International Journal of Applied Engineering & Technology

NEIGHBORHOOD CONVOLUTION AVERAGE FILTER (NCAF): A PIONEERING APPROACH TO DE-NOISE PANCREATIC CT IMAGES

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ABSTRACT

Pancreatic Cancer (PC) stands as a leading cause of mortality globally, characterized by a bleak prognosis in the current context. While several methods and techniques exist for tumor detection in organs like the brain, breast, and lungs, limited attention has been given to pancreatic tumor detection. Computer-aided screening (CAD), diagnosis, and quantitative evaluations in radiology images such as CT and MRI commonly facilitate pancreatic tumor image classification. Leveraging these methods can aid in tracking, predicting, and recommending personalized therapy as part of non-invasive cancer management. Notably, algorithms need to discern and classify pancreatic tumor types at early stages to maximize life-saving potential. Given the diverse shapes, vast sample sizes, and the need for processing and analyzing extensive databases, novel statistical methods must be adopted. Conversely, tumor detection within medical images also poses challenges due to variations in the quality of input images. Generally Gaussian noise and other types of noise will affect the classification accuracy. To classify the stage of pancreas accurately, it required quality image. Therefore it should be processed by preprocessing process to remove and improve the quality of the CT pancreatic images. This research introduced new ***Neighborhood Convolution Average Filter (NCAF)*** *to denoising the CT pancreatic images. The proposed algorithm gave higher PSNR value and lower MSE value than existing filters.*

Keywords: Pancreatic Cancer (PC),Image processing, CT pancreatic images, Neighborhood Convolution Average Filter

I INTRODUCTION

particularly highlighted in a recent report by the Pancreatic Cancer Action Network predicting that it will become the second leading cause of cancer death in the United States by 2020[1]. In India, where the annual incidence was around 170,000 in 2008 and is expected to rise, there is a pressing need for multicentric studies. These studies would enhance a systematic approach to document the processes at all levels and identify potentially avoidable risk factors associated with pancreatic cancer[2,3].

The primary cause of this disease is the delayed detection of pancreatic tumors, largely attributed to the lack of effective early detection methods. Symptoms of pancreatic tumors are often vague and can overlap with various abdominal disorders, including back or abdominal pain, weight loss, jaundice (yellowing of eyes and skin), loss of appetite, nausea, diabetes, and changes in stools[4]. Patients typically seek professional advice after experiencing these symptoms for a considerable period. Unfortunately, many are diagnosed at a critical stage, where surgery is often not possible due to the involvement of numerous unresectable blood vessels[5].

Once pancreatic cancer has metastasized to other organs, treatment becomes significantly challenging[6]. Hence, there is an urgent need for early diagnosis of pancreatic tumors, which can be facilitated by radiologists. Early detection is crucial to increase the chances of successful treatment and intervention before the disease reaches an advanced and difficult-to-treat stage[7].

While the majority of pancreatic growths are benign and do not lead to cancer, some possess the potential to transform into cancer if left untreated, categorized as precancerous[8]. Various imaging scanning techniques, including Magnetic Resonance Imaging (MRI), Computed Tomography (CT), ultrasound, Positron Emission Tomography (PET), and Positron Emission Tomography combined with Computed Tomography (PET/CT), have been employed for the specific diagnosis of pancreatic conditions [5]. Figure 1 illustrates an image of pancreatic cancer.

In the realm of medical imaging, biomedical imaging has significantly influenced several image processing techniques, with image processing and computer modeling being widely utilized. Presently, researchers in microbiology and biology heavily rely on human participation in their studies [13]. However, there is a concern about biased interpretations due to the inherent human propensity in physical processes, including the unpredictability among human experts, as well as the involvement of lengthy and costly procedures[13,14]. To achieve both objective and recursive analysis, accurate quantitative measurements, the study of large datasets, and the utilization of automated technology are often deemed essential [15,16, 17].

Figure 1. CT scan image of pancreatic cancer tissue.

