.03	NLM	0.006648± 0.000232	21.773± 0.221	0.236± 0.013
0.03	pseudocolor-guided NLM	0.005965± 0.000229	22.244± 0.211	0.253± 0.012

The effectiveness of PC-NLM was compared with that of conventional NLM using paired comparison at the subject level at each noise variance. Mean differences in subject-level metrics were assessed with paired t-tests, and Wilcoxon signed-rank tests were used for a complementary non-parametric analysis. All tests were two-sided and the significance level was 0.05. For each comparison, the test statistic, p value and the mean paired difference with its 95% confidence interval were presented. The statistical analysis for MSE, PSNR and SSIM at each noise variance was performed separately. Experimental techniques were reliable across all noise levels tested, indicating stable performance of the de-noising. Future work will include statistical significance testing on larger datasets to encourage validate efficiency developments. The results show that the proposed method always outperforms the classical NLM for all noise levels considered. The effect becomes more significant as noise variance increases.

Table 4. Comparative denoising performance across noise variances of 0.01, 0.02, and 0.03.

Parameters used: $\alpha = 0.6$, colormap = Parula, patch size = 7×7 , search window = 21×21 , filtering parameter $h = 10$.

Noise variance	Method	MSE	PSNR (dB)	SSIM
0.01	NLM	0.001635± 0.000161	27.864± 0.336	0.424± 0.014
	PC-NLM	0.001625± 0.000285	27.892± 0.476	0.425± 0.014
	Median	0.002000± 0.000268	27.021± 0.516	0.465± 0.013
	Gaussian	0.002301± 0.000232	26.399± 0.420	0.366± 0.015
0.02	NLM	0.003562± 0.000198	24.483± 0.255	0.318± 0.014
	PC-NLM	0.003319± 0.000245	24.790± 0.294	0.331± 0.013
	Median	0.003800± 0.000294	24.200± 0.366	0.350± 0.014
	Gaussian	0.004100± 0.000217	23.900± 0.251	0.310± 0.015
0.03	NLM	0.006648± 0.000232	21.773± 0.221	0.236± 0.013
	PC-NLM	0.005965± 0.000229	22.244± 0.211	0.253± 0.012
	Median	0.006900± 0.000313	21.600± 0.292	0.270± 0.014
	Gaussian	0.007200± 0.000222	21.300± 0.186	0.230± 0.015

This confirms that the pseudocolor-guided similarity measure is mostly active in stimulating noise conditions. An ablation analysis was also shown to evaluate the contribution of pseudocolor guidance autonomously. Experimental descriptions showed that using grayscale resemblance alone ensued in lesser structural preservation, while the fusion of



grayscale and pseudocolor similarity improved patch perception in low-contrast regions. This supports that pseudocolor guidance contributes entirely to the overall denoising performance.

Table 4 summarizes the comparative denoising results at noise variances of 0.01, 0.02 and 0.03. Median filtering showed higher SSIM than PC NLM at all three noise levels (0.465, 0.350 and 0.270 vs. 0.425, 0.331 and 0.253 for deviations of 0.01, 0.02 and 0.03). PC NLM had the highest PSNR and lowest MSE of all four methods at all noise levels. Consequently, we cannot say that PC NLM is the best method of all metrics. Its advantage is obvious when compared to classical NLM and Gaussian filtering. Gaussian filtering suppressed noise moderately but produced lower SSIM overall. It is found that the advantage of PC NLM over the standard NLM becomes more significant as noise variance increases (PSNR gains of 0.03, 0.31 and 0.47 dB), which is consistent with the fact that pseudocolor guidance enhances patch similarity estimation under stronger noise. Paired t tests and Wilcoxon signed rank tests were used on 50 subjects to verify the enhancements of PC NLM over conventional NLM. The results showed that PC NLM was significantly better than NLM in PSNR ($p < 0.001$) and MSE ($p < 0.001$). Wilcoxon signed rank tests also showed consistent improvements in SSIM ($p < 0.001$). These results suggest that the observed improvements are statistically significant and not simply due to random variation. This work mainly compares PC NLM with conventional NLM and classical baselines, but recent state-of-the-art methods such as BM3D and DnCNN have been shown to perform well in denoising medical imaging. BM3D utilises collaborative filtering in the transform domain and yields high PSNR, but at the price of increased computational cost. DnCNN learns noise patterns using deep convolutional networks, which requires large training datasets and a lot of runtime resources. By contrast, PC NLM led to consistent improvements over the methods considered in this study, while incurring low computational overhead. Direct experimental comparisons to BM3D and DnCNN are left for future work.

