Research Journal of Applied Sciences, Engineering and Technology 4(24): 5480-5483, 2012
ISSN: 2040-7467

Submitted: March 18, 2012 Accepted: April 14, 2012 Published: December 15, 2012

Breast Cancer Diagnosis in Digital Mammogram using Statistical Features and Neural Network

R. Nithya and B. Santhi
School of Computing, SASTRA University, Thanjavur, Tamilnadu, India-613402

Abstract: In this study, the mammogram is classified as either normal or cancer pattern. In the last few decades soft computing improves the accuracy of the breast cancer detection in digital mammograms. The standard approach for diagnosis of breast cancer is biopsy. But biopsy makes patient discomfort, bleeding and infection. The CAD (Computer Aided Diagnosis) is developed for the reason of avoid unnecessary biopsy. The statistical features are extracted from the digital mammograms. These features are fed to neural network classifier to classify it into two classes namely normal and cancer. This study describes neural network classification technique. Experiments have been conducted on images of DDSM (Digital Database for Screening Mammography) database. The performance measures are evaluated by confusion matrix. By increasing the training samples this study reveals the improved classification accuracy. This CAD system achieved 94% accuracy, 96% sensitivity and 92% specificity for diagnosis of breast cancer.

Keywords: Breast cancer, mammograms, neural network, statistical features

INTRODUCTION

Breast cancer is common diseases among women. The digital mammogram is reliable method for early detection of breast cancer. Several techniques have been used to predict the breast cancer. Imaging techniques play an important role in helping perform diagnosis of breast cancer (verma and Zhang, 2007; Schaefer *et al*., 2009). By using digital mammography, reduction in biopsy test and also cost. Mammography can identify the cancer before physical symptoms are produced. So, it can be recognized as efficient tool for early breast cancer detection. Early detection of breast cancer saves many lives. In the early stage both pattern exhibit similar characteristics, it makes classification difficult. By combining radiologist's interpretation and the computer analysis, mammogram classification can be achieved. The breast abnormalities are classified into two types: masses and calcification. The calcification appears as small calcium deposit. Calcification consists of two classes: micro calcification and macro calcification. Macro calcifications are large calcium deposit associated with non-cancerous pattern. Micro calcifications are small calcium deposit. Micro calcification is a sign of breast diseases. Masses are different in shape and appearance (Llado *et al*., 2009). The detection of masses are complicated than micro calcification because masses exhibit poor image contrast. The masses are identified by shape such as ellipse, irregular and oval. Masses appear as space occupying lesion. The presents of mass suggest high probability of breast cancer.

Image feature extraction is the most important step in breast diagnosis. Moment based feature descriptors have evolved into a powerful tool for image analysis applications. There are several type of features are extracted from the mammograms such as region-based feature, texture features and shape features. In the literature moment based statistical texture features are used for experiments. Texture information is used in wide range of applications including natural scene, remotely sensed data and biomedical modalities. Texture features have been used for medical image application including mammography. There are three major categories of texture-based techniques, namely, statistical, spectral and structural approaches (Verma *et al*., 2009). Statistical methods treat texture patterns as samples of certain random fields and extract features from the properties. In statistical approaches, texture features such as the moments of the gray-level histogram are computed. Image processing techniques are used to extract statistical features from the mammograms. Features are important parameters for detecting early sign of breast cancer. Neural network is efficient tool for pattern classification (Muthu Rama Krishnan *et al*., 2010). The CAD system is used to improve the accuracy of mammogram classification as either normal or cancer.

LITERATURE REVIEW

There are several techniques have been proposed to automate the diagnosis of breast cancer. In recent years, CAD systems have significant development with respect

Corresponding Author: R. Nithya, School of Computing, SASTRA University, Thanjavur, Tamilnadu, India-613402

to automated detection and classification of breast abnormality in digital mammograms. The CAD system is used for the purpose of pattern classification. Verma and Zhang (2007) proposed a novel neural-genetic algorithm to find the most significant combination of features in digital mammograms. The highest classification rate achieved for testing set was 85% on mammograms from the DDSM. Schaefer *et al*. (2009) used thermography based breast cancer analysis using statistical features and fuzzy classification. Experimental results on large dataset of nearly 150 cases confirm the efficacy of the approach that provides a classification accuracy of about 80%. Llado *et al*. (2009) proposed textural approach and obtained subsequent reduction in false positive rate .Their approach is evaluated using 1792 ROIs extracted from the DDSM. Verma *et al*. (2009) proposed a novel soft cluster neural network. The highest classification accuracy obtained by this approach was 93% on mammograms from the DDSM. Muthu Rama Krishnan *et al*. (2010) used statistical features with support vector machine and accuracy obtained was 93.24% on Wisconsin Diagnosis Breast Cancer (WDBC) dataset.

