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Detection of microcalcifications in digital mammogram using wavelet analysis

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Abstract: - Clusters of microcalcifications in digital mammograms are important and early sign of breast cancer. This paper presents CAD system for detection of clusters of microcalcifications in digital mammograms. Microcalcifications are tiny deposits of calcium in breast tissue. Dense nature of breast tissue and poor contrast of mammograms prohibit effectiveness in detecting microcalcifications. Thus, to detect and differentiate the microcalcifications from normal tissue, proposed system uses wavelet analysis. Proposed system also makes use of extreme learning machine which has better generalization performance at extremely fast learning speed. ELM also avoids problems like local minima, improper learning rate. In this proposed system, raw mammographic image taken from MIAS database and it is morphologically preprocessed to remove labels and noise. Then, windowing function is applied to extract sub images of 32×32. Sub images are decomposed into 4 levels and wavelet features are computed. Whole process is supported with Extreme Learning Machine which is used as classifier.

Keywords: - *Mammograms, Microcalcifications, Wavelet, Extreme Learning Machine.*

I. INTRODUCTION

Today, breast cancer is most frequent and prevalent cancer among women, especially in the western country. It is leading cause of mortality in women each year [1]. According to cancer fact sheets of World Health Organization, more than 1, 50,000 women worldwide die due to breast cancer each year. Nearly 8-13% women develop breast cancer at some point during their lives. Survival rate is directly proportional to stage at which it is detected. Clusters of microcalcifications in digital mammograms are early and important sign of breast cancer. These are considered to be best indicators for malignancy. Detection of early signs of breast cancer requires high quality images and high degree of accuracy in interpretation.

Nowadays, mammography remains most effective diagnostic technique for early breast cancer detection. Microcalcifications are tiny deposits of calcium whose general size ranges from 0.1 mm to 1 mm. And average size is 0.3 mm. When three or more than 3 deposits of calcium comes together, it forms clusters of microcalcification. Due to very small size of microcalcifications, interpretation of their presence is very difficult. They can be overlooked by radiologists. To provide confirmation to radiologists for their diagnostic decisions and to improve accuracy and sensitivity of detection, a variety of computer Aided Diagnostic (CAD) systems have been proposed, where CAD is basically computer based systems which incorporates expert knowledge of radiologists to provide second opinion in detecting abnormalities and making diagnostic decisions. But, still to detect presence of microcalcifications remains a big challenge due to fuzzy nature and poor contrast of mammograms. Microcalcifications are high frequency components with low frequency background and high frequency noise.

Thus, this paper gives a technique to detect microcalcifications in digital mammograms giving it to approach of wavelet analysis and extreme learning machine.

This paper is organized as follows: Section II gives literature review of this proposed system. Section III flow chart of the proposed system. Section IV discusses details of database collection. Section V explains complete detail methodology of proposed system. Section VI gives experimental results. Section VII provides conclusion of this proposed paper.

II. LITERATURE SURVEY

In literature, various techniques are described to detect presence of microcalcifications in digital mammograms. Bouyahia et.al. proposed wavelet based detection of microcalcifications in digitized mammograms[3]. He used undecimated wavelet transform, multi-scale product and wavelet packets transform for automatic detection of microcalcifications. M. Salmeri et.al. invented technique of mammographic image enhancement and denoising for breast cancer detection using dyadic wavelet processing [4]. He implemented a method which has its adaptability to the different nature of diagnostic relevant features in the image permitting use of same core algorithm for both microcalcifications and mass detection. Yu et.al. presented a CAD system for the automatic detection of clustered microcalcifications using neural network classifiers through two steps. In first step, microcalcification pixels are detected and in second step, individual microcalcification objects are detected [5]. Netsch et.al proposed a detection scheme for the automatic detection of clustered microcalcifications using multiscale analysis based on Laplacian-of-Gaussian filter [6]. Barman et.al. used a low pass filter to detect microcalcifications by analyzing digital mammograms [7]. Mascio et.al. developed a microcalcification detection algorithm, which operates on digital mammograms by combining morphological image processing with arithmetic processing [8]. Karssemeijer developed a statistical method for detection of microcalcifications in digital mammograms [9].
This proposed system uses extreme learning machine algorithm to train the neural network and uses Haar wavelets along with it for feature extraction to detect microcalcifications in digital mammograms.

