Neurocomputing 599 (2024) 127937

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

FCM-DCS: **Fuzzy** C means distorted contour-based segmentation model for breast cancer detection

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A R T I C L E I N F O

Keywords:
Breast cancer tissues
Distorted contour
Fuzzy logic
Image processing
ROI detection
Segmentation

A B S T R A C T

Breast cancer (BC) is a commonly diagnosed cancer among women nowadays. The cancer cells in the breast tissues are known as BC. Comprehensive research on early-stage BC detection helped to increase the survival rate and reduce the amortality rate associated with this disease. Mammogram scan analysis is a commonly used breast tissue visualization method. This image data is analyzed adequately for accurate BC diagnosis. Region of interest (ROI) identification is crucial in an image-based BC detection system. The ROI detection helps to segment the cancer tissues from the mammogram images by analyzing the heterogeneity among cancerous and normal breast tissues. Early-stage BC issues have homogeneous features as normal breast tissues. So, it is an open challenge for the researchers to develop a more accurate segmentation method during the automatic BC stages detection system. This study introduced fuzzy C means (FCM) distorted contour-based segmentation (FCM DCS) method to address the real detection issues in present studies. It uses the distorted contour (DC) based method to identify the contour of the cancer tissue from mammogram images. The DC method is performed with the help of FCM to identify the cancer tissues. Moreover, a histogram and adaptive equalization method were utilized to reduce image noise and preserve the edge features. The result analysis shows that the FCM-DC methods achieved a maximum accuracy rate (98.76 %) than comparison methods in BC detection.

1. Introduction

Cancer [1] is one of the high causes of unusual death worldwide. It is a leading health issue faced by today's world. Cancer commonly has several types [2,3], defined by where it occurs in the body. Cancer is abnormal cell growth in a specific organ or part of the body. It has many types BC [4,5], brain tumor [6], skin cancer [7], cervical cancer [8], and etc. Among these, BC is one of the most commonly identified cancer nowadays. BC can occur usually in women and rarely in men as well. This cancer forms in the breast cells and begins to grow abnormally and is called BC. These cells divide more rapidly than healthy cells and continue to gather, forming a lump or mass. The cells may spread to the lymph nodes or other body parts. BC commonly begins with cells in invasive duct carcinoma or in the glandular tissues called invasive lobular carcinoma or other cells or tissues within the breast. The BC [9] is identified by some important symptoms in the affected patients, such as a lump in the breast, swelling of part of the breast, dimpling of breast skin, etc. These symptoms are visible from the outside. But this BC also occurs without the mentioned symptoms in the early stage [10]. So, it is essential to screen the BC to protect health. It can help to find it early when treatment is less invasive and easier to treat. Mammography is an X-ray method to diagnose BC when the cancer size is small to be felt. The doctor may recommend a diagnostic mammogram for further evaluation if an abnormality is detected. Mammogram [11] can find a cancerous lump before it can be felt. Other methods suggested for BC diagnosis are ultrasound, Biopsy, and MRI. Breast ultrasound [12] waves are used to produce images of structures deep within the body to determine new lump in the breast is a solid mass or a fluid-filled cyst. Biopsy [13] is used for removing a sample of breast tissue for diagnosis. Breast magnetic resonance imaging (MRI) [14] creates the structure of the breast's interior. Regular BC screening [15] helps to find the cancer occurrence early to treat it easier. The current screening methods also lead to an increase in false positive (FP) rates. This may lead to treatment; suppose the doctor starts treatment with a false cancer report (if a patient does not have any breast cancer, but due to the false mammogram results, the doctors start the BC treatments). It may unnecessarily increase the complications. False-negative (FN) results lead to delays in the treatment. Mammogram [16–18] is the trusted diagnosis method for BC

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https://doi.org/10.1016/j.neucom.2024.127937
Received 26 September 2023; Received in revised form 28 March 2024; Accepted 27 May 2024
Available online 12 June 2024
0925-2312/© 2024 Published by Elsevier B.V.

detection at an early stage. However, it also sometimes produces FP and FN results. So, it is a challenging research field for researchers to reduce the FP and FN rate during the early stage of BC to prevent the patient's life from overtreatment and delayed treatment, respectively. This study focuses on developing an accurate earlier-stage BC detection with lesser FP and FN rates. It performs the required image enhancement phase to deal with some elements of the confusing breast anatomy while segmenting the pectoral images. This has been done with a novel effective segmentation method by integrating the FCM segmentation with the distorted contour-based segmentation model by providing seed points by getting the threshold from the distorted contour-based segmentation.

This paper is organized as part 1 describes the BC, diagnosis methods, and needs of earlier detection methods. Part 2 describes the background studies on different BC strategies. Part 3 describes the different stages of early BC detection and evaluation results of the proposed study. Finally, the result conclusion is explained in BC detection.

The FCM-DCS model innovatively merges Fuzzy C Means with distorted contour-based segmentation for breast cancer detection. Tailored to address complexities in mammographic images, it offers potential in accurately identifying cancerous regions. Novel evaluation metrics and clinical relevance further underscore its significance for improving diagnostic accuracy and patient outcomes in breast cancer management.

Motivation for advancing breast cancer detection methodologies stems from the profound impact it has on patient outcomes and healthcare systems. Early detection significantly increases the chances of successful treatment and survival rates among breast cancer patients. By developing more accurate and efficient detection techniques, clinicians can diagnose breast cancer at earlier stages when treatment options are often less invasive and more effective. Improved detection methods also help reduce unnecessary procedures and healthcare costs associated with late-stage diagnoses. Furthermore, enhancing breast cancer detection contributes to ongoing efforts in personalized medicine, allowing for tailored treatment plans based on individual patient characteristics. Ultimately, the motivation lies in saving lives, improving quality of life for patients, and advancing the overall efficacy of breast cancer care.

The significance of the FCM-DCS (Fuzzy C Means Distorted Contour-based Segmentation) model for breast cancer detection lies in its potential to revolutionize early diagnosis and treatment of the disease. By merging fuzzy clustering with distorted contour-based segmentation, the model offers a novel approach to accurately identifying cancerous regions within mammographic images. Its adaptation to the specific challenges of breast cancer detection underscores its clinical relevance and potential impact on patient outcomes.

