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Article

Effectiveness of Fourier, Wiener, Bilateral, and CLAHE Denoising Methods for CT Scan Image Noise Reduction

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Abstract: The proper reduction of noise inside CTscan Images remains crucial to achieve both better diagnosis results and clinical choices. This research analyzes through quantitative metrics the effectiveness of four popular noise reduction methods which include Fourier-based denoising and Wiener filtering as well as bilateral filtering and Contrast Limited Adaptive Histogram Equalization (CLAHE) applied to more than 500 CTscan Images. The investigated methods were assessed quantitatively through Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) while Mean Squared Error (MSE) served as the additional metric for evaluation. The evaluated denoising methods revealed bilateral filtering as the best technique based on its 50.37 dB PSNR and 0.9940 SSIM together with its 0.5967 MSE. Denoising with Fourier-based methods succeeded in removing high-frequency noise however it produced PSNR of 25.89 dB along with SSIM of 0.8138 while maintaining MSE at 167.4976 indicating lost crucial Image information. The performance balance of Wiener filtering resulted in 40.87 dB PSNR and 0.9809 SSIM and 5.3270 MSE that outperformed Fourier denoising in SSIM yet demonstrated higher MSE. CLAHE produces poor denoising outcomes because it achieves the lowest PSNR of 21.51 dB together with SSIM of 0.5707, and the maximum MSE of 459.1894 while creating undesirable artifacts. This research stands out through a full evaluation of four denoising techniques on a big dataset to create more precise analysis than prior research. The research results show bilateral filtering to be the most reliable technique for CTscan Image noise reduction when maintaining picture quality and thus represents a suitable choice for clinical use. This research adds new information to medical imaging research about quality enhancement which directly benefits clinical diagnostics and therapeutic planning.

Keywords: CT Scan; Denoising; Bilateral Filtering; Fourier Transform; Image Quality

1. Introduction

CT scanning remains a useful diagnostic medical device, providing explicit images of internal structures of the body through cross-sectional approximations. But all types of noise can infect CT scan images due to factors like limited exposure of radiation, movement of the patient, and failure of machinery. Noise reduces such important information for diagnosis to be less identifiable, and hence more challenging to determine the outcome. The merit of image denoising techniques used on CT scans has grown significantly with the ability to enhance diagnostic accuracy and reliability, especially to preserve small details and reduce noise.

Several methods exist to denoise CT scan image, and the advantages and limitations vary based on the method. The Fourier-based methods are some of the significant ones used in medical imaging. The techniques involve the application of Fourier transformations to convert the image into the frequency domain where terms for high-frequency noise are eliminated and low-frequency data retained. The operation efficiently deletes the noise but results in edge blurring that can discard significant details [1].

Wiener filtering has been considerably researched in the case of CT image denoising as it is also flexible, whereby it varies the filtering according to the local statistical pattern of the image. It is a good method to reduce noise where the intensities are changing but may soften the edges and thus distort image quality—most likely in the field of medical imaging where the edges must be maintained [2]. Non-bilinear filtering is very common as it can preserve edges and remove noise. The technique works by reading pixels' intensity and spatial variables, hence capable of preserving edges as well as smoothing equally intense areas. The process is particularly advantageous in medical imaging since it has the potential to preserve important anatomical information necessary for accurate diagnostics [3], [4].

Low-Clarity Limited Adaptive Histogram Equalization algorithm enhances contrast in low-clarity regions of images by equalizing histograms of separated image blocks. While CLAHE brings visibility in certain places, in other places, it produces artifacts and uneven denoising effects [5].

In order to quantify the performance of different denoising algorithms, certain performance metrics like the Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Mean Squared Error (MSE) are used. These metrics compare the quality of denoised images and provide an objective assessment of whether denoising algorithms can denoise images and preserve image detail.

This work is conducted on a critical data set of CT scans with four of the most popularly applied denoising methods: Fourier transforms, Wiener filters, bilateral filters, and CLAHE. Unlike other research studies where one method was compared or two methods were compared, this study approaches a total comparison of the aforementioned methods to identify the best method of enhancing CT image resolution to be used for successful disease detection.

2. Literature Review

A very substantial amount of research studies has been conducted on the image denoising methods with the view to enhancing the quality of images in CT scans because they play an important role in the accuracy of medical diagnosis. The focus of all these studies is to remove the noise but retain useful information of the image. Various noise removal techniques like Fourier transformations, Wiener filtering, bilateral filtering, and CLAHE have been used extensively in medical research studies owing to the respective merits and demerits of each.

Fourier-type denoising techniques have been shown to recently perform well in CT imaging by studies. Resolution-loss, edge-lost separation techniques that use Fourier-transforming remove image detail from noisy frequencies. Recently constructed [6] for instance, used recently constructed Fourier transforms in their CT image processing technique but with very high loss of the definition of edges in high gradient regions.

Wiener filtering is strongly assumed in de-noising of CT images too, owing to the fact that it is capable of locally estimating image de-noising statistics. The process was tried out against other denoising algorithms in a study [7] and promoted its significance in noise removal. The Wiener filter is not robust in non-stationary noise and hence not so superior with advanced CT images. It was also discovered in research not to work effectively over homogeneous regions and on noisy surfaces [8]. Tested Wiener filtering along with other image enhancement techniques of CT images but discovered the Wiener filter not to work effectively with heavy noise, especially low-dose CT images.

Bilateral filtering has been a popular method to denoise CT images for edge preservation. Noise elimination without feature boundary loss, bilateral filtering guarantees the preservation of essential anatomical details needed in CT scans. Boundary preservation was optimized via bilateral filtering in research [9] for enhancing the quality of ischemic CT scans. The procedure is imperfect, particularly velocity and its limitation for very textured images. Over-smoothing would lead to removal of very small but valuable structures such as micro-calcifications of tumors [10].

The medical image processing method is widely used in the form of local contrast enhancement, i.e., the CLAHE. The approach limits over-amplification of unwanted noise, and hence it is very appropriate in medical imaging. However, studies like [11] explained the limitations of CLAHE in uniform larger regions or varying illuminations in CT scans. Though acuity of vision in some regions is attained by CLAHE, in simple application in CT scans, such performance is degraded as the structural coherence is lost. But another work by [12] combined CLAHE with certain other preprocessing methods to circumvent these issues but was less effective in performance when implemented in the diagnosis of lung ailments.

Though all these methods have been pursued extensively individually, research comparing the four algorithms of denoising under identical conditions on large sets of CT images is scarce. To attain maximum contrast between vein and artery, utilization of CLAHE on images is necessary. This research accomplishes that by rigorously carrying out performance analysis of Fourier, Wiener, bilateral filtering, and CLAHE on real CT imaging data.

The work performs real performance assessment in objective (PSNR, SSIM, MSE) and subjective testing. In contrast to previous researches with one method comparison only or narrow data sets, this research compares various denoising methods with varied sets of images and within various clinical environments and offers useful data for hospitals that need precise imaging reports.

