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RESEARCH ARTICLE

The New Robust Adaptive Median Filter for Denoising Cancer Images Using Image Processing Techniques

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Abstract

Background/Objectives: One of the leading causes of death for women is breast cancer, and extensive research has been conducted to improve the diagnosis and detection of breast cancer using various image processing techniques. Medical imaging plays a crucial role in this domain, particularly mammography, which is widely used for breast cancer screening and diagnosis. This paper introduces a novel filtering technique called the New Robust Adaptive Median Filter (RAMF). **Method:** The suggested approach only takes into account noise-free pixels when determining the window's median. The median is computed from the remaining pixel values when the ◦ or 255 pixel values are excluded. In order to filter high densities of salt-and-pepper noise, the adaptive windowing approach is applied, which enables our algorithm to extend the size of its filtering window dependent on the local noise density. Moreover, a threshold value is employed to establish the pixel value under extreme circumstances, such as pure black and white photos with noise. **Finding:** To compare filters based metrics, we find evaluate the filters using a standardized dataset and calculate the MSE, PSNR, and UQI values for each filter. These values can then be compared to determine which filter performs better in terms of noise reduction and image quality enhancement. The Proposed Filter shows good performance in low and higher density ranges (10%-90%) to effectively reduce noise in higher density values. **Novelty:** The New Robust Adaptive Median Filter (RAMF) is a novel filtering technique that aims to reduce noise in images, particularly in the presence of highly corrupted or noisy pixels. This filtering algorithm employs an adaptive approach where the median is calculated in a processing window, but without considering the noisy pixels during the initial computation.

Keywords: Adaptive Median Filter (AMF); Weighted Median Filter (WMF); Noise Adaptive Fuzzy Switching Median (NAFSM) filter; Decision-based algorithm (DBA); Mean Square Error (MSE); Peak-Signal-to-Noise Ratio (PSNR) and Universal Quality Index (UQI)

1 Introduction

There are several sources of noise that can affect the quality of the images. These sources can introduce unwanted variations or artifacts, which may reduce the clarity and accuracy of the mammogram. Quantum Noise: Quantum noise, also known as statistical noise or Poisson noise, is inherent to any type of imaging system that relies on the detection of X-ray photons. Electronic Noise: Electronic noise can arise from various components of the mammography system, including the X-ray detector, amplifiers, and analog-to-digital converters. Motion Artifacts: Motion artifacts occur when there is unintended motion of either the patient or the imaging system during the mammogram acquisition. Scatter Radiation: Scatter radiation refers to X-ray photons that are deflected from their original path due to interactions with the breast tissue. Efforts are continuously being made to minimize noise in mammography by improving imaging technologies, optimizing acquisition protocols, and developing advanced image reconstruction and processing algorithms.

Image filtering is a crucial task in computational photography and imaging, playing a fundamental role in image processing and computer vision[(1)]. Filtering involves deriving the value of a filtered image at a specific location based on the values of the input image in a nearby neighbourhood[(2)]. Artificial intelligence techniques have significantly influenced image filtering, particularly in the development of edge-preserving filters that aim to preserve image edges while reducing noise[(3)].

Improving image quality is a primary objective of image filtering. Different algorithms, both linear and nonlinear, have been developed for this purpose[(4)]. Linear filters, such as averaging filters and Gaussian filters, are effective when the noise level is low. However, in the presence of high noise, these filters tend to over smooth sharp edges and corners. Bilateral filtering has emerged as one of the most widely used filters for noise removal while preserving edges. It offers a balance between noise reduction and edge preservation, making it suitable for various applications[(5)].

