_____

MLO Mammogram Pectoral Masking with Ensemble of MSER and Slope Edge Detection and Extensive Pre-Processing

Ch.Sarada[1], Dr. K. Vijaya Lakshmi[2], Prof. M. Padmavathamma
[1]Department of Computer Science and Engineering
CVR College of Engineering
Hyderabad, India
email: sharada.ch@gmail.com
[2] Department of Computer Science
Sri Venkateswara University
Tirupati, India
email:vijayalakshmik4@gmail.com
[3] Department of Computer Science
Sri Venkateswara University
Tirupati, India
email:prof.padma@yahoo.com

Abstract—Breast Cancer is a fatal disease. Several people are losing their lives as a result of Breast Cancer. Mammography is the most often used Breast screening modality where we can see both mass and microcalcifications and both are the two major indicators of Breast Cancer. We can see Pectoral muscle also on MLO Mammograms. Digital Image Processing based computer aided diagnosis systems are being used widely to help the radiologist in detecting mass and microcalcifications in MLO Mammograms. However, because the intensity levels of the Pectoral muscle are similar to masses, in computer aided diagnosis system, Pectoral presence in the Mammogram has a detrimental effect on identifying mass. Therefore, in computer aided diagnosis system, Pectoral muscle masking substantially enhances lesion detection. This study suggests a novel ensemble computer aided diagnosis system strategy that combines the MSER based and SlopeEdgeDetection methods with extensive pre-processing to identify and cover Pectoral muscle from MLO Mammograms. The results demonstrate that the new procedure is straightforward and improves the precision of Pectoral region covering. Compared to the average accuracy of the state-of-the-art solutions which is 94%, the suggested technique achieves an accuracy of 99%. Performance analysis makes use of the Mini-MIAS database.

Keywords- Pectoral muscle, MLO Mammogram, MSER, SlopeEdgeDection, Mini- MIAS.

I. INTRODUCTION

The Breast organ is made up of a variety of tissues, from extremely fatty to extremely dense. Each lobe of tissue has a little tube-like structure called a lobule. Small ducts deliver milk from milk glands to nipples from lobules, which have milk glands and produce milk. Breast Cancer can develop in any Breast area due to the growth of Cancerous cells. Every year, more Breast Cancer cases are being reported internationally, raising alarm bells. The most common medical examinations for Breast Cancer is mammography[1][2][12] .

We may observe two key indications of Breast Cancer in mammography: lumps and microcalcifications. The Pectoral muscle is also visible on the MLO Mammogram. Characteristics of Pectoral muscle are similar to mass. Digital Image Processing-based computer-aided systems are being utilised to assist radiologists in identifying mass and microcalcifications in MLO mammograms. However, since the intensity tissue of the Pectoral muscle is comparable to the intensity of the mass, computer-aided diagnostic tools increase false positive masses. As a result, masking the Pectoral muscle before an MLO Mammogram is highly encouraged. Fig. 1 shows MLO Mammogram with highlight of Pectoral region.

The masking of the Pectoral muscle has received several traditional treatments [3;10]. The state-of-art solutions' average accuracy is 94%. The size of the Breast organ impacts the size and shape of the Pectoral muscle. The existence of skin and operated lymph nodes alter the visibility of the Pectoral muscle. If the tissue is thick, it might be difficult to see the Pectoral muscle. It has been noted that while masking Pectoral muscle, the majority of the suggested procedures did not consider all the factors such as Pectoral form, tissue type,

135

_____

operated lymph nodes, the existence of skin, and Breast edge slope sharpness.This research proposes a Novel ensemble approach where MSER based and SlopeEdgeDetection methods are combined with widespread pre-processing to detect and cover Pectoral muscle. Section II presents a brief literature review; Section III presents a block diagram, algorithms for the proposed technique, and an explanation of the dataset. The analysis and experimental findings are presented in Section IV. In Section V, the conclusion and the future scope are briefly summarised.
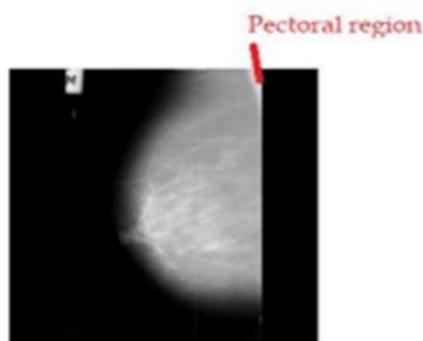

Fig 1. Sample Mediolateral Oblique Mammogram with the highlight of the Pectoral region

II. RELATED WORK

There are several Pectoral Removal methods suggested. These critical perspectives are outlined below. All of these methods make use of the Mini-MIAS database. To identify the segmentation of the Pectoral muscle, the mammographic image analysis society database (MIAS, 322 instances) is used by Woong Bae Yoon, Ji Eun Oh et al.[3]. The morphological approach and the random sample consensus procedure is used to find the Pectoral muscle. We assessed the area of the Pectoral muscles detected and contrasted manual and automatic segmentation. The outcomes revealed is 92.2%.

