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Computer Aided Diagnosis of Malignancy in Mammograms

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Abstract

Breast cancer is the second most common cause of cancer death in women. Early detection is the only way to reduce the mortality. Mammography is the best available technique used for earlier detection. But due to manual reading the performance of diagnosis varies from 65% to 85%. To improve the accuracy in diagnosis various computer aided design has been developed for the past two decades. Even then the detection rate is still not high. The proposed method consists of four steps preprocessing, Segmentation, Feature extraction and Classification. Noise and artifact removal are performed in preprocessing. Alarm region generation process with region growing method is used to segment the suspicious region. Spatial gray level dependence method is used for Feature extraction process. Extracted features are classified using support vector machine. The proposed algorithm is fully automatic and has shown 95.2% sensitivity.

Keywords: Mammogram, Computer Aided Detection, Adaptive histogram, Segmentation, Feature extraction, Support vector machine.

1. Introduction

Cancer is one of the biggest threats to human life. It is expected to become the leading cause of death in future. According to World Health Organization (WHO) cancer accounted 13% of all death in the world in 2004. Cancer is general term that refers to cells that grow larger than 2mm in every three months and multiply out of control and spreads to other parts of the body. Collection of cancer cells forms tumor which destroy the healthy tissue. Tumor breakaway and spreads to other parts of the body which is called as metastasis. Most kind of cancer is named after the part of the body where it started. Breast cancer begins in the breast tissue, it may spread to lungs but still it is breast cancer not lung cancer.

Breast cancer is the second most common cause of cancer death particularly for women in all over the world. According to Medindia "Breast cancer in India rising rapidly", it is rapidly becoming the number one cancer in females and pushing the cervical cancer to second place. According to Tata memorial hospital the breast cancer has been reported to occur in 1 woman out of 1000 during 1974-78. But today it occurs 1 in 10 which shows the necessity of taking preventive steps against this dangerous disease. At present vaccination is available to prevent some kind of cancers such as lung cancer, cervical cancer. But in the case of breast cancer the root cause is still unknown. Hence the proper preventive measures are absent. However complete curing of breast cancer is possible if it is detected in its earlier stages. Early detection will improve the survival rate of patient by 95%. Hence earlier detection is the only way to reduce the mortality.

Masses and microcalcification are two important signs that appear in mammogram. Mass detection is more difficult than microcalcification, because masses may have similar density as normal breast tissue. Microcalcification is just the collection of calcium cells. Mass will have different shapes and ill defined boundaries than microcalcification. Other confusing terms are benign and malignant. Benign refers to a condition, tumor or growth that is not cancerous. Breast cancer also known as carcinoma, it is malignant growth that begins in the tissue of the breast. Several types of breast cancer are there. 75% of breast cancers are known as ductual carcinoma which begins in the cells lining the ducts that bring milk to the nipple, 20% of lobular carcinoma begins in the milk segreting glands of the breast, 5% of other varieties of breast cancer arise from the skin, fat, connective tissues and other cells present in the breast.

Mammography is the best available technique to detect cancer cell in its earlier stages. Many other secondary methods are available such as MRT, CT, Ultrasonic. The accordance rate between these instruments and histopathological feature is low, but between mammography and histopathologic diagnosis the rate is quite high. Ultrasonic produces good contrast images but does not contain detailed information. MRI is more sensitive and it can lead to false diagnosis. Mammography is highly accurate and low cost detection method. Digital mammography is a technique for recording X-ray images in computer code instead of on X-ray film as with conventional mammography. The images are displayed on a computer monitor and can be enhanced before they are printed on film.

Normally mammogram readings are performed by radiologists. Large number of mammograms generated by screening of population must be diagnosed by relatively few radiologists. For experts it is difficult to provide accurate diagnosis due to variety of factors such as poor quality of image, benign appearance of lesions, eye fatique factor, and difficulty due to bright zone of the objects on mammogram. So that the performance of the radiologists varies from 65% to 85%. Due to the above mentioned regions a variety of computer assisted detection techniques have been proposed. In order to improve the accuracy of interpretation CAD involves two major process computer aided detection (CADe) and Computer Aided Diagnosis (CADi). Developing CAD algorithm using extracted textures from breast profile region would reduce number of unnecessary biopsies in patients with benign disease and thus avoid physical and mental suffering of patients. Thus CAD acts as a second reader and assists radiologist for accurate and efficient detection of cancer cells in the earlier stages. Thus the combination of CAD scheme and expert’s knowledge will greatly improve the detection accuracy.

