

Automatic Mammogram image Breast Abnormality Detection and localization based on the combination of k-means and Genetic algorithms methods



¹Hamid El malali, ²Abdelhadi Assir, ³Mohammed Harmouchi, ⁴Elmaati Essoukaki,

⁵Mourad Rattal, ⁶Aissam Lyazidi, ⁷Azeddine Mouhsen

^{1,2,3,7} Hassan First University of Settat, Laboratoire Rayonnement-Matière et instrumentation, Settat, Morocco

^{4, 5, 6} Hassan First University of Settat, Laboratoire Sciences et Technologies de la Santé, Settat, Morocco

h.elmalali@uhp.ac.ma

ABSTRACT

Currently, most oncologists recommend mammography as an effective medical imaging modality for the screening of breast cancer. The aim is to reduce the mortality rate due to this disease. However, several imperfections contribute to the misclassification of breast lesions. Therefore, computer-aided diagnosis (CAD) systems are tools that allow the radiologists a second opinion to improve the diagnosis accuracy. In this paper, an accurate fully automatic method for breast abnormality extraction is presented. The extracted region of interest (ROI) can be subjectively classified by radiologists or used to automatically extract the features that allow for automatic classification. The proposed method consists of two steps: the preprocessing step for delimiting the ROI by removing all the artifacts including the pectoral muscle, followed by the contrast enhancement; the second step is devoted to the extraction of the suspicious area by segmenting the ROI using the k-means algorithm to avoid any initialization. Both contrast enhancement and ROI segmentation are performed by using a genetic algorithm (GA) to achieve good results. The simulation results show the accuracy of the proposed method by comparing the center coordinates and the radius enclosing the abnormality found with those provided with the database.

Key words: CAD systems, breast cancer, mammogram enhancement, mammogram segmentation, k-means, genetic algorithm.

1. INTRODUCTION

According to the World Health Organization, breast cancer is the most frequently diagnosed cancer in women. Around the world in 2018, about 2,088,849 women are affected by this disease. The number of deaths is about 626,679 [1]. This number can be drastically reduced with early detection and diagnosis [2], [3]. Mammography is the most recommended technique by oncologists, it's among the reliable radiological examinations that can detect breast cancer early [4], [5]. However, mammogram images quality is often decreased by many factors such as the limitation of the X-ray hardware

system, the high-density breast tissue, the subtle difference in X-ray attenuation between tissues, the specific limitations of human observers, and the huge number of the screening mammograms that need to be analyzed [5]. Consequently, about 30% of breast lesions are missed during routine screening of breast cancer. The use of CAD systems can help the radiologists to reduce both the false-positive and false-negative results, the sensitivity can be increased by up to 21% in the detection of breast cancer [6], [7]. Clinical studies show that the number of false-negative results can be reduced by 5% to 15% [7]. However, many CAD systems require manual pre-processing such as the determination of the ROI as the CAD systems developed in the references [8], [9], [10], and [11]; the determination of the ROI and the initialization of the process of the segmentation as developed in the reference [12]. These manual operations will increase the diagnosis time during breast cancer screening. Consequently, the CAD systems require to incorporate automatic detection algorithms for various possible features that may indicate the presence of an abnormality [13]. This paper aims at developing a full automatic computer-aided detection and localization of breast abnormality. The extracted ROI can be subjectively analyzed by radiologists or used to continue the automatic classification by extracting the features which will be used to predict the severity of abnormality using a classifier. The proposed CAD system consists of two steps, the pre-processing step, and the segmentation step. The pre-processing step aims to eliminate all the radiopaque artifacts in the image, followed by the elimination of pectoral muscle when it comes to mediolateral-oblique view (MLO). The contrast of the ROI found is enhanced using the technique named "Adaptive Local Gray Level Transformation based on Variable s-curve for Contrast Enhancement of Mammogram Images" detailed in the reference [14]. The second step is devoted to the segmentation process using the k-means clustering algorithm combined with a GA to achieve good ROI partitioning.

The evaluation of the final results is based on a comparison of the center's coordinates and the approximate radius of the abnormality found in the simulation with those provided with the database. The rest of this paper is organized as follows: Section 2 presents the background and the problem formulation concerning The CAD systems and their stages. Section 3 discusses the proposed CAD methodology. The

results of the simulation are discussed in section 4. Finally, section V concludes the paper.

2. LITERATURE REVIEW

CAD systems are tools using computer science techniques to combine diagnostic imagine with image processing, pattern recognition, and artificial intelligence technologies to predict the classification of breast abnormality[3]. Generally, CAD systems involve the following steps: pre-processing step, segmentation step, feature extraction step, and classification step. Good final categorization depends on the effectiveness of allits steps[3], [9], [15].Moreover, the accurate identification of regions of interest allows preventing the model from unwanted patterns[16]–[18]. Consequently, mammograms pre-processing and extracting the suspicious abnormality can considerably improve the outcomes of CAD systems. The genetic algorithm is integrated into the pre-processing and segmentation steps to achieve good results.

