A Proposed Model For Denoising Breast Mammogram Images

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***Abstract*—Digital mammogram has emerged as the most popular screening technique to detect the breast cancer in its beginning and other abnormalities in human breast tissue. The paper's objective is to list the types of noise obtained with the mammography process. Then, the most used filters used by the already proposed work in the breast cancer detection are introduced and then applied to denoise the images in the Mini-MIAS database mammograms. The wiener, mean, median, adaptive median and Gaussian filters are applied on mammograms of different classes to be compared by measuring the mean squared error, the peak signal to noise ratio and the blurriness metrics. It is proved by the experimental results that the adaptive median filter is the best one denoise the salt and pepper noise. The mean filter is the best to denoise the Gaussian, speckle and poisson noise but with high blurriness value. This problem is overcome using the wiener filter in case of the Gaussian noise and using the median filter in case of the speckle and the poisson noise. The best filters for each type of noise are used together to remove any type of noise that may exist in the mammogram to achieve 11.3106 as the average mean squared error across the 322 mammograms and 37.9023 as the average peak signal to noise ratio which is the best combination leadings to the lowest mean squared error.**

***Keywords*—Mammogram, Breast Cancer, Wiener, Median, Adaptive Median, Mean Squared Error, Peak Signal to Noise Ratio.**

I. INTRODUCTION

Breast cancer is the most common cancer in women in both the developed and the developing world according to World Health Organization (WHO) [1][2]. In the developing world, there is an increasing incidence of breast cancer because of the increase in life expectancy and urbanization of western lifestyles. However, some risk reduction can be achieved with prevention and; early detection for improving breast cancer outcome and survival remains the cornerstone to control breast cancer [1].

Breast cancer is defined as a malignant tumor that starts in some cells of the breast. A malignant tumor is a group of cancer cells that can grow into the surrounding tissues or spread to distant areas of the body. The female breast is made up mainly of lobules which are the milk-producing glands, ducts that are tiny tubes that carry the milk from the lobules to the nipple, and stroma that is a fatty tissue and connective tissue surrounding the ducts and lobules, blood vessels, and lymphatic vessels. Most breast cancers begin in the cells that line the ducts and named as ductal cancers. Sometimes the malignant tumor may begin in the cells of lobules, while a small number start in other tissues. Lobular cancers start with the milk carrying ducts and spread beyond it [3][4].

From the most common breast screening technologies which are considered an easy and affordable method for diagnosing the microcalcification and clinically hidden lump tissues in the breast at the early stage of cancer, is the Mammography process. There are several imaging techniques for examining the breast such as: ultrasound, magnetic resonance imaging, X-ray imaging and emerging technologies including molecular breast imaging and digital breast tomosynthesis [5].

One of the challenges in the mammography process is the low contrast of mammogram images. This poses difficulties and challenges for radiologists to interpret results. The double reading of mammograms leads to low rate of false positives and negatives; although, the cost and workload associated with double reading are high [5]. Besides that, the main problem of the resultant mammograms is that like other medical data it is also affected with noise during the acquisition of the images. So, it is a challengeable task for researchers to denoise the mammogram images with preserving the important features of the image to detect any existing issue. Noise is defined as a random fluctuation of image intensity and appears as grains in the resultant image. The main noises affecting the mammogram images are as follows: Salt and pepper, Gaussian, speckle and poisson noise [7][8].

This paper presents a comparative study for the mammograms denoising techniques used in the recent proposed work concerning the breast cancer detection. The paper is structured as follows: Section two introduces some of the recent related work in the breast cancer detection that classify the mammogram with different types of noises after the preprocessing phase. Then, section three is the strategy of the empirical study of denoising mammograms followed by section four that lists the conducted experiments and their results. Then, the final section is the work conclusion.

II. Related work

Image pre-processing techniques are necessary to remove the noise and to enhance the quality of the image. Before any image-processing algorithm is applied on a mammogram, preprocessing steps are very important to limit the search for abnormalities without affecting the mammogram details.

