# BRAIN MRI IMAGE DENOISING USING FILTERING APPROACHES

**Kavita Singh** Research Scholar, Department of Electronics and Communication, Allahabad University, Prayagraj, India
**Dr. Rajesh Kumar*** Assistant Professor, Department of Electronics and Communication, Allahabad University, Prayagraj, India

**Abstract**
Image enhancement is very basic and one of the fundamental steps in processing of any image. It deals with the enhancement of contrast and brightness while restoration of images deals with recovering degraded images as like the original image. Image restoration includes the degradation model and recovers the original image. Restoration of images is necessary for the better picture quality. It becomes more useful in case of medical resonance image, because here the picture quality matters. With the help of better image quality, the tumors, cyst, or other problems present in the affected body part can be diagnosed better. Restoration of images deals with the less clear or blurred images. In this paper, various types of image enhancement and restoration techniques are discussed. The primary focus of this paper is to analyze that which filter gives better result for different kind of noises present into medical images using parameters like PSNR and MSE**.**
**Keywords**: enhancement, restoration, image, wiener, median, gaussian, salt and pepper, speckle;

## Introduction

Image enhancement is nothing but enhancing the picture's contrast and brightness. With the help of image enhancement, image visibility improves. It is a subjective approach. It brings out the hidden details in an image. Enhancing an image's quality for the human eye's perception is a common strategy.

Image restoration, on the other hand is the process of reconstructing the noisy or blurred images. Images can be degraded by atmospheric distortion, optical aberrations, sensor blur, motion blur and noise. Restoration of images is an objective approach. Restoration techniques are oriented towards the various models like degradation and blur models and applying the inverse process in reconstructing the original image.[1]

Image restoration has a wide area of applications in different fields like astronomy, microscopy, remote sensing, photography, surveillance, medical imaging (CT, MRI, and PET scans). Images taken in low light can cause noise, handshaking, while clicking picture, or movement of the object in a picture causes motion blur in images.

There are several types of noises that can be present in MRI picture and degrades the quality of the picture. In case of medical images, it becomes more important to reduce these noises otherwise important information can be missed out due to presence of noise that can lead to wrong diagnosis and wrong treatment that will cause risk to the human life. Removal of these noises can be done by using various kind of filters. In this paper, three basic filters are used namely, gaussian, median and wiener filter. These three filters are applied on the noisy MRI images and type of noise present in images are namely gaussian, salt and pepper, and speckle noises.

## Related work

An overview of several studies that have been conducted in the field of picture enhancement and restoration is provided in this section. Many researchers have used different approaches, models, and algorithms for reconstruction of images. Image reconstruction is the part of image processing that always grabbed attention among researchers because better picture quality is, was and will be in demand forever. Here are the papers we read to help us grasp the methods for improving and restoring medical photographs.

A novel method for enhancing medical images was introduced by Bo Li, et al. (2015) [2] and permits modifications in fractional order in accordance with the dynamic gradient feature of the entire image. The suggested method enhances an image's borders while keeping its smooth areas and subtle textures. These advancements can be very beneficial for diagnosing any abnormalities found in MRI scans by medical professionals. The adaptive fractional differential algorithm (AFDA), which is based on an improved Otsu technique to segment the edges, textures, and smooth parts of images, is the main contribution of this study. Using an adaptive fractional differential function based on the area feature of the image, this method determines the appropriate fractional order for each pixel, leading to an adaptive image improvement.

According to a theory advanced by Zahid Ullah et al. (2020) [3], the improved image quality at the pre-processing stage can significantly influence the analysis and classification of any statistical approach. The initial enhancement method utilized by the researchers had three steps: grayscale image conversion to RGB, noise removal with a median filter, and contrast amplification with a histogram equalization method. Following image enhancement, MR image features were extracted using discrete wavelet transformation, and they were further reduced using colour moments like mean, standard deviation, and skewness. The classification of human brain magnetic resonance imaging as normal or pathological is taught to an advanced deep neural network. This proposed method's sensitivity and specificity rates are 96.0% and 95.65% respectively.

Iza Sazanita Isa, et al. (2015) [4], used the median filter, adaptive filter, and average filter to analyze PSNR and MSE for speckle, salt & pepper, and gaussian noise. They found that the median filter performed well for these noise types, with a PSNR of 38.3 dB at 10% noise variance. Additionally, this study demonstrates that, with 56.2dB PSNR at 10% noise variance, the average filter is more suitable for speckle noise.

Homogeneity means difference (HMD), a powerful evaluation strategy suggested by Ying Tao Zhang et al. (2012) [5], may analyze the effectiveness of filters by summarizing the textual and structural information. The suggested method has been tested on 503 photos and shown to work effectively for denoising filters with or without contrast enhancement is also utilized.

In order to denoise the MRI pictures, Jose V. Manjon, et al. (2011) [6] suggested two novel techniques. These techniques make use of the image's self-similarity and sparsity. The first technique is the ODCT3D technique, which effectively reduces noise by utilizing the sparseness feature. The PRINLM3D method, which employs prefiltered ODCT3D data as a starting point, is the second approach. Both methods outperform the prior state-of-the-art denoising in terms of performance.

