An Automatic Mass Detection System Based On Complex and Statistical Feature

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Abstract: In the world, Breast canceris the main leading cause in the woman.Early diagnosis of the diseases and timely medical examination is the key factor to long-term survival and life quality for patients. The screening of presence breast cancer, of ambiguous margins of lesions and visual fatigue causes radiologists to miss roughly 10-30% of tumour in breast cancer. For this reason, Computer aided diagnosis systems (CADe) have been proposed to classify the density of mammograms, having as a major challenge to define the features that had better represent the images to be classified.In this paper; we show the results of feature classification over the MIAS and DDSM datasets. We compare our method with recent approaches that classified these same datasets and the results prove that our system achieves satisfactory detection performance.

IndexTerms **- Computer-aided detection (CADe) system, Mammographic mass detection,pnn.**

I. INTRODUCTION

Breast cancer is considered to be one of the most common cancers affecting women around the world. According to the World Cancer Report, breast cancer accounts for 22.9% of diagnosed cancers and 13.7% of cancer related death worldwide. For the diagnosis of the breast cancer commonly used techniques are biopsy, mammography, and thermograph and ultrasound image. Among the all, mammography is the best technique to identify breast cancer. This technique is very efficient tool to identify the breast cancer in early stage for high survival rate. This process is very easy and less side effects.When numbers of tests are involved, the ultimate diagnosis may be difficult to obtain, also for a medical expert. Specifically, where breast cancer is concerned, the treating physician is interested in ascertaining whether the patient under examination exhibits the symptoms of a benign case, or whether the case is a malignant one.Due to its reliability, mammography (an x-ray image examining method of the breast) is considered to be a most effective screening method for the detection of breast cancer. The mammograms are first digitized and then filtered/ analysed with the help of powerful image analysis techniques in order to develop computer aided diagnosing (CADe) systems for effectively assisting the radiologists.A CADe is a set of automatic or semiautomatic toolsdeveloped to assist radiologists in the detection and evaluation of mammographic image.A CADe System used with mammography, a radiologist still reads the mammogram,a computer program evaluates the mammogram and highlights suspicious regions. The goal was to reduce the human error and improve detection accuracy.

II. PROBABILISTIC NEURAL NETWORKS

In 1990, Donald F. Specht proposed a method to formulate the weighted-neighbor method in the form of a neural network. He called this a "Probabilistic Neural Network". Probabilistic neural networks are conceptually similar to K-Nearest Neighbor (k-NN) models. The basic idea is that a predicted target value of an item is likely to be about the same as other items that have close values of the predictor variables.

The architecture for PNN is shown in Figure 1. As illustrated in the figure, PNN network has four layers:

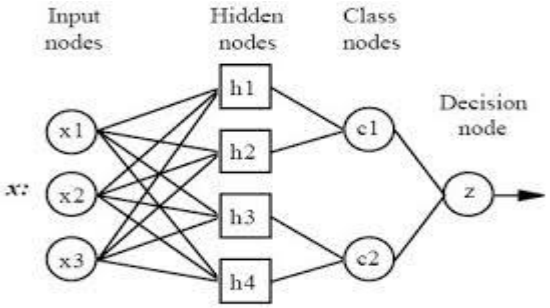


Fig. 1. Probabilistic Neural Network Architecture

Input layer-: In the input variable, each neuron represents a predictor variable. In categorical variables, N-1 neurons are used when there is N number of categories. It standardizes the range of the values by subtracting the median and dividing by the interquartile range. Then the input neurons feed the values to each of the neurons in the hidden layer.

Hidden layer-: In this layer has one neuron for each case in the training data set. The neuron stores the values of the predictor variables for the case along with the target value. When presented with the x vector of input values from the input layer, a hidden neuron computes the Euclidean distance of the test case from the neuron's center point and then applies the RBF kernel function using the sigma value. The resulting value is passed to the neurons in the pattern layer.

Pattern layer / Summation layer-: There is one pattern neuron for each category of the target variable. The actual target category of each training case is stored with each hidden neuron; the weighted value coming out of a hidden neuron is fed only to the pattern neuron that corresponds to the hidden neuron's category. The pattern neurons add the values for the class they represent.