Digital mammograms are medical images that are difficult to be interpreted. Thus, image preprocessing techniques are necessary to remove the noise and to enhance the quality of the image, then consequently make the segmentation results more accurate. Image processing is also important to improve the interoperability of the information present in the images for human visual. Image filtering is useful for many images processing techniques, including smoothing, sharpening, removing noise and edge detection.

Some of the recent work in the breast cancer detection are listed in this section especially those that passed by the preprocessing phase for the mammogram images before the detected mass classification. The main goal behind this subsection is to list the preprocessing steps implemented in the recent proposed work in order to conclude the necessity of this step. Besides proposing an overview of the possible implemented steps in the mammograms preprocessing for the recent proposed methods.

In 2015, Al-Najdawi N, Biltawi M and Tedmori S. in [9] proposed a mammogram enhancement, mass segmentation and classification method. Their dataset is collected from The King Hussein Cancer Center (KHCC) and Jordan Hospital (JH). They first preprocessed the mammogram image through several steps. The mammogram is converted to grayscale, then the orders, labels, and any artifacts are removed followed by noise removal using a combination of CLAHE and MEDIAN filter is compared with CLAHE, median, Gaussian, CLAHE & Gaussian and median & Gaussian to results in the best segmentation results for the mammogram images. Finally, the breast region was segmented using contour segmentation to get the segmented breast region. The segmented breast region's contrast was further adjusted using the histogram equalization to get the enhanced breast region. Then, the suspicious region was cropped from the enhanced breast region that was enhanced using the un-sharp masking with filling any existing holes. The cropped mass is classified by tracing the boundary of the Region of Interest (ROI) using the boundary extraction morphological algorithm by applying eroding, and then subtracting the eroded image from the original version. They measured the object roundness to detect if the mass is a circle or any other shape. Then, classifying into benign or malignant according to a threshold calculated by combining the results of object roundness metric for both MLO and CC mammogram images. The authors achieved sensitivity of 96.2% and specificity of 94.4%.

In 2017, Soulami KB, Saidi MN and Tamtaoui A. introduced a CAD system in [11] for the detection and classification of abnormalities in dense mammograms using electromagnetism-like optimization algorithm. They used Mini-MIAS database that is denoised using the two-dimensional median filter. Then, the Support Vector Machine (SVM) was carried out based on Sigmoid kernel for the mammogram classification to achieve sensitivity of 81.81% and specificity of 90.0%.

In 2018, de Moor T, Rodriguez-Ruiz A, Mann R and Teuwen J. in [10] proposed an automated soft tissue lesion detection and segmentation in digital mammography using a u-net deep learning network. The dataset used is collected from their three different vendors: General Electric, Siemens and Hologic that are preprocessed using the Gaussian filter followed by employing a deep learning convolutional neural network with modified u-net architecture. They achieved sensitivity of 81.81% and specificity of 90.9.

In 2018, Tiwari A, Bhateja V, Gautam A and Satapathy SC. proposed an ANN-based classification of mammograms using nonlinear preprocessing such that a nonlinear logistic function has been applied for enhancement (preprocessing) of mammograms. This function modifies the mammogram by defining a certain threshold, pixels having magnitude above this threshold are enhanced while the rest are suppressed. The enhancement using the aforesaid function has been carried out by combining the non-linear logistic function in a linear fashion along with a gain parameter to enhance the gray level for original ROI. Then, the Gray Level Cooccurrence matrix (GLCM) features are formulated to define the texture of the detected anomaly. Where, the detected ROI is sent to a features extraction module where a structure of quantitative data is obtained by calculating various attributes such as energy, entropy, and correlation, etc., for final classification. Finally, a Feedforward Artificial Neural Network (FF-ANN) is used as a classification tool for segregating the mammogram into normal or abnormal. The digital mammograms are taken from The Cancer Imaging Archive (TCIA) [15] which provides a classified set of images (for cancer anomalies) available publicly as a weblink. The accuracy of the proposed approach is reported to be 97%.

