

## Implementation of Hough based MSER based combined approach to mask the Pectoral muscle region

Ch.Sarada<sup>1</sup>, Dr. K.Vijaya Lakshmi<sup>2</sup>, Prof. M.PADMAVATHAMMA<sup>3</sup>

<sup>1</sup> Research Scholar, <sup>2</sup>Assistant Professor, <sup>3</sup>Professor and Principal  
<sup>1</sup> Computer Science,

<sup>1</sup> Sri Venkateswara University, Tirupati, AP, India.

### Abstract:

Breast cancer is a deadly disease. Because of Breast cancer, many beings are losing life. Mammography and Sonography are the common modalities people undergo with to detect Breast cancer. A Mammography is the first screening test used to detect Breast masses and calcifications. MLO Mammogram contains part of Pectoral muscle. The presence of Pectoral muscle in the Mammogram shows negative impact on mass detection because its grey levels are like mass grey levels. Hence, Pectoral removal improves mass detection significantly. This paper presents the performance analysis of hybrid approach "Hybridization of MSERPectoral and HoughPectoral methods" to remove Pectoral region. The result show that the new method proposed is simple and enhances the accuracy of Pectoral region removal. The proposed method improves accuracy by 98.1% against 95% of average accuracy for the state-of-the-art solutions. Mini-MIAS database is used for performance analysis. MatLab and Python are used for implementation

**Keywords:** MLO Mammogram, Pectoral muscle, MSER, MSERPectoral, Hough, HoughPectoral. Mini-MIAS

### I.Introduction

According to Cancer.net [1] statistics, many people are getting effected with deadly Breast cancer. A Mammography is the first screening test for detection of Breast Cancer. Mammography produces 2 kinds of projection views such as CranioCaudal view (CC) and Mediolateral Oblique view (MLO). Mammogram [2] is the first modality being used for discovering mass or calcifications. In case of mass discovery, Ultrasound test is done further to find a mass.

In Mediolateral Oblique Mammogram segmentation, the problem with presence of Pectoral region is that its characteristics like grey level is similar to Breast mass. So, presence of Pectoral muscle in MLO mammogram shows negative impact on mass detection. Hence, Pectoral region is to be removed from MLO Mammogram to improvise mass detection.

This paper totally concentrated on implementation and performance analysis of a Novel Hybrid approach proposed in the paper[5] where modified MSERPectoral and HoughPectoral methods are combined to detect and remove Pectoral muscle.

Section II provides brief literature survey, III provides proposed method algorithms and a detailed description of the dataset. Section IV presents the experimental results obtained and the analysis. Finally, the conclusion and future scope are briefly summarised in Section V.

### II. Related Work

Many Pectoral muscle removal solutions are introduced and being used. Some prominent approaches are listed here. all the surveyed approaches used Mini-MIAS database for experimental purpose. S.Marijeta et al.[6] introduced k-means approach along with morphological operations to detect Pectoral muscle. 68.42% are the accurate cases,19.25% are the acceptable cases and 12.42% cases are the bad cases found by this approach. P. S. Vikhe et al. [7] used grey level-based technique to find Pectoral muscle boundaries. This technique achieved 87.19% accurate cases, acceptable cases are 9.37% and inaccurate cases are 3.44%. Wavelet-based approach is used by M. Mughal et al. [8] to remove Pectoral muscle with 77.63% perfect cases, 14.59% satisfactory cases and unsatisfactory cases of 7.76%.

Syeda Iffat Naz et al. [9], Saeid Asgari Taghanaki et al. [10], Samuel Rahimeto et al. [11], Enas Mohammed Hussein Saeed et al. [12], Pascal Vagssa et al. [13] G Vaira Suganthi et al. [14] also proposed and implemented Pectoral removal methodologies.

The purpose of this paper is to show the resultant analysis of implementation of Hybrid approach with MSERPectoral and HoughPectoral[5]. It gave 98.14%accuracy, which is good improvement over existing literature surveyed methodologies.

### III. Proposed method algorithms

MLO Mammogram contains part of Pectoral nerve. Pectoral nerve shows negative impact on mass detection in turn Breast cancer detection.

This paper is to present the performance analysis of Hybrid approach proposed with MSERPectoral and HoughPectoral[5] to remove the Pectoral region. Summarised block diagram of proposed approach is shown in Fig.2.2

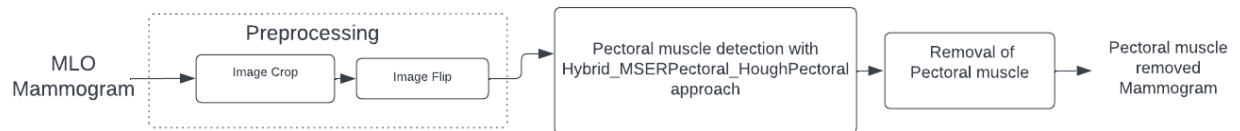


Fig.2.1 Summarised Block diagram of Proposed approach

Total steps used are three. In the step 1, from the original Mammogram, big region is clipped and the resultant image is flipped if it is left oriented. In the stage 2, the intended algorithm discovers the Pectoral area if exists. In step 3, the detected Pectoral region is pruned and then deleted.

#### A. Pre-processing:

Pre-processing phase is to crop the Breast contour from MLO Mammogram and to set the orientation of the resultant image towards right. In pre-processing, 2 steps are applied such as MLO Mammogram cropping and flipping.

