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# Automatic Segmentation of Cancerous Tissues in Breast Ultrasound Images

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***Abstract-*** Segmentation of cancerous tissues in breast ultrasound images is a challenging task that can be achieved through various image processing and machine learning techniques. This paper presents an early automatic diagnostic method for breast cancer in ultrasound images and classifying the cancer as benign or malignant. Automatic images processing-based techniques were applied to process segment and classify cancerous tissues. The proposed method for early detection of breast tumor in ultrasound images typically involves three key steps: preprocessing, segmentation, and feature extraction and classification. The accuracy of proposed method was evaluated by comparing the segmented images with the gold standard or ground truth (GT), which was manually formed by an experienced radiologist. Area-based evaluation of segmentation was performed in which root mean squared error was 0.0435 and relative absolute error was 0.2085% for the total instances. The true positive result was 96% while false positive result was 3.11 %. The early detection of breast cancer in ultrasound images using the proposed image processing-based technique accurately detect breast cancer and classify cancer as benign or malignant. It also eliminates the drawbacks in the existing methods by introducing new features like shadows in the images using masking and adjusting contrast functions.

***Keywords-*** Ultrasound Images; Breast cancer; Benign; Malignant; Segmentation; Support Vector Machine

## I. INTRODUCTION

Breast cancer, amongst all organic cancers, is the most sensitive one and is only next to liver cancer in terms of number of deaths[1]. The disease is diagnosed widely in women but may also get sprouted in men. There has been a significant amount of research and literature devoted to understanding and controlling breast cancer. This includes efforts to identify risk factors, develop screening methods, improve treatments, and ultimately find a cure for the disease. The exact cause of breast cancer is unknown; therefore, preventive measures are ineffective. It is possible to reduce the chances of further deterioration of breast cancer by detecting and treating it early.

Medical image processing has played a vital role in the diagnostic process of breast cancer. Various image processing techniques are employed to find affected breast regions in ultrasound images, and hence discover breast cancer effectively[2]. One such common and effective technique is mammography. Mammographic images are used by majority of the automatic systems for breast cancer detection. Mammography can detect most of the cancers, but is not powerful enough to find all. The detection accuracy using mammography is directly related to human error or some technical problems. The resulting false positive results need accompanying breast imaging modalities for confirmation or diagnosis. For this reason, some positive results require a follow up biopsy to determine whether the oddity is tumor or not[3].

In this paper we present an image processing-based method for the early segmentation cancerous tissues in breast ultra sound images. The proposed method involves preprocessing techniques such as noise reduction, contrast enhancement, and image normalization to prepare the input ultrasound image. Then, segmentation techniques are applied to separate the cancerous tissues from the surrounding normal tissues and identify the region of interest (ROI). Finally, feature extraction and classification techniques are used to extract meaningful features from the ROI and classify it as either benign or malignant.

Overall, the proposed method uses a combination of image processing techniques to properly segment cancerous tissues in breast ultrasound images, which can potentially improve the accuracy and efficiency of early detection and diagnosis of breast cancer.

The rest of the paper is arranged as follows. In section II we have presented review of related work. Section III describe the methodology used in the proposed work. In Section IV, we present the results and evaluation of the proposed method in detail. Finally, Section V concludes our work.

## II. REVIEW OF RELATED WORKS

Several techniques have been developed for detecting cancerous and benign tumor based on ultrasound imaging. In the work of Jiang[4] a computer aided diagnoses (CAD) system is proposed to detect and segment the tumor regions. There are two stages in the detection algorithm: localizing the tumor and delineating its borders. The first step involves using an AdaBoost classifier using Haar-like features, followed by a support vector machine (SVM). Cheng and Itoh[5] worked with 3D ultrasonic images and implemented fuzzy logic in their proposed method for the automated detection of breast tumors. The method was successful in finding ten cases of malignancy and ten benign cases. Horsch[6] used de-noised ultrasound images and applied thresholding on the enhanced abnormal masses. By combining empirical domain knowledge with a deformable shape model, Madabhushi and Metaxas[6] reduced the effects of shadowing and false positives. The method needed a reduced sample set for training, and it gives a true positive rate of 74.7%.

