Breast Cancer Diagnosis: An Intelligent Detection System Using Wavelet Neural Network

V. Dheeba[1], N. Albert Singh[2], and J. Amar Pratap Singh[1]

[1] Department of Computer Science and Engineering,
Noorul Islam University, Kumaracoil, TN, India
{deeps_3u4,japsindia}@yahoo.com
[2] Bharat Sanchar Nigam Limited, Nagercoil, TN, India
mailalbertsingh@yahoo.co.in

Abstract. Breast cancer represents the leading cause of fatality among cancers for women and there is still no known way of preventing this pathology. Early detection is the only solution that allows treatment before the cancer spreads to other parts of the body. Diagnosis of breast cancer at the early stage is a very difficult task as the cancerous tumors are embedded in normal breast tissue structures. Aiming to model breast cancer prediction system, we propose a novel machine learning approach based on wavelets. The new model, called wavelet neural network (WNN), extends the existing artificial neural network by considering wavelets as activation function. The texture information in the area of interest provides important diagnostic information about the underlying biological process for the benign or malignant tissue and therefore should be included in the analysis. By exploiting the texture information, a computerized detection algorithm is developed that are not only accurate but also computationally efficient for cancer detection in mammograms. The texture features are fed to the WNN classifier for classification of malignant/benign cancers. An experimental analysis performed on a set of 216 mammograms from screening centres has shown the effectiveness of the proposed method.

Keywords: Breast Cancer, Computer Aided Diagnosis, Mammograms, Texture, Wavelet Neural Network.

1 Introduction

Breast cancer is the second frequently diagnosed cancer among women, especially in developed countries. In western countries about 53%-92% of the population has this disease. Though breast cancer leads to death, early detection of breast cancer can increase the survival rate. The current diagnostic method for early detection of breast cancer is mammography. Mammography still remains the key screening tool because it represents the most effective, low-cost and highly sensitive technique allowing the diagnosis of a breast cancer at a very early stage [1]. The mammograms are checked by the radiologist with the aim of detecting the abnormalities, but the complex

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structures and the signs of earlydisease are very small and subtle. Mammographies are low dose X-ray projections of the breast, and it is the best method for detecting cancer at the early stage.

Microcalcifications (MC) are quiet tiny bits of calcium, and may show up in clusters or in patterns and are associated with extra cell activity in breast tissue. Usually the extra cell growth is not cancerous, but sometimes tight clusters of microcalcification can indicate early breast cancer. Scattered microcalcifications are usually a sign of benign breast cancer. 80% of the MC is benign. MC in the breast shows up as white speckles on breast X-rays. The calcifications are small; usually varying from 100 micrometer to 300 micrometer, but in reality may be as large as 2mm. Though it is very difficult to detect the calcifications as such, when more than 10 calcifications are clustered together, it becomes possible to diagnose malignant disease. But the survival depends on how early the cancer is detected. So, any MC formation should be detected at the benign stage. Hence, a Computer Aided Diagnosis (CAD) system is used to detect MC clusters [6, 12, 13]. Many different algorithms have been proposed for automatic detection of breast cancer in mammograms. Features extracted from mammograms can be used for detection of cancers [2]. Studies reports that features are extracted from the individual MCs [3, 11] or from the ROI which contain MC clusters [4].

Matthew A. Kupinski et al. [9] presents a radial gradient index based algorithm and a probabilistic algorithm for detecting lesions in digital mammograms. Shape constraints are used to regularize the partitions analyzed, and simplifying the partition selection process by using utility functions based either on a single feature or probabilities. Nevine H. Eltonsy et al. [10] presents a method based on the presence of concentric layers surrounding a focal area with suspicious morphological characteristics and low relative incidence in the breast region. The suspicious focal area is localized using the morphological features and based on the minimum distance criterion the redundant focal areas are eliminated. The presence of concentric layers around the suspected focal regions is analyzed using multiple concentric layer criterions to detect the suspicious regions.

Berman Sahiner et al. used a Convolution Neural Network (CNN) classifier to classifier the masses and the normal breast tissue [5]. First, the Region of Interest (ROI) of the image is taken and it was subjected to averaging and subsampling. Second, gray level difference statistics (GLDS) and spatial gray level dependence (SGLD) features were computed from different subregions. The computed features were given as input to the CNN classifier.

