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Classification of Mammogram Images for Detection of Breast Cancer

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Abstract: *Breast cancer is the most commonly observed cancer in women both in the developing and the developed countries of the world. The survival rate in it has improved over the past few years with the development of effective diagnostic techniques and improvements in treatment methodologies. About 1 in 8 U.S. women (about 12%) will develop invasive breast cancer over the course of lifetime. In 2014, an estimated 232,670, new cases of invasive breast cancer were expected to be diagnosed in women, along-with 62,570 new cases of non-invasive (in situ) breast cancer. By using mammogram image classification.*

I. Introduction

The objective of this paper is to build a CAD model to discriminate between cancers, benign, and healthy parenchyma. For experimental purpose, Digital Database for Screening Mammography (DDSM) is used. The experimental results are obtained from a data set of 410 images taken from DDSM for different types. Our method select 31 features from 145 extracted features; 18 of the selected features are from our proposed feature extraction method (SCLGM). We used both Receiver Operating Characteristics (ROC) and Confusing matrix to measure the performance of different classifiers. In training stage, our proposed method achieved an overall classification accuracy of 96.3%, with 92.9% sensitivity and 94.3% specificity. In testing stage, our proposed method achieved an overall classification accuracy of 89%, with 88.6% sensitivity and 83.3% specificity.

II. Methodology

- Digital Mammogram Database (DDSM)
- Feature extraction using GLCM
- Neural Classifier Training and Testing
- Mammogram Classification (Normal, Cancer)
- Performance Evaluation

Data Collection: Data for experiment in the proposed method taken from DDSM. DDSM is s resource for mammographic image. The total 250 mammograms have been used for training and testing. DDSM contains more than 2500 mammograms available at http://marathon.csee.usf/edu/Mammography/DDSM.

Feature Extraction: Feature extraction is very important part of pattern classification. To identify texture in image, modeling texture as a two dimensional array gray level variation. This array is called Gray Level co-occurrence matrix. GLCM features are calculated in four directions which are 00,450,900,1450 and four distances(1,2,3,4). Five statistical measures such as correlation, energy, entropy, homogeneity and sum of square variance are computed based on GLCM [8-13]. Table 1 provides explanation and equation for five features. The size of GLCM is determined 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 2 shows GLCM features for normal and cancer class. Ji,Jj are mean and σi, σj are standard deviation of P (i ,j), where

Classification:

Neural classification consists of two processes: Training and Testing. Neural network is the best tool in pattern classification application. The classifier is trained and tested on mammogram image. The classification accuracy depends on training. Neural network contains three layers: input layer, hidden layer and output layer [14, 15]. The designing of neural network consist a number of input, hidden, output units and activation function. The first layer has 5 nodes and second layer has two nodes. One node is needed for output

layer. The actual output is compared with desired output by error rate. For the neural network model error (E) is calculated using equation 1 $E = d\text{-}a$ (1)
Where **d** is the desired output, **a** is the actual output. The output of the network is determined by activation function such as sigmoid. Neural network are trained by experience, when fed an unknown input into neural network, it can generalize from past experience and produce a result. Five GLCM features fed to neural input layer. The output layer produce either 1(normal) or 0 (cancer). Figure 2 shows the neural network architecture.

Algorithm
Step 1: Extract features from mammograms
Step 2: Create input and target for normal class
Step 3: Create input and target for cancer class
Step 4: Initialize weights at small random values
Step 5: calculate output
Step 6:Use test patterns and calculate the accuracy
Table1.GLCMfeaturesvaluefornormal andcancerclass

We implement the FFANN four times, each time we use one of the four sets that are obtained in feature selection stage, which are SFF, GAF, USF, and ISF. In the following we preview the classifications results using mentioned performance metrics:

Classification using SFF: The total number of the features selected by forward sequential technique is 27 features; we use these features as input to the FFANN with 29 neurons in the hidden layer and three neurons at the output layer.

