Malignancy Detection in Mammogram using Gray Level Gradient Buffering Method

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ABSTRACT

Breast cancer is the second most common cause of cancer death particularly for women in all over the world. The mortality rate can be reduced only by early detection and treatment. Mammography is at present the most reliable and widespread method for early detection of breast cancer. Normally mammogram readings are performed by radiologists but mammogram reading is difficult and requires a great deal of experience. 20% to 40% of malignancy is failed to be detected at manual reading due to variety of factors such as eye fatigue and complex image structure of breast tissue. Hence the efficiency in early diagnosis is found to be reduced. Computer Aided Detection (CAD) tool could be used as second reader to assist the radiologist which helps for early and efficient diagnosis. In this paper CAD is designed using a new algorithm named Gray level Gradient Buffering (GGB) method. The designed algorithm contains 4 steps to diagnose the mammogram. Preprocessing, Segmentation, Feature extraction and Classification. Noise and Artifacts are removed in preprocessing using 2D Median filter and ROI extraction process respectively. Segmentation is carried out using Sobel operator and the proposed GGB algorithm. The features of the segmented image are extracted using Spatial Gray level Dependence Matrix and Local Binary Pattern. Support Vector Machine is used to classify the extracted features as benign and malignant. The efficiency of the proposed method is calculated using Par test which gives 99.3% Sensitivity and 98.1% Specificity.

Keywords-Mammogram, Computer Aided Diagnosis, Segmentation, Feature Extraction, Classification.

1. INTRODUCTION

Cancer is one of the biggest threats to human life. It is expected to become the leading cause of death in future. Generally it is named after the part of the body where it originated. Breast cancer begins in the Breast tissue, it may spread to lungs but still it is breast cancer not lung cancer. According to Tata Memorial hospital report in India it occurred 1 out of 1000 women during 1974-78. But the recent studies shows that it occurs 1 in10 women which shows the necessity of taking the preventive steps against this dangerous disease. At present in India vaccination is available for some kind of cancers such as cervical cancer and lung cancer. But the root cause of breast cancer is still not known. Hence proper preventive measures and vaccination is not available for breast cancer. But early detection and treatment will improve the survival rate of the patient by 95%.

MRT, CT, Ultrasonic and Mammography are the available screening methods to detect the cancer cell. The diagnosis rate between histopathology rate and mammography is quite high while comparing with other screening methods. It is inexpensive and works fairly well in all cases. Another advantage of digital mammography is it stores the result as computer code, hence it can be modified for the screening process. Due to the above mentioned reasons Mammography is considered as clinical gold standard for early detection. But due to variety of factors such as poor quality of image, benign appearance of lesions and eye fatigue factor the performance of radiologists varies from 65% to 85%. To overcome this problem many Computer Aided Detection techniques have been proposed for the past two decades. Even then the detection rate is still not high and general algorithm that can produce good result in all mammograms is still not available for the practical use. Hence much more works are needed to develop a highly efficient and effective CAD system.

1.1 Literature Survey

Implementation of computer aided detection contains various fields such as enhancing the mammogram, identifying suspected region, feature extraction from segmented mammogram, classifying the mammograms and so on. Many algorithms have been proposed to improve the efficiency of the CAD system in the above mentioned fields. Some of those methods are discussed in this section.Many attempts have been made by researchers to efficiently use the fuzzy logic and neural network methods to improve the diagnostic efficiency in cancer detection [17][23][24][32]. Genetic algorithm was used with different combination of technologies for the effective diagnosis [16]. Jinshan et al.[26] provided an overview of recent advances in the development of CAD system. Maurice et al [7] proposed a new algorithm based on the correspondence between MLO and CC views of mammograms.

Pectoral segmentation and artifact removal are the important preprocessing works. Jawad et al.[3] used morphological operation and seeded region growing method to segment the pectoral muscles. Contrast limited adaptive histogram equalization (CLAHE) and multiscale contrast enhancement algorithm are some of the effective methods in enhancing the mammograms[19][22]. Arianna et al.[14] proposed a novel algorithm for denoising and enhancement based on dyadic wavelet processing. Numerous segmentation algorithms have been proposed for segmenting the mass region. Each has its own advantage in some perspective.

