International Journal of Engineering, Science and Humanities
An international peer reviewed, refereed, open-access journal
Impact Factor 8.3 www.ijesh.com ISSN: 2250-3552

Medical Image Denoising Based on Implementing Multi-Resolution Threshold Technique

Ekta Khichi
Research Scholar, Department of Electronics and Communication Engineering Ujjain Engineering College, Ujjain
Prof. K. S. Solanki
Assistant Professor, Department of Electronics and Communication Engineering Ujjain Engineering College, Ujjain

ABSTRACT
Medical image denoising is critical for accurate diagnosis and quantitative analysis, yet preserving fine anatomical detail while suppressing noise remains challenging. This paper proposes a multi-resolution thresholding (MRT) technique for medical image denoising that combines discrete wavelet transform (DWT) based decomposition with adaptive, scale-aware threshold selection and a post-processing spatial regularization step. The input image is decomposed into multiple resolution sub bands using a suitable orthogonal wavelet (e.g., Daubechies or Symlet), separating high-frequency noise components from low-frequency structural content. For each detail sub band, thresholds are determined adaptively using a hybrid criterion that blends robust noise estimation (median absolute deviation) with local signal activity measures, enabling preservation of edges and fine textures in anatomically important regions. Both soft and semi-soft thresholding rules are explored to reduce visual artifacts and Gibbs-like distortions. After inverse wavelet reconstruction, a multi-scale bilateral filter is applied selectively to remaining residuals to further suppress speckle and salt-and-pepper noise while conserving boundaries. The proposed MRT framework is evaluated on MRI and CT datasets corrupted with synthetic Gaussian and real-world noise. Quantitative results show consistent improvements in peak signal-to-noise ratio (PSNR) and mean square error (MSE) compared to classical denoising methods (Wiener, anisotropic diffusion) and several baseline wavelet-thresholding schemes, while visual assessment confirms superior edge preservation and lesion conspicuity. Computational complexity is modest and compatible with near real-time preprocessing on modern CPUs; the method also scales to 3D volumes by applying separable 3D wavelet transforms. MRT is therefore a practical, effective approach for clinical imaging pipelines where maintaining diagnostic features is essential.

Keywords: Medical Image, Threshold Filter, Peak Signal to Noise Ratio

International Journal of Engineering, Science and Humanities
An international peer reviewed, refereed, open-access journal
Impact Factor 8.3 www.ijesh.com ISSN: 2250-3552

1. INTRODUCTION

Medical imaging has become an indispensable tool in modern healthcare, providing clinicians with critical insights for disease diagnosis, treatment planning, and monitoring of patient outcomes. Modalities such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Ultrasound, and Positron Emission Tomography (PET) generate high-resolution anatomical and functional images. However, these images are often degraded by various types of noise introduced during acquisition, transmission, or reconstruction processes. Noise in medical images reduces visual quality, obscures fine details, and may lead to inaccurate interpretation, ultimately affecting the reliability of clinical decision-making. Therefore, medical image denoising has emerged as a crucial preprocessing step to enhance image quality while preserving diagnostically relevant structures.

Traditional denoising approaches, such as Gaussian smoothing, median filtering, and Wiener filtering, can suppress noise but often blur edges and fine textures that are essential for identifying abnormalities such as tumors, lesions, or microcalcifications. More advanced methods, including anisotropic diffusion, total variation minimization, and non-local means filtering, attempt to balance noise reduction with structural preservation, yet they suffer from limitations such as parameter sensitivity, computational complexity, and reduced robustness across different imaging modalities. These shortcomings highlight the need for denoising techniques that are both adaptive and capable of discriminating between noise and clinically significant features at multiple scales.

Wavelet transform-based methods have gained significant attention in this regard due to their multi-resolution analysis capability. The discrete wavelet transform (DWT) decomposes an image into sub bands that represent different frequency components, enabling localized analysis of both spatial and frequency information. Noise, typically concentrated in high-frequency sub bands, can be suppressed through thresholding techniques, while low-frequency components retain the structural integrity of the image. Unlike traditional filtering methods that operate uniformly across the entire image, wavelet thresholding adapts to local content, offering improved edge preservation and enhanced diagnostic detail.

The multi-resolution threshold (MRT) technique extends this idea by introducing adaptive threshold selection across different decomposition levels. Instead of applying a fixed global threshold, MRT determines thresholds based on noise statistics and signal activity at each resolution level. This ensures that subtle features, such as tissue boundaries and micro-structures, are preserved while irrelevant high-frequency noise is attenuated. Furthermore, flexible thresholding strategies—such as soft, hard, or semi-soft thresholding—can be employed to balance denoising strength with artifact reduction. By integrating these strategies into a unified framework, MRT provides a versatile and robust solution for medical image enhancement.

Recent studies have demonstrated that MRT outperforms classical denoising methods in terms of quantitative metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM), as well as qualitative measures including edge sharpness and lesion visibility. Importantly, the computational efficiency of wavelet-based methods makes MRT suitable for real-time or near real-time applications, enabling seamless integration into medical imaging workflows. This is particularly relevant in scenarios where rapid image analysis is critical, such as emergency diagnostics, intraoperative imaging, and telemedicine.

In this study, we investigate the implementation of a multi-resolution threshold technique for medical image denoising, focusing on its ability to suppress noise while maintaining diagnostic accuracy. The proposed approach leverages wavelet decomposition, adaptive thresholding, and effective reconstruction strategies to deliver superior image quality across different modalities. The findings presented aim to demonstrate that MRT not only enhances visual quality but also improves the reliability of clinical interpretation, ultimately contributing to better patient care.

2. LITERATURE REVIEW

Ahmed Abdulmaged Ismael et al. [1], nowadays, digital images are often easily damaged by various forms of noise and complex processes resulting from capture, compression, encoding, transmission, storage, retrieval, etc. All these factors lead to image quality distortion and loss of visual information. To solve this problem, image denoising techniques are often used to remove various forms of noise present in degraded images while preserving the details and important signal features of digital images as much as possible. The wavelet denoising method aims to remove unwanted noise from noisy images while preserving important features. This is because it can divide the degraded image into four subbands (sub-images) and process them at their respective frequencies to preserve the image capture. The original image content is very important for reliable performance. In this study, a new hybrid additive white Gaussian noise (AWGN) image denoising system is introduced and implemented. The hybrid system is realized by the combination of two-dimensional stationary and discrete wavelet transform (2D-SWT, 2D-DWT) as multiresolution analysis techniques and median filter and Wiener filter as spatial domain filters by using the 131W filter of the wavelet family. Image processing with three-level decomposition based on hardware (haar, db, sym, coif, bior, rbio, dmey, fk), SureShrink, Bayesian and penalized thresholding techniques are applied at both high and low frequencies to differentiate and remove noise from affected pixel units, improving the results of the noise reduction process for noisy images. Then, the noise is removed by multi-stage 2D inverse wavelet transform (2D-IWT) and image reconstruction is completed using a hybrid noise reduction technique. Finally, the performance of the hybrid system was estimated and measured using the peak signal-to-noise ratio (PSNR) as a measure of image quality. Experimental evaluation showed that the results of the proposed approach were improved by about 17.5%

compared to those of the corresponding studies, and the image quality was mainly improved in the form of better noise reduction and edge preservation, rather than in the WT domain or spatial domain filters at multiple resolutions separately.

