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Full Length Research Paper

Malignancy and abnormality detection of mammograms using DWT features and ensembling of classifiers

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Breast cancer detection and diagnosis is a critical and complex procedure that demands high degree of accuracy. In computer aided diagnostic systems, the breast cancer detection is a two stage procedure. First, to classify the malignant and benign mammograms, while in second stage, the type of abnormality is detected. The classifier ensemble optimization is a method that can be applied to increase the classification accuracy at both stages. In this paper, we have proposed a novel technique to enhance the classification of malignant and benign mammograms using multi-classification of malignant mammograms into six abnormality classes. DWT (discrete wavelet transformation) features are extracted from preprocessed images and passed through different classifiers. To improve accuracy, results generated by various classifiers are ensembled. Mammograms declared as malignant by ensemble classifiers are divided into six classes. The ensemble classifiers are further used for multi-classification using one against all technique for classification. Output of all ensemble classifiers is combined by product, median and mean rule. It has been observed that the accuracy of classification of abnormalities is more than 97% in case of mean rule. Mammographic Institute Society Analysis [MIAS] dataset is used for experimentation.

Key words: Ensemble classifier, mammography, multi-classification.

INTRODUCTION

In many Western and American countries breast cancer is the most common cancer among women. According to American National Cancer Institute the population of new breast cancer cases for the 2008 in USA is approximately round about 179600, while the deaths were more than 40,700 (Govt et al., 2008). The statistical data proves that breast cancer held the second position of appearance in diagnosed new cases followed by prostate cancer comparing to other forms of cancer. Over the past decades it has become alarming that breast cancer incidence rates are increasing steadily. However, the mortality rates for breast cancer have remained relatively constant due to more effective treatment and earlier diagnosis (Broeders and Verbeek, 1997). The breast cancer mortality rate was fluctuating in different eras. It was increasing at a rate of0.4% annually between 1975 and 1990 but reduced by 2.3%.between 1990 and 2002. This decline is due to improvements in breast cancer treatment and mammographic screening.

In has been noted that approximately 10 to 30% of breast cancers are missed by radiologists during routine screening (Wallis et al., 1991) which causes high penalty in the form of biopsy. Image interpretation of mammograms can be improved using computational advancements. Many computer-aided diagnosis (CAD) systems have been proposed to improve the accuracy of interpretation. Many researchers have worked on the abnormalities of breast cancer. A few of them address calcification (Wang and Karayiannis, 1998), (Zwiggelaar et al., 1999) have talked about masses (like circumscribed lesion, stellate lesion etc) in breast and (Cheng et al., 2006) depict only asymmetry because of breast cancer but no work has been taken to consider all these abnormalities of cancer as a complete problem. This paper proposes a novel approach in which efficient classification methods for detection of breast cancer abnormalities is used.

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The main complexity about digital mammogram diagnosis is the detection of malignant images and its classification on the basis of abnormalities present. In this paper, we have investigated the accuracy of a detection methodology that uses Discrete Wavelet Transformation (DWT) features as an input to different classifiers like K nearest neighbor (KNN), artificial neural networks (ANN), Bayesian and Support Vector Machine and ensemble the results generated by these classifiers. Next, the malignant images are passed through a bank of these ensemble classifiers which are again trained for classification of different abnormalities. One against all approaches are used for multi-classification. Each ensemble classifier is trained for one abnormality. That particular classifier assigns probability to the abnormality for which it is trained. Median, mean and product rules are used to combine the result of binary classifiers. A very efficient technique for pre-processing the mammograms is used (Muhammad et al., 2010) which involves the automatic cropping of the mammograms, extracting breast region and remove other spots which are not part of breast.

Major contribution

The proposed technique is fully automatic and very robust. The resultant accuracy is enhanced using ensembling of classifiers. The strong automatic abnormality detection method is proposed. One against all different benchmark techniques are efficiently used for multi-classification. DWT features are used for classification. Different rules for combining the results of ensemble classifiers have been experimented with to enhance the probability of selection of exact class. There exist different techniques like majority voting, weighted majority voting, min, max, product and median rule. We have compared the min, product and median rule against all of these techniques. The median rule provides better results. This is a supervised method for diagnosing breast cancer. The most important and novel work done in this paper is use of DWT features and ensembling of classifiers. The proposed system achieved good accuracy for the classification of mammograms as malignant and benign.

The remainder of this paper is organized as follows: First is a discussion of the related work, followed by a description of the proposed methodology. The multi-classification criteria is discussed; experimental results are presented and analyzed. Thereafter, conclusions and future work is presented.

Related work

A number of methods have been used to classify and/or detect abnormalities in medical images, such as wavelets, fractal theory and statistical methods. Generally, these methods use features extracted using image-processing techniques. A CAD System in which features are extracted using image processing techniques is developed in (Muhammad et al., 2009) for detection of abnormalities.

A large variety of techniques have been applied to the problem of mass detection, but most follow a two-step scheme. First, one or more features are computed for each pixel, after which each pixel is classified and the suspicious pixels are grouped into a number of suspicious regions. In the second step, these regions are classified as normal or abnormal regions, based on regional features like size, shape or contrast. Two signs can indicate the presence of a lesion: a radiating pattern of spicules or a central mass. To detect the whole range from architectural distortions to circumscribed masses, both signs must be detected. The central mass is a more or less circular bright region with a diameter between 5 mm and 5 cm. Convolution of the image with a zero-mean filter with a positive center and a negative surrounding area was used by a number of research groups to detect the mass, for example with the Laplacian of the Gaussian (LoG) or a Difference of Gaussians filter (DoG).

