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# Review on Approaches Different Classification for Mammogram Image

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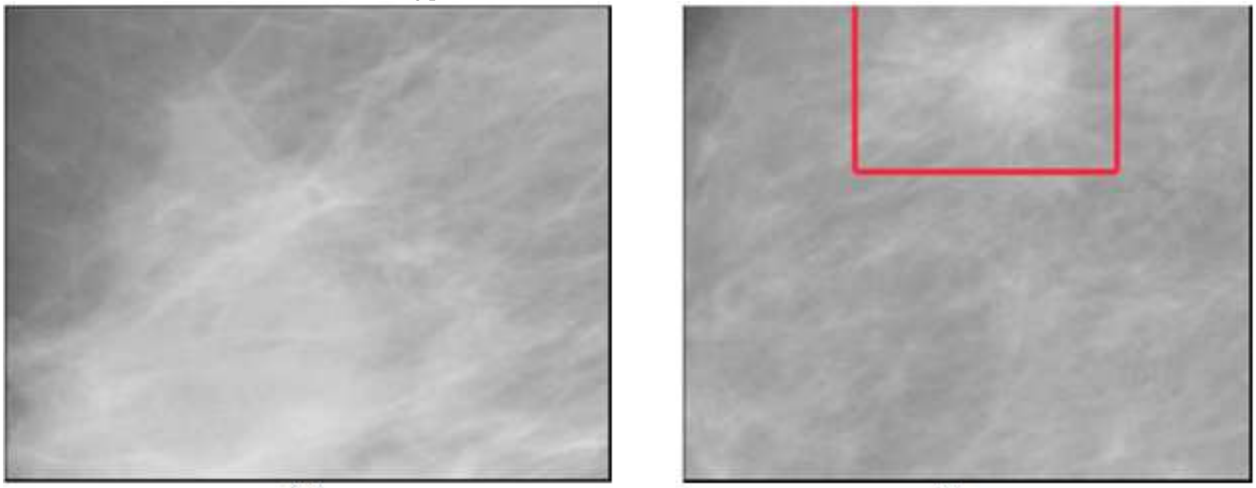
**Abstract:** ***Breast cancer remains a subject of intense. The aim of this paper is to review existing approaches of processing mammograms at different stages to detect breast cancer at the earliest. Most of techniques are used in Mammogram classification aimed to help the radiologist to classify the Mammogram as benign or malignant image. Moreover this paper helps to understand the different stages in mammograms and the already existing techniques in that area for further exploration. The review has been done in different stages namely mammogram preprocessing and classification in the recent years. The results obtained using different techniques are also reported.***

## 1. Introduction

Breast cancer affects women of all ages/ethnic groups. In spite of decades old breast cancer research regarding diagnosis and treatment, prevention continues to be the sole way to lower this disease's human toll which currently affects 1 in 8 women in their lifetime [1]. In the United States in 2012, an estimated 227,000 women and 2,200 men are expected to be diagnosed with this cancer, and around 40,000 women are expected to succumb to it [2].The term "breast cancer" includes more than one disease being an umbrella term for various cancer subtypes of the human breast. Breast cancer subtypes differing clinical presentations, and show clear cut gene expression patterns in addition to having different genetic/molecular characteristics [3,4].Breast cancer subtypes have some shared and unique causes, and contributing factors influencing prevention approaches. Mammogram cannot stop or decrease breast cancer but are supportive only in detecting the breast cancer at early stages to increase the survival rate [5]. Regular screening can be a successful strategy to identify the early symptoms of breast cancer in mammogram images [6].Medical images classification is a form of data analysis that extracts models describing important data classes. Numerous methods have been created to classify masses into benign and malignant categories by using the  classification different method .This paper illustrates the review of the literature where the computer aided system is used in different stages of mammogram classification in the recent years.[7].Shown that Figure (1).



(A) (B)

**Figure 1:** images (a) Benign (b) Malignant

Classifiers play [8] an important role in the implementation of computer-aided diagnosis of mammogram. There are many study were conducted a by using computer aided diagnosis to detect cancer automatically in mammograms without any help of radiologist or medical specialist. After that, enhancement has been performed so that cancer can be clearly visible and identifiable to classify micro-calcifications into benign and malignant.

