# Breast Pathology Changes Extraction and Measurement Based on Machine Learning and DWT

Original Scientific Paper

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***Abstract*** *– In recent years, medical image analysis has witnessed significant advancements in aiding accurate diagnosis and treatment planning. Breast tumor segmentation is a critical task in medical imaging, as it facilitates the identification and characterization of tumors for effective clinical decisions. This paper proposes a novel approach for breast tumor segmentation and analysis by integrating Fuzzy C-Means Clustering (FCM) with Discrete Wavelet Transform (DWT), called FCMDWT. This method is effective in breast diagnosis analysis, tumor size measurements, and diagnosing reports and does not require prior training in segmentation. Initially, the DWT is applied to the mammography image, decomposing it into different frequency subbands. FCM is employed on the DWT coefficients to ensure robust clustering by accommodating uncertainty and overlapping regions in the image. The experimental evaluation conducted on a comprehensive dataset and comparative analyses demonstrates the superiority of the FCMDWT approach. Furthermore, the proposed method extends beyond segmentation, incorporating tumor analysis by extracting relevant features such as size, shape, and texture. The results indicate the potential of the FCMDWT approach in not only accurate segmentation but also in providing valuable insights for clinical decision-making.*

***Keywords****:* *DWT image processing, FCM, breast mass measurements, medical image processing, tumor segmentation*

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## 1. INTRODUCTION

Cancer is a pathological state caused by aberrant cellular alterations that result in uncontrolled proliferation. Malignant breast cells often form tumors, which are masses or lumps that are termed by the specific body location where they arise. Breast cancer is the most common form of cancer in women and the second most common cause of death globally. During the first stages of breast cancer, while it is still treatable, individuals often have minor discomfort. Therefore, screening is crucial for timely diagnosis. Timely identification of cancer and timely intervention might potentially reduce mortality rates [1].

For physicians to choose the best course of therapy and, as a consequence, save at least 40% of patient's lives, they would have to understand whether a tumor exists and what kind of malignant tumor it is [2]. Cancerous growths or lumps are assemblages of aberrant cells. They can develop from any of the trillions of cells that make up the human body. The growth and behavior of tumors vary depending on their type, with malignant (cancerous), benign (non-cancerous), and precancerous tumors all exhibiting distinct characteristics. Malignant tumors arise from cells that undergo genetic mutations and proliferate in an unregulated manner, resulting in the development of a mass or growth that can infiltrate neighboring tissues and organs. These malignant cells can detach from the primary tumor and spread to other areas of the body via the circulatory and lymphatic systems, a phenomenon referred to as metastasis. Scientists have investigated different methodologies for detecting and forecasting tumor activity [3], such as employing Conditional Random Fields (CRF) [4], analyzing volumetric white ratios of diffusion tensor (DT) in mammogram images [5], and utilizing topological imaging of human breast development through magnetic resonance imaging [6, 7]. Researchers used mammography images acquired from children in a state of regular sleep to forecast the first emergence of functional breast cancers [8]. Other research endeavors have concentrated on isolating specific histological regions within the tumor's white matter and discerning the characteristics of individual cells to get a more comprehensive understanding of tumor behavior [9, 10]. Identifying and characterizing tumors accurately is essential for effective treatment and improving patient outcomes. Imaging techniques such as mammography, ultrasound, and MRI are commonly used to detect and diagnose tumors. However, these methods are not always conclusive, and additional tests such as biopsies may be needed to confirm a diagnosis. Advancements in medical imaging and machine learning technologies have shown promise in improving tumor detection and diagnosis. For example, methods based on training and testing have been developed to analyze mammogram images and detect abnormalities that may indicate cancer. These techniques have the potential to increase the accuracy and efficiency of tumor diagnosis, reducing the need for invasive procedures and improving patient outcomes [11].

This work aims to use a combination of FCM clustering, DWT methods, and BCET image enhancement to segment and measure the size of breast tumors and non-infected areas on mammogram images. This method can reduce the workload of radiologists and confirm diagnosis analysis with high accuracy.

## 2. LITERATURE REVIEW

BC is defined as the development of a malignant tumor in a woman's breast. Medical practitioners use mammography pictures to identify breast cancers at different stages. Segmentation is an essential and demanding process in the categorization and interpretation of medical imaging. The FCM approach developed by Sharma and Selvakumar [12, 13] is often used for photo segmentation. In addition, [14] introduced a method for isolating breast tumors using a combined approach that used FCM.

