Review: A Detail Comparison with Analysis of Computer-Aided Breast Cancer Detection Techniques

Saguna Ingle, Amarsinh Vidhate, Sangita Chaudhari

Department of Computer Engineering, Ramrao Adik Institute of Technology, DY Patil deemed to be University, Navi Mumbai, India.

Abstract: Breast cancer is the deadliest cancer all over the world for women. A breast Cancer diagnosis at an early stage is important for women, to minimize the damage, discomfort and provide a potential cure. Mammography is the most reliable screening tool for the identification of any signs of malignancy or abnormality about the cyst. There are many invasive cancer diagnosis methods available but that all are painful and costly. Computer-Aided Diagnosis (CAD) are dynamic tools that can support radiologists to detect and classify mammographic abnormalities. In this digitalized era, CAD is the need of the medical field. In CAD for breast cancer detection allows the oncologist and the physicians a second opinion, and it saves their time and reduces the false positive probability in the breast cancer diagnosis process. Advanced classification techniques and enhanced image processing and segmentation are needed to enhance the performance of CAD.
Keywords: Mammogram, Segmentation, Classification, Pre-processing, Image enhancement

1. Introduction

Breast cancer is the most often diagnosed cancer and the leading cause of mortality among women. It has been studied that breast cancer (BC) is the most serious and worrying cancer in the world. Figure 1 shows the GLOBOCAN 2020 statistics of worldwide breast cancer cases worldwide. It says that breast cancer is the second leading cancer in women after lung cancer. According to GLOBOCAN statistics, 2.3 million new cases of breast cancer were reported, i.e., 24.5%, 8.4% for lung cancer, 9.4% for colorectal cancer, 6.50% cervix uteri cancer, 4.90% thyroid cancer, 4.5% corpus cancer, and 4.0% stomach cancer. Statistics show that breast cancer is diagnosed in 1 in 4 women globally[1]. There are many practises or tests available to detect breast cancer, such as 3-D Ultrasound (US) Imaging (UI)[2], Mammography[3], thermography [4], Computed tomography Tomography (CT),Positron Emission Tomography (PET)[5] .Magnetic Resonance Imaging (MRI)[6].
According to studies, screening mammography is the simplest and most cost-effective method for detecting breast cancer early. It is effective to decrease the mortality rate due to breast cancer [7]. The mammograms are breast X-ray images. The typical mammographic views are cranio-caudal (CC) and medio Lateral oblique (MLO) .CC view is taken from the top of the horizontally compressed breast, and MLO is an angled side-view [8].

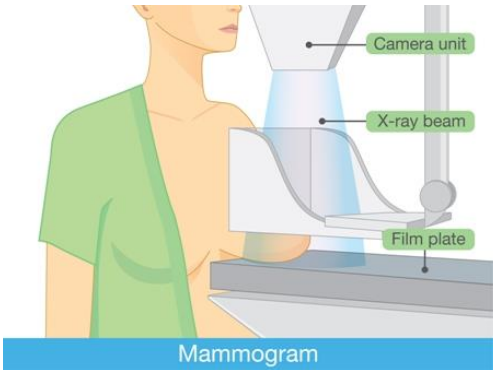


Figure 1. Mammogram test [64]

In a mammography test, each breast is placed on a flat X-ray plate as shown in Figure 2. The machine uses x-beams at lower dosages than common x-beams. The compressor will then press down on the breast to flatten the tissue. This offers a more detailed depiction of the breast. A digital mammography converts an X-ray into an electronic image of the breast that can be saved to a computer. Because the images are instantly viewable, the radiologist does not have to wait for them. Screening mammograms and Diagnostic mammograms are types of mammograms. Diagnostic

mammograms are more comprehensive than screening mammography. They often take numerous X-rays to obtain images of the breast from various angles. A radiologist may also magnify any regions of concern.
Unfortunately, mammography has a negative impact because of its low detection accuracy, with false negative results of 5% to 30% depending on the patient's age, breast density, and kind of tumour [9-11]. It is more difficult to diagnose since the contrast between the malignant lesions and the backdrop is minimal. Miss-classification of mammography in dense breasts than in non-dense breasts is higher [12]. Dense breasts increase the number of false positives and decrease test specificity, as well as the number of false negatives, resulting in malignancies being missed [13].
In this paper, Section 3 describes the extensive literature survey on various approaches used for pre-processing of mammogram images of breast cancer. Comprehensive study and performance of image enhancement techniques are summarised in Table 1 and Table 2. Section 4-detailed review of various segmentation techniques. Section 5 describes feature extraction and selection; Classification review is given in section 6 and the available datasets are listed out in section 7.

2. Computer-Aided Diagnosis

Breast cancer treatment choices and survival rates improve when it is detected early through screening and diagnostic mammography. Unfortunately, because of the human intervention and mistakes in the diagnostics, identification of type of abnormalities is prone to inaccuracy. Misdiagnosis with mammograms leads to unnecessary biopsies of benign lesions which resulting in unnecessary cost and stress for the patient. False negative is critical issue in diagnosis and early detection may minimize the treatment cost and time. To avoid such a problem double reading the mammogram which increase the recall rate is the option, but double reding of mammogram required number of radiologists which increase the diagnosis cost. The reason of false negative and false positive is, radiologists may become quickly exhausted while manually screening a large number of mammograms and losing key clues while reviewing the images. To mitigates this impact, automate the mammographic screening process is much needed. The computerized screening of mammograms i.e., CAD of breast cancer is a major topic in study.
CAD systems have been developed to improve detection of breast cancer at early stage with time and cost-effective manner by reducing the false positive and false negative. The CAD in system is very useful to less experienced radiologist who may confused in breast carcinomas appearing as microcalcifications.