2.1. Images Pre-processing

In the case of a breast abnormality, the masses are the main sign of malignancy. They are described by their shape, margin, size, location, and contrast. Masses detection by radiologists is more difficult due to their similarity to the normal tissue[15], [19].Consequently, to distinguish easily between lesions and healthy tissue the improvement of contrast and the appearance of limiting edges between areas of the mammograms is necessary. This enhancement must maintain the image brightness and information as much as possible[5], [20]. In a CAD system, the pre-processing step aims to enhance the quality of the mammograms that will be analyzed. Artifacts suppression, ROI identification, contrast enhancement, and edges sharpening are the main pre-processing required for the mammogram images [3], [13], [21], [22].Several techniques have been used for this purpose. The point-to-point transformations are among the techniques that are widely used to improve the quality of medical images. They correspond for each pixel in the input image a new value in the output one [23], [24].Among these transformations we quote: linear, nth power, nth root, logarithmic, exponential, s-curve (sigmoidal function), etc.[14], [23], [24].These transformations have varying effects on the images. To assess the quality of resulting improvement, the use of IQA measures is necessary since the subjective evaluation in the medical field requires the service of experts and not suitable for real-time applications[21].The Effective Measure of Enhancement (EME) and Edge Content (EC) parameters to evaluate respectively the improvement of the contrast and the appearance of the edges [22], while Feature Similarity Index Measure (FSIM) and Absolute Mean Brightness Error (AMBE) parameters to apprise respectively the information and brightness conservation[5], [22], [25]. Table 1 shows the expression of the above-mentioned parameters.

Table 1: The evaluation parameters expression

Parameter	Formulae
EC	$\frac{1}{M.N} \sum \sum G(x, y) $ (1)
EME	$\frac{1}{K_1 K_2} \cdot \sum_{i=1}^{K_1} \sum_{j=1}^{K_2} 20 \cdot \log \frac{I_{max}(i, j)}{I_{min}(i, j)}$ (2)
AMBE	$ E(S) - E(R) $ (3)
AMBE _n	$\frac{1}{1+AMBE} = \frac{1}{1+ E(S)-E(R) }$ (4)
FSIM	$\frac{\sum_{x \in \Omega} S_l(x) \cdot PC_m(x)}{\sum_{x \in \Omega} PC_m(x)}$ (5)

- M and N are the size of the image, $G(x, y)$ is the magnitude of gradient vector.
- K_1 and K_2 Are respectively the numbers of horizontal and vertical non-overlapping blocks into the image is divided, $I_{max}(i, j)$ and $I_{min}(i, j)$ are respectively the maximum and minimum intensity values in each block (i, j) .
- $E(R)$ and $E(S)$ are the means of the intensity of the original and enhanced images respectively.
- $PC_m(x)$ is the feature perceived at a point where the Fourier components reach maximum in phase, $S_l(x)$ is the overall similarity between the original image and the enhanced image and Ω is the whole image spatial domain.

2.2. Images Segmentation

Image segmentation aims to divide an image into distinctive regions sharing similar properties such as intensity, texture, brightness, color, and contrast[26]–[28].In the medical field, segmentation is a key step of most medical image analysis tasks, it aims to distinguish tissues from each other, tumor detection, blood cells automated classification, mass detection in the case of mammogram images, etc.[27], [28].In the literature, various image segmentation techniques have been developed based on either region-based methods, clustering methods, classifier methods, or hybrid methods which can combine two or more methods[28].

A. Threshold-based methods

The image is formed from regions with different grey levels. Its histogram has different peaks and valleys which can divide the images into different parts[28]. Two cases to be distinguished:

- Global thresholding: In this case, the image is composed of two parts separated by a single threshold value, the background and the foreground. Each pixel of the image is compared to the threshold value, the pixels below the threshold are setting to zero (background) where the pixels above the threshold are setting to one (foreground)[27]–[29].
- Local thresholding: In this case, the image contains various objects, it's characterized by a multimodal histogram. The global thresholding fails to distinguish the different regions in the whole image. The images are subdivided into sub-images to calculate the threshold value for segmenting each part, then the final result is the merging of all intermediate segmentations.

B. Region-based methods:

The principle of these methods is that an object in the image corresponds to several connected pixels according to predefined criteria such as gray level, texture, or color. The algorithm operates iteratively and requires choosing some seed points to start the partitioning process. According to the similarity criterion, the neighbors of seed are added to the region when the criterion is satisfied [27], [28]. Region-based approaches can be classified into two groups: region growing and region splitting and merging [3], [27], [28].

