IOSR Journal of Computer Engineering (IOSR-JCE)
e-ISSN: 2278-0661,p-ISSN: 2278-8727, Volume 22, Issue 3, Ser. I (May - June 2020), PP 20-24
www.iosrjournals.org

Detection of Breast Cancer Using Ultrasound Images

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Abstract:
Background*: Breast cancer is one of the leading causes of cancer death in women around the world. In order to reduce the death rate, the tumors have to be detected at the early stage. The proposed system is a new approach with automatic contouring and texture analysis to aid in the classification of Breast Lesion using Ultrasound. Firstly, the goal of removing the speckle while preserving important information from the lesion boundaries, anisotropic diffusion filtering is applied to the ultrasonic image. A marker-controlled watershed transform is used for image segmentation, automatically extracts the precise contour of breast lesions. 24 Gray Level Co-occurrence Matrix (GLCM) features are extracted from the extracted lesion. Support Vector Machine (SVM) classifier utilizes the selected feature vectors to identify the breast lesion as benign or malignant. A confusion matrix is used to describe the performance of a classification model on a set of test data for which the true values are known. It allows the visualization of the performance of an algorithm.*

Key Word*:Ultrasound Images, Gray Level Co-occurrence Matrix (GLCM), Support Vector Machine K-Nearest Neighbor, Confusion matrix.*

Date of Submission: 25-04-2020 Date of Acceptance: 08-05-2020

I. Introduction

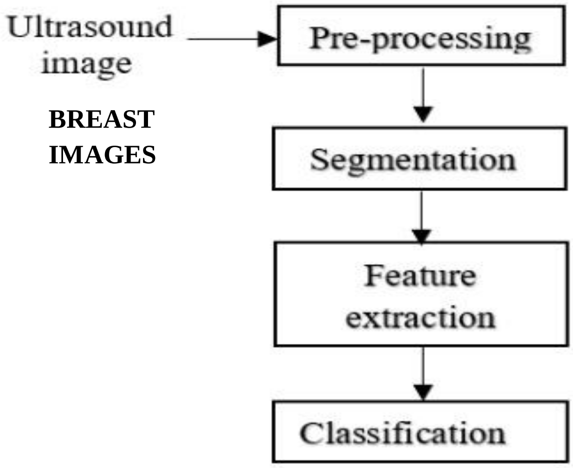
Cancer is a disease purpose cells within the body to alternate and develop out of control. Most varieties of cancer cells eventually shape a lump or mass known as a tumor, and are named after the part of the frame in which the tumor originates. The huge majority of breast cancers begin within the components of the breast tissue which might be made up of glands for milk production, referred to as lobules, and ducts that connect the lobules to nipple. The remainder of the breast is made from fatty, connective, and lymphatic tissues. Breast Cancer commonly produces no signs when the tumor is small and maximum without problems handled. Therefore, it's far very critical for girls to follow recommended screening tips for detecting breast most cancers at an early level. When Breast Cancer has grown to a length that can be felt, the maximum common bodily signal is a painless lump. Sometimes breast cancer can unfold to underarm lymph nodes and purpose a lump or swelling, even earlier than the authentic breast tumor is large enough to be felt.

II. Literature Survey

Previously, the most effective modality for detecting and diagnosing is mammography [1,2]. The pre-processing techniques and segmentation of Breast Cancer in presented in [3]. A novel approach for breast disease recognition and division in mammograms is introduced [4]. Features are extracted from the segmented region. Feature extraction values for breast cancer mammography is presented in [6]. However, there are limitations of mammography in breast cancer detection. Many unnecessary (65–85%) biopsy operations are due to the low specificity of mammography [5]. The unnecessary biopsies not only increase the cost, but also make the patients suffer from emotional pressure. Mammography can hardly detect breast cancer in adolescent women with dense breasts. In addition, the ionizing radiation of mammography can increase the health risk for the patients and radiologists. An important alternative to mammography is Ultrasound imaging.