Recently the use of adaptive median filtering as an effective technique for restoring images corrupted by different types of noise, such as Gaussian noise, salt-and-pepper noise, and impulse noise. The adaptive median filter adjusts its window size and selection criteria based on the local characteristics of the image, allowing it to adapt to different noise patterns and preserve important image details[(6)]. The adaptive nature of the AMF often requires storing multiple pixel values within the filter window. As the filter size can vary, the memory requirements may increase, especially for larger filter windows. This can be a drawback when processing images with limited memory resources. SO the article proposed RAMF. Its adapts its filter size based on the local characteristics of the image. It dynamically adjusts the filter window to better handle different noise levels and preserve image details. This adaptiveness allows RAMF to effectively reduce noise while maintaining sharpness and fine details in the image. RAMF can be implemented efficiently and can operate in real-time applications. Its computational complexity is generally lower than more advanced denoising algorithms, making it suitable for applications where real-time processing is required, such as video processing or live streaming.

Numerous filtering methods have been suggested for the replacement and elimination of Salt and Pepper noise in order to solve this problem. The Standard Median Filter (SMF), a method that is often used and renowned for its computational effectiveness and capacity to denoise images, is one such method. However, the SMF is unable to maintain the picture's fine features and edges when the noise level approaches high values, like 50%. Researchers have suggested a number of enhanced techniques to address this problem, including the Adaptive Median Filter (AMF)[(7)] and the Weighted Median Filter (WMF)[(8)]. These techniques make use of filter windows, which are matrices that usually include a set of pixel values, such as a 3x3 window with 9 pixels. The goal is to find potentially noisy pixels in the window and substitute them with the median filter or one of its versions while maintaining the integrity of the other pixels. A cutting-edge filtering method that outperforms conventional non-linear filters is the Noise Adaptive Fuzzy Switching Median (NAFSM) filter. Two phases are included in it to improve efficiency. The NAFSM filter uses the corrupted image's histogram in the first stage to identify noise-affected pixels. The second stage then processes the "noise pixels" that have been discovered, leaving the "noise-free pixels" alone.

In order to properly address the ambiguity brought on by noise in the extracted regional data, the NAFSM filtering process uses fuzzy reasoning. It combines the benefits of the fuzzy switching median filter and the Simple Adaptive Median Filter (AMF). According to the local noise the density, the AMF component of NAFSM dynamically modifies the size of its filtering windows. While this is happening, the inherited switching median filter only chooses "noise-free pixels" for further analysis. The fuzzy reasoning technique aids in the generation of exact restoration words for precisely restoring the observed "noisy pixels."

An approach called the decision-based algorithm (DBA) was created to deal with the problems caused by Salt and Pepper noise in photographs. The first step of this method is to find any noise in the image. It achieves this through comparing the pixel values inside a chosen region to the highest and lowest values anticipated in a situation with no noise. In general, the dynamic range of the noise from impulses is predicted to be between (0, 255). If the processing pixel falls between the window's lowest and highest values, it is regarded as noise-free, and no changes are applied to that pixel. The pixel value is considered noisy if it falls outside of this range. In these situations, the procedure either replaces the noisy pixel with the median value of the nearby dispensation pixels or, if the median itself happens to be noisy, with the mean value[(9)]. Although this method performs well at modest noise rates, once the noise rate reaches 70%, it finds it difficult to properly suppress impulse noise and maintain picture particulars. Additionally, when the noise level reaches 90% or higher, the device's efficiency suffers noticeably. As a result, the method does not effectively address images with high levels of noise.

2 Methodology

2.1 Dataset

The dataset used for this research was the Mammographic Image Analysis Society (MIAS) dataset[10]. The MIAS dataset consisted of a total of 322 mammogram images. These images had an original size of 1024-by-1024 pixels. Among the dataset, approximately 133 images belonged to the abnormal class, while 189 images represented the normal class. The abnormal images included various types of abnormalities. Asymmetry, characterized by increased density in one breast, accounted for 21 images. Architectural distortion, which exhibited abnormal tissue arrangement in the breasts, was present in 22 images. Calcification, the development of small calcium deposits in the breasts, was observed in 24 images. Circumscribed masses, irregularly shaped masses in the breasts that could be malignant, were found in 24 images. Additionally, there were 24 images of speculated masses, which are masses with poorly defined margins or edges. The miscellaneous class included 18 images with no confirmation of malignancy.