Training stage: Figure 1 shows the ROC curve and the Confusion ma~~trix of~~ feed-forward ANN classifier in training stage. When we have a look on this figure we can judge that we have a very good classification with high performance as shown by the largest area under the ROC curve. The Confusion matrix shows that:

- From 126 cancer cases, 105 are classified truly as cancer while the remained 21 are classified as benign,
- From 105 benign cases, 89 are classified truly as benign, and 16 cases are classified in false as a cancer,
- And 179 normal cases are classified truly as normal.

The overall classification accuracy is 91%, with 83.33% sensitivity and 84.7% specificity.

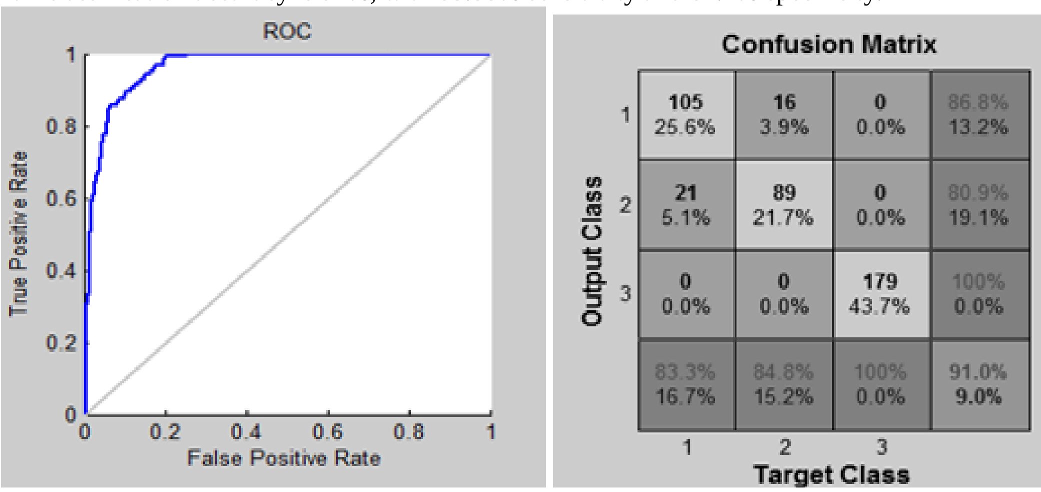

Figure 1. The ROC Curve and the Confusion Matrix Analysis of FFANN Classifier for Training using SFF Features

Test stage: As mentioned before, we use two different and difficult datasets for testing the model obtained in training stage. The difficulties of the used test datasets lead to decrease the accuracy of classification. With dataset-1 the accuracy is 82% as shown in the confusion matrix in Figure 2, and with dataset-2 the accuracy is 86% as shown in the confusion matrix in Figure 3

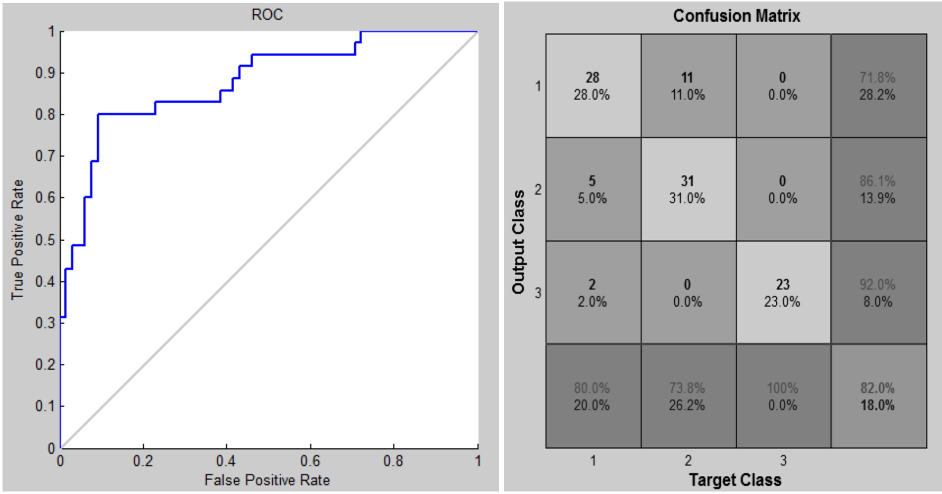

Figure 2. The ROC Curve Analysis and the Confusion Matrix of Testing Dataset-1 using SFF Features

Classification using GAF: GA method selects 18 features as the best for the classification; we use these features as input to the FFANN with 20 neurons in the hidden layer and three neurons at the output layer.

