Multiclass Classification of Mammograms using Trace Functionals

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***Abstract*—Mammography is the process of using low energy X-rays(usually around 30kvp) to examine the human breast, which is used as a diagnostic and screening tool. The goal of mammography is the early detection of breast cancer, it has been known to improve the recovery rates to a great extent. Mammogram image can be classifies into normal, benign, and malignant class. A survey has been made on the applications of intelligent computing techniques for diagnostic sciences in biomedical image classification. The main objective of this paper is to classify the breast mammograms and detect the cancerous tissues. In this paper uses the multiclass classification of SVM classifier to classify the breast images into normal, benign and malignant. SVM classifier obtained the maximum accuracy rate is 95.2%.**

Keywords- Cancer; Mammogram; svm-multiclassifier; trace transform

I. INTRODUCTION

Cancer is characterized by a significant increase of cell division compared to that of normal tissue. This difference in the rate of division is the basis of current methods of treating cancer. Breast cancer is a kind of cancer that develops from breast cells. Breast cancer usually starts off in the inner lining of milk ducts or the lobules that supply them milk. A malignant tumor can spread to other parts of the body. Breast cancer is the most common invasive cancer in females worldwide. It accounts for 16% of all female cancers and 22.9% of invasive cancers in women. In recent years, the incidence rate of breast cancer has considerably increased [1]. Breast cancer survival rate has also improved over the past few years with the development of more effective diagnostic techniques and improvements in treatment methodologies.

The National Cancer Institute estimates that there will be nearly 227,000 new cases of breast cancer diagnosed in the united states and nearly 40,000 deaths from the disease in 2012. The average American woman has a one in seven chance of developing breast cancer during her lifetime, based on a life expectancy of 85 years [2]. The most popular diagnostic technique called mammography is the process of using low-energy x-rays use doses of ionizing radiation to create images. Radiologists then analyze the images for any abnormal findings. It is use lower-energy x-rays for radiography of bones. Ultrasound, ductography, positron emission mammography (PEM), and magnetic resonance imaging (MRI) are adjuncts to mammography. Ultrasound is typically used for evaluation of masses found on mammography or palpable masses not seen on mammograms. Ductograms are used in some institutions for evaluation of bloody nipple discharge when the mammogram is non-diagnostic.mri can useful for further evaluations of questionable findings as well as for screening pre-surgical evaluation in patients with known breast cancer to detect any additional lesions.

Early and accurate detection of breast cancer not only improves the survival rate but also avoids unnecessary biopsies. An intelligent computer-aided diagnosis system can be very helpful for radiologist in detecting and diagnosing cancerous cell patterns and faster than typical screening programs. The use of CAD in medical decision support is now prevalent and pervasive across a wide range of medical applications such as cancer research, kidney stone identification, heart diseases and so on. Now, there is a tremendous opportunity for the use of data mining methods that assist the physician in dealing with this flood of patient information and scientific knowledge. In CAD software, the mammograms are first enhanced using standard image enhancement methods mainly to sharpen the boundaries of the region of interest (ROI) and to increase the contrast between the ROI and the nearby normal tissue. The ROIs are then segmented through common statistical, region-based, and morphological approaches, and significant features are extracted for subsequent clustering or classification. Reviews on CAD tools and techniques for micro calcification and mass detection can be found in [3]-[5].

In this paper, a multiclass classification of SVM classifiers has been considered. A graphical description of the classification framework has been shown in Fig. 1. Trace transform functional were used for feature extraction. The trace transform which is a generalization of the radon transform and used in data mining techniques, has been adapted with several new functionals that are specific to mammograms.

II. MATERIALS AND METHODS

The classification framework was tested on a set of 332 mammograms. The data set of these mammograms collected from hospital in JPEG format. Sample mammograms taken from normal, benign and cancerous breasts are seen in Fig. 2.

