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# Modified Multi-Wavelet Noise Filtering Algorithm for Mammographic Image Denoising using Recurrent Neural Network

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*Abstract -* The digital mammographic images are affected by several types of noises which require filters to denoise the noise level. This will help the medical practitioner to enhance the image quality of the mammograms and helps them in giving accurate diagnosis. There are so many works on image denoising technique but there are not much which gives emphasis on the mammographic images. . In application point of view medical images are classified as Multispectral Image (used for satellite surveillance), RGB standard colour scheme Image or other digital versions of the film image i.e., in our case its mammographic image. For every image type it requires different approach for denoising because in each type of image, it contains different factors in it. In denoising the mammographic image , the filtering technique that is to be applied depend on its noises at each resolution level of the microns to make the micro-classification of the cancerous tissues to that of the bright water dense patches caused by the calcium salts in the mammary glands. Thus, any single algorithm cannot provide similar performance range for different types of noise because not every method is effective for the scenario of mammographic image denoising. In the given study we have shown a method for the mammographic image denoising which is having higher accuracy and the performance range is suited for denoising applications.raphic image denoising.

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*GJCST-G Classification: F.1.1, I.2*

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*Strictly as per the compliance and regulations of:*

# Modified Multi-Wavelet Noise Filtering Algorithm for Mammographic Image Denoising using Recurrent Neural Network

Swapnil Tamrakar [α] Abha Choubey [σ] & Siddhartha Choubey [ρ]

*Abstract-* The digital mammographic images are affected by several types of noises which require filters to denoise the noise level. This will help the medical practitioner to enhance the image quality of the mammograms and helps them in giving accurate diagnosis. There are so many works on image denoising technique but there are not much which gives emphasis on the mammographic images. . In application point of view medical images are classified as Multispectral Image (used for satellite surveillance), RGB standard colour scheme Image or other digital versions of the film image i.e., in our case its mammographic image. For every image type it requires different approach for denoising because in each type of image, it contains different factors in it. In denoising the mammographic image , the filtering technique that is to be applied depend on its noises at each resolution level of the microns to make the micro-classification of the cancerous tissues to that of the bright water dense patches caused by the calcium salts in the mammary glands. Thus, any single algorithm cannot provide similar performance range for different types of noise because not every method is effective for the scenario of mammographic image denoising. In the given study we have shown a method for the mammographic image denoising which is having higher accuracy and the performance range is suited for denoising applications.

*Keywords: digital mammography, denoising, independent component analysis, wavelet shrinkage.*

## I. Introduction

The disease called Breast cancer is the most common cancer for the women of 35-55 age groups and is the cause of cancer death. In United States more than two million women are diagnosed with breast cancer treatment. The major cause of the disease breast cancer is still unknown hence the prevention is impossible. X-ray mammography imaging technique is used in breast cancer detection. Important sign of breast cancers is microclassification of clusters[1]. In mammograms this microclassifications is seen as nodular points which are of high intensity localized diffusively along the breast and with high contrast.

There is a significant challenge in detecting early signs of breast cancers that is seen on X-ray mammograms because of the major influence of several types of noises dictating the appearance of the final mammogram .The source of these noises may be from origin of malfunctioning equipment or from the faulty practices in recording the imagery data. The problem related to identifying and detecting the breast area which is inflamed with cancer virus, becomes sever with the naked eyes. This makes essential regions invisible or mixed with the noises.

From the past decades it has been observed that several denoising techniques for mammographic image denoising gives poor performance, fail to preserve the features of the image after denoising. Since number of methods are made of range of combination of fuzzy logic, wavelet transformation or of neural network [2-5,12]. So the mammograms shows varying contrast and brightness and hence the information is susceptible to being correlated [6-9]. Some researchers used wavelet transformation where it tends to provide more consolidated results than the other methods [10-11]; thus, the following study gives an effectively modelled algorithm for denoising the noisy mammographic images using multi-wavelet transformation and this will allow easy microclassification which will help radiologist to detect breast cancer easily.

