Pancreatic Tumor CT Image Preprocessing using Linear and Non-Linear Filtering Techniques

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Abstract

Medical health information study indicates that cancer is one of the most troublesome illnesses that occasionally pose as incurable. The immense amount of study being done on medical health systems is providing plenty of scope for the newest innovations in computing systems to appear. The scanned medical images contain more noisy appearance. To enhance the quality of the image, preprocessing techniques are implemented in order to bring the better visualization of the image before diagnose the disease. The core objective of this research work is to preprocess the pancreatic CT images and enhance the image quality by using suitable preprocessing techniques. Image techniques are mostly degraded by noise. An augmented enhancement technique with efficient denoising must be used to maintain the contour information and edges of the medical images. This research work implements the denoising filters such as mean, median and laplacian filters are used and the images are enhanced by Discrete Wavelet Transform (DWT) techniques are used. The performance of the techniques evaluated. From the results, image quality is increased.

Key words: Preprocessing, Pancreatic cancer, Noise filters, Discrete Wavelet Transform

1.Introduction

Pancreatic cancer is challenging to diagnose because of its rarity. Pancreatic cancer is an extremely lethal illness, with a survival rate of around 10% over a span of 5 years in the United States. Moreover, it is progressively emerging as a prevalent contributor to cancer-related deaths. Patients often come in with advanced disease because the symptoms are either absent or unclear when the cancer is still confined to a specific area. The most effective way to identify a pancreatic tumor and assess its suitability for surgery is through a high-quality computed tomography scan with intravenous contrast, utilizing a dual-phase pancreatic protocol.

The most recent advancements in computing technology for health research are being used to process data more quickly and efficiently. Research methodologies in artificial intelligence are increasingly being used to research in a variety of domains, such as health care and cognitive computing. One such field that has expanded its study into medical imaging is deep learning. Machine learning algorithms categorize cancer patients and learn to forecast each patient's optimal survival duration which, when combined with a collection of devices like the CT/PET Scan, MRI scan automates the process of identifying patients' issues. Deep learning (DL) technologies are very useful because they can effectively discover features from enormous datasets 1.

The CT provides elegant information about the diagnosis of the body. When CT is used in place of conventional imaging modalities, it provides remarkable levels of detail, including greater contrast and resolution. Evolutionary variations can be represented as normal or abnormal information in CT images. The tumor region is not accurately detected due to the presence of noise in the CT scanned images. Because even a small amount of noise also reduces the quality of classification. So, noise is preprocessed using denoising techniques. An important issue in the medical image processing is resolution which means there is a loss of quality occurs at the edges of the images. Therefore, enhancement of the resolution is used to preserve the edges and the contour information. The improvement in denoise along with the edge preservation is not enough in this method 2. The filter techniques are used to remove the unrelated neighbors from the weighted average used to denoise the image pixel. Based on the gradient and average gray values the filters are used. The median filter is typically employed to minimize noise in images caused by salt and pepper. Still, it frequently performs better at maintaining meaningful detail in the image than the mean filter. The inverse filters are used when the absence of the noise.

An essential phase in every aspect of image processing is image de-noising. Any image de-noising model's primary goal is to minimize noise while maintaining the image's edges. The linear model and the non-linear model are the two main, frequently employed models. In order to eliminate the noise and preserve the majority of the significant signal characteristics, image-de-noising techniques are employed. For this reason, filters are employed in image processing, where they are utilized to improve images or identify edges in images 3.

There are several of these filters, which work by converting the image back into a more precise representation of its pixels in order to eliminate noise 4. By considering the nearby pixels, it is possible to filter out the noisy pixels in an image. Regretfully, during the smoothing process, the original finer details may occasionally be represented by such noisy pixels. Different techniques are utilized depending on the type of noise model or noise distribution present, as there is no one-size-fits-all method for removing noise from an image.The most popular averaging or mean filtering method effectively reduces noise in the impacted image, but the resultant image has a blurry appearance. Any output pixel in this method has a value that is a linear combination of the values of the nearby input pixels. Consequently, the original pixel value is replaced with the mean value that is obtained after using all pixels—affected and unaffected—to calculate the mean.

