

Research Article

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Breast Cancer Detection using Artificial Neural Networks

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Abstract

Breast cancer is very common and is considered as the second dangerous disease all over the world due to its death rate. Affected can survive if the disease diagnoses before the appearance of major physical changes in the body. Now a day, mammographic (X-ray of breast region) images are widely used for premature revealing of breast cancer. Aim of the proposed system is to design a Computer Aided Diagnosis system (CAD) used to distinguish between benign (non- cancerous) and malignant (cancerous) mammogram. CAD system are used to help radiologist to increase his diagnosis accuracy. In the proposed system, texture features from mammogram were calculated using Gray Level Co-occurrence Matrix (GLCM) along 0°, from the calculate features most effective features having large contribution to achieve the desired output were chosen and applied to Artificial Neural Network (ANN) for training and classification, as ANN is widely use in various field such as, pattern recognition, medical diagnosis, machine learning and so on. For this research work mini-MIAS database is used and the overall sensitivity, specificity and accuracy achieved by using the proposed system is 99.3%, 100% and 99.4% respectively.

Keywords: GLCM; CAD system; ANN, Breast cancer; Features extraction; Malignant; Benign

Introduction

Death rate due to breast cancer is very high. According to WHO (World health Organization) breast cancer impact over 1.5 million women each year worldwide [1]. In 2015; 570,000 women died due to breast cancer which is approximately 15% of all death among women from cancer. In 2017 about 252,710 cases of breast cancer are diagnosed and about 40, 610 women die in America [2].

Pakistan is at alarming rate in Asia [3] with 90 thousand cases of breast cancer are being annually reported, and death rate is approximately 40,000 per year [4]. Death rate due to breast cancer can be reduce by following proper screaming and diagnosis technique at initial stage before major physical symptoms started appearing on the body. Various techniques have been used for the detection of breast cancer by using ANN, Support vector machine (SVM) etc [5-10]. Mammography is very effective and most commonly used technique for the early detection of breast cancer [11-16]. It detects a very small change in the body even.

Medical experts examine mammograms and recommend biopsy if abnormalities are found in the mammogram. Biopsy is a standard clinical approach used to detect breast cancer, it is a costly, time consuming as well as painful procedure. Radiologist recommendation is very important at this stage, in case of wrong diagnosis; patient has to go through unnecessary biopsy [5].

Automation of this analysis helps radiologist to improve his diagnostic accuracy, such type of system can be used as second reader. A CAD system is proposed which helps to classify mammogram into one of its appropriate class i.e. Benign (not harmful for the body and does not spread to other part of the body) or malignant (cell spreads to other part of the body and cause to death).

Related Work

Approach proposes Berbar [17] recommends a wavelet based contourlet method for extracting features from mammogram classification. Before extracting features, contrast stretching function 'stretchlim' was used for pre-processing. Seven features extracted from the GLCM [18] are entropy, contrast, energy, inverse difference moment, homogeneity and sum average. ST-GLCM merges seven

statistical features (i.e. skewness, entropy, kurtosis, standard deviation, smoothness, energy and mean) with texture features extracted by using GLCM. Support Vector Machine classifier was used to class mammogram into effected or normal. Mini MIAS database [19] were used for the evaluation of the system. The performance of the system was measured in term of sensitivity, specificity and accuracy. Sensitivity and accuracy achieved by this system are 97% and 97.89% respectively.

Research work presented in the study by Preetha [20] defined a method for classification of mammogram that consist of 4 stages, preprocessing stage used median filter to enhance quality of image and to remove noise from the image. The suspicious region from the enhanced image is segmented by using Histon based fuzzy c-means segmentation algorithm. After segmentation several types of features such as texture, shape and intensity are extracted from the segmented image. To check the abnormality of the mammograms ANN classifier was used to classify the image into appropriate class. Sensitivity, specificity and accuracy claimed in the work was 72.72%, 93.6% and 88.66%.