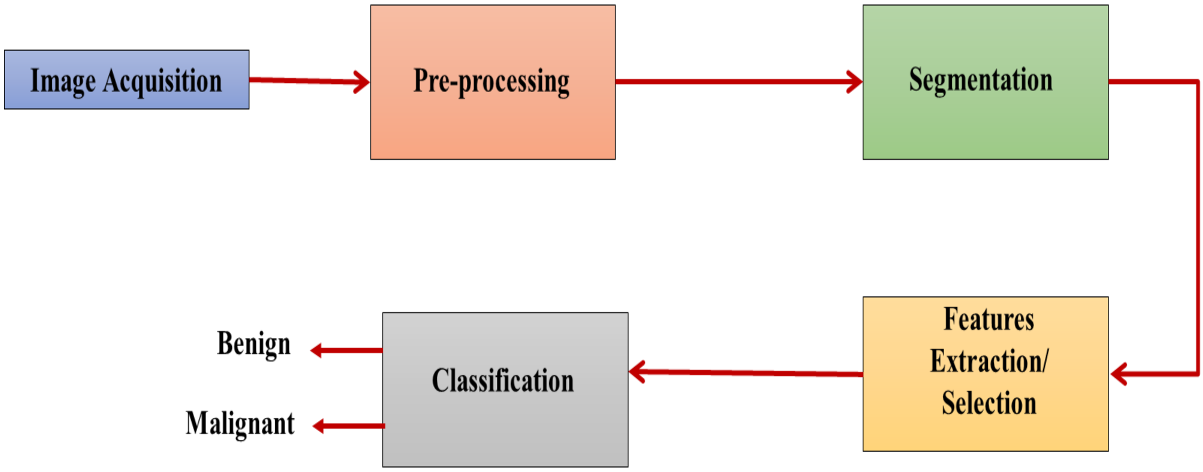


Figure 2. Stages in CAD system for breast cancer detection

Due to radiologist distraction and complex architecture of breast tissues and muscles to detect the breast tumour at early stage with CAD is challenging task. To increase the accuracy in breast cancer diagnosis and to decrease the rate of false positive and false negative, second opinion of the radiologist plays very important role. Still there are the chances of human error also it increases the burden to patients in reference to cost and time. In this digitalized era, CAD is the need of medical field. CAD for breast cancer detection provides second opinion to oncologist and the physicians, which saves their time and reduce the false positive probability in the diagnosis process. Generally, CAD system consist: Image acquisition, pre-processing, segmentation, feature extraction, features selection and classification. In this paper we are presenting the study of CAD for breast cancer diagnosis system. The various stages of CAD system with mammographic images are depicted in Figure 3.

3. Pre-processing

Image pre-processing refers to the processes performed to prepare images, before they are utilised to train and test the classification model. Main purpose of pre-processing is to increase image quality by suppressing unwanted part or enhancing some image elements that are significantly important in further processes such as segmentation and classification. When compared to other medical images, mammography images are difficult to interpret because image contain unwanted muscles, noise, artifact, poor image , weak boundaries etc. Because of these issues, pre-processing steps in machine learning model have become very important[65].Though the mammography images are the better breast cancer diagnosis modality among all the modalities, compared to other medical images, mammography images are difficult to analyse, because image contain unwanted muscles, and artifact such as labels printed on mammogram images. Another issue with mammogram images is noise. Main noise affected to mammogram images are salt and pepper, guassian, speckle and poisson noise.

3.1 Noise removal

Salt and pepper noise in the mammogram due to sudden disturbances in image signal cause of dust particle while taking the image. Speckle noise generated if the dust particles are there in the source of accusation of image. If the number of photons in the mammogram unit has changed, it produces the poisson noise. Noise in the mammogram adds a grainy look to the mammogram images, which reduces the visibility and hides important information like a small lump inside the breast. Mmammograms images do not give adequate contrast between normal breast tissues and malignant tissue, as well as between cancerous lesions and the background of tissues particularly in the dense breast [23].

To solve such problems there is a need of pre-processing the mammograms images before classification. Pre-processing of image consist of noise removal methods, image enhancement techniques, removal of background and unwanted breast parts such as pectoral muscle which lead to miss classification [70].

The mammogram's primary cordons are noisy and low-contrast images, which make ROI recognition and feature extraction difficult. It is critical to detect noise and remove it from mammogram images to improve the image quality. Mean and Median filter are the commonly used filtering techniques to remove the noise from image[24]. Image enhancement techniques in pre-processing step used to enhance the quality of image which make easy to trace the ROI from mammogram. Interpretation of anomalies or microcalcification from mammogram is very challenging because of its low contrast and low distinguishability from their surroundings [25].

Adding noise is also one of the pre-processing methods. Injecting noise into the input images may alternatively method of as data augmentation. If the images are normal, training a neural network with these normal images it might result in overfitting since the network can memorize all of the training samples. Creating a training dataset with varying amounts of noise reduces the likelihood that the neural network remembers the training data [31].

Adding noise to image will improve the performance of algorithms. Karimi et al. [32] pointed in their study that deep learning classification model, needed more training data than normal machine learning algorithm. As real-world data is not clean, deep neural networks frequently perform better during training and testing than when employed in the actual world. The solution is to add noise, adding noise improve the performance.

Bishop [33] found that adding Gaussian noise during training of the neural network model regularize the quadratic loss and improve the performance. Neelakantan et al. [34] pointed out that adding noise to the gradient during training helps training and simplification of complicated neural networks. They experimented and showed that adding noise not only helps to avoid overfitting but also can result in lower training loss. Zur et al. [35] have discovered that training neural networks with noise minimizes overfitting and increases AUC (Area Under Curve) values.

3.2 Image Enhancement techniques

Enhancement methods manipulate the contrast and intensity looks of mammography images. Many mammographic image enhancing techniques have been developed, such as frequency-based, histogram-based, filter-based and fuzzy-based. To contrast enhancement of the image Histogram equalization(HE) techniques are the most commonly used techniques.

In this paper the enhancement methods like HE, BBHE (Brightness Preserving Bi-Histogram Equalization),CLAHE (Contrast Limited Adaptive Histogram Equalization), RMSHE(Recursive Mean Separate Histogram Equalization) and MMBEBHE (Minimum Mean Brightness Error Bi-Histogram Equalization) are discussed and analysed by comparing their performance.

HE is a generally used method of enhancement it spreads out the image's intensity range. Histogram equalization does this by increasing the contrast of the image's low-contrast sections [26] [27]. It increases the contrast of noise present in the background of the image instead of useful signals this is the disadvantage of this method. BBHE (bi-histogram equalisation) divides the original grey level image into two sub-images based on the image's mean brightness. One of the sublevel images has a grey level range from lowest to mean, while the other has a grey level range from mean to highest. After the separation procedure, this approach equalizes the histograms of each sub-level image individually, resulting in a brighter, contrast-enhanced image [66]. This method preserved the brightness of the images.

CLAHE splits the image into multiple sub-images or tiles. By using bilinear interpolation, the neighbouring tiles are combined to remove the artificial boundaries. CLAHE prevents the over-amplification of noise that adaptive histogram can give rise to [28].

RMSHE is the extension of BBHE . This approach separates the mean before conducting histogram equalization, resulting in contrast enhancement while preserving brightness[29]. RMSHE divides an image into two sub-images depending on the mean of the original image. In this approach , instead of dividing the input image only once, it is decomposed recursively up to a recursion level, which increases the level of brightness. When only one mean separation is applied before equalisation, then the enhanced image from RMSHE is like the enhanced image from BBHE. Greater brightness preservation and improved contrast are the results of greater mean separation [30].
The average intensity value is used by QBHE as their separation point. It employs a quantized image's cumulative density function and conducts separate histogram equalizations across two sub images created by decomposing the input image depending on its mean. QBHE rose to popularity in order to improve on the artefacts of histogram equalisation. [67].
In DSIHE(Dualistic sub image histogram equalization), the histogram is divided into two sub-histograms with an equal number of bins , and the split is based on median value rather than mean brightness. Chen et al. [66] stated that DSIHE is better than BBHE in terms of image brightness and average information content (entropy).
MMBEBHE calculates the Mean Brightness Error (MBE) of the original image and the threshold level that produces the lowest MBE. The image must then be divided into two sub-images based on the threshold value, and equalisation has to be performed.