Farhang et al.[20] used mean shift algorithm to cluster the pixels in mammogram. Ka hu et al.[8] developed a combination of adaptive global and local thresholding to segment the multiresolution mammogram. Morphological component analysis was designed by xinbo gao et al.[13] to detect the suspicious region. Indra et al.[10] presented a combination of techniques that incorporates seeded region growing with ASB algorithm to isolate normal and abnormal regions in the breast tissue. Various algorithms based on Jacobi moments[12], SUSAN filter[14], vector quantization[28] have been tried to segment the mass from normal tissue. Yufeng zheng et al.[27] proposed a hybrid method in which Gabor feature is used with the combination of different methods to detect the cancer cells in mammogram. Mohd et al.[31] designed a method using gray level cooccurrence matrix to identify the mass region in mammogram.

After segmenting the suspected mass region, features of the segmented region should be examined to verify whether the extracted region contains mass or not. Various features like intensity histogram features, Gray level co-occurrence matrix features and intensity features are used for breast cancer diagnosis. In an comparative study Nithya et al [4] found out that GLCM outperformed the other two methods. Hence this method is used for the feature extraction process of the proposed method.

Classification is another most important process in CAD system design. Ju liu et al.[18] used improved local binary pattern operator for mass classification. Mohammad et al.[21], Fatima et al.[6], Leornardo de et al.[30] used support vector machine with combination of different techniques for the classification of masses. Naïve bayes classifier [19], K means classifier, fuzzy C means clustering [15][19] are some of the common methods used in the previous work. Kemal et al [5] designed least square support vector machine which provided effective classification compared to other methods.

2. METHODOLOGY

The proposed method is implemented and tested using MIAS (Mammographic Image Analysis Society) database. MIAS is Organization of UK research group. MIAS database is published particularly for the use of scientific research. It contains 322 images which are left and right breast images of 161 patients.

2.1 Preprocessing

Digitization noise, artifacts presents in raw mammogram will greatly affect the diagnosis result in CAD system. Preprocessing need to be performed to remove them. Film artifacts are removed in Region Of Interest extraction process. 2D Median filter is used to remove the digitization noise.

2.2 ROI Extraction Process

Region of Interest extraction process helps to extract the interested region alone from the image. Normally cancer cells appear as whiter region in mammogram. But it may be either just microcalcification or mass region. So the task of mammogram reading is to detect whether it is calcium collection or cancer cell. For this task only the brighter region of the mammogram need to be analyzed.

So in the region of Interest extraction process a special algorithm is designed to extract the brighter region alone from the mammogram. Mammographic Image Analysis society (MIAS) database is used in the proposed algorithm which provides the collection of database particularly for the research work on breast cancer. MIAS gives all the details about each mammogram will be given such as character of background tissue, class of abnormality, x and y coordinate value of centre of abnormality, radius of circle enclosing the abnormality. In the proposed algorithm for ROI extraction process x , y coordinate value and radius value of abnormal region will be given as input for each mammogram which is taken from MIAS database. The algorithm will extract the abnormal region alone from the mammogram as follows,

Let

X_C is center point of X coordinate

Y_c is centre point of Y coordinate

R is radius of abnormal region

$$nX_c=R-X_c \quad (1)$$

$$nY_c=n*Y_c \text{ where } n=1 \quad (2)$$

$TOP_{X.}$ $TOP_{Y,}$ $BOTTOM_{X,}$ $BOTTOM_Y$ are the values of four sides of ROI rectangle region. which can be calculated as follows,

$$TOP_X=nX_c–side \tag{3}$$

$$TOP_Y=nX_C–side \tag{4}$$

$$BOTTOM_X=nx_C+side \tag{5}$$

$$BOTTOM_Y=nY_c+side \tag{6}$$

By computing the above four values for each mammogram region of interest image can be obtained. The Sample of Region of Interest extracted image is shown in Figure 2 which is extracted from the Original raw mammogram shown in Figure 1.