The major contribution of the FCM-DCS model lies in its potential to enhance diagnostic accuracy, facilitate early detection of breast cancer, and streamline the clinical workflow for radiologists and healthcare providers. By providing more precise delineation of cancerous regions within mammographic images, the model enables earlier intervention and more personalized treatment strategies, ultimately improving patient outcomes and reducing mortality rates associated with breast cancer. Additionally, the model's development of novel evaluation metrics and validation techniques contributes to the broader field of medical imaging research, fostering innovation and paving the way for future advancements in computer-aided diagnosis and image analysis.

2. Background study

This section discusses some of the author's contributions to BC detection. Cell cluster formation often leads to malignant-cancerous or benign-harmless breast tissue abnormalities. Consequently, breast tissue abnormalities are represented as regions that vary from normal tissue. Early detection is crucial for preventing future problems.

Thyagarajan R et al. [19] developed a radionics feature extraction-based technique for extracting the most feature and training machines with relevant features using deep learning (DL) models to predict BC response to therapy. The authors proved that Radiomics could offer expected results based on present technology. However, the dataset in this area needs to be revised to validate the suggested strategy.

Varma C et al. [20] developed a BC diagnosis framework in Anaconda Navigator. It comprises four ML algorithms, such as Logistic Regression (LR), Support Vector Machine (SVM), K-nearest neighbour (KNN), and Naive Bayes (NB), to accomplish the performance analysis.

Amkrane Y et al. [21] developed a breast segmentation method utilizing the watershed transform technique. But this method's segmentation results provide poor results while identifying the ROI squeezed by a coloured region. The segmentation approach achieves a maximum of 88.65 % accuracy in detecting cancer.

Kumar N et al. [22] utilized thermographic images to detect BC using a deep neural network. The study featured four deep-learning networks, with the ResNet50 network scoring the highest at 88.89 %. There needs to be more study on utilizing thermal imaging to detect BC. The majority of the research in the literature has been on generic segmentation.

Khasana S et al. [23] developed a novel method for automatically identifying masses in mammography images. This study uses the Fuzzy C Means (FCM) approach to segment the tumours from the ROI. The evaluation results show that the FCM segmented the BC region with reliable accuracy.

Kiymet S et al. [24], Applied to separate cancer areas correctly and provide distinct pictures with crisp boundaries and excellent segmentation results. The concept is essential, and just a few seed points are necessary to convey the authors' intended characteristics. Concurrently, seed locations and other conditions for area growth are defined. The Harris corner recognition algorithm and the cloud technique performed well on mammography picture mdb218. The results show that our system can locate both the nibbling point and the cancer site (Calcification). It also uses selective median filtering and CLAHE to diagnose BC and has a 93 % accuracy rate.

Seleck M et al. [25] initiated a BC detection method to reduce mortality. It utilizes thermography to conduct painless and cost-effective screening to detect BC at an early stage. It allows one to seek further diagnostic testing only whenever it is required. It helps to avoid unnecessary and painful mammography screening. Even though mammography is extensively used for BC screening, the researchers discovered a substantial false-positive rate. Therefore, a biopsy must be done to confirm the cancer's presence to avoid the FP rate using the mammogram. Consequently, this finding suggests that frequent pre-mammography and post-mammography screening be incorporated to improve women's health outcomes.

Table 1 compares the accuracy percentage and False Positive rate (FPR) with various existing authors' methods and the proposed FCM-DCS method. Consequently, the studies discussed in this section clearly distinguish various methodologies to detect benign tumours in the image for an early examination and their challenges. The mammogram image analysis approaches to analyze the characteristics of cancer tissues, texture and morphological differences in specific regions using cluster analysis methods. This method assists in identifying, analyzing, categorizing, and eliminating the malignant region. However, these steps are only utilized by some researchers, which is concentrated in this research.

Some background studies identified that the researchers concentrated on diagnosing BC. The effects can be capable of using segmentation without focusing on changes in the structure of breast cancer tissues. So, these issues in the previous studies are addressed in this study by adopting the image enhancement technique by developing an effective segmentation method. Reducing FP and FN rates is the open challenge for the BC detection analysis. So, this study introduces fuzzy C means (FCM) distorted contour-based segmentation (FCM DCS) method to address the real detection issues in present studies. It uses the distorted contour (DC) based method to identify the contour of the cancer tissue from mammogram images. The DC method is performed with the help of FCM to identify the cancer tissues. Moreover, a histogram and

Table 1
Performance analysis of some of the effective segmentation methods.

Related work	Author's Contribution	Limitations	Dataset	Acc	FPRR
H Li et al., [26]	Developed a robust texture feature descriptor. The detailed textural features are extracted using more Rotation invariants with different concerned numbers of spatial transitions applied to extend the local quandary pattern.	Need to support classification model in achieving reliable accuracy rate.	MIAS	80.30 %	0.45 %
H Soleimani et al., [27]	Data-driven prediction and graph-based image analysis method is introduced for	Still, some elements of breast anatomy are confusing while segmenting the pectoral images	MIAS	97 %	0.16 %
H. Ture [28]	A rule-based contour detection method is introduced to segment patterned isocontours.	Due to the overlapping tissue in radiography, some medical images' tissue masses remain blurred or invisible.	MIAS	92 %	1.26 %
Teixeira F et al., [29]	Prepared performance analysis of various ML models on BC data.	Need improvements in prediction and testing approaches in databases containing images.	DDSM	73.9 %	6.9 %

adaptive equalization method were utilized to reduce image noise and preserve the edge features. It reduces the FP and FN rates.

A notable research gap in breast cancer detection pertains to the need for more accurate and robust segmentation methods, particularly in early-stage detection systems. Despite advancements, existing techniques often struggle to effectively differentiate between cancerous and normal breast tissues due to their heterogeneous nature. This challenge is exacerbated by the homogeneous features exhibited by early-stage breast cancer, making it difficult to achieve precise segmentation. Consequently, there is a pressing need for innovative segmentation approaches capable of accurately delineating cancerous regions from mammogram images with higher sensitivity and specificity. Addressing this gap is crucial for improving the reliability and effectiveness of automated breast cancer detection systems, ultimately leading to earlier diagnosis and better patient outcomes.