The median filter was the most often used non-linear filter because of its strong de-noising ability 5 and computational economy 6. However, this method's primary drawback was that it ignored the existence of edges in the image and instead substituted a nearby median value for the noisy pixels 7. When the noise level was excessive, edges and features were not fully recovered. The laplacian filter is used to detect the edges of the images using second order derivative to detect the edges of an images in a better way. The denoised images are enhanced by the Discrete Wavelet Transform (DWT)for image resolution provides higher quality outcomes 8.The output of the images are given as input to inverse discrete wavelet transform to reconstruct the image with enhanced edge information, leading to sharper and more defined edges.

The research paper is organized as section 2 as Literature review and the section 3 discussed the methodology is implemented for research work as well as the noise removal techniques are explained in the section 4 and the experimental result is discussed in the section 5 and the finally concluded the result in the section 6.

2. Literature Review

Zuoyong Li et al9 proposed novel noise filter that provided a global image information-based noise detection rectification approach and created an image block-based way to more precisely estimate an image's noise density. Alexandre Berthet et al 10 explained the preprocessing model with convolutional neural network. V. Durga Prasad Jasti11 used geometric mean filter is used to improve the image quality. Rubina Sarki 12 used the Contrast limited adaptive histogram equalization (CLAHE) for image preprocessing. Y. B. Dong et al13 used the noise reduction techniques like power spectra and blur filters and an inverse filtering portion. to perform the de-convolution, and low pass filtering, or compression, to eliminate noise. The average, median, and wiener filtering were utilized by S. Rajeshwari 14 et al. for image denoising, while an interpolation-based Discrete Wavelet Transform (DWT) technique was employed for resolution enhancement. The bilateral filtering was first presented by Leavline and Singh 15, reduces the ghost colors where they appear in the first image and eliminates apparition hues along edges in shading images. Wavelet filters are shown by Sharma et al. 16 to be superior to all spatial domain filters smooth over a fixed window; they can occasionally cause over smoothing and obscure images.

3. Proposed Methodology

Employing image processing methods, the valuable information is extracted from noisy images. When an image is denoised, the edges are preserved. To improve the quality of the images, filtering procedures are applied. In order to eliminate the noise and preserve the majority of the significant signal characteristics, image-de-noising techniques are employed. The two significant models linear and non linear are used frequently in filtering procedures. Figure 1 shows the overview of the proposed framework.

Every image produced through an imaging device has noise in addition to random variations in hue and brightness. The grains in the film may possibly be the source of this noise. The image noise might be thought of as the unwanted by-product of capturing images. Rician noise affects magnetic resonance imaging (MRI), while Gaussian noise affects natural images 17.The overview of the proposed work is shown in Figure 1.