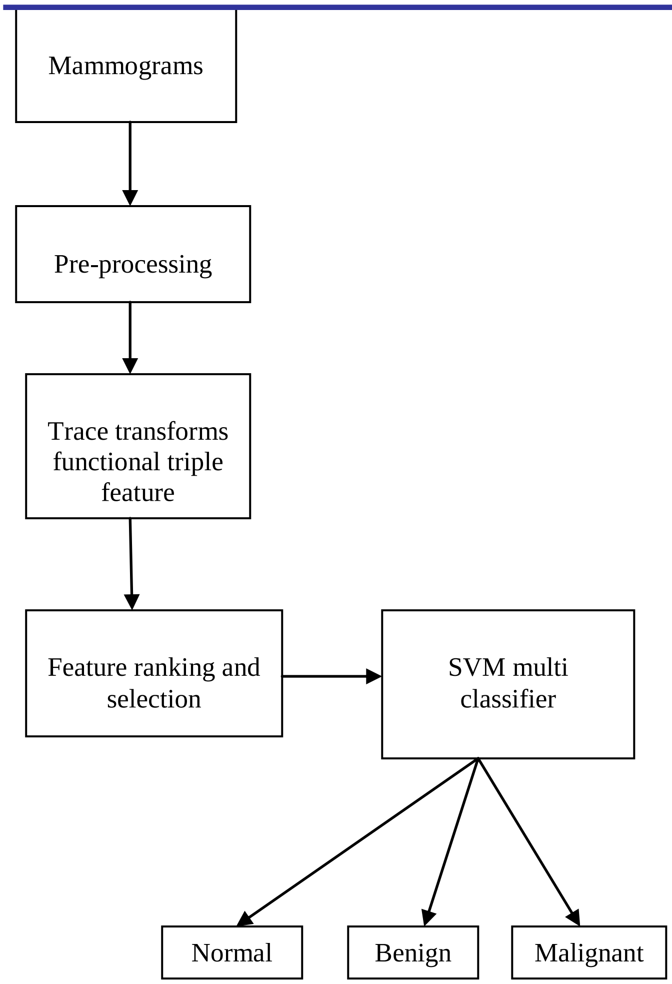

Fig. 1. Classification framework used for SVM multi classifier

All the images were acquired from patients between 45 and 70 years of age. Each image was processed in two views: the cranio-caudal view and the mediolateral-oblique view.

III. PRE-PROCESSING

In pre-processing stage the colored images are converted into gray level image. It converts the true color image RGB to the grayscale intensity image I. the RGB to grayscale by eliminating the hue and saturation information while retaining the luminance. gray level images are distinct from one-bit bi-tonal black and white images. in black and white image consist of only two colors black and white. But the gray level image consist of many shades of gray in between them.

IV. FEATURE EXTRACTION

Trace transform functional are used for feature extraction. Trace transform is the generalization of radon transform and it calculates functional of the image along line tracing through its pixels [6]. In trace transform functional the original image is transformed into mapped image, which is a 2-D function based

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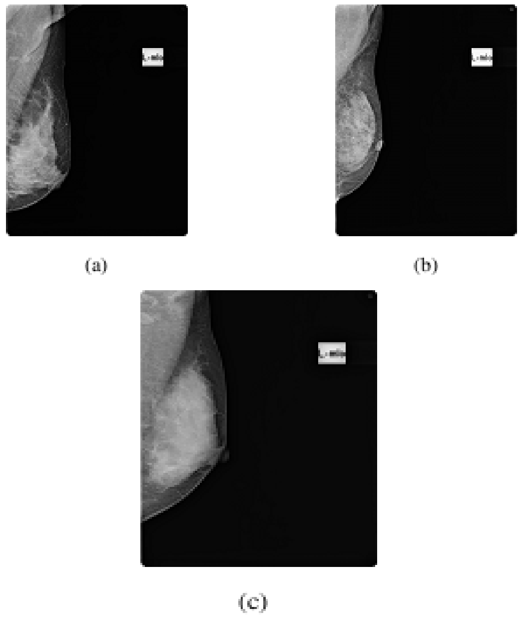

