Review on Mammography Images classification by supervised and unsupervised learning

Baljeet Kumar, Sumit Chopra
Department of Computer Science, KCCEIT SBSNAGAR

***Abstract* -** Breast cancer continues to be a significant public health problem among women around the world. It has become the number one cause of cancer deaths amongst Malaysian women. The key to improve the breast cancer prognosis is by early detection. The important sign for the breast cancer detection is the presence of lesion such as micro calcification clusters (MCCs). In this review paper, the mammogram-based approach will be focused, as it is particularly suitable for detecting this type of lesion. Detect the different classification approaches of mammography images.

Keywords - *Mammography, Classification, Machine learning, Cancer*

I. INTRODUCTION

A mammogram is a x-ray image of the breast. It can be utilized to check for breast cancer in ladies who have no signs or manifestations of the ailment. It can likewise be utilized in the event that you have a protuberance or other indication of breast cancer. Screening mammography is the kind of mammogram that checks you when you have no side effects. It can help decrease the quantity of passing's from breast cancer among ladies ages 40 to 70. Digital mammography, also called full-field digital mammography (FFDM), is a mammography system in which the x-ray film is replaced by electronics that convert x-rays into mammographic pictures of the breast. These systems are similar to those found in digital cameras and their efficiency enables better pictures with a lower radiation dose. These images of the breast are transferred to a computer for review by the radiologist and for long term storage. The patient's experience during a digital mammogram is similar to having a conventional film mammogram. Computer-aided detection (CAD) systems search digitized mammographic images for abnormal areas of density, mass, or calcification that may indicate the presence of cancer. The CAD system highlights these areas on the images, alerting the radiologist to carefully assess this area. Breast tomosynthesis**,** also called three-dimensional (3-D) mammography and computerized breast tomosynthesis (DBT), is a propelled type of breast imaging where numerous pictures of the breast from various points are caught and reproduced ("synthesized") into a three-dimensional picture set. Thusly, 3-D breast imaging is like registered tomography (CT) imaging in which progressions of thin "cuts" are gathered together to make a 3-D remaking of the body. In spite of the fact that the radiation measurement for some breast tomosynthesis frameworks is somewhat higher than the dose utilized as a part of standard mammography, it stays inside the FDA-endorsed safe levels for radiation from mammograms. A few frameworks have dosages fundamentally the same as ordinary mammography.

II. LITERATURE REVIEW

Nunes, Andre Pereira [1], presented a computational methodology is given in this paper which is used to detect masses in mammographic images. To detect suspicious regions we use K-means clustering algorithm and template-matching techniques. Extractions of geometry and texture features are done for individual level. By Simpson's Diversity Index is used for description of texture, which is used to measure the biodiversity of an ecosystem in Ecology. At last to classify the suspicious region we use SVM (Support Vector Machine). There are two classes of texture: masses and non-masses. This paper gives a conclusion for this methodology i.e. it has 83.94% of accuracy, 83.24 % sensitivity and 84.14 % specificity.

Kelly[2] in this paper we compare the performance and diagnostic yield of mammography with automated whole breast ultrasound (AWBU) and between mammography and in women with dense breast at elevated risk of breast cancer. In this paper we test the screening of AWBU from 4419 women which having routine mammography. Here we evaluate the cancer occurring during the study and subsequent 1-year follow-up. Here we also calculate the sensitivity, specificity and PPV of biopsy recommendation for mammography, AWBU and mammography with AWBU. This paper gives a result which shows that Breast cancer detection double from 23 to 46 in 6425 study using AWUB with mammography which results in the increment of diagnostic yield from 3.6 per 1000 to 7.2 per 1000 with only mammography. AWBU is significant cancer detection as compare to the individual mammography.

Leong[3]This paper gives a study on the comparison of breast cancer in western as well as Asian countries. Here there is a mini-symposium was held in Montreal , Canada at the international Surgical Week for the Breast Surgical International in 2007.Many investigation is done from Asian and Western countries presented the epidemiologic and clinical outcomes data from women with breast cancer .With the help of this comparison we come to know that there is age difference in Asian and Western countries of having Cancer like in western countries the peak age of breast cancer if between 60-70 whereas in Asian country the peak age is 40-50. The incidence is increasing and the molarity rate is decreasing in the West.

Morrell[4]In this paper we estimate the extent of over diagnosis of invasive breast cancer by screening in New South Wales, Australia with a well-established mammography screening has been done to achieve full geographic coverage. Here we use to calculate the over diagnosis to observe the expected annual incidence as a percentage of expected incidence. Last time we use this method in 1999-2001 where we estimate the expected incidence without screening from the incidence of breast cancer in (1) women in unscreened age group (2) women in all age group to the implementation of screening. Then we only adjust the estimated for trends in major risk factor for breast cancer. At last we adjust for lead time to make estimates of expected incidence in 1999-2001. These estimates are compared with the observed incidence in 1999-2001 to calculate over diagnosis for breast cancer by screening. Here 50-69 year NSW women were estimated to be 42 and 30 % by using interpolation and extrapolation.

