An Improved Automated Breast Cancer Detection Using Glrlm and Hybrid Classification Method

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Abstract:

At present, medical image processing can be exploited to discover the disease or tumor in the human body. In this paper, the mammogram medical image is taken for image processing to the diagnosis process. The breast cancer mostly happened in women that can lead to death. The mammography is one of the special screening methods of CT scan that can be employed to identify the malignant tumor in the breast at an early stage to save the patient life. However, the radiologists have not provided accurate results always about brain tumors whether it is benign or malignant because of the structure of their cells. Therefore, an enhanced computer-aided approach is presented in this paper using some effective image processing techniques for the automated detection of breast cancer. The mammogram image can be enhanced using NLM (Non-Local-Means) filtering method with adaptive histogram equalization (AHE) to enhance the quality of an image, and the clustering is done employing morphological algorithm. The relevant features will be isolated from the mammogram image using Gray Level Run Length Matrix (GLRLM) according to the shape, surface, and position of tumor cells in the breast. Subsequently, K-NN (K-nearest neighbor) method can be applied to classify the image as normal and abnormal depending on the selected features. Finally, the tumor is segmented from an abnormal image and classified into benign or malignant tumor by applying kernel-based Convolutional neural network (KBCNN). The performance of this presented method can give more than 90% accuracy than existing methods.

KEYWORDS: *Medical image processing, Mammography, Breast cancer detection, image classification, tumor classification, tumor segmentation.*

Introduction

At present, breast cancer has occurred as the second leading cause of death among women. This kind of cancer can be started as a cancerous tumor and it will be produced in cells of breast tissue that can be spreading to neighboring parts of tissues with time. This breast cancer is appeared not only in women, other than men can also be affected by this breast cancer. The present statistics were proved that this kind of breast cancer mostly happened in women. Therefore, a novel diagnostic tool has been introduced in the medical side called Medical Image Processing, in which not only discover the tumor and several diseases can also be found. There can be extensive verification that early recognition of tumors in breast and breast cancer tumor surgery significantly improve the possibilities of patient survival. Now a day, X-ray mammography is utilized as the gold standard screening technique to find the cancer tumor in the breast.

The amount of radiation received can be fewer at present days for the process of mammography compared to a breast X-ray. Computer-aided diagnosis (CAD) methods

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have been introduced to develop the accurateness of diagnostic and screening mammography effectiveness. The CAD is acted as the tool that can be employed for enhanced analysis of mammography images. By applying the CAD method, the computerized examination of mammogram images will be executed. This kind of method to prevent the problems of mammographic images that is reading by radiologists like extra time-consuming, fatigable, additional missing diagnose, fake diagnose, etc. Thus, this CAD tool will assist the radiologists to develop their presentation to discover the malignant tumor in the breast at an early stage. To the breast cancer identification task, the CAD method contains capable image processing methods for examining the information received from the hospital.

However, breast cancer tumor discovery in a mammographic image can be very hard since the huge range differed in density, size, boundary and other uniqueness of the masses of the breast. The breast masses' features can be differed in a wide range and hence the CAD scheme does not provide more accuracy with better performance and because it could not utilize the clinical necessities. As a result, in this paper, automated breast cancer detection is enhanced by improving the breast density examination of mammograms that can be missed by the radiologists exploiting effective image processing methods and it will provide good consequence on CAD detection. We focus our discussion on four major topics: mammogram image preprocessing, image clustering, feature extraction, tumor segmentation and classification in a mammogram image.

Related Works

An automated method was presented in [1], in which a deep learning mechanism and a Multi-Support Vector Machine have been exploited to detect breast cancer in the mammogram images. In [2], the masses identification in mammogram image pairs was adjusted to the breast tissue's density by applying the image processing methods and the similarity index methods have also been utilized from Convolutional neural networks (CNNs) and biology. The local binary patterns and the multi-scale fundamental image features were utilized to the process of automated stromal regions classification depending on their maturity, in grouping with an arbitrary decision trees classifier [3]. A computer-aided recognition and analysis method was presented in [4] for the discovery of breast cancer tumors using mammographic images. In this work, the Multiple-Instance Learning (MIL) paradigm was utilized. A novel pipeline has been introduced in [5] to identify the malignant tumor cells in the breast and open-source image examination software known as CellProfiler has also been employed for the extraction of the features. An algorithm was exploited according to the fuzzy inference system for the procedure of categorization of the benign and malignant tumors in the mammographic images.

In [6], a direct extraction technique of tumor was utilized on the basis of ensemble empirical mode decomposition (EEMD) for early stage finding of breast cancer tumors using ultra-wideband (UWB) microwave imaging process. In this method, for tumor recognition, the image reconstruction was recognized with only extracted signals from as located waveforms. A Least-Variance and Max-Mean method has been utilized in [7] for the discovering of tumor in the breast. A multi-phase CAD method has been developed in [8] for the discovery of breast cancer in automated 3-D breast ultrasound (ABUS). It has

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been analyzed that by applying a second finding phase that has utilized the region based classification method depending on the enthusiastic features.