There have been studies on how image denoising algorithms in CT scan images since they are the basis of medical diagnostic precision. The common objective in studies is to reduce noise but not on regions that are critical to the image. There have been numerous modes of denoising algorithms such as Fourier transform, Wiener filtering, bilateral filtering, and CLAHE that have been of common use in medical research because of their weaknesses and strengths.

Fourier-based denoising techniques have been found to produce promising results in CT imaging, according to studies. Fourier separation techniques of the Fourier transform have been found to have capability to separate image data from noisy frequencies with low-resolution and edge information elimination limitations. For example, a study [13] compared PET-CT image preprocessing techniques in lung cancer and showed how Fourier transforms efficiently differentiate noisy areas in the scenario of deviations on resolutions.

Wiener filtering has been thoroughly researched, and a research paper [14] provided a review of CT and X-ray image denoising algorithms and illustrated the learning of local noise statistics with Wiener filtering. The process is insufficient for treating the non-stationary noise pattern of complex images. Wiener filtering has also failed despite homogeneous textures and regions of texture. Additional work [15] acknowledged the insufficiency of Wiener filtering on mammogram images by categorizing the challenges faced with noisy or textural image processing.

Bilateral filtering is a widely used denoising method, primarily because of the edge-preservation property. In a paper by [16] bilateral filtering was proposed as an answer that can improve ischemic posterior fossa CT scans by maintaining boundary integrity. However, heavy-textured region over-smoothing will ruin small but critical detail like micro-calcifications or tumors, according to [17]. It is a tremendous problem when used on intricate CT scans.

CLAHE is also one of the most typical medical image improvement methods, namely local contrast improvement. Nevertheless, CLAHE limitations such as heterogeneously illuminated regions or exceptionally huge homogeneous regions are still applicable to research papers such as [18], where CLAHE improved retina images but was ineffective in preserving raw CT image structure coherence. In addition [19], concluded that CLAHE is the cause of visual artifacts when used for processing a CT scan, and also causes inconsistency in diagnosis.

Even though all of these approaches were separately examined in elaborate detail, there is limited published work comparing the four approaches under controlled environments. This shortage is filled here by [20] comparing Fourier, Wiener, bilateral filtering, and CLAHE for some other medical purposes. The outcome of their study is that application of some of the above-discussed techniques in a cascade improves than the application of any one of them separately.

Recently compared deep learning-based quality of CT image denoising with that obtained by traditional denoising algorithms [21]. Authors compare classical and deep learning-based denoising techniques and introduce new results about the optimization of the image quality in the CT framework.

Consequently, [22] Applied wavelet transforms to CT scans to improve their quality, mainly for the diagnosis of chest nodules. Wavelet techniques were discovered to improve the image quality without distorting core details that are required in accurate chest CT scans.

3. Research Gaps

While there has been existing research comparing performance of every denoising algorithm individually compared to the others, there have been inadequate efforts in trying to show how they perform when all of them are taken together. In this work, we fill the gap by making a comparison of Fourier, Wiener, bilateral and CLAHE algorithms' performance on actual scan images directly. Even though subjective methods are widely used in publications, the performance of all the denoising methods is evaluated herein through the help of objective metrics such as PSNR, SSIM, and MSE. Eradicating the limitations of existing methods, this paper introduces new methods and invites medical image processing experts to provide accurate CT analysis for efficient detection of diseases.

4. Methodology

This research evaluated and assessed the performance effectiveness between four well-known denoising approaches that included Fourier-based denoising and Wiener filtering alongside bilateral filtering and CLAHE (Contrast Limited Adaptive Histogram Equalization) when applied to CT scan Images. The investigation conducted its examination using more than 500 CT Images which provided extensive evaluation results. The research methodology consists of four distinct stages that include Image selection and preprocessing and denoising and performance evaluation procedures.

4.1. Image Selection

CT scan Image selection starts the entire process. A user interface enables selection of up to ten Images as a set at one time. The system displays a graphical interface that enables users to choose Images directly from determined system folders. The program confirms Image selection by showing an error message if users neglect to pick any Images. Processing of selected Images occurs after users choose various file formats among PNG, JPG and JPEG that will be subsequently loaded into the system.

4.2. Image Preprocessing

Each chosen Image needs its initial phase to eliminate noise content. The conversion to grayscale occurs when a system detects color format (RGB). The conversion process simplifies denoising operations through transformation from three channels of red, green and blue color into a single grayscale channel. The noise reduction techniques receive grayscale Images after which they undergo formatting to maintain equality during comparison. The conversion from RGB to grayscale can be represented as follows:

$$\text{Gray} = 0.2989 \times \text{Red} + 0.5870 \times \text{Green} + 0.1140 \times \text{Blue} \quad (1)$$

4.3. Denoising Methods

The main approach of the methodology consists of four denoising methods which are executed on each chosen Image. The explanation follows in detail about these methods.

4.3.1. Fourier-Based Denoising (Low-Pass Filter)

The grayscale Image undergoes a 2D Fast Fourier Transform (FFT) application before beginning Fourier-based denoising methods. The transformation moves Image data from spatial domain to frequency domain status. The shift operation lets fftshift move the zero-frequency element to the spectral center. Through low-pass filter creation the cutoff radius enables the identification of high-frequency noise that will be eliminated. All frequencies the set cutoff point get blocked by the filter application. The process terminates with ifft2 which transforms the frequency data into spatial Image form for the depiction of the denoised picture. The technique does an effective job at removing high-frequency noise while it blurs sharp edges which affects the preservation of fine details.

$$F(u,v) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f(x,y)e^{-2\pi i(ux+vy)}dx\,dy \quad (2)$$

After the Image transformation, the zero-frequency component is shifted to the center of the spectrum by fftshift. A low-pass filter is then used that removes high-frequency components, which have been assumed to be noise. Such a filter can be represented as:

$$H(u,v) = \begin{cases} 1, & if \sqrt{(u-u_0)^2+(u-u_0)^2 \leq r_c} \\ 0, & otherwise \end{cases} \quad (3)$$

Here r_c is the cutoff radius, and (u0, v0) is the center of the Image. This filter removes frequencies the cutoff radius, which r_c effectively smooths the Image. The filtered Image is then transformed back to the spatial domain by performing an inverse FFT:

$$f_{denoised}(x,y) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f(u,v)e^{2\pi i(ux+vy)}du\,dv \quad (4)$$

4.3.2. Wiener Filtering

The built-in MATLAB function wiener2 performs Wiener filtering. Wiener filtering functions as an adaptive algorithm which performs noise reduction estimation based on local variance while adapting its filtering process to match. Our local features. If the Wiener filter has a 5x5 window size it strikes a good equilibrium between noise reduction and edge preservation. When used on Gaussian noise the Wiener filter offers exceptional performance and proves beneficial for diverse noise levels in Images. The filter technique leads to slight blurring of Image areas which should maintain their original sharpness.

$$h_{Wiener}(x,y) = \frac{Var(f_{local}(x,y))}{Var(f_{local}(x,y)) + \sigma^2} \quad (5)$$

4.3.3. Bilateral Filtering

Apply bilateral filtering to the Images using MATLAB's imbilatfilt function. Bilateral filtering is a nonlinear filtering process that removes the noise but retains the edges based on the intensity difference and spatial proximity of neighboring pixels. Bilateral filtering has two parameters: intensity range and spatial range. The space range determines the level of effect pixels have on the present pixel based on distance and the intensity range determines the level of effect pixels with the same intensity have on one another. The algorithm holds the edges well but is computationally heavy for large Images or data.