R. Nithya [5]: This paper introduces a method for the diagnosis of breast cancer. In this paper breast cancer will be diagnosis in digital mammography by using grey level co-occurrence Matrix (GLCM). Here CAD i.e. computer aided diagnosis system using GLCM feature and neural network. For early detection of breast cancer mammography is an efficient tools .Mammogram images are classified into normal image and cancer image. By using DDSM i.e. digital database for screening mammography we examined the effectiveness, accuracy and sensitivity. By using GLCM overall accuracy can be improved.

J.S.L.Jasmine[6]in this paper we use Non Subsampled Contour let Transform (NSCT) and SVM to automatically mass classification for breast cancer. By extracting the mass features from contour let coefficient of the image we classify the masses and the outcomes are used as an input in SVM classier for the classification. The images of mammogram are classified as normal or abnormal and the abnormal severity as benign or malignant has been classified by the system. By using mammography image analyses society (MIAS) database we evaluate the system. Improved classification rate is provided by this method.

Gøtzsche [7]: The main goal of this paper is to assess the effect of screening for breast cancer with mammography on molarity and morbidity. There are various estimates of the benefits and harm of mammographic screening for breast cancer has been published and national policy varies. Here we randomly collected data and analysis has been done with no mammographic screening. In this paper eight trials were done from which we exclude a biased trial and include 600,000 women in the analyses. Result shows that breast cancer mortality was unreliable outcomes that were biased in favors of screening, mainly because of different misclassification which causes death. There is no effect of screening on cancer mortality in random manner including breast cancer.

Kojim,[8]: In this paper there is an explanation of mammography and ultrasound to find triple negative breast cancer and also investigate the features of this type . 88 patients with triple-negative breast cancer are viewed from January 2007 to April 2010 by mammography and ultrasound. Where 52 patients under go with neo adjuvant chemotherapy. Here we compare the effects of pathological chemotherapy and radiological among the patients. According to Japanese mammography guideline all the mammogram are reviewed. Ultrasound finding were classified as masses, low echoic area, distortion and calcification features noted which includes shapes, patterns, posteriors echoes, vascularity and elasticity scores. N no of mammography, triple-negative breast cancers frequently presented with a mass (62.4%). Masses with micro margin were the most frequent (39.6%), indistinct (32%) and circumscribe (20.8%) were commonly observed but speculated margins were rare (4.7 %). On ultra sound cancers were commonly present as a mass (92.5%). The result shows that there is no large difference between ultrasound and mammography.

Costa [9]: In this paper a methodology is introduced which has efficient coding along with linear discriminant analysis to distinguish between mas and non- mass from 5090 region from mammograms. The rates of success reached with Gabor wavelets and principle component analyses are 85.28% and 87.28% respectively. The model of efficient coding gives 90.07%. The result demonstrate that the independent component analysis perform successfully the efficient coding to differentiate between mass and non-mass tissue. We observed in this paper that LDA with ICA bases showed high predictive performance for some datasets and provide efficient support for a clinical investigation.

Berbar, Mohamed A [10] : In this paper there are two techniques are given on the basis of statistical and LBP features using SVM and k-nearest neighbor (KNN) classifier. Many women are suffering from the disease of breast cancer. Mammography is the effective source to detect the cancer early. CAD systems are helpful for radiologist in detection and diagnosis abnormalities early. The evaluation of introduced system is applied on DDSM i.e digital database for screening mammography. This system helps to classify normal from abnormal cases with high accuracy rate.

Fantini,et al.[11]: In this paper there is a number of results in the field ,which shows that cancerous tissue is associated with higher hemoglobin and water concentration , and lower lipid concentration with respect to normal breast tissue. Which indicates the character of breast cancer that it is lower hemoglobin saturation and stronger scattering decay as a function of wavelength are less robust. Intrinsic source of optical contrast associated with breast cancer can also be used to monitor individually for the response to neo adjuvant therapy. Optical method is used to detect breast cancer with increase in its opacity. This methods is quite matured enough to appoint in which they are capable of quantifying the optical properties of breast tissue. To determine the concentration of hemoglobin, water, lipids and oxygen saturation of hemoglobin we use near-infrared spectroscopy.

Hofvind,[12]: Main goal of this paper is to compare DCIS and stage-specific breast cancer among the participants ,non-participants . Here women are not invited to screening process. There is estimation that stage-specific breast tumor incidence rates for 640347 women having age of 50-60 have invited to the screening process in the year 1996 to 2007. There is an comparison between the women who participated, who not participated in screening process, women not invited on the basis of incidence rate and stage distribution. This comparison is done with the help of two sided Chi-squared test .The incidence of ductal carcinoma was 3times higher and invasive breast cancer was 1.5 times higher for invited participants as compared to invited non-participants. The incidence of stage 1 cancer was 2 times higher among participants as compared to the non-participants and stage 3 and stage 4 two-three times lower incidence rate. Here much other research is needed to find the difference in stage – specific incidence.