Rajesh Patil et al. [2], in medical image processing Noise removal is an important step for recreating a high-quality image like X-ray, ultrasound, MRI etc. While acquiring, transmitting, and retrieving from storage devices normally images are degraded due to noises like Gaussian, Speckle etc. So, noise must be removed from the images for proper diagnosis. Researchers are still looking for an effective noise reduction means. Wavelet Transform (WT) is considered as a powerful transform method for removal of noise. For denoising of medical images affected by Gaussian noise, various wavelets have been proposed. In this paper, various wavelets are used to study the denoising multi-modal medical images affected by Gaussian noise. Here, proposed wavelet gives better results than the wavelets which have been implemented so far now. Denoising results of medical images are compared on the basis of Root Mean Square Error (RMSE), Signal-Noise Ratio (SNR), Peak Signal-Noise Ratio (PSNR) and execution time (TE).

Rajesh Patil et al. [3], medical imaging means the methods and procedures used for creating pictures of various parts of the human body for numerous clinical objectives. These images are constantly gets dirtied by noise during picture acquisition and transmission, resulting in low quality images. Noise is the unwanted signal which corrupts the important and desirable information. The noises can be categorized into different types based on their nature and origin. e.g. Gaussian, the impulsive and speckle noise etc. The removal of noise is very necessary for proper analysis and diagnosis. Filtering noise helps to recreate a high-quality image in digital image processing for further image processing such as segmentation of images, identification, recognition and monitoring, etc. There are various approaches to denoise medical images based on transform approach, machine learning, filtering method and statistical method. These techniques or approaches is subject to noise type exist in the image. To evaluate the denoising performance, parameters like SNR, PSNR etc. are used. This paper takes a review of current denoising techniques.

Subhrajit Dey et al. [4], image denoising, is a research problem where we aim to recover noise-free images from those that are contaminated with noise. It is also a very challenging problem for all researchers in the field of computer vision. There are various types of noise which differ on the basis of distribution and behaviour, e.g., salt-and-pepper noise, Poisson noise, Gaussian noise, etc. In this paper, we focus on eliminating Gaussian noise from contaminated images. Historically, many methods have been proposed for image denoising but recently, it has been observed that in most of the cases, Convolutional Neural Network (CNN) is used which outperforms the conventional methods. Here, we propose a CNN as the base model, to which we add other modules to improve the performance of the image denoising method. Our model uses an attention-guided CNN, called (ADNet), where we add median filter layers for restoring images contaminated by Gaussian noise. We apply median filters on all the feature channels of an image as well as increase the dilation rate of the dilated convolutions in the ADNet and so we see, in case of the convolutional layers, that the receptive field size is increased, which in turn aids image denoising. By quantitative analysis, we are able to show that our model performs significantly well when tested on the BSD500 and Set12 datasets.

L. Sekanina et al. [5], the problem of developing an approximate implementation of a given combinational circuit can be formulated as a multi-objective design problem and solved by means of a search algorithm. This approach usually provides many solutions showing high-quality tradeoffs between key design objectives; however, it is very computationally expensive. This chapter presents a general-purpose method based on genetic programming for an automated functional approximation of combinational circuits at the gate and register-transfer levels. It surveys relevant error metrics and circuit parameters that are typically optimized by genetic programming. A special attention is given to the techniques capable of providing formal guarantees in terms of error bounds and accelerating the search process. Case studies dealing with approximate implementations of arithmetic circuits and image operators are presented to highlight the quality of results obtained by the search-based functional approximation in completely different application domains.

J. Lyu et al. [6], in this letter, a novel robust two-dimensional nearfield millimeter-wave (MMW) image reconstruction algorithm is developed based on compressed sensing (CS) in the presence of impulsive measurement noise. To enable the sparse MMW image recovery, the CS algorithm usually employs the popular ℓ 2 -norm as the data fidelity term and a combination of multiple sparsityinduced functions as the penalty term. The ℓ 2 -norm is non-robust against impulsive noise since the Gaussian noise distribution assumption is not valid, and the presence of impulsive noise will severely degrade the robustness of the compressive MMW image recovery. To gain more robustness performance, a complex correntropy based data-fitting term, namely complex correntropic loss (CC-loss), is used to replace the ℓ2-norm for the near-field MMW measurement contaminated by impulsive noise. In order to solve the corresponding minimization problem, an additive half quadratic method is used to transform the CC-loss term to its convex form, and then a parallel primal-dual process is used to guarantee the convergence of the proposed algorithm. In total, 150-GHz MMW experimental results show that the proposed algorithm can achieve accurate image reconstruction from compressive measurements under different impulsive noise levels.

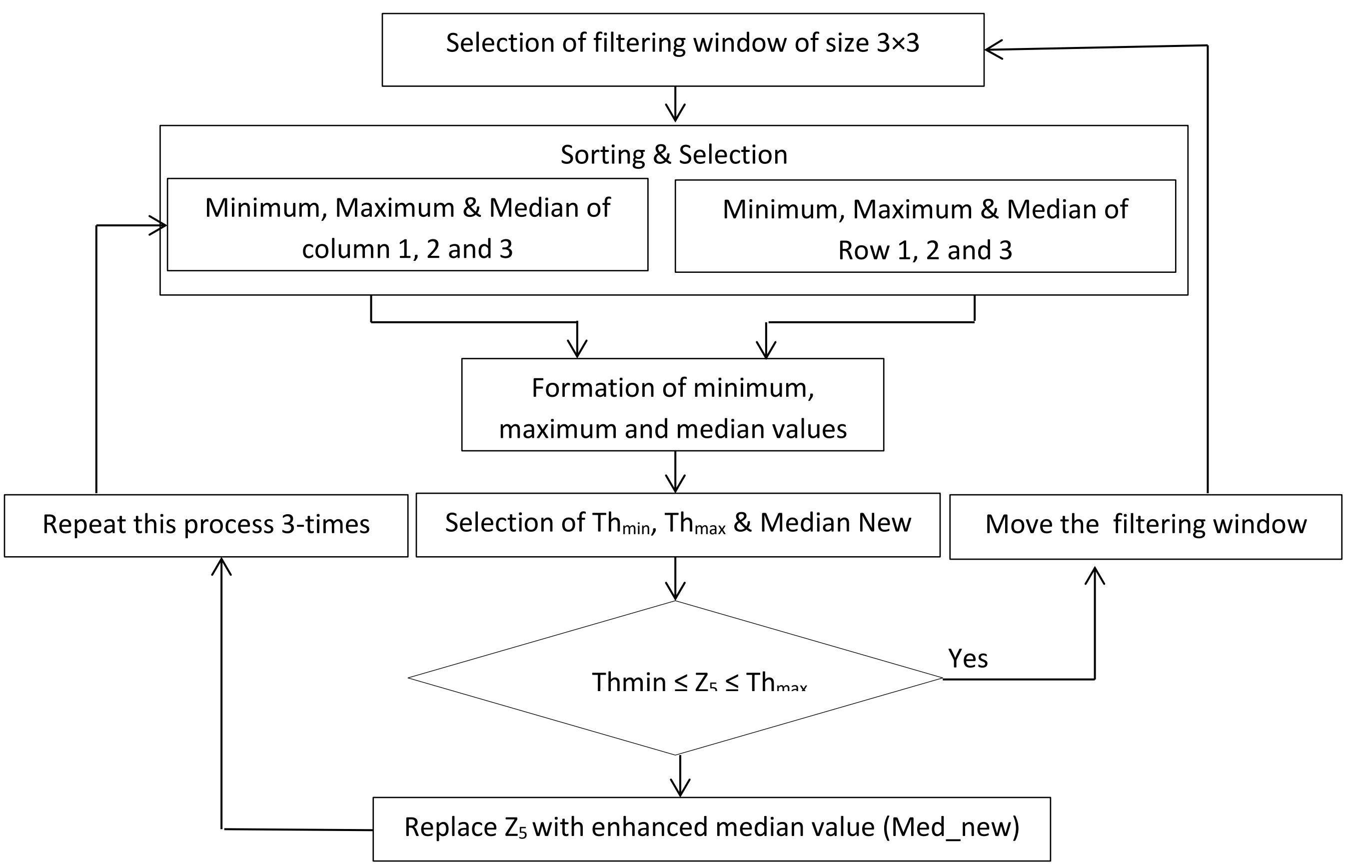
H. Y. Khaw et al. [7], most of the impulse denoisers are either median filter-based or fuzzy filter-based, which can only perform well in low noise conditions. This study presents an efficient convolutional neural network (CNN) with particle swarm optimisation (PSO) model for