## II. Methedology

### *a) Experimental Setup*

The proposed model is implemented using MATLAB R2012a under Windows platform. The experiments are conducted over the machine with hardware configurations of Intel's third generation 8-core microprocessor with Nvidea 630 graphic card, 2GB RAM giving a fine clocking speed of 2.7 GHz. The consolidated database used in the study is DDSM (Digital Database for Screening Mammography) by the University of South Florida and is available online at [13]. The images used in the study consist of three types and are classified into three types based on the amount of cancer influenced the mammary tissue. The mammographic consists of 16 bits of information and with the resolution ranging from 42-43.5 microns. The images are extracted by the scanners namely DBA, HOWTEK, & LUMSIYS. These canners are deviated based on the optical density required to extract the

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information from the mammogram images. The properties of the used images are represented in the table 1 below.

*Table 1 :* Enlisted database used in the experiment

| Cancer Influence | Size & Bits | Resolutions | Scanners |
|---|---|---|---|
| Normal<br>Cancer<br>Benign | 6.6GB 16 bits<br>6.6GB 16 bits<br>6.1GB 16 bits | 42 microns<br>43.5 microns<br>43.5 microns | DBA<br>HOWTEK<br>LUMSIYS |

*b) The Multi-Wavelet Wavelet Noise Filtering Model*

We employ the multi-wavelet transformation to breakdown the given noisy image into a pyramid of features which is linked to one another in logical manner. This will allow us to perform tree based searching & allocation for a given colour scheme which will be independent from feature decomposition for both high and low resolution image. Therefore, the image can be broken into wavelets by using the following functions as given below:

$$f(x,y) = \frac{1}{\sqrt{MN}}\sum_m \sum_n W_\phi(j_o,m,n)\,\phi_{j_o,m,n}(x,y) + \frac{1}{\sqrt{MN}}\sum_m \sum_n W_\psi^i(j,m,n)\,\psi_{j,m,n}^i(x,y)$$

Where, the indices $j_o, j, m, n$ are the non-negative integers, x & y are the pixels position at point P, M&N are the real valued tensor coefficients, $\phi$ is the scaling function and $\psi$ is the wavelet function in corresponding scaling and wavelet function is given by $W_\phi$, $W_\psi^i$. The scaling coefficients from the given noisy image are at different resolution in a mammogram while the wavelet coefficients from the feature vector in the noise retrieval step; that's the reason why different types of scanners are used in recording the mammogram which in turn is dependent on the optical density.

During the sampling phase the wavelet coefficients can be transformed into feature sets with the generalized association rule by formulating a Gaussian kernel based on the similarity of the coefficients and its characteristics from the given noisy image. The Gaussian kernel so formed s given as:

$$k(x,x') = \frac{1}{N_i}\sum_{x,y \subset R_t} |I_t(x-1,y-1) - I_t(x+1,y+1)|\, e^{\left(-\frac{\|x-x'\|^2}{2\sigma}\right)}$$

Where, $N_i$ is the total number of neighbouring pixels in the spatial region of the pixel position x,y. Here $R_t$ is the regularized threshold value, $I_t$ is the intensity of the pixel value for the diagonal of the pixel region, $\sigma$ is characterised by gradient descent of the standard deviation for a particular band at different scales of the mammogram and x' is the next pixel position. Here, the emphasis is towards evaluating the kernel and updating it by pairing the formulation in association with one another. The flow chart of the work flow process involving the denoising process is given in the figure 5 below. The threshold value of the wavelet to give a denoised image is determined as:

$$R_t(x,x') = \begin{cases} W_\phi * W_\psi^i, if\ \sigma * \phi > \psi \\ 0, \sigma * \phi \le \psi \end{cases}$$

*Algorithm:* The Multi-Wavelet Noise Filtering Algorithm (MWNFA) with RNN

Input: Noisy Mammographic Image I

Output: Denoised Mammographic Image I'