The FCM-DCS model include its innovative integration of Fuzzy C Means clustering with distorted contour-based segmentation techniques, tailored to address the heterogeneous nature of breast tissue and the complexities of early-stage breast cancer. The model's reliance on advanced image analysis methodologies and its focus on improving segmentation accuracy and efficiency set it apart from traditional approaches to breast cancer detection.

3. Methodologies of FCM-DCS: fuzzy C means distorted contour-based segmentation approach for breast cancer detection

This section discusses the methodologies adopted in this study to detect BC tissues using mammogram images. It contains three main stages; image acquisition, image preprocessing using noise suppression and enhancement, and BC detection using the FCM-DCS method.

The proposed FCM-DCS method has three stages Noise removal, segmentation, and performance analysis, as shown in Fig. 1. It shows the overall flow structure with algorithm details.

3.1. Data sources

The performance and efficiency of the proposed method are evaluated using two mammography image datasets. It is taken from Kaggle repositories; the images with a 6.3 GB memory size [30] and 442 MB memory size of the dataset [31] are two different datasets utilized in this study. The Digital Database for Screening Mammography (DDSM) has been modernized with the CBIS-DDSM (Curated Breast Imaging Subset of DDSM). Two thousand six hundred twenty digitized film mammograms from across the globe are stored in the DDSM database. It comprises ailments scientifically shown to exist, such as benign and malignant conditions. The DDSM is a helpful tool for developing and

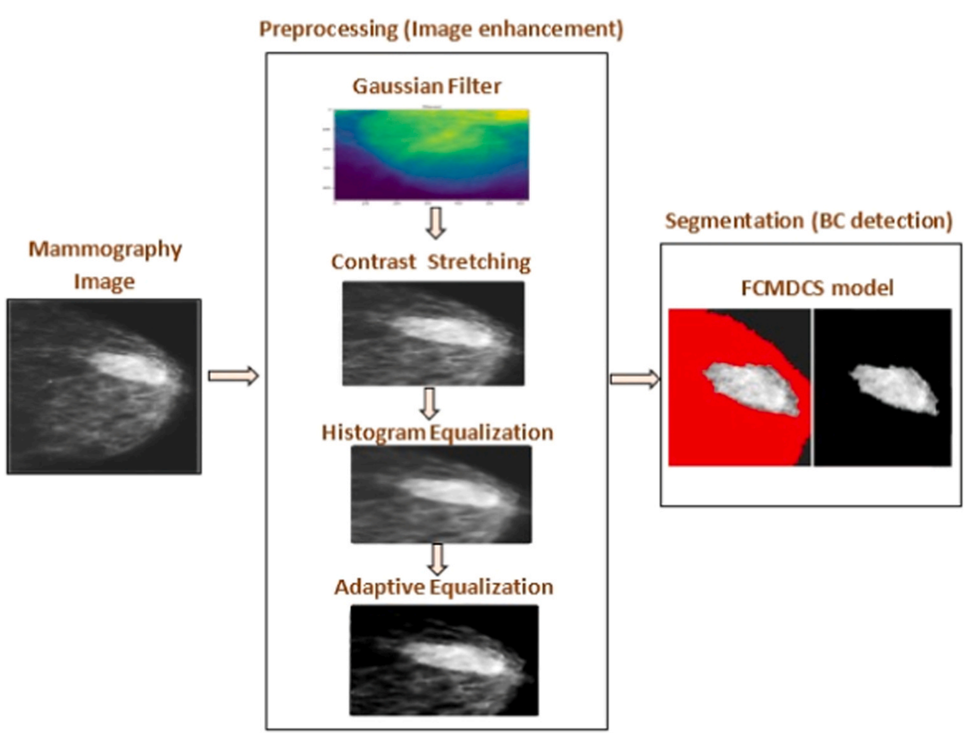

Fig. 1. FCM-DCS-based BC detection system.

testing decision support systems due to its vast database and validation against the ground truth. CBIS-DDSM is a data set chosen and curated for CBIS-DDSM by a skilled mammographer. The mammography images for this investigation are taken from MIAS and the DDSM Mammography Kaggle dataset. The original MIAS Database (digitized with a 50-micron pixel edge) has been reduced to a 200-micron pixel and clipped/padded to 1024 × 1024 pixels, containing 575 photos. The proposed model has been evaluated with these datasets. Fig. 2 shows the gallery's samples from the MIAS dataset images of BC mammograms.

Fig. 2 shows a sample input mammography image taken from the Kaggle as mentioned earlier data source.

3.2. Noise removal

Mammography enhancement essentially improves contrast, especially in prominent breasts. Mammography can differentiate between malignant and normal thick tissue, but only below the human eyesight threshold. Similarly, microcalcifications may need to be seen in a thick enough concentration. As a result, defining the characteristics of microcalcifications is challenging. Conventional image processing techniques could perform better on mammographic images. Traditional fixed neighbourhood techniques, such as un-sharp masking, are less effective owing to feature size and shape changes. Fixed or global techniques may respond to local features within a neighbourhood, but it does not change the size of the neighbourhood to account for local issues.

Histogram equalization improves the contrast of a Mammography scan for breast cancer compared to a non-equalized histogram. As a result, it may do this by effectively spacing out the most common intensity values in the BC Mammography image's intensity spectrum. When the relevant data is provided as near-contrast values, this method often improves the overall contrast of photos. As previously stated, this enhances contrast when local contrast is poor. To improve visual contrast, AHE (adaptive histogram equalization) is used in computer image processing. It performs well when local contrast and edge clarity are critical, such as individual picture parts. One of the algorithm's key goals is to reduce noise while keeping excellent image quality.

Pseudo code for noise removal
Input: Input the mammogram image
Step 1: Initialise landmark points *//Points must be near the boundary*
Step 2: Utilize Gaussian smoothing kernel
Step 3: Apply Gaussian blur image and Generate Gradient magnitude.
Step 4: For every point change, Estimate the average distance (ave_D) **Step 5:** Calculate $(E_C, E_{Cur} and E_{img})$ for each neighbour.
Step 6: Normalize Points.
Step 7: Change the position of entire points to new positions.
Output: Filtered and smoothened images

Fig. 3 depicts the original picture with a filtered mammography image. After the noise removal stage, the input image filters for segmentation. The output for the filtered image is shown in Fig. 3.

