INTRODUCTION

Breast cancer is the common cancer among the women of 35-55 age groups and is the leading cause of cancer deaths followed by lung cancers. Over more than two million women alone in the United States are diagnosed with the breast cancer treatment. Although the prevention against such deadly disease is impossible as the cause of this disease is still unknown, at the moment the early detection and prognosis/diagnosis is of vital steps in countering this disease. The imaging techniques such as X-ray mammography are primarily used in the detection of cancer. Here, in this scenario, the microclassification of clusters is the important sign of breast cancers [1]. In mammograms, these microclassifications appear as nodular points with high contrast or of high intensity localized diffusively along the breast.

However, there is a significant challenge in detection of early signs of breast cancers that appear on X-ray mammograms due to the major influence of various sorts of noises dictating the appearance of the final mamogram. These noises can be of the source of origin from malfunctioning equipment or from the faulty practices in recording the imagery data. This lead to the problem of identifying and detecting the breast area inflamed with cancer virus from the naked eyes. Thereby, making it suspicious to heavily rely on the noise corrupted imagery data surrounding the breast tissues; making essential regions invisible and allocation for a given color in logical manner. This will allow us to perform tree based searching functions as given below:

\[
t(x,y) = \sum_{m} \sum_{n} W_{i}^{l}(l_{m,n})\psi_{m,n}(x,y) + \sum_{m} \sum_{n} W_{i}^{m}(l_{m,n})\psi_{m,n}(x,y)
\]

Methods: In this study, we present a solution for the same by utilizing multi-level wavelet transformation to enable preservation of micron level details in the images.

RESULTS AND CONCLUSION: The quality denoising without elimination of the features of the mammographic imagery data by MWTA will allow the medical practitioners to easily identify and consequently diagnose properly to cancer influenced patients.

Keywords: Digital mammography, Wavelet transformation, Medical image denoising.
Where, the indices \( i, j, m, n \) are the non-negative integers, \( x \) and \( y \) are the pixels position at point \( P, M \) and \( N \) 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 \( W_{\phi}, W_{\psi} \).

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 is given as:

\[
k(x, x') = \frac{1}{N} \sum_{x, y \subseteq R_i} W_{\phi}(x_i, x_j, m, n) \phi(x_i, x_j) \psi(x_i, x_j)
\]

Where, \( N \) is the total number of neighboring pixels in the spatial region of the pixel position \( x, y \). Here, \( R_i \) is the regularized threshold value, \( I_i \) is the intensity of the pixel value for the diagonal of the pixel region, \( \sigma \) is characterized 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 toward 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 Fig. 1. The threshold value of the wavelet to give a denoised image is determined as:

\[
R_t(x, x') = \begin{cases} W_{\phi} * W_{\psi}, & \sigma > \psi \\ 0, & \sigma \leq \psi \end{cases}
\]

Algorithm: Multi-wavelet transformation algorithm (MWTA) \( x' \)

Input: Noisy mammographic image \( I \) (Fig. 2)

Output: Denoised mammographic image \( I' \)

Step 1: Read the input noisy mammographic image \( I \) and use multi-wavelet transformation (Fig. 3) to break down the given noisy image into a pyramid of features which is linked to one another in logical manner as:

\[
f(x, y) = \frac{1}{\sqrt{MN}} \sum_{m} \sum_{n} W_{\phi}(k_i, m, n) \phi(k_i, m, n)(x, y) + \frac{1}{\sqrt{MN}} \sum_{m} \sum_{n} W_{\psi}(k_i, m, n) \psi(k_i, m, n)(x, y)
\]

Step 2: For each \( (x, y) \) / whole pixels of the given image.

Evaluate Gaussian kernel (Fig. 4) in combination with the neighboring diagonal pixels by:

\[
k(x, x') = \frac{1}{N} \sum_{x, y \subseteq R_i} W_{\phi}(x_i, x_j, m, n) \phi(x_i, x_j) \psi(x_i, x_j)
\]

Step 3: Determine threshold value

\[
R_t(x, x') = \begin{cases} W_{\phi} * W_{\psi}, & \sigma > \psi \\ 0, & \sigma \leq \psi \end{cases}
\]

Step 4: End for

Step 5: Update color bands at \( x, y \) and show output \( I' \) (Fig. 5).

Step 6: End process.

CONCLUSION

We have presented the quantifying success of the proposed algorithm against the three mostly used techniques for denoising the digital mammographic images. Table 2 represents the performance range of mammographic images with different amount of noise influence represented in the form of noise percentage for a DDSM database.

Fig. 6 shows some of the samples of denoising results where mean signal error and 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 MWTA algorithm suggests the affectivity of performance for the proposed method against the previous methods. The quality
Table 2: The tabular comparison results of the digital mammograms for different images from DDSM database

| Noise percentage (%) | Wiener | Wavelet | ICA | MWTA |
|----------------------|--------|---------|-----|-------|
| 10.07                | 3.53   | 3.24    | 3.71| 5.68  |
| 25.05                | 15.97  | 13.62   | 14.05| 17.89 |
| 34.94                | 22.43  | 23.38   | 23.71| 26.34 |
| 45.28                | 33.33  | 33.79   | 34.28| 37.12 |

MWTA: Multi-wavelet transformation algorithm, ICA: Independent component analysis, DDSM: Digital database for screening mammography
denoising without elimination of the features of the mammographic imagery data by MWTA will allow the medical practitioner to easily identify and consequently diagnose properly to cancer influenced patients.

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