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Effectiveness of filtering methods in enhancing pulmonary carcinoma image quality: a comparative analysis

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ABSTRACT

In recent years, information technology has vastly improved. The quality of the image has been degraded by noise, which defeats the purpose of the noisy images. The major purpose of this paper is to find out which filters provide a better outcome while preprocessing medical images using computer tomography scans. The purpose of this paper is to remove noise from any images, whether they are real-time datasets or online datasets. To enhance an image for preprocessing, we have compared various filters; these filters are already available, but the major purpose is to identify the best filter. We compared the different parameters to find the best and finally found that the modified bilateral filtering provided a better result. The noise has been removed by using a bilateral filter, and the image clarity has not changed when using this filter. We have discussed the advantages and drawbacks of each approach. The effectiveness of these filters is compared using the peak signal-to-noise ratio, structural similarity index, contrast-to-noise ratio, and mean square error. The proposed algorithm is tested on 5 sample lung images. The results show that the modified bilateral filter produces better results.

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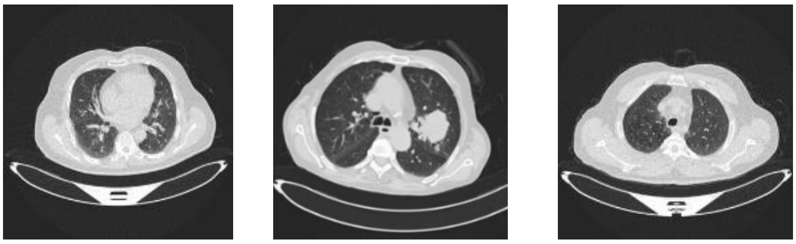
1. INTRODUCTION

Image processing techniques are now commonly used in medicinal fields to improve the earlier finding of pulmonary carcinoma and treatment in the initial phase, where time is critical to determine the disease in the patient, especially tumors. Pulmonary carcinoma, similar tumors, affect a greater number of people. There are few procedures for detecting cancerous cells [1]. Computed tomography (CT) images are used to make the majority of diagnoses. The raw images have to be cleaned and analyze before processing. Noise in the images must be removed, and unclear objects must be improved. Pre-processing, a well-known image processing method, was to increase the quality of images. The raw CT scanned images contain irrelevant items, reducing overall accuracy. The majority of diagnoses are based on CT scan images. Pre-processing is a technique used to improve interpretability and accuracy. Image pre-processing is an essential and challenging aspect. In medical image processing, the tumor segmentation task is essential to pre-process images so that feature extraction algorithm and segmentation work correctly [2]. Mean squared error (MSE) and contrast-to-noise ratio (CNR) are the most often used metrics for evaluating the quality of an image. These metrics can be derived to provide measures like peak signal-to-noise ratio (PSNR) [3]. In order to measure the quality of an image, Wang *et al*. [4] offer a new strategy and attempt to replace existing approaches like PSNR and MSE with structural similarity index (SSIM) index. The lung image database consortium (LIDC) and image database resource initiative (IDRI) are two image databases that are freely available to medical image processing researchers [5]. The tumor stages are represented in Table 1. Figure 1 represents the sample images of Figure 1(a) benign, Figure 1(b) malignant, and Figure 1(c) normal. The initial stage in detection is preprocessing. The preprocessing of an image is done with help of the following filters are median, Gaussian, and modified bilateral.

Table 1. Represents the stages of tumor

Stages of Tumor	Tumor Size
T1	<30 mm
T2	30 to 70 mm
T3	>70 mm



(a) (b) (c)

Figure 1. Sample images of (a) benign, (b) malignant, and (c) normal

In this section we use few commonly use preprocessing techniques and their merits over the others. Lee *et al.* [6] focused on evaluating the effectiveness of the fast non-local means denoising algorithm in removing noise from medical mammography images for early breast cancer detection using phantom images. The study found that the algorithm was effective at removing noise while preserving image detail, and it could potentially improve the accuracy of tumor detection algorithms and lead to earlier breast cancer detection. However, the algorithm may not be effective at removing all types of noise, particularly non-Gaussian noise, and it may not be able to remove noise that is too severe or closely intertwined with the underlying image structure. The algorithm may also require optimization for different types of medical mammography images or specific clinical scenarios. The rapid nonlocal mean (NLM) method has a lot of promise for increasing early breast cancer diagnosis, but how well it works may rely on the noise's unique properties and the clinical environment in which it is applied. Overall, the fast NLM denoising algorithm has certain benefits for enhancing the early identification of breast cancer in medical mammography images, but it may also have some drawbacks depending on the specifics of the noise and the clinical environment in which it is utilized.

