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Imaging & Machine Learning Techniques Used for Early Identification of Cancer in Breast Mammogram

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***Abstract:** Breast cancer has become a major concern of women health throughout the world and has an important cause of death among women. The important radiographic signs of cancer are the masses visible in the breast. In the initial stage, the masses in the women breast are very strenuous to detect. In many cases, it has been proven that a manual attempt of treatment methods are time consuming and inefficient. Hence there is a basic demand for well-planned methods for diagnosis of the cancerous cells with minimal human participation resulting high in precision. Mammography has been proven as an efficient technique for the identification of cancer in women breast. Automated detection of masses in breast mammogram is the major goal in the identification of cancer in women breast. Machine learning techniques can be used as an effective mechanism by the physician for the early detection of cancer in the breast. By early recognition of malignancy in the breast, patients will get treatment right from the initial stage of cancer which can save their lives.*

***Keywords :** breast cancer, computer aided detection (CAD), mammogram, machine learning (ML), region of interest (ROI) .*

I. INTRODUCTION

A malignant tumor in the breast has become one of the main reason for death among female today [1], [2]. Early diagnosis can be done via mammography which can prevent the speed of death increases among female due to breast cancer [3]. The most genuine techniques mammography assists radiologists in first step diagnosis of irregularities in the breast [4]. Developments of different pre-processing techniques for detection of masses in mammography are the prime objectives in early diagnosis of masses in the female breast. Computer-aided detection (CAD) techniques are being developed for the efficient diagnosis of masses in the breast [5], [6]. Earlier work in medical science shows that CAD system increases the accuracy of detection of masses in the breast [7], [8],[9]. CAD system also improves the accuracy rate and helps the radiologist inaccurate detection and diagnosis of masses [10], [11].

The procedure of identifying breast masses through the CAD system hold four paces. The initial one is pre-processing followed by segmentation, sparse_RIO, finally feature extraction and classification [12]. Noises and pectoral muscles are also visible in mammographic images, and it is difficult to identify lumps and pectoral muscles due to having identical pixel strength. Therefore pectoral muscle wrongly classified as masses using the CAD system. So it is required to be removed pectoral muscle to improve the classification accuracy of mammogram images [13]. The abnormality in mammogram can be identified by using the ROI. The productivity of CAD systems fully depends upon the area and structure of ROI. ROI often choose either suggest by radiologists or by image partitioning capability in CAD system [14]. Different techniques are developed for identifying masses in a mammogram. Among all these techniques, geometry and texture are used for describing the region of interest.

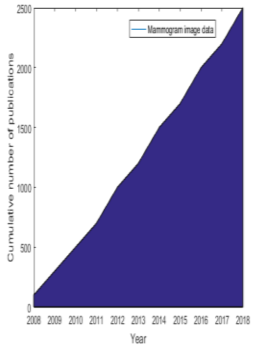

Fig. 1 Numbers of publications referring to "Mammogram image data" indexed by Google Scholar.

Fig. 1 represents the cumulative number of publications on mammogram image data domain from 2008 to 2018, which are included in the reference section. The gradual increase in publications proves the increase of interest of researchers in the domain of medical image data.

The rest of the paper is well ordered: section II includes the analysis of breast cancer detection methods, section III presents different imaging techniques used for early detection of masses in mammogram, section IV describe methodology used for diagnosing a breast mammogram,

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section V explains related work on the identification of breast masses by using different machine learning and deep learning techniques along with its critical analysis and conclusion is present in section VI.

II. ANALYSIS OF BREAST CANCER DETECTION

This section represents breast anatomy, background information on breast cancer, and clinical detection technique that are used to diagnose the disease.

A. Breast Anatomy

The basic function of the women breast is to provide milk to her child and also indicate sexual maturity. The breast is basically consist of glandular, fatty and fibrous tissues.