Training stage: The classification performance is demonstrated by the ROC curve and the Confusion matrix shown In Figure 7, as shown the area under ROC curve is large like that in Figure, which means that the performance here will be near that in case 1. The Confusion matrix could be interpreted as follow:

- From 126 cancer cases, 103 are classified truly as cancer while the remained 23 are classified as benign,
- From 105 benign cases, 90 are classified truly as benign and 15 cases are classified in false as a cancer,
- And 179 normal cases are classified truly as normal.

The overall classification accuracy is 90.7%, with 82% sensitivity and 85.7% specificity.

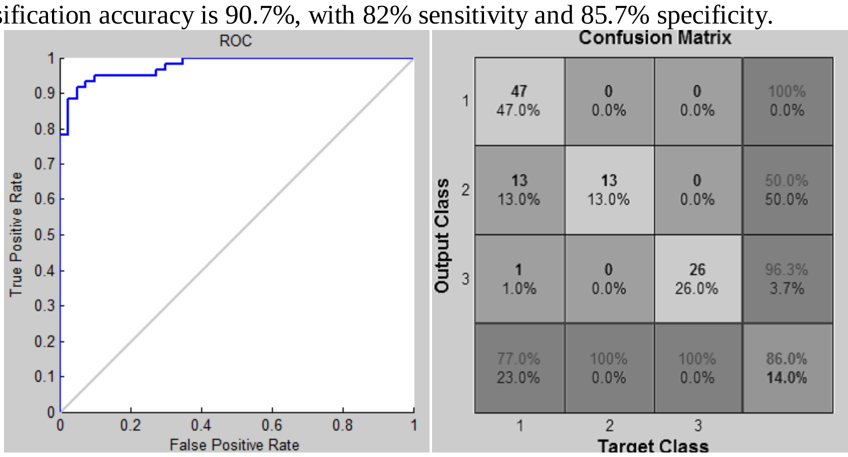

Figure 3. The ROC Curve Analysis and the Confusion Matrix of Testing Dataset-2 using SFF Features

Testing stage: After training we test the created model using two different and difficult datasets. As shown in Figure 8, the accuracy with dataset-1 is 84%. In cancer cases, 31 of 35 cases are classified truly as cancer, 2 as benign and 2 as normal. In dataset-2, the accuracy is 86%, which is better than that in dataset-1, see Figure 9.

Classification using ISF :

Shared features are the features that are selected by both sequential and GA techniques; the number of these features is 13 features. We create a FFANN with 13 neurons for input, 15 neurons for the hidden layer and 3 neurons for output layer.

Training stage: Figure 10 shows the ROC curve analysis the confusion matrix for FFANN classifier with ISF features:

- 112 of 126 cancer cases are classified truly as cancer while the remained 14 cases are classified as benign.
- With 105 benign cases, 88 are classified truly as benign and 17 cases are classified in false as a cancer,
- And 179 normal cases are classified truly as normal.

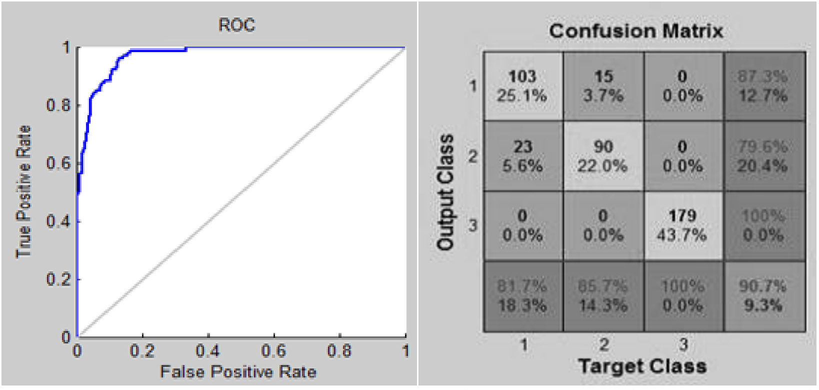

Figure 4. The ROC Curve Analysis and the Confusion Matrix of FFANN Classifier for Training using GAF Features