Many CAD schemes in combination with digital image processing have been proposed for the past two decades. Even then the detection rate is still not high due to high variance in size and shape of tumor and also due to the disturbance from the fatty tissues, veins and glands. The general algorithm that can produce good result for all images is still not available. Although significant progress has been made over the last 20 years much works still needs to be done to develop more effective CAD system.

In this paper previous works in this field are discussed in section II. Section III explains the methodology of the proposed system. Section IV gives the results of the implementation. Finally conclusions are drawn in section V.

2. Previous Research

Implementation of computer aided detection contains various fields such as enhancing the mammogram, identifying suspected region, feature extraction from segmented mammogram, classifying the mammograms and so on. Many algorithms have been proposed to improve the efficiency of the CAD system in the above mentioned fields. Some of those methods are discussed in this section.

Many attempts have been made by researchers to efficiently use the fuzzy logic, Genetic algorithm and neural network methods to improve the diagnostic efficiency in cancer detection. Jinshan Tang, Rangaraj M.Rangayyan, Ju Xu, Issam EI Naqa and Yongyivyang (2009) provided an overview of recent advances in the development of CAD system. Maurice Samulski and Nico Karssemeijer (2011) proposed a new algorithm based on the correspondence between MLO and CC views of mammograms. Pectoral segmentation and artifact removal are the important preprocessing works. Jawad Nagi, Sameen Abdul Kareem, Farrukh Nagi and Syed Khaleel Ahmed (2010) used morphological operation and seeded region growing method to segment the pectoral muscles. Contrast limited adaptive histogram equalization (CLAHE) and multiscale contrast enhancement algorithms are some of the effective methods in enhancing the mammograms.

Numerous segmentation algorithms have been proposed for segmenting the mass region. Each has its own advantage in some perspective. Farhang Sahba and anastaios Veetsanopoulos (2010) used mean shift algorithm to cluster the pixels in mammogram. Kai Hu, Xieping Gao and Fei Li (2011) developed a combination of adaptive global and local thresholding to segment the multiresolution mammogram. Indra Kantra Mitra, Sanjay Nag and Samir K.Bandyopadhyay (2011) presented a combination of techniques that incorporates seeded region growing with ASB algorithm to isolate normal and abnormal regions in the breast tissue. Various algorithms based on Jacobi moments, SUSAN filter, vector quantization have been tried to segment the mass from normal tissue. Yufeng zheng (2010) proposed a hybrid method in which Gabor feature is used with the combination of different methods to detect the cancer cells in mammogram. Mohd.khuzi, R Besar, WMD Zaki and NN Ahmad (2009) designed a method using gray level cooccurrence matrix to identify the mass region in mammogram.

After segmenting the suspected mass region, features of the segmented region should be examined to verify whether the extracted region contains mass or not. Various features like intensity histogram features, Gray level co-occurrence matrix features and intensity features are used for breast cancer diagnosis. In an comparative study R.Nithya and B.Santhi (2011) found out that GLCM outperformed the other two methods. Hence this method is used for the feature extraction process of the proposed method.

Classification is another most important process in CAD system design Jun Liu, Xiaomig Liu, Jianxun Chen and J Tang (2011) used improved local binary pattern operator for mass classification. Fatima Eddaoudi, Fakhita Regrgui, Abdelhak Mahmoudi and Najib Lamouri (2011) used support vector machine with combination of different techniques for the classification of masses. Naïve bayes classifier K means classifier, fuzzy C means clustering are some of the common methods used in the previous works. Kemal Polat and Sahil Gunes (2007) designed least square support vector machine which provided effective classification compared to other methods.

3. Methodology

3.1. Data Collection

The data used in the experiments of the proposed work was taken from MIAS (Mammography Image Analysis Society) database and DDSM (Digital Database for Screening Mammography). MIAS is an organization of UK research groups interested in understanding of mammograms. It contains left and right breast images of 161 patients. Totally 322 images are there which are selected from United Kingdom national screening programme. DDSM database provides two different views such as Crasino Caudal view (CC) and Madio Lateral Oblique (MLO) view of left and right breast images. It contains 2620 cases acquired from Massachusetts general hospital wake forest University.