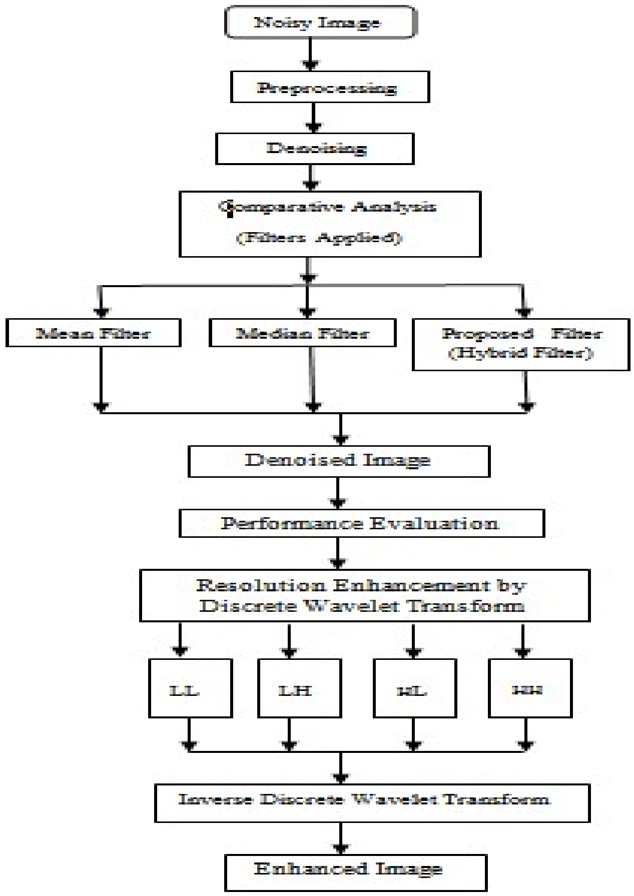

Figure 1. Overview of Proposed work

4. 1. Noise Removal Methods

4.1 .1 Linear Smoothing or Mean Filter

To reduce the amount of change in intensity between a pixel and the next, mean or linear filtering is applied. An image's pixel values are substituted by calculating the mean (or "average") value of all of its neighbors, including the image itself 20,21. Pixel values that are different from or not indicative of the surrounding pixels are removed by this type of filtering. Mean filtering is another name for average filtering. It functions by lowering the force of an image between the pixels and replacing each pixel with the average of the pixels in a square structure. When compared to other filters that are used, the average filter obscures the image content.

4.1.2 Median filters

One effective technique to remove salt and pepper and reduce noise in photos is to use a median filter. Among the non-linear strategies is this one. Replacing the image pixels from the regions where they are of median value completes the filtering process. It's a common technique for maintaining edges. It works especially well to get rid of pepper and salt noises. The median filter operates similarly to the mean filter, going pixel by pixel across the image and substituting the median value of each pixel for the value of the pixel next to it. The median pixel value from the previously sorted neighboring pixel values is used to replace the pixel under consideration once all of the pixel values from the pattern of neighbors have been sorted into numerical order. The median filter is far more efficient in eliminating noise from images without sacrificing image clarity shown in Figure 2.

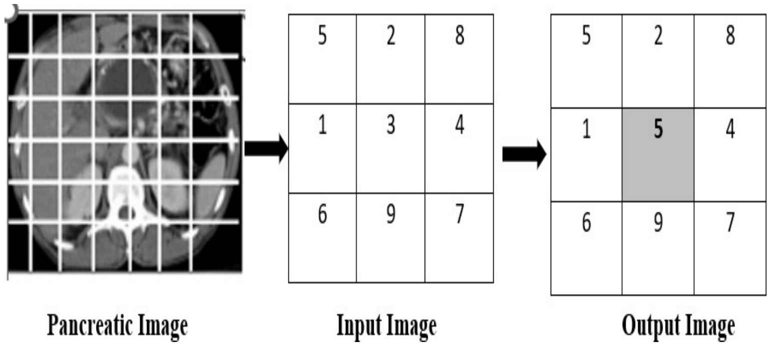

Figure 2. Median Filters

4.1.3 Hybrid Filters

The main objective in image processing is the reconstruction and image improvement under extreme conditions. To remove either Gaussian or imprudent noise from the image, hybrid filters are applied. These combine the Laplacian and median filters. It has been suggested to use blend or hybrid filters to remove blended noise from imagery that has been processed. The hybrid filter combines the properties of the Laplacian and median filters. The median filter receives the noise picture as input first, and the laplacian filter receives the output as input thereafter. A common method for edge identification in images is to employ the Laplacian function, which highlights areas of drastic changes in intensity. The proposed algorithm is shown in the Figure 3.