A Pectoral removal strategy is presented by P. S. Vikhe et al. [4] uses intensity-based thresholding to identify the boundary points of the calculated Pectoral area and the Least Square Error (LSE) method to prune the boundary points. Global thresholding-based approach is proposed by Syeda Iffat Naz et al. [6]. In this approach, the mean intensity of either the left or right quarter of an image is taken as the global threshold, and the image is then filtered accordingly. The slope is then calculated and applied to find the Pectoral muscle. The accuracy score for this method is 92.86, with 4.97 acceptable accuracy scores and 2.17% undesirable cases.

A Pectoral masking method based on geographic principles and regional growth practices is offered by Saeid Asgari Taghanaki et al. [5]. This method can identify Pectoral muscles regardless of their morphology. In 67% of situations, it provided exact findings, the best outcomes.

Bounding Box and Region Growing approaches are used in an approach developed by Enas Mohammed Hussein Saeed et al. [7] to provide more precise results. The outcome is presented in this case as the area difference between the real and bounding box, region growing, and combined areas. The analysis's findings indicate that the combined technique provided improved accuracy. According to the author, the accuracy rate for both perfect matching plus acceptable situations is 98%.

One Pectoral removal method, proposed by G Vaira Suganthi et al. [8], J Sutha, M Parvathy, and C Durga Devi, uses active contour and intensity thresholding approaches to locate the Pectorals.Ch.Sarada et al. [9] proposed a hybrid strategy based on Hough-based and the Modified Maximal Stable Extremal Regions methods to mask the Pectoral region . The achieved accuracy is 98.14%.

In the current work, goal is to design and develop a novel strategy for increasing the accuracy of Pectoral muscle detection. The adoption of the hybrid methodology produced a consequent analysis that revealed 99.063% accuracy, which is a significant increase above the approaches currently used in the literature.

III. NEW SYSTEM TO LOCATE PECTORAL MUSCLE IN MLO MAMMOGRAM

A portion of the Pectoral muscle is seen on MLO mammograms. Breast mass features are comparable to those of the Pectoral muscles. Therefore, in Digital Image Processing based computer aided diagnosis, the presence of Pectoral muscle increases false positives while locating Breast lumps in MLO Mammograms.

The MSER and SlopeEdgeDetection based algorithms are employed together in the proposed method, and extensive pre-processing is used to mask the Pectoral muscle. In total, two stages have been employed in the suggested approach. In stage1, the large contour of the image is cropped to eliminate the black background portions because they provide no information, all kinds of noise are removed, and the resultant Mammogram is set in the right orientation. The Pectoral area is located and masked at stage 2 of the proposed method, assuming it exists. The Block schematic of the suggested ensemble technique is shown in Fig. 2.
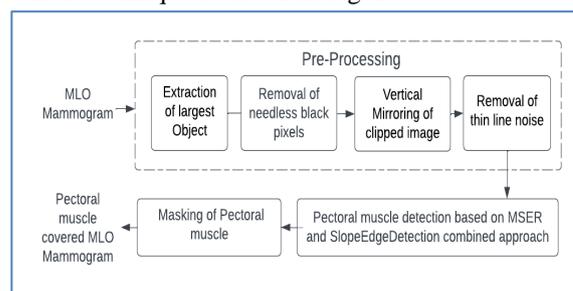

Fig. 2. Block schematic of the suggested ensemble technique

_____

A. Pre-processing

Pre-processing plays a vital role in image processing, and the same is true with Pectoral area detection also. Artefacts, including additional background, adhesive labels and unneeded black pixels, might be present in the original mediolateral oblique mammogram. Images for the left and right Breasts are left and right-oriented in the Mediolateral Oblique Mammogram database.

In the suggested method, the precise Breast object is cropped, so all unwanted labels are perfectly eliminated from the given MLO Mammogram. Then all extraneous black pixels are eliminated so that the final image has a greater chance of detecting a Hough line's slope. Noise thin lines too will be removed right in the Pre-processing stage. After pre-processing, MLO mammograms are noise-free and right-oriented.