II REVIEW OF EXISTING WORK

Suhas and Venugopal [9] employed median and mean filtering techniques to eliminate noise from medical images. This strategy was part of a broader concept, aiming to introduce an innovative approach that combines both linear and nonlinear filters. Mean and median filter values were specifically utilized to achieve more accurate readings for each pixel in the noisy image. The proposed methods and filters, based on mean, median, and midpoint, were compared using numerical metrics such as PSNR (Peak Signal-to-Noise Ratio), SNR (Signal-to-Noise Ratio), and RMSE (Root Mean Square Error). The comparison results were then contrasted with typical sound patterns.

The experimental technique has been validated to effectively preserve structural details in medical images while significantly reducing image noise. The application of this method is expected to result in a high degree of accuracy in MRI pictures, making it a promising approach in the field of medical image processing.

According to Anitha et al., the denoising of medical images required the utilization of median and Wiener filters [10]. The median filter, similar to a mean filter, is an image filter designed to reduce noise in an image. However, unlike the mean filter, the median filter accomplishes noise reduction without compromising the details present in the image. When applied to a specific pixel, the median filter alters the intensity level by making it the median value of surrounding intensity levels. This allows the replacement of poor-quality pixels with those considered good.

On the other hand, the Wiener filter reduces noise from an audio stream by first analyzing what a noise-free signal sounds like. This analysis is performed through statistical methods. The evaluation and comparison of pixel size and image clarity with conventional noise patterns lead to the conclusion that the median filter outperformed other filters in terms of both filtering and overall performance. Consequently, images filtered with the median filter exhibited higher pixel quality compared to those filtered with the Wiener filter.

Lakshmi and her colleagues [11] developed a pre-processing method using soft computing techniques for functional segmentation of MRI data. They found that denoising the image through curvelet transform is highly effective in noise removal. To ensure the accuracy and consistency of the method, quantitative testing will be essential, involving clinical scans and realistic phantoms for validation purposes.

Rong and Yong [12] introduced a novel technique that enhances the removal of salt and pepper noise from images. They utilized the Median Filter 2.0, which identifies visual noise by generating a noise-tagged matrix, considering the features of the detected noise. In this approach, pixels are skipped during processing if they are determined to be part of the signal. The median filter, widely recognized for its excellent capability in eliminating background noise and computational efficiency, is commonly employed.

The median filter works by replacing each pixel's grey value with the median value of its neighboring pixels. In cases where there is a significant amount of noise, the feature of the image may become blurred[25]. To address this, the authors developed an improved median filtering method using local histograms. This method preserves the image details while maintaining its finest quality. Histograms are employed to identify highly impulsive noise pixels in this approach[26]. A histogram serves as a visual representation, aiding in the detection of the number of occurrences of noise in pixels for each possible grayscale value. When the peak value significantly increases, the histogram provides conclusive evidence of the presence of impulse noise. The performance of the improved median filter was assessed through testing with varying noise densities, ranging from 10% to 50%, with an incremental increase of 10% at each step. These performance metrics indicate that the suggested techniques are highly effective in reducing background noise. Experimental results demonstrate not only its proficiency in preserving image details but also its suitability for regular image denoising in computer applications[27,28].

In this particular investigation, Gao and team [13] conducted a study on the segmentation of 4D CT scans of nodules taken at different time points. To minimize the size of the energy function, it was suggested to incorporate the criterion of considering the similarity of images in different phases into the graph cut approach. However, a drawback of this strategy is that it necessitates manual segmentation to initiate the process.

Ju et al. devised an alternative strategy based on graph cut [14]. This approach, drawn from data acquired from CT and PET imaging, exhibits enhanced accuracy through co-segmentation application. The strategy employs a random walk algorithm to generate output seed values for the graph cut method. Graph cut involves cutting graphs, and in this plan, two subgraphs are utilized – one for PET images and another for CT images. These subgraphs are interconnected through a specific connection penalizing the segmentation variance arising from the use of two different modalities. Simultaneously, the next step involves reducing the energy function to increase flow when the cuts are minimized.