Feature extraction phase is the key step in detecting abnormalities in mammograms [7]. Features are extracted from the ROI of the mammograms. Normal Texture measures includes mean, variance, etc which will be concatenated to a single feature vector and will be fed to a classifier to perform classification. The drawback in this method is much of the important information contained in the whole distribution of the feature values might be lost. MC clusters usually appear as a few pixels with brighter intensity embedded in a textured background breast tissue. By effectively extracting the texture information within any ROI of the mammogram, the region with abnormalities and the region without abnormalities can be differentiated. Laws texture energy measures (LTEM) has proven to be a successful method to highlight high energy points in the image. Anna et al. 2008 [8] suggests that LTEM has a best feature in analyzing texture of tissue for BC diagnosis. By considering the basic feature set like kurtosis, skewness, mean and Standard Deviation the accuracy achieved using LTEM is 90%.

The major objective of this paper is to take multiple texture features from the original image to discriminate between abnormal and the normal tissue in the breast. As a first stage, the original image is preprocessed and Region of Interest (ROI) is taken and features are extracted from the ROI image using Laws features. In the second stage, the extracted features are compared by means of their ability in detecting breast cancer using WNN. The database images have four different kinds of abnormalities namely: architectural distortions, stellate lesions, Circumscribed masses and calcifications. The proposed method is capable of detecting these abnormalities.

2 Image Preprocessing

All clinical mammograms used for this study were collected from screening clinics were positive for presence of microcalcifications. Mammograms were collected from 54 patients and all these patients have agreed to have their mammograms to be used in research studies. For each patient 4 mammograms were taken in two different views, one is the Craniocaudal (CC) and the other is the Mediolateral Oblique (MLO) view. The two projections of each breast (right and left) were taken for every case. For this study a total of 216 mammograms were taken, all the mammograms were digitized to a resolution of 290 x 290 Dots per Inch (DPI) which produces 24 bits/pixel. Each digitized mammograms was incorporated into a 2020 x 2708 pixel image (5.47 Mpixels).

The goal of preprocessing the image is to simplify recognition of abnormality without throwing away any important information. As a preprocessing step the breast area is separated from the background image. The breast area is chosen as ROI for the next stage of processing. This saves the processing rime and also the memory space. The block diagram of the proposed breast cancer detection methodology is shown in Fig. 1.

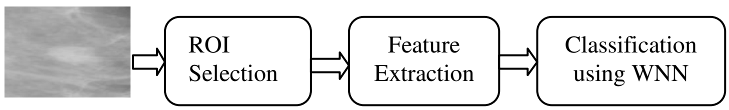

Fig. 1. Block Diagram of Proposed Methodology

3 Feature Extraction Methodology

3.1 Texture Feature Extraction

In image processing the texture of a region describes the pattern of spatial variation of gray tones (or in the different color bands in a color image) in a neighborhood that is small compared to the region. Texture features were extracted from the ROI in order to be used for classification of abnormalities. In image processing the texture of a region describes the pattern of spatial variation of gray tones in a neighborhood that is small compared to the region. By definition, texture classification is to identify the texture class in a region. The texture energy measures developed by Kenneth Ivan Laws [7] at the University of Southern California have been used for many diverse applications. These texture features are used to extract texture energy measures (TEM) from the ROI containing abnormalities and normal breast tissues [8]. These measures are computed by first applying small convolution kernels to the ROI and then performing a windowing operation. A set of 25, 5 x 5 convolution masks is used to compute texture energy, which is then represented by a vector of nine numbers for each pixel of the image being analyzed. The 2-D convolution kernels for texture discrimination are generated from the following set of 1-D convolution kernels of length five. The texture descriptions used are level, edge, spot, wave and ripple.

$$
\begin{aligned}
L5 &= [1 \quad 4 \quad 6 \quad 4 \quad 1] \\
E5 &= [-1 \quad -2 \quad 0 \quad 2 \quad 1] \\
S5 &= [-1 \quad 0 \quad 2 \quad 0 \quad -1] \\
W5 &= [-1 \quad 2 \quad 0 \quad -2 \quad 1] \\
R5 &= [1 \quad -4 \quad 6 \quad -4 \quad 1]
\end{aligned}
$$

From this above 1-D convolution kernels 25 different two dimensional convolution kernels are generated by convoluting a vertical 1-D kernel with a horizontal 1-D kernel. Texture energy measures are identified for each pixel in the ROI of a mammogram image by means of the following steps.