C. Clustering-based methods:

These techniques can be supervised or unsupervised [28]. They are used to classify the pixels of an image into several clusters [3], [27], [28]. In the final classification, the pixels of each cluster will have a high intra-class (pixels of the same cluster) similarity and a low inter-class (pixels of a different cluster) similarity. Generally, the similarity is given as the appropriate distance measure such as Euclidean distance measure [27]. In the literature, several clustering-based techniques have been used, among the most popular clustering algorithms, we quote K-means, Fuzzy C-means, and Markov Random Fields [3], [27], [28].

2.3. Genetic Algorithms

Genetic algorithms (GAs) are among the search techniques of global optimization of a problem. They are based on Darwinian theory where an individual is able to compete, survive, and reproduce [30]. Both the principles of genetics and natural selection manage the evolution process of GA [31]. The objective is to look for an optimal solution to a problem, usually in a large space by optimizing a function called fitness function. Initially, the GA randomly generates a population composed of a set of possible solutions, each solution is considered as an individual in the form of chromosome formed by a set of genes which are the variables of the problem [31], [32]. The search principle is based on three operators: reproduction, crossover, and mutation. These three operators are applied successively to each population to create a new generation until convergence [31]–[33].

3. PROPOSED CAD METHODOLOGY

The current study aims to extract automatically the suspicious area in the mammograms. The proposed CAD system

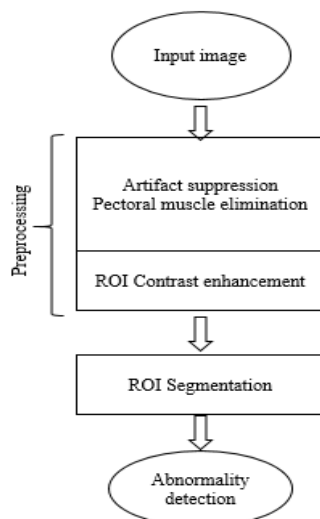


Figure 1: Flowchart of proposed method.

consists of two steps which are preprocessing and segmentation. The preprocessing step consists of two stages, automatic determination of the ROI followed by its contrast enhancement. The segmentation step allows finding the suspect area in the ROI. Figure 1 shows the flowchart of the proposed method.

3.1. Preprocessing of Mammograms

A. Artifact elimination

The background of mammogram images is often subject to a radiopaque artifact such as labels, wedges, and markers [29], [34]. Their existence affects the accuracy of the CAD's results. Consequently, removing the unnecessary details is required. The technical methodology used for this purpose is based on global thresholding segmentation followed by some morphological operations according to the following algorithm:

Algorithm 1

1. Read mammogram
 2. Apply global thresholding using $t_i = 18$ (to transform the gray-scale image into a binary one).
 3. Label each object in the binary image.
 4. Select the largest object
 5. Erode the selected binary-image using a flat disk-shaped structuring element with a radius of 5.
 6. Dilate the binary image using the same structuring element.
 7. Multiply the resulting binary image by the original one.
 8. Display the image without artifacts
-

B. ROI determination

The pectoral muscle in the MLO view of the mammograms is an important artifact that affects the segmentation process, subsequently falsifies the final categorization of CAD systems. Its suppression is a crucial step to automate the classification process. The proposed technique for pectoral muscle isolation is based on segmentation using the seeded region growing method. The key is to find the seeded pixel from which the algorithm starts the segmentation. The algorithm is as follows:

Algorithm 2

1. Read mammogram without artifacts
 2. Determination of breast orientation right to left or left to right according to the pectoral muscle.
 3. If the image is right to left then
Flipped image
 4. In the line 10, select the first pixel with intensity > 100.
 5. Run the algorithm of region growing segmentation.
 6. Display the ROI
-

C. ROI enhancement

In this step, the contrast of the found ROI is enhanced. The used technique is named "Adaptive Local Gray Level Transformation based on Variable s-curve for Contrast Enhancement of Mammogram Images" [14]. This technique is an adaptive local point to point transformation based on the non-linear sigmoidal function expressed as:

$$(1)$$

$$s = \frac{1}{1 + B^{-\frac{r-\alpha}{\beta}}}$$

Where r and s are respectively the normalized gray-level of the current pixel in the input image and its new value after enhancement in the output image in the range of $[0, 1]$, B , α , and β are respectively the basis, the center and the width of sigmoidal function in the range of $[0, 1]$. The principal is to look for the combination of a subdivision into several horizontal NBH and vertical NBV non-overlapping blocks of the image and the parameters of the sigmoidal function Eq.(1). The fitness function managing the processes of search is expressed as:

$$F(X) = \log(\log(E(Im))) \times \frac{nedgels}{M \times N} \times H(Im(X)) \quad (2)$$