Fig. 4 illustrates the resultant images of preprocessing stages using low contrast and contrast stretching, histogram equalization and adaptive equalization, respectively. In this, the resultant of Gaussian smoothing is considered the low contrast image to enhance the image. Initially, contrast stretching is applied to stretch the range of the intensity values. Next, the resulting images are utilized to apply the histogram equalization method to normalize the pixel intensity of the input contrast stretched image. Finally, adaptive equalization is adopted to improve the local contrast of the mammogram and define the edges of the image. It computes several histograms to select the local contrast. The resultant image is utilized for the segment and detects the BC.

3.3. Fuzzy C means distorted contour-based segmentation (FCMDCS)

FCM-DCS contains advantages in various image segmentation applications and image registration applications. The main challenge in FCM is finding corresponding pixels in a congested environment. There have been several recommendations for modifying FCM to various segment elements; however, many have difficulties that must be solved. FCMs may be located in a particular domain, and their curves or surfaces change in response to internal and external influences. Internal and external stresses on a model may lead the border of an object or other desired visual components to cling together. Preliminary shape information is often used to improve medical picture segmentation models, which is very successful. Particular difficulties may be well matched to the restrictions supplied by global shape knowledge when organs or structures have stable shapes and are correctly characterized by a particular shape model. More broad constraints are necessary for increasingly complex cases, such as buildings with rapidly altering or no fixed shape. The shortcomings in the FCM are reduced in this research with the help of Distorted Contour. This section discusses the functionalities of the FCMDCS model in detail. It is an efficient pixel classification method and permits a part of pixels belonging to two or more clustering centres with a membership value.

$$O_{FCM} = (A, B, Z) = \sum_{i=1}^{N} \sum_{j=1}^{c} a_{i,j}^{m} \quad d^2(z_i, \quad b_j), \quad 1 < m < \infty \tag{1}$$

The Eq. (1) minimizes the objective function (OF). In this, m denotes the blur exponent. The image vector($Z = \{z_1, z_2, \ldots, z_N \}$) comprises N pixels. The vector for the cluster centre is represented as $B = \{b_1, b_2, \ldots, b_c\}$. Euclidean distance $d^2(z_i, b_i)$ is the formula for the computed distance between the object z_i And jth cluster centre. The standard FCM algorithm fuzzy membership is assigned to each pixel in a cluster $z_{i,j}^m$. The degree of memberships.

$$0 \le a_{i,j} \le 1 \sum_{j=1}^{N} a_{i,j} = 1, \sum_{i=1}^{N} a_{i,j} \le N, \ i = 1, 2, \ldots, N \ j = 1, 2, \ldots, c \tag{2}$$

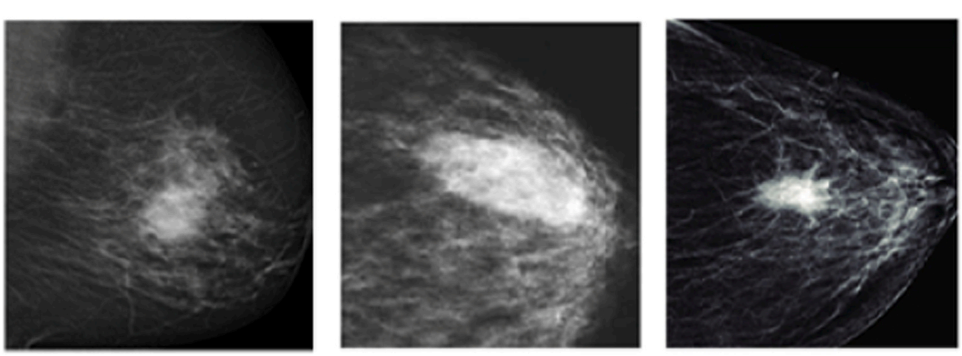

Fig. 2. Sample Mammography images.

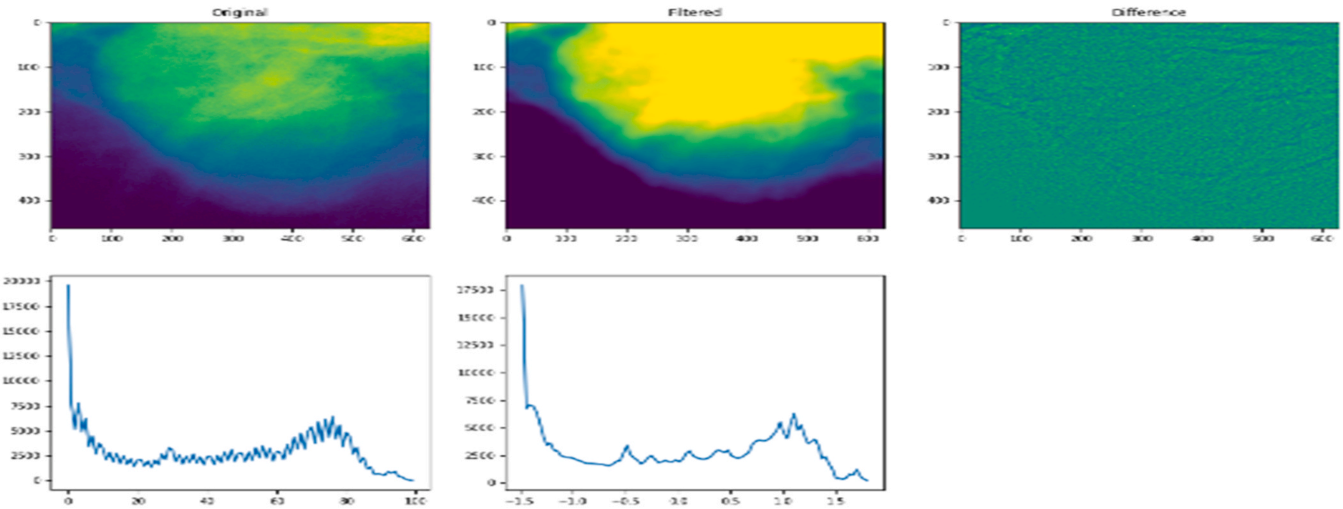

Fig. 3. Differentiations Original Filtered Image.