III TYPES OF FILTERS

Image filtering is employed to alleviate image distortions, including noise, blur, and unwanted artifacts. This technique proves highly beneficial in transforming the appearance of an image without compromising its details. Its primary purpose is to enhance image quality, facilitating improved analysis results. Additionally, image filtering plays a role in sharpening the edges of an image to highlight clear details along the edges [18]. Various types of filters are discussed below.

- **Mean Filter**

The process of smoothing images is straightforward and uncomplicated. It involves reducing the intensity differences between pixels and their nearest neighbors. This is achieved by replacing the intensity value of each pixel with the value of its neighboring pixels. This approach is akin to using a convolution filter, where convolutions are performed using a kernel. The kernel, in this context, defines the size and shape of the sampled area during the calculation of the mean. This smoothing method aims to mitigate intensity variations, potentially removing misleading pixel values present in the background[19,20].

- **Median Filter**

The filter described here is a non-linear filter utilized to eliminate noise in an image while retaining edge information. Primarily designed for removing salt and pepper-type noises, this filter operates on a sliding window concept. It systematically moves the window pixel-by-pixel across the image, replacing each value with the median value of its neighboring pixels. The median value is determined using an arithmetic order, wherein all pixel values within the window are sorted, and the average pixel value is then substituted as the predicted median value[21,22].

- **Gaussian Filter**

The described filter is a low-pass filter designed to reduce frequencies from higher to lower values, effectively eliminating noise in an image. To achieve improved results, an odd-sized kernel is applied to each pixel in the region. The filter operates based on a 2D distribution using the spread point functionality. This is accomplished through a discrete approximation by convolving the 2D Gaussian distribution function. The filter follows three standard deviations, with the distribution becoming zero from its mean. The coefficients of the kernel decrease with increasing distance from the kernel center. To maintain the Gaussian size, the kernel size should increase proportionally as the standard deviation (σ) increases[23].

- **Conditional Trimmed Mean Filter(CTM)&Enhanced CTM(ECTM)**

To preserve the structural information of the two-dimensional signal, the Cross-shaped Threshold Median (CTM) filter is applied in four different directions. Each of these filters has two tuning parameters, denoted as p and q. The parameter p is utilized to segregate the samples in the window into two subsets based on the exact difference between their signal level and a reference point. Once parameter p is appropriately adjusted, the proposed filter can effectively remove Gaussian noise. On the other hand, parameter q serves as the threshold for selecting one of the two subsets within the window. By choosing an appropriate parameter q, the proposed filter can completely suppress impulsive noise[24].

IV DATA COLLECTION

We employed the Pancreatic Dataset, This dataset is download at https://www.kaggle.com/code/adityamahimkar/lung-cancer-prediction-on-image-data. The dataset comprises 1286 CT images categorized into normal, benign, and malignant cases. Each image was resized to dimensions of 512 pixels in width and 512 pixels in height for both model training and validation. A total of 1000 images were utilized for training, while 286 images were reserved for testing purposes. Among these images, 1096 exhibited Gaussian blur noise, and 198 contained salt and pepper noise. The primary focus of this study was to address the predominant noise type, namely Gaussian blur noise[29,30].

IV PROPOSED METHOD

The proposed filter **Neighborhood Convolution Average Filter (NCAF)** involve a combination of image processing techniques, including resizing, color conversion, wavelet transform, and thresholding, aimed at denoising the CT image and preserving the structural information in the pancreatic image.