A.I. Extraction of largest Object

The largest mammography object is the actual MLO mammogram image without excess area, labels, or strips. To extract the largest object from MLO Mammogram, Ostu's[57] thresholding is applied which extracts the largest rectangular contour from the original MLO Mammogram, which is subsequently cropped. Fig.3 shows the original mammographic (MLO) image and a cropped version (b). To achieve this, it first calculates the bounding box values around the principal contour and then crops the image. Labels outside the Breast boundary will be removed after cropping. Fig. 4 shows that even labels near the Breast contour are erased here.
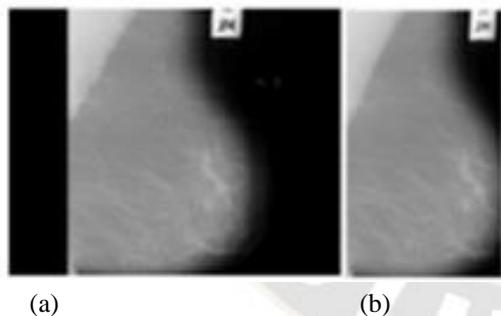

(a)   (b)
Fig.3 (a) Original Mammogram (b) Cropped Image

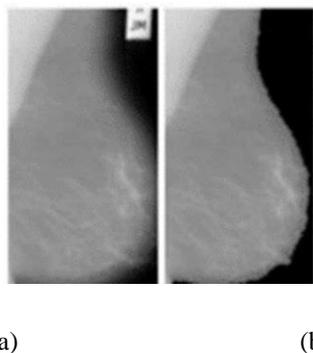(a)   (b)
Fig.4 (a) Cropped Image (b) Final Extracted large object

A.II. Removal of needless black pixels

After the largest object's extraction is done, the resultant cropped image is the clipped image containing the actual Mammogram. However, it has been noted that the resultant MLO Mammogram picture may have unnecessary black pixels at the border line between Pectoral muscle and actual Breast organ, which has a detrimental effect on locating the Pectoral muscle region. A suitable binary image mask is generated in the suggested method to eliminate extraneous black pixels from the provided image. The image is binarised by keeping the threshold. To determine whether the image is left or right-oriented, the number of non-zero pixels present in the top left corner square and top right corner square can be compared. If the mean is greater than 100, then the threshold is kept at 100 and if it is less than the mean, then the threshold is taken as mean-20. This threshold selection is necessary as some more significant pixels can be removed along with the blackish pixels.

The resulting binary picture may include holes after deleting pointless black pixels; these holes need to be filled. The suggested method fills the gaps using a flood fill technique. Every gap in this place is filled with a white, grey level. Then finally, it outputs a mask, and then it is multiplied using the bitwise-and operator with the largest object extracted to obtain the modified image. The elimination of unnecessary black pixels is described in Algorithm 1, and the filling of gaps is described in Algorithm 2.

Algorithm 1: BlackPixelRemoval(I)

Input: Original Image I

Output: Needless black pixels removed Image

Step 1:Find the binary image for the given original image I by setting all pixels whose grey level is greater than or equal to the threshold as white grey level and the remaining as black grey level.

binary_image = original Image I > Threshold

Step 2: Find seed pixel (i,j), then fill holes of a binary image with white grey level using flood filling

binary_image=call FloodFill(i,j, binary_image, white, black)

Step 3: Return resultant binary image

Algorithm 2: FloodFill((i,j), binary_image, new_color, prev_color) - primary purpose is to fill the black holes that occur amid white regions. It fills considering the neighbourhood of the hole.

Step 1: If binary_image(i,j) = black

Set the colour of the pixel (i,j) to white

Call Floodfill (i+1, j, binary_image, new_color, prev_color)

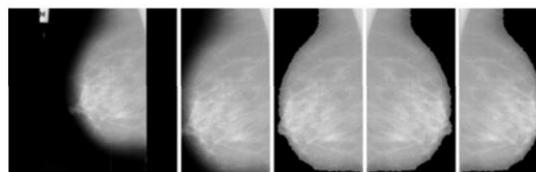Call Floodfill (i-1, j, binary_image new_color, prev_color)

Call Floodfill (i, j+1, binary_image ,new_color, prev_color)

Call Floodfill (i, j-1, binary_image,new_color, prev_color)

Step 2: Return holes filled binary_image

137

_____

After unnecessary black pixels are eliminated, all MLO Mammograms are oriented to the right direction so that the Pectoral region for all the images are present only in the top right corner, making masking of Pectoral muscle easier. The process of Mammogram flipping is described in algorithm 3. It is based on the comparison of the count of non-zero pixels.