Several works have been done to develop computer aided breast cancer detection and diagnosis tools. Eltonsy et al. (2007) proposed a technique in which presence of concentric layers surrounding a focal area with suspicious morphological characteristics and low relative incidence in the breast region is used for malignancy detection. Results were reported with 92, 88 and 81% sensitivity. Eltonsy et al. (2006) develop a procedure to detect both masses and architectural distortion by finding those points which are covered by concentric layers of image activity. Guo et al. (2005) also used Hausdorff fractal dimension and an SVM classifier to differentiate ROIs having architectural distortion. 72.5% accuracy was obtained with a set of 40 ROIs, of which 21 had normal tissue patterns and 19 had architectural distortion. Mathematical morphology was tried by Matsubara et al. (2005) to detect architectural distortion around the skin line and a concentration index to detect architectural distortion within the mammary gland. Author reported that sensitivity rates of 94% were obtained. Kom et al. (2007) introduced an algorithm for detection of suspicious masses in mammographic images that shows a sensitivity of 95.91% for mass detection, with ROC area of 0.946. Belloti (2006) presented an automatic computational tool for mass detection. The area under the ROC curve was 0.91, with standard deviation of 0.03. The CAD tool obtained a sensitivity of 85%, with 1.32 false positives per image. Miller and Astley (1994) also addressed bilateral asymmetry by measuring shape, topology, and distribution of brightness in the fibroglandular disk. For each segmented region, shape measures are computed

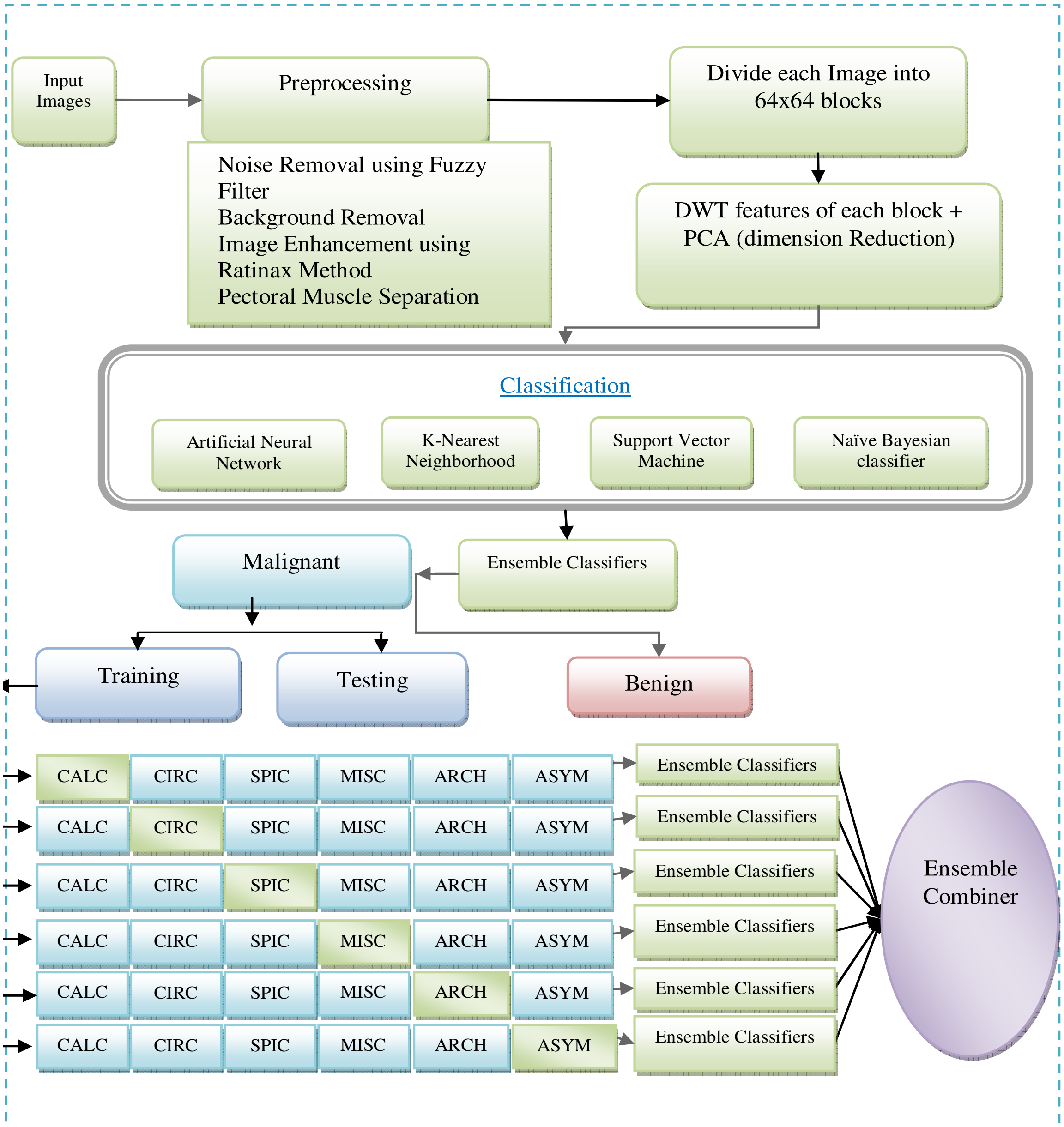

Figure 1. A block diagram of proposed system.

in order to discard bad mass candidates and texture measures are obtained from Ripley's K function. The classification step is performed using a SVM classifier. The method provides an accuracy rate of 89.30%. Campanini et al. (2004) presented an approach for detection of masses in digital mammograms that reach sensitivity around 80%. The work used images coming from the DDSM database.

THE PROPOSED SYSTEM

The proposed approach presents a CAD system for detection of breast cancer and its stage and type of abnormality in mammograms. Digital mammogram images are taken as input and passed through the system. The system identifies malignant mammograms and also mentions the type of abnormality in it. The whole system is divided into six major blocks namely pre-processing, feature extraction, ensembling of classifiers, malignancy detection, abnormality type detection and combination of performance of classifiers (one against all approach). The complete system is depicted in Figure 1.