Zhu *et al.* [7] in this research paper, an improved median filtering technique for image noise reduction is proposed, which makes use of an adjustable threshold to choose the filtering window's size. The algorithm is compared with other state-of-the-art filtering algorithms such as the conventional median filter, the Gaussian filter, and the bilateral filter. Experimental results show that the proposed algorithm outperforms these algorithms in terms of preserving image details and reducing noise and the performance analysis of average and median filters for denoising digital images involves evaluating their noise reduction capability, preservation of image details, robustness to different types of noise, computational efficiency, edge preservation, artifact generation, robustness to image content, and comparison with state-of-the-art filters. By conducting thorough experiments and considering these aspects, the effectiveness of these filters can be assessed in reducing noise while preserving important image information [8].

The strategy for identifying lung cancer in CT scans is suggested in the research, which combines pre-processing methods and segmentation algorithms. The suggested methodology involves merging two CT images, pre-processing with image enhancement, normalization, and denoising, lung region segmentation using a threshold-based strategy, and lung nodule segmentation using a 3D region-growing algorithm. The method diagnosed lung nodules on a dataset of 50 CT scans with a high level of 96% accuracy [9].

The performance of the Gaussian filter and wavelet denoising for various types of noise in images is compared in the article. According to the study, wavelet denoising surpasses the Gaussian filter in terms of lowering all noise classes and achieving greater PSNR, SSIM, and lower root mean square error (RMSE) values. The disadvantages of the wavelet denoising technique are also mentioned, including the potential loss of image features and the longer processing time. The authors claim that combining different methods may lead to better results, and that the choice of the denoising technique should be based on the particular characteristics of the image and the kind of noise [10].

Shukla *et al.* [11] discussion of applying a low-pass Gaussian filter on a noisy or deteriorated image will minimize noise and restore its appearance when employing a Gaussian filter for image restoration. The procedure involves loading the image, grayscale conversion (if required), application of the Gaussian filter with a selected sigma value to regulate blurring, and comparative display of the original and restored images. It is crucial to remember that this technique's success depends on the image and noise characteristics, and techniques that are more sophisticated can be needed for challenging restoration tasks and the Gabor filter-based face recognition technology detects faces by extracting Gabor features from them using a support vector machine or other classifiers. Although the method is excellent at overcoming face recognition issues, it has drawbacks such sensitivity to noise and the requirement for huge datasets to train the classifier [12].

In this research paper, fast adaptive bilateral filtering (FAB) is an image filtering technique that combines bilateral filtering and adaptive filtering to efficiently denoise or enhance images while preserving edges and details. FAB lowers computing costs by taking into account several pixels in a patch at once. Patch extraction, patch similarity computation, weight computation, filtering, and overlapping patch rebuilding are all involved. The employment of FAB, which provides a balance between noise reduction and edge preservation, has been used in a number of image processing applications. It is appropriate for situations and real-time applications where computational effectiveness is essential [13].

In this paper, Lung cancer classification and prediction using machine learning and image processing involves analyzing lung images to accurately diagnose and predict lung cancer. Extracting relevant features from the images and utilizing machine-learning algorithms for classification achieve this. Techniques such as feature extraction, region of interest (ROI) detection, data augmentation, ensemble learning, and transfer learning are commonly employed. The performance of the models is evaluated using various metrics. Ongoing research aims to address challenges and improve the clinical applicability of these methods for early detection and diagnosis of lung cancer [14].