Algorithm 3: SetImageOrientation(CroppedImage)
Input: CroppedImage
Output: Right-oriented cropped Mammogram
Step 1: m, n = CroppedImage.shape
Step 2: boxheight =10% of m
Step 3: boxwidth= 10% of n
step 4: Count the nonzero pixels in the left corner (size
        boxheight * boxwidth) of the cropped image.
          for i=0 to boxheight
            for j=0 to boxwidth
             if CroppedImage(i, j) >0
                count1=count1 + 1
step 5: Cropped Mammogram mirroring
        image1=verticalMirroring(CroppedImage)
step 6: Count the nonzero pixels in the left corner of
        size of boxwidth x boxheight of vertically
        mirrored image
        for ii=0 to boxheight
          for jj=0 to boxwidth
                    if image1(ii ,j j) >0
                        count2=count2+1
Step 7: if (count1 < count2)
        image = verticalMirroring (CroppedImage)

A.IV. Removal of thin line noise

As part of pre-processing, removing unnecessary thin lines is the last step and algorithm 4 shows the associated procedure. This is based on the median filtering approach, and it removes some unnecessary thin black lines present in the image

Algorithm 4: ThinLineNoiseRemoval (Image)
Input: Flipped image
Output: Thin line noise freed image Step 1. p, q = size(Image);
Step 2. for m = 2 to p-1 for n= 2 to q-1
        t1 = Image(m-1:m+1,n-1:n+1);
        t2 = reshape(t1,1,9);
        t3 = sort(t2);
        t4 = median(t3);
Step 3: return t4

Fig. 5 shows the sample outputs of pre-processing.

(a)   (b)   (c)   (d)   (e)
Fig. 5: (a) Original Mediolateral Oblique Mammogram (b) After Cropping (c) after removal of needless black pixels (c) After vertical mirroring (e) after removal of thin noise lines.

B. Finding of Pectoral region

The pre-processed MLO Mammogram is the one that is cropped, noise-free, and with crisp sloping edges and correct orientation. After the pre-processing process is done, a novel ensemble technique using MSER based and SlopeEdgeDetection techniques is applied to find the Pectoral region. This approach is written as steps in Algorithm 5. The steps are described after the algorithm.

Algorithm5:ensemble_ExtensivePreprocess_MserPectoral_SlopeEdgeDetection(Mammogram Image)
Input: Initial Mammogram Image

Output: Pectoral masked MLO Mammogram

Step 1: Apply extraction of largest object procedure and
store the resultant object in the Icropped   variable

Step 2: Icropped=call BlackPixelRemoval(Icropped)

Step 3: Icropped= call ThinLineNoiseRemoval(Icropped)

Step 4: m, n =Icropped.Shape

Step 5: Determine Pectoral regions using MSER based
method and store it in PecRegions variable

Step 6: truePecRegions= {segment | segment ∈
        PectoralRegion & segment ∈
        Height(segment)<(Height(Icropped)-100)}

Step 7: if truePectRegions=0 jump to step 12 otherwise
go with step 8

Step 8: Set the maximum area truePectRegion as the
        maxTruePectRegion by choosing it from the
list of truePectRegions

Step 9: Prepare a mask for the maxTruePectRegion area
        found in step 98

_____

Step 10: Use an Image width-height triangle to prune the resultant mask to create the pruned MSER Pectoral mask

Step 11: SlopeEdge result verification

Jump to step 13 if PecRegionwithSlopeEdge = 0

else, continue with step 12.

Step 12: Create a mask for the PecRegionswithSlopeEdge part.

Step 13: Between pruned MSER Pectoral mask and SlopeEdgePectoral Mask, select the final mask

If area(truePectRegion)> area(PecRegionswithSlopeEdge)

finalPectMask= prunedAdaptiveMSERPectMask

Else

finalPectMask = SlopeEdgePectMask

Step 14: Select the final mask among the computed MSER Pectoral or SlopeEdgeDetection

If PecRegionswithSlopeEdge = nil

and len (truePectRegion) > 0

finalPectMask= prunedAdaptiveMSERPectMask

Else If PecRegionswithSlopeEdge exist and len(truePectoralRegion)=0

finalPectMask= SlopeEdgePectMask

Otherwise

if both methods are unsuccessful, then it is decided that no Pectoral region is present.

Step 15: If finalPectMask exists

Mask the Pectoral region of MLO Mammogram

Else return "No Pectoral"

Details of MSER based and slopeEdgeDetection methods are given in sections B.i and B.ii.

B.i. MSER based method to detect the Pectoral muscle

MSER is the standard method that determines stable linked components for any grey level from 0 to 255. The MSER based approach computes stable linked components of only the Pectoral area using a limited set of grey levels.

The parameters MaxAreaVariation, MinArea, and MaxArea are utilised in MSERPectoral[9]. The region is omitted if its area exceeds 500000 since the MaxArea is set at 500000. To exclude tiny places, the MinArea is set to 50. MaxAreaVariation, which controls the most intensity variation

between extremal regions, is the most important parameter. For Mini-MIAS MLO Mammograms, the MaxAreavariation parameter in MSERPectoral[9] is set to one of these three values [0.25,0.5,0.75].