International Journal of Engineering, Science and Humanities
An international peer reviewed, refereed, open-access journal
Impact Factor 8.3 www.ijesh.com ISSN: 2250-3552

high-density impulse noise removal. The proposed high-density impulse noise detection and removal model mainly consists of two parts: the impulse noise removal and impulse noisy pixel detection for restoration. The authors' model initially leverages the powerful ability of deep CNN architecture to separate noise from the noisy image, then adopts PSO to pinpoint the most optimised threshold values for detecting impulse noisy pixels. An ensemble of these algorithms is an intelligent and adaptive solution, producing a clean output while preserving significant pixel information. Targeting to solve high-density impulse noise problems, the authors have trained their model with a massive collection of natural images and 14 standard testing images are used for validation purposes. In order to validate the robustness of the proposed method, different levels of high-density impulse noise are considered. Based on the final denoised images, their model has proven its reliability, in terms of both visual quality and quantitative evaluation, on greyscale and colour images.

3. PROPOSED METHODOLOGY

In this section identifying the noise in the image and then de-noising it using double threshold median filter as well as preserving edges of image.



International Journal of Engineering, Science and Humanities
An international peer reviewed, refereed, open-access journal
Impact Factor 8.3 www.ijesh.com ISSN: 2250-3552

Figure: 1: Flow chart of proposed method for filtering window size 3x3

We have developed the simple algorithm in which we perform the noise detection & noise removal process simultaneously. We use the smallest window size which preserves the fine details of image. The window of size 3x3 chooses for noise detection and noise removal. The window contains total 9 elements which are as follows: Z1, Z2, Z3, Z4, Z5, Z6, Z7, Z8, Z9. First step selects the maximum, minimum and median values of columns and rows. Second step stores these values and selects minimum threshold, maximum threshold and final median value. Third step use threshold values for noise detection and final median value for noise removal. We can divide the complete process into no. of steps as follows:

Table 1: Filtering window of size 3x3

	Column 1	Column 2	Column 3
Row 1	Z_1	Z_2	Z_3
Row 2	Z_4	Z_5	Z_6
Row 3	Z_7	Z_8	Z_9

Step-1:-

First we select all columns of filtering window one by one and then we find three values i.e. Maximum, Minimum and Median in each column. The mathematical expression can be shown as follow: The minimum values of rows and columns are represented as

$$\text{Min (cln1)} = \min \{ Z1, Z4, Z7\}$$
$$\text{Min (cln2)} = \min \{ Z2, Z5, Z8\}$$
$$\text{Min (cln3)} = \min \{ Z3, Z6, Z9\}$$
$$\text{Min (row1)} = \min \{ Z1, Z2, Z3\}$$
$$\text{Min (row2)} = \min \{ Z4, Z5, Z6\}$$
$$\text{Min (row3)} = \min \{ Z7, Z8, Z9\}$$

The maximum value of rows and columns are represented as

$$\text{Max (cln1)} = \max \{ Z1, Z4, Z7\}$$
$$\text{Max (cln2)} = \max \{ Z2, Z5, Z8\}$$
$$\text{Max (cln3)} = \max \{ Z3, Z6, Z9\}$$
$$\text{Max (row1)} = \max \{ Z1, Z2, Z3\}$$
$$\text{Max (row2)} = \max \{ Z4, Z5, Z6\}$$
$$\text{Max (row3)} = \max \{ Z7, Z8, Z9\}$$

The median value of the rows and columns are represented as

Med (cln1) = med { Z1, Z4, Z7}

Med (cln2) = med { Z2, Z5, Z8}

Med (cln3) = med { Z3, Z6, Z9}

Med (row1) = med { Z1, Z2, Z3}

Med (row2) = med { Z4, Z5, Z6}

Med (row3) = med { Z7, Z8, Z9}

Step-2:-

Now we have total nine values (three maximum, three minimum and three median). We will use these values to calculate threshold values (maximum threshold and minimum threshold) and median value. For these calculations, we make three different groups of these nine elements.

Max group = (Max (cln1), Max (cln2), Max (cln3) Max (row1), Max (row2), Max (row3))

Min group = (Min (cln1), Min (cln2), Min (cln3) Min (row1), Min (row2), Min (row3))

Med group = (Med (cln1), Med (cln2), Med (cln3) Med (row1), Med (row2), Med (row3))

First, we will calculate max min by choosing maximum value in min group and min max by choosing minimum value in max group. Then we choose minimum threshold by choosing minimum value in max group.

Max min = Max (Min (cln1), Min (cln2), Min (cln3) Min (row1), Min (row2), Min (row3))

Min max = Min (Max (cln1), Max (cln2), Max (cln3) Max (row1), Max (row2), Max (row3)}

median med = Med {Med (cln1), Med (cln2), Med (cln3) Med (row1), Med (row2), Med (row3))

Now these three values (max min, min max, median_med) will be furhter sorted and finally we get minimum threshold, maximum threshold and final median value as follows:

Thmax = max {min_max, median_med, max_min}

Thmin = min {min_max, median_med, max_min}

Final_med= med { min_max, median_med, max_min }

These two threshold values will be used for noise detection and final median will be used for noise removal.

Step-3:-

Now we will perform noise detection and noise removal operation using these three values i.e. Thmax, Thmin, and Med_new. We compare the central pixel with threshold values. If the central pixel is in between the Thmin and Thmax, then the pixel will be considered as noise free, then pixel will remain unchanged and window will move or slide to the next pixel. Otherwise pixel will consider as noisy and it will be replaced by median value.

If Thmin ≤Z5≤ Thmax

Then Z5 is unchanged.

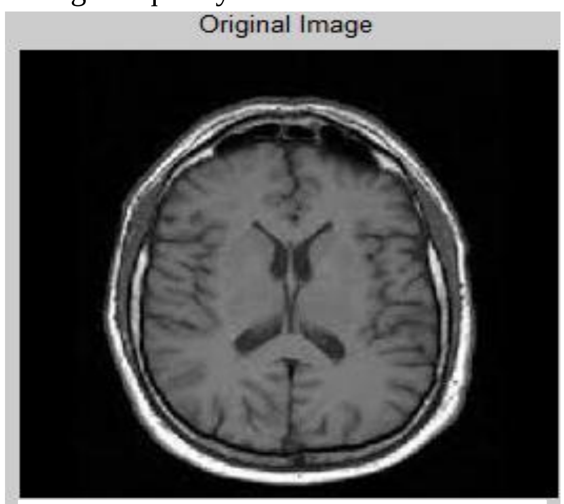
Else Z5= Med_new.