2.2 Existing Algorithm

a) Adaptive Median Filtering

Adaptive Median Filtering is a technique used for image processing and noise reduction. While it has its advantages, it also has some disadvantages that should be taken into consideration.

Adaptive Median Filtering involves more complex calculations compared to other filtering techniques. It requires multiple iterations and neighbourhood size adjustments, which can result in increased computational overhead and slower processing times, especially for larger images. The effectiveness of Adaptive Median Filtering heavily relies on selecting appropriate parameters, such as the window size and threshold levels. Determining the optimal parameter values can be challenging and may require trial and error or domain-specific knowledge. In some cases, Adaptive Median Filtering can overly smooth or blur the image, particularly in regions with subtle variations or fine details. This blurring effect may lead to the loss of important image information and result in reduced overall image quality. While Adaptive Median Filtering performs well in reducing certain types of noise, such as Gaussian or salt-and-pepper noise, it may struggle to effectively handle impulse noise. Impulse noise, characterized by sudden and sporadic intensity spikes, can result in artifacts and inconsistencies in the filtered image.

Adaptive Median Filtering may face difficulties in preserving sharp edges and boundaries in an image. It can lead to blurring or distortion of edges, causing a loss of important image features and details. The choice of window size in Adaptive Median Filtering can significantly impact the filter's performance. An inappropriate window size may result in either excessive noise removal or insufficient noise reduction. Adaptive Median Filtering assumes the presence of spatially uniform noise across the image. However, it may not be as effective in handling non-uniform noise patterns or complex noise distributions.

2.3 Proposed Algorithm

a) New Robust Adaptive Median Filter (RAMF)

The proposed algorithm focuses on a key concept of considering only noise-free pixels when scheming the median within the frame. Thus, pixels with values that range from zero or 255, which typically represent noise, are excluded from the calculation. Instead, the median is calculated based on the remaining pixel values. To achieve this, the algorithm employs an adaptive windowing approach. Using this method, the technique can adjust the filtered window's size dependent on the level of nearby noise. By doing so, the algorithm becomes capable of effectively filtering images with a high density of salt-and-pepper noise. By omitting noisy pixel values and utilizing an adaptive windowing strategy, the algorithm can provide more accurate and reliable noise reduction results, thereby preserving the details of the image.

Step 1: The algorithm begins by selecting the middle pixel of the image as the starting point. It sets an initial window size of 3x3 pixels for the processing. The scanning process will then proceed through the entire image in a specific pattern, starting from the middle pixel. The scanning process follows a sequence from the middle to the upper left corner, then to the upper right corner, followed by the lower left corner, and finally to the lower right corner of the image.

Step 2: After removing the values of 0 and 255 from the pixel values within the current window, the procedure now determines the median value.

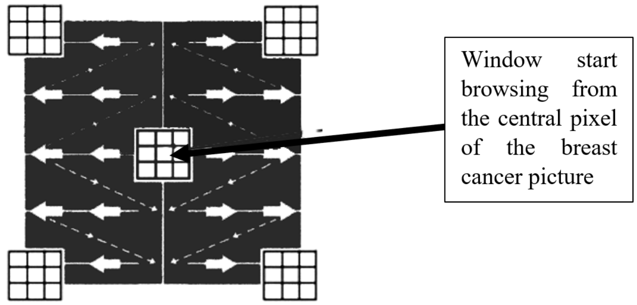

Fig 1. The suggested technique's window is being scanned

Step 3: In this stage, specific factors are checked based on the estimated median value and the amount of noise present in the present frame.

(a) if the median value and a minimum of one noise-free pixel are present in the frame, the method substitutes the centre pixel through the estimated median rate. The process then advances to Step 5 for additional processing.