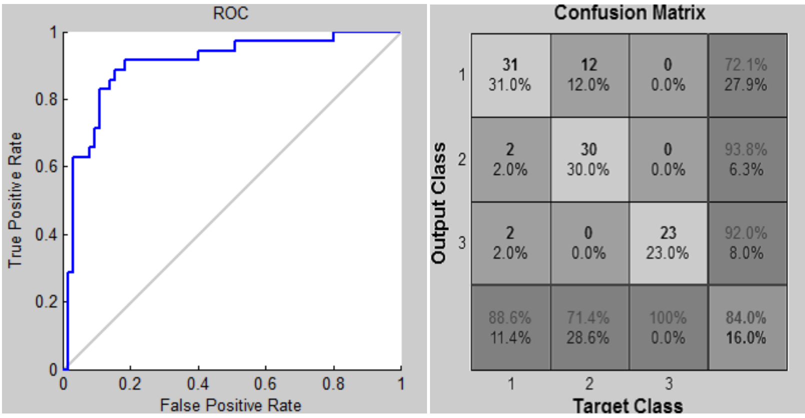

Figure 5. The ROC Curve Analysis and the Confusion Matrix of Testing Dataset-1 using GAF Features.

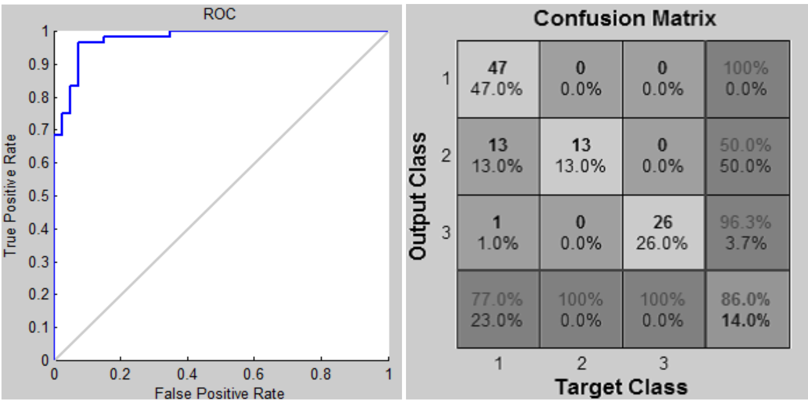

Figure 6. The ROC Curve Analysis and the Confusion Matrix of Testing Dataset-2 using GAF Features

The overall classification accuracy is 92.4%, with 88.9% sensitivity and 83.81% specificity. As shown the results is better than that obtained with either GAF or SFF.

Test stage: As shown in Figure 11, the accuracy with dataset-1 is 86%. In cancer cases, 31 of 35 cases are classified truly as cancer, 2 as benign and 2 as normal. In dataset-2, the accuracy is 89% as demonstrated in Figure 12. In general the accuracy of classification with testing datasets is better with ISF than with either SFF or GAF. But it is less than the accuracy that we obtained with training dataset.

Classification using USF: We have 31 features as a total number of the selected features by each of sequential and GA techniques. In the following we show the experiment results with training and testing data set using USF.

Training stage: Figure 13 shows the ROC curve of the classification using USF, the area under the curve is so small which means that we have the best accuracy. The total accuracy reaches 96.3% as shown in the "all" confusion matrix in Figure 13; in which we have:

- 117 of 126 cancer cases are classified truly as cancer while the remained 9 cases are classified as benign,
- 99 of 105 benign cases are classified truly as benign while 6 cases are classified in false as a cancer,
- And 179 normal cases are classified truly as normal.