MSER based method is the improvement of MSERPectoral[9].The parameters MinArea, MaxArea, MaxAreaVariation, and MinDiversity are utilised. The Minarea is set to 50, the MaxAreaVariation parameter is set to a single value of 0.75, the MaxArea area is set to 500000, and the MinDiversity is set to .7. It sweeps across only 6-7 threshold levels instead of 255 levels. Considering the mean of the square of the top left corner (size of 10% of width*10% of height) as x, it only sweeps across threshold levels from x-30 to x+30 in the space of 10, which amounts only to 6-7 thresholds. This is considered to narrow down all the parameter space to look only for the top left corner regions that contain Pectoral. It is quicker as the threshold levels are reduced to half a dozen instead of 255 threshold levels as in general MSER. This modification to MSER is performed only to suit Pectoral muscle detection much quicker than the general method. As the MaxAreaVariation value increases, the number of regions also increases, which also might contain some unstable regions; generally, taking 0.25 is best as it gives fewer and very stable regions. Taking 0.25 worked in most of the images. Still, in some of the images, due to the less visible nature(less stable region) of the Pectoral muscle, it could not produce the Pectoral mask but keeping 0.75 worked as it outputs more regions, which are not so stable as well. Due to the MaxAreaVariation parameter value of 0.75 in this MSER based approach, several repeated stable linked components are produced. To reduce these regions, which are repeated multiple times with slight variation in them, the minDiversity parameter is used to exclude areas that are overly similar to the other produced regions so that the repeated regions are controlled.

B.ii. SlopeEdgeDetection Method

Algorithm 5 is for the slopeEdgeDetection technique. It uses the probabilistic Hough line method to determine potential lines in the MLO Mammogram. Pectoral region boundary line is found from discovered Hough lines. This method is also considered along with the MSER based method because, in some very dense Breast images, MSER outputs zero regions. After removing the unnecessary black pixels, most of these images have a slope line at the Breast edge, which can be seen in the below images in the result section. This slope line is part of the Pectoral border. It can be completely drawn by this method.

$Y=mx+c$ is the line equation in the Cartesian coordinate system. Vertical lines, however, cannot be represented using this style. To depict a line, the HoughLine

_____

method uses the polar coordinate system. The line equation in a polar coordinate system is dist=mcos θ +n sin θ, where dist is the distance from the line's perpendicular point to the origin, and θ is the angle formed between the horizontal axis and this perpendicular point[10].

The Probabilistic Hough Line Transform is the more robust and efficient implementation of the Hough Line Transform[11]. The probabilistic variant gets its name because it only examines a small group of points and calculates the likelihood that they all belong to the same line. It is optimised for conventional Hough transform, a quicker and less computationally costly version. In the below algorithm, the condition in the if statement in step 3 is taken as m<0, and its absolute value is in the range of 1.5 to 10. The slope has to be negative due to the nature of the edge of the Pectoral region. The range is kept because there might be chances of detection of wrong lines other than the Pectoral edge where the slope is huge or small, which gives results for the Pectoral edge; this range is suitable for the Pectoral edge.

Algorithm 6: SlopeEdgeDetection(Image)

Input: Image

Output: Pectoral Region

Step 1: Determine the edges of the Image using canny edge detection

Step 2: Find potential lines using probabilistic Hough Transform and store them in the PHLines variable

Step 3: Determine Pectoral region triangle

  for l in PHLines:

    Extract (x1, y1), (x2, y2) from l

    Determine slope m of line equation y=mx+c

    m=(y2-y1)/(x2-x1

    Substitute (x1, y1) or(x2, y2) in y= mx +c to get c

    if c>10 and m<0 and 1.5<abs(m)<10 and c < imageheight-100

     intercept_x = -c/m

     intercept_y=c

   With these intercept values, create the polygonal Pectoral triangle.

   Compute Polygon_Pectoral=

     [(0,0), (0, intercept_x),(intercept_y,0)]

Step 4: Return the largest Polygon area as the final SlopeEdgeDetection Pectoral_Polygon

---

The SlopeEdgeDetection method is a faster variation of the HoughPectoral method [9]. In most images, the MSER based method works out. However, MSER did not give proper results in dense kind of Mammograms. SlopeEdgeDetection

approach gave better results if the border line between Pectoral region and actual Breast region is sharp and it gave good result in dense regions also. The proposed approach is the combined approach which draws the best results among both methods. The image results are shown in Section IV.

C. Database Description

The Mini-MIAS database is used to validate the suggested strategy. This database has 322 MLO Mammography images in total. Mammogram IDs are included in this database as mdb001, mdb002, through mdb322. Most Pectorals are triangular; however, some are parabolic, and some Pectoral muscles are partially exposed due to skin or lymph node surgery or similar procedures. It is a database of 161 patients with two images per patient (left Breast and right Breast), and three images are present with no Pectoral.

