Analysis of the various techniques used for breast segmentation from mammograms

Athira K S[a*], Nagesh Subbanna[d]
Center for Wireless Networks & Applications (WNA)
Amrita Vishwa Vidyapeetham
Amritapuri, India
athirakalladayil@gmail.com
nageshks@am.amrita.edu

Janaki Peruvamba Dharmarajan[b], Vijaykumar D K[c]
Department of Radiology, Department of Breast and Gynaec – oncology,
Amrita Institute of Medical Sciences and Research Center
Kochi, India
janaki19727@aims.amrita.edu
dkvijaykumar@aims.amrita.edu

***Abstract*—Studies show that the cancer that causes the breast is the most frequent type of cancer found among women. X-ray imaging, called mammography, is an imaging technique that is commonly used to detect and classify breast abnormalities. However, accurate segmentation of breast tissues and abnormalities in the mammogram is a challenge, and consequently, many techniques have been employed over the years to extract these tissues and abnormalities and classify breasts based on their vulnerability to breast cancer. In this paper, we present different approaches used for breast segmentation from mammograms. Various methods ranging from modern deep learning-based techniques like UNet, and Atlas-based techniques are reviewed, and the classical techniques such as active contour, global threshold, machine learning based methods, etc. The results of these techniques are compared in order to provide an insight into the challenges of breast tissue classification and the future challenges are highlighted.**

Keywords—mammogram, segmentation, atlas, UNet, deep learning

I. Introduction

According to World Health Organization (WHO) and Global Cancer 2020 statistics, around 23 lakh women were diagnosed with breast cancer [1]. One of the factors that predisposes breast cancer is breast density. Women with high breast density are more vulnerable to developing breast cancer in the future [2]. Therefore, WHO recommends regular screening of the breasts through mammograms as a first step towards the early detection of breast cancer. However, radiologists who are required to analyse these mammograms are often at a premium, and consequently, we have to resort to automatic analysis of breast images. One of the most important tasks of automatic classification of mammograms is to classify them based on breast density. Breast Imaging Reporting and Data System (BIRADS) is a standard for calculating breast density [3]. BIRADS categorizes images into four classes. In Class 1, the breast is nearly fatty with very little glandular tissue. In Class 2, the breast is more fatty with some glandular tissue. In class 3, the breast has some fat and more glandular tissue. Class 4 consists of more glandular tissue i.e., it has more density. In order to classify breasts based on tissue density, we need to segment the glandular and fatty tissues in the breast, determine the proportion of the total volume of the breast occupied by glandular tissues, and thus classify them into the appropriate BIRADS category.

Breast segmentation is the method of dividing digital images into its two principle constituent regions, viz, the glandular tissue and the fatty tissue. This requires segmentation of the breast region as a first step. The choice of imaging for imaging breasts is X-ray imaging, and the X-ray images of breasts are called mammograms. Mammograms contain a frontal or side view of the breast region. Fig 1 shows the two types of standard mammogram view. The typical way to segment breast tissue in mammograms is to have radiologists go over the images and then segment out the breast tissue in breast images and classify the BIRADS class to which the breast belongs. However, this is a slow, inconsistent and expensive process, and therefore, over the years, many automatic techniques have been evolved for breast segmentation. In the automatic segmentation of mammograms, one needs to segment the breast region first, and then, the glandular tissue and fatty tissue from the breast. Fig. 2 represents the breast image and corresponding breast mask.

In this review paper, the summary of different segmentation techniques that have been used, their working, their advantages, disadvantages and research gaps are mentioned. It is impossible to highlight every single paper on breast tissue segmentation, so we have grouped segmentation techniques by technique type, and then taken examples of each kind. In this paper, we have classified segmentation methods into five classes.

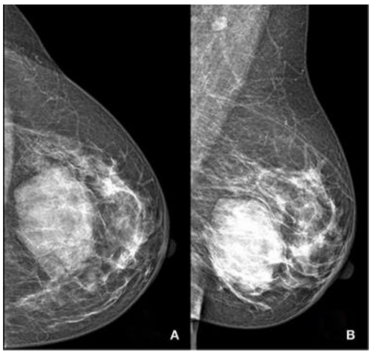

Fig. 1. A is Craniocaudal (CC) and B is Mediolateral Oblique (MLO)

979-8-3503-4745-6/23/$31.00 ©2023 IEEE

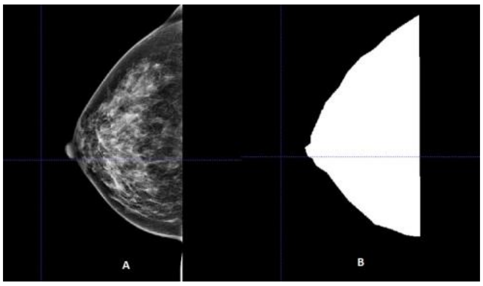

Fig. 2. A is the Breast image and B is the Breast mask

Segmentation based on edge and region, texture related segmentation, altas related segmentation, machine learning and finally deep learning based segmentation. A recent paper that covers all the techniques that have been used for breast tissue classification has been missing, so we believe that this paper will fill the missing gap in the literature survey covering techniques to date.