Three techniques for improving an image were provided by Agaian, et al. (2007) [7], including logarithmic transform histogram matching, logarithmic transform histogram shifting, and logarithmic transform histogram shaping with Gaussian distributions. These techniques make use of the characteristics of the domain histogram of the logarithmic transform and histogram equalization. These techniques also specify how to measure an improvement in image contrast using the human visual system. The methods that are being provided will choose the ideal parameter and transform automatically. These algorithms are also straightforward and user-friendly, which makes them more useful and appropriate.

Jinshan Tang, et al. (2003) [8] suggested an image improving method for JPEG compressed images. The contrast measure specified in the DCT domain provides the basis for this algorithm. This approach does image improvement during the decompression stage with no impact on the original image's compressibility. The algorithm is simple to implement and works with all DCT-based compression standards, including MPEG, JPEG, and H. 261.

A pre smooth non-local means (PSNLM) filter was suggested by Yang, et al. (2015) [9] as a way to remove Rician noise from MRI images. First, an additive noisy picture is created from a noisy image. After picture processing, pre-smoothening is carried out using conventional denoising techniques. The denoised MR image is then inversely transformed after the NLM filter has been applied to the altered picture. After that, denoising is finished. Various pre-smoothing filters, picture transformations including inverse variance-stabilizing transformations, and simulated and real patient data can be used to test the performance of the proposed method (VST). Through visual inspection and quantitative comparison of the PSNR of the simulated data, the performance of the suggested technique is assessed.

With the use of a wiener filter, Fabio Baselice et al. (2017) [10] introduced a unique denoising method for ultrasound pictures. Edges can be combined using the proposed method by changing the kernel values. With efficient noise reduction, details can also be preserved. This intrinsic characteristic is obtained by modelling the image with a local Gaussian Markov random field. The method has been tested on both simulated and actual datasets and has shown to perform better than other traditional methods. The method can combine minimal computing load, improved denoising performance, and detail preservation.

A probabilistic approach that uses MAP estimation to pixelwise detect lesions and a network-based prior as the normative distribution was proposed by Xiaoran Chen et al. (2020) [11]. Unsupervised lesion detection was treated as an image restoration issue in this study. The probabilistic model decreases the number of false positives in pixelwise detection by highlighting significant differences between the original and restored images. The model outperforms other methods based on experimental findings because it offers superior AUC and dice scores for glioma and stroke identification. This comprehensive model supports the importance of MAP-based picture restoration.

PSF estimate using an EM approach based on blind deconvolution was proposed by Nikita, et al., (2018) [12]. The suggested approach can assist doctors in making a diagnosis of a brain tumour. To conduct the experiment, five different types of tumour images—Astrocytoma, Ganglioglioma, Glioblastoma, Epidermoid, Mixed Glioma, and malignant—were used. According to the experimental findings, the regularised Lucy technique [13] took 1.524 seconds with 103 iterations while the proposed method took 0.98 seconds with 10 iterations to finish the restoration process. Compared to the regularised Lucy technique, the image quality improved. By obtaining greater values for PSNR and SSIM, the suggested methodology aids in the evaluation of image quality.

S. Suryanarayana, et. al., (2012) [14] proposed a creative method for gaussian noise detection and elimination. For estimation, a 5x5 window is used, which is divided into nine 3x3 sub windows where the test pixel is present. This information about the presence of noise in the pixel is provided by these sub windows. Using the constants k1 and k2, the maximum and lowest standard deviations are found to be 0.5 and 2, respectively. The test pixel is considered to be corrupted if the difference magnitude |-x| falls between [a, b], where is the mean of the 3x3 neighborhood around the test pixel, which is situated in the centre of the window, and x is the test pixel's intensity. The suggested approach outperforms the conventional mean filter.

Charu, et al., (2011) [15], compared different methods like Lucy-Richardson, wiener filter, and neural network approach and concluded that neural network gives PSNR value equal to 30.1135 which is better among all three approaches.

Shukla, et. al., (2021) [16], calculated different parameters like PSNR (peak signal to noise ratio), RMSE (root mean square error), SSIM (structural similarity index) and Entropy for an image using different spatial domain filters including gaussian, wiener, median and bilateral filters and found that combination of gaussian and NLM filters gives satisfactory results but NLM filters gives best results among all the filters. This experiment is carried out using 40 images.

By merging the Kernel, Sobel, and Low-pass (KSL) filtering approaches, Devasena et. al., (2011) [17] introduced a new filter known as the KSL filter. The suggested method is put into use using MATLAB, and when it is compared to similar current methods over both simulated and actual clinical MR images, it consistently performs better.

For picture denoising applications, Lalitha, et. al., (2011) [18] proposed a modified spatial filtration technique. For the purpose of reconstructing medical images that were impacted by noise, the already-existing spatial filtration approaches were enhanced. The established modified approach was created to determine the masking centre for a certain MRI picture in an adaptive manner. For the purpose of improving the modified strategy, the traditional filtration methods using mean, median, and spatial median filters were examined. The created method is contrasted with the most recent image smoothing methods. It is discovered that the suggested method offers greater reconstruction accuracy than other conventional methods.

Aye Min, et. al., (2018) [19], proposed a result based fusion binding method for enhancement of image and a combination of Adaptive K-means and morphological operation (AKMM) for tumor segmentation. In the suggested method, 110 flairs were evaluated for picture segmentation, and 40 flairs and T2 sequences were examined for image enhancement. Experimental study shows that proposed method results in higher accuracy and involves less complexity over time and performing better than existing methods.