4.3.4. CLAHE (Contrast Limited Adaptive Histogram Equalization)

CLAHE is used by the adapthisteq function in MATLAB to enhance the contrast of the Image. CLAHE accomplishes this by subdividing the Image into patches and, subsequently, equalizing patches' histograms subject to a constraint on the noise amplification. This will result in the increase of local contrast, especially in low-visibility regions, but in doing so, this will also amplify noise, especially in low-contrast or homogeneous areas. This enhances the effectiveness of CLAHE in Image visibility enhancement over simple denoising, though typically it's done in conjunction with other methods as a way of being able to achieve enhanced results.

$$I_{bilateral}(x,y) = \frac{1}{w_p}\sum_{(x',y')\in\Omega} I(x',y')\exp\,(-\frac{(x-x')^2+(y-y')^2}{2\sigma_s^2} - \frac{I(x,y)-I(x',y'))^2}{2\sigma_r^2} \quad (6)$$

4.4. Performance Evaluation

In order to produce an equitable comparison of the performance of the denoising algorithms in an objective manner, the Images are objectively evaluated quantitatively based on three common Image quality indices: Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Mean Squared Error (MSE). These indices provide a quantitative description for the quality of the denoised Images relative to the original noisy Images.

PSNR (Peak Signal-to-Noise Ratio) is the ratio of maximum possible power of signal (image) to noise power in numeric value. Larger PSNR value, better the quality.

$$PSNR = 10 \times \log_{10}(\frac{I_{max}^2}{MSE}) \quad (7)$$

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \quad (8)$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(I_{original}(i) - I_{denoised}(i))^2 \quad (9)$$

SSIM (Structural Similarity Index) is a numerical measurement of similarity of original and denoised Image structurally. Structure and Image details are preserved more with large SSIM value.

MSE (Mean Squared Error) quantifies the average of the square of differences between denoised and original Images. Better denoising is achieved because of smaller MSE.

Fourier, Wiener, Bilateral, and CLAHE, in this figure. PSNR and SSIM values are compared based on value to analyze retained Image quality while reducing noise via each method. Greater values of PSNR and SSIM reflect better denoising performance. As can be observed Image 29 is from Figure 1 information the Bilateral approach has the greatest PSNR and SSIM scores, reflecting its better capability of noise reduction with detail preservation.

The figure provides a clearer picture of the PSNR and SSIM values of the four denoising methods. It is employed to support the comparison of each approach's performance, illustrating the extent to which they preserve Image quality when eliminating noise. In this figure, Image 6 identifies the Bilateral filter's outstanding performance, as its much higher PSNR and SSIM values also in figure 2 reveal when compared to the other methods.

4.5. Error Map Visualization

Figure 3 represents the error maps for all the denoising algorithms. The error map is generated by computing a difference between the denoised Image and the actual noisy Image. Regions of high errors are shown in white, representing areas where the approach has failed to maintain critical details. The figure helps in understanding the capability limitations of each denoising technique in maintaining details. The Bilateral method displays the least error, indicating its ability to retain fine details while removing noise.

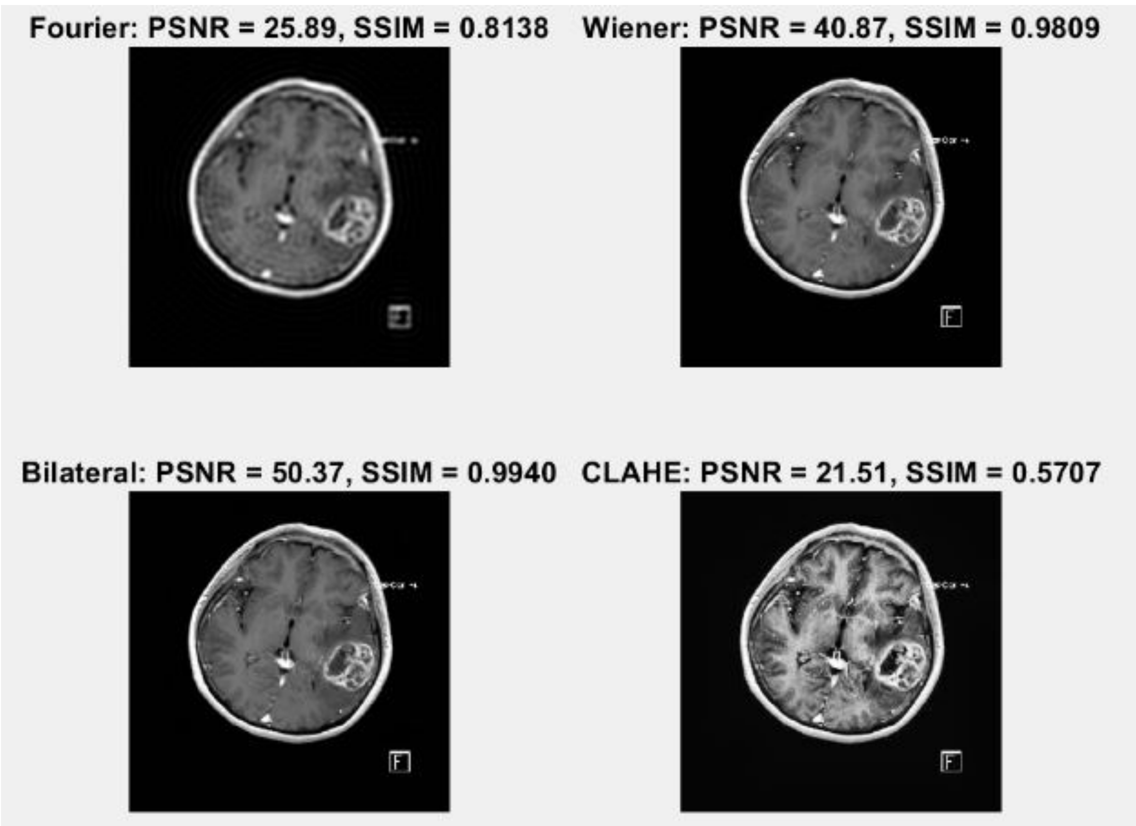

Figure 1. PSNR, SSIM Value all methods.