Like mammograms there are different image modalities like Ultrasound imaging, radio wave imaging, breast magnetic resonance imaging, breast thermal imaging etc. Ultrasound imaging uses sound waves to pass through the body. Radio waves use the electromagnetic spectrum. Breast thermal imaging is based on infrared light. Several research is going on in this field of breast thermal imaging. The paper proposed by Gopakumar S., Sruthi K. and Krishnamoorthy S on breast tumor segmentation from thermal images using modified level sets is one such research [4]. Krishna, S. and George, B proposed a solution to diagnose breast abnormality from thermal images [5]. All these methods help in early detection of breast cancers. There are around five different stages of breast cancer. Stage 0,1,2,3, and 4. Stage 0 is when the cells seem to be abnormal. Stage 1 is called an early stage where cancer starts to spread slowly. Stage 2 is called as localized where the tumor becomes 2cm to 5cm in size. Stage 3 and 4 are regional spread and distinct spread respectively. D. Khadakban, T. Gorasia Khadakban, D.K. Vijaykumar, K. Pavithran, and R Anupama [6] have proposed a paper on factors influencing the survival of stage 4 breast cancer patients after surgery and paper [7] discuss about the existence results of breast cancer cases in India during a period of 10 years.

II. Choice of Papers for Survey

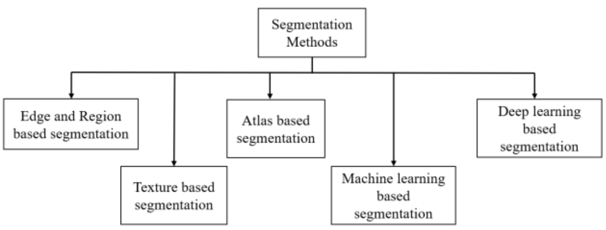

Fig. 3. Taxonomy Diagram

Various methods, ranging from modern deep learning-based techniques like UNets, and Atlas-based techniques and the classical techniques such as active contour, global threshold, machine learning based methods, etc., are reviewed. Fig. 3 shows the main five classifications of segmentation methods.

A. Edge and Region based segmentation

Neeraj Sharma, Aggarwal, and Lalit M have proposed a paper on different automated techniques for segmenting medical images [8]. This paper describes computed tomography (CT), magnetic resonance (MR) images and their segmentation. Segmentation techniques are classified into two. Gray Level feature and texture based features. Segmentation related to amplitude, edge, and region comes under gray level features. Various artifacts such as partial volume effects, artifacts due to motion, ring artifacts due to misalignment of CT detector, and noise from sensors are the main common problems in the images obtained from CT and MRI. The algorithm for segmentation is also subjected to noises, artifacts, overlaps, intensity differences etc. The threshold obtained from histogram is the base for amplitude segmentation. This technique will work well if the object and its surrounding brightness are uniform and have different gray scale values. This method is inefficient for multiple objects, each with a different gray scale value, varying across a band of values. For segmentation of image, threshold is selected based on the minima. In a graph of three peaks, there are three minima. These minima are considered for the threshold. Second type of segmentation is using the edges. This algorithm will detect the edges of images.i.e. frontier in which separate zones are identified based on the disruption in gray level, intensity etc. There are different operators that detect contours which are grounded on gradients. Gradients are generally derivatives. They are Prewitt, Sobel, Roberts which are first differential type and Laplacian the second differential type, Canny etc. Detected edges are combined into an edge chain and form a border. Relaxation of edges, detection of contours, hough transform etc are some of the methods related to edge segmentation. Third type is region based. Homogeneity is the principle behind them. Pixels with comparable characteristics are grouped together to form uniform regions. It is based on the set theory of homogeneity. Merging of regions, splitting of regions are based on region segmentation. Other ways of segmentation are model and atlas based, supervised and unsupervised. This paper gives an idea about various segmentation techniques that can be applied in CT and MR images.