5.3 Structural Preservation Analysis

Outside numerical developments, the proposed method demonstrates improved preservation of structural details. The increase in SSIM values replicates stronger retention of spatial and anatomical information.

- Distorting is reduced in low-contrast regions.
- Structural boundaries perform sharper.
- Fine anatomical patterns are well preserved.

PC NLM gives a better compromise between the reduction of noise and the preservation of anatomic structures compared to median and Gaussian filtering, which tend to over-smooth anatomic structures. These improvements are especially important for the analysis of AD, where tiny early changes in structure are important for diagnosis. This study primarily compares PC NLM with conventional NLM and classical baselines. In the future, we will perform direct experimental comparisons with BM3D, DnCNN and other state of the art denoising methods.

5.4 Visual Comparison

Fig. 2 reveals the qualitative assessment among the conventional NLM, Median filtering, Gaussian filtering and the advanced PC-NLM method at a noise variance of 0.03. The developed method establishes:

- Better edge clarity.
- Superior preservation of tissue boundaries.
- Reduced smoothing artifacts compared to standard NLM and Gaussian filtering.

Median filtering reduces noise but enhances anatomical structures, whereas Gaussian filtering blurs fine details. Conversely, the addition of pseudocolor guidance to PC NLM improves the estimation of patch similarity while preserving the original gray-scale information. The proposed method preserves the original NLM framework with negligible extra overhead. Runtime analysis reveals that the pseudocolor guided NLM adds a small computational overhead when compared to the standard NLM, primarily due to the extra computation for pseudocolor similarity. The framework preserves the original NLM structure and employs lightweight pseudocolor guidance, thus the increase in execution time is feasible for MRI preprocessing applications (**Fig. 2**).