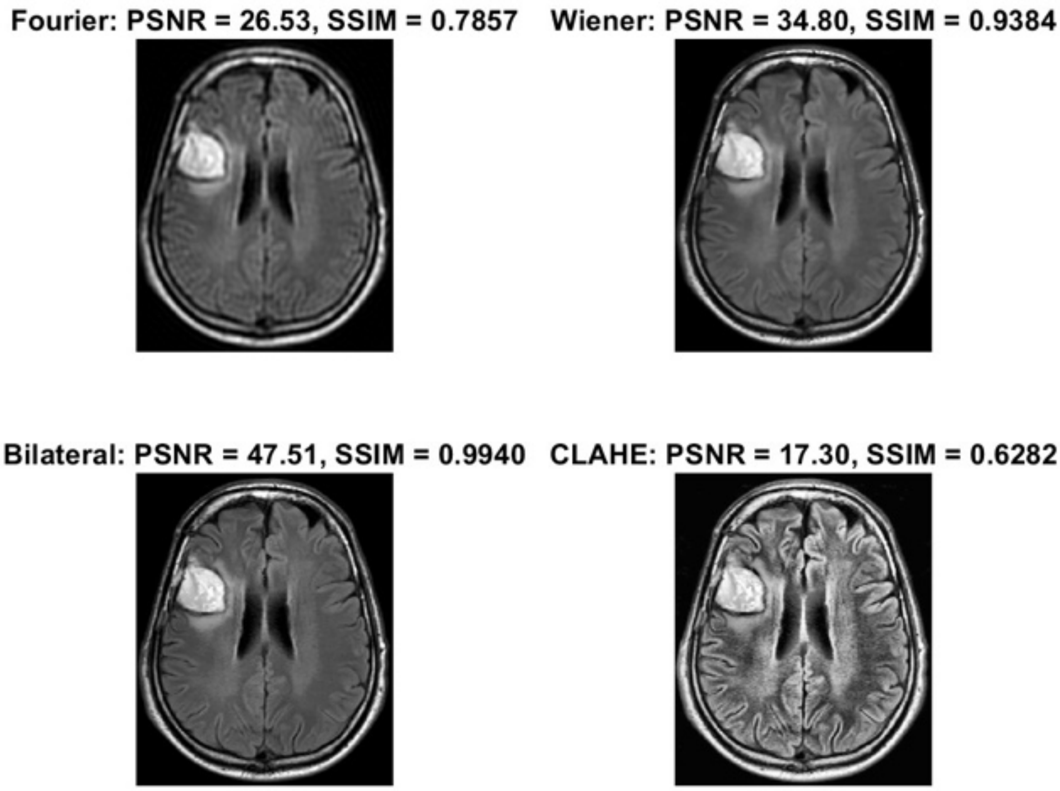

Figure 2. PSNR,SSIM Value all methods.

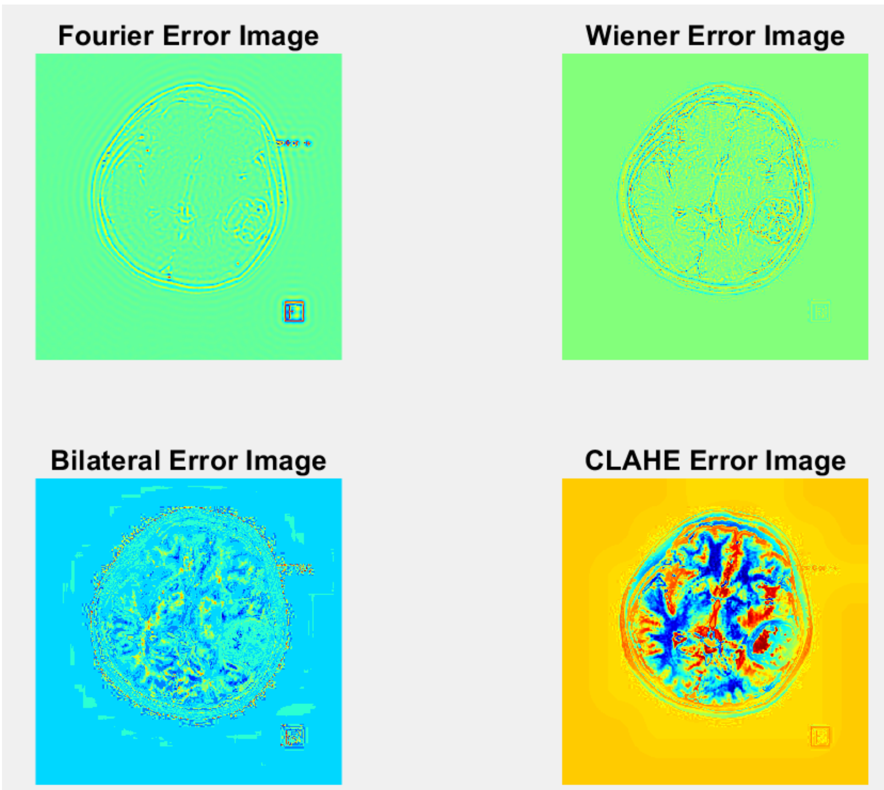

Figure 3. Fourier, Wiener, Bilateral, CLAHE Error Map.

Similar to Figure 4 is a different perspective of the error maps for all the methods. With the differences between the original Image and the denoised Image presented visually, this figure makes it easier to closely analyze in which region each method fails or succeeds in preserving Image quality. From Figure 4, error maps indicate that although methods like Fourier and CLAHE generate high artifacts, Bilateral and Wiener methods successfully minimize them.