Song *et al.* [15] in this research paper the improved adaptive weighted median filter algorithm is a method used to remove noise from images while preserving edges and details. It involves creating a window around each pixel, calculating the median value of the pixel intensities within the window, and assigning weights to neighboring pixels based on their differences from the median. The weighted median value is then computed, and the current pixel is replaced with this value. The algorithm iterates through all pixels in the image and outputs the filtered image. By incorporating weights based on pixel differences, the algorithm enhances noise reduction and maintains important image features.

Mudeng *et al.* [16] research paper focus on the structural similarity index (SSIM) is a metric used in medical image analysis to assess the similarity between images based on their structural information. SSIM has prospects in this field because it is sensitive to structural changes, aligns with human perception, incorporates multi-scale analysis, and is robust to image degradations. However, it has limitations as it primarily focuses on pixel-level similarity and lacks standardization. Medical image analysis presents domain-specific challenges, and alternative metrics designed for this purpose may provide more accurate assessments. Therefore, while SSIM is useful, its application should consider its limitations and alternatives available. The metrics of mean square error (MSE) and peak signal to noise ratio (PSNR) are used to evaluate this approach. By dividing the histogram into two subparts using fuzzy logic and the initial image's average value, the brightness of the image is preserved. With the use of a shared data set, Archana and Sahayadhas [17] describe a comparison study based on image quality by taking into account the four different filtering techniques: Gaussian filter, median filter, mean filter, and Weiner filter. These filters are used to analyze the parameters like SSIM and PSNR. This paper is ordered as follows. Section 2 explanation about method, section 3 show the experimental used to find the better results in pre-processing, at last, section 4 we conclude the paper.

2. METHOD

The Proposed method is based on the lung CT images dataset to accurately classify pulmonary carcinoma. The first steps involved in pulmonary carcinoma detection are pre-processing. Image metrics are objective measures used to evaluate the quality of an image or a video. They provide a numerical score or value that reflects how well an image or a human observer perceives video.

2.1. Dataset

The medical images from the Kaggle dataset which contains scans of 1,098 unique individuals, selected as the source for input CT images. Then are grouped into 3 clusters benign cases, malignant cases, and normal cases. The CT-scanned images consist of 120 benign cases, 562 malignant cases, and 416 normal cases.

2.2. Various pre-processing techniques

The first step is to pre-process the grayscale image to remove the noise. Various filter techniques are median filter, Gaussian filter, Laplacian, and modified bilateral filter. The corresponding states of intensity level which individual pixels can acclimate are called entropy [18]. The proposed model is validated using the metrics like mutual information [19]. To find which filters produce better results in PSNR, MSE, SSIM, and CNR. Figure 2. represents the architecture. Table 2 representation of image metrics.

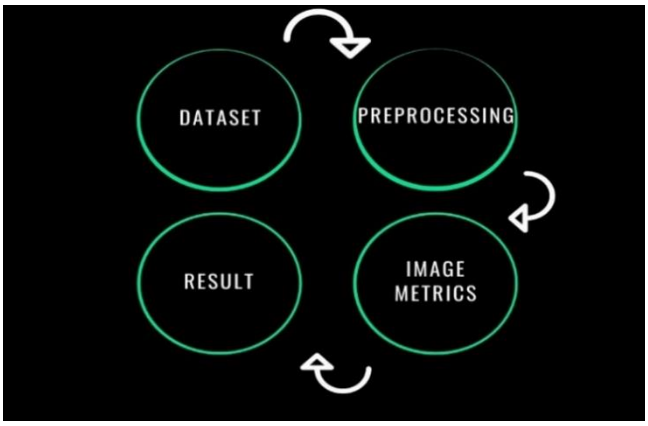


Figure 2. Architecture

Table 2. Image metrics [20], [21]

