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Detection and Classification of Breast Nodule on Ultrasound Images using Edge Feature

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Abstract

Doctor's assessment on breast cancer by using ultrasound images is time consuming and may produce difference interpretation of diagnosis results depending on several factors such as experience, fatigue and human error. Therefore, a computer system is needed to resolving difference interpretation of doctor's assessment. This study aims to develop a method for classifying breast cancer based on edge characteristics using 84 breast ultrasound images. Geometric and statistical features are used in this study to extract edge characteristics of breast cancer. The results show that the proposed method obtains good performance with accuracy of 90.48%, sensitivity of 92.50%, specificity of 88.64%, positive predictive value of 88.10% and negative predictive value of 92.86%. These results indicate that geometric and statistical features have good performance for identifying edge characteristic of breast cancer.

Keywords: *ultrasound images, breast cancer, edge characteristics, MLP.*

1 Introduction

In breast cancer case, early detection of the suspicious mass gives a better chance for the patients to be healed. Ultrasonography is one of the non-invasive modalities for breast cancer detection [1]. This machine creates an important information for generating images represented the condition of corresponding tissues. The suspicious mass seems darker or brighter than surrounding tissues.

The mass is then observed by the radiologist to determine the type of the mass and the malignancy. Along with the observation process, the radiologist defines the lesion by separating the mass area and the surrounding tissues. In image processing technique, this process is called segmentation process.

Accurate segmentation of medical images is important for image analysis and interpretation process. Since the modality and the object of interest have different characteristics, it is difficult to find the universal segmentation algorithm. Each modality and each object of interest needs to be treated in a specific way. Ultrasound images, for example, are known to have speckle noises because of the acquisition process [1]. Thus, some speckle filters are needed in the pre-processing stage. Breast as the object of interest also has different tissue characteristic compared to other objects. The characteristic may lead to the appearance of artefacts. In breast ultrasound images, low contrast mass that appears as suspicious lesion may have obstructed by the surrounding tissues. Besides, some artefacts such as lesion marks need to be removed to obtain precise mass boundaries. The ultimate challenge in general medical images segmentation task is to depict the object of interest precisely. The precise segmentation results in breast ultrasound images may help the radiologists in determining the lesion's area. Hence, optimal pre-processing and segmentation process are necessary to obtain accurate segmentation result.

Moreover, after finding the accurate mass area, analysing the characteristics of breast cancer is needed to identify the malignancy of breast cancer. There are several characteristics of breast cancer used to analyse the malignancy result such as shape characteristic, edge characteristic, texture characteristic, echogenicity characteristic, etc. [2]. Edge characteristic is one of the characteristics indicating a suspicious mass. Hence, classification of breast cancer using edge characteristic is crucial.

The aims of this work are to detect and to classify breast cancer based on edge characteristic. The proposed method is started by handling the speckle noises and lesion marks using the hybrid pre-processing technique. Segmentation process is then conducted to determine the mass area. For identifying the malignancy of breast cancer, geometric and statistic features are used. Finally, to classify the lesion, multi-layer perceptron is used.

