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ADAPTIVE THRESHOLD-BASED TUMOR DETECTION ALGORITHM FOR MAMMOGRAMS IMAGES

Taha Basheer Taha[1*]

[1*]Information Technology Department, Faculty of Applied Science , Tishk International University, Erbil-IRAQ

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Communicated by: Dr. Orhan Tug
[*]Email address:
Taha.basheer@tiu.edu.iq
[*] Corresponding Author

Abstract: Breast cancer is without doubt the leading cancer among women, and it is one of the most damaging illnesses to females that should be periodically checked. Early detection of breast cancer can reduce the mortality caused by this disease by 95%. However, studies mention that up to 25% of tumors are missed by radiologists. In this paper, a tumor detection algorithm in mammogram images is developed by relying on simple calculations that are based on adaptive thresholding and tumor area size. Low complexity calculations will ease the implementation of the algorithm in embedded systems and in real-time detection. The proposed algorithm is used to detect the circular type of tumor and it is developed with a graphical user interface to ease the process of selecting mammogram images and changing settings of threshold values and the size of tumor area. Experimental results show the ability of the algorithm to successfully detect and differentiate circular tumors from normal and fatty breast tissue.

Keywords: *Digital Image Processing; Mammograms; Image Threshold; Tumor Detection*

1. Introduction

Breast cancer is a significant health concern for women in the United States, with about 30% of all new female cancer cases being breast cancer each year. It is the most common cancer among women, except for skin cancers. In 2023, an estimated 297,790 new cases of invasive breast cancer and 55,720 new cases of ductal carcinoma in situ (DCIS) will be diagnosed in women. Tragically, breast cancer is also responsible for approximately 43,700 deaths among women annually. These statistics underscore the importance of breast cancer screening and awareness efforts to detect and treat the disease as early as possible [1]. Early detection and adequate treatment of breast cancer can be achieved if early detection is performed. Screen/film mammography has been widely recognized as an effective modality for early tumor detection. In recent years, computer-aided detection (CAD) systems have been developed to assist radiologists in analyzing mammograms and identifying potential breast cancer cases. These systems use various techniques such as artificial intelligence, machine learning, and image processing to analyze mammograms and flag potential cancer cases for further evaluation. However, While 80% of women who are brought back for additional views have good outcomes and 40% of the biopsied lesions are benign, radiologists continue to overlook 10% to 30% of malignancies[2].

The reason beyond these misses belongs to the nature of the mammogram images, as they might be poor in contrast or have some noise that affects the diagnosis process. Radiologists used to detect malignant masses by examining mammograms. However, microcalcifications are tiny deposits of calcium that are difficult to detect while also playing an important role in detecting breast cancer in its early stages. The detection of small calcifications is even more difficult for younger women who have denser breast tissues because their mammograms show larger areas of low contrast and higher brightness and because information is highly correlated. Besides these, mammographic images can also be corrupted by noise, thus generating false positives. Accordingly, enhancing mammogram images is a crucial need for better diagnosis. Image processing tools can play a major role in the achievement of this requirement. For instance, Figure 1 shows the breast tissue before and after processing the image [3][4].

