DIGITAL IMAGE PROCESSING (ENSC 895)
BREAST TUMOR SEGMENTATION PROJECT REPORT

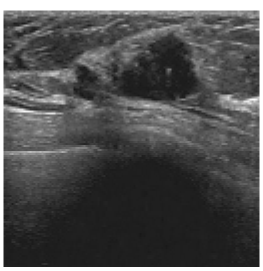
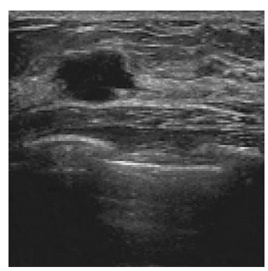
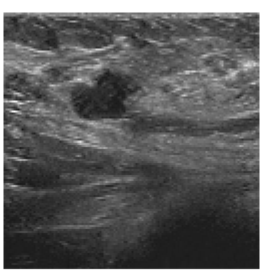
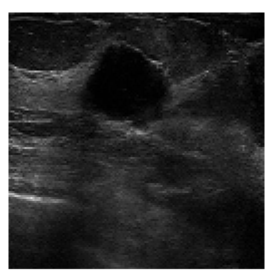
1.1 INTRODUCTION

Breast cancer poses a serious health concern for women and detecting this disease at an early stage is necessary to curtail the effects. One known method to detect these diseases at an early stage is through the use of breast ultrasound images. Breast ultrasound is preferred because of the low energy involved in the process.

1.2 OBJECTIVE

In this Project, we are provided with several ultrasound images that include benign and malignant tumours. The objective is to develop an image processing algorithm that highlights and segments the tumour in the image.

1.3 DATA SET

<table>
<tr><td>
Test Image 1</td><td>
Test Image 3</td></tr>
<tr><td>
Test Image 5</td><td>
Test Image 9</td></tr>
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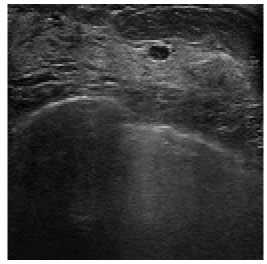
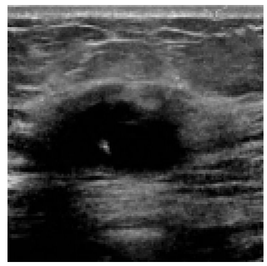
 Test Image 14	 Test Image 15
 Test Image 18	 Test Image 20

Fig 1.3: 128 by 128 Original Test Images given

The dataset consists of eight images of size 128 by 128 pixels. We are given the original images and the true masks. The true masks served as ground truth to compare our segmented tumours. The true masks or ground truth images are binary images with a high(1) corresponding to the tumour region and a low(o) corresponding to the background. The criterion used to calculate our accuracy is Jaccard Index and it is the size of the intersection divided by the size of the union of our segmented tumours and the true mask given.

1.4 INITIAL OBSERVATION

The first step taken was to do some analysis of the test images to give an insight that would guide us in creating and writing the Algorithm. From close observation of the test images, we note the following observation

1. Noise is Random
2. Noise is multiplicative.
3. Area of interest is the darkest regions.
4. Some noises have really dark regions.
5. Thin fine Edges were present that could be dealt with by some gaussian smoothing.
6. Region of interest is circular or roundish in nature

1.5 PREPROCESSING

This is the first step in any image processing project. From close observation of the images given, we can see that it contains some noise. For example some thin fine lines, and multiplicative noise. To remove the noise, we do some gaussian smoothing. As a precaution and to make our algorithm more robust, we do a little bit of median filtering and averaging also.