In 2018, Ghongade RD and Wakde DG in [16] diagnose breast cancer with a machine learning method based on Random Forest (RF) and RF-ELM classifier. MIAS database was used for digital mammogram images. In the first phase, the image was smoothed using the Gaussian filter that is used to 'blur' image and remove noise. Then, the contrast of the image was enhanced using adaptive histogram equalization. The second phase, region-based segmentation is used to segment masses from its background. Followed by the third phase which is using the gray-level co-occurrence matrix as a statistical technique to extract the texture features. The fourth phase is selecting a subset of appropriate features using the correlation-based feature selection that is used to select the high-dimensional features. This phase is necessary to reduce the feature space to improve the accuracy of classification and minimize the computation time as well. Finally, the mammograms are classified using the Random forest (RF) and RF-ELM algorithms. They resulted in average sensitivity of 80%, average specificity of 81% for RF algorithm, average sensitivity of 89% and average specificity of 91% for RF-ELM algorithm. The accuracy of RF and RF-ELM are 89% and 98% respectively.

III. THE STRATEGY OF THE EMPIRICAL STUDY OF DENOISING MAMMOGRAMS

This section introduces the filters used to denoise the mammogram images as the one shown in Fig. 1. Also, the metrics used to compare these filters' performance are defined.

A. Noises in Mammograms

The salt and pepper noise are from the noises that are generated while scanning the mammograms as shown in Fig. 2. The salt and pepper noise are obtained due to sudden and sharp changes of image signal and dust particles in the mammogram acquisition source or may be over heated faulty components. The Gaussian noise is known as amplifier noise and is generated from the electronic circuit noise and sensor noise as shown in Fig.3. Speckle noise can be considered as a multiplicative noise that is generated due to the dust particle in the image accusation source as given in Fig.4. Finally, the poisson noise is shown in Fig. 5, results from the change in the number of photons in the mammogram unit.

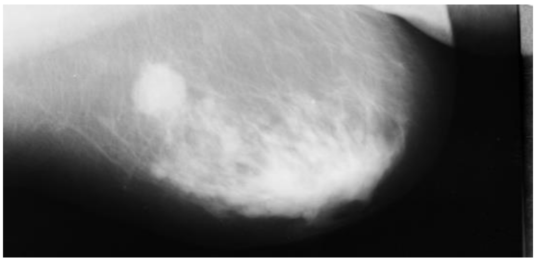

Figure 1 The Original Mammogram Image

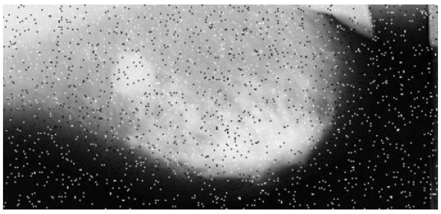

Figure 2 Mammogram with Salt and Pepper Noise

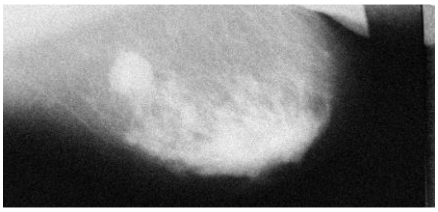

Figure 3 Mammogram with Gaussian Noise

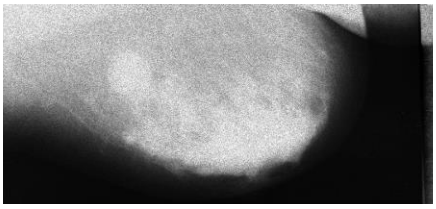

Figure 4 Mammogram with Speckle Noise

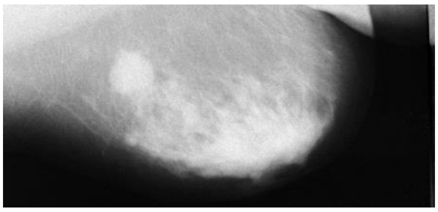

Figure 5 Mammogram with Poisson Noise

B. Most Frequent Used Filters.

The overall objective of this paper is investigating the filtering methods used to in denoising the various existing noise types in the digital mammograms focusing on the most used ones in the recent proposed works. They are as follows: Wiener, Median, Adaptive Median, Gaussian and Mean filters [17][18].