J.M. Waghmare, et. al., (2013) [20], provided a study of the effect of noise removal by means of median filtering on fuzzy c-means clustering and an improved iterative relaxed median filter-based denoising approach is proposed. The performance and outcomes of the suggested method are evaluated in comparison to those of the conventional median filter, the center-weighted median filter, the hybrid median filter, and the relaxed median filter. The suggested method has strong clustering performance for iterative relaxed median filtered images and is quite capable of removing noise from an image in terms of PSNR.

Senthilkumaran, et. al. (2014) [21], Different parameters like the Weber constant, Michelson contrast, and image contrast have been calculated and analyzed in this work, along with various histogram equalization-based enhancement methods for MRI brain images, including Global Histogram Equalization (GHE), Local Histogram Equalization (LHE), Brightness Preserving Dynamic Histogram Equalization (BPDHE), and Adaptive Histogram Equalization (AHE).

An effective thresholding-based technique for the distorted pictures caused by gaussian noise was presented by Kaur, G., et. al. (2021) [22]. Various images are subjected to the algorithms Bayes shrink and Neigh shrink sure, and the outcomes are obtained from the wavelets db-4, sym-4, and coif-4. This paper concludes that coif-4 transforms produce better results and Neigh shrink sure algorithm is more beneficial as it provides higher PSNR and lower MSE values.

A two-phase strategy was proposed by Chan, R. H., et. al., (2005) [23] for the elimination of salt and pepper noise. With the aid of an adaptive median filter, the first phase identifies the noise-contaminated pixels. A specific regularization technique is used to restore the image in the second phase. This study's findings show that the edges are better preserved and the denoising is crisper in the restored images using a particular regularizations technique.

A decision-based technique was put forth by K. S. Srinivasan, et. al., (2007) [24] for the restoration of images that have been severely damaged by impulsive noise. The suggested solution merely replaces faulty pixels with their median value or a neighboring pixel. This technique offers superior restoration outcomes up to 90% noise levels and can maintain edges without sacrificing quality up to 80% noise levels.

Singh, et. al., (2016) [25], compared different noise models and restoration techniques. This paper is a comparative study of different types of noises present in an image and the various enhancement and restoration techniques used for removal of noise.

## Noises Present in MRI images

Gaussian, Salt & Pepper, and Speckle noise are the three types of noise that are most frequently found in MRI scans. As we know that noise is unwanted signal added into the input and degrades the final output due to various reasons including atmospheric, systematic, or sometimes unknown reasons as well.

### A. Gaussian Noise

The probability density function of the normal or gaussian distributions is equivalent to the statistical noise known as gaussian noise [26]. As it occurs in amplifiers or detectors, this is sometimes referred as electronic noise [27]. Due to its tractability in mathematics, this noise cannot be avoided and is commonly employed [1]–[28]. It happens naturally, i.e., as a result of atoms' thermal vibration and radiation brought on by warm objects [29]. The grey pixels are typically distorted by this noise. The histogram is normalized in reference to the value of a grey pixel, and it frequently refers to and identifies itself as a PDF (Probability Density Function). This noise is removed using a variety of denoising filters, including median, Wiener, gaussian, and average filters.

### B. Salt & Pepper Noise

This is also known as impulsive noise [4]. This noise results from a low-quality photograph that contains both bright and dark pixels. The usual characteristics of this noise are dark pixels in bright parts and bright pixels in dark regions of the image. This noise in the image causes black and white dots to appear [30]. Dark Frame Subtraction can be used to reduce this type of noise and a median or morphological filter, which creates new data points surrounding dark and bright pixels and replaces the damaged value with the median value [26].

### C. Speckle Noise

Because the speckle noise is multiplicative, it is evident in brighter places but almost completely disappears in darker areas. Due to data transmission problems, granular noise lowers the quality of an image. This noise frequently shows up in coherent imaging systems like active radar, Synthetic Aperture Radar (SAR) images, or Magnetic Resonance Imaging (MRI) images [17]–[27].

## Materials and Methods

*a)Dataset:* For conducting the experiment, the MRI images has been taken from the online open source named as Kaggle dataset[38]. This experiment is performed with the help of MATLAB 2021a (9.10.0.1602886) 64-bit.

*b)Work flowchart:* In our experiment, we first turned an RGB image into a grayscale image, added noise to that image, and then applied various filters. To determine which filter is functioning better on which type of noise, we calculated PSNR (peak signal to noise ratio) and MSE (mean square error). The best filtration results are shown by higher PSNR and lower MSE values. Flowcharts can also be used to depict the work process.

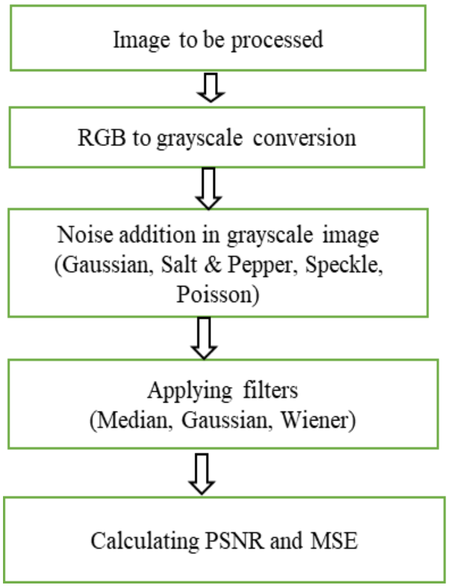



Fig. 1. Seps involved in the work process

*c) Noise Removal filters*

Denoising of an image is done by different filters or techniques. In this paper, we have used three fundamental filters namely; Median, Gaussian, and Wiener filters for different percentage of mean, noise density and variance of different noises like Gaussian, Salt & Pepper, and Speckle noise.