Kumar and Chandra [21] proposed a method in which wavelet base adaptive sigmoid function was used for pre-processing. Pre-processing was done in three steps, first wavelet decomposition, secondly image was processed by using variable gain modified sigmoid function an at last step image was processed by adaptive histogram equalization. Region of interest (ROI) was cropped after the pre-processing. 13 combined features of texture and GLCM were used in this work. For training purpose cascade feed-forward back propagation technique was used. Classification accuracy of more than 95% was claimed to be achieved by using mini MIAS database.

Xie et al. [22] proposed a system for the diagnoses of breast cancer

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based on extreme learning machine. Pre-processing was done in two stage background and second was removing pectoral muscle. Hough transform method was used for ROI. A total of 32 grey level and texture features were extracted from mammograms. Accuracy claimed by using mini MIAS database was 96.02%.

In the study by Nithya and Santhi [23] GLCM features were calculated along four angles and at four distances. Five statistical measures were determined from GLCM. For results verification mini MIAS database was taken into consideration, and were classified by using ANN. Accuracy, sensitivity, and specificity achieved by using this model was 96%, 100% and 93%.

Dheeba et al. [13] used particle swarm optimized wavelet neural network (PSOWNN) for investigation of new classification technique for the detection of abnormalities in mammograms. Algorithm is based on extraction of law texture energy measures from mammograms and classification was done by using pattern classifier. By using proposed system, they achieved 94.167%, 93.67% and 92.105% for sensitivity, accuracy and specificity respectively.

Proposed Approach

Figure 1 shows the methodology adopted in this research work. Overall system comprises of 4 stages, first one is acquisition of image, second extracting features from the mammograms, selecting more optimal features, classifier to identify appropriate class of mammogram. The suspicious parts were extracted from the mammogram by using texture features. Database for this experiment is taken from mini-MIAS this data set contains 322 mammograms, 270 images are normal (non-cancerous) and 52 images are malignant (cancerous). Every image in this database is 1024×1024 pixels. This database can be access easily [19]. Figures 2 and Figure 3 are sample images for normal and malignant class respectively.

Texture features are extracted using GLCM along 0° for each mammogram. Features represent image in a specific format that





Figure 3: Sample image of malignant class.

Variables	Image 1	Image 2	Image 3	Image 4	Image 5
contrast	0.024	0.037	0.042	0.038	0.038
Correlation	0.996	0.995	0.995	0.995	0.995
Entropy	1.195	1.233	1.277	1.262	1.115
Sum of square variance	6.986	8.385	9.065	8.723	7.535
Sum average	3.980	4.356	4.585	4.399	3.993
Sum variance	20.170	24.691	26.565	25.733	22.786
Sum entropy	1.180	1.211	1.256	1.244	1.098
Difference variance	0.024	0.037	0.042	0.038	0.038
Difference entropy	0.092	0.124	0.123	0.097	0.089
Info measure of correlation1	-0.925	-0.905	-0.906	-0.926	-0.925

Table 1: Statistical value for sample images.

focus especially on relevant information. In the next stage features are selected for training and testing; this stage is very important because classification accuracy mainly depend on careful selection of features. In the other step mammograms are classified, for this research work neural network is used as a classifier to distinguish mammogram and classify it into normal and malignant class.

Features Extraction using GLCM

Feature extraction plays a vital role for pattern classification. Gray Level Co-occurrence Matrix (GLCM) features are determine along 0° for all mammograms. In the proposed system, 10 texture features define by Haralick et al. [24] shown in Table 1 are extracted from the texture feature sub-space based on GLCM. Readers are advised to read [25-27] for the basic understating of GLCM. Numbers of gray level in an image determine the size of GLCM. For each formula given in the equations, n determine the number of grey level used. The matrix element Q (i,j) is the relative frequency with two pixels, separated by pixel distance, occur within given neighbourhood with intensity i and j. Texture features that are derived from the GLCM are given below