The organization of linear and non-linear characteristics in mathematical computer vision (namely borders) may be achieved by using the conventional methodologies proposed in [15] and [16]. Identifying the specific form of cancer is a far more challenging undertaking [17]. Malignant tumors have clustered appearances, solitary ducts, and a poorly defined bulk, among other features. Effectively differentiating between cancers of the breast and other illnesses using ultrasound imaging remains tough owing to the low contrast and indistinct borders of tumors.

An innovative computational technique for locating and segmenting breast lesions in ultrasound images was also described by [18, 19]. Breast cancer cannot be cured unless it is detected early. While [20] uses discrete wavelet transform and clustering means for tumor mass delineation on mammogram images, [21] presents a technique for detecting breast tumors by fragmenting mammogram images using simple image processing algorithms that produce good results only in real time. The twofold banalization approach used by the authors of [22] was enhanced for mammography image isolation. Finally, a contour of the objects in the original image has been created using image boundary detection, making it simpler for doctors to detect cancer in various images. To overcome the shortcomings of FCN models, the authors in [23] presented the UNet model for mass segmentation based on training and testing. UNet argued that the decoder's high-level and low-level components should be combined. Skip connections were used to maintain this fusion, allowing the UNet architecture to be utilized in several medical applications, including mammography. The authors of [24] employed an UNet model for breast mass segmentation and classification.

The segmentation's F1-score for the DDSM dataset was 90%. Baccouche et al. [25] also used a UNet model to find mass lesions in full mammograms and got the same result. Their F1-score on scanned breast images was 86.91%. Using residual units to augment edge information in place of the standard neural units in the UNet architecture, researchers of [26] suggested the Residual-Dilated-Attention-Gate-UNet model. Traditional UNet scored 0.820. SegNet also performed well on the same dataset, with an overall dice coefficient of 0.817. UNet and SegNet were compared to [27] in which SegNet and UNet were the best tumor extraction models in terms of dice scores. In addition, the UNet beat the SegNet. The UNet had a dice unit of 0.883, compared to the SegNet's 0.504.

## 3. PROPOSED APPROACH

In this study, a BT segmentation approach is proposed that combines DWT and FCM clustering. DWT is first used to decompose breast images into different frequency sub-bands, improving the visualization of tumor boundaries. FCM is then applied to segment these enhanced features using the multi-resolution representation of DWT to improve segmentation accuracy and effectively distinguish tumor tissue from healthy regions. The outcome of the processing procedure is contingent upon the quality of the mammography images produced by the medical equipment. Acquired medical images can exhibit noticeable noise due to the technical operations of the equipment. Various approaches may be used to identify and classify breast cancers and tumors. Fig. 1 exhibits the boundary detection and FCMDWT segmentation flow charts for tumors and non-infected areas of the breast.

### 3.1. DATA COLLECTION AND PREPROCESSING

Medical images have been converted to the Digital Imaging and Communication in Medicine (DICOM) standard in CBIS-DDSM, resulting in a revised version of the Digital Database for Screening Mammography (DDSM) dataset. 1467 of the 2907 mammograms, which were obtained from 1555 individuals, are mass images. Two different mammography were performed on each breast. The original photographs, which have been connected to the vast locations in which they were shot [28] are around 3000 by 4800 pixels. Also, a collection of mammograms from Kirkuk City-Iraq National Medical Laboratory was collected. These images show 389 examples of breast cancer in stages 3 and 4 with mass lesions from 208 different people. Each image was preprocessed by resizing to a uniform dimension of [256 X 256] and normalized to a common intensity range. The source data consists of a mammography of the breast, which is used to diagnose breast tumors and breast cancer. If the source image is given in RGB format, it is transformed to greyscale. To preserve the image's aspect ratio, it is resized to fit the appropriate matrix. Subsequently, the scaled pictures undergo the application of the median filter, which effectively reduces random noise while preserving the borders of the image.