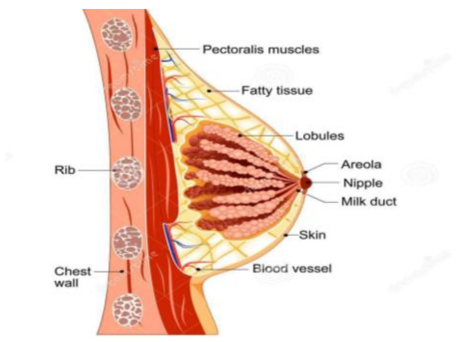

Fig. 2 Represents female breast anatomy [www. medicinenet.com/breast anatomy/article.htm]

Fig. 2 shows the basic anatomy including the structure of the female breast. An extremely visible part at the front of the breast is the nipple. At first, milk is created in the lobes and delivered into the nipple through ducts. These are untidily known as glandular tissues. Nipple and areola contain specialized muscle fibers which simulate the nipple to erect. The lymphatic system protects the body from an infection caused by microorganisms and antigens. The vasculature is responsible for blood transportation to and from the breast.

B. Breast Cancer

It is a disease in which the cells develop disorderly inside the breast. Cancer can originate in any part of the breast i.e. lobules, ducts, and connective tissue. Basically, the gland lobules produce milk, and milk carries to the nipple through ducts. In most cases of breast cancer, it begins in the ducts or lobules. Breast cancer is a common disease which affects women generally, a recent survey shows that 11491 women and 82 men have died in England and Wales in 2002 [15]. Breast cancer is developed from breast tissues. An indication of cancer may include a lump in the breast, changes in the structure of a breast, dimpling of the skin, liquid discharge from the nipple, and red patches of skin. Risk factors for developing breast cancer among female include obesity, drinking alcohol, menstruation in the early age, and family history. Affected cells can break away from their native place and move throughout the vascular or lymphatic systems. This process is named as metastasis. Generally, breast cancer is developed in the ducts or in the lobes which are called lobular cancer [16]. Benign tumors are abnormal growth but do not spread uncontrollably. Generally, benign tumors can become malignant, but malignant tumors do not become benign. Cancer is originate by the number of elements that can act singly or in composition.

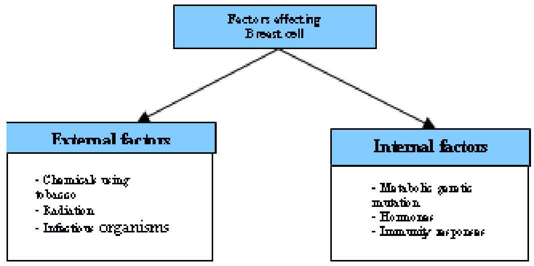

Fig. 3 Factors for the cause of cancer

Fig. 3 reflects various factors relating to the development of malignant masses in the breast. Cancer is developed in the breast not only due to internal factors such as genetic mutation, hormones, immunity responses but also due to external factors like chemicals using tobacco, exposes to radiation etc. Besides that, there are still some other factors which are also responsible for developing cancer in the breast such as the use of ethanol, hormonal misbalance, contra septic pills, early menopause etc.

Generally, breast cancer is associated with the different level of disabilities, which outline how far it has spread. The following are the levels of breast cancer:

Level '0'	• No past history • Tumour spread the ducts or lobules
Level '1'	• Affect to the lymph nodes close to the breast • Tumour is not larger than 2cm in diameter
Level '2'	• Masses size between 2cm to 5 cm • In level 2A cancer in lymph node near the breast bone
Level '3'	• In level 3A tumour is larger than 5cm and spread to lymph nodes near the breast bone • In level 3B tumour may be any size & spread to chest wall In level 3C cancer has spread to
Level '4'	• The tumour may be any size • The cancer spread other part of the body such as bones, lungs, liver

Fig. 4 Shows different levels of breast cancer
[http://www.breastcancer.org/symptoms/diagnosis/staging]

Fig. 4 clearly explain the different levels of breast cancer and out of these level, 4^{th} level is the hazard one.

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Non-invasive cancers in level'0' that present their original place whereas in level'4' the invasive cancers that spread outside the breast along with the other parts of the body. Finally, the levels of breast cancer tells whether or not cancer has an effect on other body parts.