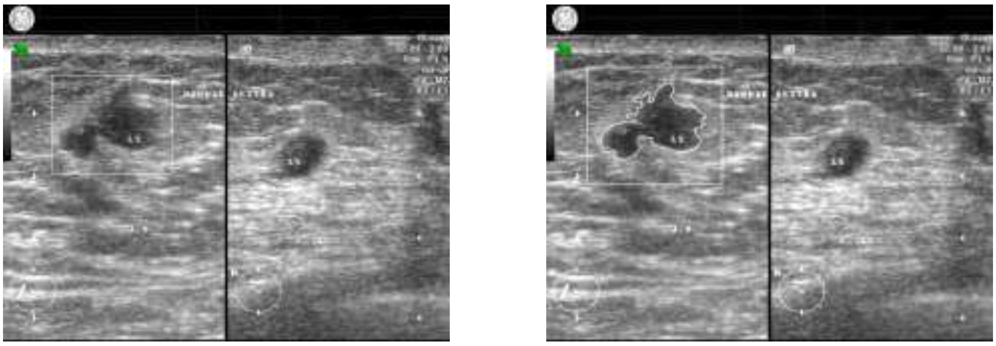
2 Related Work

Some previous study related with breast cancer classification are conducted before. Study conducted by Liao *et al*. [3] proposed sonographic and textural features for classifying breast cancer into benign and malignant classes. The authors use support vector machine (SVM), artificial neural network (ANN), and k-nearest neighbour (KNN) to validate the proposed method. Their simulation result concluded that their proposed method was accurate for classifying breast cancer. Menon *et al*. [4] proposed an automated detection and classification of breast cancer based on texture characteristic. The authors used speckle reduction anisotropic diffusion algorithm for enhancing the input image, histogram feature for extracting the images, and SVM for classifying the data. This study obtained accuracy of 95.7%. Prabhakar *et al*. [5] proposed an automated detection and classification of breast cancer using texture morphological and fractal features. The authors used tetrolet filtering for enhancing the mammography images, active contour for segmenting the nodule, statistical and fractal features for extracting the nodule, and polynomial kernel of SVM for classifying the nodule. They claimed that their proposed method was accurate for classifying breast cancer. Raha *et al*. [6] proposed an automated segmentation of breast cancer using watershed method. The authors used texture feature for identifying characteristic of breast cancer. This study achieved accuracy of 96.4%.

Some of aforementioned studies obtain high accuracy. However, most of them are used texture characteristic for classifying breast cancer. This research work uses edge characteristic to classify breast lesion.

3 Data

This works uses 84 breast ultrasound images consisting of 60 images for training dataset and 24 images for testing dataset. The training dataset consists of 30 images for irregular class and 30 images for regular class. Irregular class is lesion with irregular margin. Regular class is lesion with smooth margin. The dataset is provided by RSUP Dr. Sardjito and RSPAU Dr. Suhardi Hardjolukito Yogyakarta along with validation from the radiologists about the location and the malignancy of the mass. The validated image is called as ground truth. Irregular class indicates the malignant lesion. Regular class indicates the benign lesion. Fig. 1 shows the original breast ultrasound image data without a patient's identity, and the ground truth of the corresponding image given by the radiologist. Fig. 2 shows an example of irregular and regular lesions.



(a) (b)

Fig. 1: (a) An original breast ultrasound image, (b) ground truth image

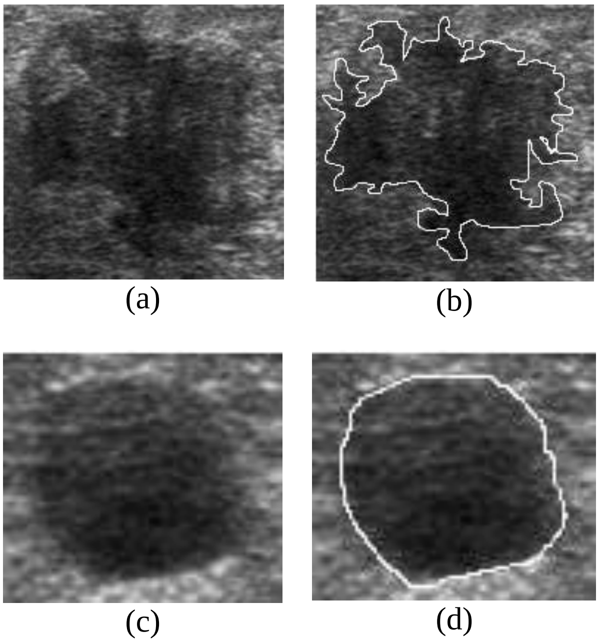


Fig. 2: (a) Region of Interest (ROI) of irregular lesion, (b) ground truth of (a), (c) ROI of regular lesion, (d) ground truth of image (c)

4 Methodology

The proposed method consists of five steps starting from pre-processing step, segmentation step, feature extraction step, feature selection step, classification step, and evaluation step as shown in Fig. 3. In this study, two filtering methods, i.e. adaptive median filtering and detail preserving anisotropic diffusion, are combined to enhance the input image. Then segmentation process is conducted to determine the lesion area. Geometric and statistic features are used to identify margin characteristic of breast cancer. Finally, multi-layer perceptron is used to classify the data into irregular or regular classes.