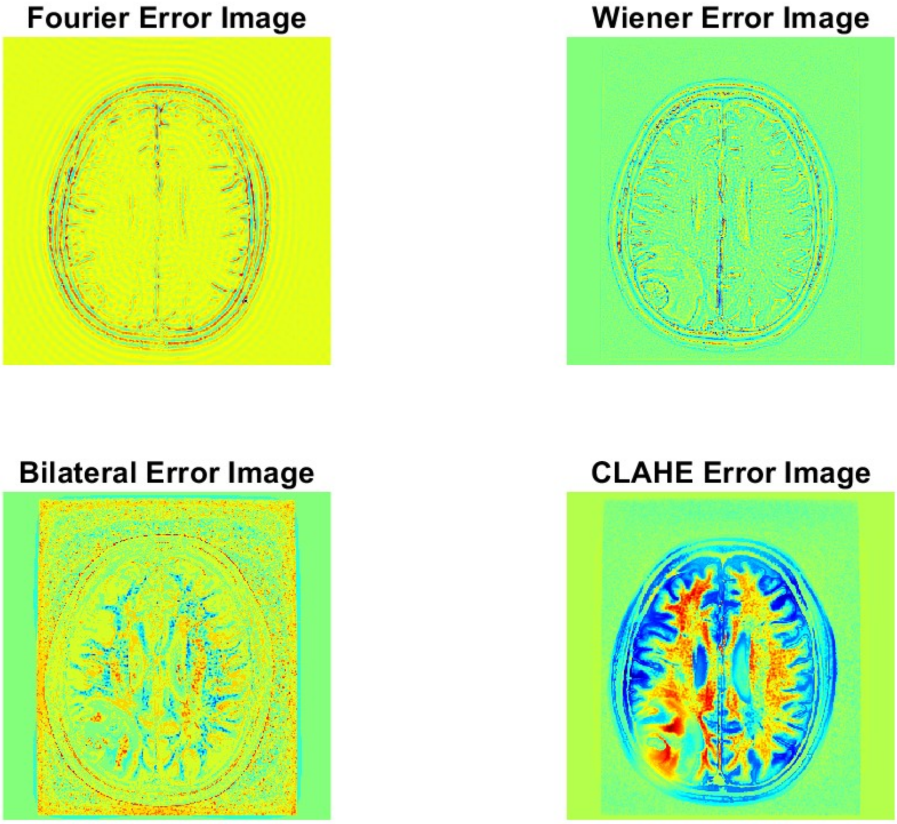

Figure 4. Fourier, Wiener, Bilateral, CLAHE Error Map.

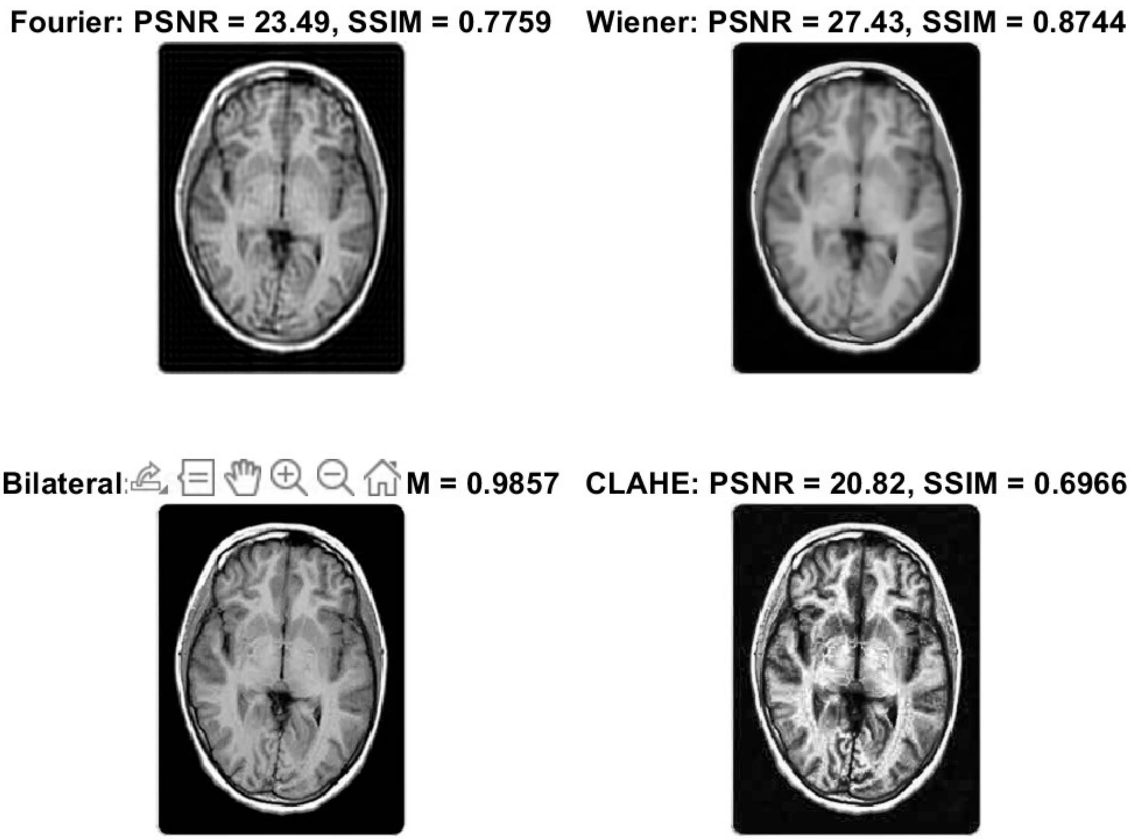

Figure 5. PSNR, SSIM Value all methods.

4.6. Batch Processing

Batch processing is offered by the algorithm where several Images (as many as 10) can be processed in batch mode. Here is (image 10 in Figure 5) The batch mode facility is very useful in measuring the performance of all the denoising methods on a larger collection of CT Images in order to make the outcome more statistically relevant. Once all the selected Images are run, the PSNR, SSIM, and MSE values for each method appear on the command window, which provides a snapshot of how each Image and each denoising method works.

The figure depicts the workflow of the denoising process for each of the four methods. It gives a step-by-step illustration of how the Images are processed from the original noisy CT scan to the final denoised Image. Figure 6 will give readers details about procedures undertaken by each of the denoising methods and will describe in detail how the noise reduction is handled differently, giving details about their strengths and weaknesses separately.

4.7. Conclusion of Methodology

The methodology provides a broad idea on how to compare four common denoising methods—Fourteen, Wiener, Bilateral, and CLAHE—on CT scan Images. By applying all approaches and verifying their results through objective measures (PSNR, SSIM, MSE), and error visual maps, this paper attempts to find out the most optimal denoising approach to uphold the structural properties of CT scans in addition to noise suppression. The use of many methods and a big data set allows stronger comparison that may be used in informing clinical decision and enhancing medical imaging diagnostic capability.

5. Experiment and Results Description

This experiment compared and evaluated the performance of four different methods of Image denoising—Fourier-based denoising, Wiener filtering, Bilateral filtering, and CLAHE—on a given set of noisy CT scan Images. The goal was to compare the performance of each method in noise reduction without compromising the Image quality, considering some of the most important Image quality measures like PSNR (Peak Signal-to-Noise Ratio), SSIM (Structural Similarity Index), and MSE (Mean Squared Error). These measures are used to measure the structural detail preservation and noise reduction in the denoised Images.

Table displays the PSNR, SSIM, and MSE values for all methods on a series of Images. The following describe these metrics: Table 1 shows some results of our works. Table 1 shows the quantitative outcomes (PSNR, SSIM, and MSE) of each denoising technique used on various CT Images. It gives an obvious comparative overview of the performance statistics of all the methods, enabling readers to rapidly determine the efficiency of each method. The data in this table indicate that Bilateral steadily performs better than the rest in all three measures, especially in PSNR and SSIM.