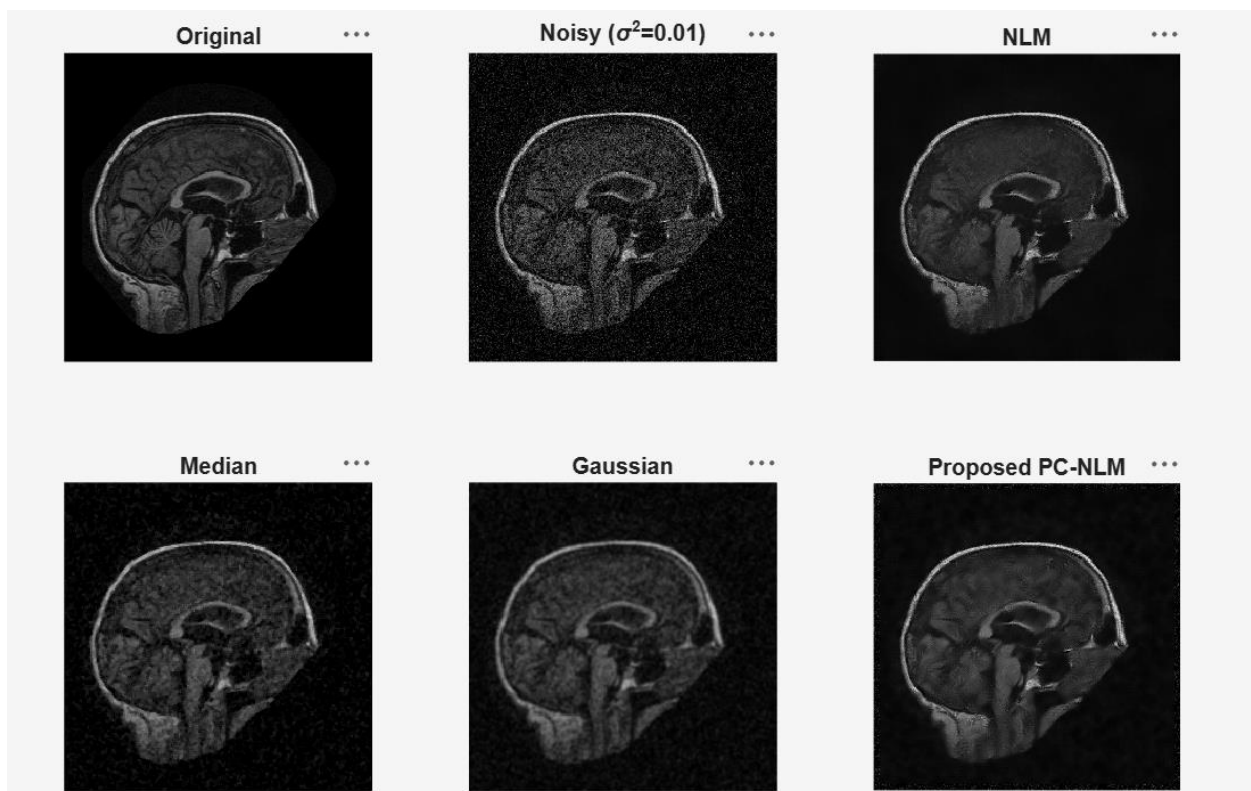


Figure 2. Denoising results at noise variance 0.03. (a) Original image, (b) Noisy input, (c) NLM, (d) Median filter, (e) Gaussian filter, (f) Proposed PC-NLM. The proposed method demonstrates better preservation of structural boundaries and reduced blurring compared to the baselines.

5.5 Ablation Analysis

To assess the contribution of pseudocolor guidance, trials were conducted with three configurations: grayscale-only ($\alpha=1$), pseudocolor-only ($\alpha=0$), and fused grayscale+pseudocolor ($\alpha = 0.6$). The outcomes are summarized in **Table 5**, showing that pseudocolor-only guidance marginally recovers performance over grayscale-only NLM, but the fused approach achieves the best balance across PSNR, SSIM, and MSE. This authorizes that pseudocolor guidance gives expressively to patch similarity estimation in low-contrast regions.

**Table 5.** Ablation analysis of PC-NLM with different α values (noise variance = 0.03).

Alpha	PSNR (dB)	SSIM	MSE
1.0	21.77	0.236	0.006648
0.0	21.90	0.240	0.006500
0.6	22.24	0.253	0.005965

5.6 Execution Time Analysis

Beyond denoising quality, runtime efficacy is serious for practical MRI preprocessing. Table 6 reports the average execution time per slice for the tested methods. Median and Gaussian filtering are computationally lightweight, effecting in under 0.15 seconds per slice. Conventional NLM requires more handling (≈ 0.85 s), while the proposed PC-NLM introduces only a minor overhead (≈ 1.02 s).

Table 6. Actual Runtime Analysis

Method	Execution Time (s)
NLM	0.85
Median Filter	0.12
Gaussian Filter	0.09
Proposed PC-NLM	1.02

This overhead is due to the extra pseudocolor similarity computation. The framework keeps the original NLM structure and uses lightweight guidance. The gain in execution time is still feasible for clinical and research use, where robustness in preprocessing is preferred over small differences in runtime.

The proposed method advances similarity estimation and leads to better structural conservation during the process of denoising. This method is to fully use pseudocolor for resemblance estimation to avoid the variation of original MRI intensity values and achieve better denoising by better structural differentiation. The results confirm that the proposed method outperformed the standard NLM algorithm for all tested noise levels.