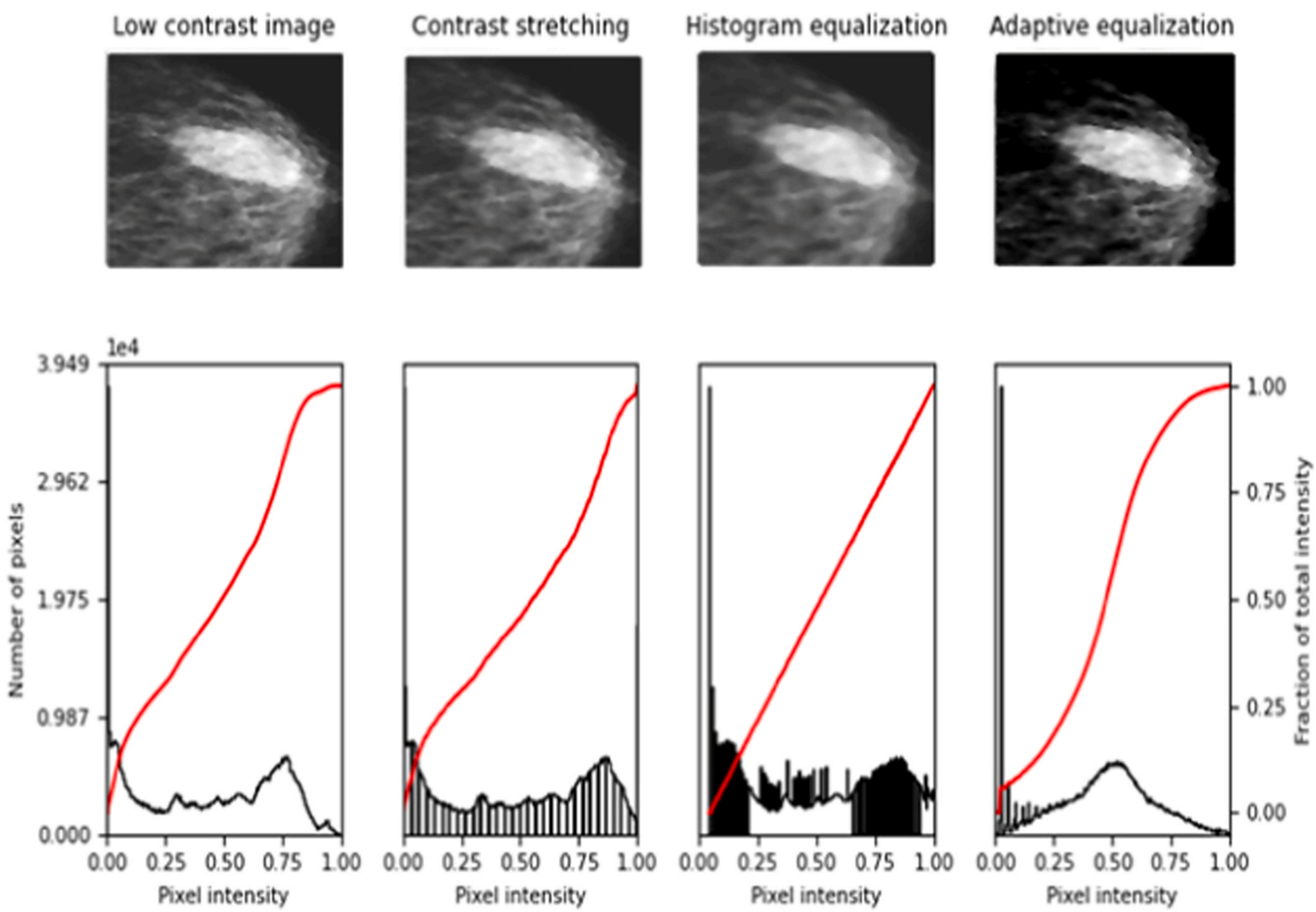

Fig. 4. Intensity graph of each preprocessing stage for a sample mammogram image.

The degree of membership satisfies the need to satisfy the rules mentioned in the Eq.(2). The cluster centres and membership degrees are constantly updated for each iterative process. Whenever the membership degree is updated, the value of OF must be closer to the minimum.

$$a_{i,j} = \frac{1}{\sum_{i=1}^{c} \left(\frac{dist_{i,j}}{dist_{i,k}}\right)^{\frac{2}{m-1}}} \tag{3}$$

$$b_j = \frac{\sum_{i=1}^{N} a_{ij}^m . z_i}{\sum_{i=1}^{N} a_{ij}^m} \tag{4}$$

The membership matrix $a_{i,j}$, and the cluster centres b_j are updated using Eq. (3) and Eq.(4). The membership of the image cannot reflect the nature of the subordinate centre in a noisy environment. To overcome the shortcomings of the FCM algorithm, it can use the location information of the pixel intensity. To reduce the negative impact of the noise on the membership calculation.

$$\begin{cases} dist_{i,j,p}^1 = \gamma_p^1 Max(0, b_{j,p}^1 - z_{i,p}^3) \\ d_{i,j,p}^2 = \gamma_p^2 \left| b_{j,p}^2 - z_{i,p}^2 \right| \\ dist_{i,j,p}^3 = \gamma_p^3 Max(b_{j,p}^3 - z_{i,p}^3, \quad z_{i,p}^3 - b_{j,p}^1) \end{cases} \tag{5}$$

The parameters γ_p^1 is a weighted coefficient of the distance measure $(dist_{i,j,p}^k)$, $\gamma_p^i \geq 0, i = 1, 2, 3 and\ p = 1, 2.$

$$dist_{i,j} = (dist_{i,j,1}^1, \quad dist_{i,j,1}^2, \quad dist_{i,j,1}^3, dist_{i,j,2}^1, dist_{i,j,2}^2, \quad dist_{i,j,2}^3) \tag{6}$$

If the parameter $\lambda_i = 1$, the fuzzy distance measure is expressed as in Eq. (6).

$$a_{i,j} = \frac{1}{\sum_{i=1}^{c} \left(\frac{\sum_{p=1}^{2} \sum_{k=1}^{3} dist_{i,j,p}^k}{\sum_{p=1}^{2} \sum_{k=1}^{3} dist_{i,j,p}^k} \right)^{\frac{1}{m-1}}} \quad k = 1, 2, \ldots.., c \tag{7}$$

$$b_j = \frac{\sum_{i=1}^{N} a_{ij}^m . \quad z_{i,p}^k}{\sum_{i=1}^{N} a_{ij}^m} \tag{8}$$

The membership matrix and clustering centre vector in Eq. (3) and Eq. (4) are optimized by using multiple objects in the local region of the pixel to retain the nature of the textural information in the mammogram using the Eq. (7) and Eq. (8) respectively.

