Gray Tone Spatial Dependence Matrices based Classification of Breast Mammograms

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Abstract
Texture plays an important role for classification of images based upon texture information. Breast mammograms have also texture so for these type of images, texture can be helpful for classification. Breast mammograms can be used to analyze the breast cancer specially for women. In this paper, gray tone spatial dependence matrices have been used for texture analysis and for feature extractions. After that, artificial neural network has been used for classification of breast mammograms by using the texture features. Before features extraction, region of interest has been calculated manually by using the information provided in the dataset. So for features extraction, these ROI images has been used for classification. A well-known standard dataset (DDMS) has been used for verification of proposed method. Different classifiers have been compared to test which classifier is most suitable for this problem. Results shows that proposed method has attained 96.13% accuracy as well as 98.38% sensitivity and 96.23 specificity.
Keywords:
breast mammograms, gray tone, spatial dependence, classification, texture

1. Introduction

Cancer is the most dangerous and leading cause of death in the whole world wide. There are different types of cancers in the different organs of human. For women, breast is the most important organ. At the baby birth, mother women used his breast to feed her milk to her child. Therefore, breast is the most important organ specially for women. There is a special care required so that it can escape from any type of disease or cancer. Due to milk transfer to child's, there are chances that may be cancer also shifted to child's if it uncured or due to unaware of such type of diseases [1]. Breast cancer is the most common cancer specially in the women. Thus there is special attention required to solve this problem. Mammography is a process that can be used to detect cancer in breast. Radiologists are the most expensive in the whole world wide. It is very difficult for a common person to bear too much expenses. Second this cancer is also diagnosed very carefully. Most of the time, it is recommended to take second opinion from other radiologist. Due to lack of funds or expenses, it is very difficult to take second opinion. Now a day, in this digital world, it is possible to introduce computer based solution to diagnose such type of cancers [2,3,4]. In the literature, many different Computer Aided Diagnosis (CAD) systems available to help the radiologist to take second opinion. Most of the existing system has some problems due to imaging poor quality. Some systems did not perform well in the case of noises or due to low radiation may be image has low quality or poor quality due to low contrast. There is CAD system available that guarantees the solution. Still, there is a room to improve the performance of these CAD systems [5,6]. Therefore, I have tried to propose a solution to detect cancer in the breast mammograms.

In this paper, a new CAD system has been proposed by using different three types of steps. First breast part of the mammograms has been extracted by using bilateral filter with logarithm transformation. This bilateral filter smooths the grey levels by preserving the edges. Log transformation has an advantage that it increases the dynamic range specially for those areas which are dark in the mammograms. Then entropy has been calculated so that thresholding can be applied to make it binary. Then seed point has been selected from white area so that adaptive contour method can start. After extracting breast part, enhancement has been performed to improve the performance. Then features extraction has been performed to classify busing ensemble classifier.

Main contribution of the proposed methods is following:

- Proposed method works well for low contrast images as well due to bilateral filter, log transformation and enhancement process.
- Adaptive contour method has been used by using the concept of entropy with active contour.
- Enhancement has been performed by using Partitioned Iterated Function System.
- Classification has been performed by ensemble classifier AdaBoost.

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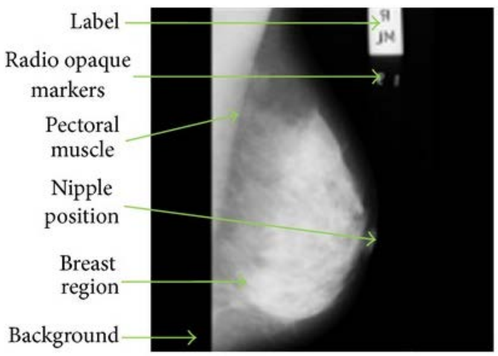

Figure 1: Mammogram Image with labeling

Table 1: List of Abbreviation used in this paper

CAD	**Computer Aided Diagnosis**
DDMS	Digital Database for Screening Mammography
SVM	Support Vector Machine
KNN	K Nearest Neighbor
BPNN	Backpropagation Neural Network