International Journal of Engineering, Science and Humanities
An international peer reviewed, refereed, open-access journal
Impact Factor 8.3 www.ijesh.com ISSN: 2250-3552

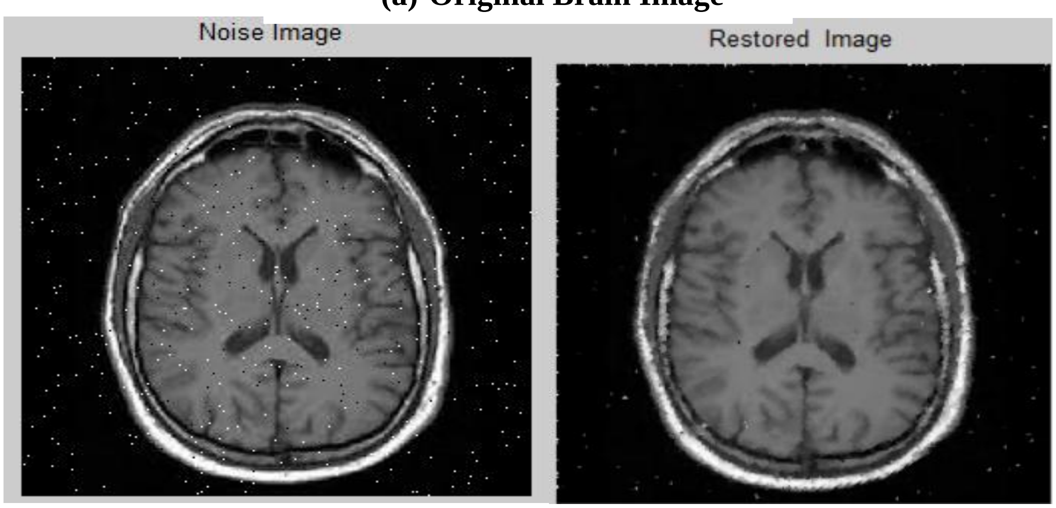
Here we are parallelly calculating the threshold values and median value. So there is no need to perform noise detection and noise removal separately.

4. SIMULATION RESULT

Clearly that the figure 2 (a) show the original image of th Brain image. Figure 2 (b) shows the 0.1 salt noise and restored image, Figure 2 (c) shows the 0.2 salt noise and restored image, Figure 2 (d) shows the 0.3 salt noise and restored image, Figure 2 (e) shows the 0.4 salt noise and restored image, Figure 2 (f) shows the 0.5 salt noise and restored image, Figure 2 (g) shows the 0.6 salt noise and restored image, Figure 2 (h) shows the 0.7 salt noise and restored image, Figure 2 (i) shows the 0.8 salt noise and restored image and Figure 2 (j) shows the 0.9 salt noise and restored image of the Brain image. From the visual outputs, it is very clear that image de-noised by proposed method has good quality.

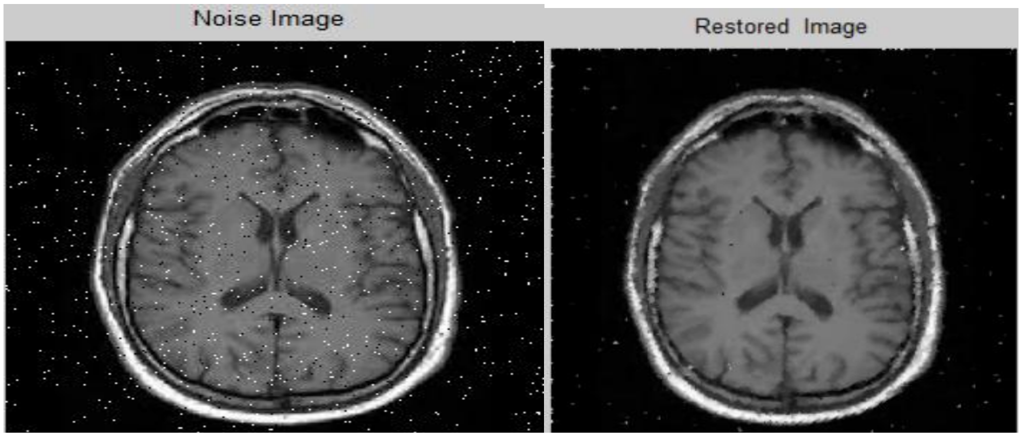


(a) Original Brain Image

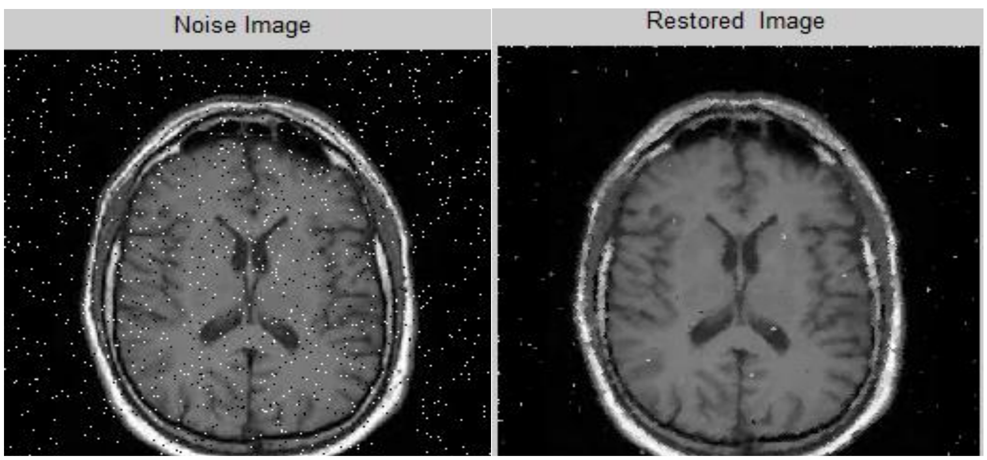


(b) 0.1 De-noiseing

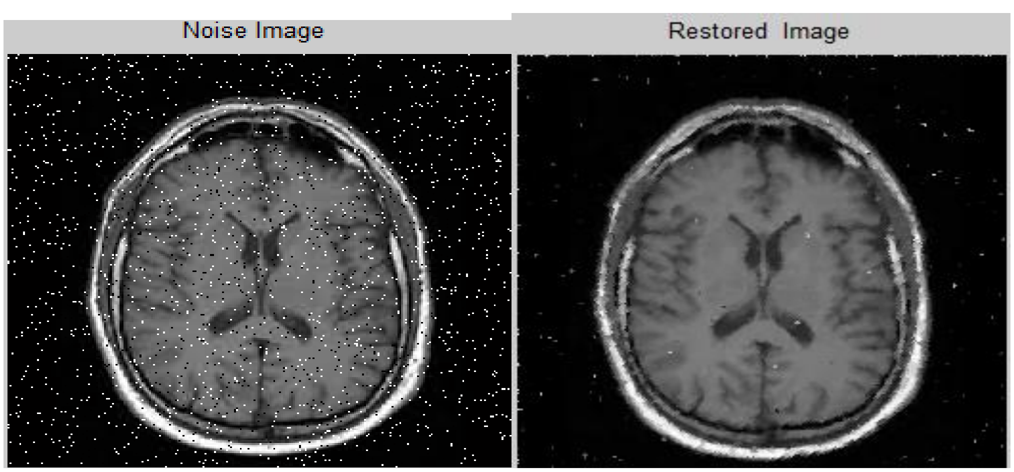
International Journal of Engineering, Science and Humanities
An international peer reviewed, refereed, open-access journal
Impact Factor 8.3 www.ijesh.com ISSN: 2250-3552