It was suggested by Ikedo[7] that whole breast ultrasound images could be used for mass detection by using bilateral subtraction with the average gray values of the mass candidate region and the contra-lateral breast region. For classifying ultrasound images, Chen[8] worked with morphology operation, histogram equalization, and fractal analysis to acquire the fractal texture features. The classification of the masses into benign and malignant was significantly better with accuracy rate up to 88.8%. Shareef[9] used the method of marker-controlled watershed transformation. The method computes foreground, background markers and watershed area. In this method, the object is marked on the input image and colors are assigned to individual object on the basis of their number in the label matrix as well as color range in the color map.

A recent work proposed by Ramesh[10] describe a novel deep-learning architecture for breast images and machine learning algorithms were used to categorize benign or malignant tumors. The decision-making capability of the physicians to identify whether a tumor is malignant or not is overcome in this work with the help of the Google Net architecture used for segmentation. The segmentation results are then offered to the Support Vector Machine, Decision Tree, Random Forest, and Naïve Bayes classifier to improve their efficiency. Although this work has provided better results in terms of accuracy, Jaccard and dice coefficient, sensitivity, and specificity compared to conventional architectures. However, the authors have used lengthy procedure before classification by machine learning i.e., Image enhancement, deep learning-based segmentation, GLCM and Shape feature extraction.

On the other hand, the proposed approach eliminates drawbacks in existing methods by extracting features like texture, shape, and intensity from the segmented regions. These features can then be used to train a classification algorithm to differentiate between cancerous and non-cancerous tissues. The proper extraction of shape and area in our proposed method can help to remove unwanted background noise and highlight specific regions of interest, while adjusting contrast can help to bring out important details that might otherwise be difficult to see in the existing methods.

Ultrasound imaging is an alternate modality for breast examination and is of great importance to clinical diagnosis of breast cancer. It can detect and determine changes such as abnormal growth in the breast tissues, among others. In fact, it is preferable than mammogram for observing breast abnormalities in women with dense breast tissue. Additionally, it is a far better imaging technique than any other method because it is affordable and easy to use. The aim of this paper is to propose a novel method for the early detection of breast cancer in ultrasound images. The proposed method accurately detects breast cancer and classifies it as benign or malignant, which may be helpful in proper medication. Additionally, the proposed method eliminates the drawbacks in the existing methods by introducing new features like shadows in the images using masking and adjusting contrast functions.

## III. METHODOLOGY

The proposed automatic detection algorithm scans and reads ultrasound images and provides information about the subsistence of cancerous tissue. Then, it classifies the tumor either as benign or malign and finds its stage based on the size of the tumor. The proposed system assists physician in proper medicine prescription. Preprocessing, segmentation and feature extraction and classification are the three important steps of the proposed system.

### *A. Pre-processing*

The preprocessing of ultrasound images is an essential step in any automatic method used to detect cancerous tissues. The primary objective of preprocessing is to enhance the image quality, remove noise and artifacts, and standardize the image's characteristics to facilitate the feature extraction and classification process. In the preprocessing step, images having different sizes are resized into standard size which is essential for feature extraction and classification. The images are also normalized which involve scaling the pixel values so that they fall within a specific range, such as [0, 1]. This step helps in reducing the effect of variations in lighting conditions, which can affect the performance of the detection algorithm.

Ultrasound imaging suffers from few inherit flaws, such as noise from the equipment and surrounding, the presence of background tissue, the anatomy such as body fats and breathing movement. Thus, de-noising is an important step, as it affects the diagnostic process. Image denoising techniques such as median filtering, wavelet filtering, and Gaussian filtering can be used to remove noise and artifacts from the images. The suggested system exercises median filters which reduces speckle noise from ultrasound images[11]. This process gives a clear image after filtration and minimum loss of image details as compared to other local mean algorithms as shown in Figure 1.