IV. RESULTS AND DISCUSSIONS

The proposed combined approach is applied to all Mini-MIAS images. It can mask the Pectoral region accurately with an accuracy score of 98% and above in 298 images (92.5%), acceptable cases with an accuracy of 96% to 97.9% are 21 (6.5%), and bad cases(which have accuracy below 96%) are 3(1%). In summary, 319 samples (298 well-segmented cases plus 21 acceptable cases) produced good results. Three are inaccurate. Three images are detected as no Pectoral as the above two methods did not give any region.

Metrics such as Global Pixel Accuracy, Intersection of Union, Dice Similarity Coefficient, Specificity and Sensitivity are measured to determine classification effectiveness, the same metrics defined in [9]. There were three images where the algorithm gave small regions, but the actual ones were big, so the accuracy score was below 96% for these images. So, it gave an inaccurate result for these three images. All the results are based on the segmentation metrics compared with the ground truth Pectoral images (drawn manually and checked by a radiologist). The mean values of the metric measures of the 319 images are shown below in Table 1 (expressed as mean +/- standard deviation of the values).

Table 1. Mini-MIAS Pectoral covering mean values of Metrics

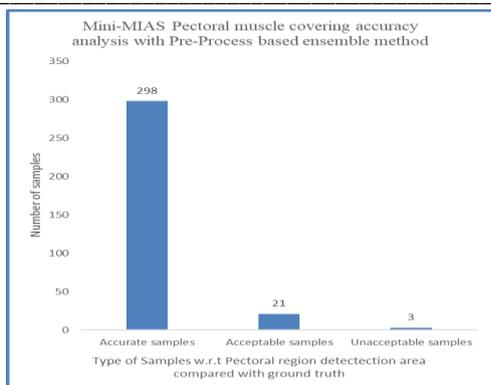| Metric Parameter	Mean Value
Global Pixel Accuracy	99.23 ± 0.52
Intersection of Union	88.23 ±10.47
Dice Similarity Coefficient	92.095 ±7.765
Specificity	99.605 ± 0.462
Sensitivity.	96.78 ± 2.59

_____

Fig. 6. Mini-MIAS Pectoral covering analysis diagram

A few examples of Pectoral muscle being detected in the Mini-MIAS MLO Digital mammography repository are provided in the figures that can be found below. Observe Fig.7 carefully, both methods detected Pectoral muscle area and the larger Pectoral muscle area detected among is taken as the final detected Pectoral area.

Fig.8 shows that the revised MSER method can be used to locate the Pectoral region, which can take on a variety of shapes including a triangle and a parabolic arc. The Radiologist claims that the Pectoral muscle can take on a triangular or parabolic shape.

The Fig.9 illustrates some Mammographic Pectoral muscle identification examples for which only the Probabilistic Hough centered approach produced results. After deleting the undesirable black pixels, the ensembled technique described produced great results.

Fig. 7 Certain samples of Pectoral muscle detection where both Probabilistic Hough and revised MSER gave result
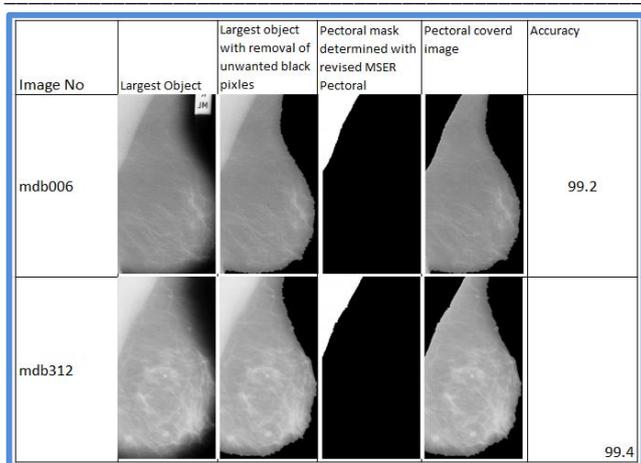
Fig. 8. Certain samples of Pectoral muscle detection with revised MSER based approach

