Automated Detection of Tumors in Mammograms Using Two Segments for Classification

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Abstract. A spread pattern of a tumor in medical images is an important factor for classification of the tumor. The spread pattern is generally not considered when we use only one segment for classification. In order to include the spread pattern for tumor analysis, we propose an approach for classification of tumors in mammograms using two segments for a mass. The proposed approach is performed in two stages. In the first stage, the system separates segments of the image that may correspond to tumors using a combination of morphological operations and a region growing technique. In the second stage, segmented regions are classified as normal, benign, or malignant tissues based on different measurements. The measurements pertain to shape, intensity variation around the mass, as well as the spread pattern. Experimental results with mammogram images of the MIAS database show reasonable improvements in correct detection of possible tumors, compared to other approaches.

Keywords: Tumor classification, spread pattern, segmentation, mammogram.

1 Introduction

Classification of objects in digital images is an important task in many applications; especially, in medicine where prevention and early diagnosis are very important. An example of such a task is the checkup done for detecting the breast cancer, which is one of the most common cancers among women and its incidence is rising in recent years. Although the primary prevention is not completely possible since the cause of this disease is not clearly understood, its treatment can be very effective if the breast cancer is detected in its early stages. Among different routine tests, mammography is one of the most common and effective methods for early detection of the breast cancer.

Because mammogram reading is a difficult and ambiguous task, many researchers try to propose automated systems to do this task efficiently. In general, research activities can be divided into two categories. In the first category, they focus on the enhancement and prompt of suspicious regions to draw the attention of physicians to those regions for detecting possible tumors. The objective of activities in the second category is to fully automate mammogram analysis.

Despite of some outstanding works for automation of mammogram analysis, there is still a long way to have a completely reliable automated system for mammogram reading. One of the problems in automated detection of masses in mammograms is

the choice of the scale. Masses vary largely in size, ranging from a few millimeters to a few centimeters. Only a few researchers on this area address the issue of scale; however, they validated their proposed methods only on a very small dataset.

Brzakovics proposed a fuzzy pyramid linking method for detection of possible tumors in mammogram images and he classified detected regions to benign and malignant for circular and stellar lesions in a hierarchical fashion [1]. Brzakovic and Neskovic then applied the fuzzy pyramid linking algorithm on a number of different scales to detect abnormal structures over a range of sizes [2]. Ng and Bischof detect the central mass of lesions using a basic template-matching scheme, which was also applied to a number of scales [3]. A circular Hough transform was used by Groshong and Kegelmeyer to detect circumscribed masses by searching for circular blobs. Their algorithm was tuned to provide similar signals for small and large tumors [4].

Mudigonda *et al.* focused on the development of gradient-based features and texture measures based on gray-level co-occurrence matrices for the classification of mammographic masses [5]. Petroudi *et al.* proposed a scheme which uses texture models to capture the mammographic appearance within the breast area. They model parenchymal density patterns as a statistical distribution of clustered, rotationally invariant filter responses in a low dimensional space [6]. However, the performance of their approach is restricted by the training set and quality of mammogram images. A neural classification scheme using fractal analysis and spatial moment distributions was proposed by V. Öktem and I. Jouny for detecting malignant tumors [7]. Although they had a low false positive detection, correct detection rate is not reasonable yet.

In this paper, we propose a new approach for automated detection of tumors (of different kinds and scales) in mammograms based on some prognostic factors: mass size, mass shape, intensity variation around mass boundaries, and spread of primary shape [8]. Different from previous works that use only one segment for classification, we extract two segments (inner and outer) for a mass, which helps us to define a spread pattern for a possible tumor if necessary. Classification is then performed using these two segments. Experimental results show that such consideration improves the correct detection of possible tumors and identification of their diagnostic stage.

The paper is organized as follows. Section 2 explains the proposed approach in detail: detection of possible tumors is described in Section 2.1, and feature extraction and tumor classification are detailed in Sections 2.2 and 2.3, respectively. In Section 3, we discuss experimental results and compare them with results of other approaches. Finally in section 4, we conclude our work and address issues for future works.

2   Automatic Detection of Tumors

Although we mainly concentrate on the recognition of three general masses: (1) normal round masses, (2) benign round masses, and (3) malignant round masses, we can also determine the type of non-circular lesions, e.g. star shape and architectural, which are suspicious to be a tumor. In order to classify these types of masses, we use different features, such as size, shape, intensity, and the spread pattern of the primary shape, e.g. ring of dehydration for malignant tumors.