Zhili Chen and Reyer Zwiggelaar have proposed a paper on removal of pectoral muscles and segmentation of breast regions in mammograms [9]. For computer-aided analysis of mammograms, breast tissue segmentation is inevitable. It is intended to separate breast tissue and contains two independent segments. First segmentation typically segments background areas containing tags, comments and frames from the entire breast zone. Thus from the background of the mammogram, the breast tissue is extracted. Second is the removal of breast muscle. The method used in this paper is automated segmentation related to histogram threshold, detection of edges, fit using least squares and contour expansion. First step is to make the histogram smooth using Gaussian. Then the global threshold is calculated using the breast tissue and minimum between the peaks of the background. The output is a binary image. The labels are removed from this by a connected component labelling algorithm. In segmentation using scale-space based edge detection, forty points are placed on the binary image boundary and for all individual points, a perpendicular line is captured. Five hundred pixels is the line length. Possible points around the boundary of the breast are detected using edge detection. These pixels are multiplied with perpendicular lines with Gaussian kernel derivative and by detecting the minima, breast contour points are obtained. Active contours or snakes help in image segmentation by growing the region. It will initiate the curve on the image and start growing towards the object boundary. A seed point is selected from the breast contour points on the line. From the seed point, the contour can grow in any direction. The paper concludes by evaluating the results for each segmentation. 66.5 percent as correct and 25 percent approximately correct for the segmentation of the background region, 63.5 percent as correct and 25 approximately correct for pectoral muscle removal. The entire result was 94 percent acceptable.

Manasi Hazarika and Lipi B Mahanta proposed a paper on enhanced detection of breast tumors by extracting the borders and improving the contrast [10]. Mammogram images are difficult to diagnose tumors due to the presence of high artifacts in the background and flat contrast. This paper proposes pre-processing methods to overcome these difficulties. It proposes three methods like segmentation of breast contour, enhancement of contrast, and removal of breast muscle. Global threshold and morphological operations are the key pillars for breast border extraction. The method to enhance the contrast is presented in two steps. First is to enhance the image globally by using bi-level histogram modification approach. Second is by using a non-linear filter on the modified image. Region growing method is applied to remove the breast muscles. The proposed method is able to create an accuracy of 98 percentage in breast border extraction for three hundred twenty-two mammogram images.

B. Texture based segmentation

Michael A Wirth and Alexei Stapinski proposed a paper to segment the breast region by snakes or active contours [11]. The functions of active contours for mammogram segmentation is explained here. Skin- air interface, also called breast contour or breast boundary is one of the features of mammograms. Extraction of these boundaries helps to find the abnormalities in the breast. The main challenge in identifying the contour is that breast contour contrast decreases when the breast tapers off. This pointing nature leads to poor visibility in the mammogram region and makes it hard to find the breast border. Active contours also called as snakes depend on local minima. The snakes will glide by considering the minimum energy path to create a boundary or contour around the desired image. Related to the energy there are intrinsic forces and extrinsic forces. Intrinsic forces will control stretching or bending capability of contours. Extrinsic forces guide the border to the desired figure. Here, in this paper the first step is to achieve a double threshold on the mammogram to identify first position to place points. A uni-modal algorithm based on threshold is used to determine the threshold. These points are passed through the algorithm to get the initial point. The edge of the image is enhanced by iterating from right to left and vice versa. Snakes movements happen based on their energy. There are some limitations in using the snakes. They are selection of first border position, sensitivity to noise and weak edge, convergence of points, manual initialization, lack of hard constraints. The algorithm has been tested in twenty-five mammograms. The algorithm produced segmentation accuracy of 98 percentage for breast region and 97 percentage for background. There are a large number of papers on regular segmentation, and even papers that delineate the working of unorthodox methods such as [12], which speaks of non-canonical Gabor schemes and their applications. Texture based segmentation is widely used in medical imaging. Mainly in MRI for brain tumor analysis. Criteria for segmenting brain tumors is given in the paper [13].

C. Atlas based segmentation

D.Ciardo, M.A.Gerardi, S.Vigorito, A.Morra, V.Dell Acqua, F.J.Diaz, F.Cattani, P.Zaffino, R.Ricotti, and M.F.Spadea worked on specific and general purpose atlas for breast cancer detection [14]. The paper estimates the contribution of specific and generic purpose libraries in ABAS of breast cancer patients. The paper has one general and nine specific libraries. These libraries are categorized based on the type of surgery and chest size obtained from computed tomography (CT) scans of two hundred breast cancer patients. Atlas serves as a template which is segmented by a radiologist. A collection of atlases is created in ABAS. The first step is to choose a template to use as a reference for enrolling all remaining atlases. A data set is created using deformation vector fields. If a new unlabeled image is obtained, it will be registered to the template and the resulting vector field is generated. These two fields will be compared. The atlas which closely resembles the resulting vector is identified as best. The boundaries will be propagated to the image that has to be labelled. The centre of mass distance (CMD), hausdorff distance averaged (AHD), and dice similarity coefficient (DSC) are used in the paper to compare the performance metrics of the conservative surgery group and the non-conservative surgery group. In conservative surgery group, left breast CMD is 8.84, AHD is 1.13, DSC is 0.8 and for right breast, CMD is 8.16, AHD is 1.78, DSC is 0.76. For non-conservative surgery group left breast CMD is 7.24, AHD is 1.13, DSC is 0.79 and for right breast, CMD is 6.78, AHD is 1.93, DSC is 0.75. The STAPLE technique in combination with specific-purpose atlases produced the best results when comparing the performance of the various libraries on the same structure.

