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Mammographic Image Classification using Texture Features

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***Abstract*—In this work, the statistical Haralick features from the texture description methods such as Surrounding Region Dependency Matrix (SRDM), Spatial Grey Level Dependency Matrix (SGLDM), Grey Level Difference Matrix (GLDM) and Run-length features from the texture description method Grey Level Run-Length Matrix (GLRLM) are widely extracted features in mammogram images. The classification process is done using Support vector machine. The performance is evaluated using sensitivity, specificity, and accuracy .The performance of GLRLM features ,GLDM features ,SGLDM features are considerably poor where as SRDM features outperforms. Based performance we can analyze that the SRDM distinguish between malignant and benign on mammogram images with high accuracy.**

I. Introduction

Bosom disease is the most often analyzed malignancy and the main source of death among females, representing 23% of the absolute malignancy cases and 14% of malignancy. It is by a wide margin the most usually analyzed disease in ladies. The worldwide weight of malignancy keeps on expanding generally as a result of the maturing and development of the total populace close by an expanding selection of disease causing practices, especially smoking, in financially non-industrial nations like Singapore, Lebanon, Armenia, New Caledonia, and so forth It is likewise assessed that by 2030 the worldwide weight of bosom malignancy will increment to more than 2,000,000 new cases each year. Moreover it is assessed that this expansion in cases will be to a great extent because of expanding frequency in creating areas of the world [1]. To relieve this issue, Computer Aided Diagnosis (CAD) framework has arisen. In this proposition work, the proposed CAD framework is carried out as the coordinated framework utilizing image handling strategies and AI calculations. Computer aided design focuses on the discovery and restriction of anomalies at a beginning stage, which stays away from the further spread of the irregularity.

II. Related work

Mammogram Image Classification System (MICS) consists of a few typical steps. First step is pre-processing for artifact and noise removal improves the quality of the breast image. The pectoral muscle regions must be

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removed before detecting the tumor cells so that mass detection can be done efficiently.

The undertaking of mammogram improvement is to hone the edges to expand the differentiation between dubious locales and the foundation [2]. Picture upgrade incorporates power and difference control, commotion decrease, foundation evacuation, edges honing, sifting, pectoral muscle expulsion, and so forth Desai et al. [3] detailed a resistant histochemical examination of steroid receptor status in 798 instances of bosom tumors experienced in Indian patients, proposes that bosom malignant growth found in the Indian populace might be organically not quite the same as that experienced in western practice. Gallagher, Wise and Nodes have broke down the properties of middle channels in detail [4, 5]. A range of non-ordinary improvement procedures has likewise been talked about. Lai et al., [6] introduced a technique utilizing changed middle separating to improve mammogram pictures. The general mammographic parenchyma and ductal examples can be demonstrated by a bunch of boundaries of relative changes. Veldkamp and Karssemeijer [7] introduced an exact versatile methodology for commotion evening out. Mudigonda et al. [8] have portrayed a strategy for the recognition of masses in mammographic pictures that utilize recursive Gaussian low pass sifting and sub-inspecting activities in a multi goal based pyramidal design as pre-preparing steps to accomplish the necessary degree of smoothing of the picture. McLoughlin et al. [9] expanded a grounded film-screen commotion evening out conspire for application to advanced mammogram pictures.

III. PROPOSED METHOD

The whole framework for Texture based Classification. First, the original image is converted to the processed image by removing noise and conduct image enhancement. The Fuzzy Edge Detector and Fuzzy Entropy Segmentation are used for preprocessing. The Haralick feature are extracted from SRDM, SGLDM, GLDM and from GLRLM texture description method the run length feature are extracted and compared both. Finally the using Support Vector machine (SVM) the images are classified.

IV. PREPROCESSING

The algorithm in mammographic is used to detect masses, usually the whole breast or specific kind of abnormalities. It is generally accepted that the detection of masses is technically more difficult than the detection of micro calcifications, because masses can be simulated or obscured by normal breast parenchyma. It is hoped that the identified structural information could be used to implement many image processing tasks.

V. FUZZY EDGE DETECTOR

In this work, we used FED for effective segmentation with membership functions.

Algorithm: Fuzzy Edge Detector (FED)

Input: Pectoral removed image

Output: Resultant edge image

Step 1: Iterate through each pixel of the 3×3 window by column, and then by row (Raster scan method)

Step 2: Fuzzify the image using triangular function associated to linguistic values black, edge, and white

Step 3: Modify the membership values by Applying fuzzy inference rule

Step 4: Mamdani defuzzification is used to Find the final pixel as edge or non-edge.