To obtain the abovementioned features in the image, we first separate possible tumors in mammograms by a new segmentation method into two different segments,

i.e. inner and outer. This process is done by a combination of morphological operations with a region growing method. Such separation makes the proposed framework distinct from the previous works that are based on one segment.

In the second stage, the detected masses are classified in a hierarchical fashion. In the first level, their sizes are checked. If they are bigger than a maximum threshold value or less than a minimum threshold value, we consider them as non-tumor. Possible tumors then proceeds to the next level of hierarchy, where we use two different classifiers which discriminate a mass based on its shape and edge intensity variations. Such classifications are done for both inner and outer segments of the mass. For both classifiers in this level of hierarchy, we use Multi-Layer Perceptron (MLP) network [9]. Finally, in the last level of classification, the final decision for a mass is made by a rule-based classifier.

2.1 Identification of Possible Tumors

The objective of the first processing stage is to identify possible tumors in mammograms. Generally, identification of possible tumors is a very difficult task due to the rich variations of gray level intensities in mammograms. Here, this process is based on the morphological techniques [10] [11] followed by an intensity growing algorithm, which finally generates two segments for a mass.

Precisely speaking, the segmentation task is accomplished by four steps: (i) cleanup the mammogram from non-informative regions, (ii) marking foreground objects using morphological operations, (iii) determining possible segmented regions by finding the locations of the regional maxima in the marked foreground objects, and (iv) extending segmented regions by connecting components of pixels based on the intensity differences during iterations. Figure 1 shows a typical mammogram and the output of each step. Now, let's examine each step in detail.

Usually, there are some areas in a mammogram image which are not under attention for classification and may increase the processing time. The first step, which is optional, considered for removing these regions. Such a cleanup is done by selecting the breast, or any part of it, as the region of interest.

In the second step, we apply a number of morphological operations for marking the foreground in the image (Fig. 1(b)). These operations are erosion, reconstruction, and dilation, defined by

$$\text{Erosion: } E(I, Se) = I \Theta (-Se) \qquad (1)$$

$$\text{Reconstruction: } R_E = \bigcup_{k=0}^{K} [E(I, Se) \oplus I] \qquad (2)$$

$$\text{Dilation: } D(I, Se) = I \Theta Se \qquad (3)$$

$$\text{Reconstruction: } R_D = \bigcup_{k=0}^{K} [D(I, Se) \oplus E(I, Se)] \qquad (4)$$

where I is the original image (after clean up) and S_e is the morphological structural element, which is a disk with radius 20 pixels in this work. Operators $\oplus$ and Θ are Minkowski addition and subtraction, respectively, which are defined by

$$A \oplus B = \bigcup_{\beta \in B} (A + \beta)$$

$$(5)$$

$$A \Theta B = \bigcap_{\beta \in B} (A + \beta)$$

$$(6)$$

In the third step, we find the regional maximal of the reconstructed image from the previous step using a connectivity array of 8-connected neighborhoods (Fig. 1(c)). A regional maximal is a connected set of constant intensity from which it is impossible to reach a point with lower intensity without first ascending, that is, a connected component of pixels with the same intensity value, t, surrounded by pixels whose values are greater than t.
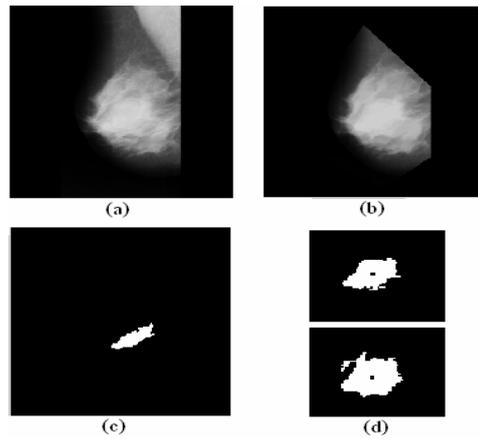
Fig. 1. Different segmentation steps. (a) Original Image. (b) Image after marking foreground. (c) Regional maximal. (d) Inner and outer segments.