Hrvoje Kalinic has proposed a survey paper on atlas-based image segmentation [15]. The paper elaborates on atlas-based image segmentation and deals with atlas selection, atlas construction, image registration, transformation, similarity measure, optimization algorithm, multi-modality registration, multi view registration, multi temporal registration etc. The first step in image analysis is the segmentation of image, and atlas-based segmentation is one of the segmentation methods that can segment images without a clear relationship between regions and pixel intensities. This could be due to missing edges or excessive noise or if anyone needs to segment objects with the same texture. There are four ways to select an atlas. First, from the set, one can be randomly selected. Second, average of all atlas was constructed and selected. Third, one which is most similar to the input image is selected as the atlas. Fourth, several individual images were used as an atlas. This approach was used before the final segmentation was introduced. A common way to create an atlas from multiple images is to pick a single from the sample (the target for creating the atlas) and transform the other images to that target. Image registration superimposes two or more images to achieve the best possible match. Image registration has three basic building blocks: transformation, similarity measures, and optimization algorithms. The process of superimposing one image over another is referred to as a transformation. Registration functions are more commonly known as energy functions, cost functions, or scores, whereas similarity measures are also known as alignment measures. It will accurately measure how similar two photographs are.

How to determine the highest possible similarity value is explained through an optimization process. The paper provided explanations of atlases, their creation, picture registration, etc.

Manish Kumar Sharma, Mainak Jas, Vikrant Karale, Anup Sadhu and Sudipta Mukhopadhyay proposed a journal on deformable registration of multi atlas for mammogram segmentation [16]. Conventional segmentation algorithms suffer from poor performance due to different image quality and breast region shapes. New machine learning methods are not immediately applicable because they require large training data sets containing segmented images. The multi-atlas algorithm will overcome these limitations. The paper uses atlas-based logic to carry out the breast segmentation by combining together the deformable image registration and clustering. Thus, the problem of very few landmarks is solved to an extent for breast image registration. Landmark-based rigid body registration followed by registration of image is a method used for breast segmentation. However, these methods stand on two things. Accuracy of detected landmarks and initial gap between two figures. The algorithm for detection of landmarks can only detect points like nipples, and edges of pectoral muscles in mammograms. Therefore, a method that automates this is not viable. Multi-atlas deformable registration considers the breast tissue aspect, size, and orientation in mammograms and also handles salt and pepper noise. The algorithm was compared with three other methods like Active contour model, Threshold in multi-level and threshold in row by row. Jaccard index and Hausdorff distance was evaluated and found better results compared to others. The survey done by Iglesias, J.E. and Sabuncu, M.R [17] on multi-atlas segmentation will give more insight into the use of multi-atlas in segmentation.

Juan Eugenio Iglesias and Nico Karssemeijer proposed a paper on the detection of landmarks using multiple FFDM atlases [18]. Computerized multi-view recognition system locates the nipple position to find the distance to match findings across images. In most of the mammograms, the nipple location on the image is not clear. Hence the boundary detection methods are less accurate in identifying the boundary and the nipple position. In this paper a multi-atlas algorithm that estimates the position of the nipple and breast muscle region are proposed. Labelled digital mammograms are mapped to the target mammogram. The labels are then transferred and combined into the target. The paper deals with three sets of datasets. Datasets A, B and C. Datasets A consist of 150 mammograms. Out of this, 76 are craniocaudal images and 74 mediolateral oblique views. All these images are labelled. The nipple position and the pectoral muscles are marked. These datasets are referred to as “FFDM Atlas”. Datasets B consist of 523 craniocaudal images and remaining mediolateral oblique images. Similarly final datasets consist of 505 CC and remaining MLO images. The methods include registration, propagation of annotations, and atlas selection. Image registration is a kind of overlap between moving and fixed images. i.e., input image and template. During registration, the moving images deform and become similar to fixed images. The labels also propagate to match with the template. The advantage of this algorithm is that it was able to locate the nipple even if it was out of the boundary. Atlas selection is based on the algorithm plus l-take away. Atlas with lowest value of cost function is selected by l number of iterations. The limitation of the algorithm is the false positives in detecting the skin folds. This method outperforms others by an error percentage of about 0.5.