By choosing the median intensity inside the window, a median filter operates over the window. The median filter is a non-linear, efficient technique that may, to some extent, discern between real visual features like edges and lines and out-of-range isolated noise. In more detail, the median filter substitutes a pixel with the median—as opposed to the average—of all the pixels in a region. Sort N2 - 1 values around the pixel and select middle value (median).

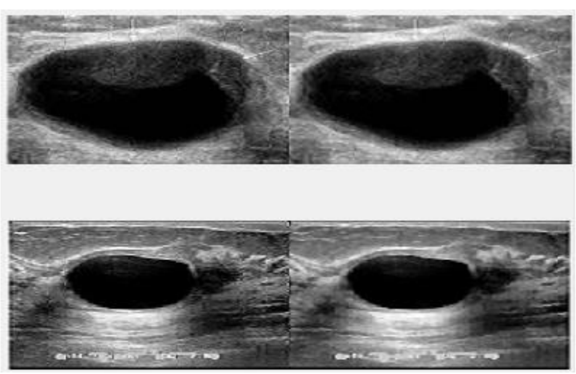


Fig.1. Median Filter Results: Left column are the original images and right are the results after applying the median filter

*B. Segmentation*

Image segmentation is the process of dividing the image into regions or segments with similar properties. In the case of breast ultrasound images, image segmentation can be used to separate the breast tissue from the background, and to identify the regions of interest, such as masses or lesions. Segmentation is performed to address the affected areas in breast ultrasound image. The proposed method performs two phases segmentation. In the first phase, it uses a combination of two functions. Ostu's based thresholding, and active contour segmentation. Ostu's based thresholding segments the mass from the breast ultrasound image using a threshold value. v in our case selected as v= l/3. Next, active contour method is applied on previously segmented image to get only the tumor area discarding areas connected to the border. Cancerous tissues are perceived as masses possessing round, oval or uneven geometry. Since there is no need of seed point selection so these masses are automatically determined.

In the subsequent step, the information obtained from the segmented object is used to apply a circular mask on the input image. The masking process scales down the image window size such that the tumor can easily be identified. To know whether a mass has acoustic shadow or not, contrast adjustment is performed which helps in proper delineating of the masses with their acoustic shadows.

*C. Features Extraction*

Feature extraction is the process of extracting meaningful information from the images. In the case of breast ultrasound images, features such as texture, shape, and intensity can be extracted from the segmented regions. These features can then be used to train a classification algorithm that can differentiate between cancerous and non-cancerous tissues. In this step, a set of morphological and statistical features are extracted. The set of features extracted is listed as follows.

Area: Area of the tumor plays a vital role in the determination of tumor. Area of malignant tumor is usually greater than benign tumor.

Shape: Shape is an important feature that can help in identification of the mass. Round shaped masses mean the presence of benign cancer and asymmetrical masses shows that malignancy is present. The shape of the mass is determined using equation 1.

$$Mass\_circularity = \frac{(Mass\_perimeter)^2}{(4\times pi\times Mass\_area)} \quad (1)$$

If circularity gets a value 1.0 it means an exact circle. In case the value is near to 0.0, it shows a prolonged polygon.

Depth to Width Ratio: A benign mass has a greater height than width, while a malignant mass has a greater width. If a tumor is wider than it is taller, the aspect ratio exceeds one and the tumor can be malignant, as shown in equation 2.

$$DepthtoWidthratio = \frac{D}{W} \quad (2)$$

Where D is the depth of the tumor and is the width of the tumor.

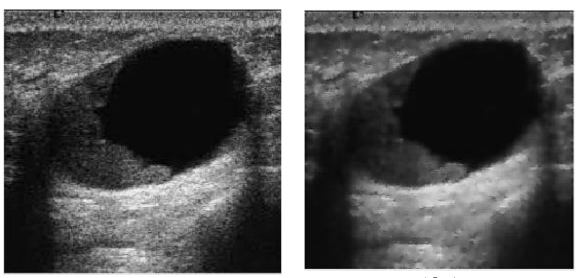
Shadowing: Lateral shadows are associated with most of the benign tumor while malignant masses show posterior shadows. Shadow can be computed by segmenting the tumor and tumor with the shadow. Lateral or posterior shadow is ensured after getting the difference between the two segmented regions in the two separate phases. Mathematically it is shown in equation 3.

$$SR_{shad} = SR_2 - SR_1 \quad (3)$$

where $SR_{shad}$ is the shadow, $SR_1$ is the segment obtained in the first phase and $SR_2$ is the segment obtained in the second phase.