The algorithm is as follows:

Algorithm 3

1. Read ROI
2. To Genetic algorithm

- Generate the initial population (50 chromosomes, (NBH, NBV, B, α , β))
- Compute fitness of the initial population equation (2)
- REPEAT** Selection (Stochastic uniform) Crossover (single point) Mutation (adaptive feasible)
- Compute fitness of the new generation equation (2)
- UNTIL** the population has converged

3. Compute enhanced ROI
 4. Display enhanced ROI
-

3.2. ROI Segmentation

To automatically identify the suspicious area in the ROI, this work proposes to use the K-Means clustering algorithm. This algorithm allows dividing the ROI into K clusters by associating each pixel to its corresponding cluster according to its intensity[28], [35].Indeed, each pixel is affected to the nearest cluster's centroid, following the Euclidean distance calculated as follows:

$$d = \|p(x, y) - \mu_j\| \quad (3)$$

Where $p(x, y)$ the intensity of the pixel is located at the coordinates (x, y) , and μ_j is the centroid of the cluster j . A good segmentation is the one that minimizes the Sum of Squared Error (SSE) of Euclidean distance between each pixel and its nearest center as define in the following equation, [33]:

$$SSE = \sum_{i=1}^K \sum_{j=1}^N \|p(x, y) - \mu_j\|^2 \quad (4)$$

As is known in the literature, the principal drawback of the k-means clustering algorithm is the random selection of initial centroid. Indeed, the quality of the final results depends strongly on the initial selection[28], [36].The proposed method to overcome this problem is to findsuitable centroids using a genetic algorithm. The adequate centroids must minimize the SSE as shows equation. (4)[37]. The number of clusters is set at three, the first cluster corresponds to the background, the second to adipose tissue, and de last to fibroglandular tissue[38], [39]. The segmentation process follows this algorithm:

Algorithm 4

1. Read enhanced ROI

2. To Genetic algorithm

- Generate the initial population (50 chromosomes of (μ_1, μ_2, μ_3))
- Compute fitness of the initial population equation (4)
- REPEAT** Selection (Stochastic uniform) Crossover (single point) Mutation (adaptive feasible)
- Compute fitness of the new generation equation (4)
- UNTIL** the population has converged

3. To K-means algorithm

- For each pixel calculate the Euclidean distances d_1, d_2, d_3 .
- Assign each pixel to the closest centroid μ_1, μ_2, μ_3
- Clustering according to the smallest distance

4. Display the suspicious area.
-

4. RESULTS AND DISCUSSION

The proposed method is tested on numerous mammogram images from the mini-MIAS database [40]. Quantitative and qualitative results show its effectiveness regarding the automation of the detection of the suspect region. The following section details the results of each stage of proposed CAD system.

4.1. Artifact Suppression and ROI Detection

The first step aims to remove all the undesirable details in the image. As shown in Figure 2(b), the radiopaque and the label artifacts are correctly removed from the original images Figure 2(a),the resulting image corresponds only to the breast profile. Also, this step flips the right-to-left oriented images into the left-to-right direction, the objective is that the pectoral muscle should appear on the left side of the image as shows mdb271 Figure 2 (b).

In the second step, from the left-to-right breast profile Figure 2 (b), the proposed algorithm can correctly initialize the process of segmentation using the seeded region growing method to remove the pectoral muscle from the mammograms. Figure 2 (c) shows the effectiveness of this step, the pectoral muscle is correctly eliminated from all the tested images.

4.2. ROI Enhancement

The third step in the proposed CAD system aims to enhance the ROI found in the second stage. The used technique is detailed in reference[14].For each image, the parameters of the adaptive transformation are given in Table 2 and the quantitative results of the enhancement are shown in Table 3. Visual inspection shows that the enhanced images in figure 2 (d) are more prominent with clear details and more visual clarity compared to the ROIs found in the second step figure 2 (c).Also, they are faithful to the original ROIs as far as brightness is concerned. The quantitative results showed in the Table 4prove the results of the subjective evaluation. Indeed, the local contrast which is evaluated by the parameter EME is increased from an average of 5.437 to 6.583 for all the ROI. The EC parameter is increased from the average of 1.277 to 2.104 for all the ROIs which indicate a better sharpness of edges. On the other hand, the brightness and the information

of original ROI are well conserved because the AMBE parameter is too low its mean is 0.646, and the FSIM parameter is maintained high close to unity, its mean is 96.45% for all the ROIs.