In first block, image of a mammogram is input to the system for pre-processing. This block perform four steps on the image and make the image ready for feature extraction. These four steps are noise removal, background removal, image enhancement and pectoral muscle removal. The feature extraction is done using DWT. The technique is made time efficient by dimension reduction

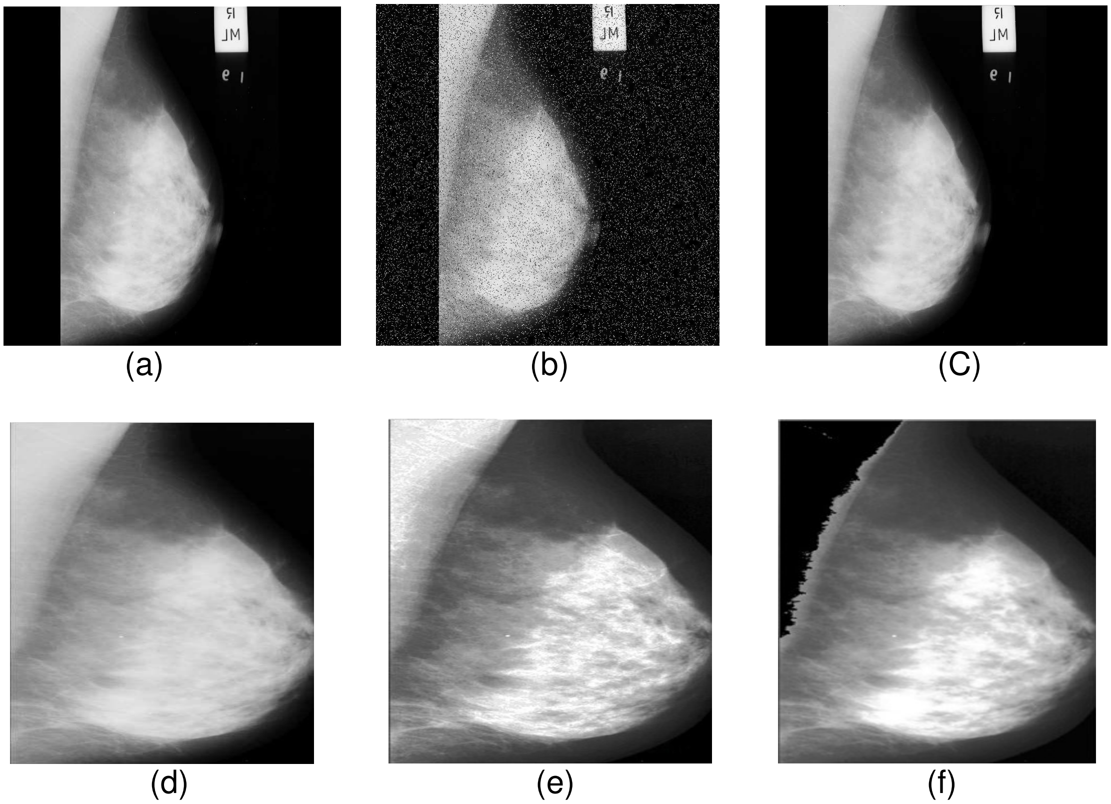

Figure 2. Preprocessing phase (a) Original (b) Noisy (C) Restored (d) Background removal (e) Enhancement using Ratinax; (f) Pectoral muscle.

using PCA. Using DWT features, the classification accuracy of ensemble classifier wins from all other benchmark techniques. The abnormality type of malignant mammogram is also detected. In this block, ensemble classifier is intelligently used for multi-classification using one against all approach. This block shows the novelty of technique because it has been observed in literature that there exists no single algorithm which can identify all types of abnormalities. However, the techniques for detection of any single abnormality at a time are presented. The last block discussed how to combine the results of all these parallel binary classifiers.

The preprocessing block

The pre-processing plays an important role in any CAD system. It minimizes the computational cost and also finds the ROI (region of interest). In breast imaging pre-processing is very necessary because those parts which are not part of breast can misguide the algorithm for classification. This will affect the performance of the proposed method. In the proposed system, image is passed through preprocessing. The procedure of noise removal using fuzzy filter (Ayyaz et al., 2009), background removal and pectoral muscle detection is discussed in (Muhammad et al., 2010).

Only the histogram equalization method for image enhancement discussed in (Muhammad et al., 2010) is replaced with retinax method because sometimes when histogram of image is tilted toward one side, histogram equalization method does not perform well. This enhancement is very important for the visibility of image properties. Retinax is an image enhancement technique which tries to model the scene at a constant light. The image is formed of two components, illumination and reflectance. If we subtract the illumination part from the image, then we can see it at a constant light. By using ratinax the dark portion of the image is enhanced and bright portion is suppressed, so that details are more visible.

$$S(x,y) = R(x,y).\,L(x,y) \tag{1}$$

where R(x, y) is reflectance part and L(x, y) is illumination part .

By taking log, reflectance and illumination parts are separated out so that we can easily subtract illumination part from original image. By taking exponent of this difference, we'll get the reflectance image.

$$R = \exp\left(\log(s) - \log(l)\right) \tag{2}$$

Retinex is full scale automatic contrast enhancement technique that enhances the blur and degraded image non-linearly and provide good results for mammogram images. The visual results of complete preprocessing phase are given in the Figure 2.