The recommended approach is compared to the existing literature in the Table 2. The associated bar graph is shown in the Fig.10. The proposed method located Pectoral region areas with higher accuracy than existing methods with accuracy of 99.067.
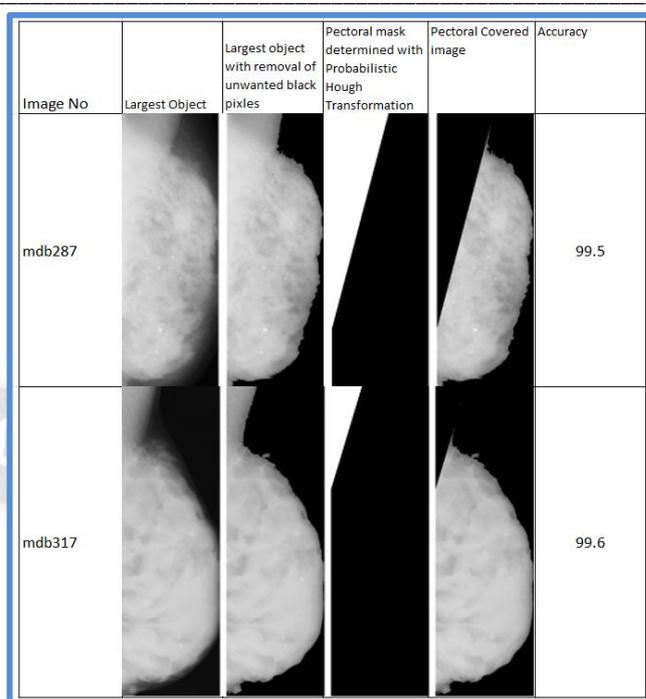

Fig. 9 Certain samples of Pectoral muscle detection with Probabilistic Hough based approach

Table 2. Comparative analysis of proposed pre-processing based ensemble system with existing literature to detect and cover Pectoral muscle

Author	Methodology used	Images accuratly segmented, acceptable and unacceptable			
		Accuratly segmented cases %	Acceptable Cases %	Unacceptable cases %	Overall accuracy acchieved (accurate+ acceptable)
S. Marijeta et.al	K-Means and Cubic polynomial	68.32	19.25	12.42	87.57
P. S. Vikhe et al.	Intensity Thresholding and Least Square Error	87.19	9.37	3.44	96.56
M. Mughal et al.	Wavelet-based approach	77.63	14.59	7.76	85.39
Syeda Iffat Naz et al.	Slope based approach	92.86	4.97	2.17	97.83
Saeid Asgari Taghanaki	Geometry rule-based approach	67 exact +18 Optimal	5	10	90
Samuel Rahimeto et al.	Ostu's muti-thresholding	not given	not given	not given	93.36
Woong Bae Yoon, Ji Eun Oh et al.	Hough Transform	not given	not given	not given	92.2
Enas Mohammed Hussein Saeed et al.	Region Growing techniques	not given	not given	not given	98
Pascal Vagssa et al.	Hough Transform	not given	93.8	6.2	93.8
G Vaira Suganthi et al.	Intensity Thresholding	not given	not given	not given	92.55
Ch.Sarada et al.	components + HoughLines	90.994	7.143	0.932	98.137
Proposed	**components + HoughLines**	**92.546**	**6.521**	**0.932**	**99.067**

_____

The comparative analysis in the Table 2 and the corresponding bar chart illustrates that the Pre-Processing based ensemble approach detects better Pectoral muscle area in significant number of samples.
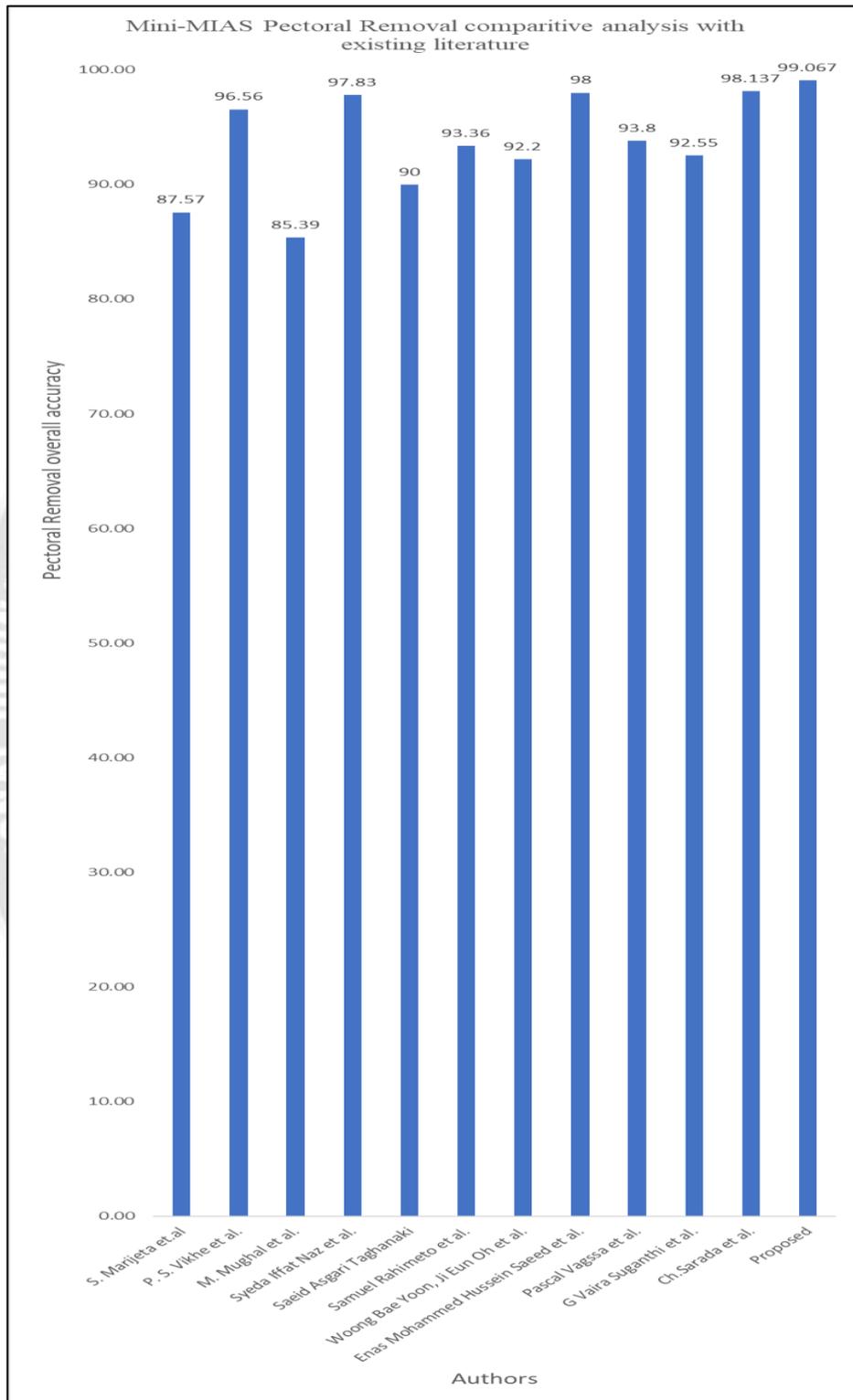