(c) 0.2 De-noising

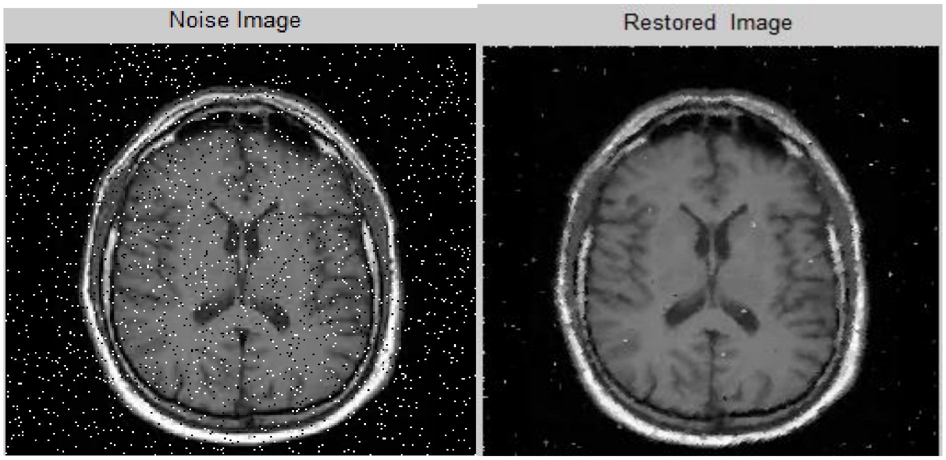


(d) 0.3 De-noiseing

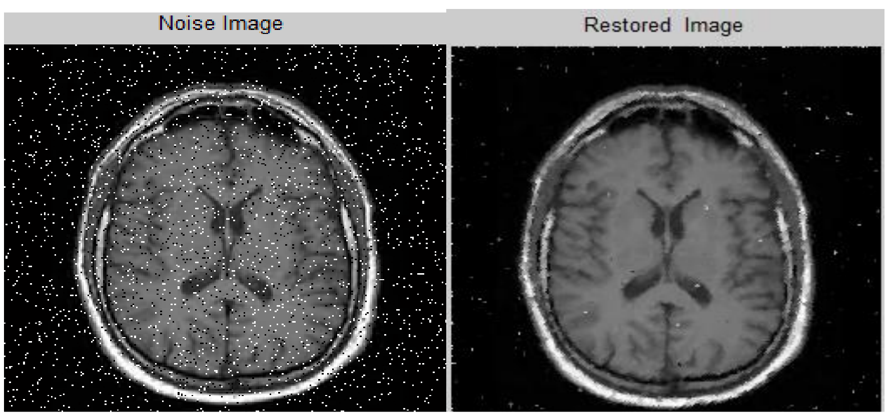


(e) 0.4 De-noising

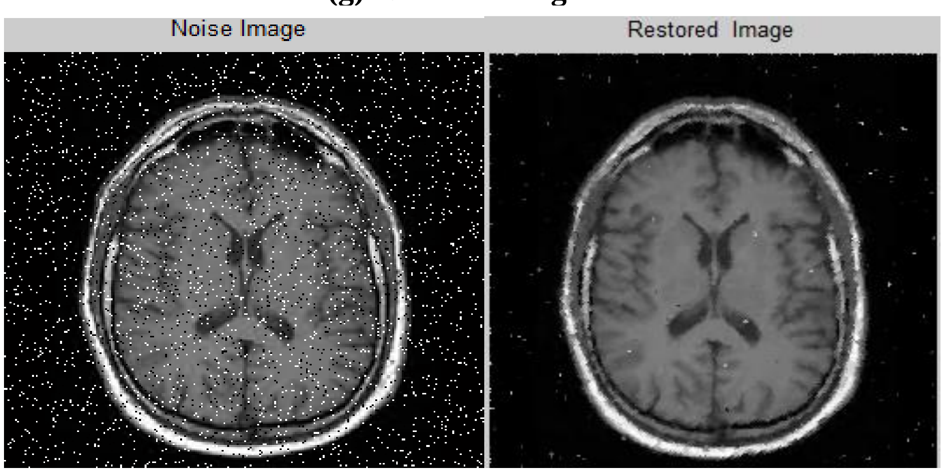
International Journal of Engineering, Science and Humanities
An international peer reviewed, refereed, open-access journal
Impact Factor 8.3 www.ijesh.com ISSN: 2250-3552



(f) 0.5 De-noiseing

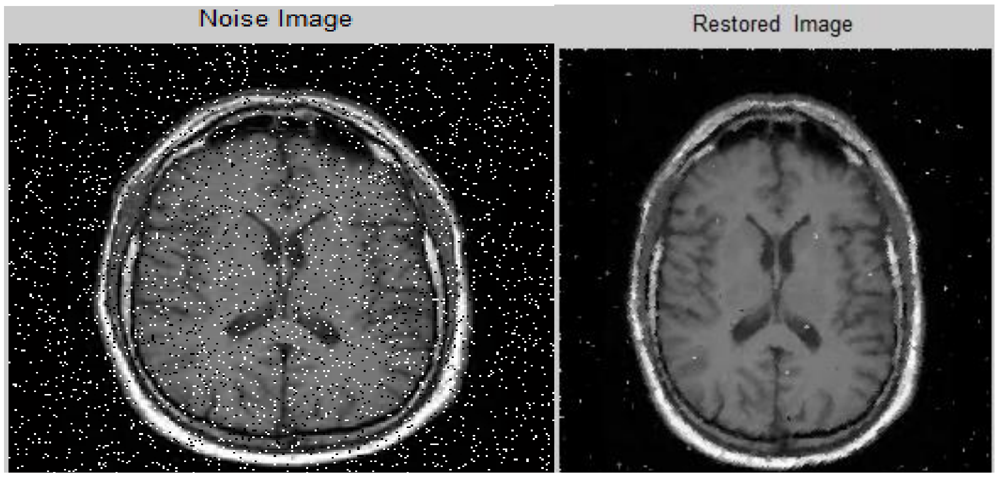


(g) 0.6 De-noising

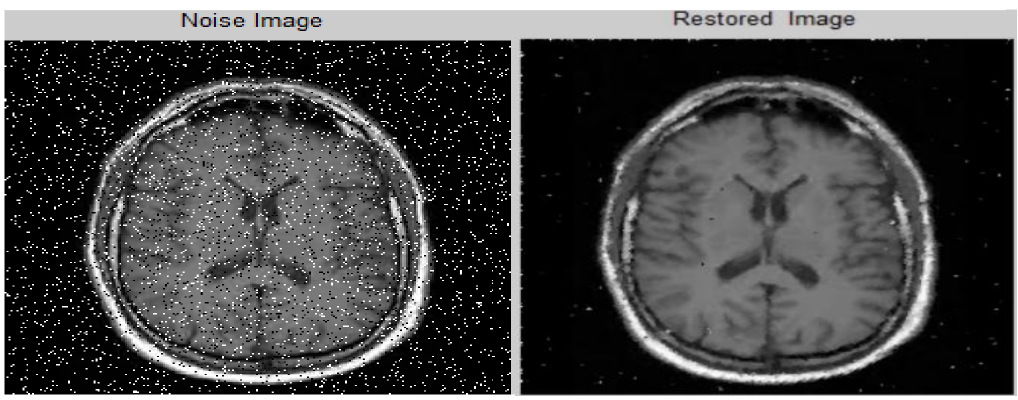


(h) 0.7 De-noiseing

International Journal of Engineering, Science and Humanities
An international peer reviewed, refereed, open-access journal
Impact Factor 8.3 www.ijesh.com ISSN: 2250-3552



(i) 0.8 De-noising



(j) 0.9 De-noiseing

Figure 2: Experimental Results of Proposed Method for real Brain Image

Table 1: Result for Medical image in 256×256 Size

PSNR (dB)					
Noise Density	0.01	0.02	0.03	0.04	0.05
Brain Image	45.786	42.940	41.139	40.168	39.025
Head Image	44.631	41.417	39.751	38.293	37.535
Heart Image	49.299	46.746	45.135	44.190	42.920
MSE					
Brain Image	1.715	3.303	5.002	6.255	8.138
Head Image	2.238	4.692	6.885	9.631	11.468
Heart Image	0.764	1.375	1.992	2.477	3.319