VI. FUZZY ENTROPY SEGMENTATION (FES)

To measure the ambiguity the fuzzy index is applied and below algorithm provide brief description.

Algorithm: Fuzzy Entropy Segmentation (FES)

Input: Pectoral removed edge image

Output: Resultant segmented image

Step 1: Read the pectoral removed edge image

Step 2: Construct the fuzzified image

Step 3: Repeat steps 4-8, $n/2 – 1$ times; where n is the number of thresholds

Step 4: Range $R = [T0, T3]$; initially $T0 = 0$ and $T3 = 255$

Step 5: Find mean (μ) and standard deviation (σ) of all the pixels in R

Step 6: T0, T1, T2 and T3 are calculated as $T0 = 0$, $T1 = \mu – k1 . \sigma$, $T2 = \mu + k2 . \sigma$ and $T3 = 255$;

Step 7: Pixels with intensity values in the interval [T0, T1], [T1, T2] and [T2, T3] are assigned σ threshold values

Step 8: T0 = T1 + 1, T3 = T2 – 1
Step 9: Find the index of fuzziness based on the distance all Subsets
Step 10: Finally, repeat step 7 with T1= μ and with T2 = μ +1

VII. Texture Discrimination Matrix

Texture plays main role in mammogram images classification. In this work we used SRDM ,SGLDM ,GLDM and GLRLM matrix for effective computation of features.

VIII. Surrounding Region Dependency Matrix

The mammogram image is transformed into a SRDM and later the features are extracted for this SRDM matrix. Figure 1 shows the algorithm of SRDM.

Algorithm: SRDM Input :Segmentated Image
Step 1: (read the Segmented Image(ROI)) Step 2 : (Iterative process for each pixel block window size 7*7) Step 3: (Outer regions of size 7*7 is R_1) Step 4 : (Outer region of size 7*7 is R_2) Step 5 : (The centre pixel value is considered as threshold value) Step 6 : (Construct the matrux M of size 24 *16) Step 7: Select the pixel values which are greater than the threshold value fro both R_1 represented I region and and R_2 represented j region. Step 8: Increment 1 of the corresponding position (I,j) of the SRDM.

Figure1: The SRDM Algorithm

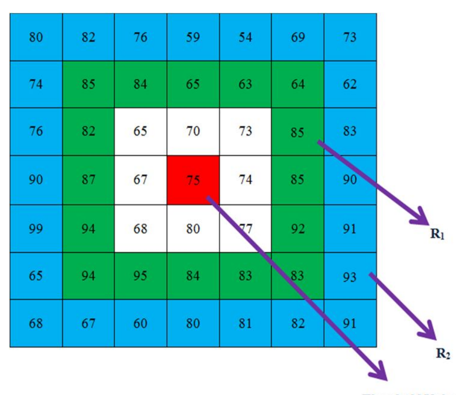

Figure2: Sub Image for constructing SRDM

Figure 2 shows a sub image of a segmented image for constructing SRDM matrix. Figure 3 shows a typical SRDM matrix.

IX. Spatial Grey Level Dependency Matrix

The features are extracted from SGLDM where the image are converted to respective matrix. Figure4 shows the algorithm of SGLDM.

Based on combinations of d and values the features are selected. Let us consider a 7 × 7 sub image of a segmented image .Suppose ,d = 1 and the angle θ = 0º and 180º, then count the number of similar pairs of pixels which are successive in horizontal direction and enter the count in to the matrix as M (73, 72) = 3.Figure 5 shows a sub image for constructing the SGLDM .Figure 6 shows a typical SGLDM matrix.

Algorithm: SGLDM Input :Segmented Image,(d, Ө)distance and direction.
Step 1: (read the Segmented Image(ROI)) Step 2 : (Iterative process for each pixel block window size 7*7) Step 3:   (Select the pixel with passing through Parameters d and Ө) Step 4 : (Construct the matrix of size 256*256) Step 5 : (If the selected pixel and consecutive pixels are same ,then the position of the selected pixel and d will be replaced by the count in the SGLDM matrix) Step 6 : (Repeat the steps 2 to 5)

Figure 4: The SGLDM Algorithm

Algorithm: GLRLM Input :Segmented Image,(d, Ө)distance and direction
Step 1: (read the Segmented Image(ROI)) Step 2 : (Iterative process for each pixel block window size 7*7) Step 3:   (Selct the pixel with passing through Parameters d and Ө) Step 4 : (Construct the 255*20 matrix in S) Step 5 : (If the selected pixel and consecutive pixels are same,then the position of the selected pixel and d will be replaced by the count in the GLRLM matrix) Step 6 : (Repeat the steps 2 to 6)

Figure 7:The GLRLM Algorithm

The texture features are extracted using Grey-Level Run-Length Matrix (GLRLM).Figure 7 shows the algorithm of GLRLM.