Materials and Methods

In this paper, five phases are suggested to detect the malignant tumor in a mammogram image at an early stage automatically depending on the CAD system. In the first phase, the mammogram image will be smoothed using the NLM method by eliminating the unnecessary noises from the breast image's background and afterward, the contrast can be enhanced by applying the AHE technique to enhance the image quality for further works.

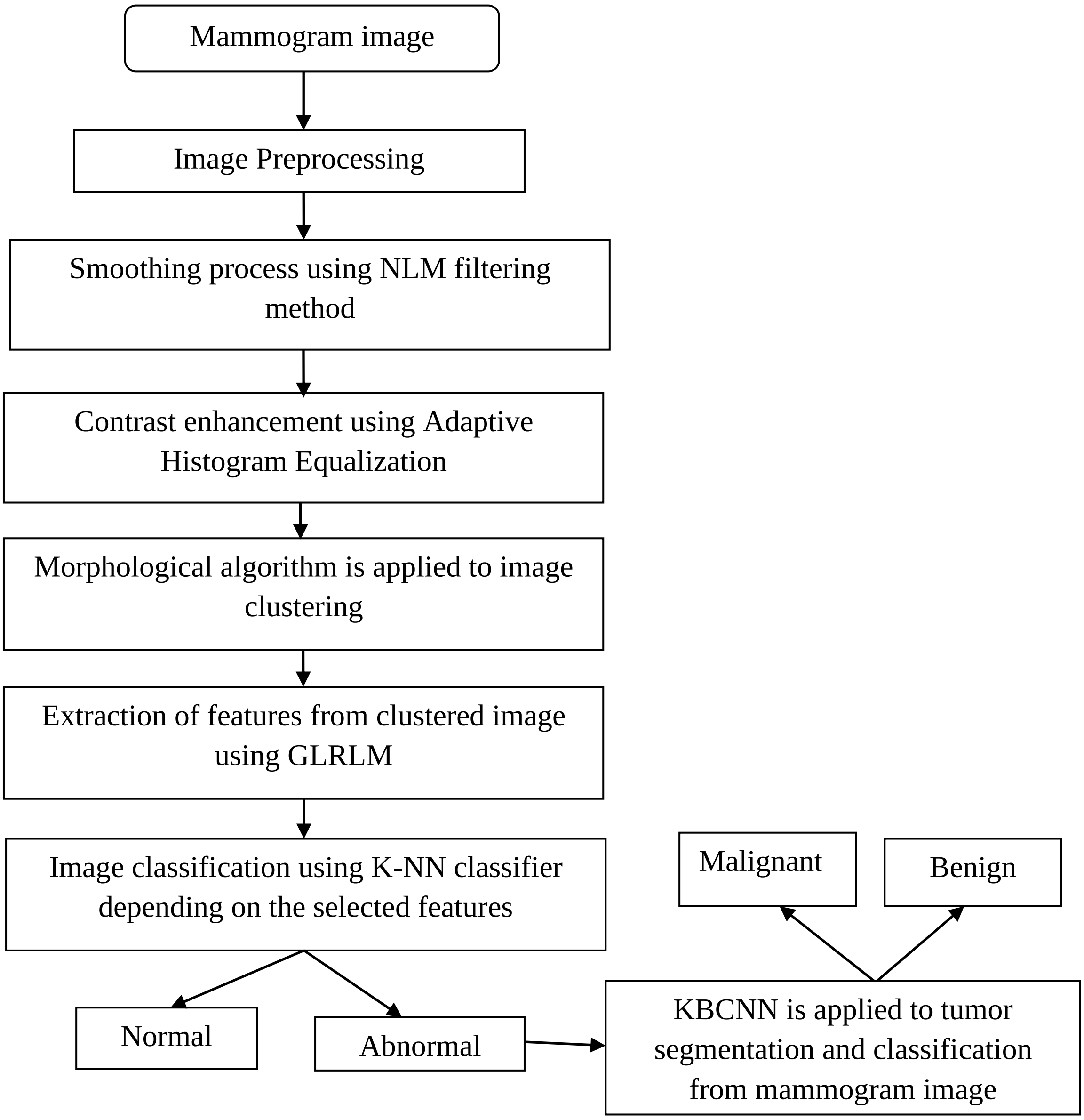

Figure 1 Architecture of proposed system

In the second phase, clustering is computed depending on the morphological operations for effective feature extraction. The GLRLM method can be utilized in the third phase to

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extract the features from the input image depending on the discovering of the classification process's accuracy. Subsequently, extracted features will be provided to the K-NN classifier and the image is classified into normal or abnormal images depending on the selected features. The image is abnormal means it has a tumor and then the kernel-based Convolutional neural network is employed to segment the tumor from the mammogram image. Finally, the segmented tumor will be categorized into benign or malignant. This kind of medical image processing will give suggestions to the doctor to execute the surgery of breast tumor and patient life can be saved immediately.
This proposed methodology having following steps:

- Image preprocessing using NLM with AHE method
- Clustering using Morphological algorithm
- Feature extraction using GLRLM technique
- Image classification using K-NN classifier
- Tumor segmentation and classification using hybrid method KBCNN and K-NN

Image preprocessing using NLM with AHE method

In this method, the NLM can be exploited to remove the unwanted noises from the mammographic image to provide image quality. The contrast limited AHE will be exploited in the smoothed image to the enhancement of image, in which the brightness will be varied between objects and mammogram image's background and it will use to continue further tasks for tumor detection, segmentation, and classification. The noises are removed from the image according to the wide range of self-similarities in the mammographic images based on the spatial field. This NLM method can assume that the given breast image having more redundancy. After that, these redundancies will be applied to eliminate the noise from the mammographic image. The gray level is compared by this NLM method in a single point and geometrical pattern is also been compared in an entire neighborhood of adjacent pixels.
Let discrete noisy mammogram image as $m = \{m(a)|a\epsilon I\}$, the computed value as $NL[m](a)$ for a pixel a in image and every pixel's weighted average in the image can be estimated by using the following equation (1).

$$NL[m](a) = \sum_{b\in I} w(a,b)m(b) \qquad (1)$$

In above equation (1), weight of pixels $w(a,b)$ can be estimated according to the similarity occurrence between the pixels a and b in image and the standard constraints $0 \leq \mathrm{w(a,b)} \leq 1$ and $\sum_b w(a,b) = 1$ will be satisfied. Every pixel in this medical image can be acted as a weighted average of each pixel. The weights can be depending on the similarity occurrence between the adjacent pixels a and b. An adjacent pixel should be described to calculate the similarity between pixels. This similarity can be estimated as a weighted Euclidean distance's lessening function using the following equation (2),

$$d = \|m(N_a) - m(N_b)\|^2_{2,\ x} \qquad (2)$$

In the above equation (2), $x > 0$ represents the Gaussian kernel's standard deviation. The larger weights are possessed in the process of estimation of the average

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than other pixels in the image when the gray level adjacent of pixel can be similar as that of $m(N_a)$. The weights will be estimated using equation (3).

$$w(a,b) = \frac{1}{P(a)} e^{-\left(\|m(N_a)-m(N_b)\|_{2,}^{2}\, x/_{h^2}\right)} \tag{3}$$

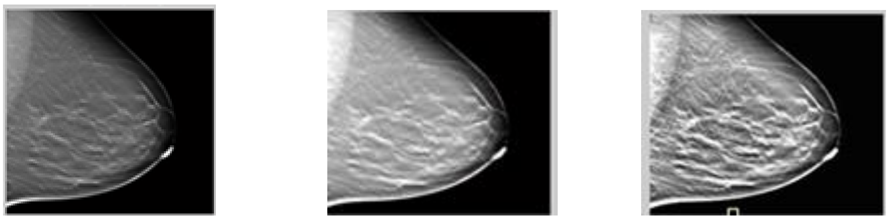
where $P(a)$ denotes the normalizing constant and it is given by

$$P(a) = \sum_b e^{-\left(\|m(N_a)-m(N_b)\|_{2,}^{2}\, x/_{h^2}\right)} \tag{4}$$

In equation (4), h can be represented as the weight decompose control parameter and $h \approx 10\sigma_n$, in which exponential function's decompose is controlled and consequently the weights' decompose will be used as a Euclidean distances' function. The parameter x denotes the adjacent filter with radius R_{sim}. The weights of x will be estimated by using (5).

$$w(x) = \frac{1}{R_{sim}} \sum_{a=q}^{R_{sim}} \frac{1}{(2a+1)^2} \tag{5}$$

In equation (5), denotes the distance between weights that can be from the filter's center. NL-means technique noise looks like white noise. The NLM method is executed on this kind of texture for the images' visual quality during its redundancy's high degree. Hence, the mammogram image has been smoothed that has established in Figure 2.



Input image Smoothed image Contrast enhanced image

Figure 2 Preprocessed mammogram Image

Consequently, contrast limited AHE is exploited to the smoothed image. This contrast limited AHE is operated as a special kind of adaptive histogram equalization that is utilized in the image. It will be worked on the small data areas in the image rather than the whole mammographic image and contrast enhancement can be executed on every small data region to obtain the matching of the output region's histogram approximately with a particular histogram. Neighboring small data regions can be combined by removing the induced boundaries bilinear interpolation. Thus, the contrast of the given image is enhanced that has shown in figure 2 to helpful of good visualization of image for doing the additional process.