International Journal of Engineering, Science and Humanities
An international peer reviewed, refereed, open-access journal
Impact Factor 8.3 www.ijesh.com ISSN: 2250-3552

RMSE					
Brain Image	1.309	1.817	2.236	2.501	2.852
Head Image	1.496	2.166	2.624	3.103	3.386
Heart Image	0.874	1.172	1.411	1.574	1.821
NAE					
Brain Image	0.077	.079	0.077	0.076	0.076
Head Image	0.089	0.090	0.091	0.091	0.091
Heart Image	0.052	0.053	0.051	0.051	0.051

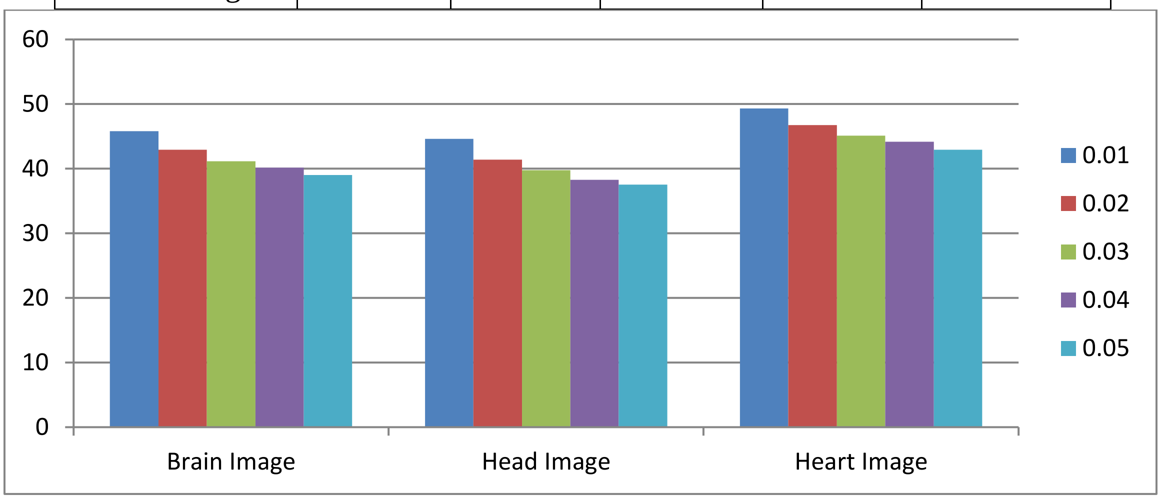


Figure 3: Graphical PSNR for 256×256 Size

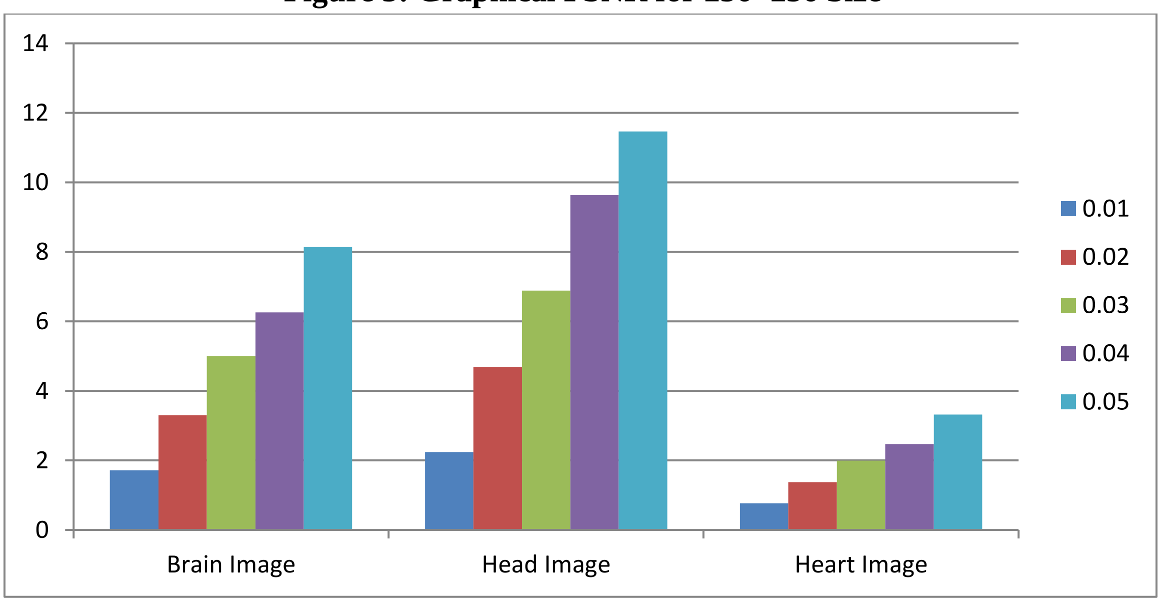


Figure 4: Graphical MSE for 256×256 Size

International Journal of Engineering, Science and Humanities
An international peer reviewed, refereed, open-access journal
Impact Factor 8.3 www.ijesh.com ISSN: 2250-3552