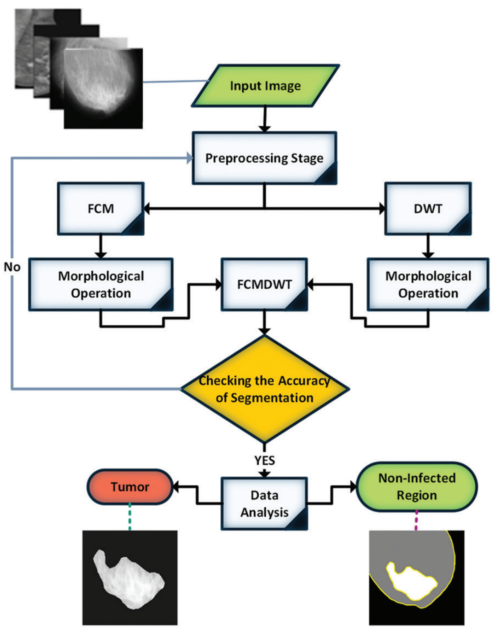



**Fig. 1.** FCMDWT segmentation flow chart and boundary detection scheme for tumor and non-tumor areas in the breast

During the scan enhancement phase of the source image, a noise-reducing filter is used to enhance the quality and contrast. We used the Balance Contrast Enhancement Technique (BCET) to improve and emphasize the region containing foreign entities such as tumors or nodules [29, 30]. From Fig. 2, we can recognize that the best mean value of high-quality mass segmentation is 80. Attributes of structural elements reveal an important aspect.

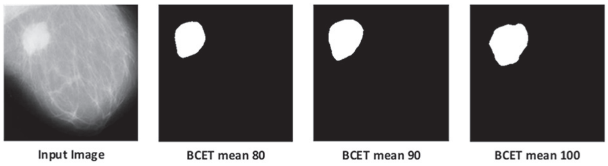



**Fig. 2.** Tumor segmentation using the different mean values of BCET

Mass segmentation or infection extraction refers to the process of extracting boundaries (lines, shape, size, and position) from medical scans. Decisions for breast cancer therapy heavily rely on medical image segmentation. Depending on the slide, segmenting a picture can result in a set of contours or a group of areas that make up the entire image. Based on the consistency of a tumor's features, including intensity, color, and texture, images may be utilized to classify whether the tumor class is benign or malignant. The thresholding method segments CT images by dividing the intensity of the screening mammography into two halves [31, 32].

### 3.2. DISCRETE WAVELET TRANSFORM (DWT)

The DWT was applied to each preprocessed image to obtain a multi-resolution representation.

The DWT technique is used in Step 1 to find the suitable threshold by dividing the source image into two sub-bands the LL subdomain and three high-frequency bands of size 83x152, which displays low-level filters, and the HH subdomain, which displays higher-level filters. Both low-pass and high-pass filters employ the thresholding technique to determine the threshold value edge enhancement. Step 2 produces a high-pass filter by imaging the remaining sub-bands with inverse wavelet transforms (horizontal, vertical, and diagonal). The LH matrix is split into a nested 3x3 matrix, the average value is calculated and assigned to the entire FCM.

The third step, which likewise divides the source image into two blocks of pixels, uses local contrast balancing to enhance an image's inherent contrast (black and white). The experimental findings demonstrate the efficiency, clearcut, and ease of understanding of the suggested approach. Smoke detection methods based on image segmentation might decrease noise interference. For this study, we utilized the DWT for its suitability in medical image analysis due to its effective edge detection.

### 3.3. FUZZY C-MEANS (FCM) CLUSTERING

The upgraded FCM method was utilized to do high-accuracy segmentation (normal area extraction) of the breast's uninfected tissue, and threshold segmentation was used to transform the enhanced breast mammography picture to black and white for extraction of the breast's infected tissue (size, location, and form). The primary methods used here are dilatation and erosion. The stroke area of items expands during the dilatation process and shrinks during the wear phase. The structural features served as the basis for these procedures. The stretch chooses the highest value and we find the lowest value by comparing all adjacent pixel values in the source image (CT image) given with the diagram part. Fig. 3 depicts the steps of the method proposed for segmenting breast masses.