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Clustering using Morphological algorithm

The image clustering is computed using a morphological algorithm after the preprocessing for the accuracy of feature extraction from the mammogram image. In this method, image components like boundaries are extracted and clustered by mathematical morphology that can be used as a tool. This type of clustering-based image segmentation can be executed on a mammogram image according to the binary image as the language of mathematical morphology will be operated as set theory. Initially, the smoothed image is converted into a binary image by applying the thresholding procedure. A global threshold can be served as the first cluster and cut in this procedure and subsequently, the mammogram image is transformed into binary image because breast tumor tissue contains the highest intensity in mammographic images, usually nearer to 1 on a gray level. In this clustering-based segmentation, the dilation and erosion morphological operations are computed.

In dilation morphological operation, two parts are taken as data. The input mammogram image is to be dilated in the first part and the structuring component called kernel is used in the second part. The mammogram image can be dilated by applying this structuring component. Let P can be a set of sample breast image that will be coordinated and Q can be set of structuring component that can also be coordinated and Qi will be a Q conversion, therefore, Q origin is at$i$. Consequently, dilation of P is executed by Q that is worked as set of every point of i such as intersection of Qi with P cannot be a null value. The dilation of the image can be estimated using the following equation (6). The dilated mammogram image has been illustrated in figure 3.

$$P \oplus Q = \{i|(\hat{Q})_i \cap P \neq \emptyset\} \quad (6)$$

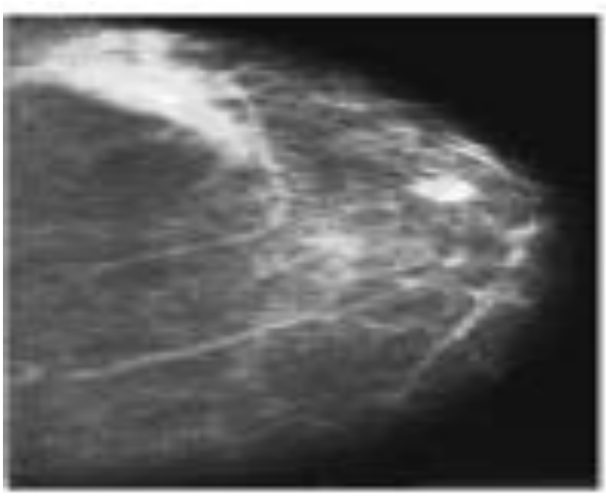

Figure 3 Dilated mammogram image

In the Erosion process, similar two parts in dilation taken as data. In the first part, input mammogram image can be eroded and the structuring component is utilized for

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erosion in the second part. This structuring component can establish how much the image can to be eroded and it is given by:

$$P \ominus Q = \{i|(Q)_i \cap P^c \neq \emptyset\} \quad (7)$$

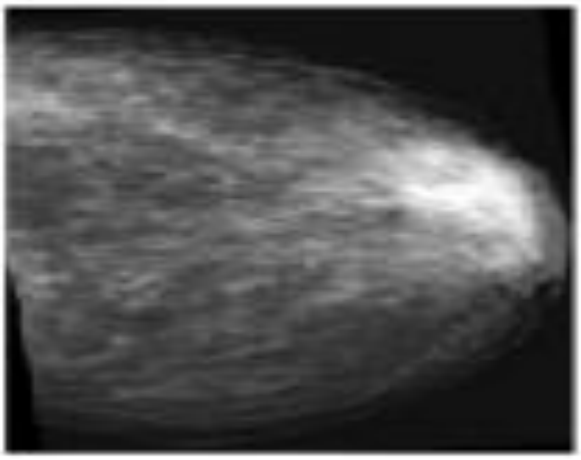

Figure 4 Eroded mammogram image

Figure 4 shows the eroded mammogram image. Thus, the mammogram image has been clustered and segmented according to the morphological operations dilation and erosion. This clustered image can give more accuracy for the process of feature extraction.

Feature extraction using GLRLM technique

The features are extracted from the clustered mammogram image by applying the Gray level run length technique and this method is utilized to extract the higher order statistical features. In the GLRLM features, the set of continuous pixels contains similar gray level. In the mammogram image, the run length is used as the number of neighboring gray levels. In this method, the run length can be estimated depending on the calculated by number of run happens at a time in the mammogram image. Let $R(x,y|\theta)$ is a gray level run length matrix, in which the $(x,y)^{th}$ component describe the number of runs occurred with gray level x and length y that can be happened in the mammogram image alongside angle θ. The GLRLM is calculated using the following equation (8):

$$\sum_{x=1}^{N_g}\sum_{y=1}^{N_r} R(x,y|\theta) \; and \; 1 \leq N_z(\theta) \leq N_p \quad (8)$$

In the equation (8), N_p denotes the number of pixels in the mammogram image, N_g depicts the number of intensity values in the mammogram image, the number of run occurrence is denoted by $N_z(\theta)$ in the input breast image all along angle θ and $R(x,y|\theta)$ is employed to indicate the run length matrix for an random way θ. The following GLRLM features can be extracted from image using following equations (9-14) to increase the accuracy of ANN classifier for the classification of image.