#### Image Cropping

This is the first stage of the process where we apply Ostu threshold method on MLO Mammogram to cut the Breast region part. Ostu thresholding uses weighted variance parameter to determine threshold. It sets the threshold in such a way that the weighted variance within the class will become minimum. Morphological operations are also applied to separate the Breast contour from the rest of the image. Fig. 3.1 shows the sample outputs of Image Crop

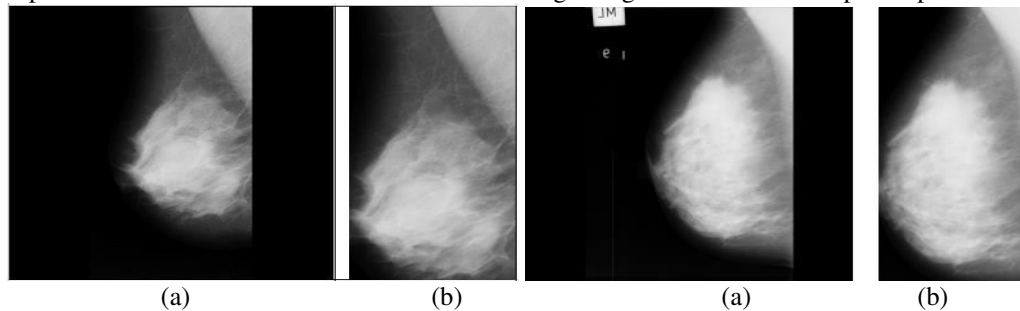


Fig 3.1: (a) Original Mediolateral Oblique Mammogram (b) After Cropping

#### B. Mirroring clipped image

After cropping, orientation of all images needs to be set towards right. Algorithm 1 is for flipping the image.

Algorithm 1: Imageflip( $I_{crop}$ )

Input:  $I_{crop}$

Output: Right oriented image

Step 1:  $hh, ww = I_{crop}.shape$

Step 2:  $bx = 10\%$  of  $hh$

Step 3:  $by = 10\%$  of  $ww$

step 4: //Computation of  $bx \times by$  mean

for  $i=0$  to  $bx$

for  $j=0$  to  $by$

sum1 = sum1 +  $I_{crop}(i, j)$

left mean = sum1 / ( $bx \times by$ )

step 5: //Image flip

image1 = flip( $I_{crop}$ )

step 6: //Computation of  $bx \times by$  mean for the flipped image

for  $i=0$  to  $bx$

for  $j=0$  to  $by$

sum2 = sum2 + image1( $i, j$ )

right mean = sum2 / ( $bx \times by$ )

Step 7: if(left mean < right mean):

image = flip( $I_{crop}$ )

step 8: return image

Fig.3.2 shows the sample left-oriented MLO image and corresponding flipped image.

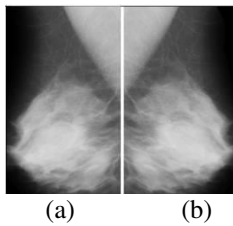


Fig.3.2: (a) Cropped left-oriented Mediolateral Oblique Mammogram (b) After flipping

### **B. Pectoral Muscle detection**

Pre-processed image is the cropped one, noise free and right oriented. To detect Pectoral muscle, a new method is implemented where MSERPectoral and HOUGHPectoral methods are applied jointly. Algorithm 2 is the hybrid algorithm implemented with Python and Matlab.

**Algorithm 2:** Hybrid\_MSERPectoral\_HoughPectoral(I)

Input: Initial Mammogram I

Output: pectoralMask

Step 1:  $I_{crop} = \text{ImageCrop}(I)$

Step 2:  $I_{crop} = \text{call Imageflip}(I_{crop})$

Step 3:  $HH, WW = I_{crop}.\text{Shape}$

Step 4: pectoralRegion= call MSERPectoral( $I_{crop}$ )

Step 5: houghPectoralRegion =call HoughPectoral( $I_{crop}$ )

Step 6: truePectoralRegion={Region | Region  $\in$  PectoralRegion},  
 filteredtruePectoralRegion={Region | Region  $\in$  Height(Region)<(Height( $I_{crop}$ )-100)}

Step 7: filteredtruePectoralRegion=0 go to step 11 else continue with Step 8

Step 8: Select the maximum truePectoralRegion from the list of filteredtruePectoralRegion

Step 9://Prepare a white mask for truePectoralRegion found in step 8

$\text{MSERPectoralMask} = [0]_{|HH|*|WW|}$

Fill the Pectoral region part of pectoralMask with grey level 255

Step 10: Trim the resultant mask with width-height triangle

Step 11://houghPectoralRegion checking

If houghPectoralRegion=0 jump to step 14 else, go on with Step 12

Step 12: // Prepare a Mask for the Pectoral region with grey level 255

$\text{houghPectoralMask} = [0]_{|HH|*|WW|}$

Fill the houghPectoralRegion part of pectoralMask with grey level 255

Step 13:// Choose the final mask among MSERPectoralMask and houghPectoralMask

If area (prunedPectoralMask)> area(houghPectoralMask)

finalPectoralMask= prunedPectoralMask

Else

finalPectoralMask = houghPectoralMask

Step 14:// Decide final mask if either MSERPectoral or HoughPectoral works or if both does not work