Finally, in the last step that is performed iteratively, we extend the regional maximal by allowing more intensity differences for pixels in the primary regional maximal to extract the inner and outer segments. The result of this step is shown in Fig. 1(d). The extension is controlled by the intensity histogram of the primary region, and we continue to extend the region with more intensity values if the weighted average of the intensity histogram changes only in a limited range without significant replacement in the histogram spectrum. Here, we defined two threshold values to control the process; one for the inner segment (T_i) and the other one for the outer segment (T_o) and $T_o > T_i$. However, there are some situations, where inner and outer segments are exactly or almost the same, as in most normal tissues.

In order to clarify the situation, let's examine the process of the regional maximal extension for the mass shown in Fig. 1. The primary intensity histogram for the re-

gional maximal is illustrated in Fig. 2(a). In the first iteration, the extended region has a histogram shown in Fig. 2(b) and the variation is still less than T_i; however, in next iteration, the extended region has a histogram with a variation bigger than T_i, so the inner segment is the one extracted in the previous step. A similar process is done to find the outer segment, but this time with threshold T_o. In this example, the last acceptable extension is related to the histogram in Fig. 2(d). As we can observe in Fig. 2(e), the extension in this step is completely changed the histogram of the primary regional maximal, which is not acceptable.
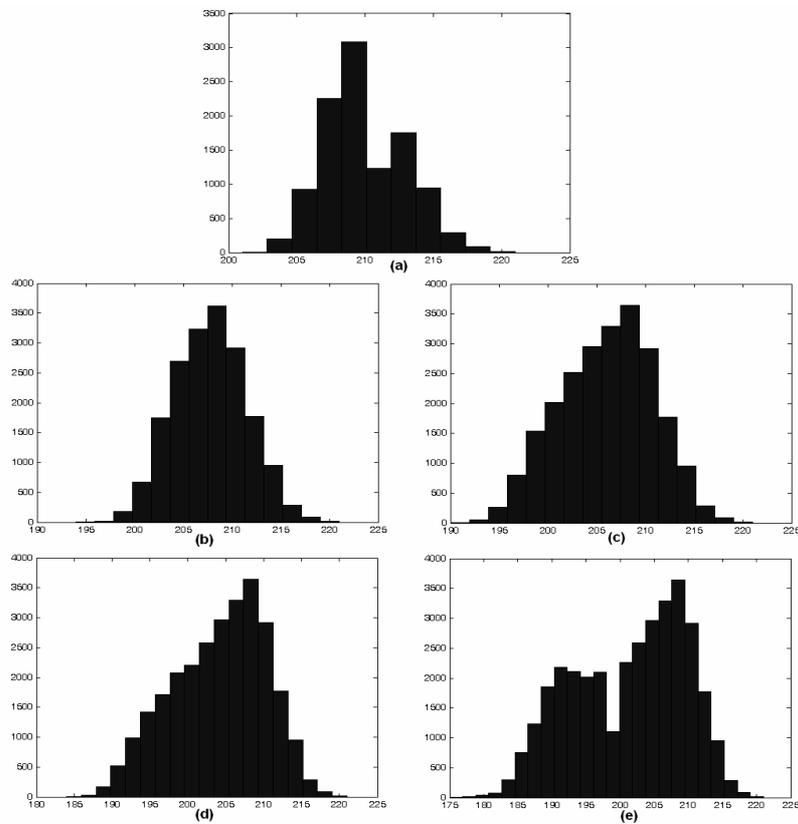
Fig. 2. Extension of the regional maximal in iteration for extracting inner and outer segments. (a) Histogram of the primary regional maximal. (b) Histogram of the extended region after the first iteration (related to the inner segment). (c) Histogram of the extended region after the second iteration. (d) Histogram of the extended region after the third iteration (related to the outer segment). (e) Histogram of the extended region after the fourth iteration (not acceptable).

2.2 Feature Extraction

Having completed the segmentation, and before starting the classification process, we should extract the corresponding features. There are different features used in the

classification stage, where each of them is related to one characteristic of the tumor lesions. These features are as follows:

Area. Area is the total number of pixels enclosed in the segmented region. Here, areas are measured for inner and outer segments, separately.