$$\text{Short Run Emphasis (SRE)} = \frac{\sum_{x=1}^{N_g}\sum_{y=1}^{N_r} R(x,y|\theta) / y^2}{N_z(\theta)} \quad (9)$$

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$$\text{Long Run Emphasis (LRE)} = \frac{\sum_{x=1}^{N_g}\sum_{y=1}^{N_r} R(x,y|\theta)y^2}{N_z(\theta)} \quad (10)$$

$$\text{Low Gray level Run Emphasis (LGRE)} = \frac{\sum_{x=1}^{N_g}\sum_{y=1}^{N_r} R(x,y|\theta)/x^2}{N_z(\theta)} \quad (11)$$

$$High\ Gray\ Level\ run\ Emphasis\ (HGRE) = \frac{\sum_{x=1}^{N_g}\sum_{y=1}^{N_r} R(x,y|\theta)x^2}{N_z(\theta)} \quad (12)$$

$$\text{Gray Level Non} - \text{uniformity (GLN)} = \frac{(\sum_{x=1}^{N_g}\sum_{y=1}^{N_r} R(x,y|\theta))^2}{N_z(\theta)} \quad (13)$$

$$Run\ percentage\ (RP) = \frac{N_z(\theta)}{N_p} \quad (14)$$

Thus, these extracted feature values are given to ANN classifier as an input to classify the mammogram image.

Image classification using K-NN classifier

In this image classification, the K-NN classifier can use the extracted features to classify the given mammogram image into normal or abnormal. The KNN does not exploit some prior knowledge about the structure of image data in the training set for the classification. In this image classification process, two stages are used such as the training stage and testing stage. The mammogram image data points contain labels with their class in the training stage. In the testing stage, data points of the breast image must be unlabelled and the k nearest data points' list can be produced as training data point to unlabelled point and their class is categorized. The following algorithm is used by the KNN classifier to classify the mammogram image:

Algorithm

Step 1: Every input data of the mammogram image can be stored in the training data set

Step 2: Each unknown pattern will be examined in the phase of the testing process.

Step 3: The Euclidean distance is estimated to locate the K-nearest patterns to the input pattern of a given image

Step 4: The confidence can be evaluated for every class Ci/K to the mammogram image classification

Step 5: The unknown pattern's class label can be established using the nearest neighbor's class labels.

Hence, the mammogram image is classified by KNN classifier into normal breast image or abnormal breast image according to the features that have been shown in figure 5 and Figure 6. Figure 5 shows the normal image that was classified by KNN classifier and the abnormal image has been illustrated in Figure 6.

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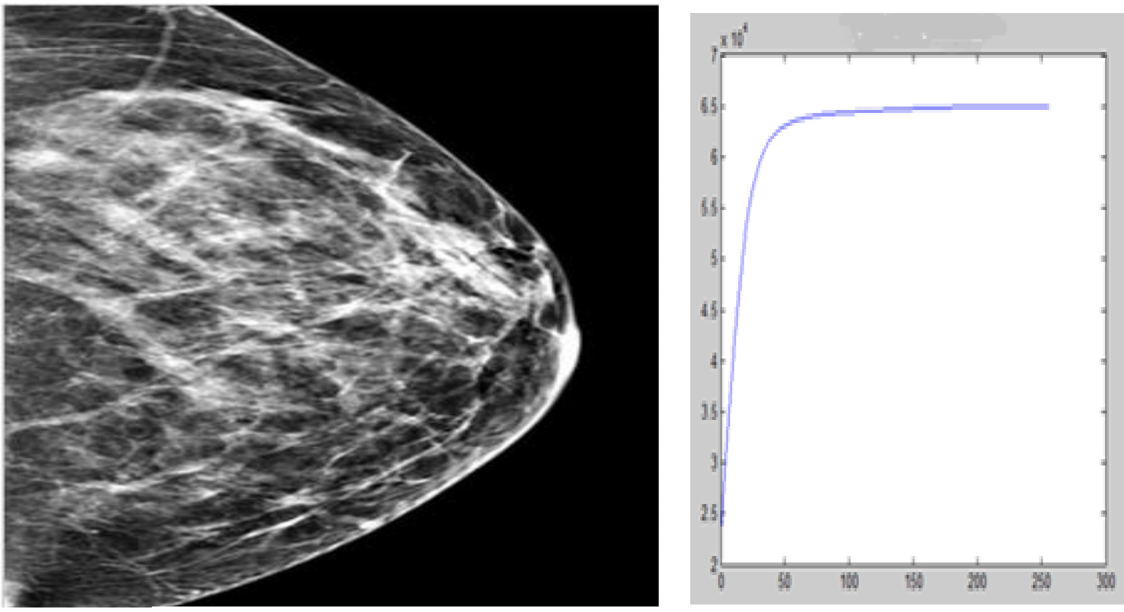
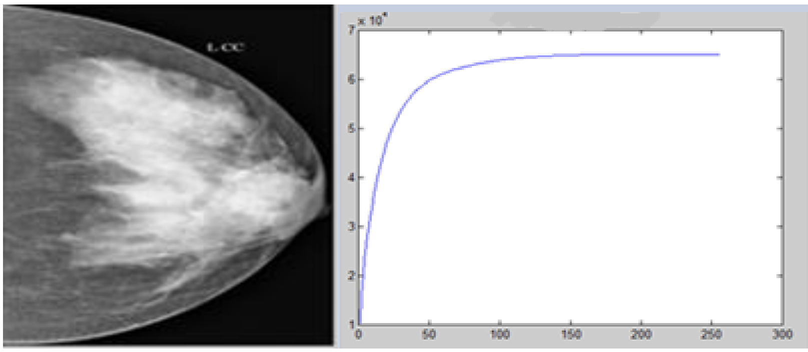