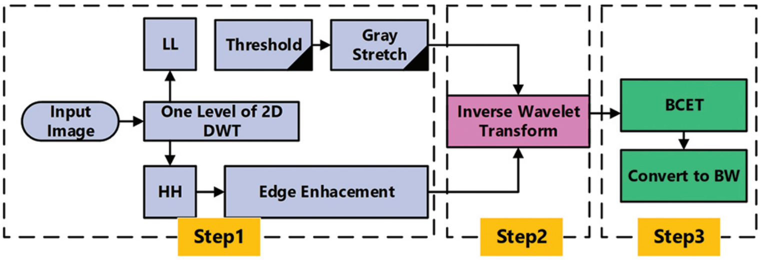



**Fig. 3.** Presented scheme of the breast mass segmentation method

### 3.4. POST-PROCESSING AND REFINEMENT

A post-processing approach was applied to refine the BT segmentation results. First, a morphological operation is performed to fill gaps within the tumor boundaries. Then, the proposed FCMDWT was used to isolate the tumor region more distinctly, removing small artifacts that FCMDWT had erroneously included. This post-processing step was essential to achieve cleaner and more precise affected area (BT) outlines and non-effected areas of the breast. The steps of applying FCMDWT segmentation on mammogram images for a complete clinical tool for mass tumor diagnosis (segmentation, measurements, and boundary detection) are presented in Fig. 4.

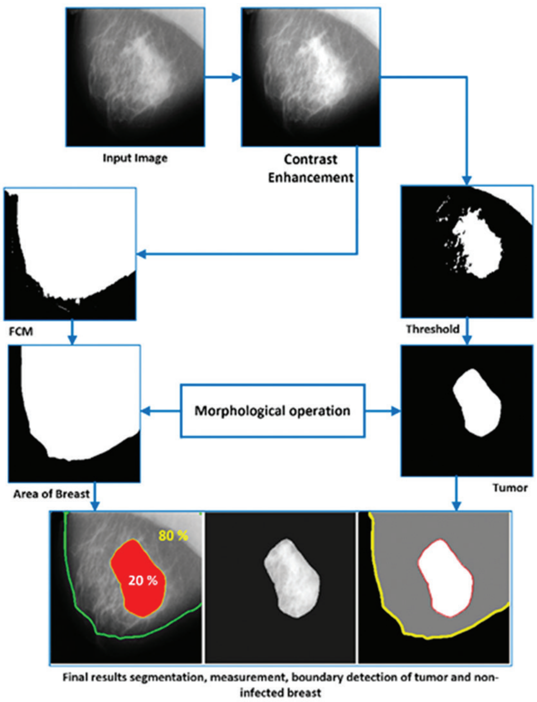



**Fig. 4.** The steps of the proposed FCMDWT segmentation method for breast diagnosis

### 3.5. EVALUATION METRICS

Breast tumor (infected region of the breast) segmentation on breast mammography images was evaluated using the Dice Coefficient (F1-score), which is defined as the geometric mean of the prediction accuracy [33]. The breast tumor, the non-infected region of the breast, and the identification of both borders are all outputs of FCMDWT segmentation. To determine whether the forecast was correct, the Jaccard coefficient of intersection over union (IoU) was used [34]. When their union splits the expected and actual bounding boxes, the result is the predicted bounding box. Predictions are labeled as "True Positive" (TP) or "False Positive" (FP) depending on whether the IOU is more than or equal to 50%.

The following formula (1) is used to determine the IOU:

$$\mathrm{IOU} = \frac{\text{area of overlap}}{\text{area of} \cup} \tag{1}$$

The IOU metric ranges from 0–1with zero signifying no overlap and one signifying perfect overlapping object segmentation.

The total area of Overlap reduced by the sum of all pixels in the two images yields the F1-score, which is calculated as follows:

$$\text{F1-score} = \frac{2\times\text{Area of Overlap}}{\text{Total combined pixels}}. \tag{2}$$

## 4. RESULTS AND DISCUSSIONS

In this study, we evaluated the provided computer-aided diagnostic system for mass breast analysis using the public CBIS-DDSM dataset as well as a private dataset as descripted in section 3.1. Several instances are shown in Fig. 5. The databases include tumors from a range of locations and disease types, as well as information about the shape, volume, texture, and size of the affected mass region surrounding the tumor size. We can observe the surface features and highlighted items both before and after an image is converted from one image form to another.