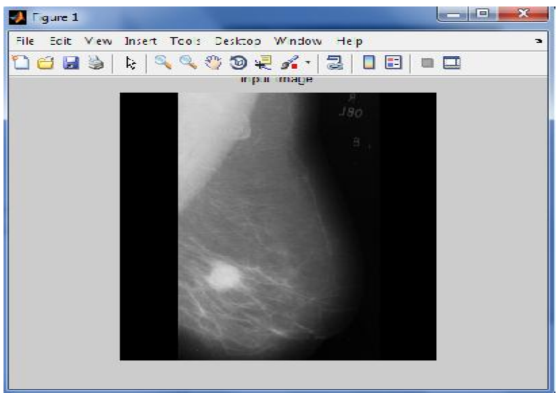


Fig.1 Mammogram input (mdb 028 from MIAS)

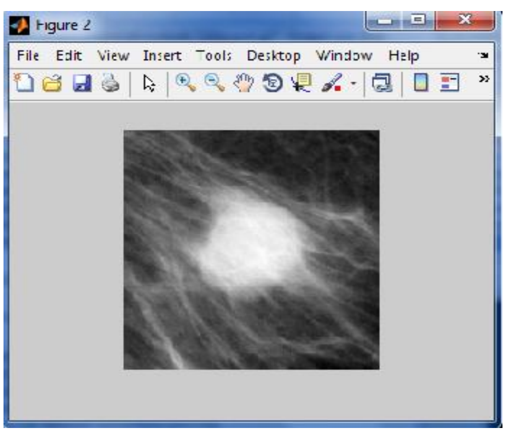


Fig.2 Image after Region of interest Extraction process

2.3 Median Filtering

In 2D median filtering process each output pixel will be replaced with the median value of each 3X 3 kernel of input image. It provides comparatively better results than other noise removal process. Another advantage of using Median filter is it will remove the noise without disturbing the edge information. ROI Extracted image is median filtered as shown in Figure 3.

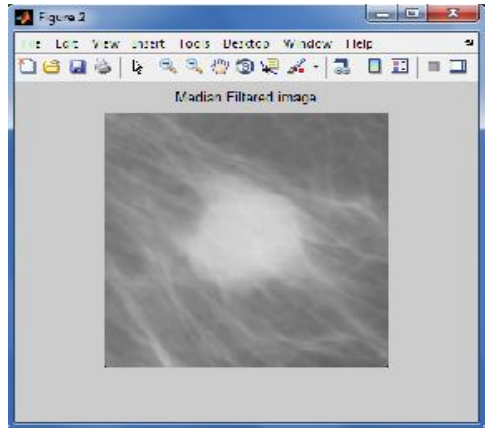


Fig.3 Image after noise removal process using Median filtering method

2.4 Contrast Enhancement

Contrast of the image is enhanced to enrich the necessary details in the image. Intensity values are added over different segments by using adaptive histogram equalization method. Contrast of each pixel relative to its local neighborhood is adaptively enhanced during this process which is known as Contrast Limited Adaptive Histogram Equalization. Hence contrast will be improved for all the levels in the image. Due to CLAHE the noise produced in homogenous area will be reduced. Figure 4. shows the result of Contrast enhancement process.

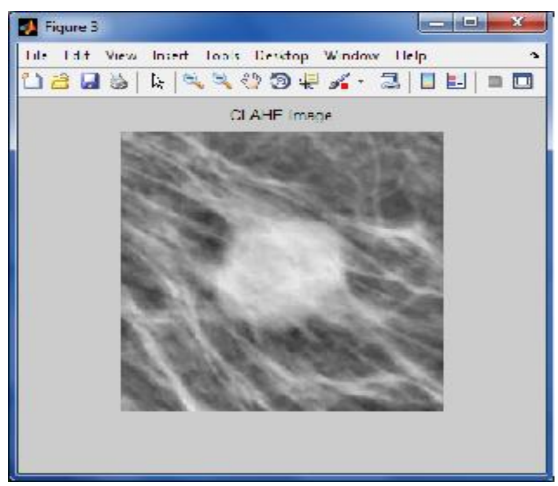


Fig.4 Image after Contrast enhancement process

2.5 Edge Detection

Edges are the regions which have high gray values and occur in image boundaries are considered as important features in image analysis. Hence Edge detection is very supportive process in image segmentation. In mammogram segmentation edge detection is necessary to enhance the tumor area. Sobel operator produces comparatively better results than any other methods such as prewitt, Kirsch and watershed algorithm. The operator consists of 3X3 convolution kernels as shown in Figure 5.