The feature extraction block

The feature extraction and selection from an image plays a critical role in the performance of any classifier. Higher accuracy of the classifier can be achieved by the selection of optimum feature set. Use of all the pixel values in classification creates a computational overhead because image is a large data set. To improve the efficiency of the classifier dimensionality reduction techniques is a good approach. There are many techniques for feature extraction for example., texture features, gabor features (Eltonsy et al., 2007), feature based on wavelet transform (Eltonsy et al., 2007), principal component analysis and spectral mixture analysis. We have used DWT features for our proposed system. The dimensionality reduction is process of elimination of closely related data with other data items in a set, as a result a smaller set of features is generated which preserves all the properties of the original large data set. Commonly used dimensionality reduction techniques are Principal Component Analysis (PCA), Discrete Cosine Transformation (DCT), DWT and Random Projection. In our system we have applied DWT and PCA on local blocks rather than on the complete image for dimensionality reduction.

DWT is extended from Continuous Wavelet Transform (CWT). CWT is a scaled and shifted version of its mother wavelet transform. CWT for continuous, square-integral function f(x), relative to the real valued wavelet, ψ(x), is defined as:

$$W_\psi(p, q) = \int_{-\infty}^{\infty} f(x)\psi_{p,q}(x)dx \tag{3}$$

$$\psi_{p,q}(x) = \frac{1}{\sqrt{p}}\psi\left(\frac{x-q}{p}\right) \tag{4}$$

where p and q are scaled and translation parameters.

DWT is a linear transformation in which image information is divided into detailed and approximation components. Detail components contain information of vertical horizontal and diagonal sub-bands of the image. These components can be obtained by applying a high pass and low pass filter on an image respectively. These components are defined by the following equations:

$$a_{j+1}[p] = \sum_{n=-\infty}^{+\infty} l[n-2p]a_j[n] \tag{5}$$

$$d_{j+1}[p] = \sum_{n=-\infty}^{+\infty} h[n-2p]a_j[n] \tag{6}$$

The malignancy detection/classification block

The classification can be done by unsupervised and supervised way. Unsupervised classification extracts natural groups, or structures, within multi-spectral data. Supervised classification is the process of using samples of known identity to classify samples of unknown identity. The characteristics apply to a supervised classification are that it requires detailed knowledge of the area and input patterns are provided with the labels. But supervised classification is more controlled and directed classification which surly enhances the accuracy. We have used four classifiers to classify the malignant and benign mammograms. A brief discussion of those classifiers is given below.

Artificial neural network

An artificial neural network (ANN), can be viewed as a system of exploitation of the biological basis of neural networks, in other words, ANN is an emulation of biological neural system. The key objective of the development of neural network is the to develop a computation model which work like human brain and be able to solve hard problems in less computation time than traditional approach (Sivandam and Deepa, 2007). Artificial neural networks are useful to solve various problems like data clustering, optimization, pattern matching and classification. The structure of a neural network is like a directed graph in which different nodes, called neurons, in layers are connected to each other with some associated weights. The output of the neuron is determined through an activation function which is sum of the product of inputs with their associated weight to that neuron.

K-nearest neighborhood

The K-Nearest Neighbor is a kind of lazy learner which means that as we provide the test data this classifier does not build any model but simply store the test-data. So this type of classifier has less work to do at start but when actual classification is performed then these classifiers become more expensive. K-Nearest Neighbors are very expensive when it is applied on a large data set. KNN is suitable for multi-modal classes as its classification decision is based on a small neighborhood of similar objects and a tie is broken randomly. The details of KNN can be found in (Mitchell, 1997).

Support vector machine

Support vector machine (SVM) is very good technique which is used for the classification purpose. SVM has also been applied on different real world problems such as face recognition, cancer diagnosis and text categorization. SVM divides the given data into decision surface. Decision surface divides the data into two classes like a hyper plane. Training points are the supporting vector which defines the hyper plane. The basic theme of SVM is to maximize the margins between two classes of the hyper plane (Steve, 1998).

Bayesian network

Naive Bayesian Classification is commonly known as a statistical classifier. It is based on the Bayes' theorem and uses probabilistic analysis for classification. Naïve Bayesian Classifier give more accurate results in less computation time when applied to the large data sets. The detail can be seen in (Mitchell, 1997)

The ensemble classification block

Ensemble is process of combining the results of multiple base learners to improve the accuracy (Chawla et al., 2002). We have used four different classifiers with different variation in results with the same data. to improve the accuracy we combine the results of these classifiers. In our case these classifiers behave as base learners. There are two major types of ensemble, bagging and boosting. Bagging is a voting method in which base learners have been trained over slightly different training sets. The training samples are being generated by bootstrap. This is the simplest technique; we use the simple method of voting.

We take different classification algorithms and using the output of each algorithm as a contribution to all classifiers. Majority voting and weighted majority voting are also used in bagging. Boosting is another kind of ensemble which is different from bagging in a way that it uses multiple classifiers in a sequence i.e. this technique start with one classifier and pass the data to second classifier which is incorrectly classified by the first classifier and then to third which is incorrectly classified by the second one and so on (Alpaydin, 2004).

Table 1. Abnormalities in mammograms.