3.1. Analysis of image enhancement methods

To evaluate the performance of image enhancement methods like HE, BBHE, CLAHE, QAHE, DSIHE, RMSHE and MMBEBHE. We measured the performance with the parameters like Peak Signal to Noise Ratio (PSNR) and Absolute Mean Brightness Error (AMBE), Lesser the AMBE and larger PSNR shows better image enhancement. PSNR is defined as a ratio of the maximum possible power of an image to the power of corrupting noise, which affects the quality of its representation.

$$PSNR = 10\log_{10}\left(\frac{(L-1)^2}{MSE}\right) = 20\log_{10}\left(\frac{L-1}{MSE}\right) \quad (1)$$

$$Where\ MSE = \frac{1}{mn}\sum_{1i=0}^{m-1}\sum_{j=0}^{n-1}(O(i,j) - D(i-j))^2$$

where L- number of maximum possible intensity levels, O- matrix data of original image, D- matrix data of processed image, m- numbers of rows of pixels, i- index of that row of the image, n- number of columns of pixels and , j- index of that column of the image.

AMBE is defined as the absolute difference between the mean of input image and the treated (Processed image with different enhancement methods)image that is output image.

$$\text{AMBE} = \text{E(X)} - \text{E(Y)} \quad (2)$$

Where E(X) is mean of input image and E(Y) is mean of (output image) treated image.

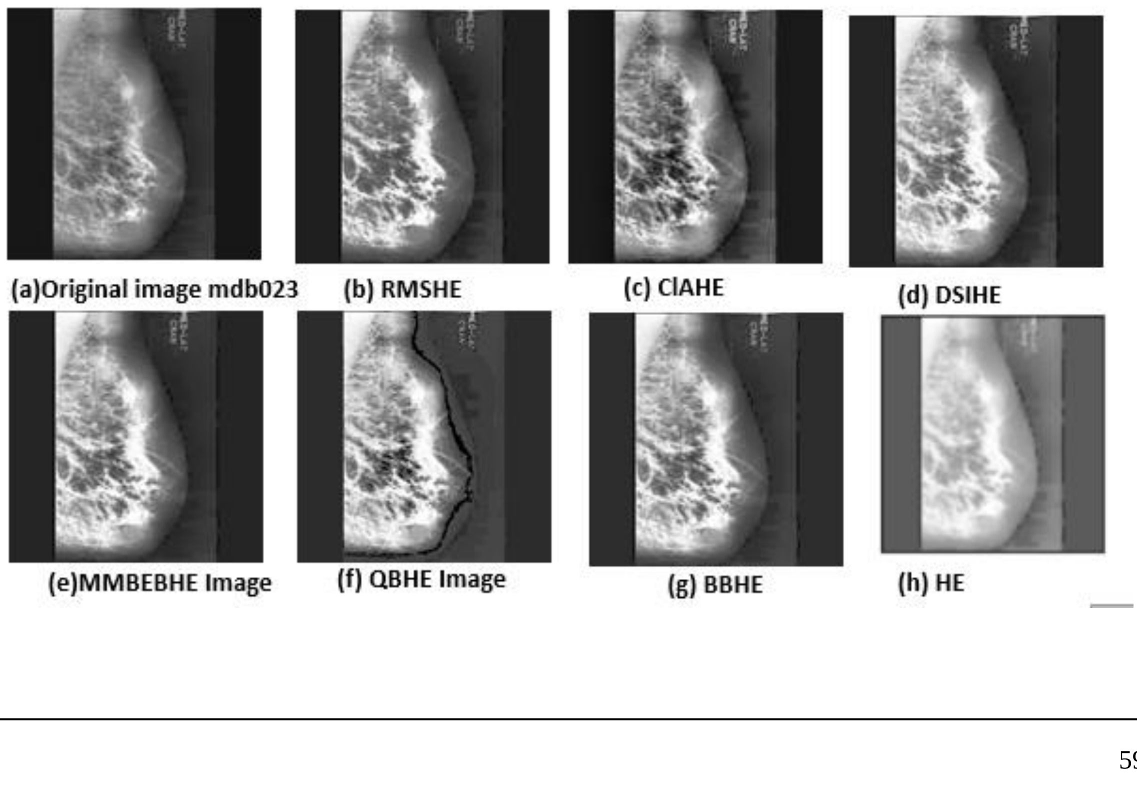


Figure 3. (a) Original mammogram image mdb023 from MIAS dataset (b) Enhanced image with RMSHE method (c)Enhanced image with CLAHE method(d) Enhanced image with DSIHE method (e) Enhanced image with MMBEBHE method (f) Enhanced image with QBHE method (g) Enhanced image with BBHE method (h) Histogram Equalization (HE)

As the HE method is global, it stretches the grey levels over the full grey level range. It results in excessive contrast enhancement, which causes an unnatural look to the processed image. BBHE addresses only over-enhancement of images, which may lose the important information. The DSIHE partitions the input image using its median only once. So, the median threshold based single partitioning mechanism does not produce the expected outcome. MMBEBHE improves the image's detailed information, as shown in Figure 3(e), but the boundary of the image is merged with the background.
QBHE enhance the mammogram image but disturb the boundary of the breast. ClAHE and RMSHE perform good with mammogram images. Brightness of original image is preserved in of MMBEBHE method shows better than BBHE and DSIHE. Table1 and Table 2 shows that the RMSHE and CLAHE perform better with mammogram images on the basis of PSNR and AMBE.