Shape. Shape feature is the signature of the boundary of a mass, obtained by calculating the Euclidian distance between the center and boundary pixels of the extracted region. Later, we will explain how we extract boundaries and calculate the center for a segment. This feature is useful for discriminating circular masses from noncircular ones, which calculated by

$$D_i = \sqrt{\left((x_i - x_c)^2 + (y_i - y_c)^2\right)} \tag{7}$$

where x_i and y_i are the coordinates of the ith edge point, and x_c and y_c are the coordinates of the center of the segmented region. Again, we compute two signatures, one for the inner segment and the other for the outer segment, however, the center of the inner segment is considered as the center point for both segments.

Edge Distance Variation. Edge distance variation is the local intensity changes around the boundary pixels of the extracted region, which is calculated by

$$I_i = abs\left(I(x_i, y_i) - m_i\right) \tag{8}$$

where $I(x_i, y_i)$ is the intensity value of the ith edge point, and m_i is its local mean. Similarly to the previous features, we extract this feature for both segments. Usually, tumors are classified by well-defined edges.

Spread Pattern. Usually, the stage of a breast cancer is based on its size and degree of spread. A typical example of a spread pattern for infiltrating ductal carcinoma [12] is illustrated in Fig. 3. In the progressive stages of a cancer, it may even spread to other parts of the breast or even other parts of the body via lymphatic vessels; however, in this work, we just consider the spread pattern for the situation where the spread is in the original site of the primary mass.

Considering the example of Fig. 3, we can easily observe that a spread pattern may be defined for this kind of tumor if two segments are extracted for the tumor based on the intensity variations around the boundary of its original site. Using this fact, we define a spread pattern as the difference between shapes (signatures) of inner and outer segments. However, this feature is not used for classification in the first and second steps of classification hierarchies. Instead, we compare the inner and outer segments in the rule-based classifier, where, for example, more similar segments can show less possibility for malignancy.

Now, let's examine how we extract edges of the segmented regions and calculate their center. For detecting edges, we apply both the Prewitt and Sobel filters to the segmented inner and outer regions, separately, and then take the union of the results.

$$Edge_s = H_{pr}(S) \cap H_{so}(S) \tag{9}$$

where $Edge_s$ is the final detected edge for the segment S, and H_{pr} and H_{so} are the results of edge detection for the segment S using the Prewitt and Sobel filters, respectively. Figure 4 shows the result of edge detection for the inner and outer segments of Fig. 1(d).
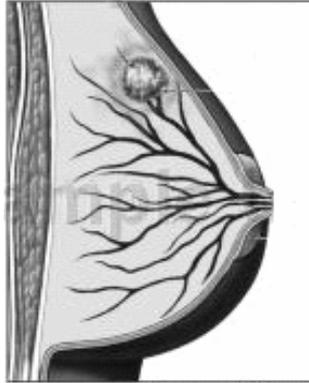
Fig. 3. A typical spread pattern for Infiltrating Ductal Carcinoma [13].
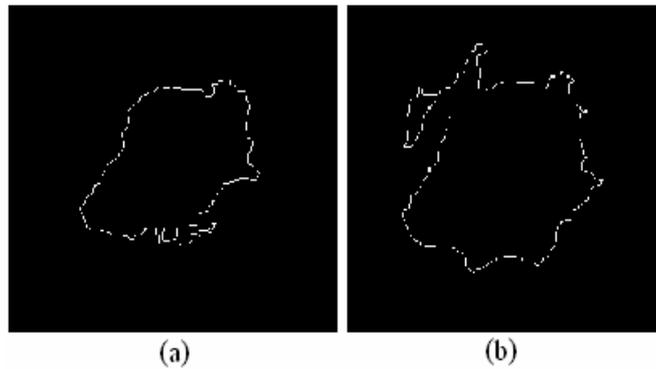
Fig. 4. Boundaries of extracted regions in Fig. 1(d). (a) Edges of inner segment (b) Edges of outer segment.

The second point is related to finding the center of a segment. As mentioned before, we only find the center point for the inner segment, and all measurements for inner as well as outer segments are performed based on this center.

Although there are some useful algorithms which locate the center of a round object, most of them are so complicated [14] [15]. Instead, we use a simple and efficient way for calculating the center that is not necessarily round.

In this method, the mean values of x and y coordinates of edge points are initially considered as coordinates of the center point. We then adjust the coordinates in iteration to find the best position for the center. This adjustment is based on the distribution of edge points around the center. Experiments show that this method is quite successful in locating the center.