Step 1: Apply the two dimensional mask to the preprocessed image i.e. the ROI to get $F(i, j)$, where $F(i, j)$ is a set of 25 $N \times M$ features.

Step 2: To generate the TEM at the pixel, a non-linear filter is applied to $F(i, j)$. The local neighborhood of each pixel is taken and the absolute values of the neighborhood pixels are summed together. A 15×15 square matrix is taken for doing this operation to smooth over the gaps between the texture edges and other micro-features. The TEM features are obtained using equation (1)

$$E(x, y) = \sum_{j=-7}^{7} \sum_{i=-7}^{7} \left| F(x+i, y+j) \right| \tag{1}$$

Step 3: The texture features obtained from step 2 is normalized for zero-mean.

4 Proposed WNN Classifier

Recently, Wavelet Neural Network (WNN) have found many applications in function approximation, pattern recognition and signal processing. Wavelets have many desired properties like compact support, orthogonality, localization in time and frequency and fast algorithms. Wavelet networks are a class of neural networks that employ wavelets as activation functions [14, 15]. To identify the true cancer pixels (abnormality) in the mammograms, a good and optimized classification method has to be employed.Wavelets are functions that satisfy certain mathematical requirements and are used in representing data or other functions. These algorithms process data at different scales or resolutions. A wavelet is a real or complex valued function $\Psi(.)$ satisfying the following conditions,

$$\int_{-\infty}^{\infty} \Psi(u)du = 0 \text{ and } \int_{-\infty}^{\infty} \left|\Psi^2(u)\right| du = 1 \tag{2}$$

There are two functions in wavelet transform namely the scale function and the mother wavelet. Wavelets are powerful signal analysis tools. They can approximately realize the time-frequency analysis using a mother wavelet. The mother wavelet has a square window in the time- frequency space. Wavelet Neural Networks are designed by employing wavelet as hidden layer activation function. The proposed Wavelet Neural Network is a three-layer structure with input layer, hidden layer and output layer. Let Ψ be the activation function and is defined as the sum of the weighted inputs plus the bias and is represented as,

$$y_k^p = \Psi(s_k^p) \tag{3}$$

Where $s_k^p = \sum_j w_{j,k} y_j^p + \theta_k$, y_k^p is the output of the k^{th} neuron when a pattern p is fed, $w_{j,k}$ is the weight from the j^{th} neuron and θ_k is the bias value of the k^{th} neuron in the hidden layer and it is defined by wavelet activation function.

5 Experimental Results

The performance of the proposed methodology was tested on digitized mammograms collected from mammogram screening centers. The WNN algorithm classifies the input image into malignant and benign regions. For the classification experiments, the training dataset contain a total of 1064 patterns from the real database. These patterns contains pixels including true individual microcalcification clusters, circumscribed masses, ill defined masses and also pixels indicating normal tissues that includes blood vessels and dense breast tissues. If a mammogram is denser the margins are obscured and not clearly seen. Hence it is difficult for a radiologist to identify the mass in a denser tissue. Fig. 2 shows the detection of a mass in an obscured mammogram using the WNN classifier.

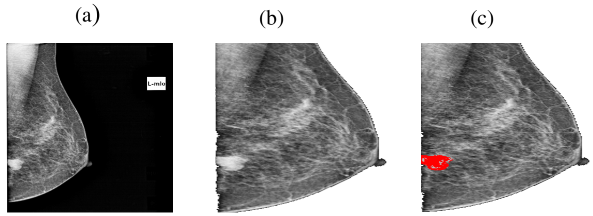

Fig. 2. Detection results of masses in mammogram (a) Original Image (b) ROI image (c) Classified Abnormality Region

Fig. 2 (a) shows the original image in the MLO view of the left breast mammogram and (b) shows the result after segmentation of ROI. Fig. 2 (c) shows the detected malignant masses in a denser mammogram. The real time mammograms are taken in varying intensities and hence detecting abnormalities in mammograms is a difficult task.