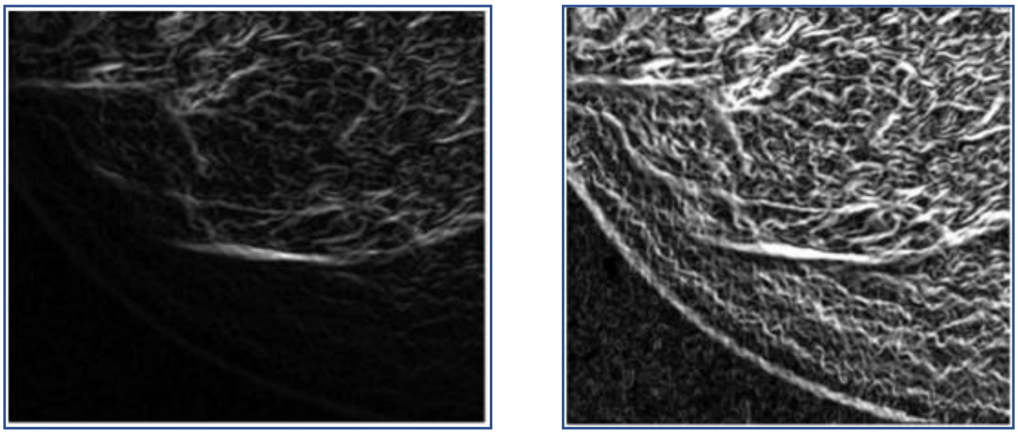


Figure 1: Breast tissue mammogram a: before processing b: after processing [4]

Hence, using image processing, the contrast can be enhanced, image features can be highlighted, and noise can be removed or eliminated. In this paper, a low-complexity method for circular tumor detection in mammograms is proposed based on a customizing threshold method. The process of tumor detection is based on simple calculations so that it can be implemented easily in real-time-based embedding systems.

In the next section, recent related works are reviewed. Section three explains the proposed tumor detection algorithm. Experimental results are presented in section four, and section five contains the paper's conclusion and future work.

2. Literature Review

For better perceptual quality of mammogram images, different systems have been developed to apply preprocessing techniques and detect the tumor or microcalcifications in these images. In the work [5], image structure features were categorized in grey images based on two categories: the first one is the second-order histogram that represents the global texture, and the second one is the wavelet decomposition, which represents the local microcalcification texture. The second category was represented by the first-order histogram. According to these features and by applying the neural network, the proposed methodology analyzed the structure of mammogram images. Salavado and Roque [3] used contrast enhancement to help radiologists interpret mammogram images more accurately. The high frequency bands of wavelets were utilized in this method for detecting the change. The aim is to improve contrast in mammographic images in order to facilitate its interpretation by radiologists. The method involves image de-noising, wavelet image analysis, and image enhancement by local adaptive operators integrated into the wavelet domain. While decomposing images into sub-bands, the low-frequency sub-band is suppressed, and then we reconstruct the image from the high-frequency sub-bands. Preliminary results indicate that the performance of this approach is acceptable. Several preprocessing steps, such as noise removal, segmentation, and edge detection, were completed. Another method of calcification detection was proposed in [6] After applying noise removal, this method was based on wavelet transform and Sobel operators to distinguish the calcification from other breast tissue in mammograms.

In the work of Naseem et al. [7], pattern recognition and artificial intelligence were combined in order to detect microcalcifications. The input image passes through the image enhancement phase, feature extraction based on morphological operations, image segmentation based on clustering, and finally the classification based on artificial neural networks. For the precise classification of benign and malignant mammography images, Researcher in [8] developed a computer program called Multiscale All Convolutional Neural Network (MA-CNN) to help doctors diagnose breast cancer more accurately. The program uses a type of artificial intelligence called convolutional neural networks to identify features in mammogram images and classify them as normal, benign, or malignant. The program uses different scales of filters to analyze the images and improve accuracy without slowing down the analysis.

ANN used in another study that recommends an enhanced DenseNet neural network model, known as the DenseNet-II neural network model. The model pre-processes mammography pictures using image normalization and data augmentation techniques, which considerably raises the recognition rate. With an average accuracy rate of 94.55%, the DenseNet-II model exceeds other widely used network models in classification accuracy, demonstrating that it is more reliable and versatile. The proposed methodology offers medical professionals more objective and accurate outcomes, indicating significant therapeutic usefulness and research relevance[9]. ANN is also used in [10] , where researchers used 40 images from the DDSM dataset and extracted GLCM, GLDM, and Geometrical features from mammogram images. They applied Convolutional Neural Network (CNN) as a classifier to improve the accuracy rate of Computer-Aided Diagnosis (CAD). The classifier's performance was measured using receiver operating characteristic. In the training stage, the proposed method achieved an overall classification accuracy of 73% for dense tissue and 79.23% for fatty tissue. CNN performed better than previous classifiers and accurately detected normal mammograms as abnormal. This approach also successfully detected overlapping tissues. This method is different from other approaches that only detect cancers in mammograms. A review of DCT and DWT approaches were presented in [11] and A survey of using image processing in mammograms was presented by Verma & Khanna [12]. These methods can be enhanced by using new clustering algorithms [13], or using parallel processing to further increase the model's effectiveness and shorten the training period, researchers can investigate leveraging parallel processing and distributed computing approaches [14]