-1	-2	-1
0	0	0
1	2	1

-1	0	1
-2	0	2
-1	0	1

Fig.5 Convolution Matrix

Convolution is the process of multiplying together two arrays of numbers of different size. The convolution is performed by multiplying the kernel shown in Fig.7 over the image. Each kernel position corresponds to single output pixel, which is calculated by multiplying together the kernel value and underlying image pixel value for each of the cells in the kernel. Let i , j implies row and column of kernel. I, J implies row and column of image. Then the output image will have (I-i+1) rows and (J-j+1) columns. Mathematically convolution operation can be written as shown in Eq.7:

$$C(x,y) = \sum_{x=1}^{i} \sum_{y=1}^{j} M(m+n-1, n+y-1) N(x,y) \qquad (7)$$

Where ,

m runs from 1 to (I – i+1) and n runs from 1 to (J – j+1)

derivatives in m and n direction are given as,

$$S_m = \{k(m+1, n-1) + 2k(m+1,n) + k(m+1,n+1)\} - \{k(m-1,n-1) + 2k(m-1,n) + k(m-1,n+1)\} \qquad (8)$$

$$S_n = \{k(m-1,n-1) + 2k(m,n+1) + k(m+1, n+1)\} - \{k(m-1,n-1) + 2k(m,n-1) + k(m+1,n-1)\} \qquad (9)$$

Generally the size of the gradient is,

$$S(m,n) = \sqrt{S_m^2 + S_n^2} \qquad (10)$$

By applying the sobel operator S_x and S_Y row wise two gradient matrix can be obtained as original image. Total gradient value can be obtained by using Eq.10.

If S(m, n) > TH(Threshold value) then it means that edge pixel has been found out. If S(m, n) < TH then there is no edge pixels. Thus the algorithm helps to identify the presence of edges in addition to that it also helps to identify the direction of the edge. Result of edge detection process is shown in Fig 6.

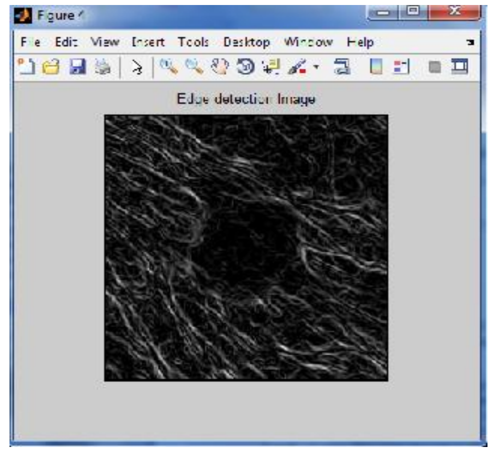


Fig.6 Image after Edge detection process

Gray level Gradient Buffering Algorithm:

S_m and S_n are calculated using Eq.8 and Eq.9 respectively. In image pixel value will be set By fixing the low and high value,.

low= 0 and high =0

Let height of input image is X and

width of input image is Y

n value varies from 1 to X

m value varies from 1 to Y.

If S(m,n) > low then low = S(m,n)

If S(m,n) < high then high = S(m,n)

Output value obtained by following the three steps given below,

1. For n→ 0 to X,
2. For m→ 0 to Y,
3. Output should be calculated by using Eq.11:

$$\text{Output} = \frac{(\text{buffer}[n*Y+m] - \text{low})}{(\text{high}-\text{low})*255} \qquad (11)$$

2.6 Feature Extraction

2.6.1. Feature Extraction by SGLD

Texture feature is used to measure the surface variation of the image. This measurement helps to differentiate abnormal and normal features. Segmentation output is given as input to feature extraction process. Spatial Gray Level Dependence is the joint probability of occurrence of gray levels i and j for the two pixels with a defined spatial relationship in an image. Spatial relationship is defined in terms of distance d and angle θ. SGLD is constructed for angles $\theta = 0^o, 45^o, 90^o$ and 135^o at distance d = 1, 2, 3, 4. Two points at distance d will have similar gray levels if the texture is course. If the texture is fine then the points will have different gray levels. Contrast, energy, homogeneity and correlation are the important features which can be derived using SGLD. Contrast of gray level values between a pixel and it's neighbor is measured using Contrast. Energy is the sum of squared elements in SGLD or uniformity. Homogeneity helps to measure the closeness in the distribution of elements in SGLD. Correlation shows the relationship of a pixel to its neighbor over the whole image.