If len ( filteredtruePectoralRegion)> 0 and houghPectoralRegion=nil //if only MSERPectoral works

finalPectoralMask= prunedPectoralMask

Else If houghPectoralRegion exist and len( filteredtruePectoralRegion)=0 //if only houghPectoral works

finalPectoralMask= houghPectoralMask

Else // If both do not work, apply HoughPectoral on truePectoralRegion of step 6 if it exists

if len(truePectoralRegion)>0

houghPectoral=call HoughPectoral(truePectoralRegion)

Prepare houghPectoralMask

finalPectoralMask= houghPectoralMask

Step 15: if finalPectoralMask exists

return finalPectoralMask

Else return nil

Algorithm 2 gave detail steps of hybrid approach for Pectoral removal .It is observed that though both methods are executed on every image, in most of cases MSERPectoral only gave accurate results. In few cases, both methods are working and in certain cases either one is working well.

Step 10 is to prune the detected Pectoral with width-height triangle. Fig. 3.3 shows the importance of pruning.

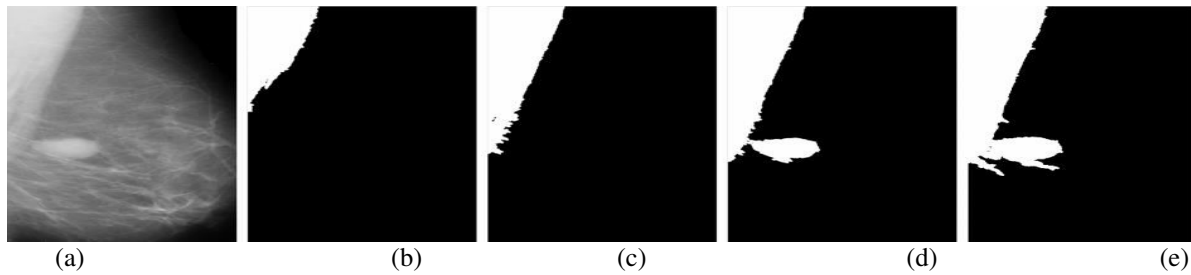


Fig.3.3 (a) Preprocessed image, (b,c,d,e) are the four regions obtained by the modified MSER algorithm after filtering (e) is the maximum. The extra mass is included in two MSER regions as the mass was closer to the Pectoral region.



Fig.3.4(b) is obtained by cutting the Fig.3.4(a) with the w-h triangle. The Fig.3.4(c) is obtained by subtracting the (b) from the (a).

Fig.3.5 shows sample detected Pectoral region where both MSERPectoral and HoughPectoral methods are working and MSERPectoral obtained area is more significant than HoughPectoral area in the first figure whereas in second figure, HoughPectoral area is more.

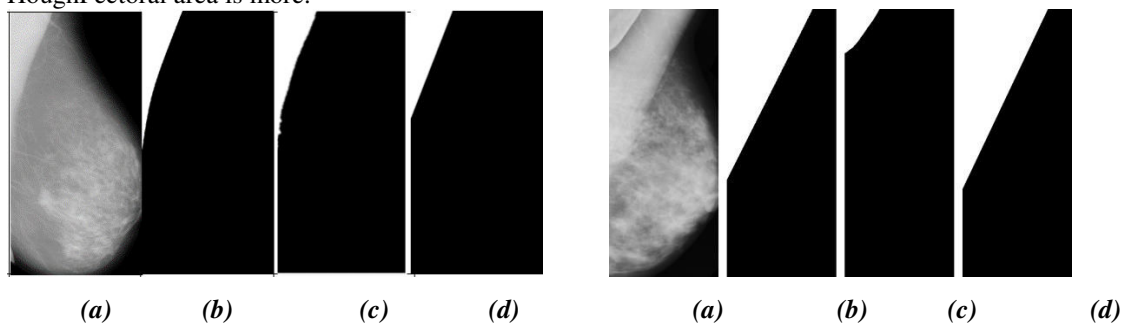
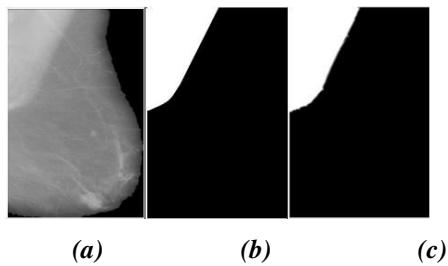


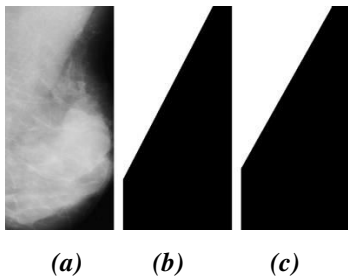
Fig.3.5: (a) Preprocessed image (b) White mask of Pectoral tissue Ground truth (c) White mask of Pectoral tissue computed by MSERPectoral, (d) White mask of Pectoral tissue computed by HoughPectoral.

For the sample image shown in figure 3.5, MSERPectoral and HoughPectoral techniques are applied to remove the Pectoral muscle. Fig. 3.5 shows cropped image, ground truth of Pectoral mask, Pectoral mask of MSERPectoral method and Pectoral mask of HoughPectoral methods. In the first image, the detected Pectoral area of the MSERPectoral method is more compared with the HoughPectoral approach. So, the MSERPectoral mask is considered as the final Pectoral mask for this image; in the second image, the HoughPectoral gives more area. So, the HoughPectoral mask is considered as the final Pectoral mask for the second image.