III. Proposed Work

Figure 1. SystemDesign



1Image pre-processing:

The principal boundaries of imaging are the low evaluation and interference with speckle. The pre-processing of images includes speckle reduction and image enhancement. Speckle is a form of multiplicative noise generated with the aid of some of scatters with random phase in the resolution cell of ultrasound beam. The main task of image pre-processing is to magnify the image and to reduce speckle without destroying the important features of ultrasound images for analysis. A Gabor filter out accompanied with the aid of anisotropic diffusion is used to reduce the speckle without losing vital information about lesions boundaries and unique structures.

1.1 Anisotropic diffusion:

Anisotropic diffusion is a technique aiming at reducing image noise without removing significant parts of the image content, typically edges, lines or other details that are important for the interpretation of the image.

2 Image segmentation:

Image segmentation divides the image into non-overlapping regions, and it will separate the objects from the background [9]. The regions of interest (ROIs) will be allocated for feature extraction. Marker controlled watershed is implemented to obtain accurate potential lesion margins. To control the flooding of watershed of transform the markers are created.

2.1 Watershed method for segmentation:

Watershed is a segmentation technique based totally on transformation that can be defined on grey scale images. The Marker Controlled watershed transformation is defined as robust and flexible approach for segmentation with closed contours, consisting of breast lesion. The marker function performs an important function to remove the spurious minima which results in over segmentation. The MCC is used to measure in conjunction with the alternative overall performance evaluation parameters were these parameters plays as important evaluation parameter of machine learning techniques when data is unbalanced. The benefit of our approach is its simplicity to be carried out, because it does now not require large computational cost to resolve complicated mathematical models.

3Feature extraction:

Feature extraction in image processing starts off evolved with the original set of calculated data. It constructs the features or the consequent values which are intended for informational, facilitating the consequent learning and disentanglement steps, by prompting higher human translations. Dimensionality diminishing is the real a part of the detail extraction. Study with a huge variety of variables normally requires for a massive quantity of memory and grouping algorithm which simplifies insufficiently to new samples. Feature extraction is an inclusive term for techniques of building combinations of the variables to get around these troubles but, it portrays the information with enough accuracy.

3.1 Morphological operation:

One of the most dominant means for the attribute extraction from an image is Morphological techniques. The study of shapes is acknowledged as Morphology. Mathematical morphology is the hypothesis of shapes depicting using sets. It is an approach to analysis of an image. It lies on the postulation that an image contains structures which can be handled by theory of set. For the situation of image, a set is a group of pixels. The elementary morphological operations are dilation and erosion as these are described using basic set operations. Dilation and erosion are created by structuring element (interrelation of set) with a pixel set of attention in an image. Structuring element holds both the origin and shape.

3.2 Edge Detection:

The Canny edge detection is edge detection operator that uses a multi-stage algorithm to detect a wide range of edges in images. Canny edge detection is a technique to extract useful structural information from different vision objects and dramatically reduce the amount of data to be processed. It has been widely applied in various computer vision systems. Canny has found that the requirements for the application of edge detection on diverse vision systems are relatively similar. Thus, an edge detection solution to address these requirements can be implemented in a wide range of situations.

3.3 Gray Level Co-Occurrence matrix:

The texture filter functions provide a statistical view of texture based on the image histogram. These functions can provide useful information about the texture of an image but cannot provide information about shape, i.e., the spatial relationships of pixels in an image. Another statistical method that considers the spatial relationship of pixels is the gray level co-occurrence matrix

To create a GLCM, use the gray comatrix function. The gray comatrix function creates a gray level co-occurrence matrix by calculating how often a pixel with the intensity value *i* occurs in a specific spatial relationship to pixel with the value *j*.

Gray comatrix analyses pairs of horizontally adjacent pixels in a scaled version of I. If I is a binary image, it is scaled to 2 levels. If I is an intensity image, it is scaled to 8 levels. In this case, there are 8 x 8 = 64 possible ordered combinations of values for each pixel pair. gray comatrix accumulates the total occurrence of each such combination, producing an 8-by-8 output array, GLCMS. The row and column subscripts in GLCMS correspond respectively to the first and second (scaled) pixel-pair values**.**

4Classification:

Based on the selected features, the suspicious regions will be classified as lesion/non-lesion or benign/malignant by various classification methods. The SVM is reliable choice for the proposed system because it is fast and excellent in ultrasound image classification. SVM will transform the original data into a feature space of higher dimension by using the kernel functions.