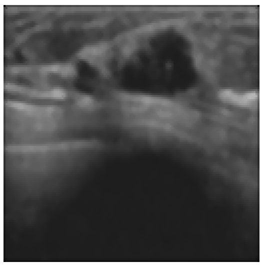
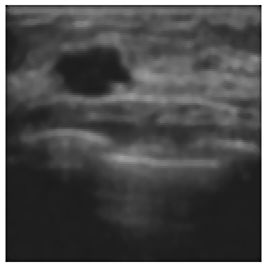
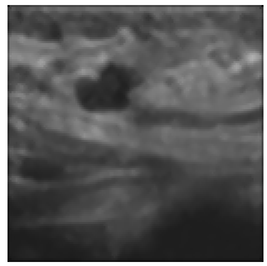
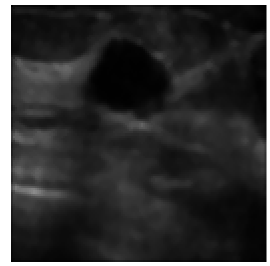
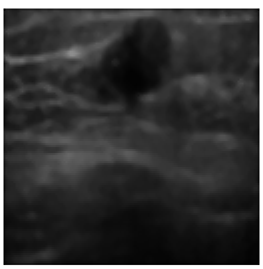
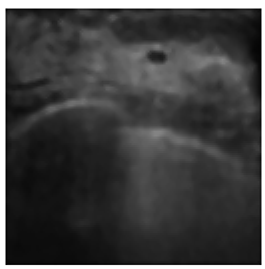
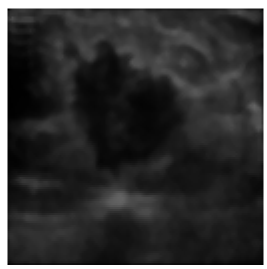
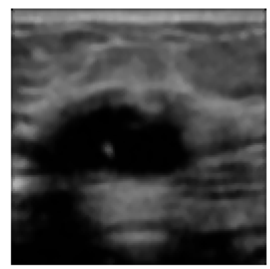
 Test Image 1	 Test Image 3	 Test Image 5	 Test Image 9
 Test Image 14	 Test Image 15	 Test Image 18	 Test Image 20

Fig 1.5: Test Image Results after Gaussian Filtering, Median Filtering and Averaging. 3 by 3 mask

1.6 OTSU THRESHOLDING

The histogram equalization averages the pixels in the image and makes for a smoother histogram and Otsu Thresholding minimizes the between-class variation in the image. Next, we perform some histogram equalization and then, Otsu thresholding. We keep the result because we will perform a logical AND on it to get the final segmented tumour.