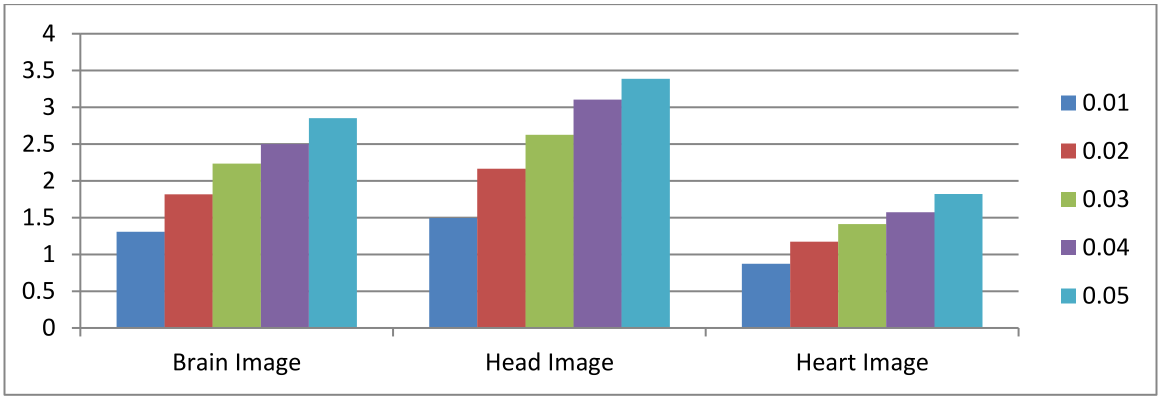


Figure 5: Graphical RMSE for 256×256 Size

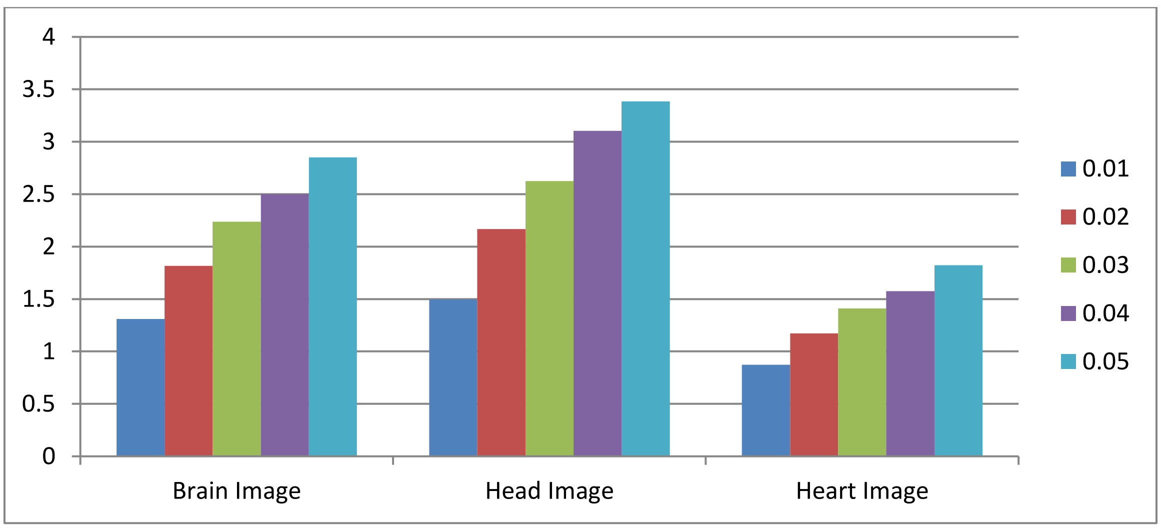


Figure 6: Graphical NAE for 256×256 Size

Table 2: Result for Medical image in 4096×4096 Size

PSNR (dB)					
Noise Density	0.01	0.02	0.03	0.04	0.05
Brain Image	50.575	47.351	45.662	44.310	42.914
Head Image	51.152	47.910	46.462	45.023	43.491
Heart Image	50.598	47.566	46.069	44.550	43.014
MSE					
Brain Image	0.569	1.196	1.765	2.520	3.324
Head Image	0.498	1.052	1.468	2.045	2.910
Heart Image	0.566	1.138	1.607	2.138	3.248

International Journal of Engineering, Science and Humanities
An international peer reviewed, refereed, open-access journal
Impact Factor 8.3 www.ijesh.com ISSN: 2250-3552

RMSE					
Brain Image	0.754	1.093	1.328	1.733	1.823
Head Image	0.706	1.025	1.211	1.430	1.705
Heart Image	0.752	1.067	1.267	1.459	1.802
NAE					
Brain Image	6.17×10^{-5}	6.26×10^{-5}	6.32×10^{-5}	6.33×10^{-5}	6.40×10^{-5}
Head Image	4.43×10^{-5}	4.68×10^{-5}	4.88×10^{-5}	4.98×10^{-5}	5.18×10^{-5}
Heart Image	5.71×10^{-5}	5.76×10^{-5}	5.79×10^{-5}	4.81×10^{-5}	5.85×10^{-5}

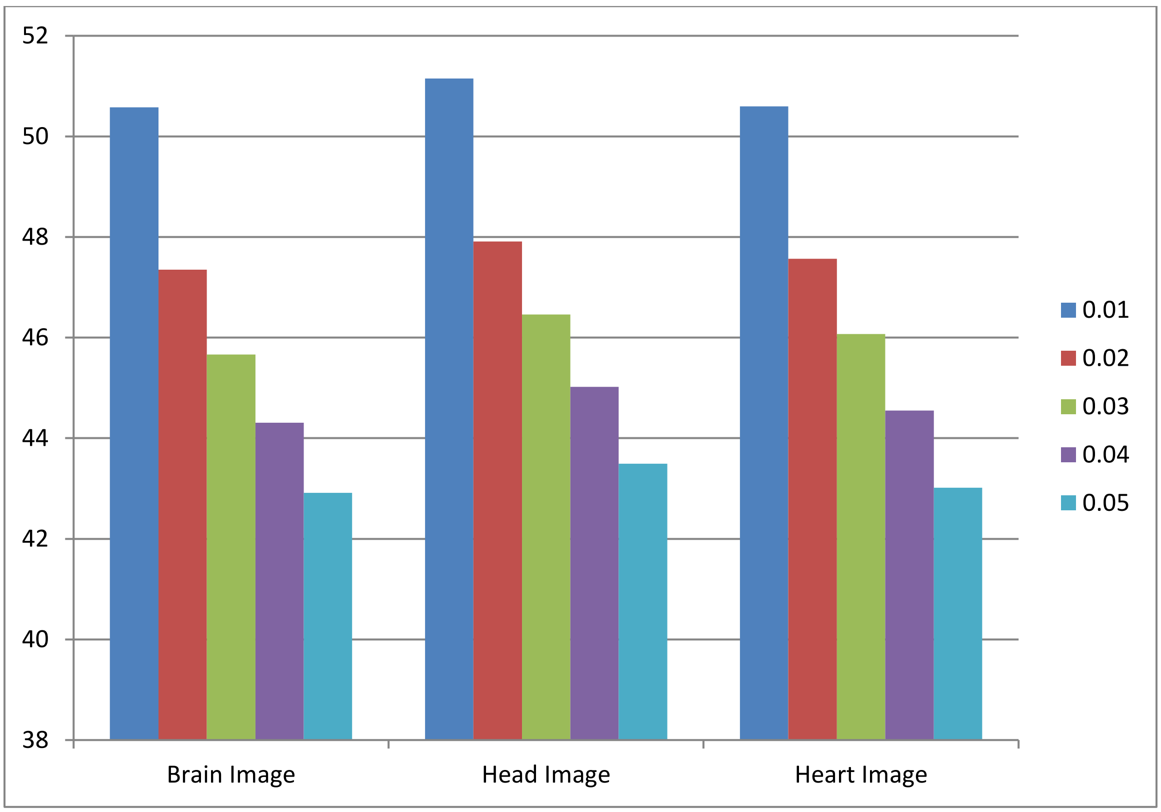


Figure 7: Graghical PSNR for 4096×4096 Size

International Journal of Engineering, Science and Humanities
An international peer reviewed, refereed, open-access journal
Impact Factor 8.3 www.ijesh.com ISSN: 2250-3552