Metric	Description	Formula
PSNR	Peak signal-to-noise ratio: the ratio between the maximum possible pixel value and the mean squared error between the original and processed image, expressed in decibels (dB)	$PSNR = 20 * \log 10\ (MAXp) - 10 * \log 10\ (MSE)$
SSIM	Structural similarity index: a perceptual metric that evaluates the structural similarity between two images, taking into account luminance, contrast, and structural information, and outputting a value between 0 and 1	$SSIM\ (x,y) = [l(x,y)]\ \hat{}\ \alpha * [c\ (x,y)]\ \hat{}\ \beta * [s(x,y)]\ \hat{}\ \gamma$
MSE	Mean squared error: the average squared difference between the original and processed images	$MSE = \left(1/_N\right) * \Sigma\ [\Sigma[(I(x,y) - K(x,y))\hat{}2]]$
SNR	Signal-to-noise ratio: a measure of the signal-to-noise ratio of an image, which compares the power of the signal to the power of the noise in the image	$SNR = 10 * \log 10 \left(^{Psignal}/_{Pnoise}\right)$

2.2.1. Median filter

It is effortless to implement a nonlinear method for noise removal. The number of neighbors represents the replacement of noisy target pixels [22]. The grayscale value of each noisy pixel is ranked using the mask based on the grayscale levels, and the values are grouped to replace the noisy values [7]. The neighbor window in the grayscale value of every point represents the center of each grayscale value of pixels [23]. The median filter keeps the image's edge clarity while reducing noise. In median filtering, noise can be effectively decreased by increasing the window size [24].

$$g\ (x,y) = med\{f(x-i, y-j)\ ,i\ ,j \in W\} \tag{1}$$

Where $f\ (x,y)$, $g(x,y)$ represents output and original images, W represents 2D mask, $n \times n$ is the kernel size i.e., 3×3, 5×5. The most common kernel size is 3×3. The median filter kernel size is 3×3. The size of kernel size may vary based on the dataset. If it is a real-time dataset or color image, the kernel size may be larger, but most of the kernel size is 3×3.

2.2.2. Gaussian filter

Gaussian filter to be the best time domain filters [25]. Gaussian filter chooses according to the weight and the shape of the function used for smoothing the linear filter. Gaussian filter is more effective in a low-pass filter to remove the noise for normal distribution. For 1-D Gaussian filter of zero represents the following expression [26]. The purpose of the Gaussian filter is to minimize distortion in the lowest and highest signals [27]. This 2-D convolutional Gaussian smoothing technique is typically used to obfuscate images and remove the subtle element and clamors. Gaussian filters typically limit the ascent and fall times while not overshooting a stage job input [28].

$$g\ (x) = e^{\frac{x^2}{2\sigma^2}} \tag{2}$$

2.2.3. Modified bilateral filter

The modified bilateral filter calculates the pixel value by two weight functions: range kernel g_r and spatial kernel g_s. The modified bilateral filter represents a Gaussian [29]. The modified bilateral-filter, on the other hand, preserves edges by taking into account intensity variations [27].

$$g_r\left(f_p\ , f_q\right) = e^{\frac{-\left(fg-fp\right)^2}{2\sigma_r^2}}\quad g_s\ (p,q)= e^{\frac{-\|(q-p)\|_2^2}{2\sigma_s^2}} \tag{3}$$

Where σ_r and σ_s are the root mean square deviation. Euclidean distance between their arguments in Gaussian filter especially in c radially symmetric [30].

$$c(\xi,x)= e^{-\frac{1}{2}\left(\frac{d(\xi,x)}{\sigma_d}\right)^2} \tag{4}$$

Effective edge information preservation in image smoothing filters is crucial since it significantly affects the final image's quality. In order to efficiently smooth images while keeping edge information, bilateral filters use functions made of spatial and color information [31]. The output picture after being processed by a bilateral filter is denoted as u_s, as illustrated in (1), where s is the central point and t is the image of any point in s's neighborhood $N(s)$.

$$\begin{aligned} u_s &= \frac{1}{Z_s}\sum_{t\in N(s)} G_{\sigma_s}(s-t)G_{\sigma_r}(g_s-g_t)g_t \\ Z_s &= \sum_{t\in N(s)} G_{\sigma_s}(s-t)G_{\sigma_r}(g_s-g_t) \end{aligned} \tag{5}$$

where G_{σ_s} and G_{σ_r} are spatial and Gaussian kernel functions. The spatial proximity factor and grayscale similarity factor are represented by the symbol σ_s. $G_{\sigma_s}(s-t)$ denotes the difference in the grey value, while $G_{\sigma_r}(g_s\text{-}g_t)$ denotes the spatial separation between point t in neighborhood $N(s)$ and other points.