Class no.	Name of abnormality	Abbreviation
1.	Calcification	CALC
2.	Well-defined/circumscribed masses	CIRC
3.	Speculated masses	SPIC
4.	Other, ill-defined masses	MISC
5.	Architectural distortion	ARCH
6.	Asymmetry	ASYM
7.	Normal	NORM

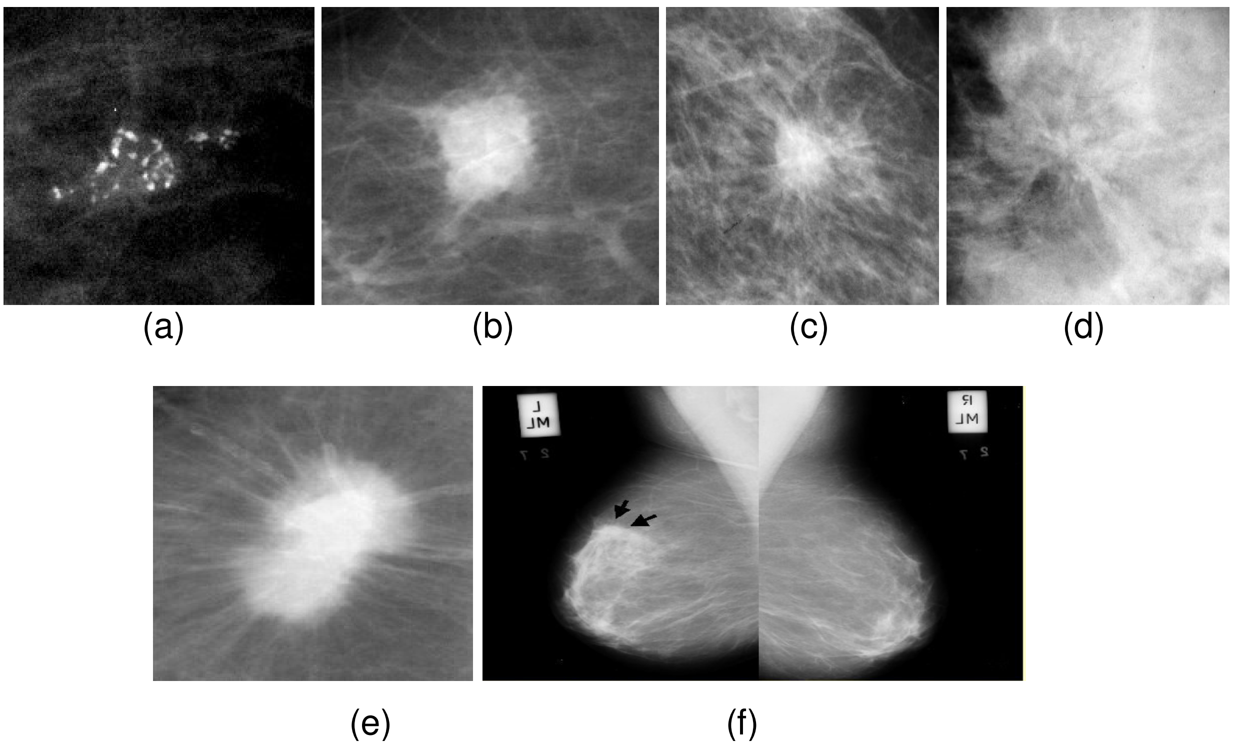

Figure 3. Breast abnormalities (a) Calcification (b) Circumscribed masses (c) Stellate lesion (d) Architectural distortion (e) Spiculated mass (Heath et al., 2000) (f) Asymmetric density in the left breast (Cheng et al., 2006).

The abnormality detection block

The classification of benign and malignant mammograms is already discussed in "The proposed system. The major challenge is to diagnose the severity of breast cancer. The class of abnormality present in data set tells us about its severity. However, in MIAS dataset abnormality of breast cancer is divided into seven classes as listed in Table 1. The micro-calcification clusters may appear in both *in-situ* and invasive breast cancer. Many of the breast cancers that are at an early stage are currently detected by the presence of micro-calcifications. Only when appearing as clusters of three or more calcifications, they are clinically suspicious. Micro-calcifications that are visible in mammograms vary in diameter roughly from 0.1 to 0.5 mm. Figure 3a shows an example of micro-calcification clusters.

These clusters can be benign as well as malignant. The differentiation between malignant and benign clusters based on mammographic appearance, is not an easy task. The classification of micro-calcifications is important, because recalling all micro-calcification clusters will result in many false positives since 80% of all clusters are due to benign processes. Calcifications are tiny granule like deposits of calcium and are relatively bright (dense) in comparison with the surrounding normal tissue (Suri and Rangayyan, 2006). An analysis of the calcifications as to their distribution, size, shape or morphology, variability, number and the presence of associated findings, such as ductal dilatation or a mass, will assist one in deciding which are benign, which should be followed carefully and which should be biopsied (Paredes, 2007).

Apart from micro-calcification clusters, one can classify the visual signs for which radiologists search during mammographic screening into three basic categories: masses, architectural distortions and asymmetric densities. These abnormalities may indicate invasive breast cancer. Masses that are sharply defined (circumscribed masses) are usually benign. However, if a mass has a faint jagged

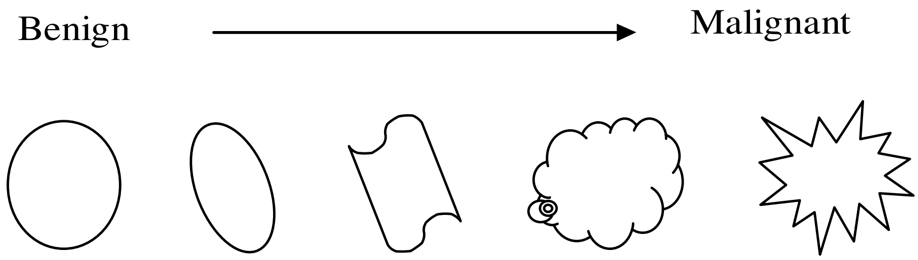

Figure 4. Morphologic spectrums of masses.