And as it can be noticed, developed systems mostly use signal transformation to transform digital images from the time domain to the frequency domain, such as wavelet transform, where images are decomposed into different frequency bands. These bands show some characteristics of the images. For instance, high frequency bands show the details of the image and significant changes in pixel values.

These methods are considered time-consuming and involve float number calculations that have their difficulties in hardware implementation. Also, simplified methods such as threshold-based detection were used in the literature in brain tumor detection by Tesawy [15] but without adaptation or size consideration, hence it was utilized and enhanced in this work and used for mammogram images.

The proposed method is based on simpler calculations and it keeps the image in the time domain, which leads to a faster implementation that can easily be used in real-time systems. The proposed method focuses on the automatic detection of circular tumors in mammogram images.

3. Methodology

The aim of the proposed algorithm is to detect the circular tumor and allocate its place in mammogram images. The work in general is characterized by the simplicity of implementation that can be used in real-time detection.

Breast tumor detection in mammography images is a demanding performing that calls for a multi-step procedure. The first stage entails interpreting the image and figuring out the average tissue density, as shown in Figure 2. The mammography images' black backdrop needs to be excluded because it can make it difficult to determine the right threshold.

The identification of circular tumor spots is the next step in the detection process. Instead of appearing in the photograph as a single white point, the tumor spots should be a continuous spot. In order to identify these dots from random camera reflection points, their area is subsequently determined. Large areas are also not included because they are thought to be fatty breast tissue.

The locations that are still classed as suspectable areas are then identified and shown in the image, with the area having the highest density. This makes it possible to spot prospective tumors and helps with breast cancer diagnosis. Overall, this multi-step method for identifying breast tumors in mammography images is successful. It involves calculating the average tissue density, determining the threshold, identifying circular tumor spots, and categorizing suspectable areas.

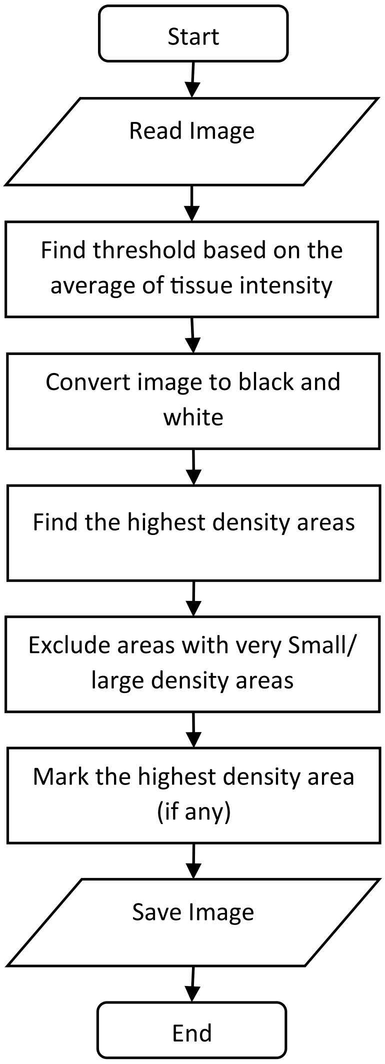


Figure 2: Flowchart of proposed detection

4. Results

After reading the mammogram image, an adaptive thresholding will be applied to eliminate the regular tissue and the background, next step is to highlight continuous and high-intensity areas, then to allocate the maximum intensity area and mark it, Finally, to border the suspicious area on the original image and show it. Different images with tumor detection results that are used from the mammogram database[16] are shown in Figure 4:

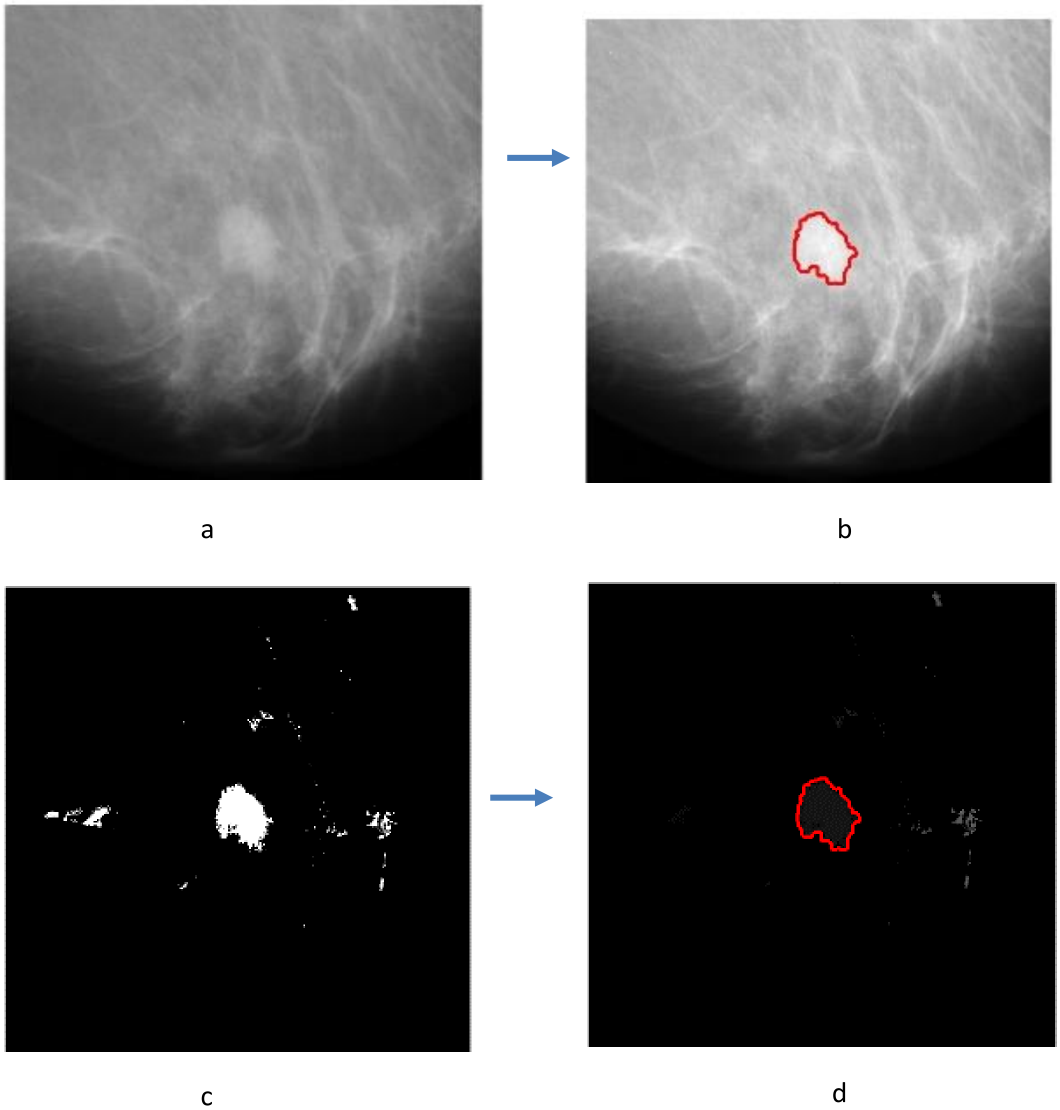


Figure 3: Detection phases: a: Original Image. b: Adaptive Thresholding. c: Tumor Place d: Tumor on original image

Promising results have been obtained employing the suggested technique of using adaptive thresholding to identify worrisome spots in mammography images. The highest tissue density, which is frequently a sign of tumor existence, was precisely located and marked by the algorithm. This method's capacity to adjust to the variation in tissue density across various mammography images is one of its advantages. The program can locate regions of increased intensity, which might represent malignancies, by estimating the average tissue density and setting the threshold appropriately.