3.2. Preprocessing

Mammograms are medical images that are difficult to interpret. Hence preprocessing is essential to improve the quality. It will prepare the mammogram for the next two process segmentation and feature extraction. Digitization noise and high frequency components in the mammography images are removed by using median filter. Edges are the more important factor in the segmentation of mammogram. The advantage of using median filter is, it removes the noise without disturbing the edges. The film artifacts such as label and x-ray marks are removed using morphological operation and thresholding method with the use of MATLAB functions. In order to reduce the variation in brightness and to achieve computational consistency images are normalized by mapping all mammograms in to fixed intensity range.

3.3. Segmentation

The goal of segmentation is to find out the entire suspicious mass region from mammogram. A mass is space occupying lesion and usually appears as a bright region on a mammogram. So contrast enhancement is implemented in order to extract the brighter region.

3.3.1. Contrast Enhancement

Contrast enhancement can be performed by increasing the brightness. It adds intensity values by using adaptive histogram equalization over different segments. It adaptively enhances the contrast of each pixel relative to its local neighborhood which produces improved contrast for all levels in the image. Adaptive histogram equalization also helps to reduce the noise produced in homogenous area.

3.3.2. Alarm Pixel Generation

Alarm pixels are produced by thresholding the contrast enhanced image. Alarm threshold is determined by histogram analysis. Segmentation through alarm pixel generation contains the following steps,

i. Histogram and accumulated histogram should be computed. H_{Fm} and $AH_{Fm.}$
ii. Using histogram gradient changes location of peaks in histogram should be found out. (A_{g1}, A_{g2}…..A_{gi}) where A_{gi} are the gray levels.
iii. Candidate of alarm threshold is chosen by following condition, T_K = { A_{gi} | When the selected alarm area < 10% of the entire region of interest}, k=p,p+1…q. AH_{Fm} can be used to calculate the selected alarm area.
iv. Alarm threshold should be one of {$T_{K,}$; k=p~q} *i.e* $T_{AM=}$ T_l $p \leq l \leq q$, such that $|A_{gi} - A_{gi-1}|$ is maximum among {| A_{gk} - A_{gi-1} | ;k=p ~q}.
v. Mark pixel at (x, y) as a candidate of alarm pixel if $I_{Fm}(X,Y) > T_{Am}$ (m=1,2,3,4).
vi. A pixel at (x,y) is considered as alarm pixel if $\sum_{m=1}^{4} I_{Am}(X,Y) \geq 4$.

3.3.3. Region Growing

Region growing method seeks group of pixels with uniform intensities. Seeded region growing performs a segmentation of an image with respect to set of points known as seed. Alarm pixel generated from the above process can be considered as seed point. Given the seed the region growing method finds the tessellation of the image into regions with property that each connected component of region meets exactly one of Ai. Each step of algorithm involves the addition of one pixel into above set. Let z be the unallocated pixel.

$$Z= \{x \,\square\, \cup_{i=1}^{n} A_i \,|N(x) \cap \cup_{i=1}^{n} A_i \neq \Phi\} \tag{1}$$

Where, N(x) is set of immediate neighbours of the pixel x. Consider the rectangular grid with immediate neighbours of 8 connected pixel x. if x Є z then N(x) meets just one of A_i . Hence i(x) Є{1, 2,…..n} to be the index such that

$$N(X) \cap A_{i\,(X)} \neq \Phi. \tag{2}$$

$$\delta(X) =|g(X) - \text{mean}_{\,g \in Ai\,(X)}\,[g(y)]|. \tag{3}$$

Where δ(X) is measure of how different x is from the region it joins and g(x) is the gray value of the pixel x. if N(x) meets two or more values of A_i then A_i will be selected according to the lowest value

$\delta(X)=\min_{x \in T} \{ \delta(X)\}$ (4)

The above process is repeated until all the pixels have been allocated.