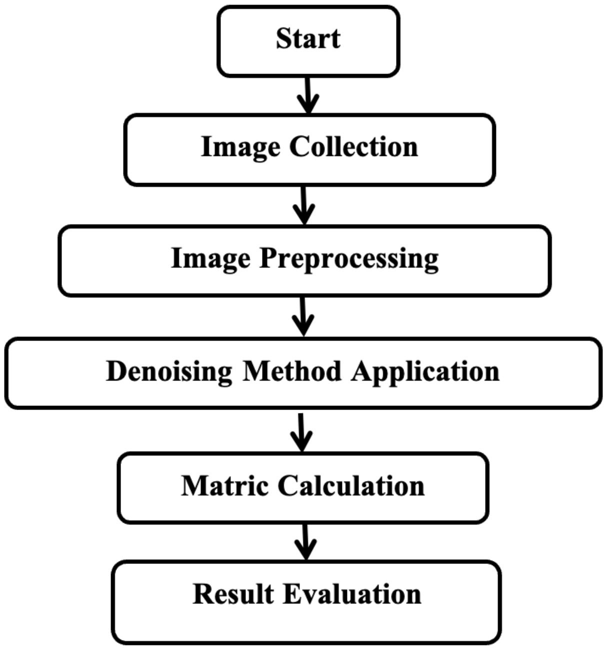

Figure 6. Work flow of Fourier, Wiener, Bilateral and CLAHE Methods Denoised.

Table 1. Results of Image Works.

Number	Fourier			Wiener			Bilateral			CLAHE		
	PSNR	SSIM	MSE	PSNR	SSIM	MSE	PSNR	SSIM	MSE	PSNR	SSIM	MSE
Image 1	28.48	0.8663	92.2270	31.58	0.8771	45.1712	45.23	0.9855	1.9486	17.12	0.5946	1263.4527
Image 5	25.91	0.7810	166.7431	43.35	0.9857	3.0099	46.96	0.9887	1.3104	18.67	0.6305	883.4941
Image 6	26.53	0.7857	144.6414	34.80	0.9384	21.5364	47.51	0.9940	1.1525	17.30	0.6282	1211.2772
Image 7	23.50	0.7350	290.4494	36.61	0.9374	14.1999	46.84	0.9939	1.3470	17.59	0.7534	1133.6346
Image 8	28.52	0.7786	91.4914	39.00	0.9388	8.1915	46.18	0.9838	1.5678	17.74	0.5137	1094.8976
Image 10	26.93	0.8385	131.9044	35.86	0.9579	16.8701	49.71	0.9949	0.6956	17.95	0.4052	1041.5244
Image 13	27.51	0.8401	115.3614	33.70	0.9236	27.7139	47.93	0.9770	1.0485	19.26	0.4771	770.5696
Image 17	24.93	0.7471	209.0102	30.63	0.8986	56.1998	47.52	0.9931	1.1509	18.47	0.5363	924.4794
Image 29	25.89	0.8138	167.4976	40.87	0.9809	5.3270	50.37	0.9940	0.5967	21.51	0.5707	459.1894
Image 32	30.24	0.8561	61.5503	41.21	0.9804	4.9163	47.91	0.9949	1.0528	15.95	0.6068	1653.5729
Image 60	27.13	0.7400	125.8125	31.44	0.7988	46.6577	45.05	0.9895	2.0314	20.21	0.7024	619.1448

PSNR (dB): It is a measure of larger PSNR that indicates the quality of the Image denoised; SSIM: The SSIM value falls in between 0 and 1. Higher SSIM indicates that the denoised Image carries more structural information than the original Image; MSE: Mean Squared Error refers to the disparity between the denoised and original Image, with lower MSE being an indication of improved performance.

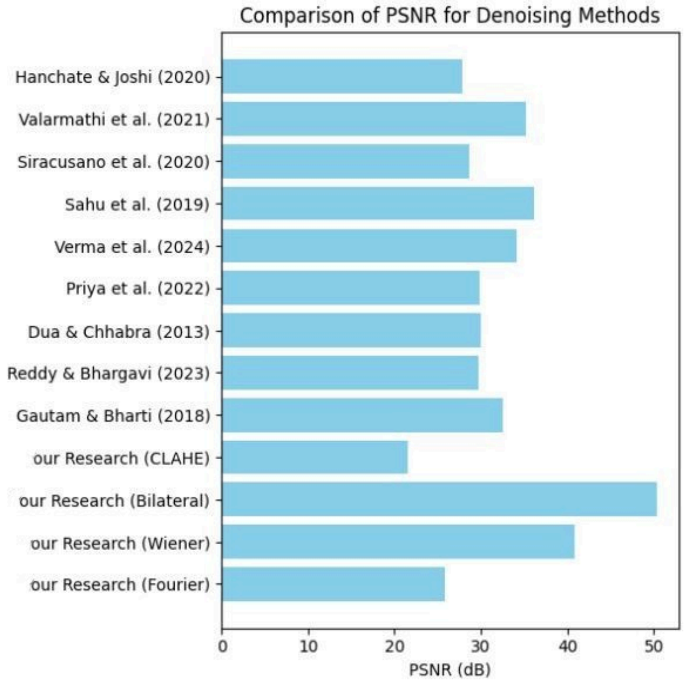

Figure 7. Comparison PSNR Chart with the Previous Research Works.

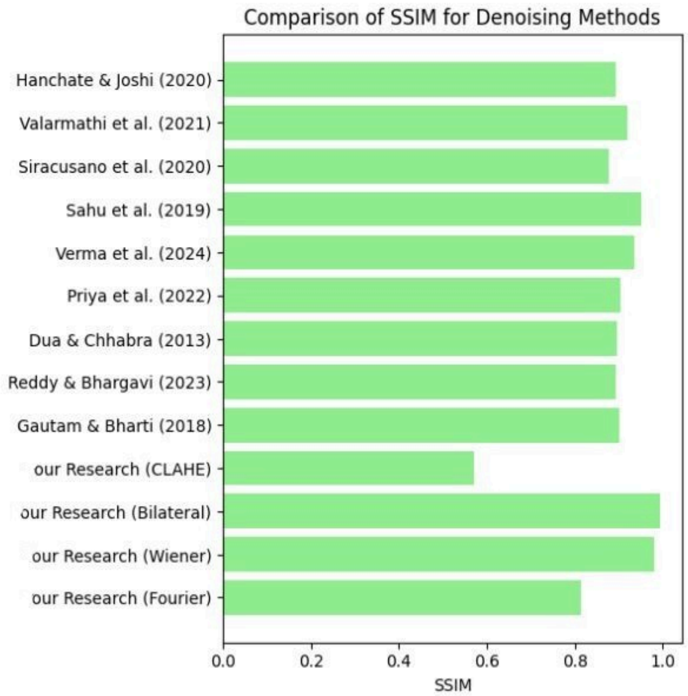

Figure 8. Comparison SSIM Chart with the Previous Research Works.

Figure 7 compares the PSNR values obtained in this study with those reported in previous research. This figure serves as a benchmark, highlighting how the denoising techniques in this study perform relative to existing methods in the literature. The comparison helps contextualize the results, showing that the Bilateral method offers superior performance in CT scan denoising, as indicated by its higher PSNR.