2.2.4. Laplacian filter

A Laplacian filter could be used to highlight the edges of an image. This filter is used to obtain provisions for edge detection. The filter is calculated using a kernel weight with every pixel value and its neighbors in an image. The Laplacian $L\ (x, y)$ of a pixel density image is given [32].

$$L(x,y)= \frac{\partial^2 I}{\partial x^2} + \frac{\partial^2 I}{\partial y^2} \tag{6}$$

3. RESULTS AND DISCUSSION

The CT images will be in digital imaging and communications in medicine (DICOM) format and converted into joint photographic experts' group (JPEG) format for further use of image processing techniques. The resolution of the images is 8 bits per pixel in JPEG format—all the JPEG images stored as 512x512 raw data. The research has done with the help of CT images from around 1098 images of benign, malignant, and normal cases of lung cancer found in different online databases; research has been done with a few filters to remove the noise and other aspects of the original images.

A different experimental simulation of image processing techniques has used other filtering techniques like the median, Gaussian, and modified bilateral filters. After image pre-processing, the filtered images' accuracy identified using the PSNR, SSIM, MSE, and CNR values. Figure 3 represents the comparison of original, modified bilateral, Gaussian, median and Laplacian filter. Table 3 represents the quality evaluation of modified bilateral filter. Table 4 denotes the effectiveness of image processing techniques of modified bilateral filter. Table 5 represents the quality evaluation of Gaussian filter. Table 6 denotes the effectiveness of image processing techniques of Gaussian filter. Table 7 represents the quality evaluation of median filter. Table 8 denotes the effectiveness of image processing techniques of median filter. Table 9 represents the quality evaluation of Laplacian filter. Table 10 denotes the effectiveness of image processing techniques of Laplacian filter.

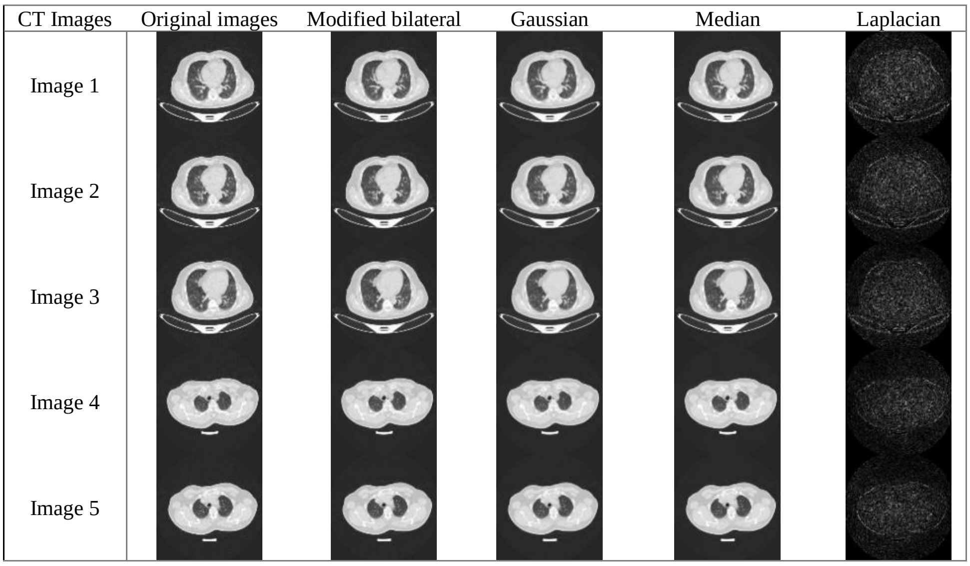


Figure 3. Comparison of original, modified bilateral, Gaussian, median and Laplacian filter