(b) The technique enlarges the opening by one pixel on each of its four corners if the median value is corrupted, suggesting that there are no noise-free pixels inside the window. In order to compute the median using the larger window, the algorithm loops back to Step 2. Up until the permitted window size has been achieved, this procedure is repeated.

(c) The algorithm moves on to Step 4 for additional processing if the largest window size, which is commonly 7x7 pixels, has been attained and still no noise-free median value has been discovered.

Step 4: The last examined pixel, which occurred immediately prior to the current centre pixel throughout the scanning process, is taken into account by the method in this phase.

(a) The technique substitutes the value of the present centre pixel with the value of the most recently treated pixel if the most recently processed pixel is not equal to 0 or 255, suggesting it is a valid pixel value.

(b) The method then moves on to take into account the present greatest window size (7x7) if the most recent analysed pixel is either 0 or 255. Then it determines how many times between 0 and 255 occur within this timeframe. It is presumed that the region was initially made up entirely of 0 values, which would depict a region of pure black, if the number of instances of 0 exceeds a given threshold value. Consequently, 0 is used in place of the centre pixel. Similarly, it is presumed that the region was initially made up of 255 values, which represents a pure white zone, if the number of instances of 255 is higher than the threshold value. In this instance, 255 is used to replace the centre pixel. Usually set at 50%, the threshold value defines the proportion of pixels contained inside the active window. This value, which is established by testing, can change depending on the specific application's requirements and noise properties. The method adjusts to deal with pure black or pure white areas and assures precise pixel replacements in accordance by taking into account the most recently processed pixel and analysing the arrangement of 0 and 255 values inside the frame.

Step 5: In this step, the algorithm slides the window to the next pixel in the image for further processing.

b) Flowchart

Below is a flowchart for the suggested technique (Figure 2).

3 Results and Discussion

a) Implementation

To estimate the planned method, a set of experiments was conducted using cancer images obtained from the Kaggle Mini-Mammogram Image Analysis Society (MIAS) database, specifically for breast cancer. The dataset used for testing consisted of 15 cancer images. The effectiveness of the suggested strategy was evaluated in comparison to the outcomes of various filters used on the same set of photographs. This comparison allowed for assessing the efficiency and efficiency of the planned method in reducing noise and enhancing image quality. The implementation of the planned technique was approved obtainable on a laptop equipped with an Intel CPU I7 running at 2.2 GHz and 16 GB of RAM. The system operated on the Windows 10 operating system. These hardware specifications provided the necessary computational resources for executing the proposed method and performing the comparative examination.

b) Metrics

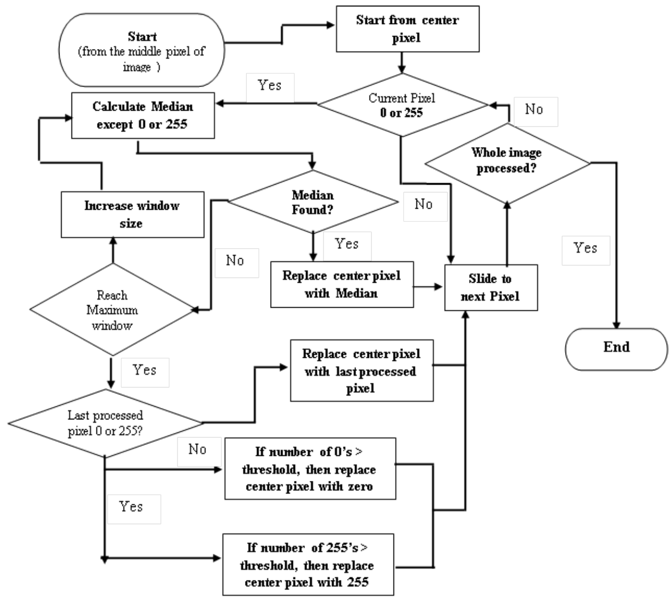

Fig 2. Flow chart of the proposed algorithm

By adding Salt and Pepper noise to the picture at several noise concentrations, the presentation of the suggested approach was assessed. Several performance metrics were assessed to determine the method's efficiency, involving:

1. Peak-Signal-to-Noise Ratio (PSNR): It determines the picture's peak signal power to noise control relation. A greater PSNR number denotes better picture quality, like SNR.
2. Mean Square Error (MSE): The sum of the average squares variance among the pixels in the original and restored images is calculated. Better quality of images is indicated by a lower MSE value.
3. Universal Quality Index (UQI): Based on elements including brightness, contrast, and structure, it gauges how comparable the original and restored images are. A higher UQI value implies that the photos are more similar.

The equations used for these performance metrics are as surveys:

Peak-Signal-to-Noise Ratio (PSNR):

$$PSNR = 10 * log10(\frac{(MAX)^2}{MSE})$$

Mean Square Error (MSE):

$$MSE = \frac{1}{MN}\sum \left((x_{ij} - y_{ij}|\right)^2$$

Universal Quality Index (UQI):

$$UQI = \frac{(4 * \sigma\_XY * \mu\_X * \mu\_Y)}{(\sigma\_X^2 + \sigma\_Y^2 + (\mu\_X - \mu\_Y)^2)}$$

c) Comparative analysis

A comprehensive comparative analysis of previous image filtering algorithms involves evaluating and comparing multiple techniques based on various criteria [11]. To perform a comparative analysis, we usually apply multiple image filtering algorithms to a set of breast cancer test images corrupted with various types and levels of noise. Adding noise to an image intentionally, known as "noise injection". It is important to note that the specific benefits of adding noise and pre-processing it later depend on the context and the specific goals of the application. Noise injection is not always beneficial and should be carefully considered based on the particular requirements and constraints of the task at hand. Differentiating informative pixels from noise pixels in scanned images can be a challenging task, as it depends on the characteristics of the image and the specific type of noise present. Machine learning algorithms, can be trained to differentiate between informative pixels and noise pixels. These models can be trained on labeled datasets, where the ground truth for informative content and noise is known. By learning from these examples, the algorithm can generalize and make predictions on unseen images, classifying each pixel as informative or noise based on learned patterns and features.

They then calculate the SSIM, MSE and UQI values for each filtered image and compare the results across algorithms. The algorithm with higher SSIM values and lower MSE and UQI values generally indicates better image quality and noise reduction performance. Different noise level in breast cancer image as shown in Figure 3.

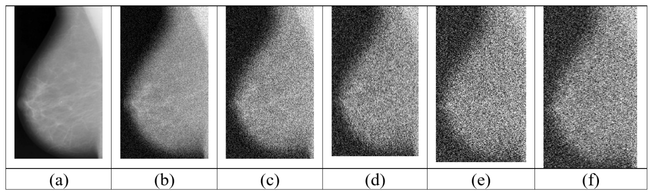

Fig 3. (a)Normal Breast Cancer picture. (b) Picture tainted by 20% noise density. (c) picture tainted by 40% noise density. (d) picture tainted by 60%noise density. (e) picture tainted by 80% noise density. (f) picture tainted by 90% noise density