Contrast

It measures grey level values between reference and its neighbour pixel, variance present in the mammograms is measured through it. Its value is high in case of Q (i,j) has huge variation in the matrix. It can be measure through equation shown below

$$con = \sum_{i=0}^{n-1} \sum_{j=0}^{n-1} \left| i - j \right|^2 Q(i, j)$$

Correlation

Correlation shows the linear dependency of grey value. The value of

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correlation will be high in case of mammogram contain linear structure up to considerable amount.

$$corr = \sum_{i=0}^{n-1} \sum_{j=0}^{n-1} \frac{(i-u_x)(j-u_y)q(i,j)}{\sigma_x \sigma_y}$$

Where

$$u_{x} = \sum_{i=0}^{n-1} iQ_{x}(i)$$

$$\sigma_{x}^{2} = \sum_{i=0}^{n-1} (i - ux)^{2}Q_{x}(i)$$

$$u_{y} = \sum_{i=0}^{n-1} jQ_{y}(i)$$

$$\sigma_{y}^{2} = \sum_{i=0}^{n-1} (i - u_{y})^{2}Qy(i)$$

$$Q_{x}(i) = \sum_{j=0}^{n-1}Q(i, j), Q_{y}(j) = \sum_{i=0}^{n-1}Q(i, j)$$

Are mean and variance of marginal distribution $Q_{v}(i)$ and $Q_{v}(j)$

j)

Entropy

Entropy is a measure of randomness, it also describes the distribution variance in a region. It can be calculated by using equation given below.

$$N = -\sum_{i=0}^{n-1} \sum_{j=0}^{n-1} Q(i,j) \log_2 Q(i,j)$$

Sum of square

It tells about variation between two dependent variables. Variance puts relatively high weights on the elements that differ from the average value of Q (i,j).

$$VA = \sum_{i=0}^{n-1} (i - u_x)^2 Q_x(i)$$

Where

$$Q_x(i) = \sum_{j=0}^{n-1} Q(i,j)$$

Sum average

Relation between clear and dense area in a mammogram.

$$SA = \sum_{k=0}^{2n-2} k Q_{x+y}(k)$$

Where

$$Q_{x+y}(k) = \sum_{i=0}^{n-1} \sum_{j=0}^{n-1} Q(i, j)$$

i+j=k.k=0,....2n-2

Sum variance

It reveals spatial heterogeneity of an image.

$$Sv = \sum_{k=0}^{2n-2} (k - SA)^2 Q_{x+y}(k)$$

Sum entropy

It is a measure of the sum of micro (local) differences in an image.

$$SE = -\sum_{k=0}^{2n-2} Q_{x+y}(k) \log_2 Q_{x+y}(k)$$

Difference entropy

Is a measure of the variability of micro differences.

$$DE = -\sum_{k=0}^{n-1} Q_{x-y}(k) \log_2 Q_{x-y}(k)$$

Where

$$Q_{x-y}(k) = \sum_{i=0}^{n-1} \sum_{j=0}^{n-1} Q(i, j)$$
$$|i-j| = k, k = 0...n-1$$

Information measure of correlation1

In this feature two derived arrays are used, first array represents the summation of rows, while the second one represents the summation of columns in the GLCM.

$$H1 = -\sum_{i=0}^{n-1} \sum_{j=0}^{n-1} Q(i, j) \log_2[Q_x(i)Q_y(j)]$$
$$H_x = -\sum_{i=0}^{n-1} \sum_{j=0}^{n-1} Q(i, j) \log_2[Q_x(i)]$$
$$H_y = -\sum_{i=0}^{n-1} Q_y(i) \log_2[Q_y(j)]$$

Difference variance

Local variability can be measure through it.

$$DV = -\sum_{k=0}^{n-1} (k - DA)^2 Q_{x-y}(\mathbf{k})$$

Above ten features are calculated for all mammograms, values of features for five mammograms are shown in the Table 1.

Features Selection

Features subset selection is used to reduce feature space that helps to reduce the computation time. This is achieved by removing noisy, redundant and irrelevant features i.e., it selects the effective features to get desire output.