## IV. RESULTS AND EVALVATION

In order to evaluate the proposed method, sixty (60) ultrasound images (35 benign and 25 malignant) of breast cancer patients of different ages were taken from Mendely Database. A radiology expert manually delineated each tumor's boundaries for each case. Figure 2 (a) shows a sample breast ultrasound image of the benign tumor having a lateral shadow associated with the tunor region. Figure 2 (b) shows the image after applying weiner and median filters.



( a ) ( b )

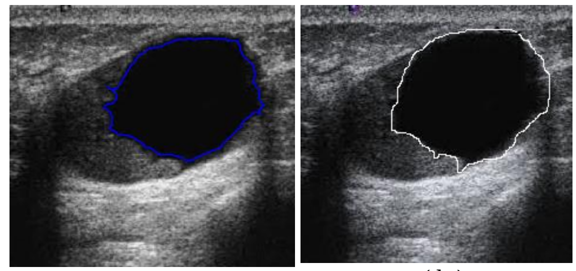
Fig. 2. The original breast ultrasound image of the benign tumor (a), and the filtered image (b) after applying the Weiner filter.

Subsequently, Otsu's thresholding, and contrast adjustment is used to get the binary image (Figure 3 (a)). The required region is obtained by ignoring tiny regions in the image and taking only largest region (Figure 3(b)). The biggest region has high probability that it is tumor.

( a ) ( b )

Fig. 3. (a) Binarized image (b) Segmented breast ultrasound image containing only tumor region

After that the centroid of the segmented object is used to mask the original image into a sub-image of the original image. Applying contrast adjustment function gives the tumor besides its posterior or lateral shadowing (Figure 4).



( a ) ( b )

Fig. 4. An original image of breast ultrasound showing the tumor's boundary as defined by the system is shown in (a), (b) illustrates how the segment was delineated by a radiologists.

Figure 5 shows the delineation of the tumor done by Automatic Detection System in blue color. The area in black color in the red boundary shows false negative while the area white color in the blue boundary shows false positive.

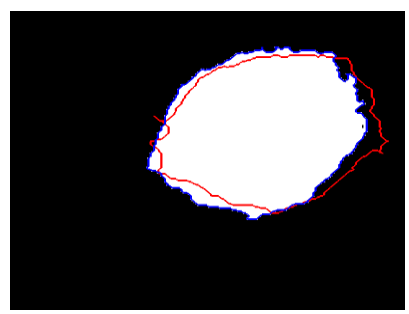


Fig. 5. Ground truth appears in the red boundary of a segmented image of a breast ultrasound, while an automatically segmented image appears in the blue boundary.

An initial training set of 30 benign ROIs and 30 malignant cancerous ROIs is used to train the classification algorithm, which is followed by a testing phase. In the later phase, a set of unknown data was given with the trained classifier for the execution of classification. A testing set was used for this phase, consisting of a set of 30 benign, and 30 malignant ROIs. Different classifiers, such as neural network classifier, support vector machine (SVM) and KNN classifier were used in the results. Neural network classifiers are powerful machine learning models that can learn complex nonlinear relationships between inputs and outputs[11]. They are particularly well-suited for image and speech recognition tasks and have been used with great success in these domains.

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SVMs are another popular classifier that work by finding a hyperplane that separates different classes of data[12]. They are particularly useful for classification problems with a large number of features or where the decision boundary between classes is nonlinear. KNN classifiers, on the other hand, work by finding the k-nearest neighbors of a new data point and using the class labels of those neighbors to predict the label of the new point[13]. They are particularly useful for small datasets with simple decision boundaries.