Figure 8 shows the sub image of a segmented mammogram image for constructing the GLRLM.Figure5.9 shows that the GLRLM is the sub image as shown in Figure 5.8.For example, let us consider, angle = 0º, M (165, 1) = 4. The count is made for all the distances in the same direction and they are summed up.

174	172	168	165	164	163	162
174	168	165	163	163	163	162
172	167	165	163	163	163	162
170	166	165	163	162	162	162
168	167	165	164	163	163	162
168	167	166	164	164	164	163
168	166	166	164	164	164	163

X. Experimental Results

From the SRDM ,SGLDM ,GLDM matrixes which is converted from mammogram images the statistical Haralick features are extracted and then by texture description method GLRLM the Run-length features are extracted. For the performance the experiments were carried out on all the 322 images with normal and abnormal cases .The data presented in Table 1 shows the sample statistical Haralick features using SRDM with 150 for the first18 images.

The performance is measure using sensitivity (SE), specificity (SP) and accuracy (Ac), further formula is given in Table II.

Algorithm: GLDM

Input:Segmented Image,(d,Ɵ) distance and direction

Step 1: (read the Segmented Image(ROI))

Step 2 : (Iterative process for each pixel block window size 7*7)

Step 3: (Select the ixel with passing through Parameters d and Ɵ)

Step 4 : (Construct the 255*255 matrix in S)

Step 5 : (IF the selected pixel and consecutive pixels are same,then the position of the selected pixel and d will be replaced by the count in the GLDM matrix)

Step 6 : (Repeat the steps 2-6)

Figure 10: The GLDM Algorithm

174	172	168	165	164	163	162
174	168	165	163	163	163	162
172	167	165	163	163	163	162
170	166	165	163	162	162	162
168	167	165	164	163	163	162
168	167	166	164	164	164	163
168	166	166	164	164	164	163

Figure 11: Sub image of a segmented mammogram image for constructing GLDM for difference=2,d=1andθ=0º

TABLE II: FORMULA FOR MEASURES

Measures	Formula
SE	TP/(TP+FN)
SP	TN/(TN+FP)
Ac	(TP+TN)/(TP+FP+TN+FN)

The entries in the confusion matrix have the following meaning:
TP–The number of correct predictions
FP–The number of incorrect predictions
FN–The number of incorrect predictions
TN–The number of correct predictions
The confusion matrix is given in Table 3. In addition, to this the measure gives high means sensitivity and specificity gives good result.

TABLE III: CONFUSION MATRIX

Actual	Predicated	
	Positive	Negative
Positive	TP	FP
Negative	TN	FN

Using SRDM, totally about 14 features are extracted and fed into SVM classifier and results are shown in Table IV. In this about 322 mammogram images. Further the SGLDM is constructed with direction choice and distance for feature extraction .The results of performance measures are tabulated in Table V. The GLRLM is constructed with direction choices for feature extraction .The results are tabulated in Table VI.

TABLE VI: RESULTS OF GLRLM FEATURE CLASSIFICATION USING SVM

Direction(θ)	Sensitivity	Specificity	Accuracy
0, 180	0.8432	1.0000	0.8725
45, 225	0.8027	0.8939	0.7954
90, 270	0.7628	0.7334	0.7423
135, 315	0.7549	0.8475	0.7206

From the Table VII, it is found that the features extracted from GLDM for distance = 1 with the direction = 0^o give superior results compared to others .The computational results are presented in Table 8.The individual performance measures are exposed in Figures13(a),13(b)and13(c).