The main aim of the proposed system was that no case of malignancy-indicating microcalcification should escape radiological analysis. We therefore started from two basic assumptions: (i) the microcalcifications have an aspect that differentiates them from the other elements of the breast because of their different X-ray opacity; and (ii) since we are looking for microcalcifications that are in an incipient stage, they involve a very small proportion of the total area of the breast because they otherwise would be clearly visible to any radiologist and there would consequently be no point in using our system. Microcalcification clusters are tiny calcium deposits and these clusters that fail to demonstrate features characteristic of benignity have to be evaluated to determine for malignancy and their exact location in the breast. A mammographically significant cluster is usually considered to be 3-10 calcific particles within a volume of 1 cm^2.

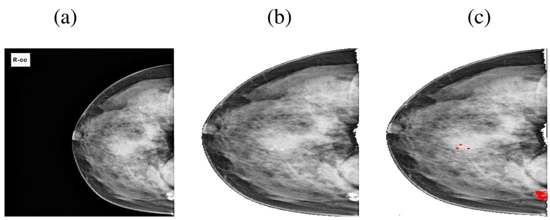

Fig. 3. Detection results of abnormality in real clinical Mammogram using WNN (a) Original Image (b) ROI image (c) Classified Abnormality Region

Fig. 3 (a) shows the ROI image of a digital mammogram in and Fig. 3 (b) shows the WNN classified microcalcification marked with red circles. The detected regions in a mammogram corresponding to tumor tissues have different texture patterns and gray levels than the normal ones and by employing WNN classifier it is possible to classify these regions. Several metrics can be determined for quantitative evaluations of the intelligent classifier. Receiver operating characteristic (ROC) curve is drawn with the sensitivity and specificity values. Fig. 4. shows the ROC curve for the proposed method. Sensitivity measures the proportion of actual positives which are correctly identified when the mammogram contains cancers tissues in it. Specificity measures the proportion of negatives which are correctly identified when cancer is not present in the mammogram. The following statistics can be defined,

$$sensitivity = \frac{TP}{(TP+FN)} \qquad specificity = \frac{TN}{(TN+FP)}$$

The overall performance of diagnostic systems has been measured and reported in terms of classification accuracy which is the percentage of diagnostic decisions that proved to be correct.

$$Accuracy = \frac{(TP+TN)}{(TP+FP+TN+FN)}$$

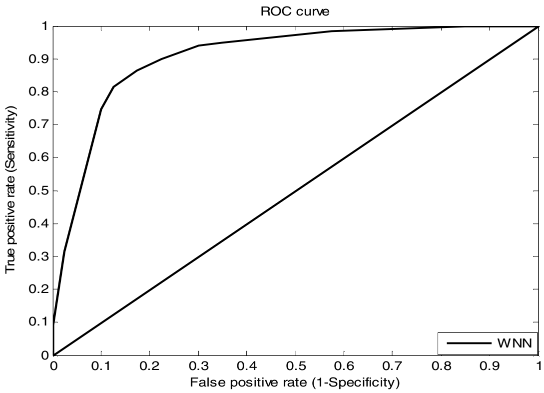

Fig. 4. ROC Curve for WNN Classifier

The WNN approach generates a sensitivity of 86.441 % with a specificity of 82.5 %. The misclassification rate is found to be 0.14557. When optimized learning is introduced, there is an improvement in classification accuracy which is 85.443%. Therefore, WNN have a great potential to be applied in automatic detection of abnormalities in mammograms by reducing the misclassification rate.

6 Conclusion

The novel approach presented in this paper demonstrated that the WNN classifier produces an improvement in classification accuracy to the problem of computer-aided analysis of digital mammograms for breast cancer detection. The algorithm developed here classifies mammograms into normal & abnormal. First, the ROI of the image is chosen then Laws features are extracted and classified using wavelet neural networks. Using the mammographic data from the real clinical centers a classification accuracy of 85.443% was achieved using the proposed approach. In our future work we would like to focus on expanding this research to find the appropriate rate for learning and momentum and test on a larger real time dataset using optimization technique applied to the WNN classifier. This might further improve classification accuracy.

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