D. *Machine learning based segmentation*

Aulia Rahmatika, Astri Handayani, and Agung Wahyu Setiawan proposed a paper on breast tissue and breast muscle segmentation in an automated way [19]. The segmentation is based on k-means and histogram. The process consists of four stages. Pre-processing, label, annotation removal, k-means classification, and breast masking generation. Median filter which works by taking the median value of the neighborhood pixels is used as the first pre-processing step to remove the noise. The image is converted to 0’s and 1’s using a threshold to remove the labels. A threshold value of 0.05 is used. Once it is done, the image undergoes morphological operations. Only the breast area is conserved and all others are neglected. Pectoral muscles are removed using k-means clustering. A six-class cluster is formed with six unique colours. Pectoral muscles will be shown in high intensity class and background will be in low intensity class. Thus, finally the breast mask is created. The algorithm is tested in twenty-five MLO images which includes fatty, glandular, and dense breasts. Out of six fatty breasts, the algorithm was able to segment 4 with well accuracy, 2 with good accuracy and 0 with very low accuracy. Out of nine glandular breasts, the algorithm was able to segment 8 with well accuracy, 1 with good accuracy and 0 with very low accuracy. Out of ten dense breasts, the algorithm was able to segment 3 with well accuracy, 0 with good accuracy and 7 with very low accuracy.

Baljinder Singh and Gagandeep Jagdev proposed a paper on Discoursing Novel Procedure for Segmentation of Mammograms [20]. The paper focuses on the process of mammogram segmentation and detection of tumors. The input image from Mammographic Image Analysis Society (MIAS) dataset is converted to Green Channel Complement (GCC). Extracting the green channel alone in an image will enhance the contrast of the image. Output is passed through Contrast Limited Adaptive Histogram Equalization (CLAHE). The CLAHE algorithm will help to improve the contrast of the image. It is divided into three sections. Tile generation, Histogram equalization and Bilinear interpolation. Corresponding to different sections of the image, it will generate histograms and use them to distribute the luminance of the image. The output is taken and morphological operations are done. Final segmentation is done using Fuzzy C-Means (FCM). FCM is a grouping algorithm that groups the data into N clusters. Each point in the dataset belongs to one or the other cluster. Points which are nearer to cluster will have high membership function and far points will have low value. Finally necessary parameters are obtained. This method measures sixteen parameters. They are Sensitivity, Specificity, Accuracy, Predicted values positive and negative. False positive and negative values, correlation coefficient, and Informedness. The algorithm could provide accurate segmentation of the mammogram image. Fifteen images from the dataset were analysed and sixteen parameters were evaluated. This approach will help to improve the accuracy of lesion detection in mammogram images.

E. *Deep learning based segmentation*

O. Ronneberger, P. Fischer, and T. Brox have proposed a convolutional neural network called UNet for segmentation of medical images [21]. UNet is a U-shaped structure with a left contracting path/encoder and right expanding

TABLE I. SEGMENTATION METHODS

Technique	Analysis	
	Methods Used	***Results***
Edge and Region based segmentation		
Automated Medical Image Segmentation Techniques	Amplitude, edge, and region	Threshold and region-based methods are better method
Segmentation of the breast region with pectoral muscle removal in mammograms	Histogram threshold, detection of edges, fit using least squares and contour expansion	94% acceptable
A new breast border extraction and contrast enchantment technique with digital mammogram images for improved detection of breast cancer	Global threshold, bi-level histogram, non-linear filter	98% in breast border extraction
Texture based segmentation		
Atlas-based Segmentation In Breast Cancer Radiotherapy: Evaluation Of Specific And Generic purpose Atlases	Specific and generic purpose libraries	Best results by specific-purpose atlases
Atlas-based image segmentation: A Survey paper	Atlas selection, construction, image registration, and transformation	Sum of squares of intensity differences (SSD) is zero for perfect overlap
Mammogram Segmentation Using Multi-atlas deformable Registration	Multi-atlas	Higher Jaccard index and Lower Hausdorff distance
Robust initial detection of landmarks in film-screen mammograms using multiple FFDM atlases	Multi-atlas, Nipple position, Breast muscle region	Error percentage of about 0.5
Machine learning based segmentation		
Automated segmentation of breast tissue and pectoral muscle in digital mammography	k-means and histogram	Pectoral muscle accuracy of 67% in fatty breast and 89% in fatty-glandular breast
Discoursing Novel Procedure for Segmentation of Mammograms	Green Channel Complement (GCC), Contrast Limited Adaptive Histogram Equalization (CLAHE)	81% accuracy
Deep learning-based segmentation		
UNet a convolutional networks for biomedical image segmentation	UNet	Warping error of 0.0003529 and Rand error of 0.0504
Images Data Practices For Semantic Segmentation Of Breast Cancer Using Deep Neural Network	DeepLab and Mask RCNN, Savitzky Golay method	Accuracy of Mask RCNN is 98% and DeepLab 95%
Deep learning approaches to biomedical image segmentation	Overview of deep learning, Performance metrics, Image methodologies,	RBM network has an accuracy of 93%