The CT Image acquisition by of a Radiologist to obtain high-quality images with a size of 3456 x 2304 pixels and a resolution of 0.03 mm/pixel. It also considers the brain images are caught by the Radiologist in RGB mode with 10 megapixels with measurements 3120x4160. Then these images resized into 256 x 256 measurements. Then Resized RGB image is converted to HSV. To extract the brightness of the image.Then convolve this 7 X 7 matrix with a 3 X 3 horizontal wise and vertical wise

The proposed collaborative approach integrates the denoising capabilities of three distinct components Convolution Gaussian Operation (CGO), Haar transform, Hysteresis Thresholding. The workflow is designed to collectively enhance image quality by leveraging the strengths of each component.

The CGO operates as a preprocessing step, strategically smoothing the image to alleviate Gaussian noise while preserving edges and fine details. By carefully tuning parameters, it effectively reduces noise levels without introducing blurring effects, contributing to the restoration of image sharpness.

The Haar transform, another preprocessing operation, is renowned for its edge-preserving properties. Its ability to capture sharp transitions in the image is harnessed, and an inverse Haar transform is subsequently applied to reconstruct the improved image.

Both the CGO and Haar transform inherently contribute to edge preservation. The CGO achieves this by selectively smoothing regions while preserving edges, and the Haar transform provides directional analysis, further enhancing edge preservation during the restoration process when combined with the Convolution. CGO demonstrate adaptability by adjusting parameters based on local image features, ensuring effective noise reduction without compromising essential image details.

Neighborhood Convolution Average Filter (NCAF)

Input: Noisy Image

Output: De-noised Image

Step 1: Read the noisy CT image of Pancreas

Step 2: Image Resize

Information of image converted to 256x256

Step 3: Colour Conversion

Resized image transformed to HSV colour model to separate and enhance the brightness of the image

Step 4: Convolution Gaussian Operation with kernel(7x7)

For each pixel, the convolution operation computes the average intensity value of the pixel and its neighbouring pixels within the kernel.

$$image[i,j] = \frac{1}{[7x7]} \sum_{k,l} \mathrm{Input}[i+k, j+l] \rightarrow (1)$$

Step 5: Apply Haar wavelet transform for noisy image and obtain Wavelet coefficients

$$g(x, y; \lambda, \theta, \psi, \sigma, \gamma) = \exp(-2\sigma 2x'2 + \gamma 2y'2) \cos(2\pi\lambda x' + \psi)$$

Step 6: 7x7 variance mask used to estimate noise variance from noisy image by horizontally and Vertically

$$Variance(\vartheta) = \left(\frac{1}{2\pi\sigma^2}\right) exp\ (-\frac{(x-\mu)^2}{2\sigma^2} \longrightarrow (3)$$

Step 7: Calculate threshold value by Equation (3)

$$T_v = \hat{\sigma}\sqrt{2\log N}$$

$\rightarrow (4)$

Step 8: Hysteresis Thresholding

if Tv &t $_{low}$: discard the edge

if T_v&; t $_{high}$: discard the edge

else: keep the edge

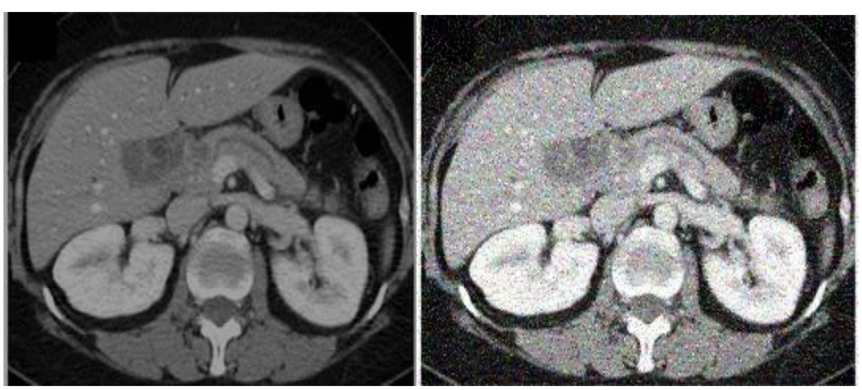
VI RESULT AND DISCUSSION

To validate the efficacy of the suggested filter, it was tested on a dataset consisting of 286 images. The denoising and enhancement were performed using the proposed **Neighborhood Convolution Average Filter (NCAF)** known for its versatility in effectively handling various types of noises especially it removes gaussian blur noise. The NCAF not only successfully removes noise but also preserves crucial edge information, all achieved with minimized computation time.