Table 1. Comparison of the AMBE performance measure between HE, CLAHE, GHE, BBHE, QBHE, DSIHE MMBEBHE, RMSHE methods

Images from MIAS Dataset	HE	**CLAHE**	BBHE	QBHE	DSIHE	MMBEBHE	**RMSHE**
mdb028	93.014	**11.154**	16.483	12.736	14.247	14.616	**3.17**
mdb023	80.243	**5.843**	4.781	3.075	0.163	1.579	**8.775**
mdb001	80.235	**6.714**	4.774	3.072	0.15	1.61	**8.79**
mdb023	67.921	**5.876**	21.984	21.118	19.358	16.948	**8.091**
mdb002	90.616	**11.709**	16.701	12.367	14.808	15.136	**2.841**
Average	82.4058	**8.2592**	12.9446	10.4736	9.7452	9.9778	**6.3334**

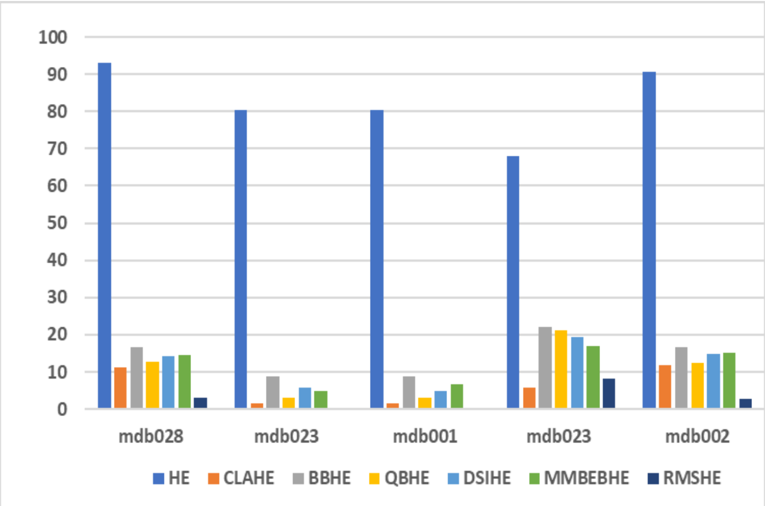


Figure 4. Comparison of the AMBS performance measure between HE, CLAHE, BBHE, QBHE, DSIHE MMBEBHE, RMSHE methods

Table 2: Comparison of the PSNR performance measure between HE, CLAHE, BBHE, QBHE, DSIHE MMBEBHE, RMSHE methods

Images from MIAS Dataset	HE	**CLAHE**	BBHE	QBHE	DSIHE	MMBEBHE	**RMSHE**
mdb028	8.666	**23.283**	14.583	13.658	14.807	14.71	**21.067**
mdb023	9.418	**26.455**	16.393	16.132	17.818	17.504	**18.071**
mdb001	9.419	**26.224**	16.388	16.134	17.818	17.493	**18.064**
mdb023	11.39	**23.09**	14.562	13.199	14.804	15.397	**18.7**
mdb002	8.89	**22.72**	14.57	13.714	14.697	14.602	**21.299**
Average	9.5566	**24.3544**	15.2992	14.5674	15.9888	15.9412	**19.4402**

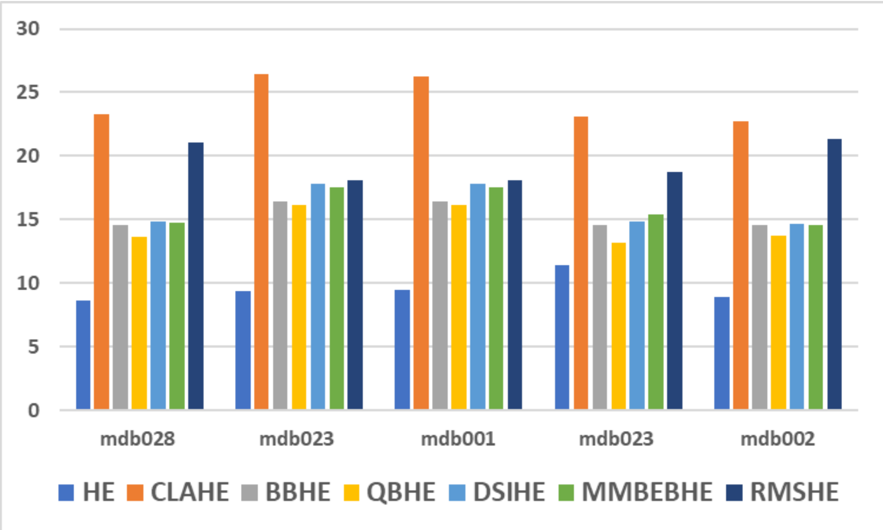


Figure 6: Comparison of the PSNR performance measure between HE, CLAHE, BBHE, QBHE, DSIHE MMBEBHE, RMSHE methods

4. Segmentation

Segmentation of the images is the procedure in which an input image is separated or divided into various subgroups of images. Separating the image into various subgroups on the basis of the similarity in the various aspects decreases the image complexity, which makes analysis simpler. In image processing, separating out the ROI and background of an image is a very critical task. Many segmentation techniques are available to separate out the ROI from the image. Widely used segmentation techniques are boundary-based or edge-based segmentation, region-based segmentation, thresholding-based segmentation, and segmentation using deep learning.

4.1. Thresholding

Thresholding is a common image segmentation technique that divides an image into two parts: the background and the foreground. In thresholding, it compares the intensities of the image pixels [37]. If a threshold value is selected on the basis of the whole image, then it's called global thresholding; and if the image is divided into subregions and then a threshold is selected according to each subdivided region, then it’s called local thresholding [38]. In bi-level thresholding, an image is separated into two parts. For images with varying surface properties, multilevel thresholding is necessary [68].
Anitha et al. [53] proposed Dual Stage Adaptive Thresholding (DuSAT) which senses the abnormality in the digital mammogram images. A doubtful mass region is recognised by the local window and global histogram thresholding method. Firstly, the global adaptive thresholding finds the doubtful section, and after that, a local thresholding based on adaptive window is applied to the enhanced uneven segmented image to gain fine segmentation [69].
The maximum entropy method, the minimum error method, and Otsu’s method are the classic thresholding techniques [38]. The Otsu’s thresholding is found to be a powerful technique towards salt and pepper noise. To get

the best result, de-noising, or noise removal, is essential to smooth the image. Domnguez et al. [40] used thresholding to segment a mammogram image . Segmentation is done on multiple levels, and from each segmented region, a set of features are calculated. In this study, researchers got 80% sensitivity and 32 % false positive segmentation. Kumar et al. [39] proposed work in which researchers used breast masses detected and segmented by using optimized region growing method.

Optimal seed point selection and optimal threshold generation have been done with the Grey Wolf Optimization (GWO) method. In this paper, global and local features are extracted. Global features include shape and texture features. Global texture features are extracted using the Grey Level Co-occurrence Matrix (GLCM) and Grey Level Run Length Matrix (GLRLM). Scale invariant feature transform (SIFT) and local binary pattern are used to extract local texture features (LBP). A combination of global and local features, supplied to the SVM classifier, which classifies the lesion into two classes, i.e., benign or malignant. The accuracy rate of a researcher was 96%.