Ramos-Pollán[13]: This paper introduces the MLC and new method for the diagnosis for breast cancer .There is an evaluation of MLC configuration to classify features vectors which is extracted from segmented regions on the image view of mammography and providing BI-RADS diagnosis. To reduce image artifacts and increase mammograms details proper combination of image processing and normalization techniques are used. This method is used under different data acquisition circumstances and exploits computer cluster to select well performing MLC configuration. There is an evaluation of 286 cases extracted from the repository owned by HSJ-FMUP. Radiologists segmented regions on CC and MLO image. To obtain classifier on an area under the ROC curve 20000 MLC configuration is evaluated.

We evaluated 286 cases extracted from the repository owned by HSJ-FMUP, where radiologists specialized segmented regions on CC and/or MLO images (biopsies provided the golden standard). Around 20,000 MLC configurations were evaluated, obtaining classifiers achieving an area under the ROC curve of 0.996 when combining features vectors extracted from CC and MLO views of the same case.

Razzaghi,[14]:In this paper there is an examination for the mammographic density and breast cancer risk in African American (AA) women and white women . Mammographic density was reported to CMR using breast imaging report and data system (BI-RADS). Increasing density was associated with the increased breast cancer risk among all women weather it is African women or white women. Monolithically increasing risk of breast cancer was observed between the highest versus the lowest BI-RADS density categories after adjustment. 40% risk is there in whites with extremely dense breast compared to those with scattered. There is low risk on AA women. The effect modification measure depends on these factors like age, obesity and exogenous hormones have strong association with breast cancer risk and race in the CBCS. In CBCS, density is linked with increase breast cancer risk.

Grzegorczyk[15]: In this paper we analyses an improvement on the issue regarding patient. That is the hurdles which is limiting patients use such as hardware level (difficulty in collecting accurate and non-corrupted data) and software level (often plagued by unrealistic reconstruction times in the tens of hour).Hardware is able to find signals down to levels compatible with sub-centimeter image resolution by keeping 2 min the exam time and the software helps to overcome the time burden and produces accurate image in less than 20 min. The combination of these two allows producing and reporting the first clinical 3-D microwave tomographic image of the breast.

Crandall[16]: The associations between breast tenderness during use of conjugated equine estrogen (CEE)therapy with or without medroxyprogesterone (MPA) therapy and subsequent breast cancer risk are unknown. New-onset breast tenderness during use of CEE + MPA was associated with increased subsequent breast cancer risk. The association of CEE + MPA therapy with increased breast cancer risk was especially pronounced among women with baseline breast tenderness.

Miller [17]: In this paper the author described the study of breast magnetic resonance imaging for the treatment of breast cancer. Man aim of this study is to evaluate the rate of mastectomy and breast conserving surgery. Preoperative MRI was associated with higher rates of mastectomy and detection of occult contralateral breast cancer, but was not associated with lower reexcision rates.

Boquete[18]: In this paper, author prosed a new approach of thermographic image analysis for the detection of cancer . The experiment performed on the tumor case images .This approach is totally based on the independent component analysis and on post processing of the images .This approach gives the 100% sensitivity and better specificity rates.

Ganesan[19]: In this paper the author review the different techniques of the mammograms. Early detection of breast cancer can improve survival rates to a great extent. Inter-observer and intra-observer errors occur frequently in analysis of medical images, given the high variability between interpretations of different radiologists. Also, the sensitivity of mammographic screening varies with image quality and expertise of the radiologist. So, there is no golden standard for the screening process. To offset this variability and to standardize the diagnostic procedures, efforts are being made to develop automated techniques for diagnosis and grading of breast cancer images. A few papers have documented the general trend of computer-aided diagnosis of breast cancer, making a broad study of the several techniques involved. But, there is no definitive documentation focusing on the mathematical techniques used in breast cancer detection. This review aims at providing an overview about recent advances and developments in the field of Computer-Aided Diagnosis (CAD) of breast cancer using mammograms, specifically focusing on the mathematical aspects of the same, aiming to act as a mathematical primer for intermediates and experts in the field.

Kamineni[20]: Author examined the body mass index of the mammograms.Obese women had significantly faster growing tumors, as measured by Ki-67. Findings add to the growing evidence that obesity may contribute to poorer breast cancer outcomes, and also suggest that increased tumor proliferation among obese women is a pathway that explains part of their excess risk of adverse outcomes.

Toriola [21]: In this paper author discussed about the breast cancer cases and the prevention method related to it. Mammography is the best technique to find out the earlier stage cancer. This method improves the sensitivity of breast cancer. Mammography technique reduce the cancer rate by early detection.

Sugitani[22]: In this paper author proposed an ultra wide band antennaarray for radar based detection of breast cancer The breast phantom materials were developed to fit the characteristics of the measured human breast tissues. A quasi-three-dimensional confocal imaging was performed using the breast phantoms. It was confirmed that the compact 4 × 4 antenna array could detect a $5 \times 5 \times 5\text{-mm}^3$ tumor phantom in an inhomogeneous structure with a glandular phantom and resolve the two separate tumor phantoms, which were located at the depth of 23 mm with the spacing of 10 mm.