III. FLOW CHART OF THE SYSTEM

In this section, flow of the proposed system is given as shown in figure 1. First of all stages, morphological preprocessing is done on digitized raw mammogram. Then skin lined breast image is produced and segmentation of that skin lined breast image is done by presenting it in 32×32 sub images. Then features are extracted from the mammograms using haar wavelet as it is easily decomposed. Then, selection of classifier is done and extreme learning machine is used as classifier to support wavelet based feature extraction. Thus the whole process is carried in above steps to detect micro calcified clusters in digital mammograms.

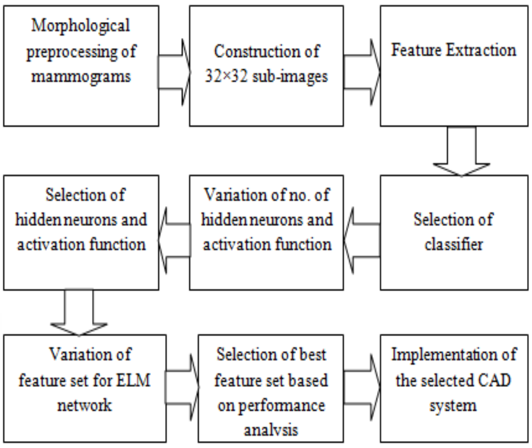

Figure 1. Block Diagram

IV. DATABASE COLLECTION

Sample images are taken from the Mammographic Image Analysis Society (MIAS) [2], an organization of research group in U.K. that are enthusiastic in the understanding in mammograms and generated a database of digital mammograms. Films in database are taken from the UK national breast screening program have been digitized to 50µm pixel edge with Joyce-Loebl scanning microdensitometer, a device linear in optical density range (0-3.2) and representing each pixel with 8 bit word. The database contains 322 digitized films and is available on 2.3 GB, 8 mm tape. It also includes radiologists truth markings, so called the ground truth on the locations of any abnormalities that may present. Database has been reduced to 200 µm pixel edge and padded so that all the images are 1024×1024.

V. METHODOLOGY

Proposed system of microcalcification detection consists of various steps, namely, Morphological preprocessing of digital mammograms, segmentation in 32×32 sub images, Texture analysis, Feature extraction which is based on haar wavelet giving it approach of extreme learning machine. Raw mammographic image is taken of size 1024×1024.

A. Morphological Preprocessing

Mammographic images are taken from the MIAS database contains dark background and other non essential components such as labels and scribbling. The gray scale mammogram images are transformed into binary format using a global threshold T_G , having a value one tenth of the maximum intensity. The objects (connected components) present in the binary image are labeled. Area of each connected component is then calculated and all the objects having an area (number of pixels) lesser than maximum (T_A) are removed. The value of T_A for MIAS database images found to be 10000. The selected breast profile is multiplied with original image to get resultant image that is free from label and other noises. Finally, the dark background is removed by cropping rows and columns that has sum value equal to zero. Thus, the breast region alone is extracted for further processing.

B. Construction of 32×32 sub-images

After this process, sub-images (ROIs) of size 32×32 are manually cropped. The size of sub-image plays an important role in classification. A large sub-image will lead to an accurate classification in the homogenous area but a bad classification along the breast skin line areas, whereas small sub-images gives optimal classification accuracy in all the regions. The smallest possible sub-image that could contain a microcalcification cluster in a 1024×1024 image is 32×32. In the normal images, random portion of size 32×32 are taken as ROIs. In the images containing microcalcifications, ROIs are taken such that the microcalcification clusters are at different positions of the sub-images. In both, background and boundary zones are considered. The sub-images that are entirely black and those containing number of zeros more than 100 (10% of total number of pixels) are not considered.