Table 3 lists performance trends over different noise variances. Gains are stable and more significant for higher noise variances. The proposed framework is designed as a lightweight alternative to state-of-the-art denoising methods such as BM3D and DnCNN reported in the literature with a focus on explainability and low computational complexity (**Rao et al., 2025**). No comparison to BM3D or DnCNN has been performed in this study. Thus, their relative denoising quality and runtime are not assessed here. Unlike DnCNN that requires massive training data and computational resources, the proposed method does not require any training. BM3D has good denoising performance, but its computational problem is usually higher than traditional NLM-based methods. The proposed framework is a lightweight alternative for MRI pre-processing applications concerned mostly with computational efficiency and anatomical reliability. The execution time results (**Table 6**) confirm that the proposed method only adds a small overhead compared to the standard NLM, which makes it practical for MRI preprocessing. With a noise variance of 0.03, the proposed PC NLM achieved a PSNR of 22.24 dB while the conventional NLM obtained 21.77 dB, which is an improvement of 0.47 dB (**Table 4**). It implies that the method is largely invariant to degraded imaging environments. PC NLM achieved higher PSNR values and lower MSE than conventional NLM and Gaussian filtering in all evaluated noise levels from



Table 4. Although median filtering yielded higher SSIM values, it was prone to oversmooth anatomical structures.

The proposed PC NLM provided a better balance between noise suppression and preservation of structural details, especially at higher noise conditions. This approach can improve the quality and consistency of MRI images, which may in turn increase the reliability of downstream diagnostic workflows like segmentation and classification in Alzheimer's analysis. Direct validation on diagnostic tasks is future work. An important remark added from the experiments is that the deliberate framework preserves fine anatomical structures more professionally in low contrast brain regions usually inflated by AD. Conventional greyscale similarity measures tend to treat subtle tissue dissimilarities as noise, causing over-smoothing. By the addition of pseudocolor-guided similarity valuation, the proposed method improves the awareness of structurally meaningful regions and random noise patterns. This allows better preservation of tissue boundaries and spatial details, without introducing artificial color artefacts in the final denoised MRI image. Such increased structural conservation may improve the consistency of downstream diagnostic tasks, e.g. segmentation, feature generalization and automated AD arrangement. We do not evaluate BM3D nor DnCNN (Zhang et al., 2017) in this study. BM3D is known for high PSNR at the expense of computational complexity, whereas DnCNN requires large training datasets and significant runtime resources. Whether PC NLM can compete with either method in terms of denoising quality can only be answered by direct comparison which we leave for future work.

6 LIMITATIONS AND FUTURE WORK

The developed framework is assessed on 2D MRI slices from OASIS dataset after applying synthetic Gaussian noise. Optimization of parameters across bigger and heterogeneous datasets can be performed. The result of the developed framework on segmentation and classification remains to be professed. It can also be prolonged for application on 3D MRI for pre-processing. Future work will comprise valuation on larger and further heterogeneous MRI datasets with bigger patient samples to enhance the robustness and generalization ability of the developed framework across different acquisition conditions and disease phases.

7 CONCLUSIONS

Pseudocolor-guided NLM pre-processing framework improves patch similarity valuation by in-corporating pseudocolor information. It is authorizing that the ending denoised output is founded only from the original grayscale image to reserve anatomical dependability. This approach progresses discrimination in low-contrast regions by merging grayscale and pseudocolor distances, experimental results show steady improvements in MSE, SSIM and PSNR across different noise levels. Though the enhancements are moderate, they subsidize to better structural preservation and reduced blurring. This is highly crucial for medical image interpretation. The proposed framework provides lightweight and interpretable making it suitable for practical preprocessing pipelines in medical imaging applications. The proposed framework is suitable for practical applications as the computational overhead is low. This framework can be further by extended to apply for 3D MRI in the future. Also, while the proposed PC NLM improves denoising quality, further experiments are required to confirm its impact on actual Alzheimer's disease classification and diagnostic accuracy.