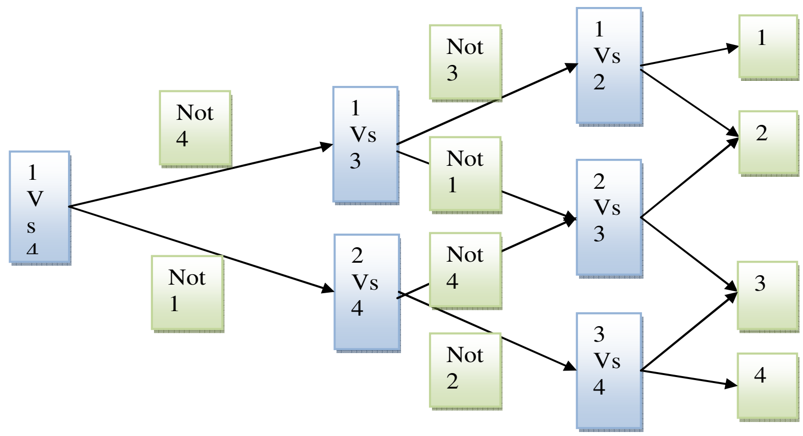

Figure 5. Binary tree of one against all approach.

edge it is likely to be malignant. If a mass is surrounded by a radiating pattern of spicules, it is called a spiculated mass or stellate lesion. Stellate lesions are highly suspicious indicators of breast cancer. A mass is a space occupying lesion seen in at least two different projections (ACR, 2003). Fat-containing radiolucent and mixed-density circumscribed lesions are benign, whereas isodense to high-density masses may be of benign or malignant origin (Paredes, 2007). A mass with circumscribed margin is shown in Figure 3b. Lesions with micro-lobular margins have wavy contours. Obscured (erased) margins of the mass are erased because of the superimposition with surrounding tissue. This term is used when the physician is convinced that the mass is sharply-defined but has hidden margins. The lesions with spiculated margins are characterized by lines radiating from the margins of a mass shown in Figure 3e. A lesion that is ill-defined or speculated and in which there is no clear history of trauma to suggest hematoma or fat necrosis suggests a malignant process (Paredes, 2007).

The shape of a mass can characterize it as benign or malignant. Masses with irregular shape usually indicate malignancy as it is depicted in Figure 4. Regularly shaped masses such as round and oval very often indicate a benign change.

An interruption of the radial ductal pattern is called "architectural distortion". These lesions are often quite subtle and can occur with both benign and malignant processes. Architectural distortions are third most common mammographic sign of cancer and are strongly suggestive of malignancy (Paredes, 2007). A mammogram with architectural distortion is shown in Figure 3d. Some masses are detected by radiologists because of asymmetry in the breast pattern between the left and right breast. Asymmetry may be a suspicious sign because in a normal breast the fibro-glandular breast pattern is often symmetric with respect to both breasts.

However, when a lesion has spicules or a faint jagged edge, it is likely to be malignant. When the edge of the lesion is sharp and well-described, it is more likely to be benign. Often, masses and micro-calcifications occur together in one mammogram, making detection and classification easier.

Asymmetry of breast parenchyma between the two sides has been one of the most useful signs for detecting primary breast cancer (Cheng et al., 2006). Asymmetric density is shown in Figure 3f. In most of the cases, global asymmetry is a normal change, but the finding can be significant if it corresponds with palpable breast lesion.

The multi classification block - Binary classifier (one against all approach)

We have used ensemble classifier for multi-classification. Conversion of binary classifier to multi-class scenario is still an ongoing research topic (Kom et al., 2007). Recently Benhui et al. (2010) and Gang et al. (2010) experimented SVM for multi-label classification. One-against-all is the earliest and one of the most widely used implementations, which constructs M classifiers with the ith one separating class i from all the remaining classes. The underlying assumption for doing so is that the classifiers are totally trustable and equally reliable. The binary tree of one against all classifiers is explained in the Figure 5.

There are two common methods to enable a binary classifier for multi classification: 1A1 (one against one) and 1AA (one against all). The 1AA approach represents the first and most common

Table 3. Results with DWT features.

Dataset	ANN	KNN	SVM	Bayesian	Ensemble
MIAS data	93.94	95.87	95.11	96.13	96.95
Real Mammograms	94.3	96.31	95.52	95.31	96.39

multiclass approach (Melgani and Bruzzone, 2004) and involves the division of an N class dataset into N two-class cases. On the other hand in 1A1 approach a machine is constructed for each pair of classes resulting in N (N-1)/2 machines. When this machine is applied to a test point, each classification gives one vote to the winning class and the point is labeled with the class having most votes. This approach can be further modified to give weighting to the voting process. The performance of 1A1 is comparatively better than 1AA; however, the 1A1 approach is more computationally intensive. The same idea is tested using optimized ensemble of classifier in place of SVM.

Although there are several classifiers that can be used for multi-classification problems but we need a classifier or a combination of classifiers which could efficiently classify the malignant mammograms into six classes with better accuracy. We observed that combining multiple classifiers such that each ensemble classifiers is trained as a binary classifier to recognizing a particular abnormality can prove to give promising results and significantly improves the generalization performance as compared to single classifiers. So we take six parallel Ensemble classifiers. Each one is trained for specific abnormality recognition. Each ensemble classifiers is responsible for one abnormality present in the image and will declare the image as that kind of abnormality or any other abnormality.

The response of each of the classifier from the classifier bank is combined by product median and mean rule. The architecture of our bank of ensemble classifiers is shown in Figure 1. We are using six ensemble classifiers. We have used MIAS database for our experiments. First we eliminate all the normal images from the dataset, and then benign images are separated. Lastly malignant images are divided into training and testing datasets randomly using hold out method. The data set is divided in the ratio of 75 to 25 as training and testing respectively. After that training is performed on 75% data. We have used six binary ensemble classifiers, this means that the data is divided into six blocks according to six abnormality classes, and each classifier is trained for a particular class of abnormality using one-against-all approach. Output of these classifiers is the probabilities that to which extent the input image belongs and does not belong to the class for which that particular classifier has been trained. Then we used our 25% testing data and applied same classifier combination rule, we have seen, this combination of classifiers produced promising results.