$$\text{Contras t} = \sum_{m,n=0}^{i-1} Xmn(m-n)^2 \qquad (12)$$

$$\text{Energy} = \sum_{m,n=0}^{i-1} (Xmn)^2 \qquad (13)$$

$$\text{Homogeneity} = \sum_{m,n=0}^{i-1} \frac{Xmn}{1+(m-n)} 2 \qquad (14)$$

$$\text{Correlation} = \sum_{m,n=0}^{i-1} (Xmn) \frac{(m-\mu)(n-\mu)}{\sigma^2} \qquad (15)$$

Xmn = Element m, n of the normalized SGLD

N is number of gray levels in the image,

The SGLD mean, calculated as: $\mu \sum_{m,n=0}^{N-1} mX_{mn}$ (16)

σ^2 The variance of the intensities

$$\sigma^2 = \sum_{m,n=0}^{N-1} Xmn\ (m-\mu) \qquad (17)$$

Sample result of feature extraction process for 20 mammograms is shown in Table 1

2.6.2 Feature Extraction Process by Local Binary Pattern

Local binary pattern is another feature extraction process which is supportive for classification process. It labels the pixels of an image by thresholding the neighborhood of each pixel and the result will be considered as binary number. Advantage of LBP is it's computational simplicity which makes it possible to analyze images in real time settings. Again Segmentation output is given as input to LBP separately. LBP worked with the eight neighbors of a pixel, using the value of the center pixel as a threshold. LBP code for a neighborhood was produced by multiplying the thresholded values with weights given to the corresponding pixels and summing up the result. The average of gray levels below the center pixel is subtracted from that of gray levels above the center pixel. Two dimensional distributions LBP and local contrast measures are used as features.

2.7 Classification

Classifiers help in diagnosing medical data in shorter time efficiently. Support Vector Machine (SVM) produces comparatively better results than any other classifiers such as Naïve and Bayesian classifiers. Results obtained from both SGLD matrix and LBP are given as input data to SVM classifier. Based on the statistical learning theory SVM classifies the given input data into two separable classes {1, -1} as Malignancy and Benign. Feature values for Malignancy case is given as input for training case. Training data consists of N datum (m_1n_1)……. (m_in_i), $m \in R^i$, $n \in \{1, -1\}$.

$$D(m) = (w*m)+w0 \qquad (18)$$

The inequality $n_x (w * m_x) + w0 \geq 1$ is produced for both n=1 and n=-1
Hyper planes are performed as follows

$$Nx[w*m_x)+w0] \geq 1 \quad x=1,\ldots i \qquad (19)$$

If data points satisfy the above inequality condition then they form support vectors. Classification process is performed based on the support vectors. Margins of hyper plane obey the following inequality,