Step I: Take noisy image

Step II: Apply Median filter

Applying median filter as under

Step 1. Select two dimensional window W of size 3*3

Assume that the pixel being processed is $C_{x,y}$

Step 2. Compute Wmed the median of the pixel values in window W

Step 3. Replace $C_{x,y}$ by Wmed

Step 4. Repeat steps 1 to 3 until all the pixels in the entire image are processed

Step III: Applying laplacian filter

Select two dimensional window W of size 3*3

Step IV: Apply discrete wavelet transform

Step 1: Decompose the images

Step 2: Set the frequency components

Step V: Here fusion takes place

In this, after combining the result of the two filters, a fusion image will be resulted

Step VI: After this, both filters output finally after removing the all type of noise

Step VII: Apply inverse discrete wavelet transform

Step 1: Reconstruct the enhanced image

Step VIII: Output the final image

Figure 3. Proposed Algorithm

4.1.4 Laplacian Filter

The Laplacian filter is used to calculate the image's second-order derivative to find edges in an image. Compared to other types of edge detection filters, the laplacian filter is more effective at extracting the image's characteristics. When the first-order derivative is performing the job, the second-order derivative must be calculated. It combines the horizontal and vertical edges found in first-order derivatives. However, we can simultaneously identify every edge in an image using the second-order derivative. We are interested in determining the vertical and horizontal second-order derivatives of the image in the Laplacian filter. Laplacian operator edge detection is an additional widely used method for identifying edges in pictures. The Laplacian edge detection method is based on the image's second derivative, as opposed to the Sobel filter-based method, which employs gradient information to detect edges which is given in the Equation 1.

A 3x3 or 5x5 matrix is the Laplacian operator, and it is applied to every pixel in an image. The Laplacian of the image at that pixel point is determined by the operator. Compared to the gradient, the Laplacian of an image gives a more comprehensive account of the edges in the image. It measures how much the intensity of the image changes at that location. By convolving the operator with each pixel in the image, the Laplacian operator is applied to the image. Convolution produces a new image that emphasizes the edges of the source image. The magnitude of the Laplacian at each pixel location is represented by this new image, which has been known the Laplacian image. The proposed flow chart is shown in Figure 4.

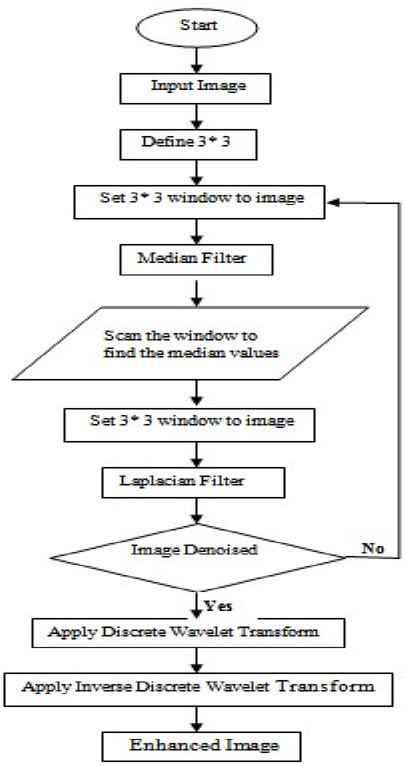

Figure 4. Flow chart for Proposed Method

In overall, Laplacian edge detection has the potential to be more sensitive to image noise, but it can also be more successful at identifying tiny features and edges at different orientations.The Figure 5 shows the laplacian filter

0	-1	0
-1	4	-1
0	-1	-1

-1	-1	-1
-1	8	-1
-1	-1	-1

Figure 5. Laplacian Filter

$$\nabla F(X,Y) = \frac{\partial^2 F}{\partial X^2} + \frac{\partial^2 F}{\partial Y^2} \tag{1}$$

- X is the columns index of the pixel.
- Y is the row index of the pixel.
- $F(X,Y)$ represents the intensity of the image at pixel X and Y.
- ∇represents the gradient.

4.1.5 Resolution Enhancement

In medical image processing, image resolution is always a cause for concern. The resolution of an image is a measure of how much detail it contains. More image details are provided by high resolution. Denoising is first used for preprocessing the image. Following denoising, there is a reduction in noise and a loss in quality along the edges of the image. In order to maintain the borders and contour details of a filtered image, resolution enhancement is employed. It's essential to maintain the edges and contour information in order to precisely segment an image. Wavelet transforms have been used in many areas of image processing, notably feature identification and recognition, image denoising, and compression of images and videos. The 1-D discrete wavelet transform (DWT) is applied along the image's rows first, and the results are subsequently dissected along the image's columns to produce the 2-D wavelet decomposition 22, 23,24 .The wavelet decomposition is shown in the Figure 6.