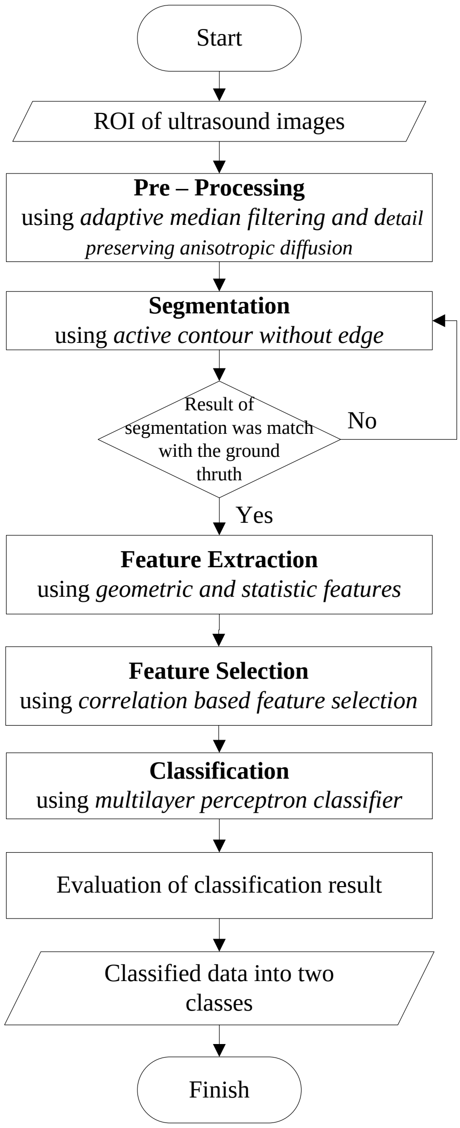


Fig. 3: Flowchart of the proposed method

4.1 Pre-processing

The pre-processing step is started by cropping the data manually based on rectangle marker given by the radiologist. In the same time, the ground truth is also cropped identically. The initial image and the ground truth are cropped on the same location and same size so that measurement of segmentation accuracy can be conducted precisely.

In this work, one of the problems on the acquisition dataset is on removal of speckle noises and lesion marks. Hence, a combination of adaptive median filtering and detail preserving anisotropic diffusion is used to resolve this problem.

4.1.1 Artifacts Removal

An adaptive median filter is used to remove unwanted artefacts such as white arrows or some letters which are pointing the location of the lesion. This filtering method works by searching median value of the neighbourhood pixels. This filtering method recognizes pixels as noise by comparing the pixel value to the surrounding neighbourhood pixels. In this research, adaptive median filter works from the smallest window size of the kernel (3x3). The size of the filter kernel is enlarged following the order of odd numbers when the desired condition has not been reached. The filter scans the image from first pixel and gathers the neighbourhood pixel values. The neighbourhood pixel values are sorted to find the median value. The median value and the central pixel value are then compared with the maximum and minimum pixel values. If the median value is smaller than the maximum value and larger than the minimum value, the first condition is met. If the central pixel value is smaller than the maximum value and larger than the minimum value, then the second condition is met. If the first and second condition are met, then the central value leaves as it is. But if the second condition fails, then the central pixel value is replaced with median value. Unfortunately, if the first condition fails, then the window size is increased based on the order of odd number until the largest size (7x7) [7]. Fig. 4 is illustrated the process of adaptive median filtering.