Aghdam et al. [41] proposed texture information based on a probabilistic adaptive thresholding technique to obtain the most possible threshold values for specific parts of the mammogram image. In this thresholding method, the threshold values were neither calculated using a histogram nor by the shape of the region. This is because of non-uniform intensities in the background region of a mammogram for which global threshold-based methods may fail. In [42], a three-class threshold method along with an edge detection algorithm was implemented for segmentation. Hybrid image segmentation along with Otsu's thresholding was used in [43] for accurate detection of a breast tumour and its size.

Thresholding is simple to implement, even in real-time applications. It is fast and computationally inexpensive. Moreover, no prior information about the image is required. Nonetheless, its performance is poor for noisy images and also for images having no peaks, broad, or flat valleys. The main disadvantage of thresholding is that it ignores an image's spatial data and thus fails to inform about the contiguousness of the segmented areas. Furthermore, only correct threshold selection can avoid under or over segmentation.

4.2. Region based segmentation

Region based segmentation identifies different sections of an image with comparable properties such as grey level, colour, and texture. This is referred to as the Region Growing or Splitting mechanism. ROI is chosen using a specified criterion based on the previously acquired result by the intensity or edge features of the image. Mean Based Region Growing Segmentation (MRGS) was implemented by Jaffery, et al. [58] The seed pixel and optimal threshold value are automatically found by MRGS in this paper, making the segmentation process extremely fast and accurate.

Rouhi et al. [60] they used the two approaches for segmentation in first approach they used automated region growing in which threshold is gained by a trained artificial neural network (ANN) and second approach used deep learning segmentation with CNN. Shanmugavadivu et al. [36] proposed work researcher used breast masses detected and segmented by using optimized region growing method. Optimal seed point selection and optimal threshold generation has been done with Grey Wolf Optimization (GWO) method. In this paper global and local features extracted. Global feature includes shape feature and texture features. Grey Level Run Length Matrix (GLRLM) and GLCM used for extracting global texture features. Local texture features extracted using and Scale invariant feature transform (SIFT) and Local Binary Pattern (LBP).

Combination of global and local features, supplied to SVM classifier which classify the lesion into two classes i.e. benign or malignant. In proposed work researcher got 96% highest accuracy. The edge of a ROI is defined by detecting discontinuities or abrupt shifts in a grey level in image. Watershed transformation [20] assumes the image to be a surface with valleys and mountains, with a pixel's grey level intensity denoting its height on the surface. Flat zones are defined as areas with consistent intensities, and their boundaries are known as 'watersheds. The watersheds are denoted by the sharp gradients in the grayscale image's topographical form, and the areas they contain are known as catchment basins.

The watershed algorithm considers a 'flooding' scenario in which water-drops fall on the watersheds and drip down to the watersheds' lower sides. This dripping of water process highlights the regions separated by the edges and brings the objects into focus. Water drops fall on watersheds and flow down to the lower sides of the watersheds, which is referred to as a 'flooding' approach. This flooding highlights the zones separated by edges as well as the items.

4.3. Clustering based segmentation

In clustering-based segmentation, Pixels are grouped into clusters, with pixels in the same cluster being more similar to those in different clusters. K-means clustering and fuzzy C-means clustering are the two types of clustering used in image segmentation. [59]. In Fuzzy C means (FCM) clustering a single data point can be a part of more than one cluster [34]. Kamil et.al.[72] used FCM and K-mean clustering algorithms for segmentation. They have taken the mammogram images from MAIS dataset. In this paper researchers analysed the performance of KNN and FCM. They got the accuracy of 94.12%, with FCM while 91.18% with K- mean.

4.4 Deep learning-based segmentation

Deep learning can easily train a model with works effectively on available data. It is a part of artificial intelligence and widely used for many applications. An artificial neural network or a multi-layer perceptron is a common deep learning approach (MLP). Artificial neural networks (ANNs) are mathematical models designed to mimic the activities of the human neurophysiological organisation. Dong et al. [44] proposed deep learning based for breast mass segmentation, researcher combines densely connected U-Net with attention gates (AGs). It contains an encoder and a decoder. The encoder is a densely connected convolutional network and the decoder is the decoder of U-Net integrated with AGs. Dong et al. compared their proposed model performance with DenseNet, state-of-the-art, attention U-Net and U-Net and founded that the proposed model performs better than other models.

5. Feature extraction and selection

In computerised aided diagnosis system features extraction and selection plays very important role. Features are key component with that we can differentiate the tumour in benign and malignant. Therefore, it is very important to select the algorithms that can be able to extract and select the important features precisely.

Uyun et al. [45] created a model that has six stages: data acquisition, pre-processing before the actual segmentation, feature extraction and selection and classification. Prepossessing done with normalisation of mammogram image, background removal with rolling ball radius of 50 pixels; removing the noise by median filtering; image contrast using CLAHE. Two type of feature descriptor used in this paper, shape domain (14 descriptors) and texture domain (24 descriptors) called GLCM. Decision tree and rule induction used for selection of features. Researcher got the best result with features like slice, integrated density, Area fraction, grey capital value, centre of mass which generated by the decision tree algorithm.

Mohanty et al. [46] proposed the framework which include four computational parts, ROI generation, texture feature extraction, optimal features selection and classification. In this paper researcher used contourlet transformation for texture features extraction and wrapper-based forest optimization algorithm for feature selection. The k-NN, SVM, C4.5, Naive-Bayes classifiers are used to classify mammograms as normal or abnormal, and then as benign or malignant. In the instance of normal-abnormal classification, all classifiers except Naive-Bayes obtained a classification accuracy of 100 percent. Furthermore, for benign versus malignant classification, the C4.5 classifier achieves a maximum accuracy of 98.74%.

Vijayarajeswari et al. [47] used hough transform for features extraction which is a two-dimensional transform. For classification SVM and LDA classifiers wear used and the models trained with 95 mammogram images. The output of houng transform algorithm given better result with canny edge detector. Canny edge image enhancement algorithm applied before use of houng transform for features extraction. Because shape features are difficult to interpret, intensity features were chosen over shape features. The intensity features entropy, mean, standard deviation, and variance, were used. Classification done with SVM and LDA classifiers and given the accuracy of 94% with SVM and 86% with LDA respectively.

Nagarajan et al. [48] has proposed texture feature extraction methods using empirical mode decomposition (EMD). The first feature extraction technique is relay on Bi-dimensional empirical mode decomposition (BEMD). With the help of BEMD on Region of Interest (ROI) of mammogram image, the ROI is decomposed into Bi-dimensional Intrinsic Mode Functions (BIMFs). BIMFs is set of different frequency components. Gray Level Co-occurrence Matrix (GLCM) and Gray Level Run Length Matrix (GLRM) features were extracted from these BIMFs. These BIMFs send as a input or features to classifier. Drawback of this method was produced BIMFs were less orthogonal to each other due to mode mixing problem. This problem was eliminated by a second method and known as Modified Bidimensional Empirical Mode Decomposition (MBEMD). The BIMFs were extracted by MBEMD on mammogram ROI in a similar way as BEMD method. BEMD or MBEMD does not require any basis function and is completely data-driven. Accuracy in classifying between benign and malignant masses is higher in the proposed method than other existing methods.