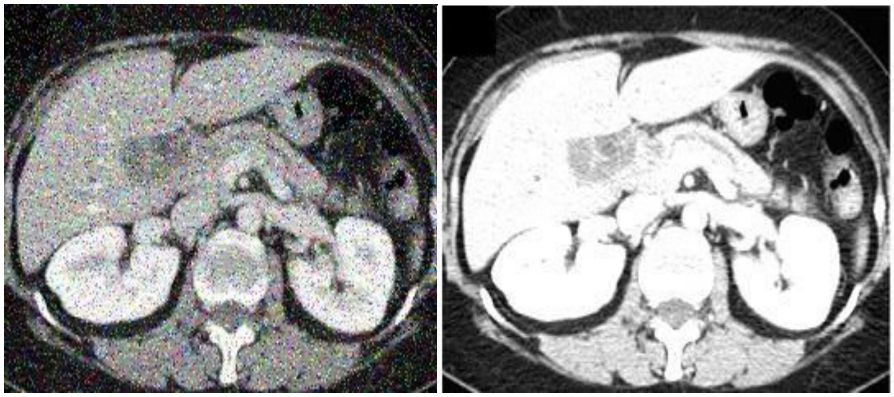
The image quality assessment was conducted using two metrics: Mean Square Error (MSE) and Peak Signal to Noise Ratio (PSNR). These metrics provide quantitative measures of the quality of the denoised and enhanced images. The proposed method was benchmarked against several existing filters, including mean, median, adaptive, and Gaussian filters.

The results demonstrated that the proposed NCAF outperforms other filters in terms of noise reduction, edge preservation, and computational efficiency. The comparative analysis was visualized in Figure 2, which depicts the original input image before any processing. The proposed filter showcased its capability in enhancing image quality, making it a promising solution for denoising applications.

Figure 2. Original input image

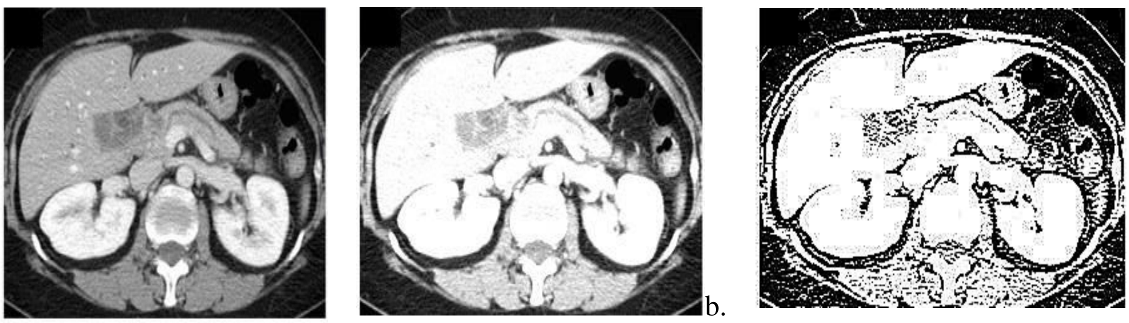


(a)Mean **(b).Median**



(c) Guassian **(d) Proposed Filter**

Figure 3. Result and Comparison of various Filter



a. Original Input Image b. After Denoised Image c. Edge preserved & Enhanced Image

Figure 4. Result of Denoised & Enhanced Image

Table 1 shows the comparison of PSNR values of mean, median, Gaussian, Adaptive filter with proposed method (CGF). For the image1.jpg the PSNR value of proposed filter is 98.276 and for the it gave highest PSNR value for mango4.jpg. The PSNR Value is calculated by using the equation (2).