*i) Median Filter*

Median filter is a very common and successful scheme for removal of Salt & Pepper Noise. It is a nonlinear filtering approach also referred as order-statistic filtering in digital image processing. This filter passes through the image pixel by pixel, replacing each pixel's value with the median of the intensity levels in the surrounding pixels with mathematical precision. The image is denoised by these filters, but the tiny details are also lost. These filters smooth an image that is why widely used as smoother in digital image processing as well as digital signal processing. This filter could significantly reduce the impact of input noise [31]. Additionally, it has the ability to maintain the image's sharp edges [32]. Median filter can also be represented by using equation (1):

$$y(n) = \text{med}\ \{x(i)\}, \text{ where } i = n, n-1, \ldots, n-M \qquad (1)$$

*ii) Gaussian Filter*

This filter helps with smoothing the image but at the same time it also causes distortion in the signal [33]. It is used in pre-processing stage for edge detection but it also results in the rise of position displacement of edges, vanishing of edges and phantom edges [34]-[35]. This filter is comparable to the median filter in that it replaces the noisy, Gaussian-distributed pixels in the image with the average value of the surrounding or nearby pixels [26]. A representation of the two-dimensional Gaussian filter is as given in equation (2):

$$G(x,y) = \frac{1}{\sqrt{2\pi\sigma}} \mathrm{e}^{(-\frac{x^2+y^2}{2\sigma^2})} \quad (2)$$

Where, $\sigma$ is the standard deviation of Gaussian filter, x and y are the co-ordinates respectively.

*iii) Wiener Filter*

Inverse filtering and noise smoothing are optimally balanced by Wiener filtering [36]. It simultaneously eliminates deblurring and additive noise [37]. This filter falls under the category of "optimal linear with noisy input data" [36]. This filter is used to filter the noisy image by comparing it with an estimated noiseless signal. This statistical method includes filtering the noise from each pixel of an image and calculating the difference between the intended output and the original input [26]. It offers deblurring and eliminates extra noise from the image. The mean square error can be used to gauge this filter's effectiveness.

Wiener filter can be expressed by equation (3) as:

$$W(m,n) = \frac{H^*(m,n)P_S(m,n)}{|H(m,n)|^2 P_S(m,n) + P_n(m,n)} \quad (3)$$

Where Ps(m,n) is the Power Spectral density of an undegraded image, H(m,n) is the degradation function, H*(m,n) is the complex conjugate of degradation, and Pn(m,n) is the Power Spectral density of Noise.

**Experimental and Simulation Results**

In this experiment, we have taken 10 MRI images of brain and tested them by applying median, gaussian and wiener filter, making percentage change in the parameters like mean, noise density and variance of gaussian, salt & pepper, and speckle noise respectively followed by calculating MSE and PSNR value for each case.

**Performance evaluating parameters:**

*a) Mean square error (MSE)-*

This variable is used to gauge how well a picture has been filtered. The MSE calculates the cumulative squared error between the original image and the compressed (filtered) image. Less mistake results with a lower MSE value. MSE can be calculated by equation (4):

$$MSE = \frac{\sum_{M,N} [I_1(m,n) - I_2(m,n)]^2}{M*N} \quad (4)$$

Where, M and N are number of rows and columns in the input image.

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

This parameter contrasts the original image's quality with that of the compressed version. An increased PSNR value denotes high-quality compression or reconstruction. PSNR is measured in decibels. PSNR is expressed as in equation (5):

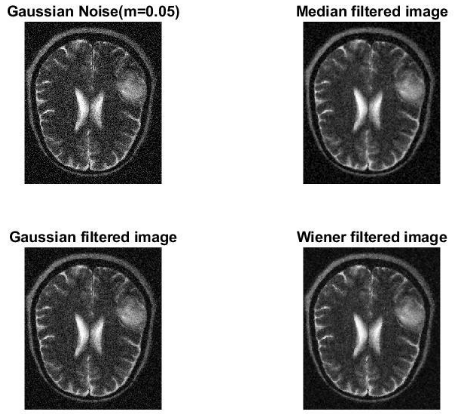
$$PSNR = 10\, log_{10}\left(\frac{R^2}{MSE}\right) \quad (5)$$

Where, R is the maximum fluctuation in the input image data type.