It has been analysed from existing systems that thresholding is easy to implement but it is very much sensitive to noise, in thresholding the segmentation depends upon grayscale and unevenness of grey level may taper the result of segmentation. Otsu thresholding better perform than traditional thresholding method as thresholding value selected automatically not manually. In region-based segmentation and watershed segmentation area with low contrast will poorly detected. In traditional clustering segmentation good result will depends upon the membership function and it's difficult to calculate the membership function. FCM perform better segmentation than traditional clustering methods. Modified and hybrid segmentation techniques also perform better than traditional one.

6. Classification

Classification is the process of identifying the pattern to which class it belongs. In Image classification refers that, it is a process of categorizing a digital image according to its visual content. Classification is the last stage of image analysis to distinguish to the normal and abnormal tumour. This is possible with the help of pattern recognition. Features of ROI extracted and selected features can be classified either by supervised or by unsupervised method. In the supervised method. In supervised learning the system must first be trained then data can test by trained system. In supervised learning data is labelled data.

In unsupervised learning unlabelled data. Separate out in classes on the basis of its similarity. it is required to train the system first and then the rest of the data can be tested by the trained system. However, an unsupervised method handled the unlabelled data and it is dependent on machine learning to describe the hidden structure of data. Common classification methods used for classification illustrate in Figure 7. Raghavendra et al. [49] classified the breast mass into three class such as benign, malignant and normal. In this approach researcher used digitized mammogram images for analysis. They used Gabor wavelet for feature extraction and Locality Sensitive Discriminant Analysis (LSDA) for features reduction. F-values are used to ranked the reduced features.

Patil et al [50] proposed breast cancer diagnosis system used median filter to remove the noise from mammogram image. For segmentation purpose researcher used optimized region growing segmentation method, to segment the tumour from image. In this work optimized region growing algorithm based on a hybrid meta-heuristic called firefly updated chicken based CSO (FC-CSO) used for segmentation purpose. Grey level co-occurrence matrix (GLCM), and grey level run-length matrix (GRLM) features extracted to feed the classifier. In this approach classification process divided in two parts. First one is convolutional neural network (CNN) and second one is recurrent neural network (RNN). GLRM, GLCM features input given to RNN, and the segmented binary image gives to CNN as a input. The result of this proposed work expresses that, AND operation of two classifier increase the accuracy. Proposed work gave an accuracy of 90.59%.

Melekoodappattu et al. [51] researcher proposed system for breast cancer detection. In proposed work researcher classify the images into three classes benign, normal, and malignant by Fruitfly Optimisation Algorithm (ELM-FOA) classification algorithm. Features extraction done with SURF, GLCM and Gabor filter. The developed model able to detect the tumours and calcifications with 99.04% accuracy. Rezaee et al. [52]in this paper first step is pre-processing, in which redundant data and noise are removed from mammogram. K-means clustering method used for separation of the masses. After segmentation feature extraction done, effective features such as Pseudo–Zernike moments, texture features and wavelet features extracted in this stage. Features reduction done with simulated annealing (SA) algorithm and Shuffled frog-leaping algorithm used for classification. Proposed model identified not only type of tumour but also stage of disease.

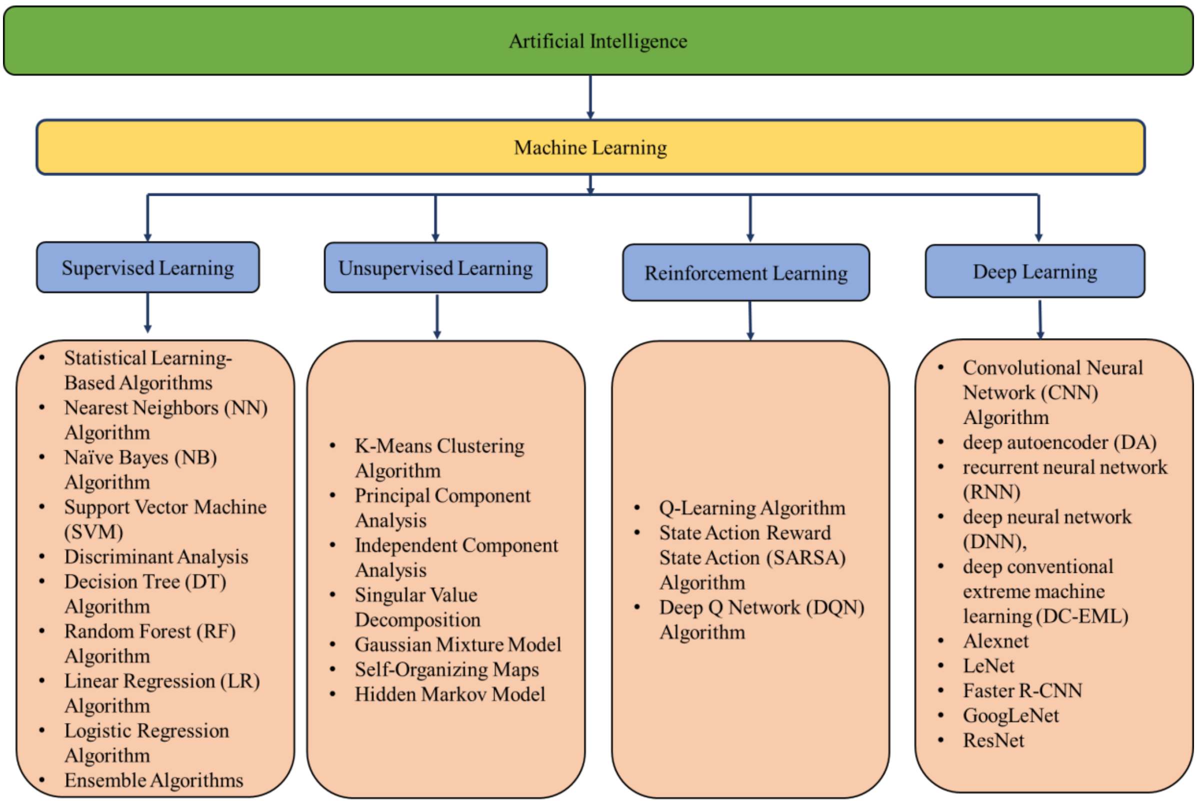


Figure 7. Classification Algorithms [74]

Agnes et al. [53] discussed, Multiscale All Convolutional Neural Network (MA-CNN) system for breast cancer diagnosis, MA-CNN based on convolutional neural network. In this work they used the images from MIAS dataset and classifier classify images into three categories such as normal, malignant and benign classes. This approach improves the accuracy of the classification without affecting the computation speed. Results showed that MA-CNN is a powerfully classify the mammography images and gives sensitivity of 96% and 0.99 AUC.