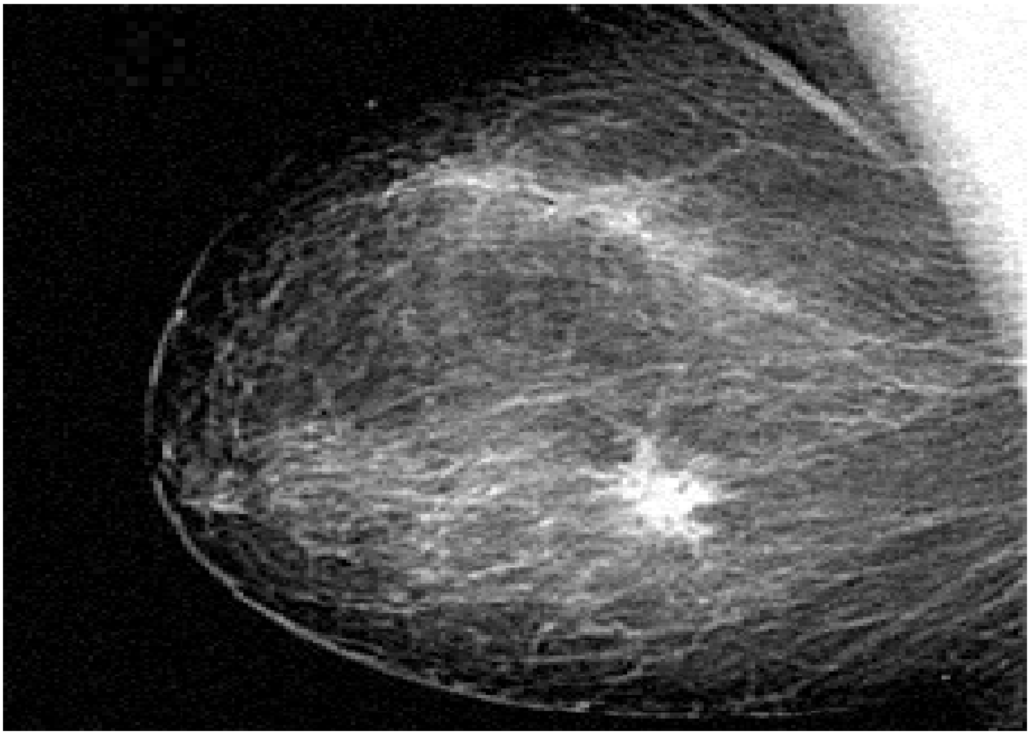


*Figure 1:* Read Input Image I

*Step 1 :* Read the input noisy mammographic image I and use multi-wavelet transformation to breakdown the given noisy image into a pyramid of features which is linked to one another in logical manner as:

$$f(x,y) = \frac{1}{\sqrt{MN}} \sum_{m} \sum_{n} W_{\phi}(j_o,m,n)\, \phi_{j_o,m,n}(x,y) + \frac{1}{\sqrt{MN}} \sum_{m} \sum_{n} W_{\psi}^{i}(j,m,n)\, \psi_{j,m,n}^{i}(x,y)$$

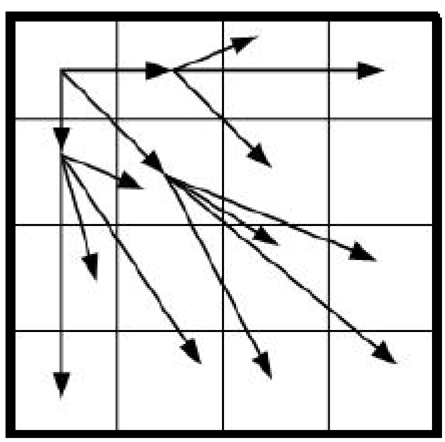

*Figure 2 :* Illustration of the decomposition of wavelets in form of logical manner by using the above equation