## 2. Review on Mammogram Image Classification

Over the years, a lot of work has been done for the Classification Techniques Mammogram. In order to understand the topic properly many papers from various journals are reviewed . So, a brief review of all the techniques developed for the detection of classification Method Mammogram has been discussed below:

Fatima Eddaoudi et al. 2011 [9] presented a masses detection algorithm based on SVM classification and texture analysi

s. The results, obtained with original mammograms, showed that 65 malignant out of 76 were classified true positive while 13 mammograms out of 19 were classified true negatives which correspond to a classification rate of 77% in average. These rates were significantly improved, achieving accuracy 95%.

M. Lundin et al [10] has applied ANN on 951 instances data set of Turku University Central Hospital and City Hospital of Turku to evaluate the accuracy of neural networks in predicting 5, 10 and 15 years breast cancer specific survival. The values of ROC curve for 5 years were evaluated as 0.909, for 10 years 0.086 and for 15 years 0.883, these values were used as a measure of accuracy of the prediction model. They compared 82/300 false prediction of logistic regression with 49/300 of ANN for survival estimation and found ANN predicted survival with higher accuracy.

S.Krishnaveni1, R.Bhanumathi2et al [11] presented a Mammogram Micro calcification to aid tumor detection and diagnosing the mammogram using Naive Bayes .The proposed method has leads to analysis an efficient method by diagnosing the mammogram using Naive bayes classifier ,used to detect micro calcification in mammograms . Which is classifies the Mammogram image as Benign or Malignant. The proposed experimental results show that when compared to several other methods Naive Bayes Classifier shows accuracy is 93.75%, specificity is 90%, sensitivity is 97.5% and precision is 97.2% for Naive Bayes Classifier.

Antony et al. [12] proposed a new approach to determine the classification of mammographic image using k-means clustering algorithm which can use different features of the image like shape, intensity values and density features and region features to compute the feature vector. They computed the mean values of intensity values of the pixels in the region extracted to compute the intensity mean value. The density measure is also computed in the similar fashion. The region metric is computed with the extracted region values and it has seven different features hidden. k-means clustering is used based on the computed feature vectors to identify the class of the input image. The proposed system reduces the space and time complexity and produces good results. It has produced classification accuracy up to 99% which is more than other methodologies in this era.

In 2007 J. Jiang et. al. [13] used Genetic algorithm for classification. They used 188 mammograms from DDSM. Extensive experiments show that the proposed GA design is able to achieve high performances in micro-calcification classification and detection, which are measured by ROC curves, sensitivity against specificity, areas under ROC curves and benchmarked by existing representative techniques.

Nikhil R. Pal et. al. 2008 [14] used neural networks for classification. The system is tested on a set of 17 mammograms comprising 10 abnormal and seven normal images which are not used in training and the system is found to perform very well. Moreover for each abnormal image, the system is able to locate the calcified regions quite accurately.

In 2009 Liyang Wei et. al. [15] used Support Vector Machine for classification. They used 200 mammograms from the Department of Radiology at the University of Chicago. Their experimental results reported 0.78 to 0.82 in terms of the area under theROC curve.

Sumeet Dua et. al. [16] used Weighted Association Rule based Classifier. He tested 322 mammograms from MIAS database they attained accuracy of 89%. M. Muthu Rama Krishnan et. al. used Support Vector Machine for classification. They have experimented with two data sets Data Set – I : 699 instances and Data Set – II : 569 instances. Database was created from the University of Wisconsin Hospitals and the classification accuracy attained is : 99.385% for dataset-I and 93.726% for dataset-II.
Wener Borges Sampaio et. al. [17] used Cellular Neural Networks for classification. They attained the Sensitivity of 80% and rates of 0.84 false positives per image and 0.2 false negatives per image, and an area under the ROC curve of 0.87.

Amir Tahmasbi et. al. [18] used Multi-layer Perceptron for 322 Mammograms from MIAS data base. The designed systems yield Az = 0.976, representing fair sensitivity, and Az = 0.975 demonstrating fair specificity.