C. Causes of Breast Cancer

Till date, the exact region of breast cancer is not known. Doctors are unable to point out why one woman develops breast cancer and another doesn't. Most of the cases the doctor identify the breast cancer caused by damage to a cell's DNA, improve some risk factors such as consuming alcohol and family history of cancer.

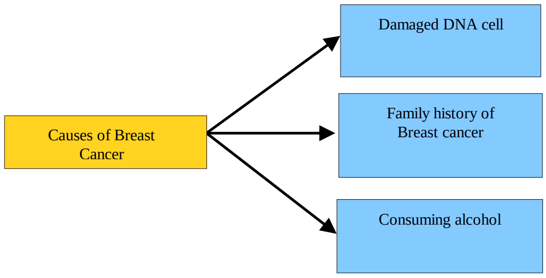

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Fig. 5 Shows different causes of breast cancer.
[https://www.health.com/breast-cancer]

D. Prevention of Breast Cancer

There are things you can do to reduce the risk of developing breast cancer. Change of lifestyle can decrease the risk of developing breast cancer [17]. These changes include:

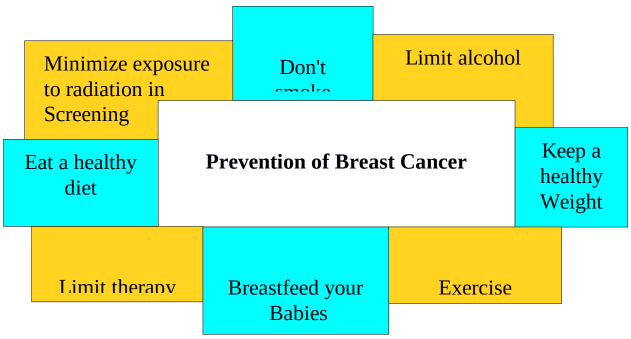
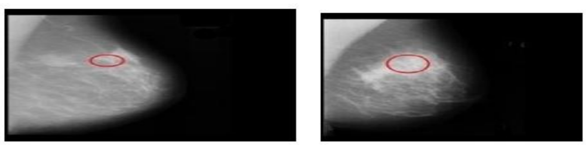


Fig. 6 Shows different key points to prevent breast cancer.
[https://www.cancer.gov/breast-prevention]

E. Clinical Detection

Abnormality in the tissue of an organism is called a lesion. Basically, there are two types of lesions. Non-cancerous called benign and cancerous called malignant lesions. Breast lesion is identified through self-breast examination, test by physicians or through mammograms[18], [19].



(a) (b)

Fig. 7 shows (a) Benign masses and (b) Malignant masses in micro calcifications [20].

Breast cancer can be detected in its earlier stage. Since long ago it has been recommended that female should attain periodic breast self-examination (BSE). Now it has been challenged. Canadian meta analyst has failed to prove that BSE minimizes breast tumor mortality. As such, BSE has not been recommended by the Canadian meta analyst at present. To detect cancer at the early stage some countries have enforce screening programme, where women are invited for x-ray imaging of the breast. Women between the age of 50 and 70 are invited for screening in every three years [21].Some have argued that the outcome of asymptotic breast screening is disputed and such screening may even be detrimental to the health of women. Olsen et al. (2001) argue that there is no genuine confirmation that screening mammography reduces mortality and argues that screening may result in distress unnecessarily aggressive treatment [22].

III. BREAST IMAGING FOR EARLY IDENTIFICATION OF MASSES

This section presents x-ray mammogram the most regular appearance of clinical imaging techniques which is used to identify cancer in its early stages and discuss the other imaging modalities in brief.

A. X-Ray Imaging

It is the first among all existing modality to acquire imaging for observing cancer in the breast. The screening mammogram is used for women who have no breast masses symptoms. This technique is not suitable for women with thick breast. Another disadvantage of x-ray mammography is the exposure of patients to the x-ray ionizing radiation, which may induce cancerous cells. In addition, the screening process is sometimes painful because the breast has to be pressed between flat surfaces to improve picture standard [23].