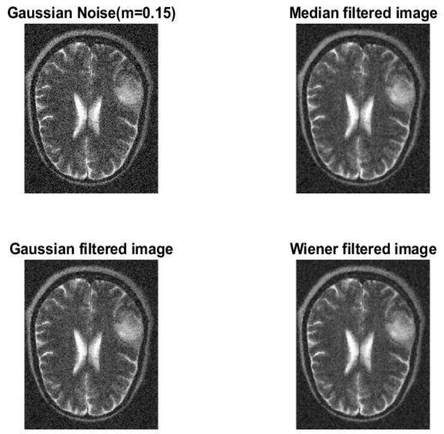
**Table No.1: Average MSE and PSNR value of ten MRI images**

| Type of Noise | % Change in Parameters | Type of Filter | | | | | |
|---|---|---|---|---|---|---|---|
| | | Median | | Gaussian | | Wiener | |
| | | MSE | PSNR | MSE | PSNR | MSE | PSNR |
| Gaussian | Mean | | | | | | |
| | 0.05 | 88.212 | 30.08 | 114.88 | 29.07 | 89.81 | 30.03 |
| | 0.15 | 406.22 | 23.25 | 438.68 | 23.34 | 394.63 | 23.68 |
| | 0.2 | 681.76 | 21.33 | 699.26 | 21.22 | 663.15 | 21.75 |
| | 0.5 | 3765.01 | 13.87 | 3721.57 | 13.93 | 3691.15 | 13.96 |
| Salt & Pepper | Noise density | | | | | | |
| | 0.05 | 21.44 | 36.847 | 158.26 | 28.222 | 232.46 | 26.748 |
| | 0.15 | 35.77 | 34.459 | 460.30 | 23.353 | 392.60 | 24.033 |
| | 0.2 | 52.12 | 32.746 | 622.97 | 21.977 | 465.94 | 21.755 |
| | 0.5 | 731.99 | 21.246 | 1771.26 | 17.53 | 1086.10 | 13.966 |
| Speckle | Variance | | | | | | |
| | 0.05 | 50.93 | 33.42 | 49.60 | 33.178 | 45.06 | 33.99 |
| | 0.15 | 111.33 | 29.878 | 135.12 | 29.159 | 132.65 | 29.609 |
| | 0.2 | 138.46 | 28.941 | 176.21 | 28.128 | 176.04 | 28.529 |
| | 0.5 | 295.29 | 25.69 | 225.58 | 24.695 | 383.93 | 25.001 |

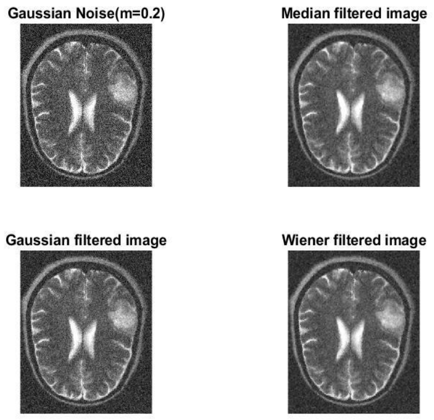
The above table (1) shows the calculated average of MSE and PSNR values of ten brain MRI images using different types of noises (Gaussian, Salt and Pepper and Speckle) at different parameters (Mean, Noise density and Variance) for Median, Gaussian and Wiener filters.



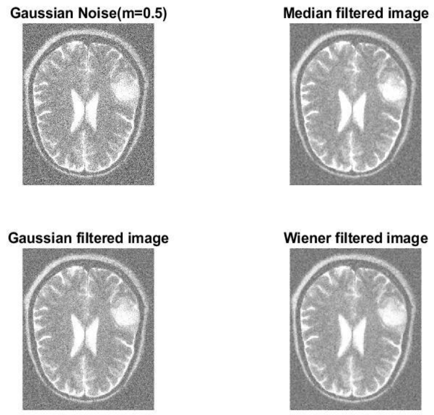

(a) Gaussian noise with mean value 0.05




(b) Gaussian noise with mean value 0.15

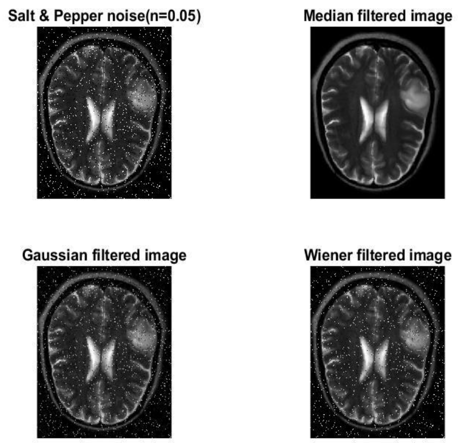



(c) Gaussian noise with mean value 0.2

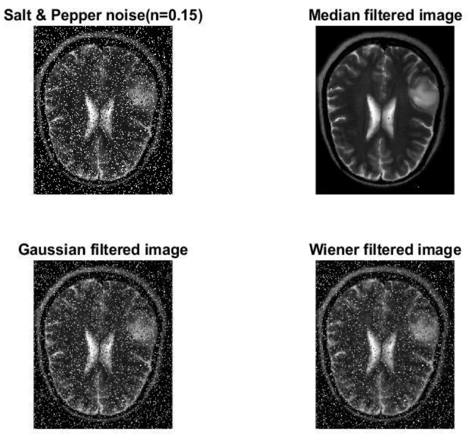



(d) Gaussian noise with mean value 0.5

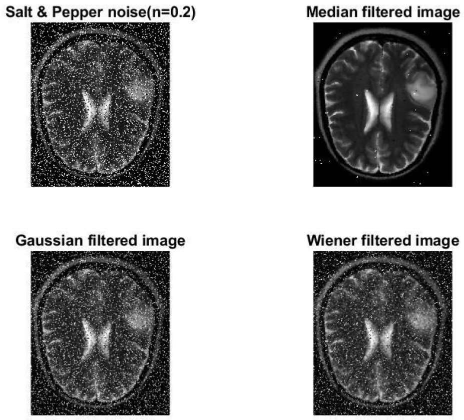
**Fig. 2 Gaussian Noise and Filtered Images:** (a) With mean value 0.05, (b) With mean value 0.15, (c) With mean value 0.2, (d) With mean value 0.5