Table 3. Quality evaluation of modified bilateral filter

Name	PSNR (dB)	SSIM	MSE (Squared Units)	CNR (dB)
Image 1	76.58748681	0.001426697	0.999982614	12.20548688
Image 2	76.48421509	0.001461029	0.999981892	12.12366504
Image 3	76.51836686	0.001449585	0.999982042	12.18296196
Image 4	75.6416733	0.001773834	0.99997824	19.40991854
Image 5	76.48421509	0.001461029	0.999982022	19.09628052

Table 4. Effectiveness of image processing techniques of modified bilateral filter

Name	Entropy (bytes)	Mutual information (nat)
Image 1	6.024509	0.6722857653
Image 2	6.036341	1.162082103
Image 3	6.009681	1.301693502
Image 4	5.438811	4.175871403
Image 5	5.468659	0.6979809262

Table 5. Quality evaluation of Gaussian filter

Name	PSNR (dB)	SSIM	MSE (Squared units)	CNR (dB)
Image 1	36.10239058	0.928655575	15.95296097	12.20548688
Image 2	36.28895245	0.935798905	15.28217316	12.12366504
Image 3	36.59400263	0.940992483	14.24557877	12.18296196
Image 4	38.50205002	0.950619863	9.180690765	19.40991854
Image 5	38.42120895	0.949254268	9.353183746	19.09628052

Table 6. Effectiveness of image processing techniques of Gaussian filter

Name	Entropy (bytes)	Mutual information (nat)
Image 1	6.024508964	4.175871403
Image 2	6.0363408	1.301693502
Image 3	6.009681083	1.162082103
Image 4	5.438810762	0.672285765
Image 5	5.468658729	0.697980926

Table 7. Quality evaluation of median filter

Name	PSNR (dB)	SSIM	MSE (Squared units)	CNR (dB)
Image 1	36.42406032	0.904066389	14.81406784	12.20548688
Image 2	36.73201779	0.915122193	13.79998398	12.12366504
Image 3	37.11814464	0.922547931	12.62600327	12.18296196
Image 4	38.4008323	0.934724733	9.397171021	19.40991854
Image 5	38.35359371	0.933081737	9.49994278	19.09628052

Table 8. Effectiveness of image processing techniques of median filter

Name	Entropy (bytes)	Mutual information (nat)
Image 1	6.024508964	4.175871403
Image 2	6.0363408	1.301693502
Image 3	6.009681083	1.162082103
Image 4	5.438810762	0.672285765
Image 5	5.468658729	0.697980926

Table 9. Quality evaluation of Laplacian filter

Name	PSNR (dB)	SSIM	MSE (Squared units)	CNR (dB)
Image 1	7.252295	0.123844	12241.96	0.14262
Image 2	7.594752	0.123379	11313.71	0.142487
Image 3	7.908599	0.123349	10524.96	0.140184
Image 4	9.398115	0.121277	7469.11	0.138949
Image 5	9.42371	0.120597	7425.221	0.140369

Table 10. Effectiveness of image processing techniques of Laplacian filter

Name	Entropy (bytes)	Mutual information (nat)
Image 1	4.610102	0.997237
Image 2	4.571216	0.991617
Image 3	4.520532	0.991127
Image 4	4.35519	0.988186
Image 5	4.360889	0.98885

4. CONCLUSION

This paper uses filters for preprocessing such as median, Gaussian, Laplacian, and modified bilateral filters for 1,098 CT scan images. This preprocessing aims to reduce the noise and other aspects of medical images to enhance better quality. The performance regarding PSNR, SSIM, MSE, and CNR values is evaluated. Finally, the modified bilateral filter produces PSNR-76.58748681, SSIM-0.001426697, MSE-0.999982614, and CNR-12.12366504, in all preprocessing aspects when compared with other filters. Our study demonstrates that bilateral filtering is an effective image filtering technique for enhancing the quality of pulmonary carcinoma images. Its ability to reduce noise while preserving important details makes it a valuable tool in improving the accuracy of cancer detection and diagnosis. Further research can focus on optimizing the parameters of bilateral filtering and exploring its integration with other image processing techniques for even better results. The purpose of this paper is to identify the researcher to find out which filter produces better result when they use medical imaging.

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