Mammogram image GLRLM Feature graph

Figure 5 Normal Mammogram image



Mammogram image GLRLM Feature graph

Figure 6 Abnormal Mammogram image

Tumor segmentation and classification using hybrid method KBCNN and K-NN

If the given mammogram image is abnormal, then the KBCNN is applied to segment the tumor from an image and this segmented tumor will be classified by KNN classifier as benign or malignant depending on the tumor features such as shape, structure, and location. Figure 7 shows the KBCNN architecture for the tumor segmentation process. At two different phases, the neural networks can be trained for the tumor segmentation in a mammogram image. For the convolution layer of CNN, the first phase will be utilized and the second phase is employed for the entirely interrelated layer. The convolution weights of kernel-based CNN can be copied in the primary broadcast learning process and subsequently, the training samples of mammogram images will be categorized into target classes by ANN classifier. From the mammogram image, the connected layers and non-target classes' pairs can be trained wholly in the second phase.

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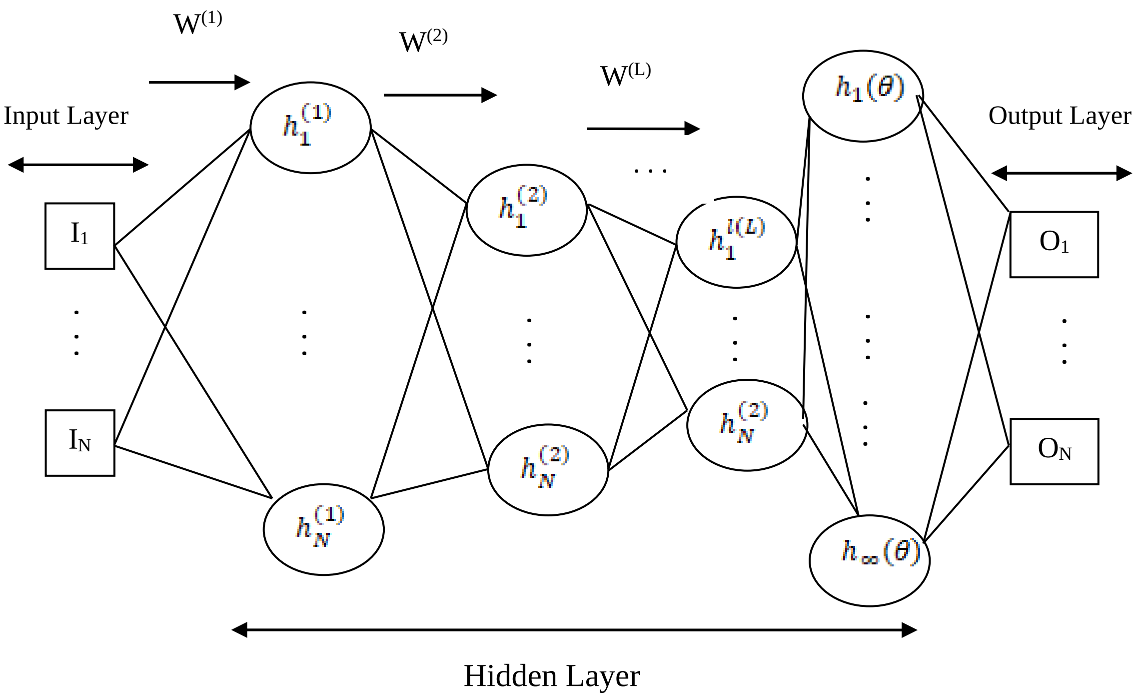
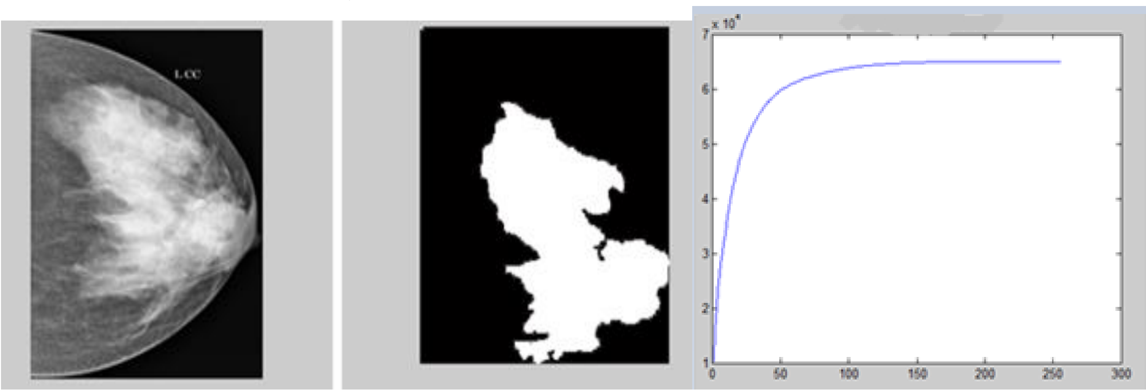