2. Proposed Method

Proposed method consists of different phases to complete the whole process. Figure 1 shows sample image from dataset and it clearly shows that this mammogram images has many different parts inside it. There is some portion that is background, some portion shows muscles that is not part of the area where we have to find out cancer. Therefore, it is important to remove all these unwanted parts and segment the required part for further analysis. In the first phase, segmentation has been performed to extract the region of interest. In the second phase, there is also required to enhance the quality of the image so that it can be shows clearly visible and easily identifiable. Thus enhancement has been performed to improve the quality of mammograms. After that, features are required to classify those regions. As figure 1 shows that mammograms show clearly texture on the image. So Texture features has been extracted and later used for classification. As we know in our daily life that different experts can give their opinion and finally conclusion has been designed by combining the opinions of all those experts. Similar concept has been used in this paper to classify mammograms. Ensemble classifier AdaBoost has been used that can combine the performance of different classifiers and finally decide the output by using the texture features. Details of all these phases has been given below in detail

2.1 Region of Interest Extraction

In this paper, Digital Database for Screening Mammography (DDSM) dataset has been used. This is most widely used dataset in this domain. It contains more than 2000 patient images. Each patient case has been evaluated by expert radiologist and provide annotation. Location of the masses also provided with the dataset in the form of chain code. By using this chain code, information, ROI has been extracted from each case that can be used for later enhancement and features extraction. Random 1200 images have been selected from this whole dataset for evaluation. It contains equal cases. Some ROI are bigger in size and some are less so to make it balance, all ROI converted to 256x256 fixed sizes as shown in Figure 2.

2.2 Enhancement of Breast

Enhancement has been performed by using the concept of Partitioned Iterated Function System [8]. This function performs a special task on the image that is known as contractive transformations. First transformation of the pixel intensities calculated by using two special parameters that can adjust the brightness as well as darkness in the images. The detail of this method has been given in [8]. I just used this method and it perform well as compare to histogram based methods like histograms equalization, adaptive histogram equalization or contrast limited adaptive histogram equalization methods. By using this process, it produces a low pass image. After that, final enhanced image can be calculated by adding the difference of the original and low pass images. This enhanced image is better and it also plays role to improve the performance of the proposed method.

2.3 Features Extraction

Features represents the characteristics of the image based upon, it can be deciding the type of objects in the images. Thus to classify the breast part whether it is benign or malignant, features of breast part is required to classify. There are different types of features available in the literature that can be used for classification. Shape based feature are not important because there is no specific shape of the lesion inside the breast part through which it can be decide into benign or malignant. Texture is the most import in breast part that can play a role to distinguish the benign and malignant. Therefore, in this paper, I also used a special type of the texture that is known as Gray Tone Spatial Dependence Matrices based Texture Features [11,12].