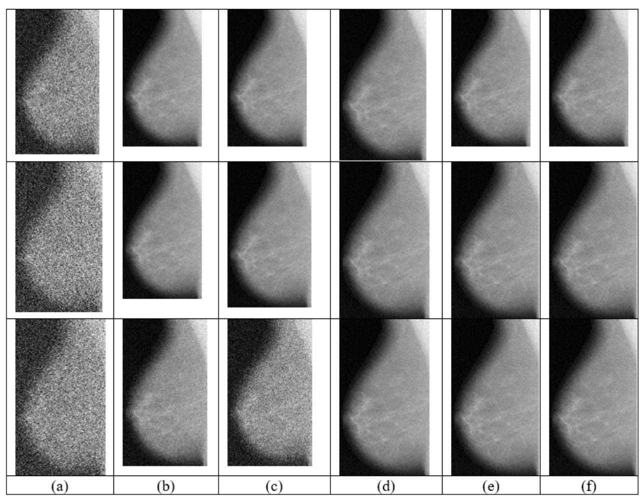

Fig 4. Outcomes of various filters for Breast Cancer image. (a) Noise image (b) Output of SMF. (c) Outputof AMF. (d) Output of DBA. (e) Output of NAFSM. (f) Output of RAMF Row 1–Row 3show processed results of various filters for BreastCancer.jpg image tainted by60%, 80%, and 90% noise densities

Figures 5, 6 and 7 present the comparison results among various denoising algorithms, namely the Noise Adaptive Fuzzy Switching Median filter (NAFSM), Adaptive Median Filter (AMF), Standard Median Filter (SMF), Decision Based Algorithm (DBA) and the Proposed System(RAMF). The comparison is conducted in terms of three performance metrics: Mean Square Error (MSE), Peak-Signal-to-Noise Ratio (PSNR) and Universal Quality Index (UQI).

Figure 5 shows the PSNR values obtained by each denoising method. A higher PSNR value specifies better image quality and noise decrease. From the results, it can be observed that the Planned Process(RAMF) achieved the maximum PSNR value, indicating superior noise reduction compared to the other methods.

Figure 6 presents the MSE values, which measure the normal absolute change among the normal and denoised images. A lower MSE value indicates better accuracy in noise reduction. In this case, the Proposed Algorithm (RAMF) achieved the lowest MSE value, indicating better preservation of image details compared to the other methods.

Figure 7 displays the UQI values, which assess the similarity between the original and denoised images in terms of luminance, contrast, and structure. A higher UQI value designates better resemblance among the images. The Planned Procedure (RAMF) achieved the highest UQI value, indicating better preservation of image quality and structure compared to the other methods.