In the case of women below the age of 50 years with thick breast, where film mammography has been proved as a total failure to identify cancer cell but digital mammography became successful to identify cancer cell in such cases. It provides the better result for women in case of failure of identifying cancer cell in x-ray image [24]

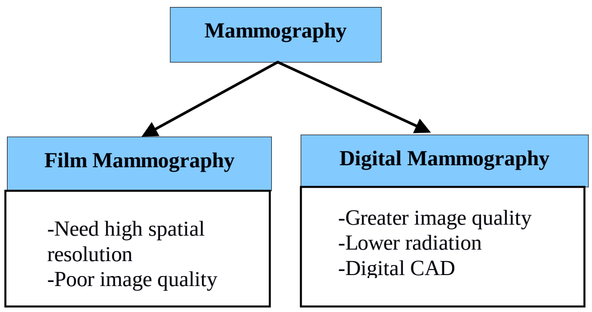


Fig. 8 Types of mammogram

The benefits of digital mammography are (i) It can be stored and manipulate more easily (ii) Easily can be adjusted by its darkness, contrast and brightness(iii) Reduced radiation dose.

The disadvantages of digital mammography are that they are more expansive and not widely available. Similarly the disadvantages of film mammography, it is less sensitive for women with dense breast. An x-ray technique is risk full in the cases of pregnant women and women with dense breast, an ultrasound techniques has been recommended for them.

B. Ultrasound Imaging

Generally, in ultra sounding technique create pictures of the single plane. It produces pictures in real time with 25 frames per second approximately. Due to adding some advances in ultrasound technology, it is able to recognize masses size 3 mm [25]. Current reviews suggest a predictive value of almost 98% for detecting invasive lobular carcinoma when both mammography and ultrasound imaging is used for screening. The result of current study shows that due to the increase of breast density, breast cancer identification rate also increases with the use of ultrasound screening [26].

C. Magnetic Resonance Imaging(MRI)

MRI is an effective tool used for surgery of breast. Due to the effect of advanced features like temporal resolution and partial resolution in MRI, small invasive cancers and ductal carcinoma in situ are identified . In MRI, a 3-5 Tesla and RF coils are used to yield 3D pictures of the breast. In comparison with other imaging approaches, it is more costly and requires an intravenous injection of gadolinium[27].

Table-I: Different imaging techniques for detection of cancer in the breast

Imagi-ng Techn ique	Operating Frequency Range	Radiatio-n Safety	Effectiveness	Patient s Comfo rts	Time Required	Cost
Mamm ogram	30 Petahertz to 30 Exahertz	Ionizing Radiation	Few mm tumors detected Not fruitful for thick breast	Unbear able	Less than 5 min	Low
Ultraso und	2 to 20 megahertz	Non-ionizing Radiation	Few mm tumors detected. Fruitful for thick breast	Comfor table	15 to 20 min	Low
MRI	1 to 100 Megahertz	Non-ionizing Radiation	Few mm tumors detected. Fruitful for thick breast	Unbear able	45 min to 1 hour	High

Table-I Combining all the three techniques provide the better result of identifying ductal carcinoma in situ and invasive cancer and reduced the rate of false detection.

The above Table-I shows a comparative study of different techniques used in the detection of cancer in women breast based on their effectiveness, radiation safety, patients comfortless, time consumption and cost. The study reflects that each technique has its advantages and disadvantages. Combination of all these techniques can provide better outcomes in identifying cancer in situ. However, mammography still plays a major role in detecting masses in the breast due to its low cost and less time consumption.

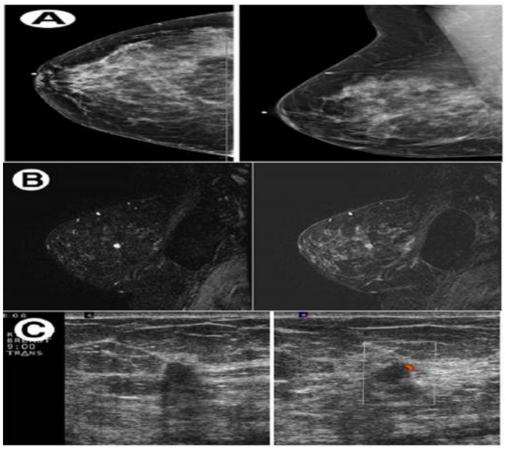


Fig. 9 (A) 59 years old women mammography screening never finding any suspicious masses with a strong family history of breast cancer (B) on the same day at a 9-o' clock posture suspicious masses was detect using MRI (C) ultrasound images of the right breast shows mass with irregular shape in 9-o' clock region [28].