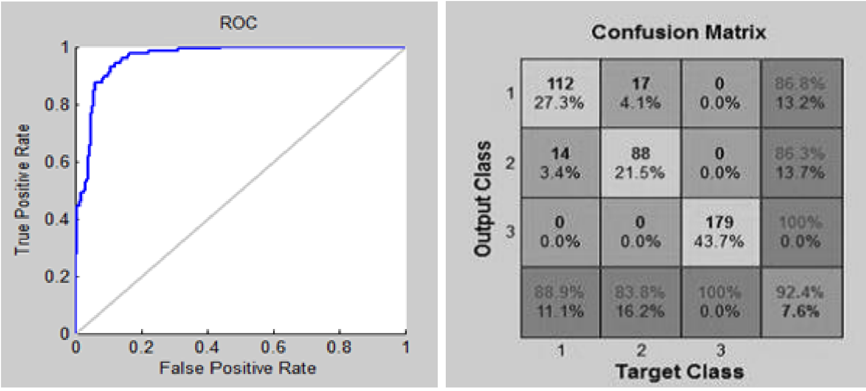

Figure 7. The ROC Curve Analysis and the Confusion Matrix of FFANN Classifier for Training using ISF Features

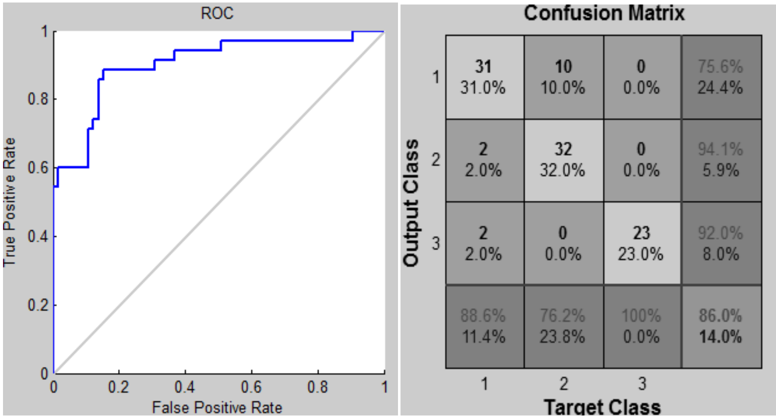

Figure.8. The ROC Curve Analysis and the Confusion Matrix of Testing Dataset-1 using ISF Features

So with union features we have the best performance, but it takes more time. The overall classification accuracy is 96.3%, with 92.9% sensitivity and 94.3% specificity.

Test stage: As shown in Figure 14, the accuracy of the classification with dataset-1 is 88%. In cancer cases, 31 of 35 cases are classified truly as cancer, 2 as benign and 2 as normal. Figure 15 shows the confusion matrix and ROC curve for the classification with USF, The accuracy of the classification is 89%, it is better than that with SFF, GAF, or ISF.

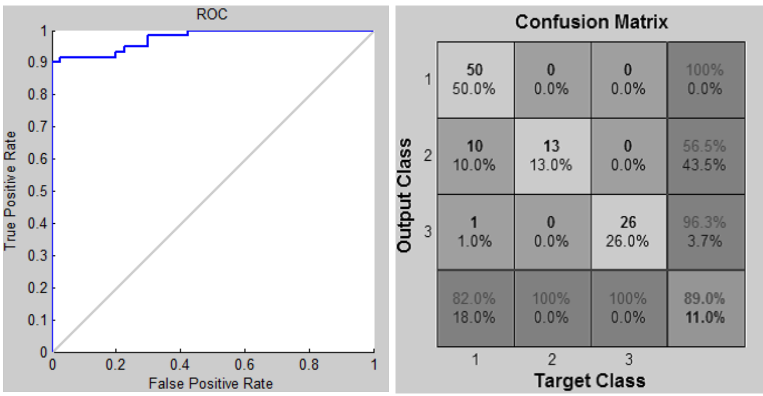

Figure.9. The ROC Curve Analysis and the Confusion Matrix of Testing Dataset-2 using ISF Features