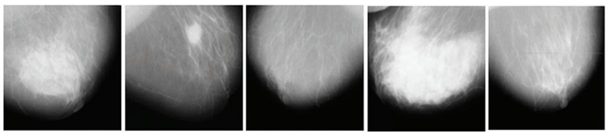
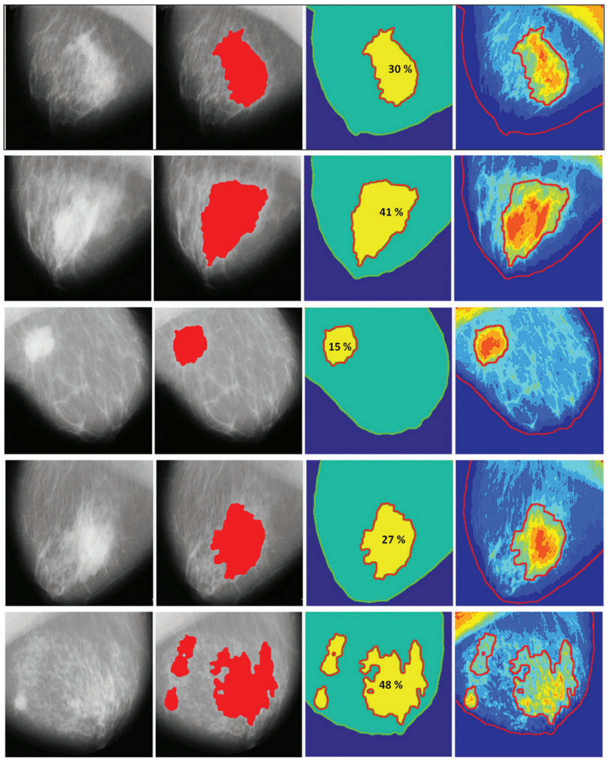


**Fig. 5.** Mammographic images of the breast obtained from a study's data

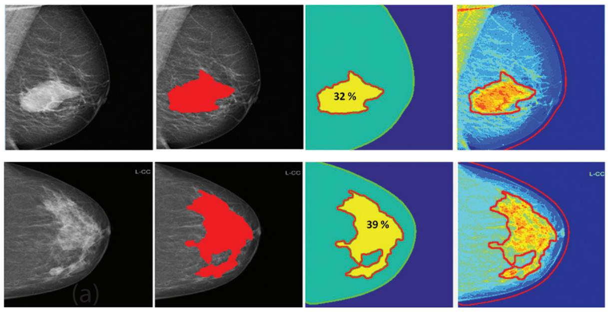
We experimented with a variety of breast tumor photos, all of which were 512 by 512 pixels in size, as a segmentation example. Fig. 6 and Fig. 7 show the results of various examples of breast tumor segmentation and identification using a unique segmentation approach, arranged from left to right. The original breast photos are presented in the first column, the segmented tumor results are presented in the second column, and the extracted tumor is located on the input image in the third column to help specialists better understand the location of the mass. The outlines of the breast tumor (which was extracted malignancy) and healthy breast areas are shown in the fourth column. The final row is indicated by semantic processing utilizing a color map (jet).




(a) (b) (c) (d)

**Fig. 6.** Outcomes of the malignancy localization approach are provided, where (**a**) is the input images, (**b**) and (**c**) results of FCMDWT segmentation, and (**d**) mass and non-infected area is colored and localized with color-code based on FCMDWT localization on breast mammogram images (CBIS-DDSM)

Results from Fig. 6 and 7 ((b), (c), and (d)) may assist in the identification of nonspecific kinds of breast mass by the computer-aided diagnostic detection system and radiography (benign or malignant). By identifying cancers at an earlier stage, specialists may be able to save patients' lives. A survey of the scientific literature revealed that there are several issues with current molecular techniques and classifications, including their inability to identify objects, their inability to produce the same outcomes, and their lack of adequate quality control, the segmentation with high accuracy. Extracting breast tumors with the proposed approach FCMDWT in Fig. 6(b and c) and Fig. 7(b and c) enables specialists to make the right treatment decisions and provide an accurate diagnosis, which increases the chances of successful treatment as it allows for a precise examination of the tumor in terms of location, size, shape, and degree of spread.