Dhaware et al. [54] compared the classification Artificial Neural Network (ANN), Decision Tree (DT), Support Vector Machine (SVM). SVM constructs a set of hyperplanes in a high dimensional space, which is used for regression or classification. The advantages of SVM include avoiding fitting and efficient methods. The disadvantage of SVM includes high algorithm complexity and its running speed is slow. The merits of ANN include robust to noisy training dataset and high very efficiency for large dataset. The disadvantage of ANN is high computational cost and lazy learner. The advantage of decision tree include easy interpreting and it requires little efforts from users. The limitation of DT includes high classification error rate.

Chougrad et al. [55] merged three datasets i.e., DDSM, BCDR, INbreast and build a novel and huge dataset to train CNN models which boost the training or learning process of CNN. Global contrast normalization used for normalization. With CNN classifier researcher got 98.94 accuracy on merged dataset. Kaur et al. [56] proposed approach, used Mini-MIAS dataset. In this approach feature extraction done with K-mean clustering used for Speed-Up Robust Features (SURF) selection. For classification deep neural network and Multiclass Support Vector Machine (MSVM) are used. Researcher compare the accuracy of proposed technique using K-mean clustering with MSVM with decision tree and it found that proposed method is better than decision tree method. Accuracy (ACC), sensitivity and specificity in case of three classes, i.e., normal, benign and malignant, using the proposed method are 95%, 94% and 98%, respectively. In this paper, a detailed study done on existing CAD systems for mammogram screening and a brief summary is tabulated in Table 3.

Table 3. Review of classification algorithm (Acc-accuracy, Sp- Specificity, Se-Sensitivity)

Author	**Pre-processing**	**Features**	**Segmentation**	**Feature extraction**	**Feature selection/reduction**	**Classification**	**Dataset**	**Performance**
[57] Wang *et al.* (2017)	Median filter (MF) for noise reduction, homomorphic filtering (HF) was used to remove multiplicative noises, logarithmic enhancement, region-growing method-removes the unwanted background contents, pectoral muscle removal by thresholding		Region growing Followed by thresholding	Fraction Fourier transform (FRFT)	The principal component analysis (PCA)	(Jaya to train the weights and biases of feedforward neural network) Jaya-FNN	MIAS	Acc-92:27± 3:49 Se - 92:26 ± 3:44 Sp - 92:28 ±3:58
[50] Patil *et al.* (2020)	Median filter for the noise removal	Grey level co-occurrence matrix (GLCM), and gray level run-length matrix (GRLM)	Firefly updated Chicken swarm optimization FC-CSO				AND operation of two classifier (RNN+CNN)	Acc- 0.90598 Se -0.92424 Sp -0.89881
[53] Agnes *et al.* (2019)	Images smoothing -average filter Image binarization - global thresholding				Analysis of Variance (ANOVA)	mini-MIAS dataset	Multiscale All Convolutional Neural Network (MA-CNN)	Acc- 96.47%
[60] Rouhi *et al.* (2015)	The local area histogram equalization, Manual cropping and the median filtering is applied to suppress noise	Intensity, textural, and shape features	CNN whose parameters are determined by using a genetic algorithm	Two methods proposed 1.ANN and region growing 2.CNN and region growing	Genetic algorithm	MIAS and DDSM	MLP	Second method perform better than first Acc- 96.47% Se-96.87% Sp -95.94%
[61] Gardezi *et al.* (2015)	Manual cropping		Manual cropping	Texture features from completed local binary pattern (CLBP) and curvlet	Fusion of CLBP and curvlet features		Nearest neighbor classifier	Acc- 96.68% Se-98.9%
[62]. J. Dheeba *et al.*, 2014			Global thresholding	Laws Texture Energy Measures			Particle Swarm Optimized Wavelet Neural	96.85%
[63]. Ragab *et al.* (2019)	(CLAHE)		Threshold and the region-based method.	deep convolutional neural network (DCNN) and pre-trained architecture AlexNet		DDSM and CBIS-DDSM	SVM	Acc- 87.2% Se- 0.862 Sp-87.7 %

7. Datasets for mammogram images

Most frequently used dataset for breast cancer detection listed out in this section. Digital Database for Screening Mammography (DDSM) is a database used in breast cancer diagnosis [14]. South Florida University compiled this dataset. DDSM hold mammogram data with 3000 × 4800 pixels, resolution of 42 microns, and 16 bits. This dataset involves of 2,620 mammography images and separated into 43 volumes. For each case there are four images of MLO views and CC views of left and right breast. Benign and malignant masses in all mammograms are recognized by skilled radiologist.

A skilled mammographer selected and vetted a subset of the DDSM [15]data for inclusion in the CBIS-DDSM collection. The pictures were decompressed and saved in DICOM format. Updated ROI segmentation and bounding boxes, as well as pathologic diagnosis, are given for training data [16].

The Mammographic Image Analysis Society (MIAS), a UK-based scientific organization, has developed a collection of digital mammograms [17]. Mammographic pictures are available at the University of Essex's Pilot European Image Processing Archive (PEIPA). The dataset contains 322 mammography pictures in total and is provided on 2.3GB 8mm tape. The database was shrunk to a 200-micron pixel boundary and padded/clipped so that all pictures are1024 × 1024. INbreast Dataset obtained from Porto's S. Joao Hospital Centre [19]. It includes 410 images of digital mammogram. A radiologist assigned a standardized Breast Imaging-Reporting and Data System (BI-RADS) category to all lesions, including masses, after evaluating a mammogram. The INbreast dataset is not publicly available on the web, however it may be accessed through a request [18].

The Breast Cancer Digital Repository (BCDR) [21] is a collection of cases of Breast Cancer patients which manually labelled by expert radiologists. This Data contain clinical information such as detected anomalies, BIRAD classification, breast density etc. BCDR provide mass outlines, and Image based features computed from mammogram MLO and CC view. Currently, the BCDR comprises 1734 patient cases. Which include mammography as well as ultrasound images, clinical history, lesion segmentation, and chosen pre-computed image-based descriptors.

The BCDR is contain two repositories first repository is a Film Mammography-based Repository i.e., BCDR-FM and second is Full Field Digital Mammography-based Repository (BCDR-DM). Both repositories were supplied by the Faculty of Medicine – Centro Hospitaller Sao Joao, at University of Porto (FMUP-HSJ). BCDR include normal and abnormal breast mammogram data. This data included mammography lesions outlines, anomalies observed by radiologists, pre-computed image-based descriptors as well as related clinical data [22]. Table 4 explain characteristics of the mentioned commonly used datasets for breast mammograms.