path/decoder. UNet helps to localize and distinguish borders of images by doing classification on every pixel. Here, a sophisticated architecture called Fully Convolutional Network is made. They modified and extended their architecture to use very few training images and provide more accurate segmentation. A continuous layer was added to the regular contract network and the pooling function was changed by an up-sampling function. So, these layers boost the resolution of the output. From the analysis, the warping error was 0.0003529 and rand error of 0.0504. Saikumar Yellari, Janaki Peruvamba Dharmarajan, Sanidhya Shilendra Karve, Vijaykumar DK, and Nagesh Subbanna [22] proposed a paper on the use of UNet in breast density calculation. They used UNet for breast tissue segmentation and later density calculation.

Luqman Ahmed, Muhammad Munwar Iqbal, Hamza Aldabbas, Shehzad Khalid, Yasir Saleem and Saqib Saeed introduced a paper on data practices on images using deep neural networks for semantic segmentation [23]. The segmentation of mammograms is based on deep learning methods. It will help to detect, classify, and analyse the lesion. The two publicly available breast cancer data sets such as MIAS and Curated Breast Imaging (CBIS) Subset of the Digital Database for Screening Mammography (DDSM) are used for the analysis. The methodology includes the removal of noise/artifacts, muscle region removal, and deep learning-based instance segmentation. DeepLab and Mask RCNN are the two segmentation frameworks used. The proposed method consists of a pre-processing algorithm that includes the removal of noise, artifacts, and breast muscles. This algorithm is designed for right sided mammograms. If the mammogram is left-sided, it has to be flipped. Edges are flattened using the Savitzky Golay method. The resulting image is split into 512 x 512 patches of equal size. Small patches that remain smaller than 512 by 512 are padded with boundaries to create a data set of the same size. Masked RCNN and Deep Lab are trained using the prepared data set. The performance was evaluated using accuracy, precision, and recall. The Mask RCNN has an accuracy of 98%, and DeepLab has an accuracy of 95%.

Intisar Rizwan I Haque and Jeremiah Neubert proposed a paper on segmentation methods based on deep learning [24]. It starts by an overview of techniques like deep learning (DL), machine learning (ML), classifier based on DL, convolutional neural network (CNN), Restricted Boltzmann Machines (RBMs), auto-encoders, sparse coding, adversarial networks that can create new datas (GANs), recurrent Neural Networks (RNNs) etc. and mentions about different approaches to implement deep learning architecture. Several performance measures such as accuracy, precision, recall, F1 measure, Jaccard similarity index (JSI), and modified hausdorff distance (MHD) are evaluated here. All the studies are grounded on statistical results and the approach was effective for the given scenario with limited datasets. The limitation with deep learning-based classifiers is lack of generalizability and the requirement for huge datasets. The usage of huge datasets leads to huge cache and RAM demands for training. Lack of sufficiently large datasets is another challenge. Most datasets are not public. Convolutional neural networks are widely used in medical images. Various imaging modalities including histopathology are using convolutional neural networks [25]. The document provides a summary of works based on the deep learning theory.

III. Results and Discussion

We now provide an overview of the advantages and disadvantages of the various classes of techniques mentioned in this paper that have been used in breast classification and segmentation. Table I will summarise the various approaches to mammogram segmentation discussed in this paper. It will provide a summary of the paper's methods and results.

The region-based approach [26] is a straightforward idea that performs well in terms of noise and allows users to select numerous criteria at once. However, they have some drawbacks, including the need to specify the seed point and the fact that different seed locations provide different results. They are also time-consuming methods with limited accuracy. Segmentation using edge-based techniques is simple for humans to understand and is effective for images with strong contrast. However, this class of techniques is quite noise sensitive and struggles with images that have low contrast and continuous change. If the image contains numerous edges, it won't work. The segmentation method based on active contours, which is grounded on texture, is unable to separate images that have overlaps, or indistinct contours. Other drawbacks include the fact that dealing with large-sized images will take too long, the algorithm will get stuck in local minima, and even the smallest features will be taken into account when reducing the energy.