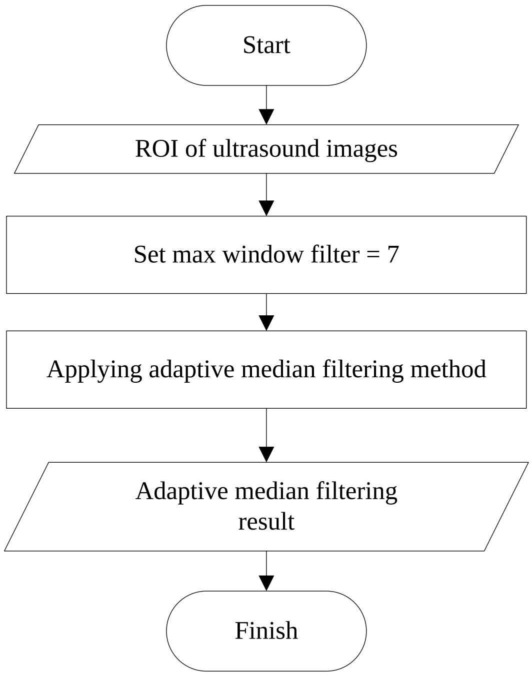


Fig. 4: Adaptive median filtering process

4.1.2 Advance Speckle Suppression and Contrast Enhancement

Anisotropic diffusion filter proposed by Perona-Malik [8] is a filtering approach in scale-space and edge detection problem. The technique becomes a high quality edge detector as the object boundaries remain sharp after filtering. In images with strange and various noises, anisotropic diffusion needs to be implemented using local contrast and noise estimation. Yu and Acton proposed a derivation of anisotropic diffusion namely speckle reduction anisotropic diffusion (SRAD) to overcome speckle noises which initially raised from ultrasonic and radar imaging [9]. SRAD performs better than traditional speckle filters and also better than conventional anisotropic diffusion in the term of mean preservation, edge localization, and variance reduction [10]. However, SRAD depends on linear approximation of the speckle model assumed. Detail preserving anisotropic diffusion (DPAD) is designed to cover SRAD limitation and focuses on the estimation of the coefficient of both signal and noise on the speckled images [11]. DPAD filter combined with the prior filter works by reducing speckle noises and keeping the details of ultrasound images. This DPAP filter was adopted from Kuan's filter [12] using partial differential equation (PDE) approach. The derived Kuan's filter function is shown in Equation (1).

$$c_z = \frac{1 + \frac{1}{c_{i,j,t}^2}}{1 + \frac{1}{c_{u,t}^2}} \tag{1}$$

Here, $c_{i,j,t}$ is defined by Equation (2) and $c_{u,t}$ is defined by Equation (3).

$$c_{i,j,t} = \sqrt{\frac{\frac{1}{|\mu_{i,j}|}\sum \rho\epsilon\mu_{i,j}(I_v - \bar{I}_{i,j})^2}{\bar{I}_{i,j}{}^2}} \sqrt{\frac{|\mu_{i,j}|}{|\mu_{i,j}| - 1}} \tag{2}$$

$$c_u^2 = \min(c_{i\,j}^2) \tag{3}$$

First, the filter estimates the diffusion function by implementing Equation (2). Second, the filter also calculates the noise estimation based on Equation (3). Finally, the full function of DPAD is applied and the isotropic diffusion step is calculated. In this research, the filter works with 0.2 time steps in each iteration. This work uses 100 iterations. Fig. 5 shows the flow of advanced speckle noise suppression and improvement of contrast by using the DPAD filter.