C. Texture Analysis

Texture analysis is a potential method for studying lesions such as micro-calcifications. In this paper, texture analysis of mammograms intends to identify specific region of interest (microcalcifications). Textural features contain information about the spatial distribution of tonal variations. The scheme of tone lies on the intensity of the pixels within the defined region (gray level values in gray scale image). Thus, the texture in the sub image describes the pattern of variation in gray level values in a neighborhood. This will prove the textural features that could be used for solving classification problems on non-homogenous data such as mammograms.

D. Wavelet based feature extraction

The wavelet transformation is used to analyze different frequencies of an image using different scales. This is flexible approach than Fourier transform, enabling analysis of both local and global features present in the image. Here, orthogonal wavelet transform is used as it allows an input image to be decomposed into a set of independent coefficients, corresponding to each orthogonal basis. Orthogonal implies that there is no redundancy in the information presented by the wavelet coefficients, which results in an efficient representation of desirable features. Haar wavelet is used for decomposition as it is best suited for extracting high frequency components (microcalcifications) from mammographic image. The mammographic image is decomposed into 4 levels. The approximate and the three detailed components are extracted consecutively for 4 levels by replacing the input image for 2nd-4th level decomposition by the approximate component of the respective previous level. The features that are extracted for classification are the energy and infinity norm for all the 4 components at each level.

Energy, $E = \sum\sum ||M_{pq}(x,y)||^2$

Infinity norm = $\sum |x|^{p^{1/p}}$

Where, P is the maximum row sum of x.

D. Extreme Learning Machine

In this proposed system, Extreme Learning Machine is selected as classifier. For selecting ELM as a classifier, ROC graph is used. Receiver Operating Characteristics (ROC) is a technique for visualizing, organizing, selecting classifier based on performance. It depicts relative tradeoffs between true positive rate and false positive rate. One point in the ROC is better than the other if it is to the northwest of the first. ELM comes under the class of SLFN (Single Layer Feed Forward Network) whose learning speed is thousand times faster than conventional feed forward network. It has better generalization as the input weights and hidden layer biases can be randomly assigned if the activation functions in the hidden layer are infinitely differentiable.

With N number of hidden neurons and activation function g(x), the ELM algorithm can be summarized as:

i. Assign input weights w_i and biases b_i.
ii. Calculate hidden layer output matrix H.
iii. Calculate the output $\beta = H^{*}T$ weights, where H^{*} the
Moore-Penrose generalization inverse of the matrix H.

The Structure of ELM network is as follows:

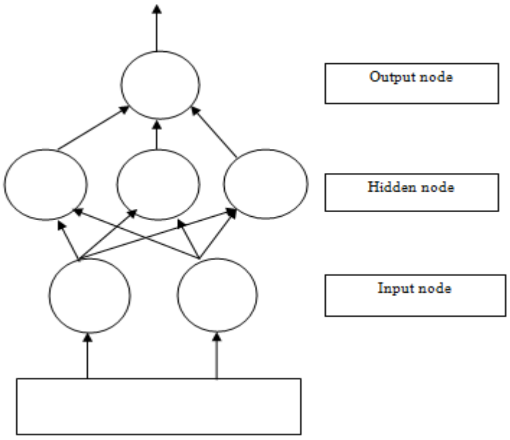

Figure 2. Structure of ELM network

The design of ELM based classification requires selection of user defined parameters namely,
i. Number of hidden neurons
ii. Activation function

Number of hidden neurons ranges from 5-80 (maximum number of input samples) for three different activation functions namely, unipolar, bipolar, and Gaussian.

VI. EXPERIMENTAL RESULTS

The combination of ELM and wavelets feature extraction is used to build CAD system that automatically locates the presence of microcalcifications in digital mammograms.

A. Morphological Preprocessing:

In this process, raw mammographic images are taken as input and morphological operations are carried out to eliminate the undesirable components from raw mammographic images.