MATERIALS AND METHODS

An overview of research methodology for classification of normal and cancer pattern is given in Fig. 1 and it involves data collection, feature extraction, neural network training and testing.

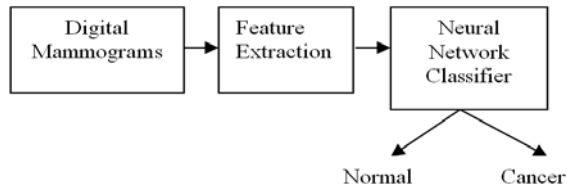

Fig. 1: An overview of research methodology

Image dataset: The digital mammograms used for this experiment obtained from DDSM and it was downloaded from the http:// marathon. csee.usf. edu/ Mammography/ DDSM. The total 250 mammograms were utilized for training and testing (125 normal and 125 cancer).

Feature extraction: Texture analysis is based on statistical properties of the intensity histogram moments. The image histogram contains information about the content of image. Grey level based features like average intensity, average contrast, smoothness, third moment, uniformity and entropy extracted from the digital mammograms. The formulae for every feature are shown in Table 1. For each of the formulae: z_i is a random variable indicating intensity, $p(z_i)$ is the histogram of intensity levels in a region, L is the number of possible intensity levels and 'm' is the mean (average) intensity. These features are as shown in Table 2.

Table 1: Formulae for statistical moment

Moment	Expressio	Measure of texture
Mean	$m = \sum_{i=0}^{L-1} z_i \, p(z_i)$	Average intensity
Standard deviation	$\sigma = \sqrt{\mu_2(z)} = \sqrt{\sigma^2}$	Average contrast
Smoothness	$R = 1 - \frac{1}{1+\sigma^2}$	Smoothness of intensity in a histogram.
Third moment	$\mu 3 = \sum_{i=0}^{L-1} p\,(z_i - m)^3 p(z_i)$	Skewness of the histogram
Uniformity	$U = \sum_{i=0}^{L-1} p^2\,(z_i)$	Uniformity of intensity in the histogram
Entropy	$e = -\sum_{i=0}^{L-1} p\,(z_i) \log_2 p(z_i)$	A measure of randomness

Table 2: Statistical features for the mammogram images

Image id	Image class	Average intensity	Average contrast	Smoothness	Third moment	Uniformity	Entropy
Mam1	Normal	69.5967	35.11347	0.01861	-0.07705	0.07059	5.59239
Mam2	Normal	73.67541	30.29273	0.01392	-0.21687	0.03016	6.19349
Mam3	Normal	60.60543	32.32825	0.01582	-0.01065	0.09455	5.66164
Mam4	Normal	36.19452	41.98268	0.02639	0.77714	0.20963	4.65060
Mam5	Normal	68.68612	43.03107	0.02769	-0.07939	0.03865	5.97751
Mam6	Cancer	50.08544	49.18930	0.03588	0.26286	0.18727	4.70950
Mam7	Cancer	50.32452	29.32724	0.01305	-0.11470	0.23603	4.19086
Mam8	Cancer	37.02695	42.77781	0.02732	0.78444	0.05047	5.62079
Mam9	Cancer	49.29640	36.43984	0.02001	0.57828	0.04239	5.70384
Mam10	Cancer	67.23113	31.05172	0.01461	-0.11765	0.04448	6.04602

Classification-neural classifier: Neural classifier is processed in two phases namely training phase and testing phase. In training phase, weights are updated. The supervised training phase is based on the back-propagation algorithm. In testing phase, mammograms are classified based on this updated weight. The neural classifier consists of three layers such as input, hidden and output layer. The sigmoid activation function is used for both hidden layer and output layer (keles *et al*., 2011; Buciu and Gacsadi, 2010). The weights between input and hidden layer and the weights between hidden layer and output of neural network are updated to achieve optimum classification (Delogu *et al*., 2007; Vasantha *et al*., 2010). The updated weight value will improve the overall classification accuracy. The results are based on initial weight value. In feature extraction phase, six features are computed. Among these features four relevant features are identified including third moment, entropy, smoothness and uniformity. The identified features are fed to input layer. The output layer produces classification of mammograms either normal or cancer.