C. Measured Metrics

The Peak Signal to Noise Ratio (PSNR), the Mean Squared Error (MSE) and the blurriness metrics are used for the evaluation of the quality of the image.

The peak signal-to-noise ratio is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation as in (1). PSNR is usually expressed in terms of the logarithmic decibel scale since many signals have a very wide dynamic range.

$$\begin{aligned} PSNR &= 10 \cdot \log_{10}\left(\frac{MAX_I^2}{MSE}\right) \\ &= 20 \cdot \log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right) \end{aligned} \tag{1}$$

The PSNR is most commonly used as a measure of quality of reconstruction in image compression. It is most easily defined via the Mean Squared Error (MSE) which for two m×n monochrome images I and K where one of the images is considered a noisy approximation of the other as defined in (2).

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}\left\|I(i,j) - K(i,j)\right\|^2 \quad (2)$$

In general, a good reconstructed image is one with low MSE and high PSNR. That means that the image has low error and high image fidelity. The blurriness metric of the images after filtering is measured according to the idea in [19]. The blur annoyance on a picture is quantified by blurring it. Then, comparing the variations between neighboring pixels before and after the low-pass filtering step. Hence, the first step consists of the computation of the intensity variations between neighboring pixels of the input mammogram then a low-pass filter is applied on it and also the variations between the neighboring pixels are computed. Then, the comparison between these intensity variations is used to evaluate the blur annoyance. So, a high variation between the original and the blurred image means that the original mammogram was sharp whereas a slight variation between the original and the blurred mammogram means that the original image was already blurred [19].

IV. EXPERIMENTS AND RESULTS

The five mentioned filters in the previous section are applied to denoise the mammographic images to find the most optimum filter shall be used with each noise type that can be exist during the mammogram scanning process. Several experiments are conducted using the mammogram images in the Mini-MIAS database [20] since the basic purpose of medical image processing is to diagnose and examine medical images in a more effective, accurate and efficient manner. The experiments have been done using MATLAB.

A. *Experiment 1: Denoising images from the salt and pepper noise*

This experiment has been done by adding salt and pepper noise of density 0.5 to different three mammograms of different types: Benign well-defined/circumscribed masses in mdb001lm, Asymmetry malignant tumor in mdb110rl and normal tumor in mdb322rm. The salt and pepper noise are obtained due to sharp and sudden changes of image signal and dust particles in the image acquisition source or over heated faulty components. The three mammograms are denoised using the five filters mentioned before. The experimental results given in TABLE I show that the adaptive median filter is the most appropriate filter that works to denoise the salt and pepper noise and with appropriate blurriness value.

B. *Experiment 2: Denoising images from the Gaussian noise*

This experiment has been done be adding zero-mean, Gaussian white noise with variance of 0.01 to the same mammograms used in the previous experiment: mdb001lm, mdb110rl and mdb322rm and then denoised using the five filters. The experimental results in TABLE II show that the mean filter achieves the best performance to denoise the Gaussian noise but with higher blurriness value that can be treated by using the wiener filter with mask 3*3. Wiener filter achieves less blurriness value while denoising the mammograms compared with the mean filter.

TABLE I. THE FILTERS RESULTS ON THE MINI-MIAS DATABASE TO REMOVE SALT AND PEPEER NOISE OF DENSITY 0.5

Evaluation Metrics	**Filter**	**mdb001lm**	**mdb110rl**	**mdb322rm**
MSE	Wiener [3*3]	55.9695	64.2997	95.5637
	Median [3*3]	9.2651	9.817	12.0074
	Adaptive Med [15*15]	**1.0843**	**1.0717**	**1.2344**
	Gaussian Sigma = 0.06	39.8373	41.8049	51.5485
	Mean [3*3]	56.5317	65.3234	97.0387
PSNR	Wiener [3*3]	30.6853	30.0827	28.3619
	Median [3*3]	38.4963	38.245	37.3703
	Adaptive Med [15*15]	**47.8133**	**47.864**	**47.2503**
	Gaussian Sigma = 0.06	32.1619	31.9525	31.0426
	Mean [3*3]	30.6419	30.0141	28.2954
Blurriness	Wiener [3*3]	0.13563	0.13627	0.14107
	Median [3*3]	0.040803	0.040475	0.046755
	Adaptive Med [15*15]	**0.28751**	**0.29046**	**0.30354**
	Gaussian Sigma = 0.06	0.06191	0.06255	0.06691
	Mean [3*3]	0.152	0.15303	0.15807