*Step 2 :* for each(x,y) //whole pixels of the given image. Evaluate Gaussian kernel in combination with the neighbouring diagonal pixels by:

$$k(x,x') = \frac{1}{N_i} \sum_{x,\ \subset R}^{y\ \ t} |I_t(x-1,y-1) - I_t(x+1,y+1)|\, e^{\left(-\frac{\|x-x'\|^2}{2\sigma}\right)}$$

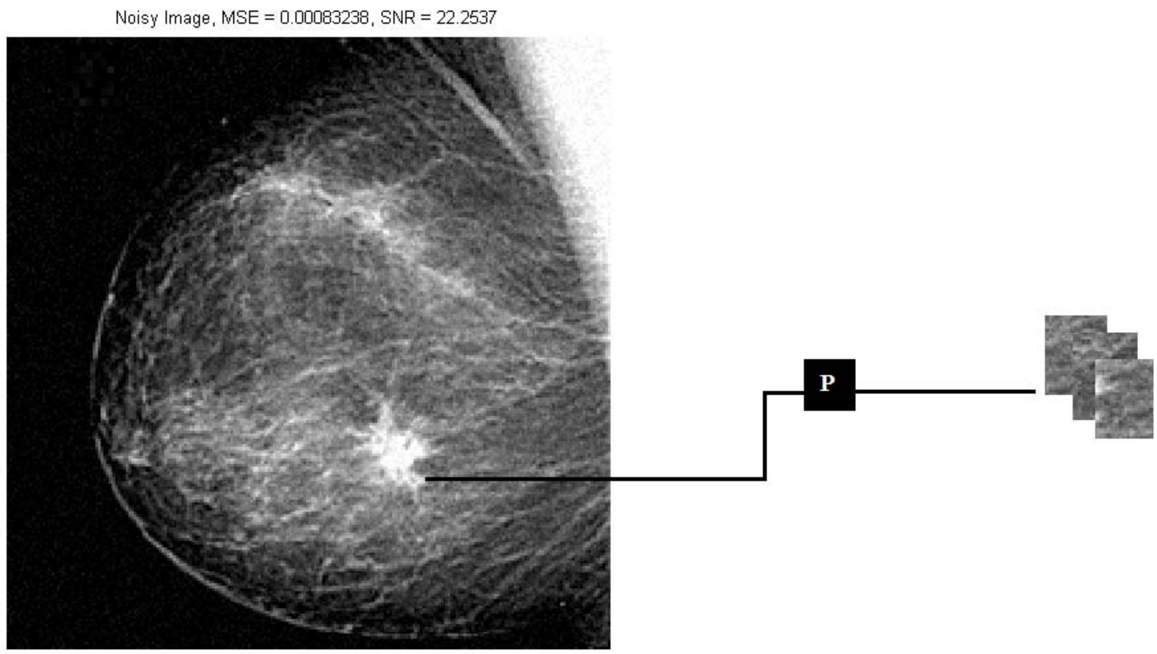


*Figure 3 :* Illustration of the formation of Gaussian kernels of wavelets localised in a neighbouring region of the pixel position x,y

*Step 3 : Initalize*thresholding for $U_1$ (weight matrices of the input layer):

$$R_t(x,x') = \begin{cases} W_\phi * W_\psi^i, if\ \sigma * \phi > \psi \\ 0, \sigma * \phi \leq \psi \end{cases}$$

*Step 4 :* end for

*Step 5 : Use* recurrent Neural Network to make the algorithm adaptable to denoising for different noise types; with the help of following equation:

$$H_T^{(i)} = sig\left(U_1 W_\phi + tanh\left(W_\phi^{T-1}, W_\psi^{T-1}\right)\right)$$