The choice of machine learning algorithm(s) used to implement a method depends on various factors, including: The nature of the input data. For example, image data may be well-suited for neural network classifiers, while text data may be better suited for SVMs or KNN classifiers. The complexity of the problem. For example, if the problem involves detecting subtle patterns in the data, a neural network may be a good choice. If the problem is simpler and the data is well-separated, an SVM or KNN classifier may be sufficient. The size of the dataset: Some algorithms may be more efficient or effective for large datasets, while others may be more suitable for smaller datasets. For example, KNN classifiers may be computationally expensive for large datasets, while SVMs may be more efficient. However, it is possible to use combination of different classifier to achieve best results. Ultimately, the choice of algorithm(s) used will depend on the specific requirements of the problem and the characteristics of the data.

The proposed algorithm uses a combination of SVM and ANN classifiers to leverage the strengths of both models. The SVM is used to extract important features from the ultrasound images, which are then passed to the ANN for classification. Alternatively, the ANN is used to preprocess the images and extract features, which are then fed into the SVM for classification.

In the proposed method we have used different classification techniques for features extraction. As shown in the Table 1 and Table 2 we have used five statistical and seven morphological features that have high power of defining the masses clearly. The classification techniques are True Positive (TP) Rate, False Positive (FP) Rate, Precision, Recall, F-Measure, Mathews Correlation Coefficient (MCC), Receiver Operating Characteristic (ROC) Area and PRC Area. The results of SVM for different classification techniques are shown in Table 1 while for ANN the results are shown in Table 2. As shown in the Tables, the values are between -1 and +1. The vale +1 shows correct prediction, 0 means random prediction and -1 shows wrong results.

Table 1. Class based Accuracy of SVM

| Class | TP Rate | FP Rate | Precision | Recall | F-Measure | MCC | ROC Area | PRC Area |
|---|---|---|---|---|---|---|---|---|
| Benign | 0.969 | 0.000 | 1.000 | 0.969 | 0.684 | 0.951 | 0.984 | 0.990 |
| Malignant | 1.000 | 0.031 | 0.933 | 1.000 | 0.966 | 0.951 | 0.984 | 0.933 |
| Weighted Average | 0.978 | 0.010 | 0.980 | 0.978 | 0.978 | 0.951 | 0.984 | 0.973 |

Table 2. Class based Accuracy of ANN

| Class | TP Rate | FP Rate | Precision | Recall | F-Measure | MCC | ROC Area | PRC Area |
|---|---|---|---|---|---|---|---|---|
| Benign | 0.938 | 0.000 | 1.000 | 0.938 | 0.968 | 0.906 | 1.000 | 1.000 |
| Malignant | 1.000 | 0.063 | 0.875 | 1.000 | 0.933 | 0.906 | 1.000 | 1.000 |
| Weighted Average | 0.957 | 0.019 | 0.962 | 0.957 | 0.957 | 0.906 | 1.000 | 1.000 |

Table 3: Comparison of the results of the proposed method with the state-of-the-art methods

| Method Used | TP % | FP% | Accuracy % |
|---|---|---|---|
| **Histogram Based** [14] | 91.7 | 11.9 | 90.2 |
| **Texture based** [15] | 93.4 | 10.3 | 92 |
| **Clustering based** [16] | 94.7 | 9.5 | 96 |
| **Active Contour Model** [17] | 91 | 11.2 | 92 |
| **Neurotrophy based** [18] | 92.4 | 7.2 | 93 |
| **Region Growing Method** [19] | 95 | 7.1 | 96.4 |
| **Proposed Method** | **96** | **3.11** | **96.7** |

Table 3 compares the results of the proposed method with the state-of-the-art methods. The results are compared in terms of true positives, false positives and accuracy. True positive (TP) is the correctly segmented pixels while false positive is incorrectly segmented pixels.

True positive is the area which is common between the automated segmented area (by the algorithm) and the manually segmented (by the radiologist) area. The higher the value of TP, the more accurate the result is. False positive is the area present in the segment A (Automated segmented region) that is not part of the traced region (traced manually by radiologist). False positive is the extent to which the system is giving wrong results. Accuracy is a measure of how well the algorithm segment the region (the tumor) in the ultrasound image. Accuracy can be defined in terms of true positives (TP) and false positives (FP). The accuracy of a segmentation algorithm can be expressed as the ratio of the true positive region to the total region.