Fig. 10. Comparative analysis chart of new pre-processing based ensemble system with existing literature to detect and cover Pectoral muscle

_____

V. CONCLUSION AND FUTURENWORK

In this work, a pre-processing-based ensembled approach for identifying and covering Pectoral muscle is proposed. The results obtained after applying a hybrid approach post pre-processing of the image are heling us in eliminating the undesirable black pixels such that the pectoral border line is sharper and probability of the Pectoral muscle identification increased. The suggested solution outperformed the current methods. In 99% cases Mini-MIAS samples, it is able to accurately detect the Pectoral region area.

The obtained image could further be fed as input to the lump detect algorithm for better accuracy of Prediction of Breast Cancer.

REFERENCES

[1] https://my.clevelandclinic.org/health/diseases/2116 9-dense-Breast-tissue

[2] Donoser, M. and Bischof, H. "Efficient Maximally Stable Extremal Region (MSER) Tracking".

[3] Woong Bae Yoon, Ji Eun Oh, Eun Young Chae, Hak Hee Kim, Soo Yeul Lee, Kwang Gi Kim, "Automatic Detection of Pectoral Muscle Region for Computer-Aided Diagnosis Using MIAS Mammograms", BioMed Research International, vol. 2016, Article ID 5967580, 6 pages, 2016. https://doi.org/10.1155/2016/5967580

[4] P. S. Vikhe and V. R. Thool "Detection and Segmentation of Pectoral Muscle on MLO-View Mammogram Using Enhancement Filter", (2017).

[5] Samuel Rahimeto · Taye Girma Debelee · Dereje Yohannes · Friedhelm Schwenker "Automatic Pectoral muscle removal in mammograms", Springer 2019

[6] "Geometry Based Pectoral Muscle Segmentation from MLO Mammogram Views", Saeid Asgari Taghanaki, IEEE Biomedical & Pharmacology Journal, September 2020.

[7] Enas Mohammed Hussein Saeed, Hayder Adnan, "Pectoral Muscles Removal in Mammogram Image by Hybrid Bounding Box and Region Growing Algorithm ", 2020.

[8] G Vaira Suganthi, J Sutha, M Parvathy and C Durga Devi "Pectoral Muscle Segmentation in Mammograms", Biomed Pharmacol J 2020

[9] "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

[10] https://web.ipac.caltech.edu/staff/fmasci/home/astro_refs/Houg hTrans_lines_0 9.pdfctor-look- for-on-a-mammogram.html

[11] "Robust Detection of Lines Using the Progressive Probabilistic Hough Transform", J. Matas, C. Galambos and J. Kittler

[12] S. Suguna Mallika, D Rajya Lakshmi, "Mutation Testing and Its Analysis on Web Applications for Defect Prevention and Performance Improvement", International Journal of e-Collaboration (IJeC) 17 (1), 71-88

144