Decision layer-: The decision layer compares the weighted votes for each target category accumulated in the pattern layer and uses the largest vote to predict the target category.

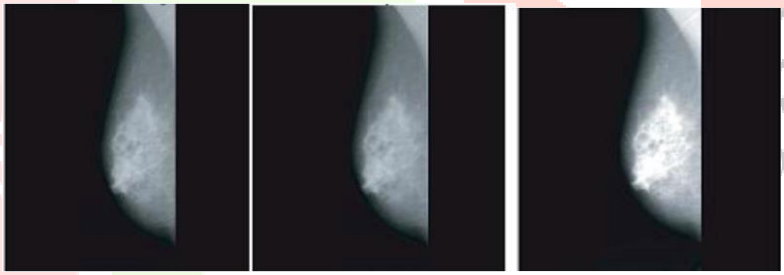
III. FEATURE EXRACTION METHOD

In the pattern classification feature extraction method pays very important role. The features should have similar values for the patterns within the same class and have significant difference in different classes .Feature extraction methods, Gray Level Co-Occurrence Matrix (GLCM) & Optical Density Co-Occurrence Matrix (ODCM).

Gray Level Co-Occurrence Matrix (GLCM): To identify texture in image, modeling texture as a two dimensional array gray level variation. This array is called Gray Level co-occurrence matrix.In the GLCM method, it ex examining the textures that considers the spatial relationship of the pixels. This method is statistical method. The size of the GLCM is calculated by number of gray level in an image.For each of the formula: G is the number of gray level used. The matrix element P (i, j |Δx, Δy) is the relative frequency with two pixels separated by pixel distance (Δx, Δy), occur within a given neighborhood, one with intensity i and other with intensity j .Table 1 shows GLCM features for Normal, Benign Malignant images.

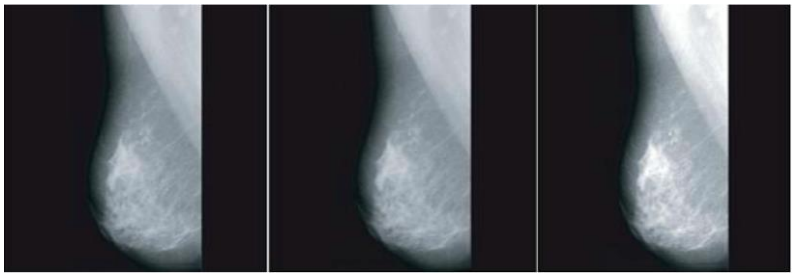
Optical Density Co-Occurrence Matrix (ODCM):For the Optical density image, Optical Density Co-Occurrence Matrix (ODCM) is used. An optical density image can be obtained by converting the intensity of the gray-level image into optical density and linearly mapping each optical density value to an image with 8-bit depth information . 255 is the maximum optical density value and 0 was the minimum optical density value. The intensities were high and close and making it difficult for human eyes to determine the difference in a dense density mammogram .

IV. EXPERIMENTAL RESULT



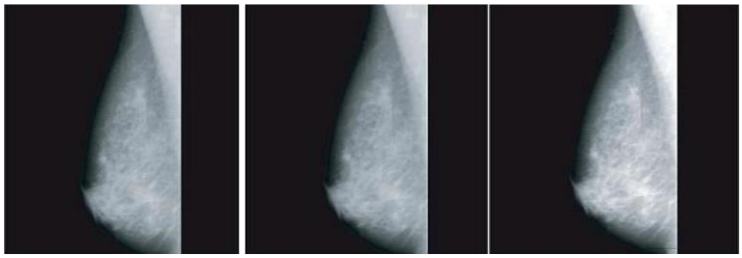
(A) (B) (C)

Fig. 2. (A) Normal mammogram (B) Smoothed image (C) After enhancement processing



(A) (B) (C)

Fig. 3 (A) Benign mammogram (B) Smoothed image (C) After enhancement processing



(A) (B) (C)

Fig 4. (A) Malignant mammogram (B) Smoothed image(C) After enhancement processing

Based on the values of the statistical feature, basic classification of normal, benign, and malignant mammogram images. Gary level statistics provide the texture measures like mean, standard deviation, entropy and range gives in table I.