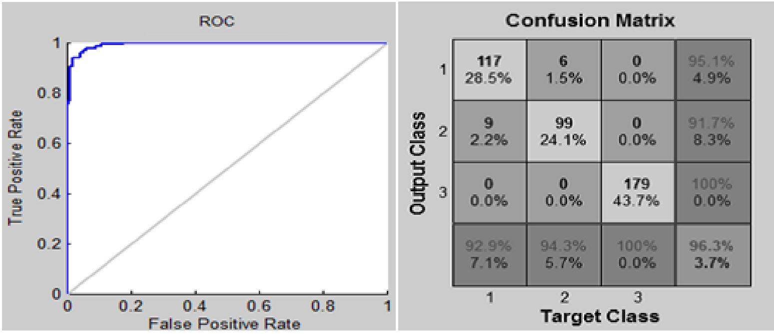

Figure 10. The ROC Curve Analysis and the Confusion Matrix for FF-ANN Classifier using USF Features

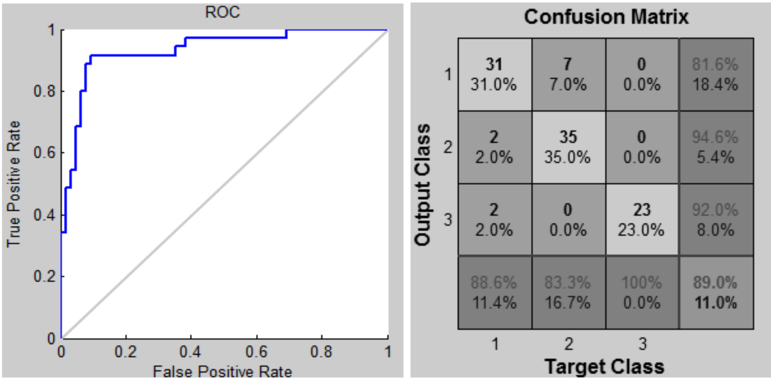

Figure 11. The ROC Curve Analysis and the Confusion Matrix of Testing Dataset-1 using USF Features

In, Table 6.1, we show a simple comparison in accuracy between our method and others. Actually, direct comparison of these systems is so difficult because most of these studies done on different databases and.

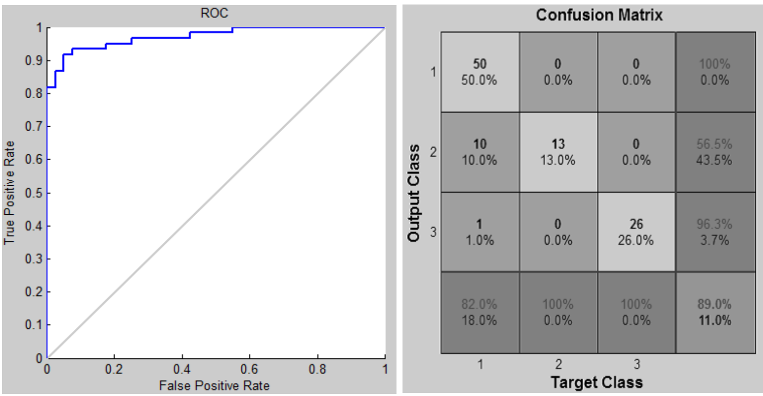

Figure.12. The ROC Curve Analysis and the Confusion Matrix of Testing Dataset-2 using USF Features

Table 3. Comparison of Accuracy between the proposed Method and Others

Author	Training dataset	
	Size	Accuracy
Pohlman[8]	51	76%-93%
Hadjiiski [22]	348	81%
Jiang [7]	211	72.7%
Surendiran [27]	300	87%
Zheng [5]	3000	87%
Proposed method	410	89% - 96.3%

III. Conclusion

The method employed in this paper has given better performance. The CAD system is developed for the classification of mammogram into normal and cancer pattern with the aim of supporting radiologists in visual diagnosis .This paper has investigated a classification of mammogram images using GLCM features. The maximum accuracy rate for normal and cancer classification is 96%. For future work, GLCM features combined with statistical moment features to improve

The results in classification of mammogram images. Using proper feature selection method accuracy may be improved efficiently. The effectiveness of this paper is examined on DDSM (Digital Database for Screening Mammography) database using classification accuracy, sensitivity and specificity. The overall accuracy can be improved by most relevant GLCM features, which is selected by feature selection algorithm.

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