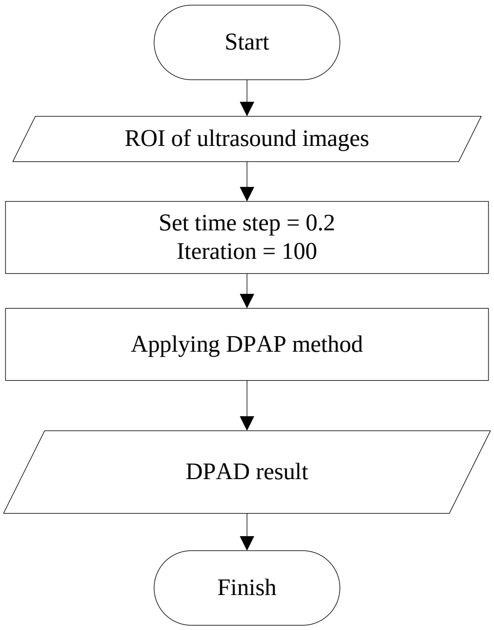


Fig. 5: DPAD process

4.2 Segmentation

In the segmentation stage, one of the most well-known methods is called active contour model which was firstly introduced by Kass *et al*. [13] is used in this work. Active contour works by analysing the differences of pixel to find and determine the object area. This method can be done by using Equation (4). This method has been developed in several versions such as active contour balloon model [14], gradient vector flow [15], and active contour without edges (ACWE) [16]. Segmentation phase is executed using ACWE. Iteration for the snake evolution is set up to 100 times.

$$E_{snakes} = \int_0^1 E_{img}\big(v(s)\big) + E_{int}\big(v(s)\big) + E_{ext}\big(v(s)\big)\, ds \qquad (4)$$

Here, E_{img} indicates the energy of original image, E_{int} is internal energy of image, E_{ext} is external energy of images. Energy of image is calculated to attract the snake on the characteristics that appear in the image. Internal energy of image indicates an energy used to preserve the smoothness of curve line formed by snakes. External energy of image is representation of an energy caused by human interaction such as giving a marker or label on the image [17].

4.3 Feature Extraction

There are eighteen features consisting of convexity, solidity, ratio aspect, compactness, circularity, dispersion, rectangularity, eccentricity, orientation, chain code differences, tortuosity, orientation, mean, variance, deviation standard, mean II, variance II, and deviation standard II [18]. Mean II, variance II and deviation standard II are obtained through isolation region of the lesion edge [18]. For extracting edge characteristic, some objects such as area of object, convex hull, convex hull area, convex hull perimeter, and center of mass or centroid should be calculated before. Fig. 6 shows all steps of feature extraction stage carried out in this study.

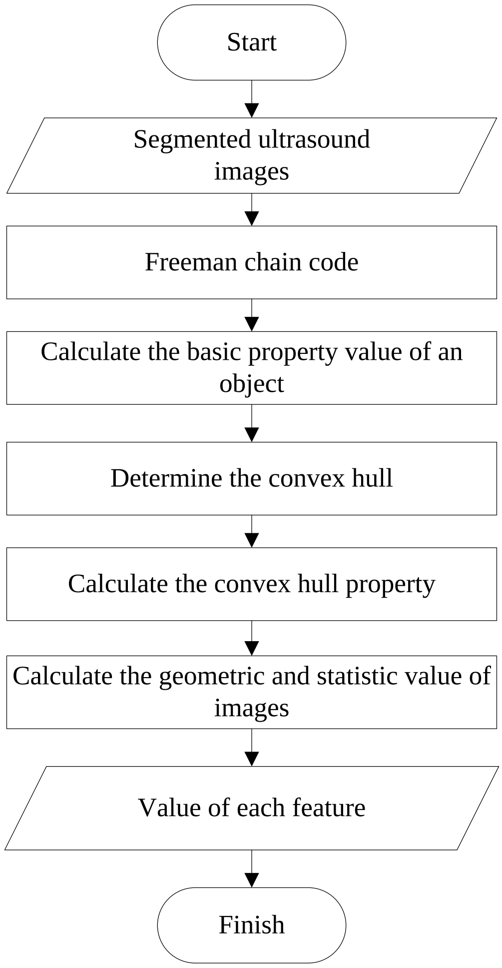


Fig. 6: Feature extraction process

4.4 Feature Selection

Feature selection is used for reducing data dimensions, improving prediction accuracy, producing more compact and easy-to-understand data and reducing execution time. More compact data and reduced execution time are very important to handle large amounts of data. Several feature selection methods are used in this work such as correlation based feature selection (CFS), information gain and wrapper subset evaluation. Some feature selection methods are used to select the best method in achieving the highest accuracy.