Fig. 2. Sample mammograms: (a) Normal; (b) Benign; (c) Malignant.

on a set of parameters (Ø, ρ) that identifies each line criss-crossing its domain. This trace transformed image is a 2-D function and then converted to a string of 1-D arrays using the set of functional called diametric functional. Third functional called circus function is used to calculate a single number, it is referred to as the triple feature. Various combination of trace functional produce different triple features and the triple feature is unique for every image. Functional are usually used to invariant rotation, translation, and scaling. An example of a set of trace transform images for normal, benign, and malignant seen in Fig. 3(a)-(c).

A. *Triple Feature Extraction*

This paper deals with the application of trace transform functional used for feature extraction from mammograms. Tables I-III shows the trace functional T, diametric functional P, and circus functional Φ, are used to extract features. The objects are subjected to linear distortions in the form of rotation, scaling, and translation are the assumptions of the trace transform feature extraction. That means the image remains same is viewed from a linearly distorted coordinate system. If the original coordinate system of image is C_1 and the distorted coordinate system is C_2, an image F(x, y) seen from C2 will be same as image seen from C1 because the transformation is linear that preserves lines. If L(C1;ϕ, p, t) is a line coordinate system C1,the

$$g(F; C_1; \phi, p) = T(F(C_1; \phi, p, t)) \qquad (1)$$

where $F(C_1; \phi, p, t)$ means the values of image function along the chosen line. A triple feature is defined with the help of two more functional p and Φ so the triple feature Π is defined as

$$\Pi(F, C_1) = \Phi\{P\{T\{C_1; \phi, p, t\}\}\}. \qquad (2)$$

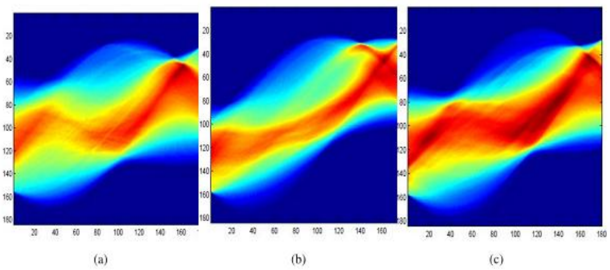

Fig. 3. Typical trace transform images. (a) Normal [Fig. 2(a)]; (b) Benign [Fig. 2(b)]; (c) Malignant [fig. 2(c)].

TABLE I.

TRACE FUNCTIONALS T USED TO PRODUCE THE 2-D FUNCTIONS.HERE X_I IS THE GRAY VALUE OF THE IMAGE AT POINT I ALONG THE TRACING LINE, AND N IS THE TOTAL NUMBER OF POINTS CONSIDERED ALONG THE TRACING LINE

S.No	Trace Functional
1	$\sum_{i=1}^{N} x_i$
2	$\sum_{i=1}^{N} i x_i$
3	$\frac{1}{N}\sqrt{\sum_{i=1}^{N}(x_i-\hat{x})^2}$
4	$\sqrt{\sum_{i=1}^{N} x_i^2}$
5	$Max_{i=1}^{N} x_i$
6	$\sum_{i=1}^{N-1}\lvert x_{i+1}-x_i\rvert$
7	$\sum_{i=1}^{N-1}\lvert x_{i+1}-x_i\rvert^2$
8	$\sum_{i=4}^{N-3}\lvert x_{i-3}+x_{i-2}+x_{i-1}-x_{i+1}-x_{i+2}-x_{i+3}\rvert$
9	$\sum_{i=1}^{N-1}\lvert x_{i+1}-x_i\rvert^3$
10	$\frac{1}{N}\sqrt{\sum_{i=4}^{N-3}(x_i-\hat{x})^2}$
11	$\sum_{i=4}^{N-3} i x_i$
12	$\sum_{i=4}^{N-3}(x_i-\hat{x})^2$
13	$\sqrt{\sum_{i=1}^{N}(x_i-\hat{x})^2}$
14	$Max_{i=1}^{N} x_i$-$Min_{i=1}^{N} x_i$
15	$\lvert\sum_{i=4}^{N-3}(x_i-\hat{x})^2$-$\sum_{i=4}^{N-3} i x_i\rvert$
16	$\lvert\sqrt{\sum_{i=1}^{N}(x_i-\hat{x})^2}$-$\sqrt{\sum_{i=1}^{N} x_i^2}\rvert$

TABLE II.