$$Y(T) = U_2\ .\ tanh\left(H_T^{(i)}.\ b_{t-1}\right)$$

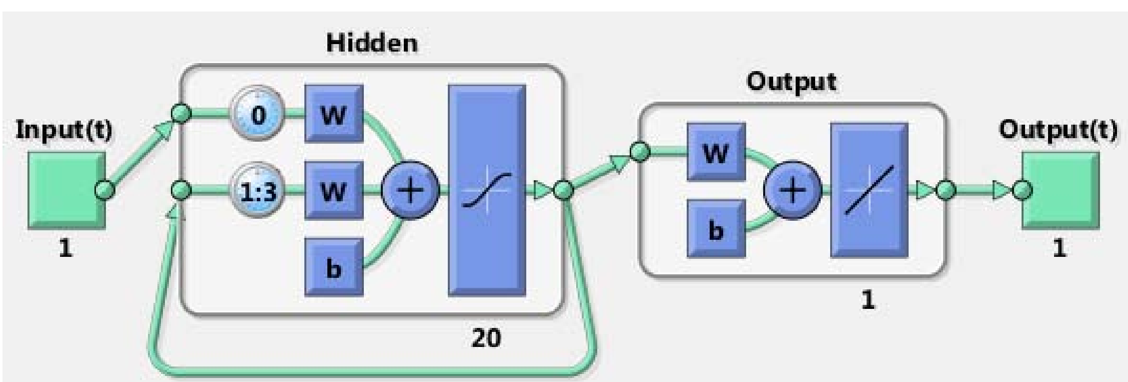


*Figure 4 :* Illustration of the architecture for the trained recurrent neural network

Where, $H_T^{(i)}$ is the hidden layer at time T, tanh is the activation function, $W_\phi^{T-1}$& $W_\psi^{T-1}$is the scaling and wavelet function for the pixel evaluated at time step T-1, Y(T) is the output of the output layer, U is the weight matrix, $b_{t-1}$is the bias from the previous time step T-1, $U_1$& $U_2$are the weight matrices of the input layer and the recurrent layer from the hidden layer respectively. Here we have used 20 hidden neurons of one layer.

*Step 5 :* Update Colour bands at x,y based on recurrently adjusted weight matrix $U_2$& Show Output I'

$$R_t\left(x, x'\right) = Y(T)$$

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*Figure 5 :* Output Denoised Image I