2.3 Classification of Extracted Regions

As mentioned before, we perform classification in a hierarchical fashion. Figure 5 shows different levels of classification hierarchy, developed in this work.
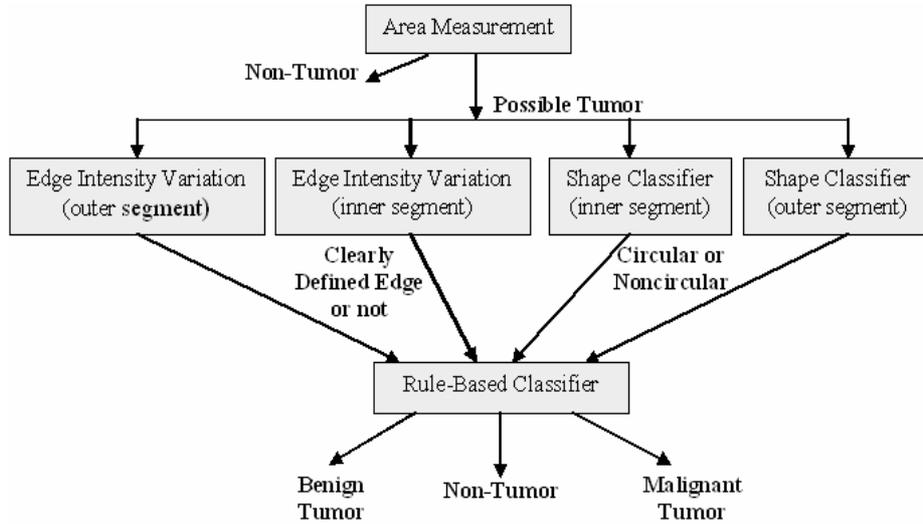
Fig. 5. Levels of hierarchy in the classification stage.

Area Classifier. The area classifier separates the masses to non-tumor and possible tumor based on their sizes, i.e. the area feature. Through experimentation, the minimum and maximum levels are set to be 0.001 and 0.1 of the image resolution, respectively. The segmented area is not a tumor then, if:

$$Area_{out} < Area_{\min} \tag{10}$$

$$Area_{in} > Area_{\max} \tag{11}$$

where $Area_{in}$ and $Area_{out}$ are the size of inner and outer segments, respectively.

Shape Classifier. For this classifier, we use an MLP network with one hidden layer with 50 neurons, 100 neurons in the input layer, and one output neuron which discriminates between circular and noncircular segments. The input is the shape (signature) feature vector. The classifier has been trained using the backpropagation algorithm for a noise free circle, a number of elliptical shapes with different minor and major access and orientation, as well as some of the real circular and noncircular masses from 80 different mammograms, which are totally around 100 training feature vectors.

Edge Intensity Variation Classifier. For this classifier, similar to the shape classifier, we use another MLP network with one hidden layer with 50 neurons, 100 neurons in the input layer, and one output neuron which discriminates the masses with clearly defined edges (possible tumor cases) from those ones with not clearly defined edges. The input vector is the edge intensity variation feature vector. The classifier has been trained using the backpropagation algorithm for 80 different mammograms.

Rule-Based Classifier. This classifier is somehow the most important one in the classification hierarchy, because the final decision is made in this level. The rules used in this classifier are based on the characteristics of tumors, such as clearly defined edges for the tumor case, determined by experts in this field [8], as well as through experimentation. Table 1 summarizes a list of the major rules. In Table 1, the rules related to the spread pattern are excluded. Based on the rules, the system decides which category the mass belongs to. For example, if both segments are circular with clearly defined edge intensity variations, the possibility of malignancy is increased, especially for the case that there is less similarity between inner and outer segments with respect to their spread pattern.

Table 1. Major rules used in rule-based classifier

Shape	Edge Intensity Variation	Final Decision
Both segments circular	Both segments clearly defined Only one segment clearly defined Neither segments clearly defined	Malignant Benign Non-Tumor
Only one segment circular	Both segments clearly defined Only inner segment clearly defined Only outer segment clearly defined Neither clearly defined	Malignant Possible Benign Possible Malignant Non-Tumor
Neither segments circular	Inner segment clearly defined Only outer segment clearly defined Neither clearly defined	Possible Tumor Undecided Possible Non-Tumor

3 Experimental Results

The processed images, with sizes of 1024 x 1024, have been selected from the Mammographic Image Analysis Society (MIAS) database, which is very well-known in this area, and usually used by researchers to evaluate their algorithms. The dataset consists of a variety of normal mammograms as well as mammograms with different types of abnormalities, such as circumscribed masses, calcification, speculated masses, and so on, with different characteristics and severity of abnormalities [16].