4.5 Classification

Having extracted the best features related to edge characteristic, the process is followed by classification to distinguish lesions into regular and irregular class. This study uses multilayer perceptron (MLP) classifier which is an artificial neural network architecture widely used in the field of education and applications. The simple MLP architecture is illustrated in Fig. 7 [19].

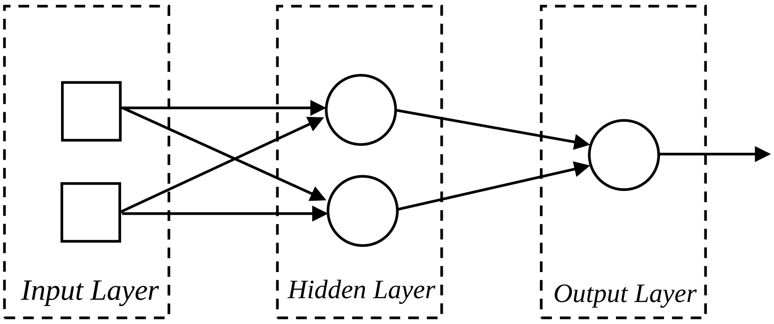


Fig. 7: Architecture of MLP

4.6 Evaluation

Evaluation is conducted by calculating the accuracy, sensitivity, specificity, positive predictive value (PPV) and negative predictive value (NPV) [20].

a) Accuracy
   Accuracy can be calculated by comparing the amount of correctly classified data with overall classification results. The measurement can be done by Equation (5).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}\ x\ 100\% \tag{5}$$

   Here, TP indicates true positive value, TN is true negative value, FP is false positive value and FN is false negative value.

b) Sensitivity
   Sensitivity is a measurement of the method's predictive ability to select a particular class instance from a series of databases corresponding with the true positive rate. Sensitivity can be calculated using Equation (6).

$$Sensitivity = \frac{TP}{TP + FN}\ x\ 100\% \tag{6}$$

c) Specificity
Specificity is an index used to measure the uniqueness of each class. Specificity can be done using Equation (7).

$$Specificity = \frac{TN}{TN + FP} x\ 100\% \tag{7}$$

d) PPV
Positive predictive value is a comparison value between TP with the number of TP and FP. Equation (8) is used to calculate PPV.

$$PPV = \frac{TP}{TP + FP} x\ 100\% \tag{8}$$

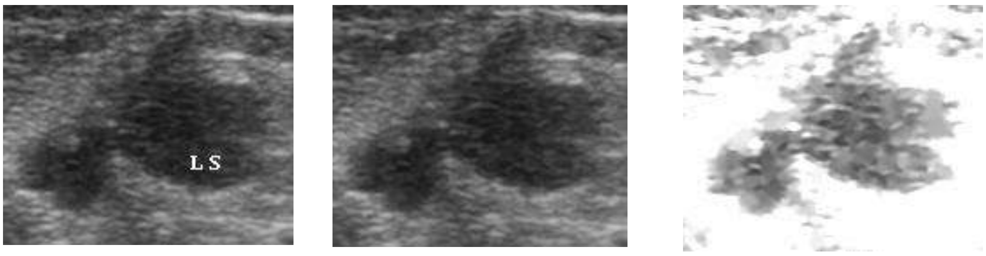
e) NPV
Negative predictive value is a comparison value between TN with the number of TN and FN. Equation (9) is used to calculate NPV.

$$NPV = \frac{TN}{TN + FN} x\ 100\% \tag{9}$$

5 Results, Analysis and Discussions

5.1 Pre-processing Result

This section displays visual results of image processing at the ROI cutting stage, marker emphasis and reducing the speckle noise. Fig. 8 shows the results of this step. The ROI image, adaptive median filtering result and DPAD result are respectively depicted in Fig. 8 (a), Fig. 8 (b) and Fig. 8 (c). The result shows that adaptive median filtering has good performance for emphasising marker and label as shown in Fig. 8 (b), furthermore DPAD also has good performance for suppressing the speckle noise as shown in Fig. 8 (c).