*Step 6 :* End Process

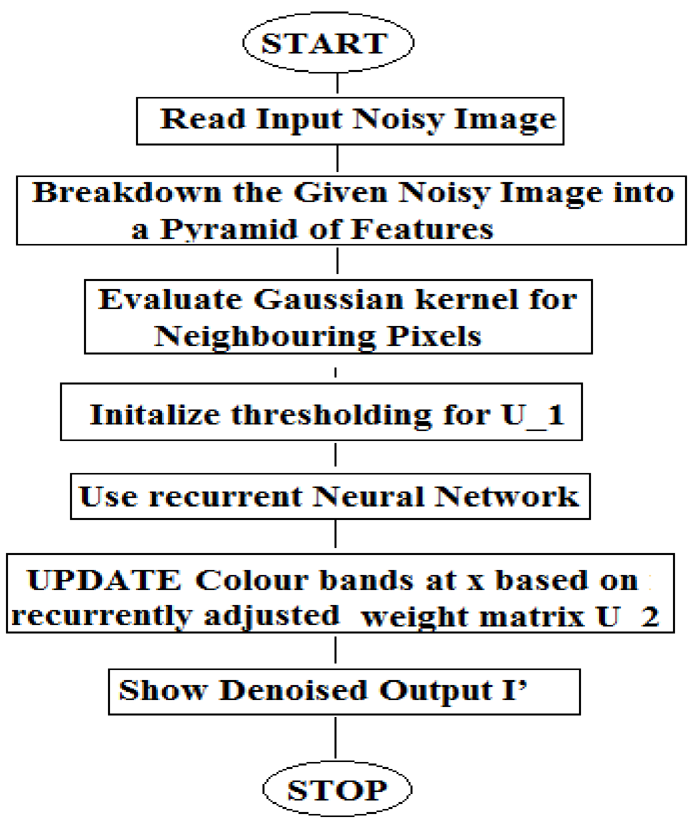


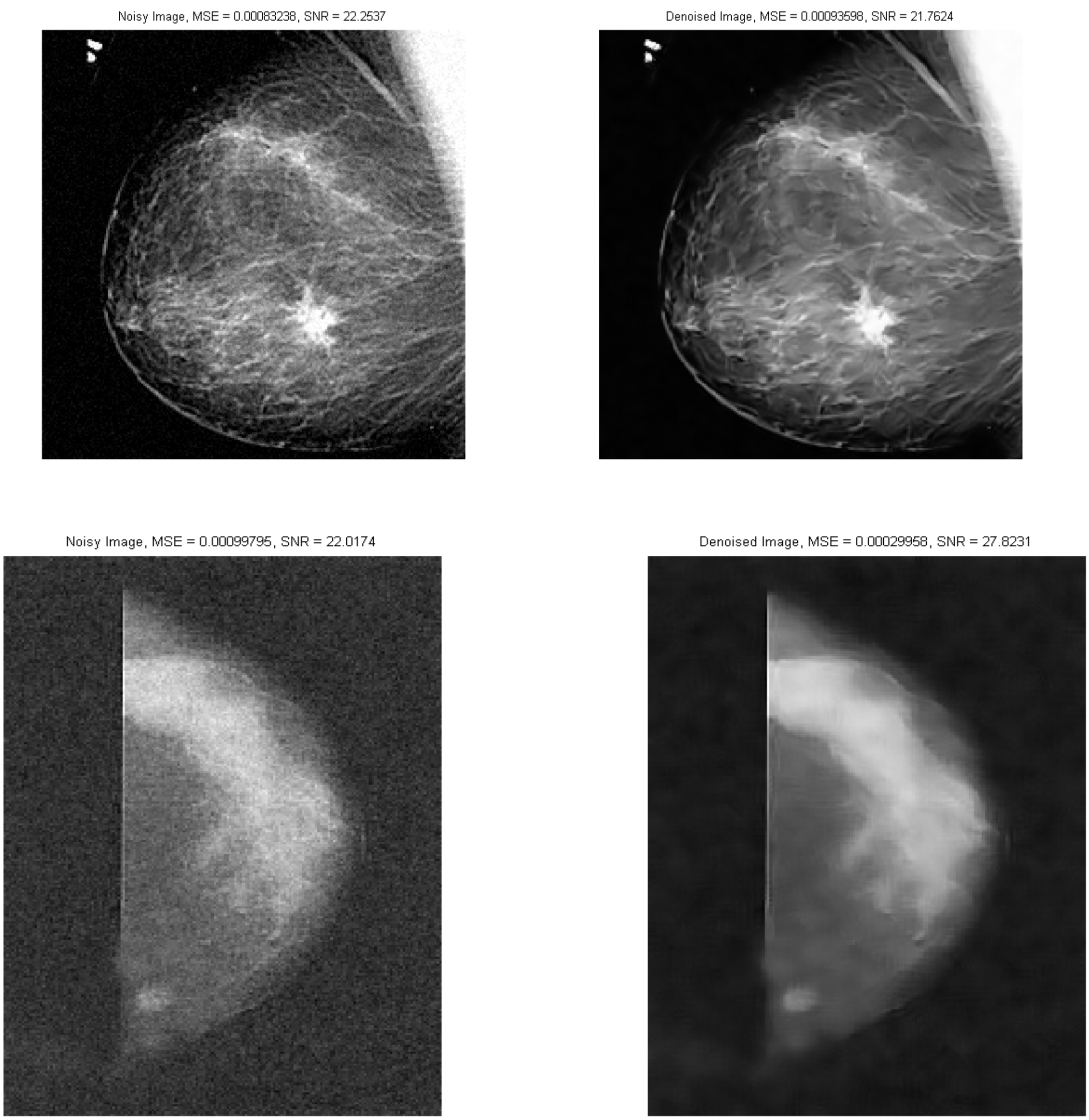

*Figure 6 :* Flow chart of the MWNFA+RNN algorithm