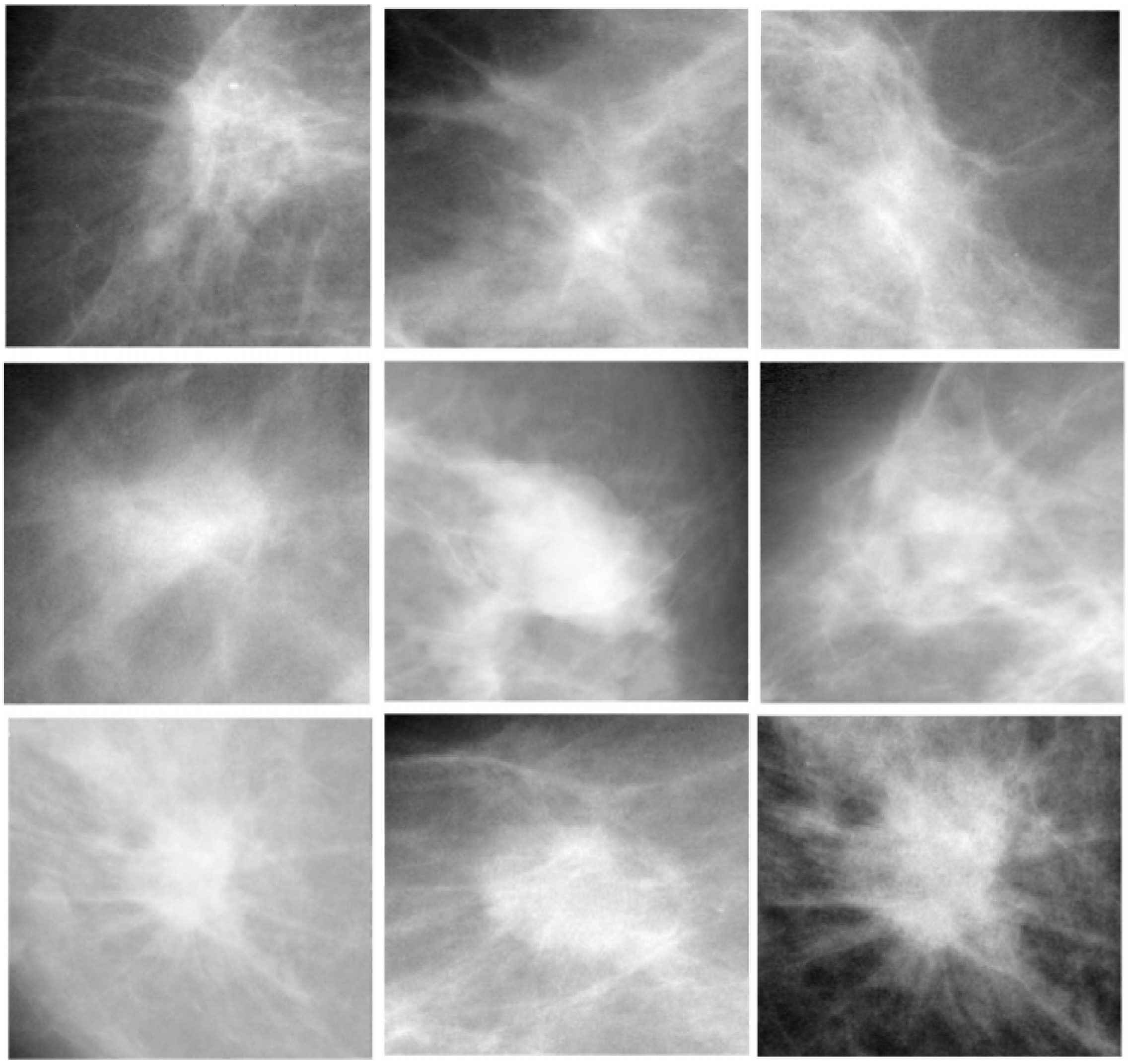

Figure 2: Region of Interest (ROI) extracted by using chain code

These features can be extracted by using a simple process. First quantization has been applied on the the grey values of the breast part. After that, distance need to be calculated For this, neighbor points on different directions can be used. As there are four different directions like 0°, 45°, 90°, and 135°, so for each direction, distance calculate for neighbor points. Then for every pixel in the breast, correlation has been calculated by using the eight neighborhood on central pixel. Process has been shown in Figure (3).

Gray tone spatial dependency has been calculated for each direction by using the information of the neighboring pixels around the central pixel and it has been shown in figure (4). In this table there is a special form to represent the occurrences of the neighbor for each pixel has been shown. Like # (i, j) shows that how many times pixel gray tones i and j appear neighbors in the process. have been as neighbors

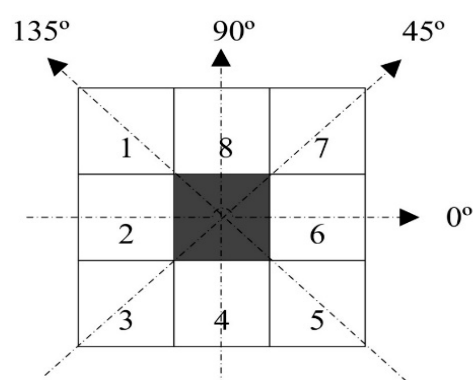

Figure 3: Four Directions at four different angles

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Gray level	1	2	3	...	N_g
1	#(1, 1)	#(1, 2)	#(1, 3)	...	#(1, N_g)
2	#(2, 1)	#(2, 2)	#(2, 3)	...	#(2, N_g)
3	#(3, 1)	#(3, 2)	#(3, 3)	...	#(3, N_g)
...	...	...	...	...	...
N_g	#(N_g, 1)	#(N_g, 2)	#(N_g, 3)	...	#(N_g, N_g)

Figure 4: Representation of Gray Tone Spatial Dependence Matrices

After performing this step, twelve features have been extracted like mean, variance, skewness, kurtosis, angular second moment, contrast, correlation, inverse difference moment, entropy, difference variance, difference entropy, information measures of correlation, and maximal correlation coefficient. These features are well known and available in the literature proposed by Haralick R. M. [13].