Unsupervised techniques like K-means [27] classification are simple and straightforward. But there is no set formula for choosing the number of clusters; it must be defined in advance. The K-means outcome is dependent on outliers, and it struggles with categorical variables. Unsupervised approaches that require a lot of calculation time include fuzzy C-means. It takes too long to compute and is noise-sensitive.

Atlas based segmentation [28] is a type of approach that is very effective for a heterogeneous set of volumes. But the time consumption for the construction of the atlas is more and requires experts for marking the atlas.

Finally, deep learning techniques such as U-Nets [29] are adaptable and can be used for any logical image masking task in deep learning-based segmentation. It doesn't have any completely connected layers but achieves good accuracy for the given dataset. However, the drawbacks include the necessity for a powerful GPU for larger images, the requirement of a rather large data set, the high cost of network training, and the limited availability of pre-trained models.

The data above shows that segmentation based on atlases and U-Nets is among the best techniques and is the most commonly used in practise these days. They can segment images with a variety of different volume sets. Even if atlas generation or training of networks takes more time, the problem can be handled by registering the image after down sampling, using a parallel processing environment like the Graphics Processing Unit (GPU), or by limiting the amount of pixels processed. Atlas-based approaches and deep learning based techniques have been successfully applied to a number of imaging modalities and fields, including neuroimaging, cardiac imaging, and pulmonary imaging. They have not received too much attention yet in terms of breast region segmentation in mammograms

IV. Conclusion

In this paper, we have presented a survey of diverse techniques used for breast segmentation in mammograms. Different techniques ranging from classical segmentation like edge, region, amplitude, and threshold to modern methods like UNet, Atlas, machine learning, and deep learning methods are explained here.

References

[1] B. S. Chhikara and K. Parang, "Global cancer statistics 2022: the trends projection analysis," Chemical Biology Letters, vol. 10, no. 1, pp. 451–451, 2023

[2] V. A. McCormack and I. dos Santos Silva, "Breast density and parenchymal patterns as markers of breast cancer risk: a meta-analysis," Cancer Epidemiology Biomarkers & Prevention, vol. 15, no. 6, pp. 1159–1169, 2006

[3] C. Balleyguier, S. Ayadi, K. Van Nguyen, D. Vanel, C. Dromain, and R. Sigal, "Birads™ classification in mammography," European journal of radiology, vol. 61, no. 2, pp. 192–194, 2007

[4] S. Gopakumar, K. Sruthi, and S. Krishnamoorthy, "Modified level-set for segmenting breast tumor from thermal images," in 2018 3rd international conference for convergence in technology (I2CT). IEEE, 2018, pp. 1–5

[5] S. Krishna and B. George, "An affordable solution for the recognition of abnormality in breast thermogram," Multimedia Tools and Applications,
vol. 80, no. 18, pp. 28 303–28 328, 2021

[6] D. Khadakban, T. Gorasia-Khadakban, D. Vijaykumar, K. Pavithran, and R. Anupama, "Factors associated with better survival after surgery in metastatic breast cancer patients," Indian journal of surgical oncology, vol. 4, pp. 52–58, 2013

[7] P. Viral, K. Pavithran, K. Beena, A. Shaji, and D. Vijaykumar, "Ten-year survival outcome of breast cancer patients in india," Journal of Carcinogen esis, vol. 20, 2021

[8] N. Sharma, L. M. Aggarwal et al., "Automated medical image segmentation techniques," Journal of medical physics, vol. 35, no. 1, p. 3, 2010

[9] Z. Chen and R. Zwiggelaar, "Segmentation of the breast region with pectoral muscle removal in mammograms," Medical Image Understanding and Analysis (MIUA), pp. 71–76, 2010

[10] M. Hazarika and L. B. Mahanta, "A new breast border extraction and contrast enhancement technique with digital mammogram images for improved detection of breast cancer," Asian Pacific journal of cancer prevention: APJCP, vol. 19, no. 8, p. 2141, 2018

[11] M. A. Wirth and A. Stapinski, "Segmentation of the breast region in mam- mograms using active contours," in Visual Communications and Image Processing 2003, vol. 5150. SPIE, 2003, pp. 1995–2006

[12] N. K. Subbanna and Y. Y. Zeevi, "Existence conditions for discrete non-canonical multiwindow gabor schemes," IEEE transactions on signal pro-cessing, vol. 55, no. 10, pp. 5113–5117, 2007.