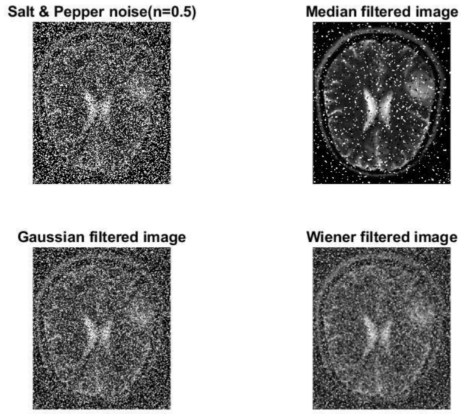

(a) Salt & Pepper noise with 5% noise density




(b) Salt & Pepper noise with 15% noise density

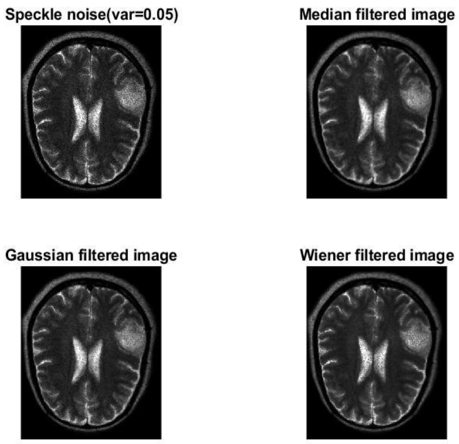



(c) Salt & Pepper noise with 20% noise density

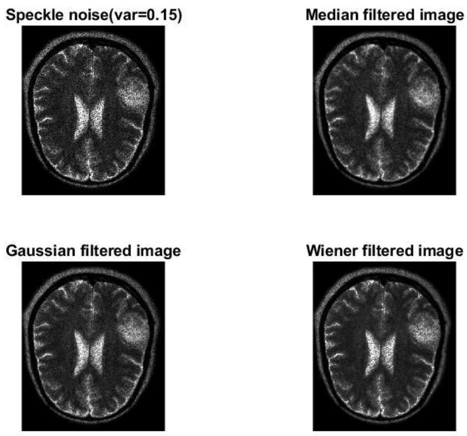



(d) Salt & Pepper noise with 50% noise density

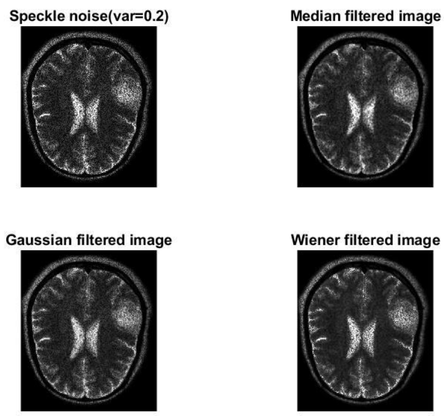
**Fig. 3. Salt & Pepper Noise and Filtered Images:** (a) with 5% Noise Density, (b) with 15% Noise Density, (c) with 20% Noise Density, (d) with 50% Noise Density