EXPERIMENTAL RESULTS

The database used into this work is freely available at internet and is named as the Mammographic Institute Society Analysis (MIAS) (MIAS DB). The specification of the data is given in the referred site. Another real time dataset used for experimentation is taken from Shaukat Khanum Memorial Cancer Hospital and Research Center (SKMCH and RC) Lahore, Pakistan. The dataset contains records of 80 patients in which 37 patients are benign and 43 are malignant. The data is not publically available and is taken on special request by promising of not to disclose it.

Results with DWT features

The second type of feature, we have used for classification is DWT feature. After applying DWT of each image we have calculated the PCA of each image as a feature reduction technique and to improve the computational complexity. After calculating PCA, we have sorted the PCA coefficients which give us the highest representative features at the start. Then we have applied the classifiers by selecting different features and we have found that accuracy of classifiers remains approximately unchanged with the feature vector of size seven or more. Therefore, we have used seven top PCA features of each image for the construction of feature vectors. To improve the accuracy we have ensemble the results produced by the classifiers which results 96.39% for real mammogram data and 96.95% for MIAS data. After that we have further improved our results by optimizing the weights assigned to each classifier during ensemble. For this purpose we have used Genetic Algorithms initially starting with population size of 100 which results in 97.63% accuracy for real mammogram data and 97.45% MIAS dataset.

Table 2 gives a very clear picture of the performance of each classifier we have used and also the improvement in the results which we have achieved using ensemble classifier.

Performance measures

We have tested the performance of these classifiers by calculating and analysis of accuracy, sensitivity and specificity for malignancy detection. These are defined as follows:

Accuracy: number of classified mass / number of total mass

$$(TP+TN)/(TP+TN+FP+FN) \quad (7)$$

Sensitivity: number of correct classified malignant mass / number of total malignant mass

$$(TP)/(TP+FN) \quad (8)$$

Specificity: number of correct classified benign mass / number of total benign mass

$$(TN)/(TN+FP) \quad (9)$$

Accuracy, sensitivity and specificity of different algorithms

Table 3. Performance measure of classification of malignant and benign mammogram for DWT feature.

Technique	Accuracy (%)	Sensitivity (%)	Specificity (%)
NN + DWT features	93.94	91.3	94.3
Baysian + DWT features	95.11	94.1	90.2
KNN + DWT features	95.87	92.7	92.7
SVM + DWT features	96.13	91.3	91.1
Ensemble	96.95	93.2	93.6

Table 1. Ensemble Accuracy for multi–classification using one against all approach.

Serial	Abnormality type	Abbreviation	Mean rule (%)	Median rule (%)	Product rule (%)
1.	Calcification	CALC	97.5	95.2	96.2
2.	Well-defined/ circumscribed masses	CIRC	98.1	93.5	97.3
3.	Speculated masses	SPIC	94.3	94.2	96.5
4.	Other, ill-defined masses	MISC	95.2	96.2	95.1
5.	Architectural distortion	ARCH	96.3	96.4	95.4
6.	Asymmetry	ASYM	97.5	97.3	94.5

Table 2. Ensemble accuracy for multi–classification using one against all approach.

Serial	Author/Technique	Problem addressed	Results reported (%)	Our proposed method results (%)
1	Campanini presented multi resolution and SVM-based featureless approach	Mass detection	80	95.2
2	Kom used a linear transformation filter algorithm for enhancement; and local adaptive thresholding technique was developed to detect the mass in the different image.	Mass detection	95.91	95.2
3	Eltonsy used a multiple-concentric-layers-based algorithm.	Mass detection	92	95.2
4	Eltonsy developed a method to detect masses and architectural distortion by locating points surrounded by concentric layers of image activity.	Architectural distortion	93.1	96.3
5	Guo used the Hausdorff fractal dimension and an SVM classifier.	Architectural distortion	72.5	96.3
6	Matsubara used mathematical morphology	Architectural distortion	94	96.3
7	Miller and Astley used a semi automated texture based procedure	Bilateral asymmetry	86.7	97.5

are given in Table 3.

Table 3 discusses the results of malignancy detection in mammogram images. Three important measures accuracy, specificity and sensitivity are taken to measure the performance of the proposed method. It has been observed that in case of ensembling of classifiers the accuracy is quite good as compare to single classifier. Table 4 shows the abnormality detection results of ensemble classifier using DWT features. These results are compiled using mean, median and product rule and it has been seen that the performance of proposed method approximately remain consistent in case of mean and median rule for the detection of abnormalities in the mammogram.

The abnormality detection rate is also satisfactory. Table 5 compares the abnormality detection results presented in table 4 with the recently reported results of different authors. It has been seen that proposed technique shows comparable performance with existing techniques.

Conclusion

The proposed system is developed for diagnosing the breast cancer from mammogram images. The system performs the diagnosis in multiple phases. In first phase preprocessing on mammogram image is done which minimize the computational cost and maximize the probability of accuracy. In second phase DWT features are extracted. These extracted features are used for classification of mammogram into malignant and benign. Later, the malignant images are again classified using one against all technique to find abnormalities present in the mammograms. In first classification phase when benign and malignant images are separated, different classifiers are experimented but ensemble classifier is found better for the MIAS dataset. It has been observed that linear classifiers are performing better than the other ones. This is because of the linearity present in the dataset. One against all method for multi classification gave promising results. All experiments show that the proposed system gives good results as compared to the recently proposed techniques. We have achieved average accuracy of classification 97.45% in detection of malignant and benign mammograms from MIAS dataset. The results of median rule are better than others in case of classification of abnormality types.