Engstrøm[23] In this paper reclassification of breast cancer into molecular subtypes provides more precise information regarding outcome compared to conventional histopathological grading and to study breast cancer-specific survival in the different molecular subtypes.

Gøtzsche [24] In this paper the main goal is to assess the effect of screening for breast cancer with mammography on mortality and morbidity. Here by choosing random trials we used to do comparison of screening without doing any mammographic screening. These random trials are picked from world health organization international clinical trial registry. There is a consideration in this paper that the screening reduces breast cancer mortality by 15 % and 30 % for the over diagnosis and over treatment. These results shows that every 2000 women invited for screening throughout 10 years we can avoid one woman from dying from breast cancer and 10 healthy women had been treated unnecessarily.

Drukteinis[25] this paper shows that an optimal breast cancer screening will ultimately require a personal approach which is based on the metrics of cancer risk with selective application of specific screening technologies . As this breast cancer screening is a subject of intense and at times, passionate debate. Mammography is the best way to detect the breast cancer by screening or other method. It is very important to detect breast cancer because this will help to save the life of many women’s if we successfully detect the features of breast cancer early. There are various technology developed in term for detection .In this paper we study about current controversy and promising new technologies that will improve detection of breast cancer. Here an optimal breast cancer screening is introduces for the detection of breast cancer. It gives the knowledge of breast density, characteristics etc.

Hussain, Muhammad. [26] The key idea of our approach is to exploit the textural properties of mammograms and for texture description, to use Weber law descriptor (WLD), which outperforms state-of-the-art best texture descriptors. The basic WLD is a holistic descriptor by its construction because it integrates the local information content into a single histogram, which does not take into account the spatial locality of micropatterns. Author extend it into a multiscale spatial WLD (MSWLD) that better characterizes the texture micro structures of masses by incorporating the spatial locality and scale of microstructures. The dimension of the feature space generated by MSWLD becomes high; it is reduced by selecting features based on their significance. Finally, support vector machines are employed to classify ROIs as true masses or normal parenchyma.

De Oliveira, Fernando SoaresSérvulo, [27] This work proposes a methodology for the discrimination and classification of regions extracted from mammograms as mass and non-mass. The Digital Database for Screening Mammography (DDSM) was used in this work for the acquisition of mammograms. The taxonomic diversity index (Δ) and the taxonomic distinctness (Δ), which were originally used in ecology, were used to describe the texture of the regions of interest. These indexes were computed based on phylogenetic trees, which were applied to describe the patterns in regions of breast images. Two approaches were used for the analysis of texture: internal and external masks.

Abdel-Nasser, Mohamed, et al [28] This paper proposes a computer-aided diagnosis system to analyze breast tissues in mammograms, which performs two main tasks: breast tissue classification within a region of interest (ROI; mass or normal) and breast density classification. The proposed system consists of three steps: segmentation of the ROI, feature extraction and classification. Although many feature extraction methods have been used to characterize breast tissues, the literature shows no consensus on the optimal feature set for breast tissue characterization. Specifically, mass detection on dense breast tissues is still a challenge. In the feature extraction step, They propose a simple and robust local descriptor for breast tissues in mammograms, called uniform local directional pattern (ULDP). This descriptor can discriminate between different tissues in mammograms, yielding a significant improvement in the analysis of breast cancer. Classifiers based on support vector machines show a performance comparable to the state-of-the-art methods.

Jen, Chun-Chu[29] This paper proposes a detection method for abnormal mammograms in mammographic datasets based on the novel abnormality detection classifier (ADC) by extracting a few of discriminative features, first-order statistical intensities and gradients. As tumorous masses are often indistinguishable from the surrounding parenchyma, automatic mass detection on highly complex breast tissues has been a challenge. However, most tumor detection methods require extraction of a large number of textural features for further multiple computations.

Chu, Jinghui, [30]The authors developed a multiple stage method for breast mass detection. The proposed CAD scheme consists of five major components: (1) preprocessing based on morphological enhancement, which enhances mass-like patterns while removing unrelated background clutters, (2) segmentation of mass candidates based on the SLIC method, which groups mass and background tissue into different regions, (3) prescreening of suspicious regions using rule-based classification that eliminates regions unlikely to represent masses, (4) potential lesion contour refinement based on distance regularized level set evolution, and (5) FP reduction based on feature extraction and an ensemble of under sampled support vector machines. two thirds of the available masses were used for training the system, and the remaining masses and non-mass dataset were used for testing.

Khan, Salabat,[31]They investigate the performance of six different approaches for directional feature extraction for mass classification problem in digital mammograms. These techniques use a bank of Gabor filters to extract the directional textural features. Directional textural features represent structural properties of masses and normal tissues in mammograms at different orientations and frequencies. Masses and micro-calcifications are two early signs of breast cancer which is a major leading cause of death in women. For the detection of masses, segmentation of mammograms results in regions of interest (ROIs) which not only include masses but suspicious normal tissues as well (which lead to false positives during the discrimination process). The problem is to reduce the false positives by classifying ROIs as masses and normal tissues. In addition, the detected masses are required to be further classified as malignant and benign.