3.4. Feature Extraction

Texture feature is useful in differentiating normal and abnormal pattern. Texture is an alteration and variation of surface of the image. Texture is characterized as the space distribution of gray levels in neighbourhood. There are two types of texture measures first order and second order. In the first order texture measure are statistics calculated from individual pixel. In second order relationship between neighbour pixels is considered. In the proposed method Spatial Gray Level Dependence (SGLD) matrix is used for feature extraction which comes under second order texture measure.

Second order statics can be used to model the relationship between pixels within the breast region by constructing SGLD matrix. A SGLD matrix is the joint probability of occurrences of gray levels i and j for the two pixels with a defined spatial relationship in an image. Spatial relationship is defined in terms of distance d and angle θ. SGLD matrix is constructed at a distance d=1, 2, 3, 4 and for angles θ=0, 45, 90 and 135. If the texture is course and distance d is small then pair of points at distance d should have similar gray levels. If the texture is fine and distance d is comparable to the texture size then gray level of the two points would be different. Hence texture coarseness should be analyzed with various values of distance d. From SGLD matrices a variety of features may be extracted. Texture descriptors derived from SGLD are contrast, Energy, Homogeneity and Correlation.

$$\text{Contrast}=\sum_{i,j=0}^{n-1} pij(i-j)^2 \quad (5)$$

$$\text{Energy} = \sum_{i,j=0}^{n-1} (pij)^2 \quad (6)$$

$$\text{Homogeneity} = \sum_{i,j=0}^{n-1} \frac{pij}{1+(i-j)} 2 \quad (7)$$

$$\text{Correlation} = \sum_{i,j=0}^{n-1} (pij) \frac{(i-\mu)(j-\mu)}{\sigma^2} \quad (8)$$

P_{ij} = Element i, j of the normalized symmetrical GLCM

N is number of gray levels in the image

The GLCM mean, calculated as: $\mu = \sum_{i,j=0}^{N-1} iPij$ (9)

σ^2 The variance of the intensities

$$\sigma^2 = \sum_{i,j=0}^{N-1} Pij(i-\mu) \quad (10)$$

Where,

Contrast is the contrast between a pixel and it's neighbour.

Energy is the sum of squared elements in SGLD or uniformity.

Homogeneity is closeness of the distribution of elements in SGLD.

Correlation shows how correlated a pixel is to it's neighbor over the whole image.

3.5. Classification

Classifiers are used in wider range for medical diagnosis. It helps to examine the medical data in shorter time and more detailed. Over different type of classifiers Support Vector Machine produces perfect classification result in breast cancer diagnosis. Result obtained from SGLD matrix is given as input data to SVM classifier. SVM is a reliable classification technique based on statistical learning theory. SVM can classify the given data set into two seperable classes {1, -1}. SVM uses separating hyperplane to classify the classes. Training data is given as input to SVM classifier which consists of n datum

$(x1, y1), ., (x^n, y^n), x \in R^n, y \in \{1, -1\}$.

Separating hyper planes are performed as follows

$D(x) = (w * x) + w0$ (11)

The inequality $y_i (w * x_i) + w0 \geq 1$ is produced for both y=1 and y=-1

$Y_i [(w * x_i) + w0] \geq 1$,i=1,…n (12)

if data points satisfy the above inequality condition then they form support vectors. Classification process is performed based on the support vectors. Margins of hyper plane obey the following inequality,

$y_k * D(x_k) / \|_y\| \geq \Gamma, \; k = 1,2 \ldots n$ (13)

We can maximize the margin by minimizing w as follows,

$\Gamma \times w = 1$. k = 1,2. . . , n. (14)

In the case of non separable data slack variable ξ_i is added as follows

$Y_i [(w * x_i) + w0] \geq 1 - \xi_i$ (15)

In the case of non linear data, non linear input should be converted to high dimensional linear feature via kernels. In the proposed method RBF kernels are used