TABLE VII: RESULTS OF GLDM FEATURE CLASSIFICATION USING SVM

Distance(d)	**Direction(θ)**	**Sensitivity**	**Specificity**	**Accuracy**
1	**0**	**0.8576**	**1.0000**	**0.8879**
	45	0.8245	0.9000	0.8475
	90	0.7934	0.8900	0.8272
	135	0.7198	0.8365	0.8165
	180	0.7305	0.8900	0.8389
3	0	0.6578	0.8975	0.7123
	45	0.6345	0.8805	0.7023
	90	0.7867	0.8978	0.7365
	135	0.7945	0.9000	0.7456
	180	0.7687	0.8634	0.7635
5	0	0.7423	0.8532	0.8234
	45	0.7345	0.8241	0.8223
	90	0.7356	0.9000	0.7723
	135	0.6986	0.8934	0.7975
	180	0.7349	0.9000	0.7272
7	0	0.8256	0.9150	0.7356
	45	0.7076	0.9000	0.7645
	90	0.6732	0.8900	0.7542
	135	0.7240	0.9000	0.8124
	180	0.7174	0.8958	0.7978
9	0	0.8256	0.9124	0.8354
	45	0.8450	0.9000	0.8216
	90	0.8345	0.9067	0.8034
	135	0.8256	0.8989	0.7645
	180	0.73045	0.9000	0.7834

TABLE VIII: COMPUTATIONAL RESULTS

Methods	Sensitivity	Specificity	Accuracy
SRDM	0.8934	1.0000	0.9023
SGLDM	0.8575	1.0000	0.8989
GLDM	0.8576	1.0000	0.8879
GLRLM	0.8432	1.0000	0.8725

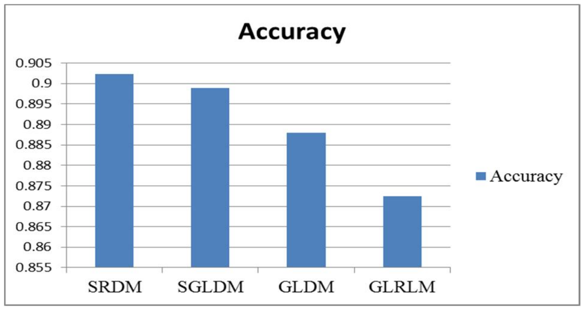

Figure13(a):Performance of A cof feature extraction methods

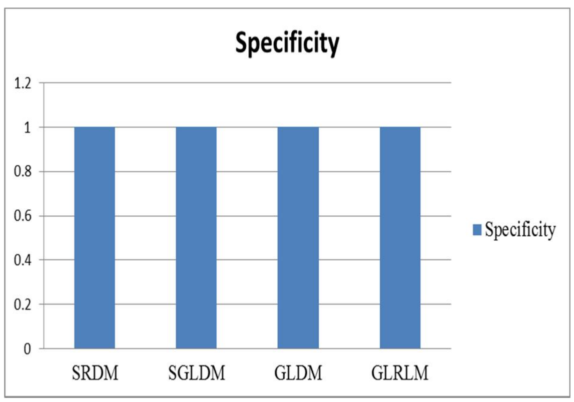

Figure 13 (b): Performance of SP of feature extraction method

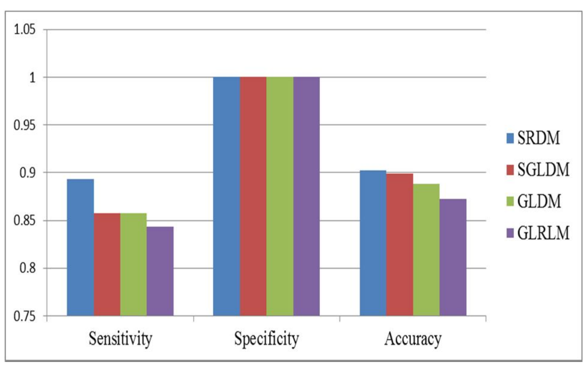

Figure 14: Relative performance measures of feature extraction methods

In addition , the comparison results of various proposed method is shown in Figure 14. Here the feature is considered individual for comparison. From above results in table and figures we analyze that the SRDM feature achieves good result when compare to other texture features. These analyses conclude that the SRDM features achieve the best classification accuracy for distinguishing between malignant masses and benign masses on mammogram images.

XI. CONCLUSION

In this work, the experimentation is conducted on mammogram images .The texture method like SRDM, SGLDM, GLDM are extracted using Haralick feature and the run-length feature which is extracted from the texture description method GLRLM .The classification is done using SVM. The classification performances of these data sets are tabulated. The performances of classifiers for the texture analysis methods are evaluated using various statistical parameters such as sensitivity, specificity, and accuracy .The performance analysis shows that SRDM features out performs.

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