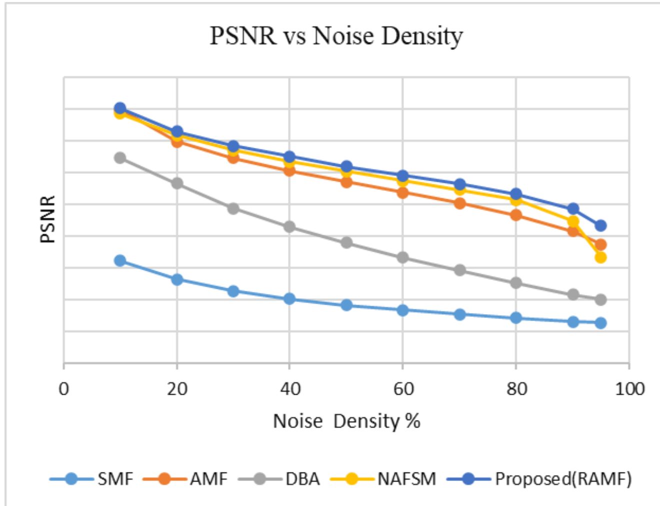

Fig 5. Comparison of PSNR

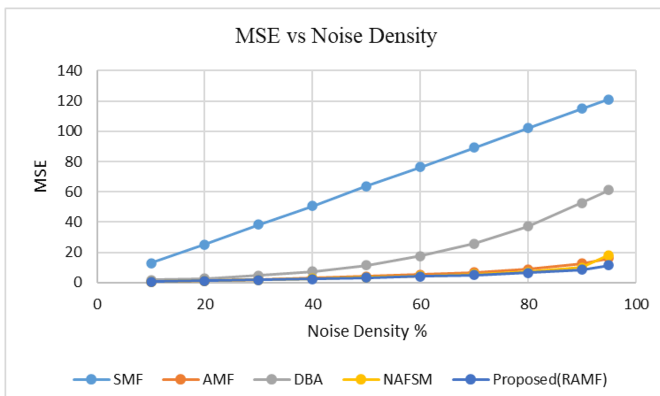

Fig 6. Comparison of MSE

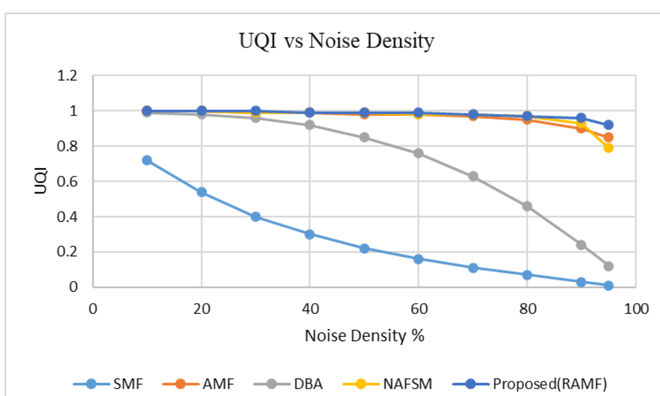

Fig 7. Comparison of UQI

Based on these comparison tables, it can be concluded that the Planned Procedure outperformed the other denoising methods in relations of PSNR, MSE, and UQI, indicating its effectiveness in reducing noise while preserving image quality and details.

The use of a maximum window size of 7x7 in the proposed algorithm is advantageous in preserving edges and details, even in the presence of high-density noise, such as 95%. By using a larger window size, the algorithm can capture more contextual information and better preserve image features.

Additionally, the algorithm's approach of not considering noisy pixels during the median calculation contributes to its faster performance compared to other Median Filters. By excluding noisy pixels from the median calculation, the algorithm avoids the need to process and compare these noisy values, which can reduce computational complexity and speed up the filtering process. These characteristics of the proposed algorithm, namely the larger window size and exclusion of noisy pixels, make it suitable for efficiently handling images with high-density noise while preserving important image details. However, it's worth noting that the specific implementation details and performance of the algorithm can vary based on factors such as the noise characteristics, parameter settings, and the specific requirements of the application.

While this method itself does not directly identify cancer, it can play a role in improving the overall image quality, which in turn may aid in the identification and analysis of potential cancerous features. The improved image quality resulting from proposed technique can enhance the diagnostic confidence of radiologists. Clearer images with reduced noise artifacts allow for better visualization and analysis of breast tissue, potentially leading to more accurate assessments of abnormalities and reducing the chances of false-positive or false-negative interpretations. This can ultimately improve the overall diagnostic accuracy and patient outcomes in breast cancer screening and diagnosis.

4 Conclusion

A RAMF technique for removing Salt and Pepper noise in breast cancer photos is presented in this study. With regard to both low- and a high level of noise, the technique has good reduction of noise characteristics. The suggested algorithm performs better than the SMF and AMF, which struggle to maintain important details at noise levels as high as 50%. The NAFSM and DBA, two recently created approaches, show efficient filtering at greater concentrations but suffer from a streaked impact when the noise intensity reaches 80%. Conversely, our approach utilises a novel strategy of beginning image reading from the centre point to get satisfactory results even at high noise density. The method is also excellent at identifying and recovering pure black and pure white areas that were distorted by salt and pepper noise shown in Figure 4. The algorithm features a more exact technique of calculating the median, further adaptability, and careful evaluation of threshold values, which leads to greater detail retention and visual quality. The technique's constrained window size also aids in its efficient computation. The future extensions of the RAMF in breast cancer imaging will likely involve combining it with advanced techniques such as deep learning, optimizing for real-time processing, incorporating multi-modal imaging fusion, and considering personalized noise models. These advancements aim to enhance the accuracy, efficiency, and personalized nature of breast cancer detection and diagnosis.

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