The local intensity is essential for accurate segmentation, but the FCM must improve handling inappropriate borders and intensity. So, the Distorted Contour (DC) method is combined with the FCM to overcome the drawbacks in the FCM segmentation model.

The image segmentation was performed using the picture contours provided by coarse segmentation. Fine-segmented nuclei are evaluated for potential areas of interest during fine segmentation. By examining the region characteristics, such as the region area and the average area across all segmented areas, as well as eccentricity and the region diameter-to-perimeter ratio, it can identify the crossing contours with a large number of intersecting objects. Segmentation of the DCS starts with uneven borders due to the inhomogeneous intensity distribution inside the initial outlines. It is used in local image data of the DCS model to compensate.

$$\in 1 = \xi c(A(I) - I - d1\ )2.dc + \zeta c(DCS)) \tag{9}$$

In Eq. (9), the A(I) is an average filter, and d is represented the intensity averages of the different images. The contour denotes C.

Fig. 5 illustrates the segmentation results of the FCM-DCS model. The FCM is used to segment similar features from the mammogram images. The FCM segmented pixels' groups are considered the input to the DC segmented to segment the un-sharp edges. The proposed method comprises a mark deemed noise, maintained by minimizing the information

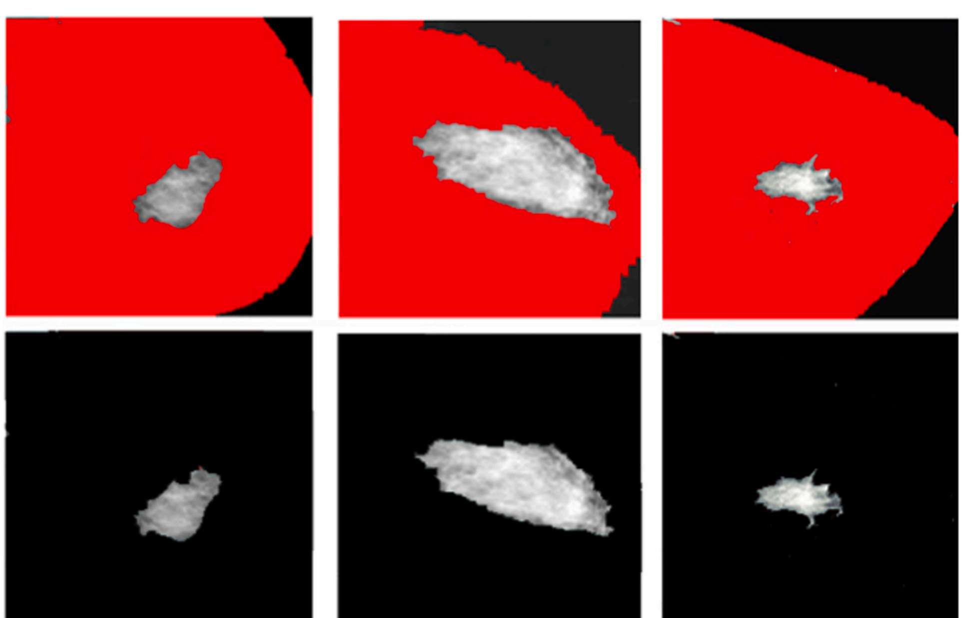

Fig. 5. Segmented FCM-DCS.

necessary to operate. The step-by-step proposed FCM-DCS Breast cancer detection process is explained in the following algorithm.

Algorithm. : FCM-DCS-based BC detection.

Input: Initialize the image set Z and the threshold ε ;

Output: segmented breast cancer tissue image

Step 1: $X = \{z_{i,j},\ \ i = 1,2,\dots,m \quad j = 1,2,\dots n\}$ // $m \times n$ size of the input image matrix

Step 2: $A = \{a_{i,j}\}$ *// membership function*

Step 3: Compute the centre vector

$$v_j = \frac{\sum_{i=1}^{N} a_{ij}^{m} . z_{i,p}^{k}}{\sum_{i=1}^{N} a_{ij}^{m}}$$

Step 4: Use Eqn (5) and Eqn (6) to Compute Fuzzy distance.

Step 5: $A' = \{a'_{i,j}\}$ *// Update membership function*

Step 6: If $\|A' - A\| < \varepsilon$ than

stop

Else

$A = A'$

Return to step 3.

Step 7: Reframe the new BC // Use Image matrix Z and membership function U to reframe segmented image Z'.

Step 8: Call DCS function *// Give landmark point to start (point should be close to boundary) from* Z'

Step 9: Generate gradient magnitude for each mammogram image.

Step 10: Point modification stage

Step 11: Point normalisations

Step 12: if points > threshold point

Move the point to form a new output matrix. *// Detected BC tissues.*

Output: Detected lesion region of the BC cancer tissues

The FCM-DCS model uses preprocessed images as input to perform BC detection. The image and the threshold value are initialized to compute the threshold, the number of segments and the membership function. Then, it randomly computes the cluster centre. Compute distance among each pixel intensity with cluster centre. Each cluster has one cluster centre, and the fuzzy membership function normalizes the pixel intensity to improve the local intensity pixels' quality. It updates the cluster centre and the position of all pixels in each iteration. The segmented pixels with improper edges reduce the segmentation accuracy. So, in this study, the DCS method is applied to the resultant matrix to segregate the cancer tissues. The performance of the proposed BC detection method is discussed in the subsequent section.

4. Performance analysis

The FCM-DCS is developed in Python version 3.8. The mammography imaging data sets from CBIS-DDSM and MIAS BC database are analyzed (The data source information is given in the previous section). The performance of the FCM-DCS model is compared with the performance-wise best two segmentation models, such as the ROI [24] based method and the Deformable model [28]. The proficiency of the FCM-DCS is assessed using accuracy, Signal to mean square error (SMSE), FP prediction rate, and FN prediction rate.

$$SignaltoMeanSquareError = \frac{(S_i - S_i')}{n} \tag{10}$$

The segmentation error is estimated using the SMSE in Eq. (10). It is stated and measured in decibels (dB). The 'S_i'is indicates the 'i'th pixel in

Table 2
SMSE.