(b) (c) (d)

**Fig. 7.** Outcomes of the malignancy localization approach are provided, where (**a**) is the input images, (**b**) and (**c**) results of FCMDWT segmentation, and (**d**) mass and non-infected area is colored and localized with color-code based on FCMDWT localization on breast mammogram images (Private dataset)

The Fig. 6(d) and Fig. 7(d) help analyze and detect small tumors that may be difficult for doctors to see directly. It is also possible to predict from the shape whether the tumor is benign or malignant by analyzing patterns of stored medical data and comparing them with previous cases. The FCMDWT results help in achieving a more accurate diagnosis and providing customized treatment plans, which increases the efficiency and effectiveness of treatment and contributes to improving the quality of healthcare provided to patients.

Combining the two methods makes it possible to accurately locate tumors in medical images, as well as to accurately and quickly segment tumors in breast images. Images with edges identified and tumor and normal breast regions calculated (shown in Table 1).

**Table 1.** The detected concerns and their performance analysis, including the non-affected and eliminated breast regions

| Data | Damaged areas (mass) % | Execution Time (s) |
|---|---|---|
| image 1 | 30 % | 2 |
| image 2 | 41 % | 2 |
| image 3 | 15 % | 2 |
| image 4 | 27 % | 2 |
| image 5 | 48 % | 2 |

Calculating the extent of the afflicted sections by a tumor is made easier by differentiating between normal and malignant cells. The effectiveness of our suggested strategy is demonstrated by the determined area being displayed in pixel units. This paper compared our method to those in [24-27], as indicated in Table 2, for the identification and segmentation of breast tumors. Instead of depending on the empirically challenging to diagnose border lines between cancerous and non-cancerous breast sections to realize tumor location, visual analysis demonstrates that our approach outperforms the alternative in segmenting breast mass. By applying a color map to the data, our method can accurately locate tumor regions and non-cancerous breast regions on the original input image while only detecting tumor regions. This helps in displaying the current figure's color map and customizing it as shown in Fig. 6 (e) and Fig. 7 (e).

Using the FCMDWT segmentation technique, a comprehensive clinical tool for huge quantities of discovering tumors is needed, and segmentation architecture models have been developed. Radiologists can use this technology to help them find breast cancer more quickly by using it to help them identify what kind of tumor it is and how it looks. After segmentation, the edge detection of breast and tumor is applied based on the developed segmentation approach. Fig. 8 demonstrates the results of the method used to find the contours of the normal area (non-infected area) and the infected tissues (tumors).

**Table 2.** Performance analysis of the suggested architectures and cutting-edge techniques

| Source | Methods | F1-score | IoU |
|---|---|---|---|
| Soulami et al. [24] | End-to-end UNet | 90.5 | -- |
| Baccouche et al. [25] | Connected-ResUNets | 86.91 | 90.82 |
| Zhuang et al. [26] | Residual-Dilated-Attention-Gate-UNets (RDAU-NET) | 82.00 | -- |
| Singh et al. [27] | UNet | 88.30 | -- |
| Singh et al. [27] | SegNet | 50.40 | -- |
| Proposed Architecture | FCMDWT Segmentation | 96.47 | 97.34 |

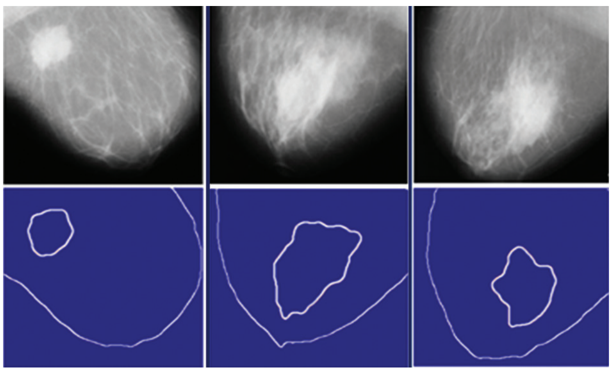


**Fig. 8.** Results of contour detection of normal breast and tumor, where the first line indicates the source images and the second line indicates the boundary detection of tumor and the breast based on developed FCMDWT segmentation approach

While SegNet and UNet were the best segmentation models in terms of dice scores of breast mass on mammogram images, we compared the developed method in this article to UNet and SegNet, and FCMDWT's qualitative predictions were more accurate, as seen in Fig. 9. The validation set, consisting of 30 volumes with 1325 2D slices, was used to compare the two predicted segmentations.