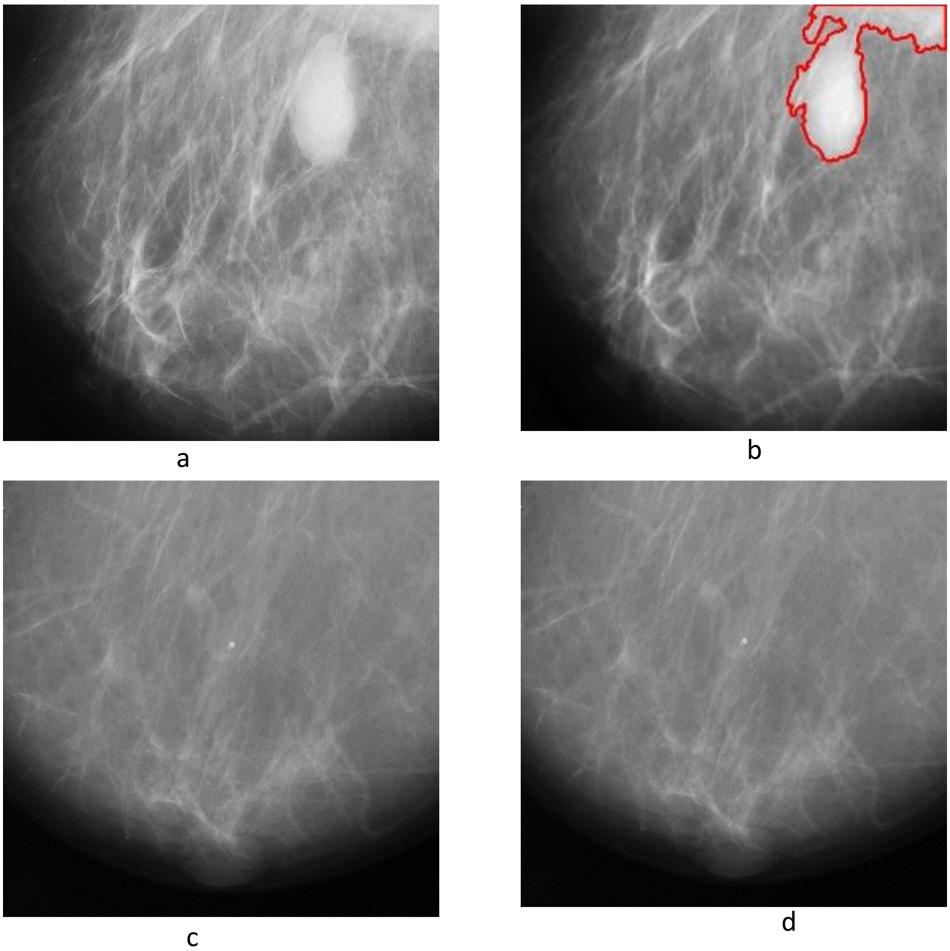
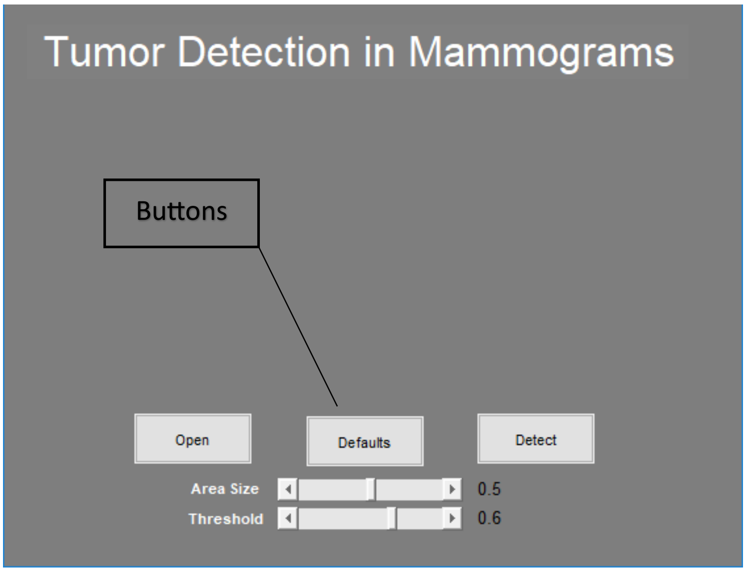