Sharma, Vipul [32] In this paper author proposed a hybrid approach for the classify the mass from the mammograms by using correlation-based feature selection (CFS) and sequential minimal optimization (SMO).The texture analysis is done on a region of interest selected from the mammogram. CFS is used to differentiate between the breast tissues density. The classification is performed using SMO. the performance of this method provides high accuracy results.

DeSampaio, Wener Borges[33] In this paper, the methodology is divided into two main part according to the objectives of the difficulties comes into the detection of masses. The first method is used to detect the density of breast is either dense or non-dense. In this part segmentation is done according to the structure of masses. In this paper micro genetic algorithmic process is used to select the region which containing lesions. The second part of this methodology used for the reduction of false positive. False positive is based on the DBSCAN and proximity ranking of the textures of the ROIs.

Oliver, Arnau,[34] In this paper, the author proposed an approach for the density segmentation of the mammographic images this method is totally based on the pixel based classification. This approach result checked by comparing manual annotation with automatically obtained estimations.Transversal analysis of the breast density analysis is based on the two techniques craniocaudal (CC) and mediolateral oblique (MLO).

Li, Yanfeng,[35] In this paper mass classification method is proposed without the use of segmentation process of the region of masses. Two techniques are combined in these approaches that are texton analysis with multiple subsampling. Before performing texton-based classification, intensity and rotation normalization are applied. This method is tested on the mass regions from Digital Database for Screening Mammography (DDSM) database.

Rehman, AwaisUr[36] In this paper a new approach diverse features based breast cancer detection (DF-BrCanD) system is proposed to detect the breast cancer. This work increased the radiologist diagnosis process. SVM and RBF kernel is used for the classification of mammographic images. This approach provide the better accuracy result for the detection of cancer from mammograms.

Liu, Xiaoming,[37] In this paper author proposed an automatic mass detection method for the mammographic images .in this method firstly find the suspicious region that named as multiple concentric layers approach. The data set is also trained in this method. The Initial regions are also refined by narrow band based active contour (NBAC).This method improve the accuracy of the masses . The texture features are computed from gray level co-occurrence matrix (GLCM) and completed local binary pattern (CLBP). Finally, the ROIs are classified by means of support vector machine (SVM), with supervision provided by the radiologist's diagnosis.

Petroudi, Styliani, [38] This work presents the estimation of spatial dependence (SD) or otherwise called co-occurrence matrices on the Instantaneous Amplitude (IA) evaluated for different frequency scales using Amplitude-Modulation Frequency-Modulation (AM-FM) methods. Texture has been shown to be an important feature for mammographic image analysis. This multiscale texture analysis method captures both spatial and statistical information and is thus used to quantify image characteristics for breast density classification. AM-FM demodulation is used to estimate the IA at different frequency scales using multiscale Dominant Analysis. Following normalized SD matrices are evaluated on the IA estimates for each scale, for the segmented breast region, providing IA amplitude co-occurrence relative frequencies. These are used to represent the relative variations in the breast tissue, characteristic to the different breast density classes. Classification of a new mammogram into one of the density categories is achieved using the k-nearest neighbor method and the Euclidean distance metric.

Beura, Shradhananda[39] In this paper mammogram classification process is proposed to classify the breast tissues as normal, benign or malignant. Feature matrix is generated using GLCM to all the detailed coefficients from 2D-DWT of the region of interest (ROI) of a mammogram. Features can be separated by taking the help of t-test and f-test separately. The BPNN classifier is used to classify the features. Two standard databases MIAS and DDSM are used for the validation of the proposed scheme.

Rouhi, Rahimeh, [40] In this paper two methods are used to detect the mass of benign and malignant from the mammograms. Segmentation of images is done by automated trained artificial neural network. In the second method segmentation is done by using cellular neural network whose parameters determined by genetic algorithms. To evaluate the performance of the proposed methods different classifiers (such as random forest, naïve Bayes, SVM, and KNN) are used.

Li, Xi-Zhao, [41] In this paper, two classes of texture features, one based on textons derived from local pixel intensity variation and one based on oriented tissue structure characteristics are measured on different regions of the breast in an effort to clarify the potential contribution of texture independent of local tissue density to estimate breast cancer risk. The region just behind the nipple is found to be the most significant local region for estimating risk, but estimates based on the entire breast perform better. Texton features are found to perform better than features based on oriented tissue structure.

Miranda, Gisele Helena [42] In this paper author applies new method to fuzzy logic to improve the presentation of features related to the image description. This approach used the BIRADS methods for the classification. They construct a fuzzy inference system. This method improves the accuracy of the already present methods.

Anitha,J.[43]In this paper, an automatic segmentation method is proposed to identify and segment the suspicious mass regions of mammogram using a modified transition rule named maximal cell strength updation in cellular automata (CA). In coarse-level segmentation, the proposed method performs an adaptive global thresholding based on the histogram peak analysis to obtain the rough region of interest. An automatic seed point selection is proposed using gray-level co-occurrence matrix-based sum average feature in the coarse segmented image. Finally, the method utilizes CA with the identified initial seed point and the modified transition rule to segment the mass region.