$$nk * D(mk) / ||n|| \geq \Gamma, \quad k=1,2\ldots i \qquad (20)$$

We can maximize the margin by minimizing w by using the following equation

$$\Gamma \times w = 1. \qquad k = 1,2. \ldots, i. \qquad (21)$$

Table 1
Feature of Extraction Result

Image ID	**Class**	**Contrast**	**Correlation**	**Energy**	**Homogeneity**
Mdb 028	Malignant	0.0347	0.5098	0.7970	0.9606
Mdb 075	Malignant	0.1183	0.6008	0.8822	0.9516
Mdb095	Malignant	0.1009	0.6243	0.6599	0.9397
Mdb110	Malignant	0.0502	0.6428	0.9315	0.9205
Mdb148	Malignant	0.1075	0.7145	0.7655	0.9166
Mdb179	Malignant	0.1273	0.7370	0.7104	0.9423
Mdb188	Malignant	0.1069	0.6014	0.6990	0.9833
Mdb211	Malignant	0.0349	0.6155	0.9091	0.9243
Mdb239	Malignant	0.1299	0.6265	0.7844	0.9898
Mdb271	Malignant	0.1107	0.7303	0.6708	0.9508
Mdb012	Benign	0.4024	0.7034	0.2367	0.8804
Mdb025	Benign	0.3241	0.7285	0.2840	0.8772
Mdb025	Benign	0.3241	0.7285	0.2840	0.8772
Mdb063	Benign	0.1752	0.7041	0.5600	0.9026
Mdb097	Benign	0.3033	0.6103	0.2743	0.8725
Mdb132	Benign	0.2273	0.5173	0.1986	0.8899
Mdb160	Benign	0.5596	0.6656	0.5503	0.8566
Mdb188	Benign	0.3300	0.7059	0.4716	0.8928
Mdb207	Benign	0.4065	0.6395	0.3549	0.8741
Mdb248	Benign	0.0725	0.6649	0.5657	0.9002
Mdb314	Benign	0.1150	0.7300	0.4772	0.9169

In the case of non separable data slack variable ξx is added as follows,

$$n_x[(w*m_x)+w0] \geq 1-\xi x \quad (22)$$

In the case of non linear data, non linear input should be converted to high dimensional linear feature via kernels. In the proposed method RBF kernels are used which is given I Eq.23:

Where RBF kernels can be written as follows $k(m,m') = \exp(-\|m-m'\| / \sigma^2)$ (23)

Where σ is positive real number.

3 RESULTS AND PERFORMANCE EVOLUTION

After classification process the given mammogram input will be classified as malignant or benign. The result will be given as message box immediately as shown in Figure.7.

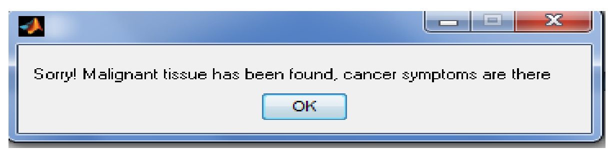


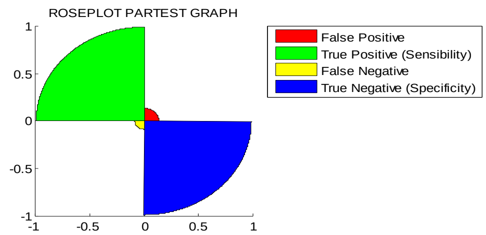
Fig.7 Final result is shown as Message box

In MIAS database 54 mammograms are cancerous and 268 mammograms are normal. Classification result of the proposed method for 322 mammograms is shown in Table 2.

Table 2
Classification Result

		True positive	True Negative	False Positive	False Negative
Number of cases	322	52/54	267/268	2/54	1/268

Perfect test is one type of ROC curve method which is used to evaluate the performance of the proposed method. The classification result of 322 mammograms is given as input to partest method. The result will be given as graphical representation as shown in Figure 8. which also gives the sensitivity and specificity of the proposed method.



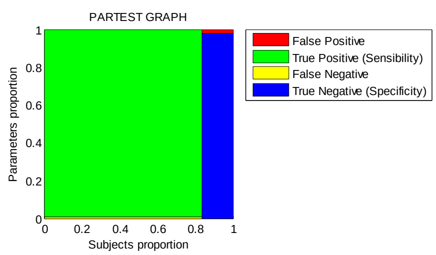


Fig.8 Performance Evaluation Result

4 CONCLUSION

In the proposed method Computer Aided Diagnosis of Breast cancer has been designed using a novel approach which shows very low misclassification rate 0.9%. The main advantage of the proposed work is it is fully automatic and there is no need of any human interruption. The proposed ROI Extraction method helps to sharpen the process to suspected region alone. sobel operator helps to enhance the suspected region. The proposed Gray Level Gradient Buffering method effectively segments the suspected region so that the features can be sharply extracted using Spatial Gray Level Dependence matrix method and Local Binary Pattern method. Extracted features from the above two methods are classified using support Vector machine. The performance of the proposed method is evaluated using partest method which shows 99.3% sensitivity and 98.1% specificity. It is quite high while comparing with the previous results. Hence, the proposed method is more preferable to assist the radiologists for early and accurate detection of malignancy. It can act as second reader of mammogram to increase the efficiency in breast cancer diagnosis.

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