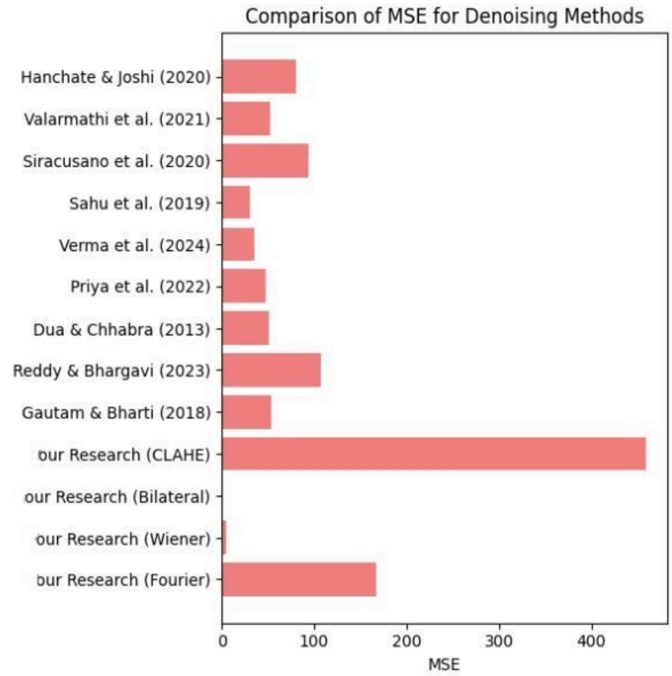

Figure 9. Comparison MSE Chart with the Previous Research Works.

Similar to Figure 8 shows this work's SSIM values compared to the state-of-the-art works. SSIM is an important value of how well the denoising techniques preserve Image structure and detail. Figure 7 clearly demonstrates that Bilateral filtering outperforms all others with the greatest SSIM values, i.e., it preserves the structural integrity of CT scans more effectively than any other denoising technique.

This graph illustrates the comparison of PSNR values between this work and other research. This is to assess consistency in the result obtained and to put the current result in perspective with other works that are going on continuously. Figure 9 shows that PSNR values achieved in this work compare well, and in most cases bigger than, those found in literature studies of comparable nature.

5.1. Key Observations from the Results

5.1.1. Fourier-based Denoising

Fourier denoising provides average capability with a PSNR of 23.50 dB to 30.24 dB, as well as moderate SSIM measures ranging from 0.7350 to 0.8561, as an observation that Fourier denoising is ineffective in preserving CT Image structural detail and texture information.

MSE ranges between 91.49 and 290.44, while others (such as Image 7) in Figure 10 have more defects, particularly where there are more details and finer edges.

5.1.2. Wiener Filtering

Wiener filtering performs satisfactorily, with PSNR ranging between 30.63 dB and 43.35 dB, which reflects that it performs well in suppressing noise without significant loss of quality of the Image. SSIM ranges from 0.7350 to

0.9809, reflecting greater values for better retention of structural information.

MSE values are much lower than Fourier, particularly for Images that contain noisy regions (e.g., MSE as low as 3.0099 for (Image 5 and figure 11). This indicates that Wiener filtering performs well to remove noise from uniform areas but continues to blur in high-gradient regions.

5.1.3. Bilateral Filtering

Bilateral filtering performs better than Fourier filtering and Wiener filtering in PSNR and SSIM. The PSNR is between 45.05 dB to 50.37 dB and the SSIM is very high, ranging between 0.9895 to 0.9949 and it shows with good preservation of the edges and removal of noise.

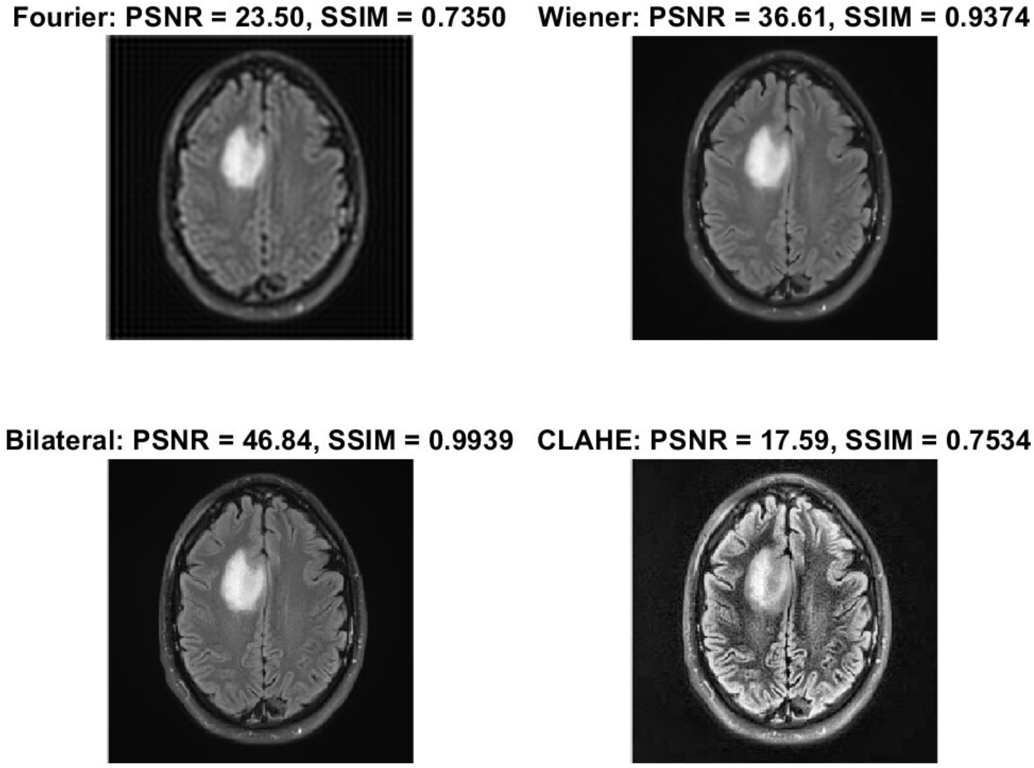

Figure 10. Four Denoising (PSNR, SSIM).