Rouhi, Rahimeh[44] In this paper, author proposed two hybrid algorithms based upon region-based, contour-based and clustering segmentation techniques to recognize benign and malignant breast tumors. First provides the accuracy in segmentation and second method controls the level set. Intensity, shape and texture features are extracted from tumors, and the appropriate features are then selected by another GA algorithm.

Xie, Weiying[45] Author proposed an approach that is based on the extreme machine learning . In this feature selection is done by SVM (Support vector Machine) and ELM (Extreme learning Method). ELM method classifications are compared with state-of-art classification method .This system provides good performance on the basis of following specificity, sensitivity and accuracy parameters. The results also compared with PSO_SVM.

Xie, Weiying[46] The author proposed the supervised classification method in this paper. Classification technique using a minimum number of intensity-based features (texture features) and the comparisons of the supervised and fuzzy approaches and obtaining the maximum classification rate with minimum risk. This paper describes SVM (linear and RBF kernel) and k-NN supervised techniques and a novel fuzzy rule-based system approach for medical image classification.

Sonar, Poonam [47]This paper defines the rule mining method for the avoidance of problem in classification in mammogram images. Authors propose graph theory based objective function to optimize association rules such that graph generated by the optimized rules is simple graph with simple walk. The proposed algorithm is tested on mammogram images for classification of images into benign and malignant classes. This approach provides better result with good performance.

Khan, Salabat,[48]They investigate the performance of six different approaches for directional feature extraction for mass classification problem in digital mammograms. These techniques use a bank of Gabor filters to extract the directional textural features. Directional textural features represent structural properties of masses and normal tissues in mammograms at different orientations and frequencies. Masses and micro-calcifications are two early signs of breast cancer which is a major leading cause of death in women. For the detection of masses, segmentation of mammograms results in regions of interest (ROIs) which not only include masses but suspicious normal tissues as well (which lead to false positives during the discrimination process). The problem is to reduce the false positives by classifying ROIs as masses and normal tissues. In addition, the detected masses are required to be further classified as malignant and benign.

Dhungel,Neeraj[49] In this paper the author proposed a multi -view deep residual neural network (mResNet) for the classification of mammograms. In this approach binary segmentation maps are automatically produced. This approach works on layers. All the layers are interconnected with each other. This approach provides a good accuracy rate.

Aminikhanghahi, Samaneh,[50] In this paper, the author introduces a new classification method which is a combination of Gaussian Mixture Model and Fuzzy logic system. They classify the regions of mammograms. They perform their experiment on the data set of the University of Florida. The results show that the proposed technique will improve the diagnostic accuracy and reliability of radiologists' image interpretation in the diagnosis of breast

III. LITERATURE REVIEW FINDINGS

Author Name	Year	Technology Used	Description
Costa, Daniel D. et al	2011	Classification of breast tissue in mammograms using efficient coding	LDA with ICA bases showed high predictive performance
Berbar, Mohamed A et al.	2012	Breast mass classification using statistical and local binary pattern features	Provides normal from abnormal cases with high accuracy rate.
Junior, Geraldo Braz, et al	2013	False positive reduction using Gabor feature subset selection	presents a methodology for reducing false positives by analyzing the diversity of approaches with improved spatial decomposition
Reyad, Yasser A.,et al.	2014	Comparison of statistical, LBP, and multi-resolution analysis features for breast mass classification	study of the effects of different features to be used in a CAD system for the classification of masses.
Hussain, Muhammad et al.	2014	Mammography using multiscale spatial Weber law descriptor and support vector machines.	WLD (MSWLD) that better characterizes the texture micro structures of masses
de Oliveira, et al.	2015	digital mammograms using taxonomic indexes and SVM	describe the texture of the regions
Abdel-Nasser. et al.	2015	Mammographi images using a uniform local directional pattern	This descriptor can discriminate between different tissues in mammograms
Jen, Chun-Chu et al.	2015	Automatic detection of abnormal mammograms in mammographic images	Detection method for abnormal mammograms in mammographic datasets
Chu, Jinghui, et al.	2015	Morphological enhancement and SLIC	Multiple stage method for breast mass

		superpixel segmentation	detection.
Khan, Salabat, et al.	2017	Gabor feature extraction approaches for mass classification in mammography.	Performs directional feature extraction for mass classification

IV. CONCLUSION

The vast amount or research related to analysis of mammography, as well as widespread interest from the medical community stimulates the development of commercial CAD systems [7]. To date, there are three commercial systems of CAD that are successfully developed and get the approval from the US Food and Drug Administration (FDA), i.e. ImageChecker [18], MammoReader[19], and Second Look[20]. Although there are many outstanding performances have been achieved by CAM systems, the challenges and future directions of research are still remaining. [5] have listed some suggestions on how to improve the performance of CAM in future.

REFERENCES

[1]. Nunes, Andre Pereira, Aristofanes Correa Silva, and Anselmo Cardoso De Paiva. "Detection of masses in mammographic images using geometry, Simpson's Diversity Index and SVM." International Journal of Signal and Imaging Systems Engineering3.1 (2010): 40-51.