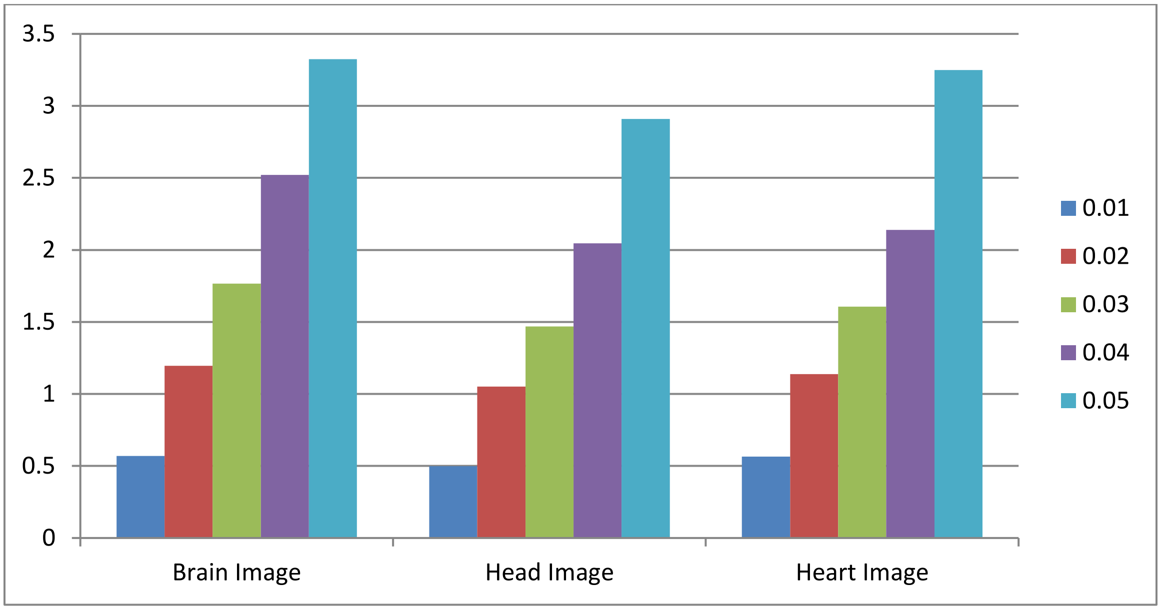


Figure 8: Graghical MSE for 4096×4096 Size

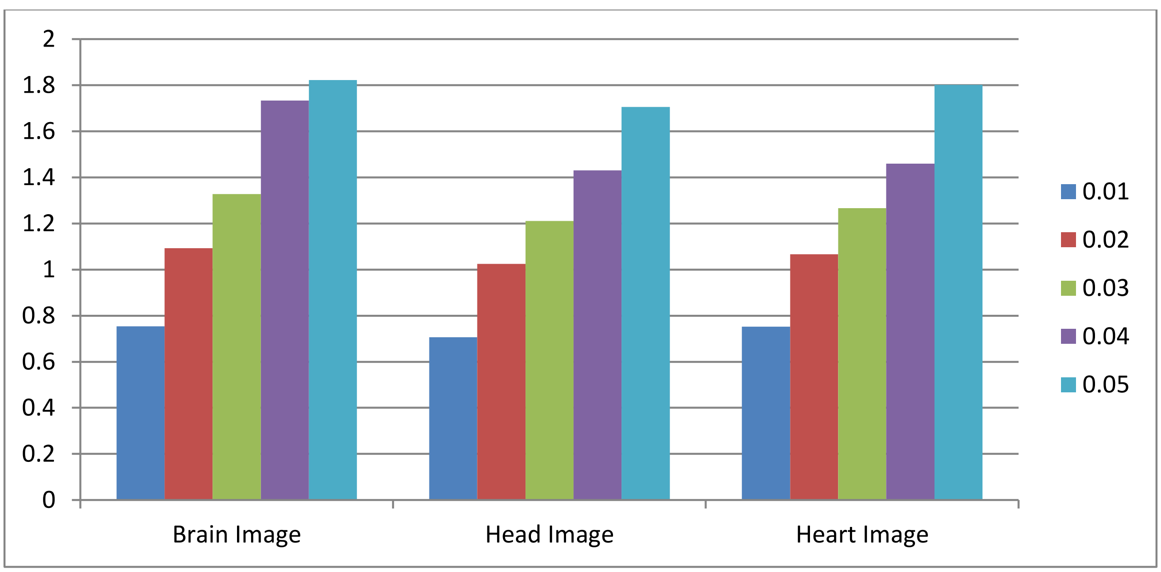


Figure 9: Graphical RMSE for 4096×4096 Size

5. CONCLUSIONS

In this work, a multi-resolution threshold (MRT) technique was explored for effective denoising of medical images while preserving diagnostically significant structures. Unlike conventional filtering approaches that often compromise edge sharpness and fine anatomical details, the proposed method leverages wavelet-based multi-resolution decomposition to separate noisedominated components from meaningful image features. By applying adaptive thresholding across different resolution levels, the technique achieves a balance between noise suppression and detail preservation, thereby enhancing the visual quality and diagnostic reliability of MRI, CT, and other medical imaging modalities.

Experimental evaluation demonstrated that MRT consistently improves both objective metrics, such as PSNR and MSE and subjective visual quality compared to traditional denoising techniques. The adaptability of the thresholding strategy allows the method to remain robust under varying noise conditions, making it suitable for a wide range of clinical imaging scenarios. Furthermore, its computational efficiency ensures that the technique can be integrated into real-time or near real-time medical imaging pipelines, supporting applications such as telemedicine, emergency diagnostics, and intraoperative visualization.

REFERENCES

[1] Ahmed Abdulmaged Ismael and Muhammet Baykara, “Image Denoising Based on Implementing Threshold Techniques in Multi-Resolution Wavelet Domain and Spatial Domain Filters”, Traitement du Signal, Vol. 39, No. 4, pp. 1119-1131, 2022.

[2] Rajesh Patil and Surendra Bhosale, “Multi-Modal Medical Image Denoising using Wavelets: A Comparative Study”, Biomedical & Pharmacology Journal, Vol. 16(4), p. 2271-2281, 2023.

[3] Rajesh Patil, S. J. Bhosale, “Medical Image Denoising Techniques: A Review”, International Journal on Engineering, Science and Technology, Volume 4, No 1, 2022.

[4] Subhrajit Dey, Rajdeep Bhattacharya and Ram Sarkar, “Median Filter Aided CNN Model for Removal of Gaussian Noise from Images”, IEEE Recent Advances In Intelligent Computational Systems (RAICS), IEEE 2020.

[5] L. Sekanina Z. Vasicek and V. Mrazek "Automated search-based functional approximation for digital circuits" in Approximate Circuits Cham Switzerland:Springer vol. 26 pp. 175-203 2019.

[6] J. Lyu D. Bi X. Li and Y. Xie "Robust compressive two-dimensional near-field millimeter-wave image reconstruction in impulsive noise" IEEE Signal Process. Lett. vol. 26 no. 4 pp. 567-571 Apr. 2019.

[7] H. Y. Khaw F. C. Soon J. H. Chuah and C.-O. Chow "High-density impulse noise detection and removal using deep convolutional neural network with particle swarm optimisation" IET Image Process. vol. 13 no. 2 pp. 365-374 Feb. 2019.

[8] S. S. Sadrizadeh S. Kiani M. Boloursaz and F. Marvasti "Iterative method for simultaneous sparse approximation" Sci. Iran. vol. 26 no. 3 pp. 1601-1607 2019.

[9] J. Chen Y. Zhan and H. Cao "Adaptive sequentially weighted median filter for image highly corrupted by impulse noise" IEEE Access vol. 7 pp. 158545-158556 2019.

[10] R. Abiko and M. Ikehara "Blind denoising of mixed Gaussian-impulse noise by single CNN" Proc. IEEE Int. Conf. Acoust. Speech Signal Process. (ICASSP) pp. 1717-1721 May 2019.

[11] U. Erkan L. Gökrem and S. Enginoğlu "Different applied median filter in salt and pepper noise" Comput. Elect. Eng. vol. 70 pp. 789-798 Aug. 2018.

[12] L. Stankovic and M. Brajovic "Analysis of the reconstruction of sparse signals in the DCT domain applied to audio signals" IEEE Trans. Audio Speech Language Process. vol. 26 no. 7 pp. 1220-1235 Jul. 2018.

[13] L. Gao X. Li D. Bi and Y. Xie " A q -Gaussian maximum correntropy adaptive filtering algorithm for robust sparse recovery in impulsive noise " IEEE Signal Process. Lett. vol. 25 no. 12 pp. 1770-1774 Dec. 2018.

[14] Javaheri H. Zayyani M. A. T. Figueiredo and F. Marvasti "Robust sparse recovery in impulsive noise via continuous mixed norm" IEEE Signal Process. Lett. vol. 25 no. 8 pp. 1146-1150 Aug. 2018.

[15] R. Sujitha, C. Christina, De Pearlin et al., “Wavelet Based Thresholding for Image Denoising in MRI Image” International Journal of Computational and Applied Mathematics. ISSN 1819-4966 Volume 12, Number 1, 2017.