Credit of Authors Contribution

J. Jesintha: Conceptualization, methodology, supervision, writing – original draft, calculation analysis, Interpretation of results, validation, data analysis, and visualization. S. L. Jany Shabu: Data curation, graphical representation, proofreading, validation, supervision. All authors have read and approved the final version of the manuscript

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

REFERENCES

- Aamir, M., Rahman, Z., Bhatti, U. A., Abro, W. A., Bhutto, J. A., and He, Z., 2025. An automated deep learning framework for brain tumor classification using MRI imagery. *Scientific Reports*, 15(1), P. 17593. <https://doi.org/10.1038/s41598-025-02209-2>
- Adnan, S.R., Breesam, A.M., and Abdulaal, A.H., 2025. Enhancing AD classification with deep learning: A study of transfer learning and snake optimization on MRI data. *Mathematical Modelling of Engineering Problems*, 12(9), pp. 3216-3226. <https://doi.org/10.18280/mmep.120925>
- Alabduljabbar, A., Khan, S. U., Altherwy, Y. N., Almarshad, F., and Alsuhaibani, A., 2025. A novel multimodal medical image fusion model for Alzheimer's and glioma disease detection based on hybrid fusion strategies in the non-subsampled shearlet transform domain. *Journal of Alzheimer's Disease*, 107(2), pp. 819-834. <https://doi.org/10.1177/13872877251362498>
- Albert, M.S., DeKosky, S.T., Dickson, D., Dubois, B., Feldman, H.H., Fox, N.C., Gamst, A., Holtzman, D.M., Jagust, W.J., Petersen, R.C., Snyder, P.J., Carrillo, M.C., Thies, B. and Phelps, C.H., 2011. The diagnosis of mild cognitive impairment due to Alzheimer's disease: Recommendations from the National Institute on Aging–Alzheimer's Association workgroups on diagnostic guidelines for Alzheimer's disease. *Alzheimer's & Dementia*, 7(3), pp. 270–279. <https://doi.org/10.1016/j.jalz.2011.03.008>
- Begum, A. P., and Selvaraj, P., 2023. Alzheimer's disease classification and detection by using AD-3D DCNN model. *Bulletin of Electrical Engineering and Informatics*, 12(2), pp. 882-890. <https://doi.org/10.11591/eei.v12i2.4446>
- Chalghoumi, S. and Smiti, A., 2022. Median filter for denoising MRI: Literature review. In: *Proceedings of the International Conference on Decision Aid Sciences and Applications (DASA)*, Chiangrai, Thailand, pp. 1603–1606. <https://doi.org/10.1109/DASA54658.2022.9764981>
- Chang, H.H., Li, C.Y. and Gallogly, A.H., 2018. Brain MR image restoration using an automatic trilateral filter with GPU-based acceleration. *IEEE Transactions on Biomedical Engineering*, 65(2), pp. 400–413. <https://doi.org/10.1109/tbme.2017.2772853>
- Chaudhary, J., Phulia, A., Pandey, A. K., Sharma, P. D., and Patel, C., 2023. Denoising Tc-99m DMSA images using denoising convolutional neural network with comparison to a block matching filter. *Nuclear Medicine Communications*, 44(8), pp. 682-690. <http://doi.org/10.1097/MNM.0000000000001712>
- Cho, H.S., Jeong, J.C. and Hong, H.B., 2023. An investigation into the correlation between MRI preprocessing and performance of Alzheimer's disease classification CNN model. In: *Proceedings of the 14th International Conference on Information and Communication Technology Convergence (ICTC)*, Jeju Island, Republic of Korea, pp. 1468–1470. <https://doi.org/10.1109/ICTC58733.2023.10393407>