[13] B. H. Menze, A. Jakab, S. Bauer, J. Kalpathy-Cramer, K. Farahani, J. Kirby, Y. Burren, N. Porz, J. Slotboom, R. Wiest et al., "The multimodal brain tumor image segmentation benchmark (brats)," IEEE transactions on medical imaging, vol. 34, no. 10, pp. 1993–2024, 2014

[14] D. Ciardo, M. A. Gerardi, S. Vigorito, A. Morra, V. Dell'Acqua, F. J. Diaz, F. Cattani, P. Zaffino, R. Ricotti, M. F. Spadea et al., "Atlas-based segmentation in breast cancer radiotherapy: evaluation of specific and generic purpose atlases," The Breast, vol. 32, pp. 44–52, 2017

[15] H. Kalinic, "Atlas-based image segmentation: A survey," Croatian Scientific Bibliography, pp. 1–7, 2009.

[16] M. K. Sharma, M. Jas, V. Karale, A. Sadhu, and S. Mukhopadhyay, "Mammogram segmentation using multi-atlas deformable registration," Computers in biology and medicine, vol. 110, pp. 244–253, 2019

[17] J. E. Iglesias and N. Karssemeijer, "Robust initial detection of landmarks in film-screen mammograms using multiple ffdm atlases," IEEE transactions on medical imaging, vol. 28, no. 11, pp. 1815–1824, 2009

[18] J. E. Iglesias and M. R. Sabuncu, "Multi-atlas segmentation of biomedical images: a survey," Medical image analysis, vol. 24, no. 1, pp. 205–219, 2015

[19] A. Rahmatika, A. Handayani, and A. W. Setiawan, "Automated segmentation of breast tissue and pectoral muscle in digital mammography," in 2019 International Conference of Artificial Intelligence and Information Technology (ICAIIT). IEEE, 2019, pp. 397–401

[20] B. Singh and G. Jagdev, "Discoursing novel procedure for segmentation ofmammograms," in 2020 Indo–Taiwan 2nd International Conference on Computing, Analytics and Networks (Indo-Taiwan ICAN). IEEE, 2020, pp. 21–27

[21] O. Ronneberger, P. Fischer, and T. Brox, "U-net: Convolutional networks for biomedical image segmentation," in Medical Image Computing and Computer-Assisted Intervention–MICCAI 2015: 18th International Conference, Munich, Germany, October 5-9, 2015, Proceedings, Part III 18. Springer, 2015, pp. 234–241

[22] S. Yellari, J. P. Dharmarajan, S. S. Karve, D. Vijaykumar, and N. Subbanna, "Estimation of breast density from human mammograms using u-nets," in 2022 6th International Conference On Computing, Communication, Control And Automation (ICCUBEA. IEEE, 2022, pp. 1–6

[23] L. Ahmed, M. M. Iqbal, H. Aldabbas, S. Khalid, Y. Saleem, and S. Saeed, "Images data practices for semantic segmentation of breast cancer using deep neural network," Journal of Ambient Intelligence and Humanized Computing, pp. 1–17, 2020

[24] I. R. I. Haque and J. Neubert, "Deep learning approaches to biomedical image segmentation," Informatics in Medicine Unlocked, vol. 18, p. 100297, 2020

[25] C. S. Vikranth, B. Jagadeesh, K. Rakesh, D. Mohammad, S. Krishna, and R. A. AS, "Computer assisted diagnosis of breast cancer using histopathology images and convolutional neural networks," in 2022 2nd International Conference on Artificial Intelligence and Signal Processing (AISP). IEEE, 2022, pp. 1–6

[26] D. A. Zebari, D. A. Ibrahim, and A. Al-Zebari, "Suspicious region segmentation using deep features in breast cancer mammogram images," in 2022 International Conference on Computer Science and Software Engineering (CSASE). IEEE, 2022, pp. 253–258

[27] I. A. Lbachir, I. Daoudi, and S. Tallal, "Automatic detection of suspicious lesions in mammograms by histogram-peak-analysis based k-means," in 2018 9th International Symposium on Signal, Image, Video and Communications (ISIVC). IEEE, 2018, pp. 16–21

[28] A. Daly, H. Yazid, B. Solaiman, and N. E. B. Amara, "Multi-atlas based segmentation of human cerebellum," in 2020 17th International Multi-Conference on Systems, Signals & Devices (SSD). IEEE, 2020, pp. 485–490.

[29] Z. Wang and L. Zhang, "Semantic segmentation of brain mri based on u-net network and edge loss," in 2020 19th International Symposium on Distributed Computing and Applications for Business Engineering and Science (DCABES). IEEE, 2020, pp. 154–157