[2]. Leong, S. P., Shen, Z. Z., Liu, T. J., Agarwal, G., Tajima, T., Paik, N. S.,&Foulkes, W. D. (2010). Is breast cancer the same disease in Asian and Western countries?. World journal of surgery, 34(10), 2308-2324.

[3]. Gøtzsche, Peter C., and Margrethe Nielsen. "Screening for breast cancer with mammography." Cochrane Database Syst Rev 1 (2011).

[4]. Kojima, Yasuyuki, and Hiroko Tsunoda. "Mammography and ultrasound features of triple-negative breast cancer." Breast Cancer 18.3 (2011): 146-151.

[5]. Berbar, Mohamed A., Yaser A. Reyad, and Mohamed Hussain. "Breast mass classification using statistical and local binary pattern features." Information Visualisation (IV), 2012 16th International Conference on.IEEE, 2012.

[6]. Fantini, Sergio, and Angelo Sassaroli. "Near-infrared optical mammography for breast cancer detection with intrinsic contrast." Annals of biomedical engineering 40.2 (2012): 398-407.

[7]. Hofvind, Solveig, Christoph I. Lee, and Joann G. Elmore, "Stage-specific breast cancer incidence rates among participants and non-participants of a population-based mammographic screening program." Breast cancer research and treatment 135.1 (2012): 291-299.

[8]. Ramos-Pollán, R., Guevara-López, M. A., Suárez-Ortega, C., Díaz-Herrero, G., Franco-Valiente, J. M., Rubio-del-Solar, M., ...& Ramos, I. (2012). Discovering mammography-based machine learning classifiers for breast cancer diagnosis. Journal of medical systems, 36(4), 2259-2269.

[9]. Razzaghi, H., Troester, M. A., Gierach, G. L., Olshan, A. F., Yankaskas, B. C., & Millikan, R. C. (2012). Mammographic density and breast cancer risk in White and African American Women. Breast cancer research and treatment, 135(2), 571-580.

[10]. Grzegorczyk, T. M., Meaney, P. M., Kaufman, P. A., & Paulsen, K. D. (2012). Fast 3-D tomographic microwave imaging for breast cancer detection. IEEE Transactions on Medical Imaging, 31(8), 1584-1592.

[11]. Crandall, C. J., Aragaki, A. K., Cauley, J. A., McTiernan, A., Manson, J. E., Anderson, G., &Chlebowski, R. T. (2012). Breast tenderness and breast cancer risk in the estrogen plus progestin and estrogen-alone women's health initiative clinical trials. Breast cancer research and treatment, 132(1), 275-285.

[12]. Miller, Benjamin T., Andrea M. Abbott, and Todd M. Tuttle. "The influence of preoperative MRI on breast cancer treatment." Annals of surgical oncology 19.2 (2012): 536-540.

[13]. Boquete, L., Ortega, S., Miguel-Jiménez, J. M., Rodríguez-Ascariz, J. M., & Blanco, R. (2012). Automated detection of breast cancer in thermal infrared images, based on independent component analysis. Journal of medical systems, 36(1), 103-111.

[14]. Ganesan, K., Acharya, U. R., Chua, C. K., Min, L. C., Abraham, K. T., & Ng, K. H. (2013). Computer-aided breast cancer detection using mammograms: a review. IEEE Reviews in biomedical

[15]. Kamineni, A., Anderson, M. L., White, E., Taplin, S. H., Porter, P., Ballard-Barbash, R., ...&Buist, D. S. (2013). Body mass index, tumor characteristics, and prognosis following diagnosis of early-stage breast cancer in a mammographically screened population. Cancer Causes & Control, 24(2), 305-312.

[16]. Toriola, Adetunji T., and Graham A. Colditz. "Trends in breast cancer incidence and mortality in the United States: implications for prevention." Breast cancer research and treatment 138.3 (2013): 665-673.

[17]. Sugitani, T., Kubota, S., Toya, A., Xiao, X., &Kikkawa, T. (2013). A Compact 4$\times $4 Planar UWB Antenna Array for 3-D Breast Cancer Detection. IEEE Antennas and Wireless Propagation Letters, 12, 733-736.

[18]. Engstrøm, M. J., Opdahl, S., Hagen, A. I., Romundstad, P. R., Akslen, L. A., Haugen, O. A., ... &Bofin, A. M. (2013). Molecular subtypes, histopathological grade and survival in a historic cohort of breast cancer patients. Breast cancer research and treatment, 140(3), 463-473.

[19]. Gøtzsche, Peter C., and KarstenJuhlJørgensen. "Screening for breast cancer with mammography." The Cochrane Library (2013).

[20]. Drukteinis, J. S., Mooney, B. P., Flowers, C. I., &Gatenby, R. A. (2013). Beyond mammography: new frontiers in breast cancer screening. The American journal of medicine, 126(6), 472-479.

[21]. Reyad, Yasser A., Mohamed A. Berbar, and Muhammad Hussain. "Comparison of statistical, LBP, and multi-resolution analysis features for breast mass classification." Journal of medical systems 38.9 (2014): 100.