Figure 4: Tumor detection samples, original images (a,c) Detected Tumor (b), No tumor (b).

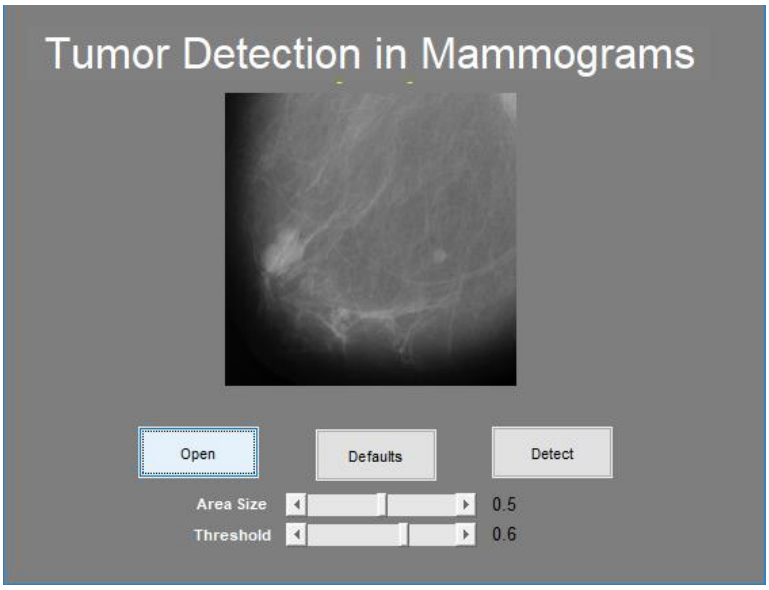
A drawback is that it might not be able to find small tumors or malignancies in places with little tissue density. Furthermore, the algorithm may mistakenly classify regions of dense tissue as suspicious when in reality they are caused by other reasons like overlapping tissue. Radiologists may find the proposed method to be a valuable tool for spotting questionable spots in mammography images as a result of its overall encouraging outcomes. To evaluate the efficacy and generalizability of this strategy, more research and validation on larger datasets are required.

In addition, In contrast to other studies, the proposed method is neither a time-to-frequency domain transform that relies on float number calculations such as the discrete wavelet transform (DWT), nor an artificial neural network (ANN) that requires a relatively complex implementation and training time. For instance, the proposed method could detect tumors without the need to transform the image from the time domain to the frequency domain. Consequently, the system can easily be implemented using embedded systems such as Field Programmable Gate Array (FPGA) devices and it can run in real time[17, 18].