After extracting all these features, average and range of all features can be used to calculate the averages of all these individual features so total 2x12 features extracted from each breast part to classify. As these features shows that these are sufficient features for classification so no need to apply features selection on these features.

Algorithm _: 2D Haralick Features Calculation

1) Quantize the gray value of each pixel to N_g levels.
2) Generate the pattern matrices on all of the four directions, 0°, 45°, 90°, and 135°.
3) Calculate 14 Haralick features from each pattern matrix on each direction separately for four directions in total.
4) Calculate the mean and range of each feature over the four directions.

2.4 Backpropagation Neural Network based Classification

For classification, backpropagation neural network has been used. General architecture of backpropagation neural network (BPNN) has been shown in Figure 5.

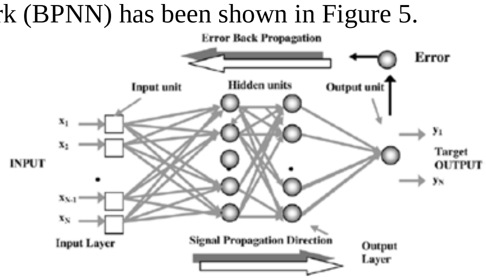

Figure 5: Architecture of backpropagation neural network (BPNN)

This BPNN architecture has three different layers namely Input Layer that takes input from feature file, Hidden Layer that calculate hidden weights by using input from Input Layer and Output Layer that can be used to show output. In this case, there is binary problem to classify into benign and malignant so output layer has two neurons. The edges between layers can be used for weights adjustment. Initially, weights have been assigned randomly but later it can be adjusted. It is a supervised network, so input features can be used as input at input layer and then activation function has been applied on the computed weights on all neurons. In this way, network learn by adjusting the weights until optimized set of weights calculated for all inputs.

If there are N input features, then there are N input units in the input layer with L hidden units that lies on hidden layers. These hidden layers are not fixed. It can be changed. There is no fix rule to use fix number of hidden units. There are one or two W output units at output layers. By using backpropagation algorithm, there are two stages one forward and other is backward pass. In forward pass, input features can be used at input layer. In case there are p samples then

$\mathbf{x_p = (x_{p1}, x_{p2}, \ldots x_{pn})}$

All these input can be used at hidden layers and multiplied with the weights between the links input and hidden layer and then calculated sum on all hidden units. After that activation function has been used on hidden units by using following:

$$net_j = \sum_{i=1}^{n} w_{ji} x_i \quad (1)$$

And the activation function applied on these net

$$oh_j = \int(net_j)$$

At the output layer, output units can be calculated by using following:

$$net_k = \sum_{j=1}^{L} w_{kj} oh_j \quad (2)$$

And the activation function applied on these output net

$$oo_j = \int(net_k)$$

In the Backward pass, first need to calculate the difference between actual and desired output that is known as error.

$$E = (d_k - oo_k)$$

Delta can be calculated

$$\delta o_k = (d_k - oo_k) oo_k (1 - oo_k) \quad (3)$$

Error can be calculated for all hidden units at hidden layers

$$\sum_{k=1}^{W} \delta o_k w_{kj}$$

$$\delta h_j = (oh_j)(1 - oh_j) \sum_{k=1}^{W} \delta o_k w_{kj} \quad (4)$$

Weights can be calculated between the hidden and output layers by using following:

$$wed_{jk} = \delta o_k (oh_j) \quad (5)$$

Similarly, these weights can be calculated between input and hidden layer by using following:

$$wed_{ij} = \delta h_j (x_i)$$

At the end, weights are updated by using the following equation on both layers.

$$w_{jk}(t+1) = w_{jk}(t) + \eta(wed_{jk}) \quad (6)$$

3. Results and Discussion

To test the performance of the proposed method, different quantitative measures has been used. Accuracy, sensitivity, specificity and Area under The Curve (AUC) has been used. These can be calculated by using mathematical equations shown in equations (5). (6), and (7). Accuracy can be calculated by using

$$\frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (5)$$

Sensitivity can be calculated by using

$$\frac{(TP)}{(TP + FN)} \quad (6)$$

Specificity can be calculated by using

$$\frac{(TN)}{(TN + FP)} \quad (7)$$

Where TP is True positive, FP is false positive FN is false negative and TN is true negative

Dataset has been divided into different ratios but to show results only 50-50 ratio has been used that mean 50% dataset has been used for training and 50% for testing.