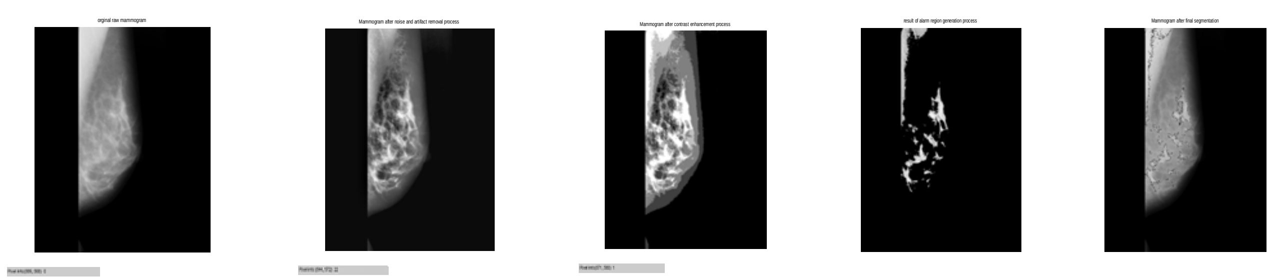
$k(x,x') = \exp(-\|x-x'\| / \sigma^2)$ (16)

Where σ is positive real number

4. Result and Discussion

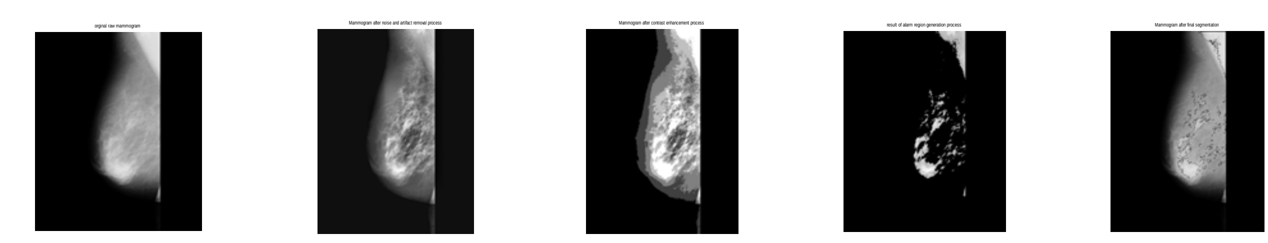
Experiments are conducted on the image taken from both MIAS and DDSM database. 250 mammograms have taken for experiments in which 125 are normal and 125 are abnormal. 75% of images are used for training and 25% of the images are used for testing phase. Some samples of the result are shown. Figure 1, 2, 3 shows some samples of segmentation process. Sample Results of feature extraction process for 20 mammograms are given in Table 1. Classification results for 250 mammograms are given in Table 2.

Figure 1: Image id: mdb 056. (a) Original mammogram (b) Mammogram after noise and artifact removal process (c) Mammogram after contrast enhancement process (d) Mammogram after alarm region generation process (e) Mammogram after final segmentation.



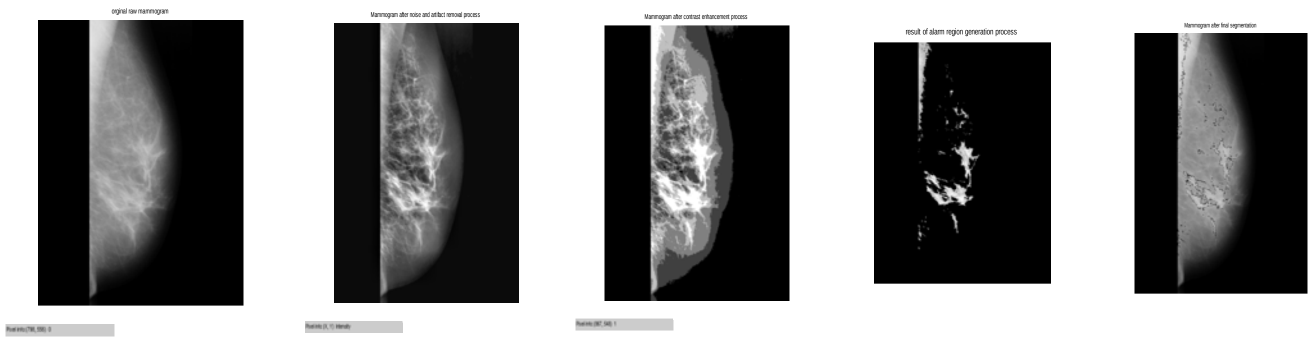
(a) (b) (c) (d) (e)

Figure 2: Image id: mdb 071. (a) Original mammogram (b) Mammogram after noise and artifact removal process (c) Mammogram after contrast enhancement process (d) Mammogram after alarm region generation process (e) Mammogram after final segmentation.