4.1 SVM:

Support vector machine (SVM) classifier uses hyper planes to separate instances of various classes. The data is mapped to a higher dimensional space where it can be linearly separated using kernel trick. The optimal separator is a line which can efficiently separate the given input data into two classes namely Benign and Malignant by giving maximum margin between the two classes.

IV. Result

Figure 2: Output results for pre-processing and segmentation phase for breast image with Malignant feature

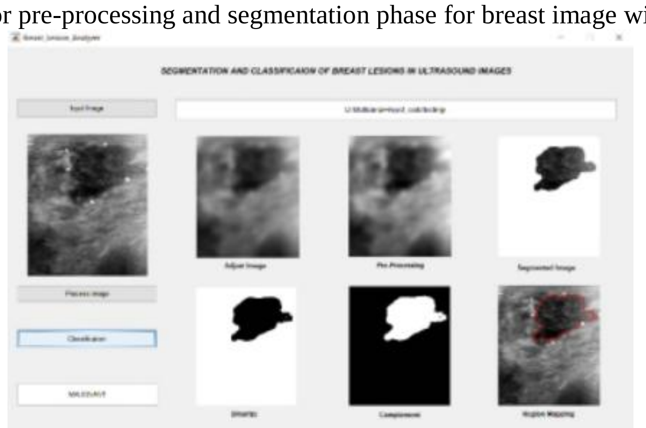


Figure 3: Output results for pre-processing and segmentation phase for breast image with Benign feature

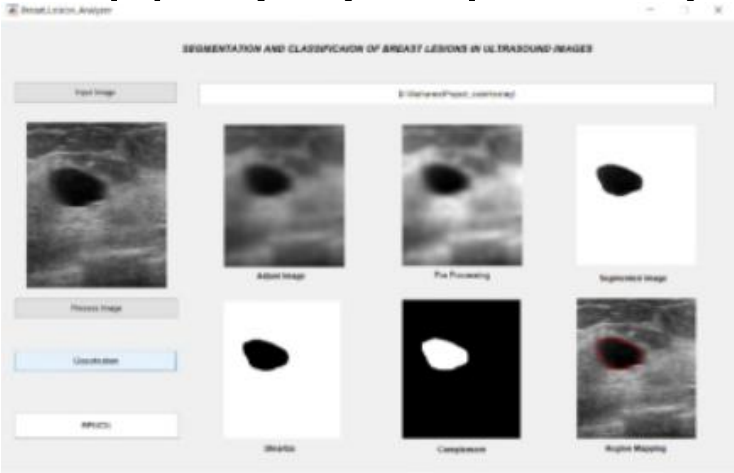


Figure 4: The performance of the proposed method

Parameters	Proposed method
Accuracy	94.11
Sensitivity	91.67
Specificity	100.00
MCC	87.40

Figure 5: Confusion matrix

Actual Class	Predicted Class	
	Is Benign	Is Malignant
Is Benign	11	1
Is Malignant	0	5
Total =17	11	6

Table I

The confusion matrix shows the ways in which our classification model is confused when it makes predictions. We have taken around seventeen images in which twelve images are Benign, five images are malignant. During the classification eleven images out of twelve are correctly detected as benign which is true, one images is detected as Malignant which is false, remaining five images are detected as Malignant which is true.

V. Conclusion

This work presents a segmentation and classification method for breast lesion in Ultrasound images. The technique pre-processes the images with an anisotropic diffusion filtering, in order to preserve and enhance useful information in the lesion boundaries, unlike from other filtering techniques that blur the image. SVM classifier efficiently classifies the Benign and Malignant and also works faster than ANN. The proposed method has the accuracy of 94.11%, which is more efficient compared to other system, confusion matrix allows identification of confusion between classes. The confusion matrix plots the rows correspond to the predicted class (output class) and the columns correspond to the true class (Target class). The diagonal cells correspond to observations that are correctly classified. The off-diagonal cells correspond to incorrectly classified observations. Both the number of observations and the percentage of the total number of observations are shown in each cell.

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Ms Malapriya S,etal. "Detection of Breast Cancer Using Ultrasound Images." *IOSR Journal of Computer Engineering (IOSR-JCE)*, 22(3), (2020), pp. 20-24.