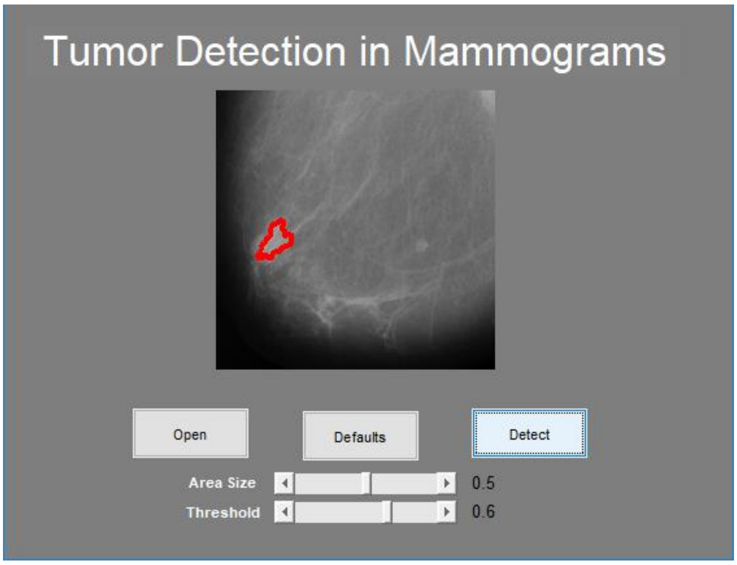
To simplify the process of using the proposed system, a graphical user interface (GUI) is designed to allow application users to browse mammogram images and detect the tumor if it exists. The user can browse the image by pressing the "Open" button and then press the "Detect" button to detect the tumor. The area of detectable tumor can be increased or decreased using the slider captioned "Area Size", and since mammograms may vary in contrast, the "threshold" slider can be adjusted to change the threshold bias between dark and light areas. A user can restore default values by pressing on the "Restore" button. The GUI implementation is shown in Figure 5.


Tumor Detection in Mammograms
Buttons
Open
Defaults
Detect
Area Size
0.5
Threshold
0.6

a


Tumor Detection in Mammograms
Open
Defaults
Detect
Area Size
0.5
Threshold
0.6

b



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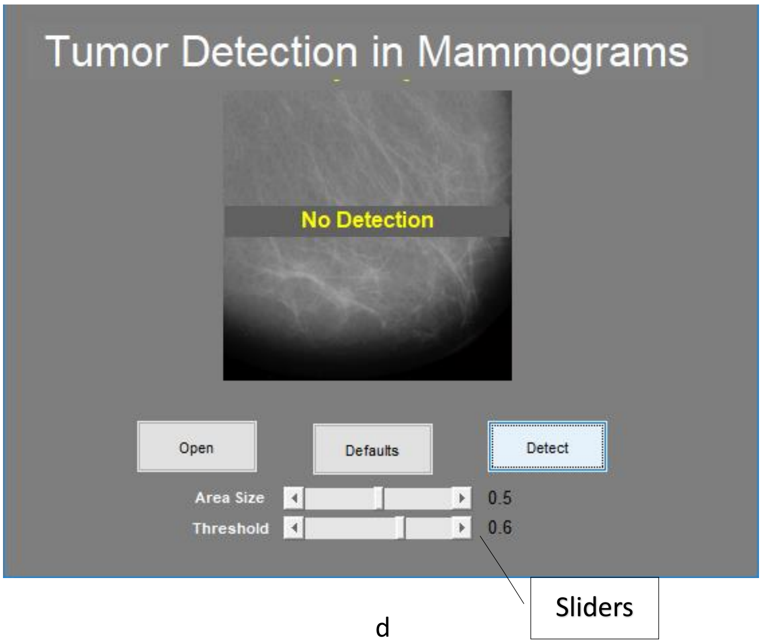

d

Figure 5: Graphical User Interface Implementation

5. Conclusion

Using image processing tools, the process of tumor detection in mammograms can be enhanced to help radiologists obtain more accurate results. The proposed work provides a new detection algorithm for circular tumors that is based on low-complexity calculations using adaptive thresholding and area size. The proposed systems could detect tumors and differentiate them from normal and fatty breast tissue. To ease the process of detection, the algorithm can be executed using a graphical user interface that helps the radiologist select images and change system settings. Future work focuses on implementing the system on FPGA systems, and enhancing the algorithm to discover different types of breast tissue using low-complexity texture mapping methods.

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