TABLE II. THE FILTERS RESULTS ON THE MINI-MIAS DATABASE TO REMOVE WHITE GAUSSIAN NOISE OF VARIANCE 0.01

Evaluation Metrics	**Filter**	**mdb001lm**	**mdb110rl**	**mdb322rm**
MSE	Wiener [3*3]	**26.6871**	**28.2861**	**29.9322**
	Median [3*3]	28.3395	29.0444	38.0797
	Adaptive Med [15*15]	40.1572	43.1829	50.1238
	Gaussian Sigma = 0.06	54.6465	57.1003	71.6802
	Mean [3*3]	**18.6391**	**20.1739**	**23.1109**
PSNR	Wiener [3*3]	**33.9018**	**33.6491**	**33.4034**
	Median [3*3]	33.6409	33.5342	32.3579
	Adaptive Med [15*15]	32.1272	31.8117	31.1644
	Gaussian Sigma = 0.06	30.7892	30.5984	29.6108
	Mean [3*3]	**35.4605**	**35.1169**	**34.5266**
Blurriness	Wiener [3*3]	**0.15572**	**0.15696**	**0.1672**
	Median [3*3]	0.15085	0.15208	0.16178
	Adaptive Med [15*15]	0.11454	0.11535	0.11919
	Gaussian Sigma = 0.06	0.10217	0.10353	0.10648
	Mean [3*3]	**0.19943**	**0.19999**	**0.20604**

C. Experiment 3: Denoising images from the speckle noise

This type of noise is added to the same mammograms: mdb001lm, mdb110rl and mdb322rm. The experimental results in TABLE III show that the mean filter achieves the best performance to denoise the speckle noise but with high blurriness value that can be treated by using the median filter or the wiener filter with mask 3*3.

TABLE III. THE FILTERS RESULTS ON THE MINI-MIAS DATABASE TO REMOVE SPECKLE NOISE OF VARIANCE 0.01

Evaluation Metrics	Filter	mdb001lm	mdb110rl	mdb322rm
MSE	Wiener [3*3]	18.0162	18.639	25.0196
	Median [3*3]	**14.0398**	**15.8415**	**23.2869**
	Adaptive Med [15*15]	23.4088	26.7082	36.5577
	Gaussian Sigma = 0.06	31.9709	36.5021	47.206
	Mean [3*3]	**6.874**	**7.845**	**12.048**
PSNR	Wiener [3*3]	35.6082	35.4606	34.182
	Median [3*3]	**36.6912**	**36.1668**	**34.4937**
	Adaptive Med [15*15]	34.471	33.8983	32.535
	Gaussian Sigma = 0.06	33.1173	32.5416	31.4248
	Mean [3*3]	**39.7927**	**39.2189**	**37.3557**
Blurriness	Wiener [3*3]	0.1617	0.1647	0.16675
	Median [3*3]	**0.19532**	**0.19041**	**0.18578**
	Adaptive Med [15*15]	0.1383	0.13584	0.13426
	Gaussian Sigma = 0.06	0.12205	0.12056	0.1196
	Mean [3*3]	**0.267**	**0.26065**	**0.24901**

D. Experiment 4: Denoising images from the poisson noise

Finally, the last noise type that can be obtained with the mammograms is the Poisson noise. The experiment is done by adding Poisson noise to the same mammograms: mdb001lm, mdb110rl and mdb322rm. The experimental results as shown in TABLE IV show that the mean filter achieves the best performance to denoise the poisson noise but with high blurriness value that cannot be treated by using the median filter as done in case of the speckle noise as the blurriness value is somehow high. The wiener filter has been used to filter the same mammograms but higher MSE is obtained. So, in this case the median filter can be used followed by using one of the sharpness algorithms to maintain the blurring occurred.