DIAMETRIC FUNCTIONALS P USED FOR ANALYSIS IN THIS PAPER.HERE,X_I IS THE VALUE OF THE TRACE TRANSFORM AT ROW I ALONG THE COLUMN TO WHICH THE FUNCTIONALS IS APPLIED, AND N IS THE TOTAL NUMBER OF ROWS OF THE TRACE TRANSFORM

S.No	Diametric Functional
1	$Max_{i=1}^{N} x_i$
2	$Min_{i=1}^{N} x_i$
3	$\sqrt{\sum_{i=1}^{N} x_i^2}$
4	$\frac{\sum_{i=1}^{N} i x_i}{\sum_{i=1}^{N} x_i}$
5	$\sum_{i=1}^{N} i x_i$
6	$\frac{1}{N}\sqrt{\sum_{i=1}^{N}(x_i-\hat{x})^2}$
7	$\sum_{i=1}^{N-1}\lvert x_{i+1}-x_i\rvert$

V. FEATURE RANKING AND SELECTION

The feature selection procedure is carried out by selecting a class separability criterion C and then computing its value for all available features x_k, $x_k = 1, 2, \ldots, m$. the C value is ranked in descending order and the best C value is named x_{i1}. The second best feature is calculated the cross-correlation between x_{i1} and the remaining features. The procedure carried on all values of K and rank the best features. The required number of features are then chosen from the ranked list of features.

TABLE III.

CIRCUS FUNCTIONALS Φ USED FOR ANALYSIS IN THIS PAPER. HERE, XI REFERSTO THE VALUE OF THE CIRCUS FUNCTION AT ANGLE I,AND N IS THE TOTAL NUMBER OF COLUMNS OF THE TRACE TRANSFORMTABLE TYPE STYLES

S.No	Circus Functional
1	$\sum_{i=1}^{N-1}\lvert x_{i+1}-x_i\rvert^2$
2	$\sum_{i=1}^{N-1}\lvert x_{i+1}-x_i\rvert$
3	$\sqrt{\sum_{i=1}^{N} x_i^2}$
4	$\sum_{i=1}^{N} x_i$
5	$Max_{i=1}^{N} x_i$
6	$Max_{i=1}^{N} x_i$-$Min_{i=1}^{N} x_i$

VI. CLASSIFICATION

Classification is the most important step in diagnostic and detection of mammograms. Wide range of classifiers are available and each of them has merits and demerits. The disadvantage of the one-class classification of GMM classifier is that the accuracy value is obtained only on 92.4% and it uses one class classification method so it takes long time function and detection is not accurate in GMM classifier. In this paper proposed multiclass classification of SVM classifier and to classify the normal, benign, and malignant mammograms at a short time period.

A. Support Vector Machine (Svm) Classifier

In support vector machine classifier the data from two classes are used to determine a margin hyper plane between the two classes. The distance from the hyper plane to the nearest data points on each side called support vectors it is maximal. SVM constructs a hyper plane or set of hyper plane in a high or infinite dimensional space, and it can be used for classification, regression, or other tasks. The largest distance to the nearest training data point of any class (called functional margin) is achieved a good separation between the hyper planes. In general larger the margin the lower the generalization error of the classifier.