For this research work, rank feature method is using to select optimal features that contribute more toward target output. This function rearranges the features from top to bottom according to their contribution. In this work top six ranked features are selected for training the network. List of selected features is shown in Table 2.

Classification

Artificial Neural Network (ANN) classifier is used in this work as it is a commonly used classifier for breast cancer classification [28-36]. Neural Network composed of simple elements that are inspired by biological neuron operates in parallel. We train neural network to perform specific function by adjusting weights between elements. Neural network is trained to get desired output. Such situation is shown in Figure 4. The network is adjusted based on the comparison with the output and the corresponding target until the network output matches the target. ANN classifier is based on two steps, i.e. training and testing. Classification accuracy depends on training.

Optical Features					
F1	Sum variance				
F2	Sum of square variance				
F3	Correlation				
F4	Sum entropy				
F5	Entropy				
F6	Difference variance				

Table 2: Optimal features selected by using rank method.









From the selected data base 70% data is used for training, 15% data for testing and remaining 15% data is used for validation. Neural network contains three layers namely input layer, hidden layer and output layer. Parameter used for artificial neural network are shown in the training window (Figure 5).

Training function Levenberg-Marquardt is used for training the network, it shows good results in training and classification. Other training function resilient back propagation, Conjugate Gradient with Powell etc. are used; from all these training function Levenberg-Marquardt is selected by comparing classification accuracy, training time to converge and mean square error. Optimize network architecture used in this study has 20 neuron. Optimize network is selected by observing mean square error (mse) for different values of hidden neurons.

Regression analysis

Regression analysis is a statistical process to estimate association among all variables. In the regression plot output from network are plotted versus the target set shown in the Figure 6. In the regression plot perfect fit is indicated by dotted line while the solid line shows the output from the network. Solid line perfectly equal to dashed line is achieved if the classifier predicts 100% accurately. The difference between two line shows there are some sample which are not correctly predicted by network. Data is represented by circle. In the plot shown below value of R is 0.718, this value also shows the result accuracy. The value of R equals to 1 shows 100% prediction (Figures 7 and 8).



	Data division	Specificity	Sensitivity	Accuracy
Overall results by using mini MIAS Database	Training	99.0%	100%	99.1%
	Validation	100%	100%	100%
	Test	100%	100%	100%
	Overall	99.3%	100%	99.4%

Table 3: Overall summary of the results.

Performance Evaluation

The problem under evaluation is binary classification, the parameters used for weighing are accuracy, specificity, and sensitivity.

These parameters are defined as:

Sensitivity=TP/TP+FN \times 100

Specificity=TN/TN+FP \times 100

Accuracy=TP+TN/TP+TN+FP+FN × 100

Where TP is true positive, TN is true negative, and FP and FN are false positive and false negative respectively. Sensitivity measures the percentage of truly predicted cancer class, specificity measures the percentage of truly predicted benign/normal class and accuracy is percentage of rightly predicted cancer and normal cases. Data is rotated five time and the best result out of fivefold is shown in the confusion matrix below. Overall results of confusion matrix are summarizing in the Table 3. In training set there are 226 mammograms, 193 are normal and 33 are malignant; network predict all benign as benign, out of 193 normal cases 2 samples are miss classified. Validation set comprises of 48 samples, 42 are normal and 6 are malignant, network predict all normal and malignant correctly. Test set consists of 48 samples, 37 normal and 11 malignant; prediction is 100% for this dataset.

Discussion and Future Work

In the proposed solution 10 texture features from GLCM are calculated along 0° are under consideration. Further sample space is reduced to 6 features. In future more, features can be considered, and other dataset can be used to increase robustness of system.

Conclusion

To reduce the death rate due to breast cancer it is very essential that cancer must be identified at initial stage. Mammograms from mini-MIAS database are used in this research work for experiment. This database comprises of 322 mammograms, out of which 270 are normal and 52 are cancerous. Ten texture features from the GLCM were calculated along 0°, Features space is further reduced to six features by using the rank features method. Results show accuracy of 100% for validation and test data, and overall accuracy achieved by using the proposed method is 99.4%.

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