Fig.3.6 shows sample detected Pectoral region where only the MSERPectoral method works, and Fig.3.7 shows sample Pectoral region detected where only the HoughPectoral method works.



**Fig.3.6:** (a) Pre-processed image, (b) White mask of Pectoral tissue ground truth (c) White mask of Pectoral tissue computed by MSERPectoral.



**Fig.3.7** (a) Pre-processed image, (b) White mask of Pectoral tissue ground truth (c) White mask of Pectoral tissue computed by HoughPectoral.

Only the HoughPectoral method works here. MSERPectoral approach does not work in this image since it is dense. In few dense cases, both approaches won't work, so the final step applied where HoughPectoral applied on the max of the MSERPectoral regions without any filtering.

For example, Fig.3.8(a) shows the cropped image (b) shows Pectoral region detected by MSERPectoral method. HoughPectoral method also did not work here directly on the cropped image. So, applied HoughPectoral on the MSERPectoral unfiltered region. Fig. 3.8(e) shows accurate Pectoral mask detected by HoughPectoral method.

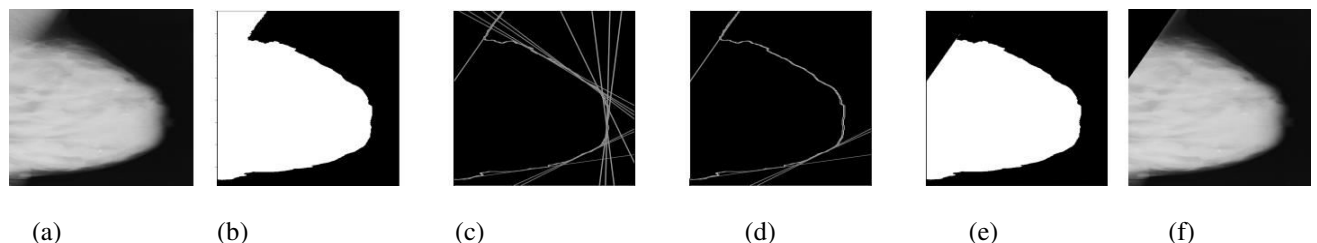
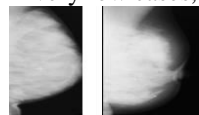


Fig 3.8: (a) Cropped Image (b) MSERPectoral region (c) Hough lines on Canny edges (d) Short listed Hough lines (e) Pectoral region mask (f) Pectoral removed image

In very few cases, the algorithm does not work. Fig 3.9 shows related samples.



**Fig 3.9**

Detail algorithms of MSERPectoral and HoughPectoral methods are given in sections B.i and B.ii.

### B.i MSERPectoral

MSERPectoral is the adaptive MSER[4] method computes most stable connected components of Pectoral region for few grey levels only. Algorithm 3 gives detail steps of MSERPectoral.

**Algorithm 3:** MSRPectoral( $I_{crop}$ )

Input:  $I_{crop}$

Output: Detected Pectoral

Step 1: Height, Width  $\leftarrow I_{crop}$ . Shape

Step 2: // Compute connected components

for th=255 to x-20 // x is determined by the mean of the top left corner of cropped Mammogram image

XImage  $\leftarrow [0]_{height \times width}$

for i=0 to height

```

for j=0 to width
    if Icrop [i , j] <= th
        if Icrop [i , j] is neighbour for any pixel in an XImage
            XImage[i, j] = Icrop [i, j]
        Add computed connected components from XImage to component tree.
Step 2: //Computation of Variation
    variationth = ( areath+Δ - areath-Δ ) / areath
    add computed variationth to variation list
Step 3: // Select regions with a local minimum from the variation List
    R = {r | r ∈ variation_list, and it is the local minimum}
Step 4: // Determination of largest region
    Area_of_Max_Pectoral_Region = 0
    Max_Pectoral_Region = -1
    for R in Pectoral_Regions:
        if area( R ) > Area_of_Max_Pectoral_Region:
            Area_of_Max_Pectoral_Region = Area(R)
            Max_Pectoral_Region = R
Step 5:
    Return Max_Pectoral_Region

```

With the parameters MaxAreaVariation, MinArea, and MaxArea, the improved MSER algorithm is implemented in Matlab. The MinArea is set to 50 to exclude very small regions, and the MaxArea is set to 500000, indicating if the region's area is more than 500000, the region is excluded. This maximum area option will be helpful when MSER assigns the entire Breast as the region. MaxArea variation, which determines the maximum intensity fluctuation between extremal regions, is the most important parameter. Size and shape of stable regions is alike in size over a range of delta( $\Delta$ ) thresholds. The usual value of delta( $\Delta$ ) lies between 0.1 and 1.0. For Mini-MIAS images, the MaxAreavariation parameter is set to one of these three values [0.25,0.5,0.75]. It works as follows:

1] First, keep the 0.25 value and filter the regions as described in Algorithm 3; if it gives 0 areas, go to the 2nd step; else, proceed with filtered regions.

2] Keep the 0.5 value and filter the regions; if it gives 0 areas go to the 3rd step; else, continue with filtered regions.