Three measures have been used to check the performance of proposed method. Different classifiers have been used to compare and test the good classifier for this problem. I have used different classifiers to test the performance to show that which classifier is best suitable for this problem. Results has been shown in Table (2). These results shows that by using proposed method with backpropagation neural network, it performs best in all cases. Support Vector Machine (SVM), K nearest neighbor (KNN), Decision Trees (DT), artificial Neural Network (ANN) and ensemble classifier has been compared by using the same features set. These results shows that ensemble has best accuracy, sensitivity, specificity as well as AUC. Table (2) shows enhancement is better to improve performance. Therefore, to compare with existing methods, I used ensemble classifier by using enhancement and also select the best ration that is 60-40 where 60% data used for training and 40% used for testing.

Table 2. Different Classifiers Results Without Enhancement

Classifier	Trainin g-Testing	Accuracy (%)	Sensitivity (%)	Specific ity (%)
SVM	50-50	90.12	88.17	89.35
KNN	50-50	86.54	90.02	88.15
Decision Tree	50-50	89.14	88.87	89.17
BPNN	50-50	94.23	94.03	95.18

Table 2. Comparison with existing methods

Research	Year	Accuracy
Daniel et. al. [10]	2011	90.07
X. Liado et. al. [9]	2009	91.23
Fatemeh et. al. [11]	2010	85.9±0.03
Ioan B. et. al. [12]	2011	84.37
Proposed Method	2017	94.23

After that I have compared with existing methods to test the performance of proposed method. Results has been shown in table (3). These results shows that proposed method shows best results as compare to all other existing methods in both accuracy as well as sensitivity. The main reason of the improved performance is good features of the breast part ROI, most suitable features extraction and BPNN classifier also plays important role to increase the performance. Same performance measures used as well as other parameters for classifiers.

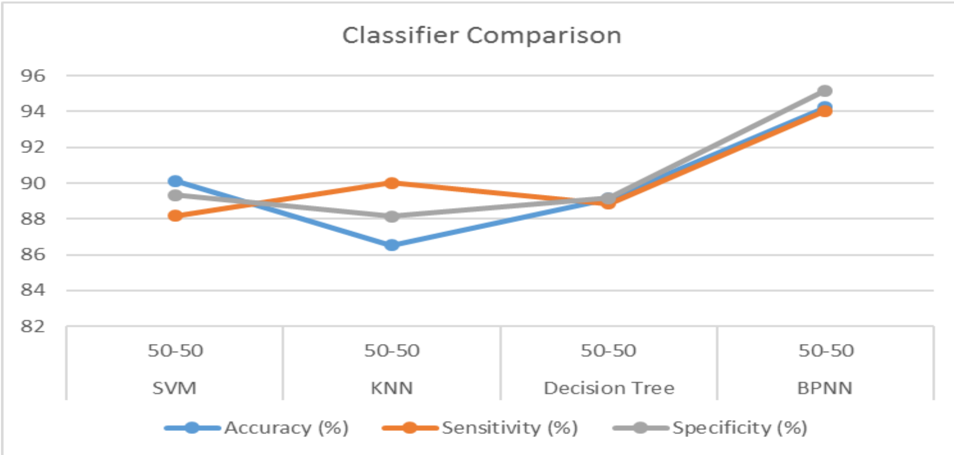

Figure 6: Comparison of different classifiers

Conclusion and Future Work

A computer aided diagnosis (CAD) system has been proposed that can extract gray tone based features to represent the texture in mammograms. First ROI has been extracted by using chain code information provided by radiologist for DDMS dataset. Features has been extracted only from ROI to differentiate benign and malignant. At the end classification has been performed by using BPNN and also tested other classifiers like SVM, KNN. In the future, deep learning will be explored for this problem.

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