An improved discrete wavelet transform is proposed to improve image resolution. The contour information and edges are preserved by the enhanced DWT. The Peak Signal to Noise Ratio is used to assess the effectiveness of the resolution enhancement technique. To separate an input image into distinct sub-band images, one level DWT is utilized. The input image's high frequency components are contained in three high frequency sub-bands: HH, HL, and LH. The terms low-low (LL), low-high (LH), high-low (HL), and high-high (HH) relate to the sub-band images are shown in the Figure 7.To encompass the entire frequency range of the original image, the frequency components of those four sub-bands are interpolated. An image's pixel count can be increased by applying the interpolation technique. To produce an enhanced high resolution image, the image's high frequency sub-band is interpolated to its low frequency sub-bands.

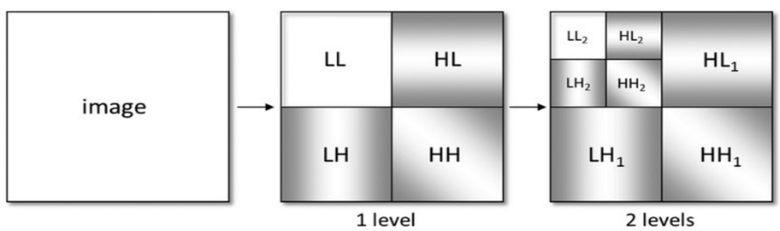

Figure 6. Wavelet Decomposition

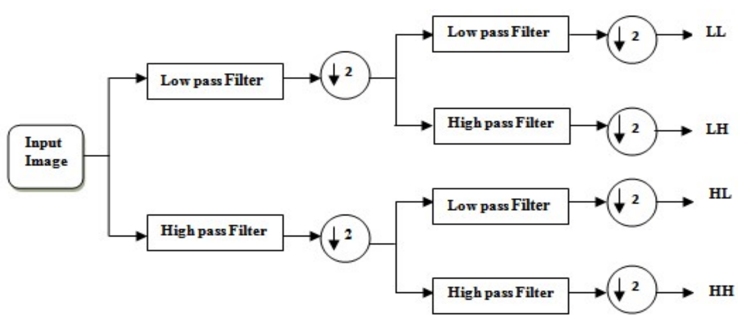

Figure 7. Block diagram of Discrete Wavelet Transform

The proposed resolution enhancement method used the low resolution image (LL sub-band) as its input without quantization. Consequently, the input image is employed during the decomposition process rather than low-frequency sub-band images, which contain less information than the original input image 25, 26. In order to improve the discrete wavelet, transform, the input low-resolution image is decomposed using half of the decimation factor.

4.1.6 Inverse Discrete Wavelet Transform

Reconstruction is the process of assembling separate parts back together to create the original image without sacrificing any information. An image can be rebuilt using the approximation and detail coefficients obtained via decomposition in the Inverse Discrete Wavelet Transform (IDWT). IDWT, it is possible to efficiently minimize or eliminate noise while keeping crucial aspects of the image.For applications like edge detection and segmentation, IDWT assists in rebuilding the image with improved edge information, resulting in sharper and more defined edges. By recreating the image with better quality from the compressed wavelet coefficients, IDWT can aid in the reduction of these artifacts.

5. Performance Evaluation

The method employed for automatic computer-aided diagnostics uses distinct image processing methods. The image quality after preprocessed is analyzed by using various parameters like Signal to Noise Ratio (SNR), Peak Signal to Noise Ratio(PSNR),Mean Square Error(MSE), and Structural Similarity Index Measures(SSIM). The peak signal to noise ratio is used for measurement of the quality between original and denoised images. Mean square error is calculated first and then the PSNR is computed. The cumulative square error between the original and denoised images are calculated by mean square error.