Figure 7 KBCNN Architecture

In this method, KBCNN and KNN classifier is combined for segmentation and classification process, in which the Kernel is used to enhance the performance of CNN to the segmentation of breast tumor and tumor classification in a mammogram image. CNN contains advantages of high efficiency, fast deep learning, and only a hidden layer feature extraction process. The KNN is used in this paper to extract and categorize the hidden layer by alternately adding layers and sub-model layers to the distinctive hidden layer. Thus, the tumor is segmented from the mammogram image with help of KBCNN and afterward, the segmented tumor will be classified by KNN classifier into benign or malignant breast tumor. The first abnormal image was segmented by KBCNN, in which the tumor is segmented and afterward the segmented tumor is classified as a malignant tumor by ANN classifier according to the extracted GLRLM features that have been shown in Figure 8. In Figure 9, the segmented tumor has been classified as a benign tumor based on its features.



First Abnormal image Tumor segmentation GLRLM Feature graph

Figure 8 Malignant Tumor Classified By ANN

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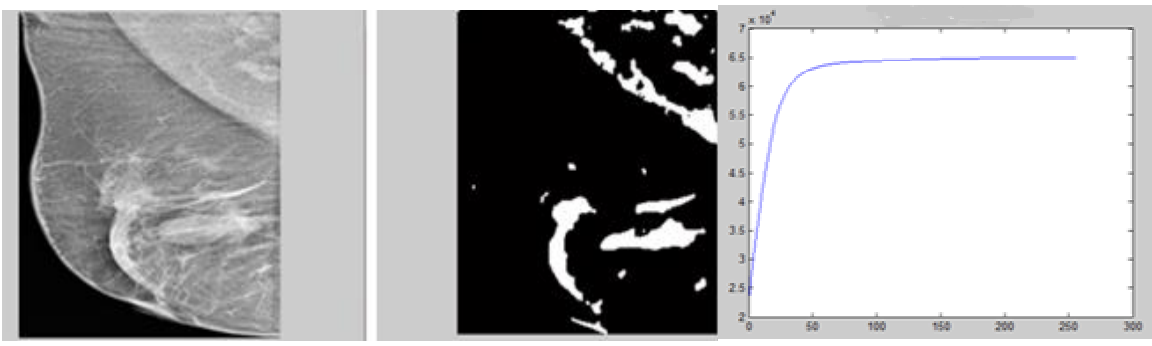

Second abnormal image Tumor segmentation GLRLM Feature graph

Figure 9 Benign Tumor Mammogram image

Results and Discussions

In this section, the performance of presented automated breast cancer detection on CAD system is evaluated and it will be compared with the existing methods multi-support vector machine, standard-CNN, and Multiple-Instance Learning in terms of error rate, accuracy, sensitivity, specificity and false classification ratio that can be utilized.

Error rate

The error rate will be computed according to the total number of imperfect tumor segmentation and tumor classification in the testing process. The optimum probable error rate can be in the value of 0.0, while the very worst can be in the value of 1.0. The minimization of this error rate will be the prime objective for any classifier. The error rate of proposed and existing methods are estimated by the following equation:

$$Error\ Rate = \frac{FP+FN}{TP+TN+FN+FP} \tag{15}$$

Where TP represents the True Positive, TN can be the True Negative; FP indicates the False Positive and FN denote the False Negative. A number of correctly segmented and classified tumor pixels in mammogram image is described by the true positive and number of wrongly segmented and classified tumor pixels can be described by the TN. FP can describe the number of imperfectly segmented and classified tumor pixels of mammogram image and the number of wrongly segmented and classified non-cancerous tumor pixels in the image.

The comparison chart of error rate has been illustrated in Figure 10. From the above chart, the proposed automated breast cancer detection system has taken less error rate during the tumor segmentation and classification in mammogram image compared to existing methods multi learning paradigm [3], Standard CNN [2] and multi support vector machine [1].