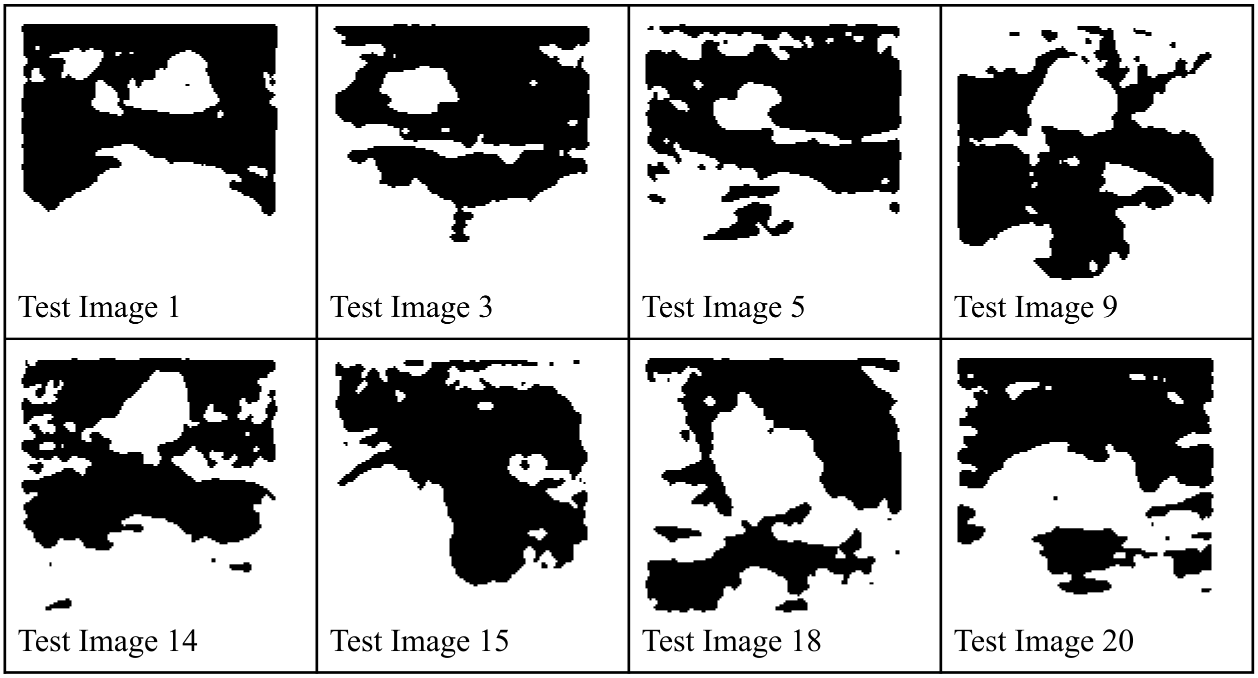


Fig 1.6: Inverted Otsu Thresholded Images

1.7 MORPHOLOGICAL IMAGE RECONSTRUCTION

Here, we take advantage of the observation that our area of interest (tumours) are circular. Some we try to identify all circular blobs in the image. To do this we take the following steps.

1. We create a circular structuring element(disk or circular) or kernel and perform a closing operation.
2. Then we do image reconstruction using the closed image.
3. To get the circular regions in the image, we subtract the reconstructed image from the original one
4. We threshold the image and add the thresholds to the segmented image.
5. We fill the holes in the binary image
6. We perform opening with a disk of mask 3 to remove more noise

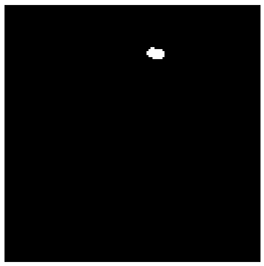
 Test Image 1	 Test Image 3	 Test Image 5	 Test Image 9
 Test Image 14	 Test Image 15	 Test Image 18	 Test Image 20

Fig 1.7: Reconstructed Image Results

1.8 LOGICAL OPERATION(COMBINING OTSU AND RECONSTRUCTED IMAGE RESULTS)

Next, we perform a Logical AND on the inverse of the otsu thresholded image and our reconstructed image

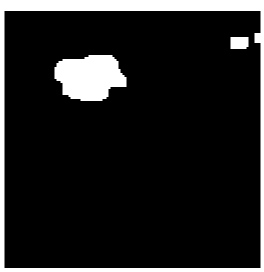
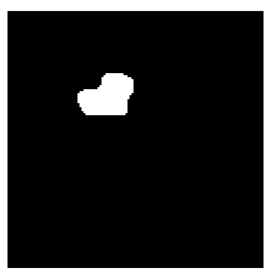
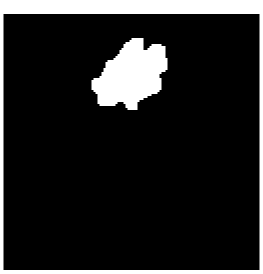
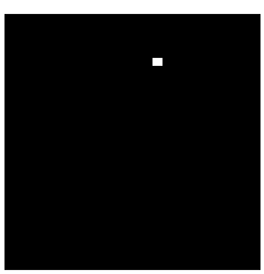
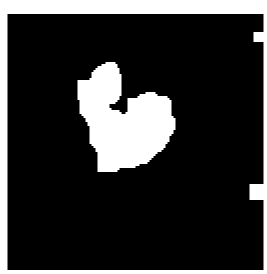
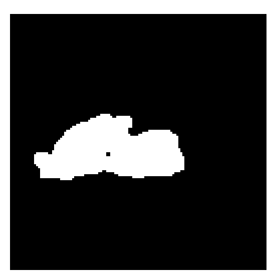
 Test Image 1	 Test Image 3	 Test Image 5	 Test Image 9
 Test Image 14	 Test Image 15	 Test Image 18	 Test Image 20

Fig 1.8: Results from Logical AND of Otsu and Reconstructed Image

1.9 IMAGE CLEANING UP

Notice some tiny holes in the results. We fill holes again and dilate the image with a disk mask of size 3. We use the smallest possible mask to avoid heavy distortion of the result

2.0 SELECT LARGEST BLOB

We see that Test Image 1 and Test image 3 have 2 blobs. Since the true mask indicates the largest blob as the single tumour. We write a custom code to select the largest Blob