(a) (b) (c)

Fig. 8: (a) ROI image (b) adaptive median filtering result (c) DPAD result

Table 1 shows the obtained result using adaptive median filtering. This method can effectively remove the marker.

Table 1: Validation of pre-processing result

No.	Data	Number of image with marker	Number of image without marker
1	ROI images	61 images	23 images
2	Adaptive median filtering result	35 images	49 images

5.2 Segmentation Result

ROI images that have been processed and improved quality are then segmented to obtain the lesion area and the edges. In this section, active contour is applied to segment the lesion area. Correct segmentation result is the segmented images which closed to the ground truth. For validating the segmentation result, the segmented image should be matched with the ground truth. This validation process should be controlled by the radiologist to obtain a good segmented result. The result of applying active contour method can be seen in Fig. 9. The ground truth image and segmented image are respectively depicted in Fig. 9 (a) and Fig. 9 (b). The result shows that active contour method has good performance to segmenting lesion area as shown in Fig. 9 (b). Segmentation result in Fig. 9 (b) is almost close to the ground truth. Then for validating the segmentation result, evaluation should be done by calculate the accuracy, sensitivity, and specificity of segmentation result. Validation result is shown in Table 2.

(a) (b)

Fig. 9: (a) Ground truth image (b) segmented image

Table 2: Validation result of segmentation process

TP	TN	FP	FN	Accuracy	Specificity	Sensitivity
662138	840377	136013	110365	87.85 %	86.81 %	90.09 %

5.3 Feature Extraction Result

Feature extraction is performed on the area and edge of the segmentation result. This study uses 18 features as shown in Table 3. Feature extraction result using geometric features are summarized in Table 4. Feature extraction result using statistic features are summarized in Table 5.

Table 3: All features that used in this study

No.	Geometric Feature	No.	Statistic Feature
1	Convexity	1	Mean
2	Solidity	2	Variance
3	Aspect ratio	3	Deviation Standard
4	Compactness	4	Mean II
5	Circularity	5	Variance II
6	Dispersion	6	Deviation Standard II
7	Fourier Descriptor		
8	Chain code differences		
9	Tortuosity		
10	Extent / Rectangularity		
11	Orientation		
12	Eccentricity		

Table 4: Summarize of feature extraction result for geometric features

Image	Geometric Features											
	1	2	3	4	5	6	7	8	9	10	11	12
1	0.89	0.93	0.92	0.68	3.59	0.51	71.1	1.93	0.57	0.76	-12.7	0.42
2	0.86	0.94	0.56	0.60	0.70	0.56	97.4	1.86	0.67	0.76	5.06	0.82
3	0.78	0.84	0.74	0.48	0.35	0.43	75.3	1.93	0.56	0.67	-7.71	0.71
4	0.79	0.83	0.43	0.34	0.15	0.54	60.3	2.29	0.67	0.66	-81.8	0.93
5	0.88	0.95	0.58	0.62	0.63	0.55	87.7	2.12	0.68	0.76	-0.41	0.82
6	0.92	0.92	0.31	0.53	0.44	0.64	53.0	2.02	0.81	0.74	2.74	0.93
7	0.91	0.94	0.66	0.71	2.75	0.55	42.4	1.95	0.67	0.74	-7.24	0.71
8	0.86	0.95	0.37	0.43	0.17	0.63	59.9	2.35	0.71	0.67	7.24	0.93
9	0.95	0.97	0.37	0.64	0.84	0.68	37.9	1.90	0.80	0.75	2.79	0.89
…	…	…	…	…	…	…	…	…	…	…	…	…
84	0.81	0.90	0.42	0.46	0.33	0.54	57.2	2.12	0.66	0.75	-1.1	0.89