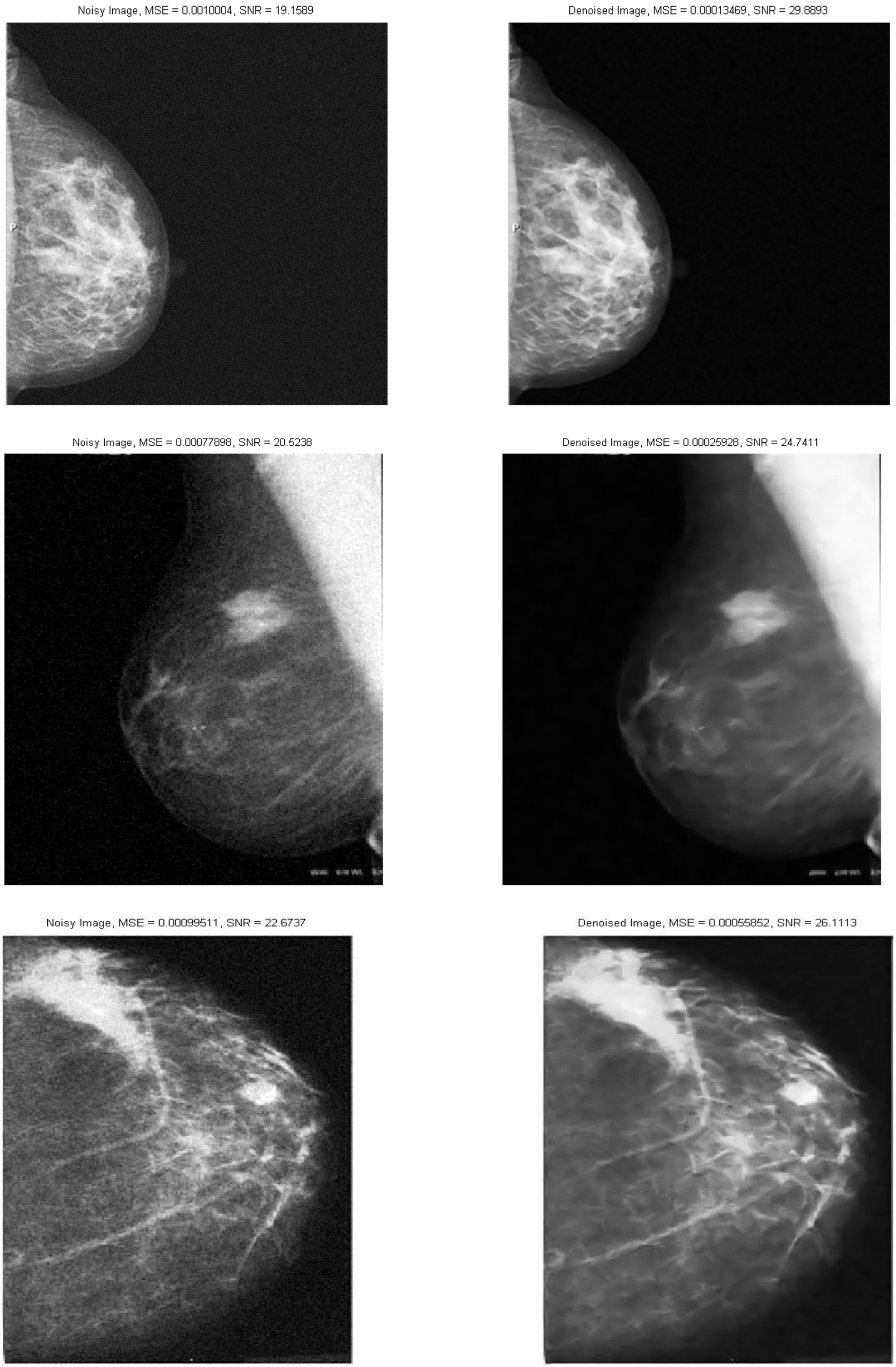
## III. Conclusion

*Table 1 :* The tabular comparison results of the digital mammograms for different images from DDSM database