(a) (b) (c) (d) (e)

Figure 3: Image id: mdb 056. (a) Original mammogram (b) Mammogram after noise and artifact removal process (c) Mammogram after contrast enhancement process (d) Mammogram after alarm region generation process (e) Mammogram after final segmentation.



(a) (b) (c) (d) (e)

Table 1: Result of feature extraction process for normal and cancer classes

Image id	Image class	Homogeneity	Energy	Correlation	Contrast
Mam1	Cancer	0.992	0.912	0.920	0.191
Mam2	Cancer	0.993	0.723	0.923	0.161
Mam3	Cancer	0.989	0.900	0.879	0.160
Mam4	Cancer	0.992	0.921	0.917	0.168
Mam5	Cancer	0.990	0.865	0.852	0.161
Mam6	Cancer	0.992	0.895	0.931	0.185
Mam7	Cancer	0.994	0.843	0.912	0.133
Mam8	Cancer	0.995	0.741	0.911	0.132
Mam9	Cancer	0.987	0.909	0.890	0.189
Mam10	Cancer	0.992	0.900	0.956	0.108
Mam11	Normal	0.842	0.448	0.250	0.890
Mam12	Normal	0.828	0.506	0.302	0.198
Mam13	Normal	0.825	0.386	0.369	0.994
Mam14	Normal	0.842	0.438	0.333	1.021
Mam15	Normal	0.770	0.511	0.440	0.910
Mam16	Normal	0.772	0.297	0.647	0.670
Mam17	Normal	0.774	0.419	0.680	0.431
Mam18	Normal	0.779	0.519	0.784	0.521
Mam19	Normal	0.825	0.286	0.369	0.994
Mam20	Normal	0.826	0.375	0.446	0.897

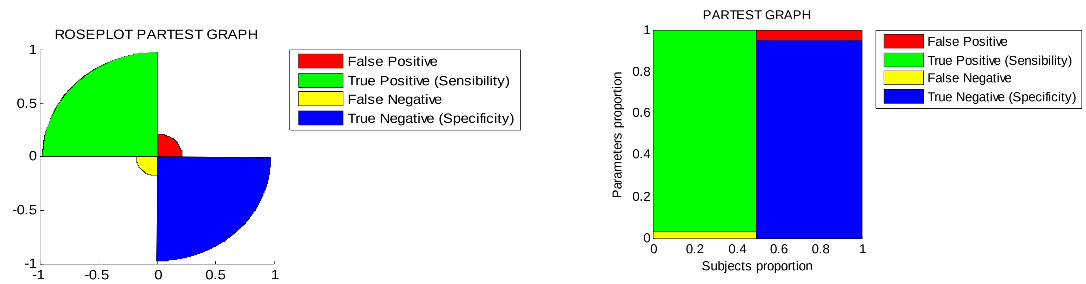
Table 2: Classification result

		True positive	True Negative	False Positive	False Negative
Number of cases	250	118/125	119/125	7/125	6/125
Percentage	100	94.4%	95.2%	5.6%	4.8%

4.1. Performance Evaluation

Perfect test method is one of the methods in ROC curve method. Perfect test method is used to evaluate the performance of designed algorithm. The result obtained from the classification process is given as input. The result is shown as graphical representation in Figure 4, which gives the sensitivity and specificity of the proposed method

Figure 4: Graphical representation of the result



5. Conclusion

In the proposed work we have designed a new computer aided detection method to detect the mass region in the mammogram. This method is completely automatic and does not need any human interruption. Preprocessed image is segmented by using alarm pixel generation process in combination with seeded region growing. Segmented image contains the suspected region which is given for feature extraction process. The extracted features are classified in to normal and abnormal region using support vector machine method. The performance of the proposed method is evaluated using perfect test method which gives the sensitivity and specificity of the result with graphical representation. The sensitivity of the proposed method is 95.2% and specificity is 94.4%. Hence the proposed method is highly desirable in order to assist the radiologist in the detection of malignant region and to improve the diagnostic accuracy.

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