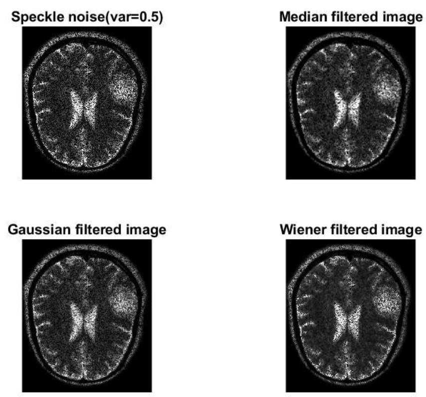

(a) Speckle Noise with variance 0.05




(b) Speckle Noise with variance 0.15



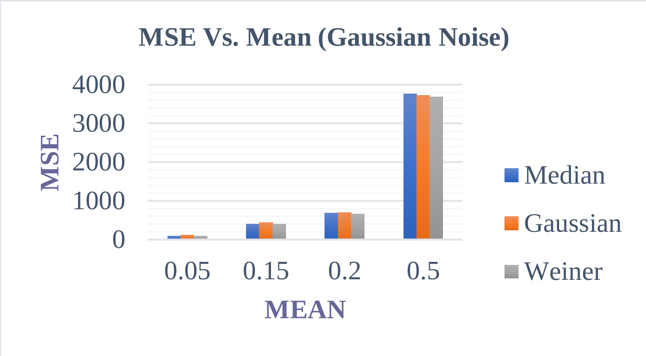

(c) Speckle Noise with variance 0.2



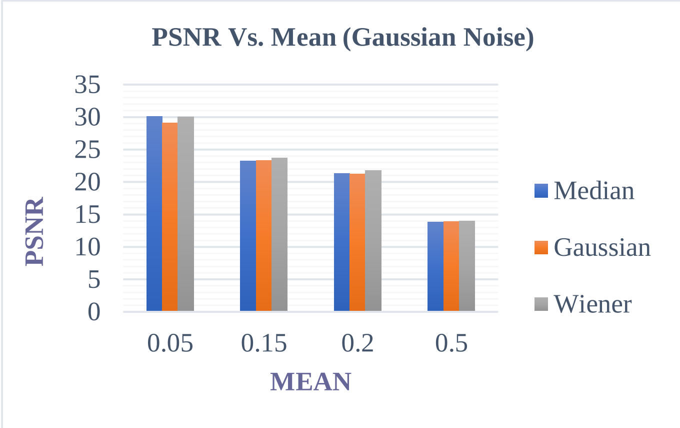

(d) Speckle Noise with variance 0.5

**Fig. 4 Speckle Noise and Filtered Images:** (a) with variance 0.05, (b) with variance 0.15, (c) with variance 0.2, (d) with variance 0.5

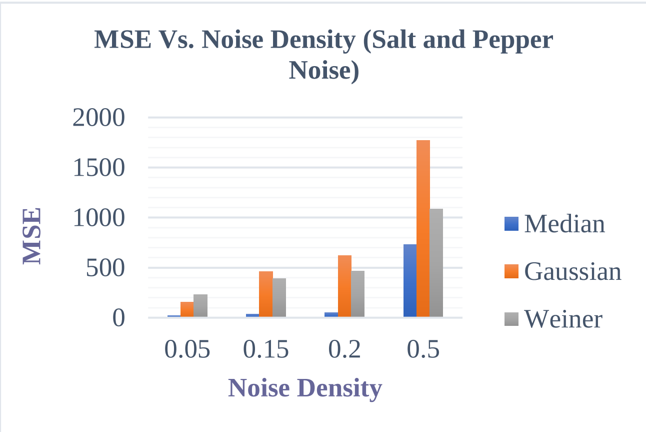
Figure 2, 3 and 4 represents the simulation results of Brain MRI images that are degraded with Gaussian, Salt and Pepper and Speckle noises with different values of mean, noise density and variance. The effect of these noises on different filters like Median, Gaussian and Wiener filter can also be seen by these figures.



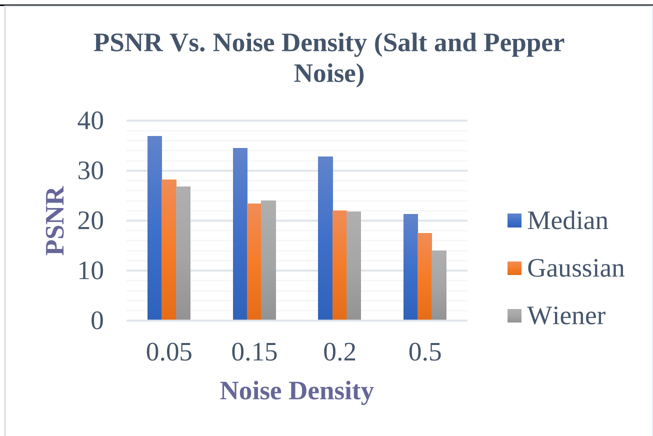

(a) MSE at different Mean value for Gaussian Noise



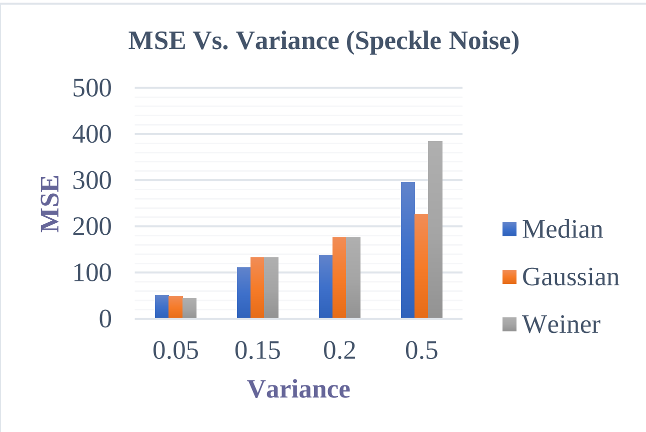

(b) PSNR at different Mean value for Gaussian Noise

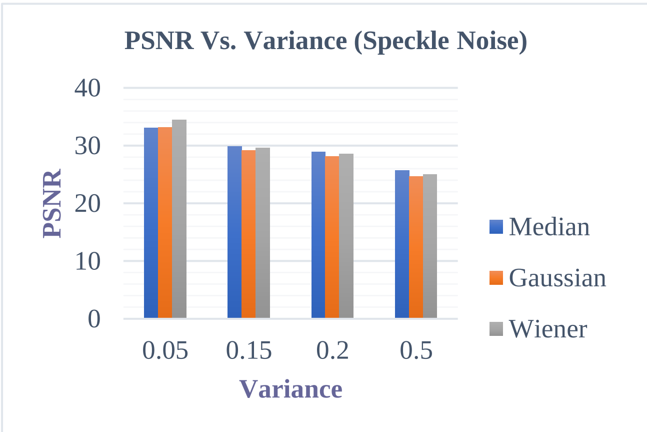



(c) MSE at different Noise Densities for Salt & Pepper Noise




(d) PSNR at different Noise Densities for Salt & Pepper Noise



| | |
|---|---|
| (e) MSE at different Variance for Speckle Noise | (f) PSNR at different Variance for Speckle Noise |