3] Keep the 0.75 value and filter the regions; if it gives 0 areas, go to the 4th step; else, proceed with filtered regions.

4] Output that the MSER algorithm does not give any regions after filtering with various MaxAreaVariation values.

In most cases, keeping 0.25 works out, but in very few cases, it does not work; keeping 0.5/0.75 can produce the desirable regions in those cases. The example cases are shown in below figure where Fig.3.10 (c) gives regions directly for 0.25 value of MaxAreaVariation, for Fig.3.10 (a) 0.25 does not work out, so 0.5 value is kept, which gives regions, whereas, for Fig.3.10 (b), it does not provide any area for 0.25 and 0.5, so kept 0.75 and got areas for this.

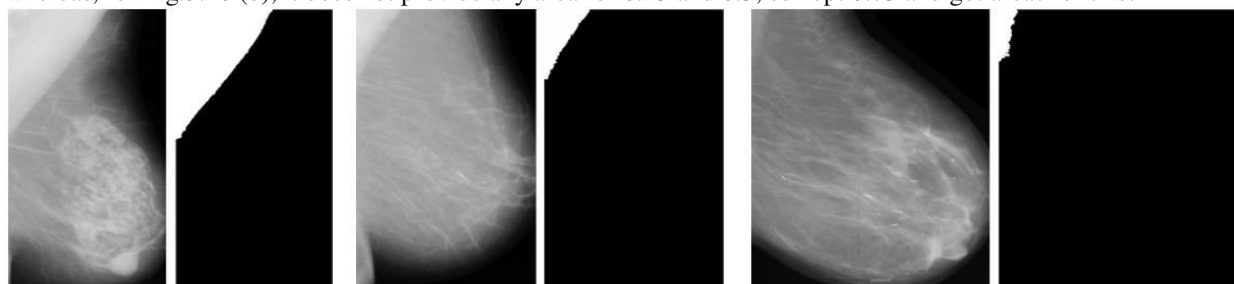


Fig.3.10 (a) Maxarea variation 0.75

(b) Maxarea variation 0.5

(c) Maxarea variation 0.25

### B.ii HoughPectoral Method

Algorithm 4 is for the HoughPectoral technique. Using Hough lines, the HoughPectoral technique determines the pectoral region.

**Algorithm 4:** HoughPectoral(Image)

Input: Image

Output: Pectoral Region after applying Hough method

Step 1: HoughLines=call getHoughLines(Image)

Step 1: SortedEdges=Sort (Edges)//Edges are sorted in ascending order wrt dist

Step 2: Pectoral line = shortlistedEdges [0]//Take the shortest edge pectoral line

Step 3: pectoral\_linelength= length (pectoral line)

Step 4: angle=angle(pectoral\_line)//determine pectoral line angle with x-axis

Step 5: intercept\_x = pectoral\_linelength/cos(angle) //cos(angle) is cosine of angle

Step 6: intercept\_y = pectoral\_linelength/sin(angle)//sin(angle) is sin of angle



Step 7: // With these intercept values, create the polygonal Pectoral triangle.

Polygon\_Pectoral=[(0,0), (0, intercept\_x ),(intercept\_y,0)]

Step 8: return Polygon\_Pectoral

Algorithm 5 is for detecting line endpoints using the Houghline method, and Algorithm 6 is for Canny edge detection. Houghline is detected based on edges returned by the Canny edge technique. Canny is one of the edge detection method used by Houghline method.

**Algorithm 5:** getHoughLines(Image)

Input: Image

Output: Hough line with line endpoints

Step 1: Detect the Initial edges of the given Image using a Canny or Sobel edge detector.

Step 2. Map edge points to Hough space and are stored in the accumulator.

Step 3: Interpret the mapped edge points using the hough\_line and hough\_line\_peaks functions of the skimage python library.

Step 4: //For each finite length line, determine the x-intercept and y-intercept

for each line  $\in$  Lines

angle, d=line.Angle, line.Distance

x\_intercept = d/np.cos(theta)

y\_intercept = d/np.sin(theta)

Step5: Get the line with the least distance among the shortlisted lines and return it with its corresponding intercepts.

For Pectoral muscle detection, suitable min angle and max angle are 30 and 70 respectively, and the min distance and max distance are 100 and 600 respectively.

**Algorithm 6:** Canny(Image)

Input: Image

Output: Canny Edges

Step 1: Remove noise from the given image using a filter like the Gaussian filter

Step 2: Compute intensity Gradient magnitude and directions

Step 3: Find edges by applying gradient magnitude threshold.

Step 4: Filter edges by applying a double threshold.

Step 5: Using hysteresis, suppress all weak edges.

Step 6: Return all potential edges.

### C. Pectoral Removal

After Pectoral region gets detected, it is to be removed. Following is an algorithm used to remove detected Pectoral region.

**Algorithm 8:** Pectoral\_Deletion

Output: Pectoral Eliminated image

Step 1: First, input the cropped image(Icrop)

Step 2: Pect\_Mask =call Hybrid\_PectoralMSER\_HoughPectoral(Icrop)

Step 3: if Pect\_Mask = nil, proceed to Step 6; else, go to Step 4

Step 4:// Apply the Final Pectoral Black Mask to remove the Pectoral region from the cropped image.