E. Experiment 5: Denoising images from the four types of noise

The last experiment is done by adding the four types of noise to all mammograms in the MIAS database: Salt and pepper, Gaussian, Speckle and Poisson noises. The salt and pepper noise and the Gaussian noise are added with different density to the images. The salt and pepper noise are added to the mammograms with density that varies from 0.001 to 0.05 and the Gaussian noise variance varies from 0.001 to 0.05 as well. The speckle noise is added with variance 0.001 since it exists in the mammograms with a small amount. All mammograms are resized to 1024*1024. The filters applied are those that are fitting to each noise type as a result of experiment 1, 2, 3 and 4. They are implemented in different

TABLE IV. THE FILTERS RESULTS ON THE MINI-MIAS DATABASE TO REMOVE POISSION NOISE

Evaluation Metrics	Wiener [3*3]	mdb001lm	mdb110rl	mdb322rm
MSE	Median [3*3]	10.8422	10.6598	13.1126
	Adaptive Med [15*15]	**6.9817**	**7.5476**	**10.101**
	Gaussian Sigma = 0.06	15.0154	16.6323	21.7218
	Mean [3*3]	25.4183	28.0204	35.2187
	Wiener [3*3]	**4.9589**	**5.5262**	**7.4572**
PSNR	Median [3*3]	37.8136	37.8873	36.9879
	Adaptive Med [15*15]	**39.7252**	**39.3867**	**38.1212**
	Gaussian Sigma = 0.06	36.3994	35.9553	34.7958
	Mean [3*3]	34.1133	33.6901	32.6971
	Wiener [3*3]	**41.211**	**40.7405**	**39.4391**
Blurriness	Median [3*3]	0.17702	0.18402	0.18966
	Adaptive Med [15*15]	**0.2164**	**0.21506**	**0.21045**
	Gaussian Sigma = 0.06	0.14497	0.14391	0.14285
	Mean [3*3]	0.12341	0.12316	0.12329
	Wiener [3*3]	**0.27472**	**0.27618**	**0.2658**

sequence till getting the one achieving the lowest MSE and the highest PSNR near to those that are achieved by each experiment as shown in Table V.

The selected sequence of filters applied to denoise the mammograms from the four types of noises are: Adaptive median filter with maximum mask size of 21 followed by the median filter that denoises in the best manner with mask size 9 then the Wiener filter with the same mask size and finally the mean filter with 3 mask size. Different mask sizes are applied starting from 3 to 12 to get the best size that fit the noise using each filter.

TABLE V. THE FILTERS RESULTS ON THE MINI-MIAS DATABASE TO REMOVE POISSION NOISE

# of mammograms	Average MSE	Average PSNR
322	11.3106	37.9023

I. CONCLUSION

Removal of special markings and noise existing in medical images increases the quality of image segmentation. Preprocessing and enhancement of mammograms is necessary to improve the visual quality and detectability of the anomalies present in the breasts. Multiple filters are used for noise denoising and contrast enhancement for the Mini-MIAS mammogram images. From the experiments and results it is concluded that the adaptive median filter is the best from the five filters for removing the salt and pepper noise. It is found that the mean filter achieves the best performance in denoising the Gaussian noise but with higher blurriness value that can be treated by using the wiener filter with mask 3*3 that achieves less blurriness value while denoising the mammograms compared with the mean filter. The mean filter as well achieves the best performance to denoise the speckle noise but with high blurriness value. This value can be treated by using the median filter or the wiener filter with mask 3*3. In case of the poisson noise, it is found that the mean filter achieves the lowest MSE but with high blurriness value that cannot be treated using the median filter as done in case of the speckle noise as the blurriness value is somehow high. The wiener filter has been used to filter the same mammograms but higher MSE is obtained. So, in this case the median filter can be used followed by using one of the sharpness algorithms to maintain the blurring problem. These filters are applied in the following sequence: The adaptive median filter, the median filter, the Wiener filter and finally the mean filter to denoise all the MIAS database achieving the lowest MSE compared with the other most used filters and obtaining the maximum PSNR as well.

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