IV. METHODOLOGY TO DIAGNOSING NORMAL AND ABNORMALITY IN BREAST MAMMOGRAM

Mammogram pre-processing requires prior knowledge to select appropriate methods to implement a CAD system. The methodology technically consists of following steps as shown in the following diagram[29], [30].

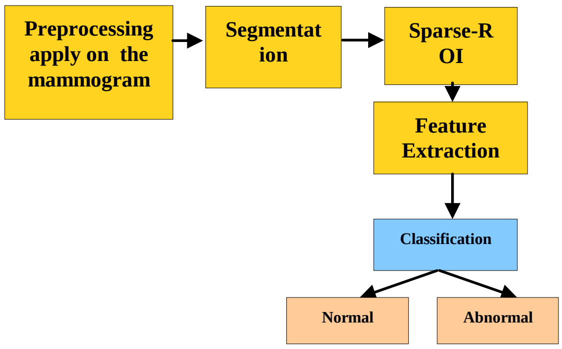


Fig. 10 Steps are showing breast abnormality detection

(i) Pre-processing:- Pre-processing is necessary in case of a mammogram to separate region of masses. In this step noise, artifacts and pectoral muscles can be removed from each mammogram.

(ii) Segmentation:- In this phase identify ROI from the mammogram and partition the given into meaningful homogeneous region.

(iii) Sparse ROI:- Sparse-ROI is to model the irregular shaped mass, it assists the faultless diagnosis by the doctors.

(iv) Feature Extraction and Classification:- This method capture optical content of a picture. The attributes extraction procedure represents a raw picture in its minimized form to assist decision-making procedure such as classification.

Following diagram shows different feature extraction techniques used in mammogram image [31].

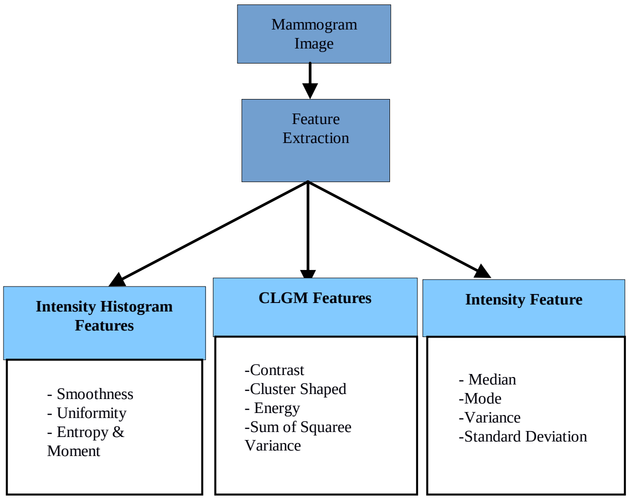


Fig. 11 Shows different feature extraction techniques used in screening mammogram

In many papers, the author have used texture features for extracting the meaningful and non- redundant features. Many classifiers used these features and provide better performance to classify benign and malignant masses in mammogram image.

V. RELATED WORK

In the literature, the different approach is used to identify and categorize the abnormality existing in the mammogram. A lot of research has been done on the shape and textual features of the screening mammogram. A second order statistics follows GLCM for masses classification and they obtained more than 90% accuracy. Maitra et al. [32] used a gray level concurrences matrix for feature extraction from MIAS database to identify abnormal masses.

According to Anitha et al. [33], two significant factors i.e shape and size are used to classify masses in the mammogram. Based on these two significant factors masses can be classified in to speculated, calcifications, architectural distortion, circumscribed, asymmetry and non-masses types. The CAD system is being designed form on image pre-processing technique proceed by different first and second order attributes removal technique for grouping of lumps. Basically, the texture attributes are removed from ROI of an x-ray image. Cropping technique is used to separate ROI which exclude the undesired portion of the mammogram.