[22]. Hussain, Muhammad. "False-positive reduction in mammography using multiscale spatial Weber law descriptor and support vector machines." Neural Computing and Applications 25.1 (2014): 83-93.

[23]. De Oliveira, Fernando SoaresSérvulo, "Classification of breast regions as mass and non-mass based on digital mammograms using taxonomic indexes and SVM." Computers in biology and medicine 57 (2015): 42-53.

[24]. Abdel-Nasser, Mohamed, et al. "Analysis of tissue abnormality and breast density in mammographic images using a uniform local directional pattern." Expert Systems with Applications 42.24 (2015): 9499-9511.

[25]. Jen, Chun-Chu, and Shyr-Shen Yu. "Automatic detection of abnormal mammograms in mammographic images." Expert Systems with Applications42.6 (2015): 3048-3055.

[26]. Chu, Jinghui. "A novel computer aided breast mass detection scheme based on morphological enhancement and SLIC superpixel segmentation." Medical physics 42.7 (2015): 3859-3869.

[27]. Sharma, Vipul, and Sukhwinder Singh. "CFS–SMO based classification of breast density using multiple texture models." Medical & biological engineering & computing 52.6 (2014): 521-529.

[28]. De Sampaio, Wener Borges. "Detection of masses in mammograms with adaption to breast density using genetic algorithm, phylogenetic trees, LBP and SVM." Expert Systems with Applications 42.22 (2015): 8911-8928.

[29]. Oliver, Arnau,. "Breast density analysis using an automatic density segmentation algorithm. " Journal of digital imaging 28.5 (2015): 604-612.

[30]. Li, Yanfeng, "Texton analysis for mass classification in mammograms." Pattern Recognition Letters 52 (2015): 87-93.

[31]. Rehman, Awais Ur, NaveedChouhan, and Asifullah Khan. "Diverse and Discrimintative Features Based Breast Cancer Detection Using Digital Mammography." Frontiers of Information Technology (FIT), 2015 13th International Conference on.IEEE, 2015.

[32]. Liu, Xiaoming, and ZhigangZeng. "A new automatic mass detection method for breast cancer with false positive reduction." Neurocomputing 152 (2015): 388-402.

[33]. Petroudi, Styliani,"Evaluation of spatial dependence matrices on multiscale instantaneous amplitude for mammogram classification." 6th European Conference of the International Federation for Medical and Biological Engineering.Springer, Cham, 2015.

[34]. Beura, Shradhananda, BanshidharMajhi, and Ratnakar Dash. "Mammogram classification using two dimensional discrete wavelet transform and gray-level co-occurrence matrix for detection of breast cancer." Neurocomputing 154 (2015): 1-14.

[35]. Rouhi, Rahimeh, . "Benign and malignant breast tumors classification based on region growing and CNN segmentation." Expert Systems with Applications 42.3 (2015): 990-1002.

[36]. Li, Xi-Zhao, Simon Williams, and Murk J. Bottema. "Texture and region dependent breast cancer risk assessment from screening mammograms." Pattern recognition letters 36 (2014): 117-124.

[37]. Miranda, Gisele Helena Barboni, and JoaquimCezar Felipe. "Computer-aided diagnosis system based on fuzzy logic for breast cancer categorization." Computers in biology and medicine 64 (2015): 334-346.

[38]. Anitha, J., and J. Dinesh Peter. "Mammogram segmentation using maximal cell strength updation in cellular automata." Medical & biological engineering & computing 53.8 (2015): 737-749.

[39]. Rouhi, Rahimeh, and Mehdi Jafari. "Classification of benign and malignant breast tumors based on hybrid level set segmentation." Expert Systems with Applications 46 (2016): 45-59.

[40]. Xie, Weiying, Yunsong Li, and Yide Ma. "Breast mass classification in digital mammography based on extreme learning machine"Neuro computing 173 (2016): 930-941.

[41]. Khachane, MonaliY.,and R. J.Ramteke. "Modality based medical image classification. " Emerging Research in Computing, Information, Communication and Applications. Springer Singapore, 2016.597-606.

[42]. Sonar, Poonam, DiptiJadhav, and UdhavBhosle. "Optimized association rules using objective function for mammography image classification. "Communication and Signal Processing (ICCSP), 2016 International Conference on. IEEE,2016.

[43]. Khan, Salabat,. "A comparison of different Gabor feature extraction approaches for mass classification in mammography." Multimedia Tools and Applications 76.1 (2017): 33-57.

[44]. Dhungel, Neeraj, Gustavo Carneiro, and Andrew P. Bradley. "Fully automated classification of mammograms using deep residual neural networks." Biomedical Imaging (ISBI 2017), 2017 IEEE 14th International Symposium on. IEEE, 2017.

[45]. Aminikhanghahi,Samaneh,"A new fuzzy Gaussian mixture model (FGMM) based algorithm for mammography tumor image classification. " Multimedia Tools and Applications 76.7 (2017): 10191-10205.