$I_{decrm} = I_{crop} \& \text{invert}(\text{Final\_mask\_pectoral})$

Step 5: Store Pectoral Eliminated image obtained from step 4(Ipecrm) and jump to step 7

Step 6: Display "No Pectoral Present in the image"

Step 7: End

### Example for Pectoral Removal

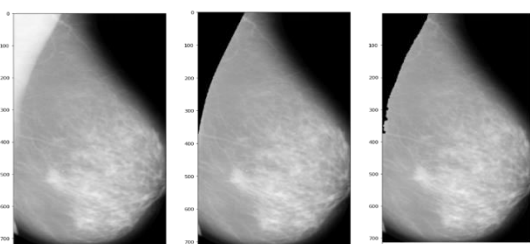


Fig.3.11(a) Cropped MLO Mammogram (b) Cropped one with ground truth (c) Pectoral removed Mammogram

#### D. DATABASE DESCRIPTION

The proposed approach is verified on the Mini-MIAS database. A total of 322 MLO Mammography images are there in this database. In this database, Mammogram ids are given as mdb001, mdb002, till mdb322. As far as Pectoral shape is concerned, most of them have a triangle shape, some have a parabolic shape, and specific Pectoral muscles are visible partially due to lymph node surgery, skin surgery, or like.

According to the background tissue, three kinds images are observed in Mini-MIAS- Fatty, Fatty-glandular and Dense-glandular[3]. Fatty tissue looks dark. When more fatty tissue is in the Mammogram, it is easier to find mass form in the Breast. Glandular tissue is thick and hard. Fatty-glandular tissue is a combination of fatty and glandular tissue. The breast is referred to as dense when there is more glandular tissue present. The mammogram is hard and white when dense. In Dense Mammograms, masses are hidden behind tissue, so challenging to detect masses in such Mammograms.

#### IV. Performance Metrics and Results Analysis:

For experimental purposes, Mini-MIAS is used. The analysis is done on every image of Mini-MIAS. Mini-MIAS contains a total of 322 images. Out of 322 images, three images do not have Pectoral region. So, a total of 319 images were analysed with the metrics.

For performance analysis, we used the abbreviations PG for the ground truth Pectoral region and PP for the predicted Pectoral region.

FP represents the count of pels that are wrongly categorized as the part of Pectoral region and FN represents total count of Pectoral region pels categorized as the background. TP represents total count of predicted Pectoral muscle pels that are correctly categorized. TN represents total count of predicted non-Pectoral pels that are correctly categorized.

Metrics such as Global Pixel Accuracy (GPA), Intersection of Union(IoU), Dice Similarity Coefficient (DSC), Specificity and Sensitivity are measured to determine the effectiveness of classification.

The sensitivity and specificity measures are frequently used to assess classification tasks—are. One is that IoU and GPA values are determined by sensitivity and specificity, making these two metrics essential measures. introduced to determine how well segmentation models separate the pectoral muscle. We provide these two indicators for two primary reasons Another benefit is that the model's classification of the actual pectoral muscle area can be understood more intuitively by sensitivity.

The algorithm successfully detected the three no pectoral images as it did not produce any regions. However, there was another set of 3 images where the algorithm did not make any pectoral region, but they have pectoral muscle. So it gave an inaccurate result for these three images. Another set of images which gave incorrect results was mdb065,mdb288, and mdb318, which are very dense.

The algorithm produced 290 images above an accuracy score of 98%, considered well-segmented. There were 23 images between 96 - 98%, considered acceptable because the FP and FN rates were less than 4%, and the sensitivity in these 23 images was above 90%. Six images gave inaccurate results, out of which the three images are mdb065,mdb288, and mdb318, as described above. There were another three images(mdb169,mdb221,mdb226) where mser gave a small region compared to the ground truth, so the accuracy score in these three images was well below 96%. So total cases which gave satisfactory results are 313(290 well segmented + 23 acceptable). Six are inaccurate. The other three images are no pectoral images that are detected correctly. So total accurate results are 313+3=316.

The mean values of the metric measures of the 313 images are shown below in figure 4.1 ( expressed as mean +/- standard deviation of the values)

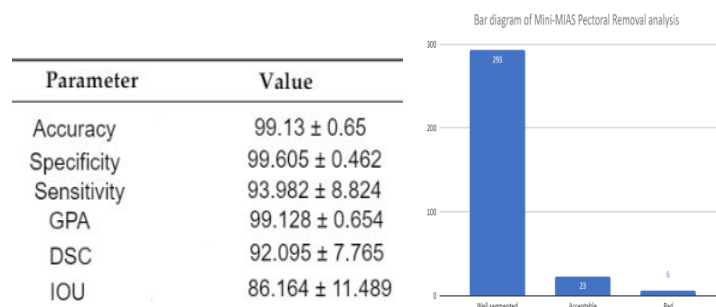


Figure 4.1

Chart 4.1- Mini-MIAS Pectoral removal analysis chart

The pectoral removal analysis summary chart of Mini-MIAS is shown in Chart 4.1. The accuracy achieved is (316/322) 98.14% which is a good improvement over surveyed approaches.