Number of Mammography cancer images	SMSE (dB)		
	ROI based segmentation	Deformable model	FCM-DCS (Disorderd contour)
10	11.26	8.04	3.75
20	12.28	9.54	3.32
30	12.12	9.25	3.57
40	13.63	9.93	4.54
50	13.57	10.18	4.68
60	13.68	10.65	4.47
70	14.15	11.47	4.38
80	14.72	12.31	4.82
90	14.56	12.42	5.67
100	15.64	12.96	5.98

the original image, and the'$S_i^{'}$'denoted the boosted anisotropic filter smoothened pixel intensity. The 'n' indicates sample mammogram images count.

$$SegmentationAccuracy(\%) = \frac{TP + TN}{n} * 100 \tag{11}$$

The segmentation accuracy is evaluated using Eq. (11). The notation 'n' indicated the cancer image counts. Positively segmented samples and negatively segmented samples are represented as TP, TN respectively.

Table 2 includes the SMSE evaluation results obtained by different segmentation methods considered in this study for BC detection. Many cancer photographs in the 10–100 are considered adequate for experimental purposes. Several techniques, including fuzzy Clustering and the DCS model, have been attempted and compared to the recommended method. One hundred cancer wizards have been gathered for scientific purposes. The resultant value of the proposed Distorted Contour Based technique is superior to the others in reducing segmentation errors.How many cancer photos have been successfully segmented is divided by how many cancer images have been wrongly segmented? Slightly less than one per cent of the total number of cancer images evaluated as input is used to represent genuine positive/FN samples. The segmentation accuracy may be expressed theoretically as a percentage (per cent) and quantified in percentage.

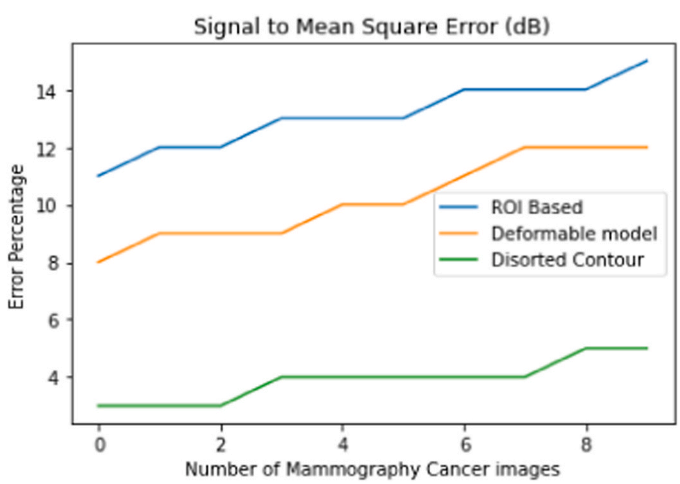

Fig. 6. Measure of SMSE.

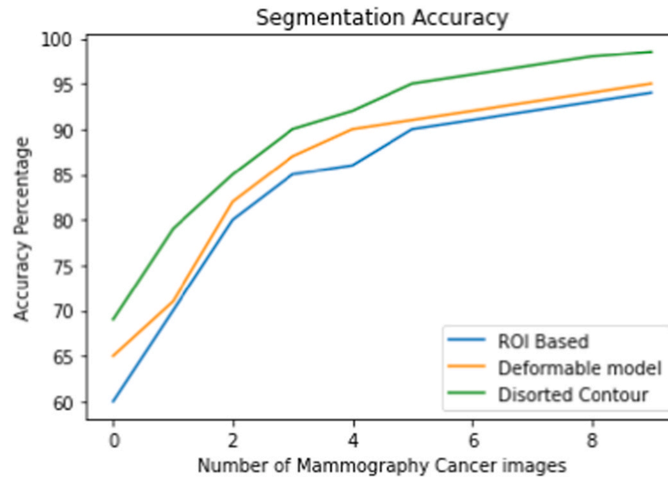

Fig. 7. Measure of Segmentation Accuracy.

Fig. 6 compares the Signal to mean square error for ROI-based segmentation, Deformable model, and distorted contour model-based segmentation. The x-axis denotes the number of mammography cancer images, and the Y-axis denotes the number of values. It clearly shows that the proposed method outperforms in segmenting BC tissues.

Table 3 contains accuracy rate comparison results of different segmentation such as ROI, Deformable, FCM-DCS methods. The analysis results show that the DC-based FCM model obtained a maximum accuracy rate in segmenting the pixels. The higher segmentation accuracy indicates that the FCM-DCS method is more efficient than the comparison method.

The segmentation accuracy is differentiated from ROI-based segmentation, Deformable, and FCM-DCS, as shown in Fig. 7. The X-axis denotes the number of mammography cancer images, and the Y-axis denotes the accuracy percentage. The graph values indicate that the FCM-DCS model obtained maximum accuracy than the comparison model.

Table 4 contains the accuracy, false negatives and false positives (FPR) achieved by the FCM-DCS method while segmenting the BC detection in mammogram images for MIAS and DDSM datasets. Overall

Table 3
Segmentation Accuracy.

Number of Mammography cancer images	Segmentation Accuracy (%)		
	ROI based segmentation	Deformable model	FCM-DCS model (Disorderd contour)
10	60.21	65.17	69.23
20	70.01	71.54	79.54
30	80.77	82.23	85.47
40	85.62	87.27	90.59
50	86.57	90.37	92.53
60	90.12	91.23	95.31
70	91.62	92.47	96.32
80	92.35	93.45	97.54
90	93.79	94.74	98.23
100	94.24	95.37	98.76

Table 4
Overall performance analysis of three approaches.

Related work	Dataset	Accuracy	False -Positive-reduction rate	False -Negative reduction rate
FCM-DCS	DDSM	97.9 %	0.40 %	0.35 %
FCM-DCS	MIAS	98.76 %	0.14 %	0.15 %

Table 5
Performance Comparison of Accuracy.