Table 5: Summarize of feature extraction result for statistic features

Image	Statistic Features					
	1	2	3	4	5	6
1	48.52	29.58	875.05	71.30	24.43	597.07
2	80.07	31.61	999.39	70.24	16.14	260.38
3	63.72	26.41	697.26	59.32	14.38	206.78
4	66.02	27.99	783.57	60.94	12.79	163.70
5	83.4	34.55	1193.85	77.52	35.20	1238.73
6	111.00	40.36	1629.14	86.23	16.39	268.60
7	73.76	47.86	2290.46	82.10	37.28	1389.58
8	88.43	39.31	1545.66	73.35	28.73	825.60
9	86.78	30.57	934.56	91.28	42.68	1821.25
…	…	…	…	…	…	…
84	54.28	49.33	2433.92	45.04	26.93	724.96

5.4 Feature Selection Result

Feature selection result of each method is shown in Table 6. Geometric features in classification process are more dominant than statistic features. This result is used for classification step.

Table 6: Feature selection results

No	CFS	Information Gain	Wrapper Subset Evaluation
1.	Compactness	Convexity	Solidity
2.	Solidity	Solidity	Variance 1
3.	Dispersion	Aspect ratio	
4.	Tortuosity	Compactness	
5.	Convexity	Dispersion	
6.	Extent / rectangularity	Tortuosity	
7.	Fourier descriptor	Extent / rectangularity	
8.	Standard deviation 1	Fourier descriptor	
9.	Standard deviation 2	Standard deviation 1	
10.	Variance 1	Standard deviation 2	
11.	Variance 2	Variance 1	
12.	Aspect ratio	Variance 2	
13.	Mean 1	Orientation	
14.	Orientation		
15	Eccentricity		

5.5 Classification Result

The characteristics that have been obtained in the previous stage are then used for the final process of image processing. As described earlier, in this study, breast ultrasound image lesions are classified based on edge characteristics to be regular and irregular classes. Table 7 shows the classification results. According to Table 7, wrapper subset evaluation method obtains the highest accuracy of 90.48 %. It indicates that wrapper subset evaluation method is the best method for selecting efficient features. The classification results also indicate that geometric and statistical features have good performance for classifying breast cancer based on characteristic of margin.

Table 7: Classification result

Features	Number of features	Accuracy (%)	Specificity (%)	Sensitivity (%)	PPV (%)	NPV (%)
All features	18	82.14	81.40	82.93	80.95	83.33
CFS	13	83.88	85.00	81.82	85.71	80.95
Information gain	15	79.76	82.05	77.78	83.33	76.19
Wrapper subset evaluation	**2**	**90.48**	**88.64**	**92.50**	**88.10**	**92.86**

5.6 Discussion

In this research, image quality improvement needs to be done to remove markers that given by radiology and speckle noise on ultrasound image as radar image arising from the acquisition process. The first problem successfully handled by adaptive median filtering method. While the second problem successfully handled by the DPAD. The weakness of this method is less able to remove thick markers. The result of image quality improvement is then used in the segmentation process. Segmentation using active contour produces the accuracy of 85.75%. This method needs a lot of time for computation process because the number of masking and iteration should be inputted manually. The segmentation results are then used to perform feature extraction. After all the feature values are calculated then the feature selection is performed to obtain the most influential features. This research uses geometric feature and statistic feature. However, for selecting the efficient features, some feature selection method such as CFS, information gain and wrapper subset evaluation are used in this work. Selected features of each method is then used for the classification process using MLP. The classification result using wrapper subset evaluation obtains the highest accuracy of 90.48%. This result indicates that wrapper subset evaluation is the best feature selection method for selecting features. It also indicates that geometric and statistical features are able to identify edge characteristics of breast cancer.

6 Conclusion

Detection and classification of breast cancer ultrasound image has been conducted by extracting characteristic of edge. Evaluation of this study is conducted by measuring the accuracy, sensitivity, specificity, PPV and NPV. The highest results respectively are 90.48%, 92.50%, 88.64%, 88.10% and 92.86%. These achieved accuracy, sensitivity, specificity, PPV and NPV denote that geometric features have good performance for classifying breast cancer based on edge characteristic.

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