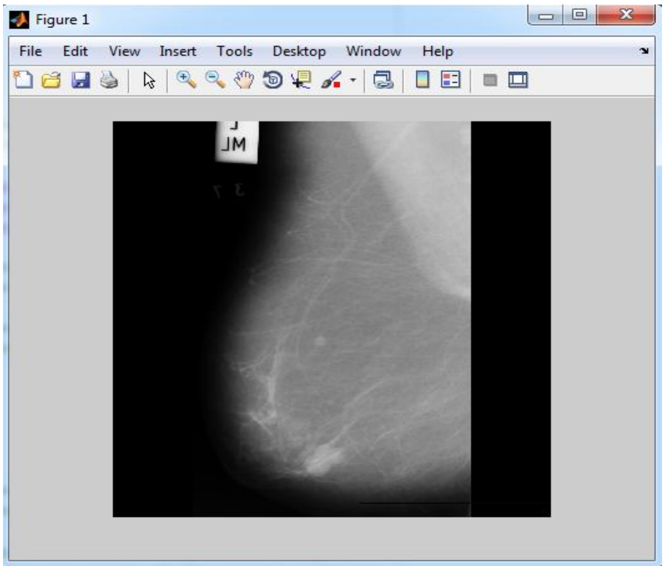

Figure 3. Original mammogram image

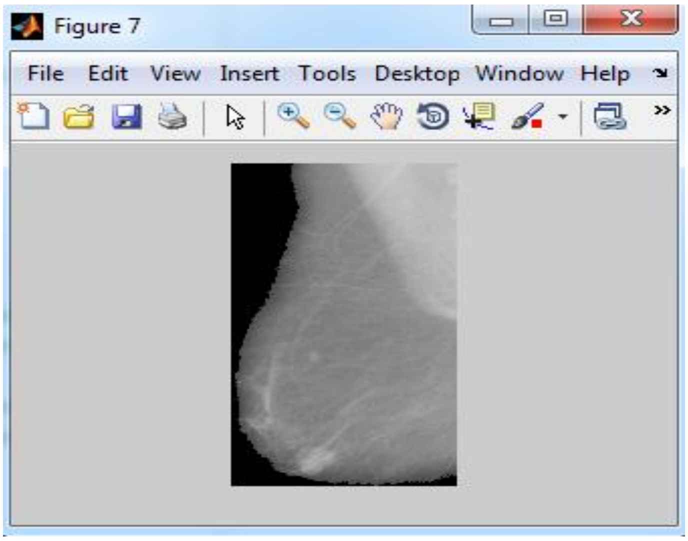

Figure 4. Image after label and background removal

B. Segmentation

A windowing function is then used after preprocessing mammographic image from top left to bottom right such that it produces sub images of size 32×32 at each instance.

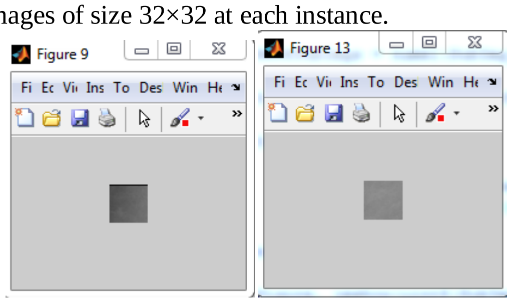

Figure 5. 32×32 sub images

C. Final Result after whole CAD implementation

After implementing CAD system for detection of clustered microcalcifications, final results for the CAD system is shown in figure 6 is as follows:

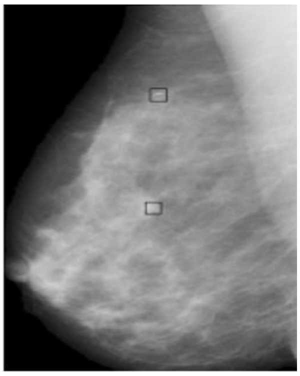

Figure 6. Microcalcifications detection

VII. CONCLUSION

Proposed method which uses wavelet feature extraction which improves sensitivity and performance of the CAD system for detection of micro calcification in digital mammograms. Original mammogram is preprocessed by morphological operations to remove the label and background and segmented in 32×32 sub images of skin lined breast images. Selected wavelet based feature extraction of sub images are used for classification and for this system extreme learning machine is used as classifier and backbone of whole system. Combination of wavelet analysis and extreme learning machine proves proposed system best in its performance.

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