Table 4.1 Analysis of Certain Pectoral Muscles detected by both PectoralMSER and HoughPectoral methods.

| Image Name | Preprocessed Image | Ground Truth Pectoral Mask | Computed Pectoral Mask with PectoralMSER | Pectoralmask with HoughPectoral | Pectoral removed Image | Accuracy and Remarks         |
|------------|--------------------|----------------------------|--|---------------------------------|------------------------|------------------------------|
| mdb018     |                    |                            |  |                                 |                        | 99.9% - canny has more area  |
| mdb113     |                    |                            |  |                                 |                        | 99.8% - canny has more area  |
| mdb199     |                    |                            |  |                                 |                        | 98.67% - mserr has more area |

Table 4.2. Analysis of specific Pectoral Muscles detected by only the MSERPectoral approach

| Image Name | Preprocessed Image | Ground Truth Pectoral Mask | Computed Pectoral Mask | Original Image with Ground Truth | Pectoral removed Image with Ground Truth mask | Pectoral Removed Image with computed mask | Accuracy |
|------------|--------------------|----------------------------|------------------------|----------------------------------|---|---|----------|
| MDB005     |                    |                            |                        |                                  |   |   | 99.353   |
| MDB009     |                    |                            |                        |                                  |   |   | 99.811   |
| MDB027     |                    |                            |                        |                                  |   |   | 99.287   |
| mdb055     |                    |                            |                        |                                  |   |   | 99.307   |
| MDB268     |                    |                            |                        |                                  |   |   | 99.53    |

Table 4.1 shows that among the MSERPectoral mask and HoughPectoral mask, the larger mask is selected as the final Pectoral mask. From Table 4.2, the proposed approach shows that it can detect the Pectoral region where the Pectoral region could be in any shape, i.e. triangle or parabolic shape.

Ground truth is tested by an experienced Radiologist from a reputed Hospital. According to the Radiologist, either a triangular or a parabolic shape can be seen in the pectoral muscle. If any axillary node is operated, the Pectoral muscle may not appear appropriately because part of it gets hidden behind the operated axillary node.

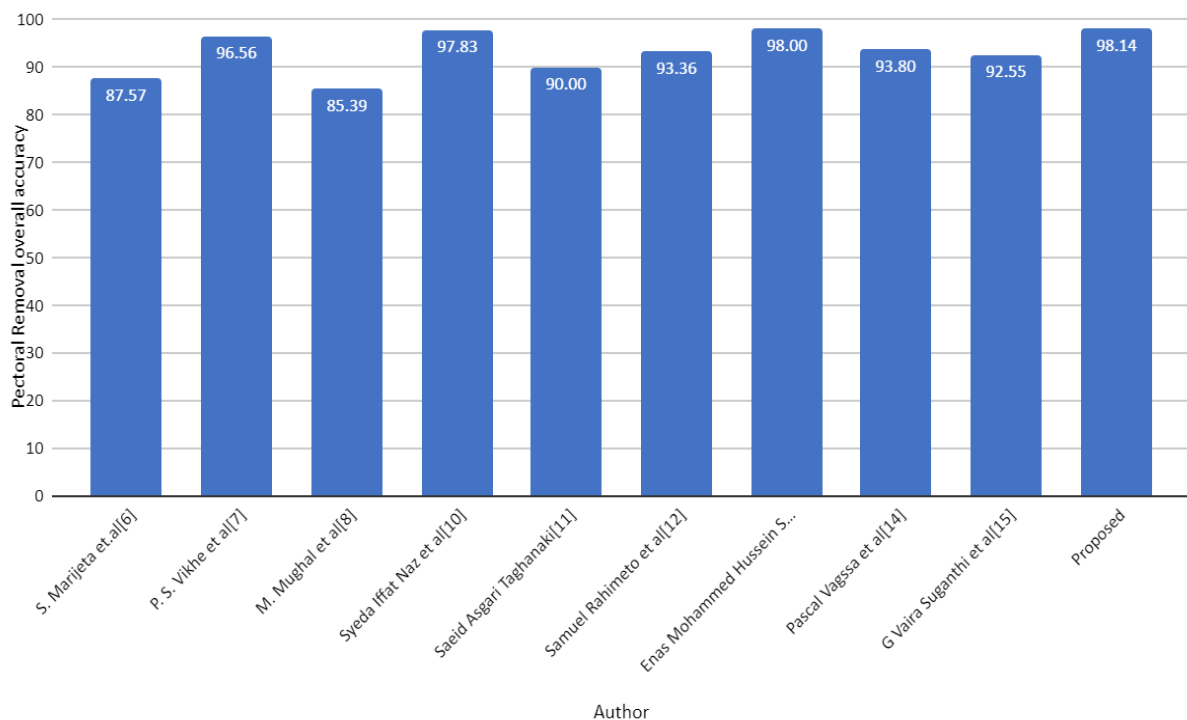
The table below shows the proposed approach's comparative analysis with existing literature. The proposed method has shown significant improvement over the existing literature.