Extensive techniques are growing for the identification of x-ray masses in its early stage. Among the existing, mainly two groups for explaining ROI are shape and texture. Dong et al. [34] focus on texture features. In texture, the masses are characterised on fundamental and second order statistics. Similarly, the anatomy of the masses can be characterized based using attributes like size, circumference, density etc.

Most of the researcher used textural attributes for detecting masses in the breast x-ray. Texture attributes are categorized into first and second order statistics. Histogram features and intensity features followers fundamental statistics based on its independent pixel value, whereas GLCM follows second-order statistics based on its neighboring pixels. Kim et al. [35] developed a new analysis technique called surrounding region dependence method (SRDM), for identifying cluster micro calcification in digitized x-ray. A back propagation neural network with its three layers is used to classify masses in the mammogram. SRDM features provide 93% in terms of the ROC curve and the authors acquired ROI of size 128×128 pixels.

Soltanian-Zadeh et al. focus on four different methods used in texture and shape feature extraction for detecting an abnormality in the mammogram image. Traditional shape quantifier, Co-occurrences based technique of Haralick, wavelet transformation, and multi-wavelet transformation are used for extracting shape and texture features in the mammogram. Out of these four multi-wave performed well, and normal shape attributes is superior to Haralick and wavelet. KNN classifier is used for detecting malignancy of given microcalcification clusters

Khuzi et al.[36] investigate the texture attributes skill to well known between the unreasonable expectation of masses and the non-masses area in screening mammogram. Authors are used GLCM for extracting different features in mammogram image. The four attributes used in this examination of masses are variance, energy, uniformity, and association. Sameti et al.[37] developed feature extraction methods to detect the masses in its early stage. The attribute estimation is all carried over the object zone. The ROI is only used for detecting background intensity of an image. Analysis of features belongs to this object region can clearly distinguish between the normal and abnormal region of mammogram masses. Experimentation for all ROI, they have chosen 256×256 image size. Yu et al.(2010) applied prototype based and statistical texture attributes to investigate the performance of clustered micro calcification. For detecting suspicious masses in mammogram first use the wavelet filter. In the second stage extract the neighborhood of suspicious masses using texture feature based Markova random field and surrounding region dependence method. For each ROI of MIAS uses the common size of 88×88 pixels. Zang et al. [38] proposed two novel techniques i.e GLCM and GLAM to describe texture properties of mammogram image. GLCM and GLAM distinguish the spatial relationship between the reference sample and the neighbor sample in an image. An experiment was supervised on different pictures stored in MIAS database and using these two techniques suspected region of mammograms are extracted automatically. A suitable segmentation algorithm used to detect the suspected region of masses. Xie et al. [39] are extracted features from masses region along with its boundary to identify benign or malignant. Here authors are used SVM and ELM to classifying benign and malignant masses. Sampaio et al. [40] were used micro-genetic, phylogenetic and LBP techniques to detect an abnormality in mammogram images and observed the false positive rate is reduced. In this paper, authors are used 32×32 window for dense and non-dense breast and extract the mammogram features using a well-known technique i.e ROI.

In most of the jobs, analyzers use a stable bulk for ROI. Costa et al. [41] are used different ROI sizes of mammogram images for feature extraction and 32×32 pixels for mass regions. Authors are used principal component analysis, Gabor wavelet and self-supporting component analysis for attribute extraction.

García-Manso et al. [42] used self-supporting component analysis for attribute extraction and applied these techniques on mammogram images stored in DDSM database. The authors have used two sizes of window 32×32 and 64×64 pixels provide better performance compared to 128×128 pixel size. Using large size window performance will be degraded and computation time will increase.

Sharma et al. [43] categorize fatty tissue and thick tissue in mammograms operates correlation based attribute collection and continuous minimal optimization (SMO) techniques. Authors have used the mini-MIAS database and apply different techniques to choose ROI. In this experiment a stable area of ROI of 200×200 pixels was used for mammogram feature extraction and concludes that computational cost reducing with reducing the size of ROI.