Stylianos D. Tzikopoulos et. al.[19] used Support Vector Machines for classification of 322 Mammograms from MIAS data base. They achieved Classification Accuracy as 84.47%.

Iuan F. Ramirez Villegas et. al. [20] used Support Vector Machines. They used 23 mammograms from Mias Database and attained 93.75 % accuracy.

Again in 2012 Arnau Oliver et. al. [21] used Neural Networks is for classification. 23 mammograms from Mias Database are used and that classification accuracy reported is 93.75. Loris mammograms using Support Vector Machines (SVM), The proposed system successfully achieved 93% classification accuracy, which is considered as a good result when compared with similar works in the same research field. Nanni et. al. [22] used support vector machine for classification. 584 Mammograms from DDSM are used for experimental analysis and they are able to attain the area under the ROC curve as Az of 0.97. Discriminant fusing analysis based Classifier is used by Jun-Bao Li et. al. [23] in which 42 mammogram from MIAS Database were taken and the classification accuracy reported is 95.88%.

Meenakshi Sundaram K. et. al. [24] applied image mining technique on mammogram to classify the cancer diseases. It can be classified into normal, benign and malignant. They proposed Fuzzy Association Rule Mining. Experiments have been taken dataset with 300 images taken from MIAS of various types to improve accuracy using minimum number of rules to patterns. The experiments and results of the FARM gives better performance compared with existing method.

## 3. Review On Multi-Classification Mammogram Image

Keyvanfard, F., et al [25] they proposed a multi classifier system composed of three classifiers. That used dynamic features to classify breast lesion in DCE-MRI, Several neural networks classifiers like MLP, PNN, GRNN, and RBF has been presented on a total of 112 his to pathologically verified breast lesions to classify into benign and malignant groups. Also, support vectormachine has been considered as classifier. Before applying classification methods, feature selection has been utilized to choose the significant features for classification. Finally, to improve the performance of classification, three classifiers that have the best results among all applied methods have been combined together that they been named as multi- classifier system. For each lesion, final detection as malignant or benign has been evaluated, when the same results have been achieved from two classifiers of multi-classifier system. The results show that the proposed methods are correctly capable to feature selection and improve classification of breast cancer.

Patel, BC, et al. [26] proposed Mammography feature analysis and mass detection in breast cancer images. In this work, a comparison of the performance between the features of Discrete Wavelet Transform (DWT) and Spherical Wavelet Transform (SWT) based on the classification results of normal, benign and malignant stage was studied. Classification was performed using Linear Discriminant Classifier (LDC), Quadratic Discriminant Classifier (QDC), Nearest Mean Classifier (NMC), Support Vector Machines (SVM) and Parzen Classifier (ParzenC). We have obtained a maximum classification accuracy of 81.73% for DWT and 88.80% for SWT features using SVM classifier. PriteeKhanna&Shubhi Sharma directed toward the development of a computer-aided diagnosis (CAD) system to detect abnormalities or suspicious areas in digital mammograms and classify them as malignant or non malignant. Original mammogram is preprocessed to separate the breast region from its background. To work on the suspicious area of the breast, region of interest (ROI) patches of a fixed size of 128×128 are extracted from the original large-sized digital mammograms. For training, patches are extracted manually from a preprocessed mammogram. For testing, patches are extracted from a highly dense area identified by clustering technique. For all extracted patches corresponding to a mammogram, Zernike moments of different orders are computed and stored as a feature vector. A support vector machine (SVM) is used to classify extracted ROI patches. The experimental study shows that the use of Zernike moments with order 20 and SVM classifier gives better results among other studies.

M. Mavroforakis et al. [27] presented analyzed at various clinical features for benign/malignant classification and performed statistical analysis tests on those features. Multiple linear and non-linear models were applied during the classification process, including LDA, least-squares minimum distance, K-nearest-neighbors, RBF and MLP. Optimal classification accuracy rates reached 81.5% for texture-only classification and 85.4% with the introduction of patient's age as an example of hybrid approaches.