For training, we used 80 mammograms from various categories with different complexity, from highly textured to those that appear hazy. With these data, we trained shape and intensity variation classifiers, and also obtained threshold values for area measurement and some of the rules for the rules-based classifier.

The evaluation was carried out on 60 mammograms including 12 training mammograms and 48 other mammograms (different from the training data). These data contain specific types of tumors including 15 round-shape non-tumors, 15 round-

shape benign tumors, and 5 round-shape malignant tumors. The remaining 25 contains noncircular masses (15 tumor and 10 non-tumor cases).

In the segmentation stage, the system was successful in isolating possible tumors. In this stage, while tumors identified in about 88.5% (31/35) of the cases for the complete sample set that consists of circular and noncircular masses, identification was almost precise for the circular tumors (95% (19/20)).

In the classification stage, and in the second level of hierarchy, the mean square error (MSE) for the shape classifier was almost zero. However, there was 3% misclassification for the edge intensity variation classifier, which is caused by imperfect segmentation of noncircular masses.

The overall accuracy of the proposed system for different categories are summarized in Table 2, where the accuracy is defined by the percentage of correct detections and different categories are non-tumor, benign tumor, and malignant tumor for round-shape masses, individually, and all other noncircular cases, together.

Table 2. Percentage of correct detection for different categories

	Using Two Segments	Using Inner Segment Only	Using Outer Segment Only
Normal (circular mass)	86.7% (13/15)	73.3% (11/15)	73.3% (11/15)
Benign (circular lesion)	93.3% (14/15)	80% (12/15)	60% (9/15)
Malignant (circular lesion)	80% (4/5)	60% (3/5)	20% (1/5)
Noncircular (correct detection)	68.0% (17/25)	56% (14/25)	40% (10/25)

From Table 2, we note that the best result is for round-shape benign lesions that have well-defined edges and are segmented almost precisely in the first stage. For non circular cases, the most false detections occurred for calcifications which are usually very small spots in mammograms, and speculated masses which are not identified quite well in the segmentation stage.

In order to show the improvement of the tumor classification in the proposed method, we have included the results of the experiment for the cases where only one segment is used for classification in Table 2. As indicated, the results of classification using two segments show a considerable improvement in the accuracy, compared to the results of classification when we use only of the inner or outer segment for classification.

Besides, a comparison between the proposed approach and some of the previous works shows that the detection accuracy for different types of tumors with different shapes is increased in our proposed system. The results of this comparison have been summarized in Table 3. Although the accuracy of the proposed system is quite reasonable, it is expected to improve even more if we do a more precise segmentation of

Table 3. Comparison of total accuracy in some different approaches

Proposed Approach	AMA [1] [*]	GCM-Based Mass ROI [5]	GCM-Based Mass Margins [5]	Fractal Analysis/ Spatial Moments [7] [**]
82.9% (29/35)	85% (17/20)	74.4% (29/39)	82.1% (32/39)	70% (21/30)

[*] evaluated only for round and star-like tumors
[**] evaluated only for malignant tumors

noncircular masses as well as enough considerations for calcifications and speculated masses.

In Table 3, while the Automated Mammogram Analysis (AMA) approach has been evaluated only for round and star shape tumors, and fractal analysis/spatial moments method consider just malignant tumors, the other approaches have be evaluated for all kinds of masses with different sizes, shapes, and complexities.

4   Conclusion

In this paper, we have presented a novel approach for detection and classification of masses in mammograms. In this work, we extract two segments, inner and outer, for a mass in a mammogram in order to define a spread pattern for tumor lesions. A spread pattern of the tumor in the medical images, in addition to other parameters of the mass, such as size and shape, is an important factor for the classification. Using these two segments, we try to detect tumors in the classification stage which is done in a hierarchical fashion. Experimental results show that tumor detection in this approach outperforms other methods using only one segment for classification. The correct detection rate of the system is expected to be improved further if we perform more precise segmentation for noncircular masses.

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