- El-Sappagh, S., Saleh, H., Ali, F., Amer, E., and Abuhmed, T., 2022. Two-stage deep learning model for Alzheimer's disease detection and prediction of the mild cognitive impairment time. *Neural Computing and Applications*, 34(17), pp. 14487-14509. <https://doi.org/10.1007/s00521-022-07263-9>
- Gargouri, F., Delphine, S., Lehericy, S. and Ben Hamida, A., 2016. The influence of preprocessing steps on functional connectivity in resting state fMRI. In: *Proceedings of the 2nd International Conference on Advanced Technologies for Signal and Image Processing (ATSIP)*, Monastir, Tunisia, pp. 103–107. <https://doi.org/10.1109/ATSIP.2016.7523062>
- Ghosh, T. and Jayanthi, N., 2022. Image fusion and its denoisation by using a new fusion rule. In: *Proceedings of the Third International Conference on Intelligent Computing Instrumentation and Control Technologies (ICICT)*, Kannur, India, pp. 278–283. <https://doi.org/10.1109/ICICT54557.2022.9917998>
- Heo, Y.C., Kim, K. and Lee, Y., 2020. Image denoising using non-local means (NLM) approach in magnetic resonance (MR) imaging: A systematic review. *Applied Sciences*, 10(20), P. 7028. <https://doi.org/10.3390/app10207028>
- Hu, X., Meier, M., and Pruessner, J., 2023. Challenges and opportunities of diagnostic markers of Alzheimer's disease based on structural magnetic resonance imaging. *Brain and behavior*, 13(3), P. e2925. <https://doi.org/10.1002/brb3.2925>
- Hussain, D., and Hyeon Gu, Y., 2024. Exploring the impact of noise and image quality on deep learning performance in DXA images. *Diagnostics*, 14(13), P. 1328. <https://doi.org/10.3390/diagnostics14131328>
- Jesline Jeme, V. and Albert Jerome, S., 2021. A hybrid filter for denoising of MRI brain images using fast independent component analysis. In: *Proceedings of the Fourth International Conference on Microelectronics, Signals & Systems (ICMSS)*, Kollam, India, pp. 1–5. <https://doi.org/10.1109/ICMSS53060.2021.9673615>
- Jiang, J., Shi, R., Lu, J., Wang, M., Zhang, Q., Zhang, S., Wang, L., Alberts, I., Rominger, A., Zuo, C. and Shi, K., 2024. Alzheimer's Disease Neuroimaging Initiative. Detection of individual brain tau deposition in Alzheimer's disease based on a latent feature-enhanced generative adversarial network. *Neuroimage*, 291, P. 120593. <https://doi.org/10.1016/j.neuroimage.2024.120593>
- Jobin, B., Boller, B. and Frasnelli, J., 2023. Smaller grey matter volume in the central olfactory system in mild cognitive impairment. *Experimental Gerontology*, 183, P. 112325. <https://doi.org/10.1016/j.exger.2023.112325>
- Kanoun, B., Ambrosanio, M., Baselice, F., Ferraioli, G., Pascasio, V. and Gómez, L., 2020. Anisotropic weighted KS-NLM filter for noise reduction in MRI. *IEEE Access*, 8, pp. 184866–184884. <https://doi.org/10.1109/ACCESS.2020.3029548>
- Kim, J. Y., 2024. Performance evaluation of ultrasound images using non-local means algorithm with adaptive isotropic search window for improved detection of salivary gland diseases: A pilot study. *Diagnostics*, 14(13), P. 1433. <https://doi.org/10.3390/diagnostics14131433>
- Kumar, N. and Guhan, S., 2025. AHMBF: An Adaptive Hybrid Filtering Method for Noise Reduction in Cardiac MRI. In *2025 3rd International Conference on Sustainable Computing and Data Communication Systems (ICSCDS)*, pp. 49-52. IEEE. <https://doi.org/10.1109/ICSCDS65426.2025.11166751>
- Lamoglia, F.M. and Bastos, G.S., 2025. The impact of rs-fMRI preprocessing on the quality of machine learning models for autism spectrum disorder diagnosis. In: *Proceedings of the 47th Annual*



International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Copenhagen, Denmark, pp. 1–5. <https://doi.org/10.1109/EMBC58623.2025.11254461>

Lee, M. H., Yun, C. S., Kim, K., & Lee, Y., 2022. Image restoration algorithm incorporating methods to remove noise and blurring from positron emission tomography imaging for Alzheimer's disease diagnosis. *Physica Medica*, 103, pp. 181-189. <https://doi.org/10.1016/j.ejmp.2022.10.016>