Sepehr M. H. Jamarani et al [28] presented an approach for early breast cancer diagnosis by applying combination of ANN and multi-wavelet based sub band image decomposition. The proposed approach was tested using the MIAS mammographic databases and images collected from local hospitals. The best performance was achieved by BiGHM2 multi-wavelet with areas ranging around 0.96 under ROC curve. The proposed approach could assist the radiologists in mammogram analysis and diagnostic decision making.

S. Usha, al [29] proposed an automatic mammogram classification technique using wavelet and Gabor filter. Correlation feature selection is used to reduce the feature set and selected features are classified using different decision trees. Classification accuracy is achieved Decision stump 80.00%, J4870.00%,CART 60.00%, Decision stump with CFS 80.00%, J48 with CFS 80.00%, CART with CFS 70.00%.Future work can explore optimizing the classifiers for improving the accuracy.

Mohammed J.Islam et al [30] presented a computer aided mass classification method in digitized mammograms using Artificial Neural Network (ANN) and performing benign-malignant classification on region of interest (ROI) having mass. A major mass classification mammographic characteristic is texture. ANN exploits this to classify mass as benign or malignant. Statistical textural features in characterizing masses are mean, standard deviation, entropy, sleekness, kurtosis and uniformity. This method aims to increase classification process efficiency objectively to reduce many false positive of malignancies. Three layers artificial neural network (ANN) with seven features was proposed to classify marked regions into benign or malignant achieving 90.91% sensitivity and 83.87% specificity which is promising compared to a radiologist's 75% sensitivity.

Ganesan et al. [31] proposed an automated diagnosis of mammogram images of breast cancer using Discrete Wavelet Transform and Spherical Wavelet Transform Features. Classification accuracy is achieved 75.67%, 59.41%, 81.73 and 54.05% for QDC, NMC, SVM and ParazenC respectively for DWT and SWT using ten-fold cross validation. Our results is comparable the work in the literature which achieves 80% accuracy. Future work can explore optimizing the classifiers for improving the accuracy.

Hashem B. Jehlol, et al [32] they propose automatic process of mammography classification. They use several machine learning algorithms such as Random forest (RF), The Naive Bayes (NB), C4.5, The multi-layer perceptron (MLP) and Decision Table (DT).The goal is to find the best combination for feature extraction algorithm and classification algorithm, which gives good results in the classification of mammograms. With high accuracy can support the radiologists to take an accurate diagnostic decision .The best results were achieved in the case of using combination of random forest classifier and the second-order features with 98.8% classification accuracy.

Jong Pill Choi et al [33] compared the performance of an Artificial Neural Network, a Bayesian Network and a Hybrid Network used to predict breast cancer prognosis. The hybrid Network combined both ANN and Bayesian Network. The Nine variables of SEER data which were clinically accepted were used as inputs for the networks. The accuracy of ANN (88.8%) and Hybrid Network (87.2%) were very similar and they both outperformed the Bayesian Network. They found the proposed Hybrid model can also be useful to take decisions.

M. Arfan Jaffar[34]proposes a computer aided diagnosis syst em that performs three different tasks. In the first task, breast segmentation has been performed by using a mixture of bila teral filter, log transformation, adaptive active contour and e ntropy. Then enhancement has been performed by using the concept of Partitioned Iterated Function System. At the end most suitable texture features has been extracted and classifi ed by ensemble classifier that performs well as compare to o ther classifiers. An ensemble classifier AdaBoost has been u sed to classify those features by using the concept of intellig ent experts. The standard dataset has been used for validatio n of the proposed method by using well known quantitative measures. Proposed method has been compared with the exi sting method. Results show that proposed method has achiev ed 96.74% accuracy as well as 98.34% sensitivity.

## 4. Conclusion

Breast cancer is the main cause of death among women. Earl y detection and diagnosis through regular screening and time ly treatment can prevent cancer. This paper presents a revie w of different techniques and classifier used in mammogram . The overall literature survey says that there are various met hods are already used on mammogram. The various classific ation techniques applied are classifying the images with beni gn and malignant. Due to more number of multi-classifier W e achieve better performance in terms of accuracy.

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