Table 4.3 Comparative analysis with existing literature

| Table. Comparative analysis with existing literature |   |  |                       |                      |  |
|--|---|--|-----------------------|----------------------|--|
| Author   | Methodology used                                | % of Images well segmented, accepted and bad cases |                       |                      |  |
|  |   | well segmented                                     | acceptable            | bad cases            | overall accuracy achieved(well segmented+accepted) |
| S. Marijeta et.al[6]                                 | K-Means and Cubic polynomial                    | 68.32  | 19.25                 | 12.42                | 87.57  |
| P. S. Vikhe et al[7]                                 | Intensity Thresholding and Least Square Error   | 87.19  | 9.37                  | 3.44                 | 96.56  |
| M. Mughal et al[8]                                   | Wavelet-based approach                          | 77.63  | 14.59                 | 7.76                 | 85.39  |
| Syeda Iffat Naz et al[10]                            | Slope based approach                            | 92.86  | 4.97                  | 2.17                 | 97.83  |
| Saeid Asgari Taghanaki[11]                           | geometry rule-based approach                    | 67 exact +18 Optimal                               | 5                     | 10                   | 90   |
| Samuel Rahimeto et al[12]                            | Ostu's multi-thresholding                       | not given  | not given             | not given            | 93.36  |
| Enas Mohammed Hussein Saeed et al[13]                | Bounding Box and Region Growing techniques      | not given  | not given             | not given            | 98   |
| Pascal Vagssa et al[14]                              | Hough Transform                                 | not given  | 93.8                  | 6.2                  | 93.8   |
| G Vaira Suganthi et al[15]                           | Intensity Thresholding                          | not given  | not given             | not given            | 92.55  |
| <b>Proposed</b>                                      | <b>Stable Connected components + HoughLines</b> | <b>90.993(293/322)</b>                             | <b>7.143 (23/322)</b> | <b>1.863( 6/322)</b> | <b>98.136</b>                                      |

The below diagram is the bar diagram of the above table.

Bar diagram Mini-MIAS Pectoral Removal comparative analysis with existing literature



## V. Conclusion and Future Scope:

This paper presents result analysis of hybrid technique that can identify the pectoral muscle region regardless of its appearance or visibility MATLAB and Python are used to perform implementation. Mini-MIAS database is utilised for testing. The suggested approach outperformed previous approaches in 98.14% of cases for Mini-MIAS, yielding an acceptable outcome. The updated MSERpectoral and Houghtransform algorithms are used in the hybrid approach with extensive filtering to produce the pectoral region.

Future work is to further improve the accuracy result of the pectoral segmentation by edge enhancement and image pre-processing with further modifications of MSER where the parameters are automatically selected based on various characteristics like density and mean and decrease the inaccurate cases;also reducing the computation time within a few steps rather than combining approaches which contain multiple action. The proposed approach is applied only to the Mini-MIAS database. So, we must execute the proposed approach on other databases to find its consistency. In future work, we also work on new approach to detect Breast masses.

#### References:

- [1] <https://www.cancer.net/cancer-types/breast-cancer/statistics>
- [2] [https://www.cdc.gov/cancer/breast/basic\\_info/mammograms.html](https://www.cdc.gov/cancer/breast/basic_info/mammograms.html)
- [3] <https://my.clevelandclinic.org/health/diseases/21169-dense-breast-tissue>  
[https://www.mvtec.com/doc/halcon/13/en/segment\\_image\\_mser.html](https://www.mvtec.com/doc/halcon/13/en/segment_image_mser.html)
- [4] Donoser, M. and Bischof, H. Efficient Maximally Stable Extremal Region (MSER) Tracking.
- [5] "A Novel Approach to remove Pectoral muscle from Mediolateral Oblique Mammograms with Hybridization of MSERPectoral And HoughPectoral methods ", International Journal of Emerging Technologies and Innovative Research (www.jetir.org | UGC and issn Approved), ISSN:2349-5162, Vol.9, Issue 8, page no. ppf269-f276, August-2022, Available at : <http://www.jetir.org/papers/JETIR2208526.pdf>
- [6] S. Marijeta, A. Gavrovska, M. Milan, I. Reljin and B. Reljin "Breast Region Segmentation and Pectoral Muscle Removal in Mammograms", Telfor Journal, Vol. 8, No. 1, 2016.
- [7] Detection and Segmentation of Pectoral Muscle on MLO-View Mammogram Using Enhancement Filter P. S. Vikhe and V. R. Thool
- [8] M. Mughal, N. Muhammad, M. Sharif, Tanzilla Saba and A. Rehman, "Extraction of breast border and removal of pectoral muscle in the wavelet domain," Biomedical Research, Vol 28, 2017.
- [9] Syeda Iffat Naz, Monika Shah and Mohammed Imamul Hassan Bhuiyan "Automatic Segmentation of Pectoral Muscle in Mammogram Images Using Global Thresholding and Weak Boundary Approximation" 2020 International Conference on Computer Science and Software Engineering (CSASE), Duhok, Kurdistan Region – Iraq.
- [10] "Geometry Based Pectoral Muscle Segmentation from MLO Mammogram Views" Saeid Asgari Taghanaki, *IEEE Biomedical & Pharmacology Journal*, September 2020.
- [11] Samuel Rahimeto · Taye Girma Debelee · Dereje Yohannes · Friedhelm Schwenker, "Automatic pectoral muscle removal in mammograms" Springer 2019
- [12] Enas Mohammed Hussein Saeed, Hayder Adnan, "Pectoral Muscles Removal in Mammogram Image by Hybrid Bounding Box and Region Growing Algorithm
- [13] Pascal Vagssa1\*, Nafissatou Mallam Doudou2, Tchoning Jolivo3, Olivier Videme4, Dina Taiwé olyang1 "Pectoral muscle deletion on a mammogram to aid in the early diagnosis of breast cancer" Multicraft International Journal of Engineering, Science and Technology
- [14] G Vaira Suganthi, J Sutha, M Parvathy and C Durga Devi "Pectoral Muscle Segmentation in Mammograms"