Table I: GLCM feature values for Normal, Benign Malignant images:

Sr.No.	Image Name	Image Class	Mean	Variance	Range	Standard Deviation	Entropy
1	50.jpg	Normal	2.17912E-06	5.983600472	1.42E-08	2.44614E-05	-0.005762476
2.	81.jpg	Benign	2.25098E-06	6.384737438	1.6E-08	2.5268E-05	-0.005989892
3.	148.jpg	Malignant	1.79804E-06	4.073805879	2.35E-08	2.01837E-05	-0.004666348

From the above results it can be conclude that the statistical features extracted from the mammogram images are use full parameters for classification. The proposedclassification method gives the flexibility to radiologist for analysing abnormality in mammograms and to help him in such detection of changes in breast tissues. This study presented a pixel intensity statistical feature for the classification of mammograms.

V. COMPARATIVE ANALYSIS OF MASS CLASSIFICATION USING DIFFERENT APPROACH

1.Complex feature.

2.Statistical feature.

S.no	Method's	Accuracy
1	Complex Texture Features	98.71%
2	Statistical Features	98%

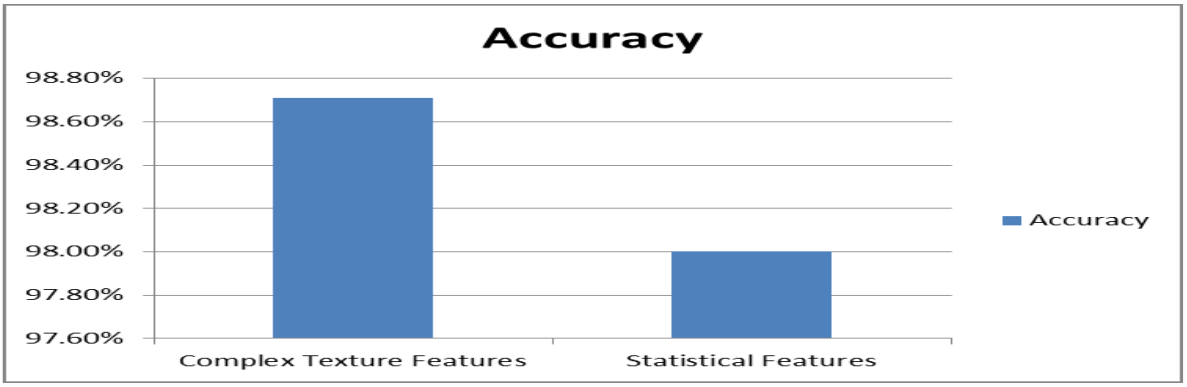


Fig 5: Performance Measure

All these technique focused on the statistical feature extraction. As we compared our proposed classifier method is 0.986, performance of our proposed system is satisfactory when compared with several previous method that worked with the same databases.The predicted performance is evaluated in terms of the accuracy, the respective formula are given as

Accuracy = (TP+TN)/(□□TP+TN□□+FP□□+FN□□)×100

WhereTN is the number of true negatives, TP is that of true positives, FP is that of false positives and FNdenotes the number of false negatives.The Accuracy which measures the global performance of the algorithm about the correct decisions. The obtained classification accuracy of statistical feature method is 98% and Complex texture feature is 98.60%.

V. CONCLUSION

This paper presented a classification of mammograms based on two various method 1.Complex Texture Features and 2.global statistical feature extraction. Furthermore, themammograms were categorized into three distinct class :normal, benign, and malignant. It analyses data from different individuals suffering from different types of cancer.It contains data collected from several individuals with a particular cancer or healthy people. As a next step, we can do test on various kinds of cancerous tissue and can try finding the present stage of the cancerous patient. and our Experimental results show that Complex Texture Features is better then existing system. with high accuracy.

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