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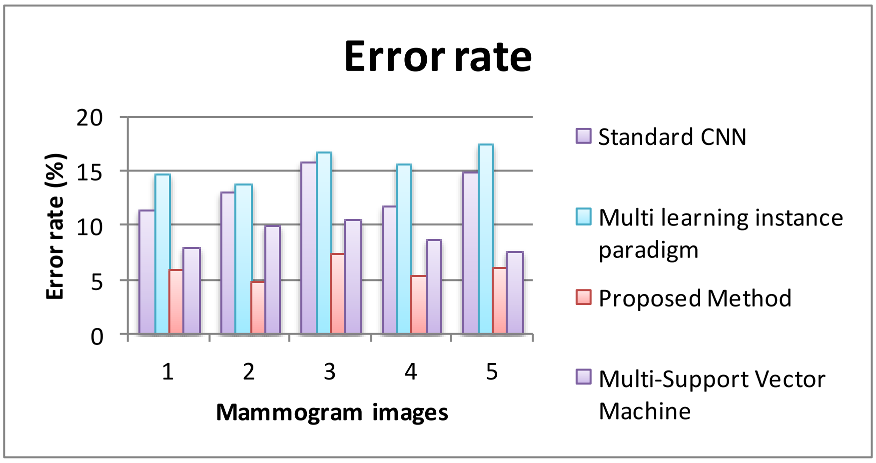

Figure 10 Error rate of proposed and existing methods

Accuracy, Sensitivity and Specificity

The accuracy, sensitivity and specificity of proposed and existing methods have been evaluated using the following equations (16-18)

$$Sensitivity = \frac{TP}{TP+FN} \quad (16)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (17)$$

$$Accuracy = \frac{TP+TN}{TP+FN+TN+FP} \quad (18)$$

Table 1 Performance analysis of proposed and existing methods

Parameters	Proposed Method (%)	CNN [2]	Multi-SVM [1]	Multi Instance Learning Paradigm (%) [3]
Accuracy	95.8	87.9	88.7	85.9
Sensitivity	94.0	88.2	90	86
Specificity	93.9	85.7	89.4	83.9

Table 1 shows the proposed and existing methods' performance analysis. From above Table 1, the presented automated breast cancer detection system has taken 95.7 percentage of the accuracy, sensitivity in the percentage of 94, 93.9% specificity compared to existing methods. Hence, our proposed method can give an effective performance to detect the cancer tumor in the mammogram image.

False Classification Ratio

The false classification ratio of presented and existing works has been established in Figure 11. The below comparison chart has clearly illustrated that this enhanced automated breast cancer detection system has given a low percentage of false

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classification ratio during the tumor classification in mammogram image than existing methods standard CNN, multi-SVM and multi-instance learning paradigm. Hence, enhanced breast cancer detection will give effective tumor segmentation and tumor classification in a mammogram image at an early stage.

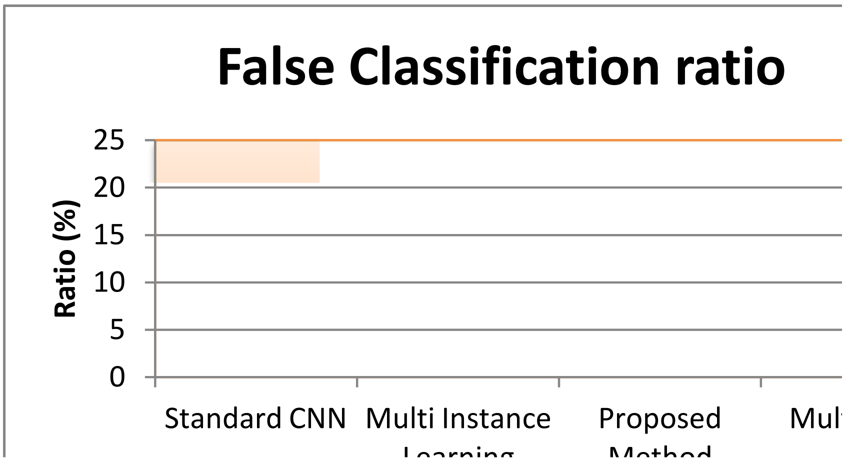

Figure 11 False classification ratio

Conclusion

In this paper, automated breast cancer detection has been presented using an efficient image processing methods. This presented method can improve the CAD system's performance to detect the malignant tumor automatically in the breast. In this method, the given mammogram image was smoothed and enhanced with the help of the NLM filtering method and the AHE method. Afterward, the preprocessed image has been clustered with morphological operations for the method of feature extraction and the features were extracted from the mammogram image according to the GLRLM features. Subsequently, these extracted features were given to the ANN classifier to classify the breast image into normal or abnormal. Lastly, the tumor has been segmented using KBCNN from the abnormal image and after that the segmented tumor was classified into benign or malignant tumor by the ANN classifier. By using this method, the malignant tumor will be detected at an early stage with high accuracy and a low error rate. This proposed method will offer a good suggestion to the doctor who treats the patient affected by breast cancer and therefore, the patient life will be saved.

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