Table 2: Decision vectors for the tested images

image	NBH	NBV	B	α	β
Mdb010	73	79	9.378	0.482	0.001
Mdb028	73	71	7.626	0.532	0.0005
Mdb134	70	70	6.475	0.633	0.004
Mdb184	71	70	9.193	0.580	0.0008
Mdb271	71	88	8.183	0.582	0.0005

Table 3: Quantitative Results of all tested mammogram

image	EME		EC		AMBE	FSIM
	ROI(c)	ROI(d)	ROI(c)	ROI(d)		
Mdb010	6.991	8.252	0.958	1.575	0.283	98.35%
Mdb028	5.651	6.830	1.143	1.830	0.314	97.45%
Mdb134	5.152	6.187	1.855	3.117	0.735	94.57%
Mdb184	4.752	6.038	1.245	2.068	1.036	96.62%
Mdb271	4.641	5.606	1.187	1.929	0.865	97.17%
mean	5.437	6.583	1.277	2.104	0.646	96.45%

4.3. ROI Segmentation

The fourth step in this study is the segmentation which allows identifying the suspicious area in the ROI. K-means clustering algorithm combined with a genetic algorithm is the used method in this work according to the algorithm 4. The objective is to find adequate centroids to achieve good segmentation. Table 4 shows the found grayscale centroids for each mammogram. Table 5 shows the spatial coordinates of the center of abnormality as well as the radius of the circle enclosing it (in pixels). The coordinate system origin is the bottom-left corner of the image. Table 6 shows the errors concerning the radii of the abnormalities as well as those of the coordinates of the centers found with the simulation compared to their values provided in the mini-MIAS database[40]. The quantitative and qualitative results show the accuracy of the proposed method in terms of tumors detection in all tested images. Indeed, subjective evaluation from figure 2(e) shows that the algorithm can automatically extract the suspicious area in each mammogram image in a very efficient manner. This can be justified by the quantitative results found. Indeed, Table 5 shows that each ROI has its gray-level centroids. The centroid of the first cluster corresponding to the background is nearly the same for all the ROI (the grayscale 9); the second and the third clusters corresponding respectively to the adipose and fibroglandular tissues are varying from an ROI to another. This shows the difficulty of initializing the K-means algorithm's centroids and justifies the use of the genetic algorithm to look for adequate centroids. The exploitation of these centroids in the segmentation process allows extracting the tumors correctly. The results of Table 6 shows that the experimental founding coordinates and radii of the tumors are closer to their real values provided in

the mini-MIAS database. Indeed, the results of Table 7 shows that the most important error concerning the Abscissa of tumors is 2 pixels for the ROI of the image mdb010, while the one concerning the ordinate is the 5 pixels for the ROI of the image mdb028. For the radii, the highest error is 4 pixels for the two ROIs of the images mdb028 and mdb277. Finally, according to the ROI size which is 1024×1024 pixels, the experimental errors of simulation didn't exceed 0.48% of the size, it can be concluded that the proposed method is very accurate in terms of the automation of the suspicious area extraction from the mammogram images.

Table 4: The abnormality's Centroid(gray-level)

image	μ_1	μ_2	μ_3
Mdb010	9	112	246
Mdb028	9	144	235
Mdb134	9	100	136
Mdb184	8	112	246
Mdb271	9	115	242

Table 5: Coordinates and radius of the abnormality (pixel)

image	x	y	R
Mdb010	523	426	35
Mdb028	337	319	52
Mdb134	469	727	47
Mdb184	352	628	111
Mdb271	784	267	64

Table 6: Relative error to the information provided with the database (pixel)

image	$ x - x_c $	$ y - y_c $	$ R - R_t $
Mdb010	2	1	2
Mdb028	1	5	4
Mdb134	0	1	2
Mdb184	0	4	3
Mdb271	0	3	4

5. CONCLUSION

This paper presents an automatic extraction of suspicious areas in mammograms. This operation is crucial for the accuracy of a breast cancer diagnosis. The method consists of removing the radiopaque artifacts using the segmentation based on the global thresholding algorithm, followed by the suppression of pectoral muscle using the segmentation based on the seeded region growing method. The ROI found is enhanced using a technique named "Adaptive Local Gray Level Transformation based on Variable S-curve for Contrast Enhancement of Mammogram Images". Finally, The enhanced image is segmented using an improved version of the k-means algorithm. The genetic algorithm is used to look for the adequate centroids that will achieve good partitioning. Simulation results show the effectiveness of the proposed method in terms of accuracy of abnormality extraction. In future work, we will continue the automatic classification process by extracting the features and finally predicting the severity of the lesions using a classifier