Accuracy = (TP) / (TP + FP)

If an experiment detects a region of interest which 70% overlaps with ground truth but 30% does not overlap, we will set a threshold for true positive. Therefore, if the threshold set it 70% then it will be considered as true positive. But if the threshold is high for example 90% then it will be considered as false.

Thus, unless we know what the threshold value is, we cannot decide whether a positive is true or false. True Negative has not been considered. As we are interested in the segmented lesion only. The images having no lesion (tumor) does not show any segment in the binarize image and was left unconsidered. Up to the extent of our knowledge, in medical imaging applications, false negatives may be less critical if they are balanced by a high specificity, i.e., a low rate of false positives. It may be more important to avoid false positives that can lead to unnecessary biopsies or treatment than to minimize false negatives.

Automatic segmentation of cancerous tissues in breast ultrasound image is an active area of research in medical image analysis. Several existing methods are available in the literature. The proposed method should be compared with existing methods in terms of accuracy, true positives, false positives, efficiency, and clinical applicability. The existing thresholding-based methods segment the image by setting a fixed threshold value and considering all pixels above the threshold as the object of interest. This method is simple and fast, but it is sensitive to noise and may not work well when the image has uneven illumination.

Region-growing based techniques start with a seed pixel and grow a region by adding adjacent pixels that have similar properties until the whole object is segmented. This method is also simple, but it may not work well for complex shapes and can be sensitive to initial seed selection. In edge-based methods, edges are detected in the image using edge detectors such as the canny edge detector, and then extract the object boundary from the edges. This method can produce accurate results, but it may not work well when the edges are not well defined or when there are noise and artifacts in the image.

Histogram-based approach for the segmentation of cancerous tissues involves analyzing the distribution of pixel intensities in the breast ultrasound images. This approach is simple and effective for the automatic segmentation and classification of cancerous tissues in breast ultrasound images but may not be suitable for all types of images or tumors. Texture analysis is a technique that characterizes the visual patterns in an image based on the arrangement of pixels. Texture-based can be an effective approach for early detection of breast cancer but involve the use of image processing techniques, texture analysis, and machine learning algorithms to automatically detect and classify cancerous tissues.

Clustered-based method use clustering algorithms to group similar pixels together based on their intensity values or other features. The resulting clusters can then be used to identify and segment cancerous tissues. A clustered-based approach can be effective for segmenting and classifying cancerous tissues in breast ultrasound images, especially when combined with machine learning algorithms. However, selecting the appropriate clustering and classification methods and optimizing their parameters can be challenging and may require domain expertise. An active counter-based method for automatic segmentation and classification of cancerous tissues in breast ultrasound images classify multiple images in a short amount of time, which is useful for large-scale studies. On the other hand, accuracy of the method may be affected by the quality of the ultrasound images, the choice of feature extraction method, and the availability of annotated datasets for training and validation.

Neurotrophy based approach shows promise for automatic segmentation and classification of cancerous tissues by computing the neurotrophy of different regions in the breast ultrasound image, it is possible to identify regions with high neurotrophy as potential cancerous areas. However, further research is needed to optimize the specific algorithms and parameters used to achieve accurate and reliable results.

The results shows that the proposed approach segments the image into regions corresponding to cancerous tissue and healthy tissue with high accuracy compared to the existing approaches. However, it is also essential to evaluate the proposed method on a large and diverse dataset and compare it with the existing methods using standard evaluation metrics such as Dice similarity coefficient, Jaccard index, sensitivity, specificity, and execution time.

## V. CONCLUSIONS

The development of automated methods for the segmentation and classification of cancerous tissues in breast ultrasound images can help to improve the accuracy and efficiency of diagnosis. The proposed method has higher accuracy for early detection of breast cancer in ultrasound images. In addition, it has the ability to exclude more normal regions from the tumor region than existing methods. The suggested approach achieves an improved accuracy of 96%.

Overall, the proposed method is advantageous for early detection of cancer in ultrasound images.

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