| Noise percentage (%) | Wiener | Wavelet | MWNFA | MWNFA+RNN |
|---|---|---|---|---|
| 10.07 | 3.53 | 3.24 | 5.68 | 7.68 |
| 25.05 | 15.97 | 13.62 | 17.89 | 17.89 |
| 34.94 | 22.43 | 23.38 | 26.34 | 35.34 |
| 45.28 | 33.33 | 33.79 | 37.12 | 45.12 |

We have presented the quantifying success of the proposed algorithm against the three mostly used techniques for denoising the digital mammographic images. The above table 1 represents the performance range of mammographic images with different amount of noise influence represented in form of noise percentage for a DDSM database. The figure 6 shows some of the samples of denoising results where MSE (Mean Signal Error) & SNR (Signal to Noise Ratio) are the two standard parameters used to compare the performance of denoising. The assessment of comparative performance results for the denoising methods with that of the MWNFA algorithm suggest the affectivity of performance for the proposed method against the previous methods. The quality denoising without elimination of the features of the mammographic imagery data by MWNFA+RNN has improved the previous denoising technique and shall effectively make the medical practitioner to easily identify and consequently diagnose properly to the cancer influenced patients.




Noisy Image, MSE = 0.0010004, SNR = 19.1589
Denoised Image, MSE = 0.00013469, SNR = 29.8893
Noisy Image, MSE = 0.00077898, SNR = 20.5238
Denoised Image, MSE = 0.00025928, SNR = 24.7411
Noisy Image, MSE = 0.00099511, SNR = 22.6737
Denoised Image, MSE = 0.00055852, SNR = 26.1113

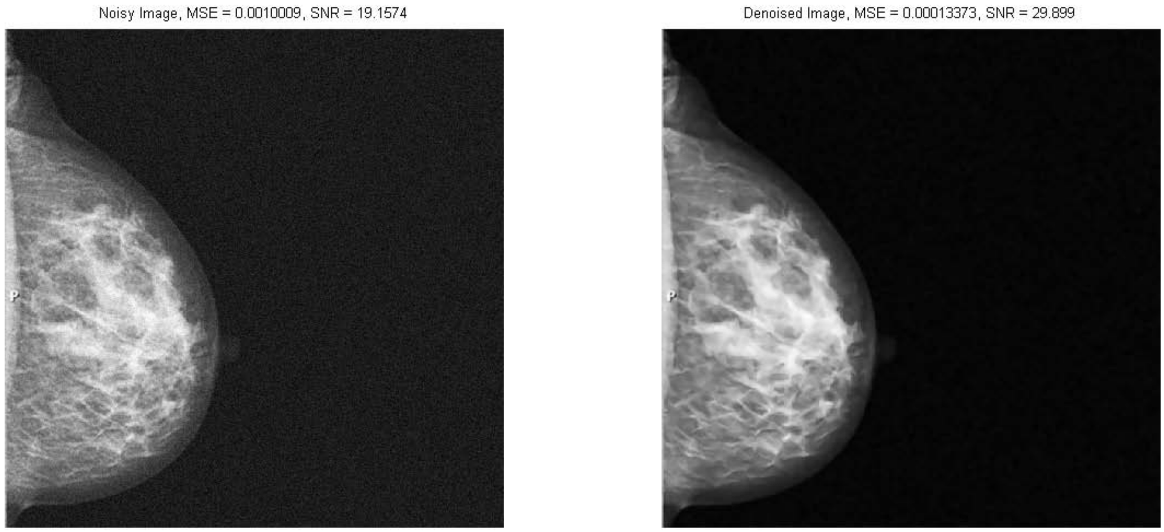



*Figure 7:* Sample results of the denoised mammographic images from the DDSM database

## IV. Acknowledgement

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