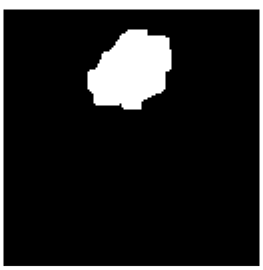
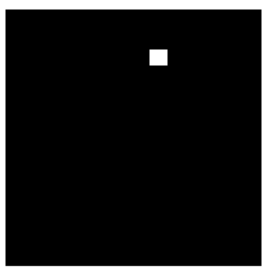
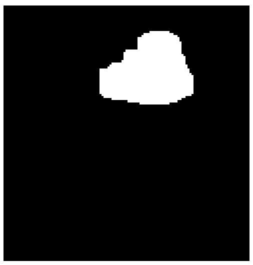
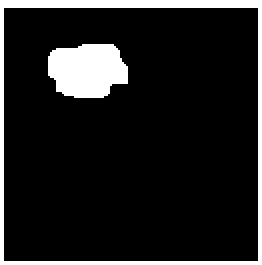
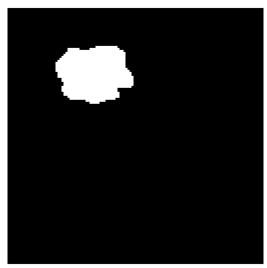
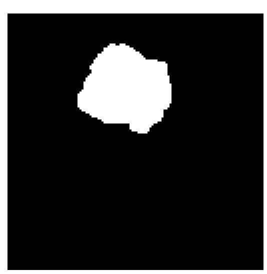
 Test Image 1	 Test Image 3	 Test Image 5	 Test Image 9
 Test Image 14	 Test Image 15	 Test Image 18	 Test Image 20

Fig 2.0: Results after Image Cleaning up

2.1 RESULTS AND EVALUATION

The Algorithm detects a portion of the tumour in all test images. To measure the accuracy, we use an index called the Jaccard Index. It measures the size of the intersection against the size of the union of the test images and true masks.

RESULTS	TRUE MASKS
 Test Image 1	 Mask 1
 Test Image 3	 Mask 3
 Test Image 5	 Mask 5
 Test Image 9	 Mask 9

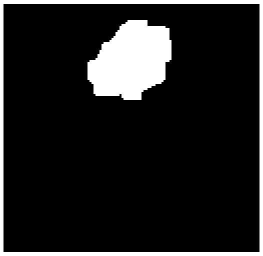
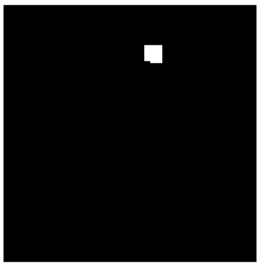
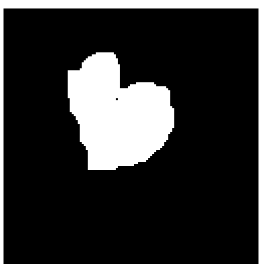
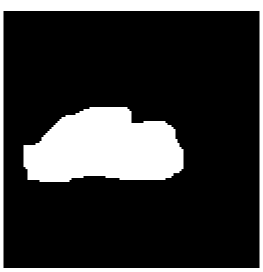
 Test Image 14	 Mask 14
 Test Image 15	 Mask 15
 Test Image 18	 Mask 18
 Test Image 20	 Mask 20

Fig 2.1: Final Results from Custom Algorithm compared against True masks

2.1.1 JACCARD INDEX

Image	**Jaccard Index**
Test Image 1	0.8774
Test Image 3	0.8995
Test Image 5	0.8617
Test Image 9	0.8547
Test Image 14	0.7066
Test Image 15	0.4303
Test Image 18	0.7046
Test Image 20	0.7223
AVERAGE	**0.757**

Fig 2.1.1: Accuracy(Jaccard Index) of each Image

CONCLUSION

We have demonstrated a method to detect breast tumour regions from ultrasound images. An assumption was made that only one tumour region was present in each image. Our Algorithm is very generic in the sense that it basically identifies circular blobs of dark regions after suppressing the noise. Then uses some method and ingenuity to detect the breast tumour region. The Average Accuracy is about 0.757 which is really good and can be used as a base for improvement.