$$PSNR = 20\log_{10}\frac{255}{RMSE} \qquad \rightarrow (2)$$

RMSE (Root Mean Square Error) is calculated through the square root of MSE.

$$MSE = \frac{1}{M*N}\sum_{j,k}(f(j,k) - g(j,k))^2$$

$$RMSE = \sqrt{MSE} \qquad \rightarrow (3)$$

Table-1: Comparison of PSNR values

Image	Mean Filter	Median Filter	Gaussian Filter	Proposed filter
Image1.jpg	82.637	73.213	54.715	**98.276**
Image 2.jpg	82.172	73.614	56.761	**98.124**
Image 3.jpg	82.218	73.534	57.443	**98.278**
Image 4.jpg	81.331	73.142	57.388	**98.104**
Image 5.jpg	81.128	74.341	55.043	**98.692**

Table 2 shows the comparison of proposed filter with existing methods for MSE values of mean, median, Gaussian and Adaptive. Proposed filter acquired minimum error value than other existing method.

Table-2: Comparison of MSE values

Image	Mean Filter	Median Filter	Gaussian Filter	CTM	GCF Filter
Image1.jpg	1.022	1.012	1.212	1.312	0.211
Image2.jpg	1.021	1.042	1.119	1.231	0.211
Image3.jpg	1.023	1.011	1.294	1.123	0.213
Image4.jpg	1.023	1.032	1.219	1.213	0.211
Image5.jpg	1.023	1.023	1.259	1.321	0.212

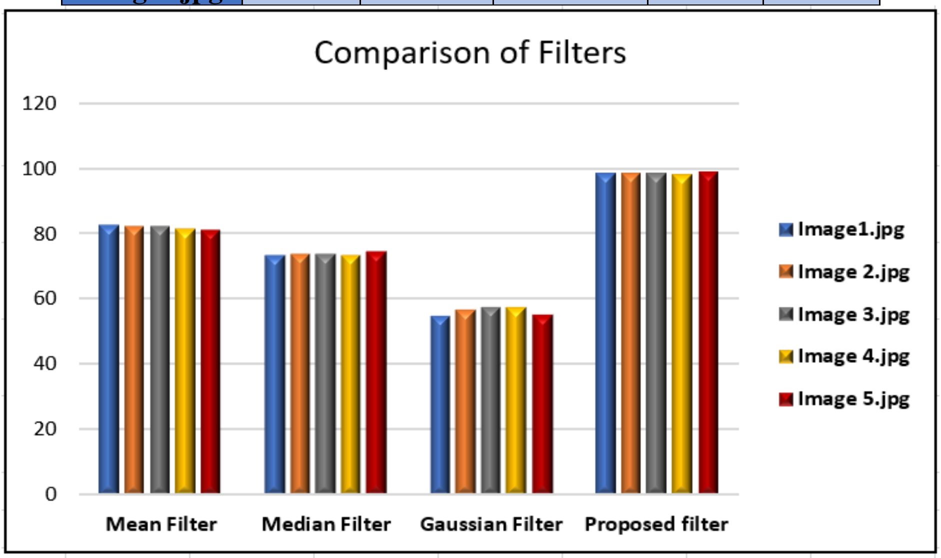


Figure 5. Comparison of PSNR values

V. CONCLUSION

The present research introduces a novel algorithm aimed at efficiently filtering noise within CT images of pancreas. This paper thoroughly examines various existing algorithms, analyzing their advantages and identifying areas for improvement. The proposed algorithm employs enhanced methods for noise reduction in CT images while also focusing on preserving edge details. Comparative analysis reveals that the proposed algorithm yields higher PSNR values compared to existing methods, indicating superior noise reduction performance. Additionally, the mean square error of the proposed algorithm is significantly lower than that of other existing filter algorithms. Consequently, it is concluded that the proposed system offers improved accuracy compared to other existing algorithms.

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