5.1 Signal to Noise Ratio (SNR)

The proportion of the average signal to the power of the predicted component for the input and segmented images is represented by the signal to noise ratio (SNR). Here is the Equation 2 computes the SNR values.

$$SNR = 10 \log 10 \left(\frac{\sum_{i=1}^{M} \sum_{j=1}^{N} (g_{i,j}^2 + f_{i,j}^2)}{\sum_{i=1}^{M} \sum_{j=1}^{N} (g_{i,j}^2 - f_{i,j}^2)} \right) \tag{2}$$

Where

The original image is $g_{i,j}$

The segmented image is $f_{i,j}$ when $i, j = 1, 2.,$

M, N is the range of index and cross range index respectively

5.2 Peak Signal to Noise Ratio

The proportion of the mean signal to the power of the predicted component for the input and segmented images is represented by the signal to noise ratio (SNR). Here is the Equation 3 computes the PSNR values.

$$\mathrm{PSNR} = 10\log_{10}\left(\mathrm{peakval}^2\right)/\mathrm{MSE} \tag{3}$$

Where the peak value is indicated as MAX

5.3 Mean Square Error

The main purpose of the evaluation is to determine how the denoised image and the input image differ in quality. Equation 4 separates the Euclidean distance square to the input and output image.

$$\mathrm{MSE} = \frac{1}{MN} \sum_{n=0}^{M} \sum_{m=1}^{N} \left[\hat{g}(n,m) - g(n,m)\right]^2 \tag{4}$$

5.4 Structural Similarity Index Measure

The luminance, texture and contrast are used to measure the image structural changes are given in the **Equation 5**

$$\mathrm{SSIM}(\mathbf{x},\mathbf{y}) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \tag{5}$$

6. Experimental Results

The noisy images are taken as input and the images are passed through mean, median and laplacian filters to denoise the image. Then the denoised images are passed on through hybrid filter to obtain better results. Table 1 shows the SNR values and the Figure 8 shows the performance of Signal to Noise. Performance of Peak Signal to Noise is shown in the Figure 9 and the table Figure 6.3 and 6.4 Performance of Mean Square Error and Performance of Structural Similarity Index Measure

Table 1.SNR Values

Input Image	Mean Filter	Median Filter	Laplacian Filter	Proposed Filter (Median/ Laplacian)
Image 1	9.67	13.44	17.27	17.12
Image 2	10.83	10.67	18.91	16.89
Image 3	11.12	11.18	12.76	10.10
Image 4	13.95	14.39	19.04	15.78
Image 5	8.13	10.56	17.51	10.00
Image 6	10.11	9.19	8.25	15.14
Image 7	12.75	12.13	14.58	17.68
Image 8	13.71	15.39	16.00	19.25
Image 9	11.05	12.69	13.76	12.48
Image 10	8.70	9.89	10.11	18.18

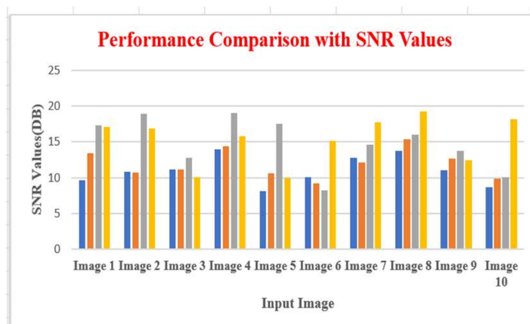

Figure 8 Performance of Signal to Noise

Table 2.PSNR Values

Input Image	Mean Filter	Median Filter	Laplacian Filter	Proposed Filter (Median/ Laplacian)
Image 1	25.32	22.87	24.61	29.32
Image 2	27.51	25.10	25,97	27.13
Image 3	28.0	31.47	30.16	32.48
Image 4	31.07	37.56	33.00	36.58
Image 5	36.42	43.00	44.18	49.12
Image 6	38.71	44.00	40.15	39.28
Image 7	45.72	49.92	47.19	50.19
Image 8	48.65	38.76	44.52	48.64
Image 9	47.28	46.42	48.15	58.36
Image 10	48.98	48.78	51.16	54.78