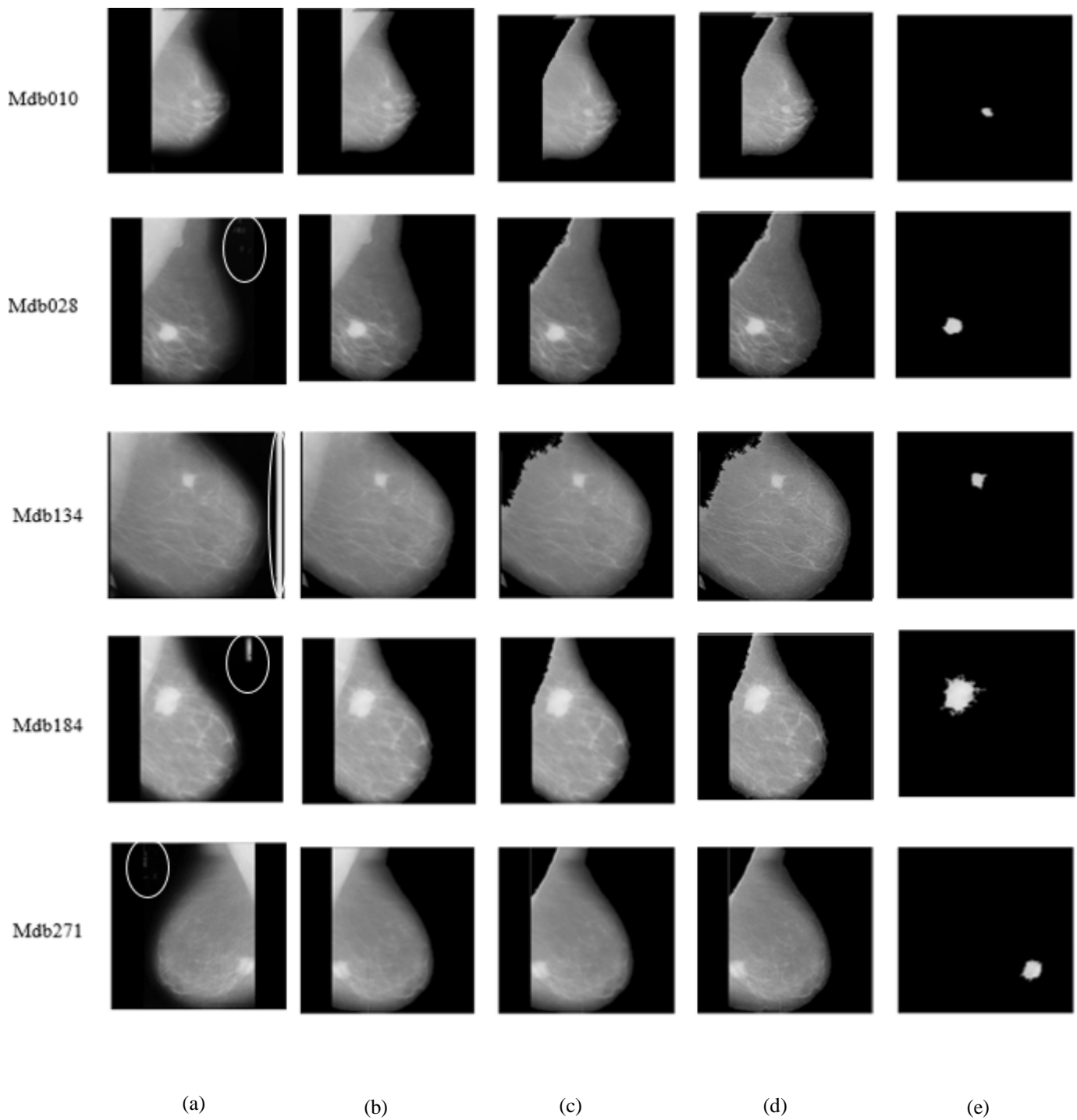


Figure 2: (a) Original image, (b) oriented image and artifacts suppression, (c) Pectoral muscle elimination, (d) ROI enhancement, (e) Tumor detection.