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REFERENCES

Alpaydin E (2004). Introduction to Machine Learning. The MIT Press Cambridge Massachusetts, London, England, pp. 360-363.
American College of Radiology (ACR) (2003). ACR Breast Imaging Reporting and Data System. Breast Imaging Atlas, 4th Edition, Reston, VA. USA.
Ayyaz H, Muhammad AJ, Anwar MM, Asmatullah Ch (2009). “Detail Preserving Fuzzy Filter for Impulse noise removal.” Int. J. Innov. Comput. Inf. Control, (IJICIC) l.5 (12).
Bellotti R (2006). “A completely automated CAD system for mass detection in a large mammographic database.” Med. Phys., 33: 3066.
Benhui C, Liangpeng M, Jinglu H (2010). “An Improved Multi-Label Classification Method Based On SVM With Delicate Decision Boundary.” Int. J. Innov. Comput. Inf. Control, 6(4): 1605-1614.
Broeders MJM, Verbeek ALM (1997). Breast cancer epidemiology and risk factors. Q. J. Nucl. Med., 41(3): 179-188.
Bruce LM, Adhami RR (1999). "Classifying Mammographic Mass Shapes Using the Wavelet Transform Modulus-Maxima Method." IEEE Trans. Med. Imag., 18(12): 1170-1177.
Campanini R, Dongiovanni D, Iampieri E, Lanconelli N, Masotti M, Palermo G, Riccardi A, Roffilli M (2004). A novel featureless approach to mass detection in digital mammograms based on support vector machines. Phys. Med. Biol., 49: 961-975.
Chawla N, Eschrich S, Hall LO (2002). Creating Ensembles of Classifiers. Proc. IEEE Int. Conf. Data Min., pp. 580-581.
Cheng HD, Shi XJ, Min R, Hu LM, Cai XP, Du HN (2006). "Approaches for Automated Detection and Classification of Masses in Mammograms." Patt. Recognit., 39(4): 646-668.
de Paredes ES (2007). Atlas of Mammography. 3rd Edition, Lippincott Williams and Wilkins, Philadelphia, USA.
Eltonsy N, Tourassi G, Elmaghraby A (2006). “Investigating performance of a morphology-based CAD scheme in detecting architectural distortion in screening mammograms.” Proc. 20th Int. Congr. Exhib. Comput. Assist. Radiol. Surg.
Eltonsy N, Tourassi G, Elmaghraby A (2007). A concentric morphology model for the detection of masses in mammography. IEEE Trans. Med. Imag., 26(6): 880-889.
Estimated new cancer cases and deaths for 2008. http://seer. cancer.gov/cgi-bin/csr.
Gang C, Tian-jiang W, Li-yu G, Perfecto H (2010). “Multi-Class Support Vector Machine Active Learning For Music Annotation.” Int. J. Innov. Comput. Inf. Control, 6(3): 921-930.
Guo Q, Shao J, Ruiz V (2005). “Investigation of support vector machine for the detection of architectural distortion in mammographic images.” J. Phys. Conf. Ser., 15: 88–94.
Heath M, Bowyer K, Kopans D, Moore R, Kegelmeyer P Jr. (2000). (2000). "The Digital Database for Screening Mammography." Proceedings of the 5th International Workshop on Digital Mammography, Toronto, Canada,pp. 212-218.
Kom G, Tiedeu A, Kom M (2007). Automated detection of masses in mammograms by local adaptive thresholding, Comput. Biol. Med., 37(1): 37-48.
Matsubara T, Fukuoka D, Yagi N, Hara T, Fujita H, Inenaga Y, Kasai S, Kano A, Endo T, Iwase T (2005). “Detection method for architectural distortion based on analysis of structure of mammary gland on mammograms.” Proc. 19th Int.. Congr. Exhib. Comput. Assist. Radiol. Surg., 1281: 1036-1040.
Melgani F, Bruzzone L (2004). Classification of hyperspectral remote sensing images with support vector machine. IEEE Trans. Geosci. Rem. Sens., 42(8): 1778-1790.
MIAS. http://skye.icr.ac.uk/miasdb/miasdb.html.
Miller P, Astley S (1994). “Automated detection of breast asymmetry using anatomical features,” in State of the Art in Digital Mammographic Image Analysis. Ser. Machine Perception Artif. Intell., 9: 247-261.
Mitchell T (1997). Machine Learning, (McGraw-Hill). Learning one more thing. Technical Report, CMU-CS-94-184.
Muhammad AJ, Ayyaz H, Anwar MM, Asmatullah Ch (2009). “Fuzzy Entropy And Morphology Based Fully Automated Segmentation Of Lungs From Ct Scan Images.” Int. J. Innov. Comput., Inf. Control, 5(12B): 4993-5002.
Muhammad AJ, Bilal A, Nawazish N, Ayyaz H, Fouzia J, Anwar MM (2010). “Multi domain Features based Classification of Mammogram Images using SVM and MLP.” ICIC Express Lett., 4(3).
Sivandam SN, Deepa SN (2007). Principles of Soft Computing, Wiley India, pp. 11-29.
Steve R (1998). Gunn,Support Vector Machines for Classification and Regression, Technical Report.
Suri JS, Rangayyan RM (2006). Recent Advances in Breast Imaging, Mammography, and Computer-Aided Diagnosis of Breast Cancer, SPIE, Bellingham, Washington, USA.
Wallis M, Walsh M, Lee J (1991). “A review of false negative mammography in a ymptomatic population." Clin. Radiol., 44: 13-15.
Wang T, Karayiannis N (1998). Detection of microcalcification in digital mammograms using wavelets. IEEE Trans. Med. Imag., 17(4): 498–509.
Zwiggelaar R, Parr TC, Schumm JE, Hutt IW, Taylor CJ, Astley SM, Boggis CRM (1999). Model-based detection of spiculated lesions in mammography. Med. Image Anal., 3(1): 39-62.