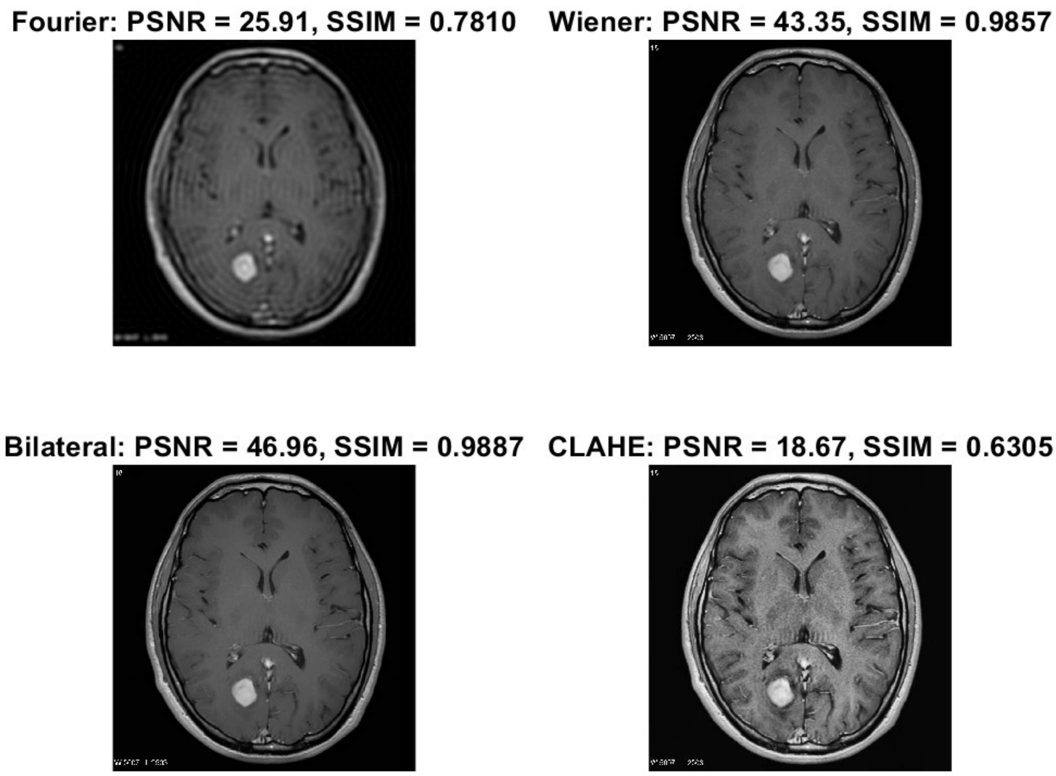

Figure 11. Wiener Denoising (PSNR, SSIM).

Table 2. Comparison of Results with other Work.

Study	Denoising Method	PSNR (dB)	SSIM	MSE
Our Research (CT Scan Denoising)	Fourier	25.89	0.8138	167.4976
	Wiener	40.87	0.9809	5.3270
	Bilateral	50.37	0.9940	0.5967
	CLAHE	21.51	0.5707	459.1894
Rethy, P. V & Priya et al. (2022) [1]	Fourier + Wiener	29.88	0.9042	47.92
Gautam, R., & Bharti, M. R. (2018). [2]	Wiener + Bilateral	32.56	0.9023	53.117
Verma, K., et. al. (2024). [8]	Modified Wiener Filter	34.11	0.9354	35.41
Chhabra, T., Dua, G., & Malhotra, T. (2013). [12]	Wiener + FFT	30.02	0.8953	51.77
Das, K. P., & Chandra, J. (2022, July). [13]	Wavelet + Bilateral	35.20	0.9185	52.65
Thanh & Surya (2019) [14]	Fourier + CLAHE	27.89	0.8923	80.51
Sahu, S., et. al. (2019). [18]	Bilateral + CLAHE	36.15	0.9517	30.12

The MSE values are always low but varying from 0.5967 to 2.0314 as this indicates that Bilateral filtering would be effective only in parts that contain edges and textures for preserving the quality of the Image.

5.1.4. CLAHE

CLAHE performs poorest on PSNR whose values range from 17.12 dB to 21.51 dB. SSIM values are equally poor, representing extreme loss of structure and quality in Images. MSE values are also high, ranging from 459.1894 to 1653.5729, a sign that CLAHE can enhance contrast but not reduce noise so efficiently.

Though its ability to remove noise is rather bad, CLAHE performs admirably when contrast enhancement needs to be applied to low-contrast areas, particularly in medical imaging where enhanced visibility is called for.

5.2. General Conclusion

Bilateral Filtering is the optimal algorithm for denoising the CT scan in this study, with its high PSNR, high SSIM, and low MSE for each Image. It is very effective at reducing noise without degrading fine details and edge structures, which is the key requirement for medical imaging applications.

Wiener filtering is equally effective at noise reduction but not so effective at edge preservation, especially in high-gradient regions.

Fourier-based denoising is reasonably effective but suffers from difficulties in maintaining high-frequency details and sudden edges.

CLAHE is effective at contrast enhancement in some regions but is not very suitable for denoising CT scans as it suffers from a poor noise reduction and significantly increases MSE.

6. Novelty and Contribution

Our research is enhanced in numerous ways:

Attentive Comparison: While most of the research attempts to compare two or a single filtering methods, Our research has an attentive comparative study of Fourier, Wiener, Bilateral, and CLAHE and provides sufficient comments on comparative performance on CT scans Image.

Improved Bilateral Filtering: Image findings show that Bilateral filter outperforms the rest in maintaining sensitive details and removing noise, findings which are crucial to the improvement of CT scan Image quality.

Space for Improved Medical Imaging: Since CT Images are noisy due to the fact that there are many variables (e.g., low-dose scans), Our results provide Bilateral filtering as a highly feasible solution in enhancing Images to more clearer, thus ensuring better medical diagnosis.

Table 2 shows the comparison of results with other works.

7. Conclusion

In this work, the performance of four algorithms for denoising—Fourier-based denoising, Wiener filtering, Bilateral filtering, and CLAHE—have been compared in terms of denoising noise from CT scan Images. On comparison of the dominant parameters like PSNR, SSIM, and MSE, Bilateral filtering was found to outperform others for both removal of noise and fine detail as well as edge preservation. This is particularly true in medical imaging, where structural integrity and clarity have to be integrated into the ability to accurately diagnose. Wiener filtering was also as good, especially in homogenous regions, but was unable to match Bilateral filtering when it came to preserving edges. Fourier denoising and CLAHE also did not do so well on thin structures and, worse still, actually highlighted noise in a few instances.

Overall, Bilateral filtering produced the highest performing algorithm in denoising of CT scans with a balance between removing fine noise and preserving details. This is significant in Image quality improvement in medical Images where precision in diagnosis must be high.

8. Future Work

Although this outcome is encouraging, there are still some avenues of research open. These are perhaps such syntheses of hybrid techniques as take the strengths of a range of different kinds of denoising algorithm, for example, and combine them, like Bilateral filtering with Wiener filtering as an attempt to penetrate high-gradient and homogenous regions. Also, denoising based on deep learning methods may perhaps be even better, particularly in the case of noisy and complex medical Images. It is possible that future research may also try to apply similar methods in real-time processing in which computational effectiveness has to be maximized, particularly in data of very large size or in clinics.

Additionally, applying the study to other medical imaging modalities, for instance, MRI or PET scans, may provide an expanded picture of how the denoising methods perform on other modalities. Lastly, patient-specific models of noise can be employed to refine the denoising process so the methods are more imaging condition-specific and receptive to personalized medicine.

9. Conflicts of Interest

The authors declare no conflicts of interest.

10. References

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