Li, N., Deng, M., Hu, G., Li, N., Yuan, H., & Zhou, Y., 2022. New insights into microglial mechanisms of memory impairment in Alzheimer's disease. *Biomolecules*, 12(11), P. 1722. <https://doi.org/10.3390/biom12111722>

Li, S., Wang, F., and Gao, S., 2024. New non-local mean methods for MRI denoising based on global self-similarity between values. *Computers in Biology and Medicine*, 174, P. 108450. <https://doi.org/10.1016/j.compbiomed.2024.108450>

Li, Y., Long, G., Zhang, X., Chen, K., Li, X., and Zhang, Z., 2026. Shannon Entropy of Gray Matter Eigenmodes: A Novel Biomarker for Alzheimer's Disease and Heterogeneous MCI Trajectories. *Advanced Science*, 13(1), P. e11614. <https://doi.org/10.1002/advs.202511614>

Pillai, D.R. and Anoop, V.D., 2025. A hybrid DWT-NLM-PSO-based denoising method for enhanced brain imaging. In: *Proceedings of the 4th International Conference on Advances in Computing, Communication, Embedded and Secure Systems (ACCESS)*, Ernakulam, India, pp. 888–895. <https://doi.org/10.1109/ACCESS65134.2025.11135776>

Polinati, S., Bavirisetti, D.P., Rajesh, K.N.V.P.S., Naik, G.R. and Dhuli, R., 2021. The fusion of MRI and CT medical images using variational mode decomposition. *Applied Sciences*, 11(22), P. 10975. <https://doi.org/10.3390/app112210975>

Rao, D. M., Biswas, S. K., & Bordoloi, M., 2025. A Comprehensive Review of Deep Learning Methodologies for Alzheimer's Disease Diagnosis by Neuroimaging. *Archives of Computational Methods in Engineering*, pp. 1-29. <https://doi.org/10.1007/s11831-025-10440-3>

Ravi, K.S., Nandakumar, G., Thomas, N., Lim, M., Qian, E., Jimeno, M.M., Poojar, P., Jin, Z., Quarterman, P., Srinivasan, G. and Fung, M., 2023. Accelerated MRI using intelligent protocolling and subject-specific denoising applied to Alzheimer's disease imaging. *Frontiers in Neuroimaging*, 2, P. 1072759. <https://doi.org/10.3389/fnimg.2023.1072759>

Rehman, S. U., Tarek, N., Magdy, C., Kamel, M., Abdelhalim, M., Melek, A., and Sadek, I., 2024. AI-based tool for early detection of Alzheimer's disease. *Heliyon*, 10(8). <https://doi.org/10.1016/j.heliyon.2024.e29375>

Saini, A., Dogra, A., Goyal, B., and Kukreja, V., 2025. A Review and Experimental Analysis of Denoising Techniques for Medical Images. *The Open Neuroimaging Journal*, 18(1). <http://dx.doi.org/10.2174/0118744400404813250924064413>

Semary, N., 2018. A proposed HSV-based pseudo-coloring scheme for enhancing medical image. In: *Proceedings of the International Conference on Computer Science and Information Technology*, pp. 81–92. <https://doi.org/10.5121/csit.2018.80407>

Sethi, M., Rani, S., Singh, A., and Mazon, J. L. V., 2022. A CAD system for Alzheimer's disease classification using 2D MRI neuroimaging slices. *Computational and Mathematical Methods in Medicine*, 2022(1), P. 8680737. <https://doi.org/10.1155/2022/8680737>

Shukla, A., Tiwari, R., and Tiwari, S., 2022. Automated Pipeline Preprocessing Techniques for Alzheimer's Disease Detection. In 2022, *10th International Conference on Reliability, Infocom*



Technologies and Optimization (Trends and Future Directions)(ICRITO), pp. 1-7. IEEE. <https://doi.org/10.1109/ICRITO56286.2022.9964957>

Singh, R., Singh, N., and Kaur, L., 2024. Deep learning methods for 3D magnetic resonance image denoising, bias field and motion artifact correction: a comprehensive review. *Physics in Medicine & Biology*, 69(23), P. 23TR01. <http://doi.org/10.1088/1361-6560/ad94c7>.