Training algorithm:

Step 1: Extract features from mammograms
Step 2: Create input and desired output for normal pattern
Step 3: Create input and desired output for cancer pattern
Step 4: Initialize weights and activation function.
Step 5: Compute error
Step 6: Update weight

Testing algorithm:

Step 1: Extract features from mammograms
Step 2: Create input for normal pattern
Step 3: Create input for cancer pattern
Step 4: Calculate output

Performance measure: The performance of this system is evaluated based on the experiments such as classification accuracy, sensitivity and specificity are calculated using confusion matrix (verma *et al*., 2009). These measures are associated with binary classification and they evaluate performance of a test. In binary classification divide dataset into two categories. Sensitivity measures how well the test predicts one category (Burak Tosuna *et al*., 2009). Specificity measures how well the test predicts the other category. Accuracy is evaluated using sensitivity and specificity:

Classification accuracy = (TP+TN) / (TP+FP+TN+FN)
Sensitivity = TP/ (TP+FN)
Specificity = TN/ (TN+FP)

Where TN: True Negative (correct normal diagnosis)'; FN: False Negative (incorrect normal diagnosis); TP: True Positive (correct cancer diagnosis); FP: False Positive (incorrect cancer diagnosis).

EXPERIMENTAL RESULTS

This study conduct experiments on a set of 250 mammograms obtained from DDSM database. The experiments were run using 200 mammograms (100 normal, 100 cancer) for training and 50 mammograms (25 normal, 25 cancer) were used for testing. In the first stage of this experiment is conducted to extract statistical features from the mammograms. In the second stage, the extracted features are fed into neural network classifier. The neural classifier classifies the images as normal image or cancer image. The number of hidden units and output threshold were adjusted to achieve optimum classification. The experiments were performed by changing the number of training samples and the results are reported. For testing accuracy of the classifier, 50 mammograms are tested by a different number of training samples such as 70% (140 out of 200), 80% (160 out of 200) and 90% (180 out of 200). Classification results are displayed using confusion matrix in Table 3 to 5 details the performance of different training samples for the classification of normal and cancer patterns in digital mammograms. The training sample 90% shows the best result. In Fig. 2, comparisons of performance measures are depicted. Performance measures are shown in Table 6.

Table 3: Confusion matrix (training data -70%; testing data -50)

	Predicted	
Actual	cancer (positive)	normal (negative)
Cancer (positive)	24 (TP)	1 (FP)
Normal (negative)	6 (FN)	19 (TN)

Table 4: Confusion matrix (training data -80%; testing data -50)

	Predicted	
Actual	cancer (positive)	normal (negative)
Cancer (positive)	24 (TP)	1 (FP)
Normal (negative)	5 (FN)	20 (TN)

Table 5: Confusion matrix (training data -90%; testing data -50)

	Predicted	
Actual	cancer (positive)	normal (negative)
Cancer (positive)	23 (TP)	2 (FP)
Normal (negative)	1 (FN)	24 (TN)

Table 6: Accuracy, sensitivity and specificity for testing result

Performance measure (%)	70% training	80% training	90% training
Accuracy	86	88	94
Sensitivity	80	83	96
Specificity	95	95	92

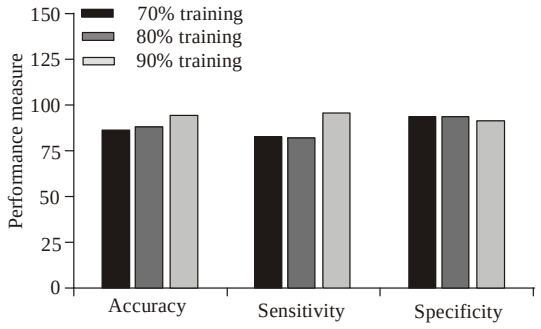

Fig. 2: Performance measure comparisons

CONCLUSION

The method employed in this study has demonstrated that the ideas of increasing the training samples points out the improvement in classification accuracy. By changing the architecture of neural classifier may improve the classification accuracy. Fuzzyfication of neural input may also increase the performance. The highest accuracy obtained by this approach was 94%. For future study statistical features combined with GLCM (Gray-level co-occurrence matrix) features could be used to improve the results in classification of mammogram images.

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