Abdel-Nasser et al. [44] used a local directional pattern for breast masses classification. Authors have used a mini-MIAS database for experiment, and comparing different size (32×32,64×64,75×75 and 150×150 pixels) ROI and finally classify mammogram masses using support vector machine.

Houssami et al.[45] exploring different AI methods in breast cancer detection. Authors are pinpoint the recent gaps in the clinical translation of AI systems into regular breast cancer screening practice.

Table-II : Different technique used for detection of masses in the breast

Authors/years	Techniques used	Dataset used	Result Obtained	Qualitative analysis
Subashini et al., [46]	Statistical feature extraction technique used to extract attributes from mammogram picture and finally used SVM to classify breast tissues if fatty, glandular and dense	Mini-MIAS digital database	It provides 95.44% accuracy to classify mammogram into fatty, glandular and dense class.	Naturally, women breast are dense or composed of more glandular tissues when young. It will create the problem for the radiologist to identify masses in mammogram. Authors are easily classified fatty, glandular and dense tissue using first and second order statistical feature extraction technique along with SVM.
Kus et al. ,[47]	Median filter used to remove noise and mammogram image border is being identified using magnitude and maximal gradient value of the window.	MIAS dataset	It provides 99% accuracy on 84 mammograms used from MIAS data set, which is being chosen randomly	Authors are used the innovative gradient based technique for breast boundary detection and it is an important pre-processing stage of mammography processing.
Mustra et al., [48]	Use specific variance improvement method on splitting breast regions to obtained excessive contrast gain.	MIAS dataset	It provides 99.07% accuracy using MIAS dataset	The proposed method will helpful to find out dissimilarity between breast tissue and background. The author is test proposed automatic partitioning mask with the hand-drawn partitioning mask in order to get the percentage of dissimilarity.
Oleiwi et al., [49]	First and second order statistics texture were used for feature extraction from mammogram and classify these mammogram using different classifier like Naive Bays, MLP, Random forest	MIAS database	96.8% and 98.8% accuracy provided by Random forest classifier by using first order and second order statistics texture.	Here the authors create two groups of mammogram images which are stored in MIAS database by using different classifier and finally conclude random forest is better than others.
Yi et al., [50]	CNN	DDSM database	85% accuracy for mammogram tumour classification	Create a novel approach to visualize the most meaningful features that will be helpful to predict benign or malignant class.
Carneiro et al., [51]	Deep Convolution Neural Network	DDSM database	90% accuracy	Multi-view classification is possible without the input image pre-registration, which prepare final CNN classifier to evaluate the patient's chances of growing breast cancer. Each view separately trained by high-level feature produced in CNN.
Xie et al., [52]	Feature Extraction is done by the combination of SVM and ELM. Finally, ELM used for classifying mammogram masses.	MIAS dataset	96.02% accuracy	Using selected feature vector and efficient ELM classifier, it provides better accuracy.

Jiao et al., [53]	Introduce a collective idea i.e CNNs land parasitic metric layer for masses classification in breast	96.7% accuracy	DDSM database	The classification performance of breast masses improves by using the combined model of CNN layer and metric learning layer.
Jiao et al., [54]	Deep CNN used for extraction of attributes and linear SVM used for mammogram masses classification.	96.7% accuracy	DDSM database	Top rank and medium rank attributes are extracted using CNN. Then classifier used to estimate classes of test images based on extracted features
Ribli et al. [55]	Faster R-CNN has belonged to Region Proposal Network	85% accuracy	DDSM database	Improve performance of the model on the publicly available IN breast dataset

VI. CONCLUSION

Now for mammogram classification uses several CAD and CAM techniques. The intelligent system has some pre-processing, partitioning, ROI selection, removal of attribute and categorization stages. Execution of these structures is mainly dependent on the real selection of ROI from suspected area of mammogram image. In the above study represent the different technique used for feature extraction and finally a good performance classifier used for classifying benign and malignancy mammogram image. However, automatic feature extraction in mammogram image remains a challenging problem. Traditional methods are not able to handle it in a well-organized manner. In order to overcome this shortcoming, several deep learning techniques are used. The main goal of using deep learning technique to extract the attributes automatically from mammograms and finally classify it using a well-known classifier.

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