Table 4. Datasets for breast mammograms

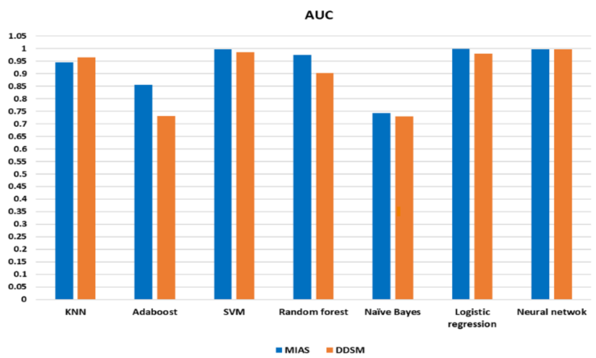
Sr no	Dataset	Modality	View	Cases	Classes available	Image format	Number of images
1	DDSM	Mammography	CC/MLO	2620	N, B & M	JPEG	10,480
2	CBIS-DDSM	Mammography	CC/MLO	6775	N, B & M	DICOM	10,239
3	MIAS	Mammography	CC/MLO		N, B & M	PGM	322
4	INbreast	Mammography	CC/MLO	115	N, B & M	DICOM	410
5	BCDR	Mammography	CC/MLO	1734	N, B & M	TIFF	3703FM (Film mammography) - 3612 DM (Digital mammography)

7.1. Analysis of image classification algorithm

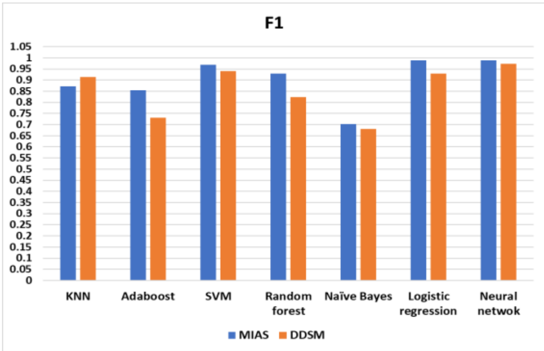
To analyse the performance of different classification algorithm available for breast cancer detection for mammogram images. We trained different machine learning and deep learning algorithms with 407 mammogram images from MIAS dataset and 1000 images from DDSM dataset. Out of 407 we taken ,206 malignant images and 201 benign images from MIAS and 500 benign and 500 malignant mammogram images from DDSM dataset. We have taken near about the same number of images to avoid dataset imbalance problem, that lead classifier divert the result to class which contain more images. Dataset imbalance affect the accuracy of classifier. In this analysis we analysed the performance of KNN, SVM, Random Forest, Naïve bayes, Neural network, Adaboost and logistic regression on the basis of parameter like AUC, F1, precision and recall. Table 5 and Figure 8 shows that SVM, logistic regression and neural network perform better than other classifiers.

Table 5: Classifier's performance evaluation on the basis of AUC, F1, Precision and Recall

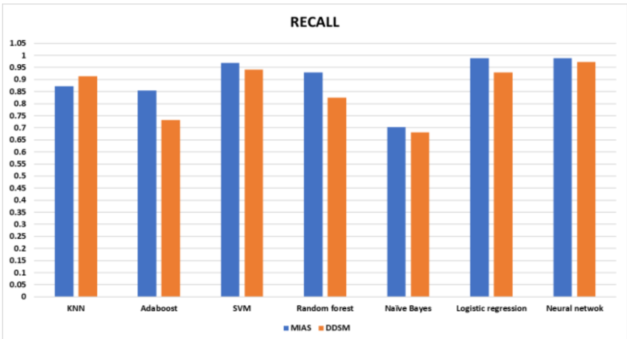
	MIAS Dataset				DDSM dataset			
Model	**AUC**	**F1**	**Precision**	**Recall**	**AUC**	**F1**	**Precision**	**Recall**
KNN	0.945	0.872	0.873	0.872	0.964636	0.912946	0.914035	0.913
Adaboost	0.855	0.855	0.856	0.855	0.732	0.731983	0.732059	0.732
SVM	0.996	0.968	0.968	0.968	0.985452	0.939999	0.940028	0.94
Random forest	0.974	0.929	0.929	0.929	0.9027	0.823943	0.82442	0.824
Naïve Bayes	0.742	0.702	0.705	0.703	0.729694	0.680997	0.681007	0.681
Logistic regression	0.999	0.988	0.988	0.988	0.98054	0.929	0.929002	0.929
Neural netwok	0.997	0.988	0.988	0.988	0.996848	0.973	0.973017	0.973



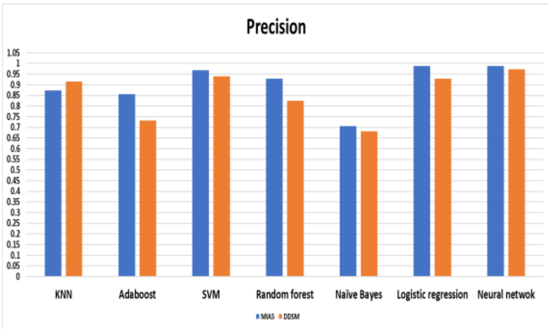
(a)



(b)



(c)



(d)

Figure 8. Performance evaluation of classifier algorithm on the basis of (a)AUC (b)F1(C) Recall and (d) Precision

8.Conclusion

Breast cancer is the most common type of cancer and the leading cause of death among females worldwide. Because of the many characteristics associated with breast cancer, certain anomalies may be misunderstood, resulting in false positive results and painful biopsies. CAD (Computer-aided detection) algorithms have been created to assist radiologists in providing an accurate diagnosis while reducing the number of false positives and false negatives results.

Typical processes in CAD were thoroughly investigated in this paper. Image pre-processing, image segmentation, features extraction, feature selection, and classification techniques have been commonly used in the computer assisted detection and diagnosis system using mammography images. To increase the overall performance of computer-aided detection and diagnostic systems, more advancements in each algorithm stage are necessary. There is no standard dataset available for validation of results; hence, comparing researcher's research techniques on a single platform is difficult.

There are numerous potential directions that might help to enhance the CAD system for mammogram images. Very few works done on classification of tumour in more than two classes, such as norm al, abnormal and benign, If CAD diagnose the tumour in to proper class it will help to avoid unnecessary painful biopsy.

Pre-processing of image before segmentation and classification is very important phase but very limited work done on this area as compare to classification. Very few works done on removal of unnecessary part of mammogram images such as artifact, label and pectoral muscles which lead classification to wrong prediction.

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