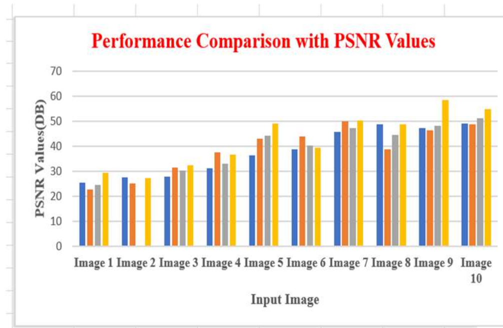

Figure 9 Performance of Peak Signal to Noise

Table 3.MSE Values

Input Image	Mean Filter	Median Filter	Laplacian Filter	Proposed Filter (Median/ Laplacian)
Image 1	6.79	5.61	7.10	7.89
Image 2	5.48	7.41	6.90	6.12
Image 3	8.97	8.97	8.12	8.45
Image 4	4.66	8.52	7.16	8.34
Image 5	9.04	5.83	6.47	4.10
Image 6	5.19	5.17	5.90	3.15
Image 7	5.44	4.11	5.78	6.14
Image 8	6.80	6.09	7.14	7.98
Image 9	6.67	5.55	5.21	5.26
Image 10	5.66	3.89	4.09	4.78

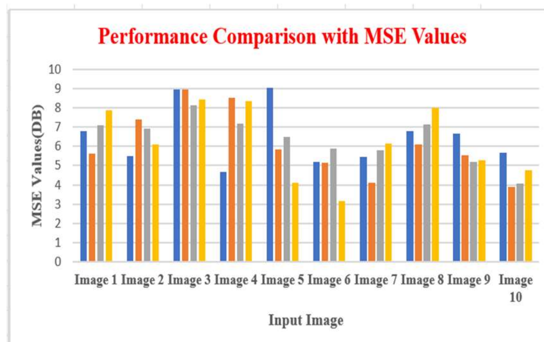

Figure 10 Performance of MSE Values

Table 4 .SSIM Values

Input Image	Mean Filter	Median Filter	Laplacian Filter	Proposed Filter (Median/ Laplacian)
Image 1	0.91	0.93	0.92	0.94
Image 2	0.89	0.91	0.83	0.89
Image 3	0.93	0.95	0.92	0.99
Image 4	0.94	0.95	0.94	0.91
Image 5	0.93	0.94	0.93	0.97
Image 6	0.98	0.98	0.99	0.99
Image 7	0.97	0.92	0.98	0.96
Image 8	0.97	0.93	0.90	0.97
Image 9	0.92	0.94	0.96	0.96
Image 10	0.94	0.94	0.91	0.94

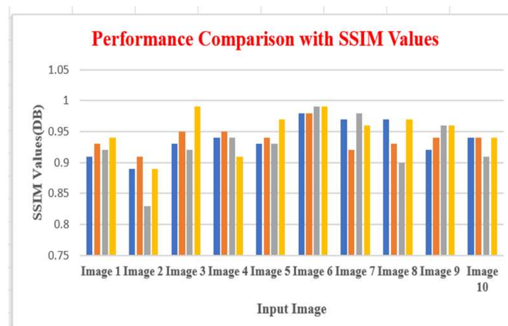

Figure 6.4 Performance of Structural Similarity Index Measure

7. Conclusion

The technique used in the research for removing noise from medical images is to employ laplacian filters alongside with the mean and median. The proposed method employed parameters like SNR, PSNR, MSE, and SSIM and integrated the median and laplacian filters. The outcomes are compared. The images are reconstructed using the inverse discrete wavelet transform after the resolution of the original images is enhanced using the discrete wavelet transform. Based on these findings, the recommended approach improves image accuracy for diagnosis and provides better results.

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