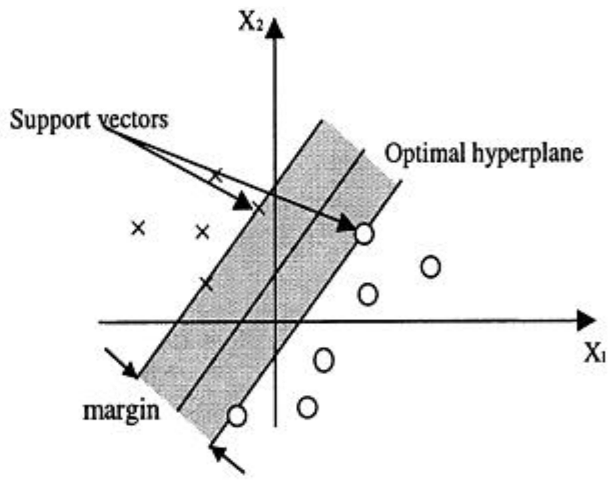

Fig. 4. Hyper plane separates training examples

VII. RESULTS AND DISCUSSION

In this paper, the multiclass classification of mammograms using trace functional provides an interesting results. The feature extraction functions depends solely on the user, given the fact that there are no constraints in selecting the functional. The only constraint is the functional has to prove rotational invariance and in this paper chosen with all functional. Wide array of features are provided using the triple feature selection with every increase in p and Φ, giving a twofold increase in the number of available features because there are no limitations in combination either with the diametric or circus functional. A sample of the top 10 features obtained by the combination of functional gives the result is shown in table IV. The extraction of triple features are then classified using the SVM multi-class classifier. Multi class classification of SVM provides the better results and obtained the high accuracy at 95.2%. The output obtained is as shown in fig. 5.

TABLE IV.

COMBINATION OF FUNCTIONALS THAT GIVE THE BEST CLASSIFICATION ACCURACY. THE NUMBER REPRESENT THE CORRESPONDING FUNCTIONALS IN THE RESPECTIVE TABLES

Trace Functionals (T)	Diametric Functionals (P)	Circus Functionals (Φ)
6	1	1
6	2	1
6	2	5
14	3	4
15	5	3
8	6	4
9	6	2
5	2	1
6	5	6
3	2	5

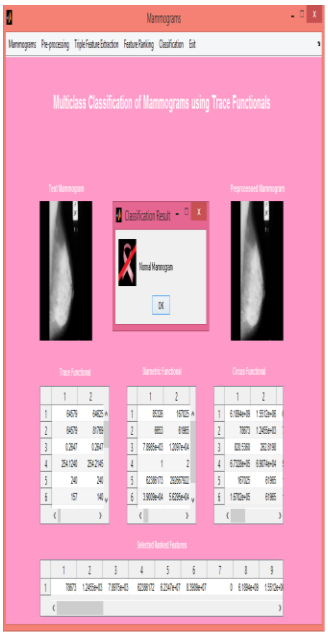

Fig. 5. Feature extraction and classification output in GUI

The loaded mammogram was correctly classified as normal, similarly all other mammographic images are loaded and correctly classified by using SVM classifier and features extracted by using trace transform functional and obtained with accuracy 95.2% is higher than GMM classifier. So the proposed method is used to correctly classify the normal, benign, and malignant mammograms and provide the better accuracy.

TABLE V.
COMPARISON OF ACCURACY

Method	Accuracy
Trace transform with GMM	92.4%
Trace transform with SVM multi-classifier	95.2%

VIII. CONCLUSION

A novel framework for multi-class classification methodology in mammographic image analysis has been proposed. Trace transform functional were used for feature extraction. Trace transform which is generalization of radon transform and popularly used in data mining techniques has been adapted. The application of trace transform to the problem of mammographic image analysis is rare. In this paper proposed the trace transform functional can be easily modified and by users according to the type of image under consideration. The extracted features from the trace functional coupled with the SVM classifier obtained the highest accuracy of 95.2% compared to other classifiers. SVM classifier has many advantages than the other classifiers and provide better accuracy.

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