REFERENCES

1. World Helth Organization, “**CANCER TODAY**,” 2020. [Online]. Available: www.cancer.gov/. [Accessed: 06-Jul-2020].
2. K. Akila, L. S. Jayashree, and A. Vasuki, “**Mammographic Image Enhancement Using Indirect Contrast Enhancement Techniques A Comparative Study**,” *Procedia Comput. Sci.*, vol. 47, pp. 255–261, 2015.
3. A. Jalalian *et al.*, “**FOUNDATION AND METHODOLOGIES IN COMPUTER-AIDED DIAGNOSIS SYSTEMS FOR BREAST CANCER DETECTION**,” *EXCLI J.*, vol. 16, pp. 113–137, 2017.
4. A. Jain, S. Singh, and V. Bhateja, “**A robust approach for denoising and enhancement of mammographic images contaminated with high density impulse noise**,” *Int. J. Conver. Comput.*, vol. 1, no. 1, p. 38, 2013.
5. K. Panetta, A. Samani, and S. Agaian, “**Choosing the Optimal Spatial Domain Measure of Enhancement for Mammogram Images**,” *Int. J. Biomed. Imaging*, vol. 2014, pp. 1–8, 2014.
6. J. Dheeba, N. Albert Singh, and S. Tamil Selvi, “**Computer-aided detection of breast cancer on mammograms: A swarm intelligence optimized wavelet neural network approach**,” *J. Biomed. Inform.*, vol. 49, pp. 45–52, 2014.
7. M. J. G. Calas, B. Gutfilen, and W. C. de A. Pereira, “**cad and mammography: Why use this tool?**,” *Radiol. Bras.*, vol. 45, no. 1, pp. 46–52, 2012.
8. A. S. Dhas and V. Vijikala, “**An improved CAD system for abnormal mammogram image classification using SVM with linear kernel**,” vol. 28, no. 12, pp. 5499–5505, 2017.
9. B. Vikrant *et al.*, *Haralick Features-Based Classification of Mammograms Using SVM*, vol. 1. Springer Nature Singapore Pte Ltd. Information Systems Design and Intelligent , pp 787-795, 2018.
10. R. Rabidas, A. Midya, J. Chakraborty, and W. Arif, “**A Study of Different Texture Features Based on Local Operator for Benign-malignant Mass Classification**,” *Procedia Comput. Sci.*, vol. 93, no. September, pp. 389–395, 2016.
11. Y. Ben Youssef, E. Abdelmounim, B. Abdelaziz, M. boujjida “**TEXTURE PATTERN IN ABNORMAL MAMMOGRAMS CLASSIFICATION USING SUPERVISED MACHINE**,” *J. Theor. Appl. Inf. Technol.*, vol. 95, no. 17, pp. 4059–4068, 2017.
12. Y. Ben Youssef, E. Abdelmounim, and B. Abdelaziz, “**Mammogram Classification Using Support Vector Machine**,” IGI Global, *Handbook of Research on Advanced Trends in Microwave and Communication Engineering*.
13. M. Mustra, M. Grgic, and R. M. Rangayyan, “**Review of recent advances in segmentation of the breast boundary and the pectoral muscle in mammograms**,” *Med. Biol. Eng. Comput.*, vol. 54, no. 7, pp. 1003–1024, 2016.
14. H. El malali, A. Assir, M. Harmouchi, M. Rattal, A. Lyazidi, and A. Mouhsen, “**Adaptive Local Gray Level Transformation based on Variable S-curve for Contrast Enhancement of Mammogram Images**,” in *Embedded Systems and Artificial Intelligence*, 2020, vol. 1076, pp. 671–679.
15. S. Z. Ramadan, “**Methods Used in Computer-Aided Diagnosis for Breast Cancer Detection Using Mammograms: A Review**,” *J. Healthc. Eng.*, vol. 2020, 2020.
16. Z. Sha, L. Hu, and B. D. Rouyendegh, “**Deep learning and optimization algorithms for automatic breast cancer detection**,” *Int. J. Imaging Syst. Technol.*, no. January, pp. 1–12, 2020.
17. W. E. Fathy and A. S. Ghoneim, “**A deep learning approach for breast cancer mass detection**,” *Int. J. Adv. Comput. Sci. Appl.*, vol. 10, no. 1, pp. 175–182, 2019.
18. H. Behzadi-khormouji *et al.*, “**Deep learning, reusable and problem-based architectures for detection of consolidation on chest X-ray images**,” *Comput. Methods Programs Biomed.*, vol. 185, p. 105162, 2020.
19. D. A. Spak, J. S. Plaxco, L. Santiago, M. J. Dryden, and B. E. Dogan, “**BI-RADS® fifth edition: A summary of changes**,” *Diagn. Interv. Imaging*, vol. 98, no. 3, pp. 179–190, 2017.
20. Z. Yao, “**Image Enhancement Based on Bi-Histogram Equalization with Non-parametric Modified Technology**,” *IEEE 22nd int conf Parallel and Distributed Systems*, 2016.
21. J. V.L and R. Gopikakumari, “**IEM: A New Image Enhancement Metric for Contrast and Sharpness Measurements**,” *Int compt appvol.* 79, no. 9, pp. 1–9, 2013.
22. S. Gupta and R. Porwal, “**Appropriate Contrast Enhancement Measures for Brain and Breast Cancer Images**,” *Int J Bio Imaging*, no. 1, 2016.
23. A. Gandhamal, S. Talbar, S. Gajre, A. F. M. Hani, and D. Kumar, “**Local gray level S-curve transformation -- A generalized contrast enhancement technique for medical images**,” in *Computers in Biology and Medicine*, vol. 83, pp. 120–133, 2017.
24. R. C. Gonzalez and R. E. Woods, *gonzales-r-c-woods-r-e-digital-image-processing-2ed-pr entice-hall-2002.pdf*. 2002.
25. X. M. and D. Z. Lin Zhang, Lei Zhang, “**Correspondence FSIM: A Feature Similarity Index for Image**,” *IEEE Trans. IMAGE Process.*, vol. 20, no. 8, pp. 2378–2386,