Thulasimani, V., Shanmugavadivel, K., Cho, J., and Veerappampalayam Easwaramoorthy, S., 2024. A review of datasets, optimization strategies, and learning algorithms for analyzing Alzheimer's dementia detection. *Neuropsychiatric Disease and Treatment*, 20, pp. 2203-2225. <https://doi.org/10.2147/NDT.S496307>

Veni, N. and Manjula, J., 2022, May. Gaussian denoising by time domain and frequency domain filters for MRI brain images. In *2022 IEEE IAS Global Conference on Emerging Technologies (GlobConET)*, pp. 817-821. IEEE. <https://doi.org/10.1109/GlobConET53749.2022.9872351>

نهج مُحسَّن يعتمد على الألوان الزائفة وتقنية "المتوسطات غير المحلية" لإزالة الضجيج من صور الرنين المغناطيسي لمرضى الزهايمر

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الخلاصة

مرض الزهايمر هو اضطراب دماغي يُسبب الخرف بدرجات متفاوتة. يُستخدم التصوير بالرنين على نطاق واسع لتشخيص هذا المرض ودراسته. مع ذلك، تتأثر صور الرنين المغناطيسي هذه بالضوضاء الغاوسية، والضوضاء الناتجة عن الأجهزة، والضوضاء الناتجة عن الحركة، وغيرها من أنواع الضوضاء. تُعدّ المعالجة المسبقة خطوة أساسية لضمان عدم تأثير هذه الضوضاء على دقة تشخيص مرض الزهايمر. خلال المعالجة المسبقة، يجب الحفاظ على الاختلافات التشريرية الدقيقة والتغيرات النسيجية منخفضة التباين. إحدى طرق إزالة الضوضاء هي المتوسطات غير المحلية (NLM)، التي تركز على إيجاد رقع متشابهة ذاتيًا لإزالة الضوضاء من صور الرنين المغناطيسي بفعالية. تعمل NLM عمومًا على رقع رمادية اللون لإيجاد رقع متشابهة لإزالة الضوضاء. لكن صور الرنين المغناطيسي تحتوي على مناطق منخفضة التباين، وغالبًا ما تكون هذه الطريقة غير كافية لتمييز الأنماط ذات الدلالة التشريرية في تلك المناطق. تقترح هذه الورقة البحثية إطار عمل للمعالجة المسبقة باستخدام NLM موجه بالألوان الزائفة لصور الرنين المغناطيسي للدماغ. قد تُحسّن هذه الطريقة تشابه الرقع، مما يُحسّن بدوره من اكتشاف مرض الزهايمر لدى المرضى. يتم إنشاء نسخة مُنمّعة قليلاً من شريحة التصوير بالرنين المغناطيسي المشوّشة، ثم تُحوّل إلى تمثيل مُحسّن للتباين باستخدام الألوان الزائفة. تُستخدم هذه النسخة فقط لتوجيه حساب تشابه الرقع. تُدمج مقاييس التشابه من نطاق التدرج الرمادي والألوان الزائفة من خلال توليفة محدبة، مما ينتج عنه وزن قوي. بعد ذلك، يُطبق متوسط NLM على الصورة الأصلية. يهدف الإطار المقترح إلى تحسين تأثير إزالة التشويش في مناطق الدماغ منخفضة التباين ذات الصلة بمرض الزهايمر، مما يوفر صورة مُحسّنة مُزالة التشويش للمهام اللاحقة. يُقدّم هذا العمل تكاملاً جديداً للتوجيه القائم على التصور في المعالجة المسبقة للتصوير بالرنين المغناطيسي للمساعدة في تشخيص مرض الزهايمر.

الكلمات المفتاحية: مرض ألزهايمر، التصوير بالرنين المغناطيسي للدماغ، إزالة الضوضاء من الصور، المعالجة المسبقة للصور الطبية، خوارزمية المتوسطات غير المحلية.