The Mann-Whitney test was employed to determine if there was a statistically significant difference between the predicted segmentation approach implemented by multiple methods and the ground truth labels. The predicted segmentation using FCMDWT (p-value = 0.13) was identical to the actual segmentation. According to this investigation, there was no statistically significant difference between the two approaches' projected segmentation and ground truth labels (p-value = 0.112 and 0.047, respectively). This demonstrates that the segmentations generated by these three approaches are distinct from one another. The loss, and accuracy of segmentation performance are provided in Table 3 to highlight the quantitative variations in accuracy, loss, and p-values between the actual results and those predicted by the U-test.

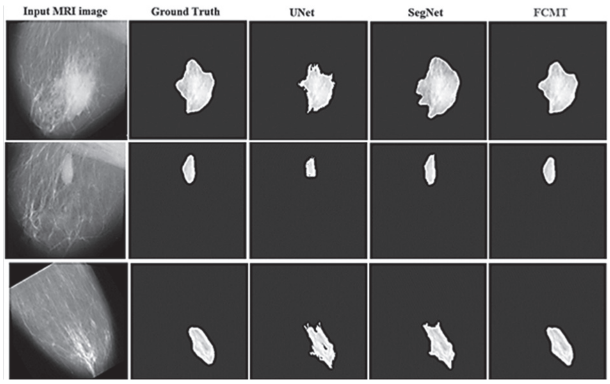



**Fig. 9.** The results of UNet and SegNet, FCMDWT qualitative predictions segmentation

**Table 3.** The accuracy iou, loss and p-value comparison between developed method fcmdwt, unet, and segnet

| Methods | Accuracy (IoU) | Loss (Binary Cross-Entropy) | P-Value |
|---|---|---|---|
| FCMDWT | 93.85 | 0.01 | 0.153 |
| UNet | 76.15 | 0.065 | 0.112 |
| SegNet | 68.54 | 0.073 | 0.047 |

The processing time of the proposed methods is not provided because some of the methods are machine learning-based while others are not (FCMDWT). Therefore, a comparison of these different methods is not applicable, since some contain a training time while others do not.

Most of the methods presented in recent years are based on machine learning, although machine learning models can produce extremely good results, they also have some limitations. The main factor affecting machine learning algorithms is data [24-27]. Class imbalance is a major problem that researchers face in almost every field. To overcome this problem, there are some methods that can be used to augment the data or there are methods that can be used to evaluate the outcomes of the algorithm. In our proposed method, the class imbalance problem does not limit the approach since it is not a machine-learning method.

Our method increases the precision of contour detection of the target object (tumor region and normal breast). Furthermore, the methods of UNet and SegNet have a lower percentage of pixels which are mistakenly thought to be the margins of breast cancers.

## 5. CONCLUSION

Initially, the FCM clustering algorithm is used to partition the normal area of the breast. Furthermore, the tumor zone is segmented using the thresholding approach. By integrating these methodologies, the research shows that the boundary or perimeter map of infected and non-infected parts of the breast may be determined with enhanced accuracy and precision. This method has several potential uses in clinical practice. Enhancing the precision of breast cancer extraction and localization may facilitate the identification and treatment of tumors by medical experts. Furthermore, it has the potential to decrease the need for intrusive medical procedures like biopsies and operations, which may be expensive, time-consuming, and have inherent dangers and adverse consequences. In summary, the research demonstrates that the use of machine learning and advanced image processing approaches can enhance the exactness and accuracy of breast cancer diagnosis. As these methodologies progress and improve, they possess the potential to transform clinical practice and enhance patient results. The experimental findings clearly show that the technique suggested in this work produces robust estimators that exhibit excellent picture quality for examination by medical professionals. Radiologists, who are medical specialists, assessed the edge maps, segmentation, and measurements found in cases of breast tumor pathology. The accuracy achieved by the devised segmentation and measuring approach surpasses the estimates made by similar specialists. An IoU of 98.41 and an F1-score of 96.47 were achieved. The experiment demonstrated the efficacy of the FCMDWT approach in performing edge detection, even in the presence of high levels of noise. The developed technique can also be utilized to detect lung pathology associated with COVID-19 infections with a few minor alterations. The created technology can be applied to lung segmentation, CT image pathology, and other areas where it is possible to identify cancerous cells. The authors of this study declare that the suggested method can pick up more features, making it simpler to identify the type of infected area.

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