Segmentation Technique	DDSM	MIAS
DRD-UNet	93.12	94.23
DDA-AttResUnet	94	95.1
FCM-DCS	97.9	98.76 %

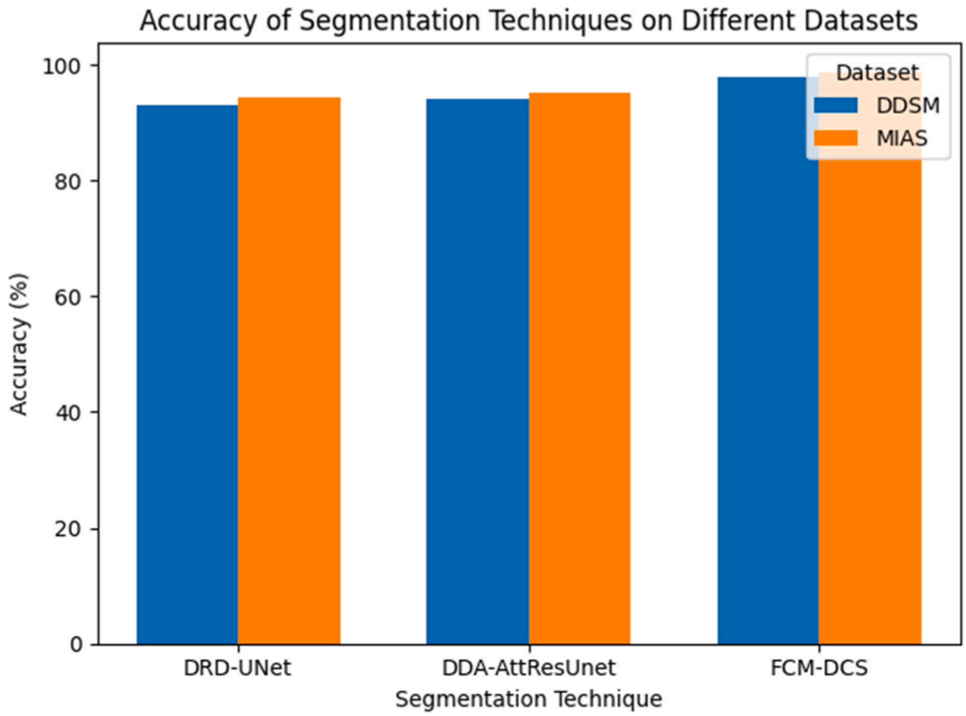

Fig. 8. Comparison of Accuracy.

performance analysis of three segmentation approaches is given. The table values show that the FCM-DCS provides better performance for MIAS dataset images.

The performance analysis of different BC detection models proves that the FCM-DCS method performs well than the comparable models. The overall evaluation results of the BC segmentation models show that the FCM-DCS method achieved the research objective.

Table 5 presents a comprehensive comparison of the accuracy achieved by three distinct segmentation techniques—DRD-UNet, DDA-AttResUnet, and FCM-DCS—across two significant datasets, DDSM and MIAS. The accuracy values, expressed as percentages, serve as indicators of the efficacy of each technique in accurately delineating breast cancer regions within the respective datasets. Notably, DRD-UNet exhibits commendable accuracy, achieving 93.12 % on the DDSM dataset and 94.23 % on MIAS, showcasing consistent performance with a slight improvement on the MIAS dataset. DDA-AttResUnet shows further enhancement over DRD-UNet, achieving 94 % accuracy on DDSM and 95.1 % on MIAS, indicating moderate improvement across both datasets. However, the most striking performance is demonstrated by FCM-DCS, which significantly surpasses both DRD-UNet and DDA-AttResUnet with remarkable accuracies of 97.9 % on DDSM and 98.76 % on MIAS. Such substantial improvements signify the superior capability of FCM-DCS in accurately identifying breast cancer regions within mammographic images. These findings underscore the potential of FCM-DCS to revolutionize breast cancer detection, potentially leading to earlier diagnoses and improved patient outcomes. Fig. 8, likely depicting this comparison graphically, provides a visually accessible representation of the accuracy disparities among the segmentation techniques, facilitating a more intuitive understanding of their respective performances.

Histological slides stained with Hematoxylin and Eosin are vital for cancer diagnosis. This paper introduces DRD-UNet for breast cancer segmentation, outperforming traditional UNet models on BCSS Challenge data. Additionally, DDA-AttResUNet enhances breast tumor segmentation in BUS imaging, promising improved diagnosis and patient outcomes [32,33].

5. Conclusion

Thus, the study has introduced the most effective, reliable and low-cost early-stage BC detection method to achieve the research objective. The mammogram images contain much information about the breast structure and tissue conditions. Still, early-stage BC biomarker features can only be identified directly with an efficient mass abnormality detection algorithm. So, this study's research objective addresses some of the leading gaps in the present BC detection-based studies. It shows a low-dose mammography x-ray to visualize the internal breast tissue structure. It introduces an FCM-DCS method to achieve the research objective. The performance of the FCMDCM shows that the segmentation method improves the BC detection accuracy up to 97.9 % for the DDSM dataset and 98.76 % for the MIAS dataset. It proves that the FCM with the DCS approach to segment BC images-based adaptive equalization method enhanced the pixel quality and accurately segmented similar cancer tissue in the abnormal structural regions with the help of DCS for seed point selection.

Moreover, the noise reduction, Histogram equalization, contrast, and adaptive equalization support the FCMDCM method to reduce the FN and false favorable rates. The FCM-DCS method is suggested to construct the segmentation to predict BC better and identify anomalies in breast tissue while diagnosing breast cancer. Texture analysis is another application beyond the identification of BC. This method extracts areas of interest from biological images using the appropriate threshold limit. The texture analysis, thresholding, and segmentation steps help to improve visibility and detection. The feature extraction and automatic classification are not concentrated in this study. This study is extended to handle different picture formats rapidly with minimal processing delays without relying on aspects like raw images and deep learning-based techniques that can be suggested to improve the segmentation, feature extraction and BC classification results and also to improve the automatic BC classification performance.

CRediT authorship contribution statement

B. Krishnakumar: Writing – original draft. K. Kousalya: Writing –

review & editing.

Funding

No fund received for this project

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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