**Fig. 5 Graphical Representation of Average MSE and PSNR values of MRI images**: (a) MSE for Gaussian Noise, (b) PSNR for Gaussian Noise, (c) MSE for Salt & Pepper Noise, (d) PSNR for Salt & Pepper Noise, (e) MSE for Speckle Noise, (f) PSNR for Speckle Noise

**Analysis of Results**

When Gaussian noise with a mean value of 0.05 affects MRI images, the MSE and PSNR values for the median filter are 88.212 and 30.08dB, respectively. The MSE and PSNR values for the Gaussian filter are 114.88 and 29.07dB, respectively. The estimated MSE and PSNR values for the Wiener filter are 89.81 and 30.03 dB, respectively.

When Gaussian noise with a mean value of 0.15 affects MRI pictures, the values for MSE and PSNR for the median filter are 406.22 and 23.25 dB, respectively. The estimated MSE and PSNR values for the Gaussian filter are 438.68 dB and 23.34 dB, respectively. The MSE and PSNR values for the Wiener filter are 394.63 dB and 23.68 dB, respectively.

When Gaussian noise with a mean value of 0.2 affects MRI pictures, the computed values for MSE and PSNR for the median filter are 681.76 and 21.33, respectively. MSE and PSNR for the Gaussian filter are 699.26 and 21.22 dB, respectively. The estimated MSE and PSNR values for the Wiener filter are 663.15 and 21.75 dB, respectively. Figures 5(a) and (b) show the performance of MSE and PSNR values at various mean values for Gaussian noise graphically.

The computed value of MSE and PSNR for Median filter is 21.44 and 36.84 dB, respectively, when Salt and Pepper Noise is injected in MRI images with Noise density 0.05. The measured MSE and PSNR for the Gaussian filter are 158.26 and 28.22 dB, respectively. The estimated MSE and PSNR values for the Wiener filter are 232.46 and 26.74 dB, respectively.

The MSE and PSNR for the median filter are 35.77 and 34.45 dB when the noise density of salt and pepper noise in MRI images is 0.15. The MSE and PSNR values for the Gaussian filter are estimated as 460.30 and 23.35 dB, respectively. The estimated MSE and PSNR values for the Wiener filter are 392.60 and 24.03 dB, respectively.

The computed values of MSE and PSNR for Median filter when Salt and Pepper noise with noise density 0.2 affects MRI pictures are 52.12 and 32.74 dB, respectively. MSE and PSNR for the Gaussian filter are 622.97 and 21.97 dB, respectively. The MSE and PSNR values for the Wiener filter are 465.94 dB and 21.75 dB, respectively.

The computed value of MSE and PSNR for Median filter is 731.99 and 21.24 dB, respectively, when Salt and Pepper noise is added into an MRI picture with noise density 0.5. The MSE and PSNR values for the Gaussian filter are 1771.26 dB and 17.53 dB, respectively. The estimated MSE and PSNR values for the Wiener filter are 1086.10 and 13.96 dB, respectively.

Fig.5(c) and (d) gives the graphical representation of performance of MSE and PSNR values at different noise densities for Salt and Pepper noise.

When MRI images are disturbed with Speckle Noise with variance 0.05, the calculated value of MSE and PSNR for Median filter is 50.93 and 33.42 respectively. For Gaussian filter, the calculated value of MSE and PSNR is 49.60 and 33.17 dB respectively. For Wiener filter, the estimated value of MSE and PSNR is 45.06 and 33.99 dB respectively.

When Speckle noise affects the MRI images by variance 0.15, the obtained value of MSE and PSNR for Median filter is 111.33 and 29.87 dB respectively. For Gaussian filter, the value of MSE and PSNR is 135.12 and 29.15 dB respectively. For Wiener filter, the estimated value of MSE and PSNR is 132.65 and 29.609 dB respectively.

When Speckle Noise affects the MRI images by variance 0.2, the calculated value of MSE and PSNR for Median filter is 138.46 and 28.94dB respectively. For Gaussian filter, the value of MSE and PSNR is 176.21 and 28.12dB respectively. For Wiener filter, the value of MSE and PSNR is 176.04 and 28.52dB respectively.

When the MRI images affected by Speckle noise with variance 0.5, the calculated value of MSE and PSNR for Median filter is 295.29 and 25.69 dB respectively. For Gaussian filter, the value of MSE and PSNR is 225.58 and 24.69dB respectively. For Wiener filter, the estimated value of MSE and PSNR is 383.93 and 25 dB respectively.

Fig.5(e) and (f) gives the graphical representation of performance of MSE and PSNR values at different variance for Speckle noise.

## Conclusion

From above result and analysis, when MRI images are affected by low Gaussian noise, then Median filter works well. For higher value of Gaussian Noise, Wiener filter is performing better. When MRI images are affected by the Salt and Pepper Noise, then Median filter outperforms than the formers. When the MRI images are degraded by Speckle Noise then for lower value of variance, Wiener filter performs good and for higher value of variance, Median filter performs better. From above discussion, we are in position to conclude that Median filter performing well if MRI images are affected by any type of noise.

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