- 2011.
26. S. Mokri, M. Saripan, A. Nordin, M. Hamiruce N, Zulkarnain, “**Level Set Based Whole Heart Segmentation in Non-Contrast Enhanced CT Images,**” *Int. J. Adv. Trends Comput. Sci. Eng.* vol. 8, no. 3, pp. 39–45, 2019.
 27. M. sadat Fasihi and W. B. Mikhael, “**Overview of current biomedical image segmentation methods,**” *2016 Int. Conf. Comput. Sci. Comput. Intell.*, pp. 803–808, 2016.
 28. A. Norouzi *et al.*, “**Medical Image Segmentation Methods, Algorithms, and Applications,**” *IETE Tech. Rev.*, vol. 31, no. 3, pp. 199–213, 2014.
 29. N. S. Ali Ibrahim, N. F. Soliman, M. Abdallah, and F. E. A. El-Samie, “**An algorithm for pre-processing and segmentation of mammogram images,**” *Proc. 2016 11th Int. Conf. Comput. Eng. Syst. ICCES 2016*, pp. 187–190, 2017.
 30. A. H. A. H. Ayoppan, M. F. Ibrahim, and M. H. Mohd Zaman, “**A genetic algorithm with online learning approach for improving loop closure detection of a visual SLAM,**” *Int. J. Adv. Trends Comput. Sci. Eng.*, vol. 8, no. 1.6 Special Issue, pp. 159–166, 2019.
 31. C. M. Anderson-Cook, *Practical Genetic Algorithms (2nd ed.): Randy L. Haupt and Sue Ellen Haupt*, vol. 100, 2005.
 32. P. Hoseini and M. G. Shayesteh, “**Efficient contrast enhancement of images using hybrid ant colony optimisation , genetic algorithm , and simulated annealing,**” *Digit. Signal Process.*, vol. 23, no. 3, pp. 879–893, 2013.
 33. M. Karnan and K. Thangavel, “**Automatic detection of the breast border and nipple position on digital mammograms using genetic algorithm for asymmetry approach to detection of microcalcifications,**” *Comput. Methods Programs Biomed.*, vol. 87, no. 1, pp. 12–20, 2007.
 34. J. Nagi, S. A. Kareem, F. Nagi, and S. K. Ahmed, “**Detection Using Digital Mammograms,**” *IEEE EMBS Conf. Biomed. Eng. Sci.*, no. December, pp. 87–92, 2010.
 35. V. Chaurasia and C. Agarwal, “**A Survey Of K-Means And GA-KM The Hybrid Clustering Algorithm,**” *Int. J. Sci. Technol. Res.*, vol. 3, no. 6, pp. 119–122, 2014.
 36. N. Dhanachandra, K. Mangleam, and Y. J. Chanu, “**Image Segmentation Using K-means Clustering Algorithm and Subtractive Clustering Algorithm,**” *Procedia Comput. Sci.*, vol. 54, pp. 764–771, 2015.
 37. H. El malali, A. Assir, M. Harmouchi, A. Lyazidi, and A. Mouhsen, “**Fully Automatic Computer Aided Detection of Breast Cancer based on Genetic Algorithm Optimization.**” *IEEE 1st ERASET*, 2020.
 38. J. A. Rosado-Toro *et al.*, “**Automated Breast Segmentation of Fat and Water MR Images Using Dynamic Programming,**” *Acad. Radiol.*, vol. 22, no. 2, pp. 139–148, 2015.
 39. P. Juneja, E. J. Harris, and P. M. Evans, “**Investigation of the accuracy of breast tissue segmentation methods for the purpose of developing breast deformation models for use in adaptive radiotherapy,**” *J. Phys. Conf. Ser.*, vol. 489, no. 1, 2014.
 40. S. J *et al.*, “**The mini-MIAS database of mammograms,**” 1994. [Online]. Available: <http://peipa.essex.ac.uk/info/mias.html>. [Accessed: 01-Jan-2017].