Some Segmentation Approaches of Breast Magnetic Resonance Imaging Tumor in Computer Aided Detection Systems: A Review

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Abstract: - This article discusses the approaches and procedures that have been applied to MRI breast tumor segmentation particularly as well as breast segmentation systems in general. The review begins by outlining the various breast screening methods and contrasting Magnetic Resonance Imaging (MRI) with other methods like Mammography, X-ray, and Ultrasonography. Next, it is emphasized how important Computer Aided Detection (CAD) systems are for Breast MRI. Review and comparison of supervised, unsupervised, and semi-supervised breast MRI tumor segmentation techniques are done. The study concludes with a discussion and recommendations based on the methods examined.

Key-Words: - Segmentation, Breast Images, MRI, CAD.

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1 Introduction

The most frequent malignancy in women worldwide is breast cancer, [1], [2]. The International Agency for Research on Cancer (IARC), an intergovernmental organization affiliated with the World Health Organization of the United Nations, projected that 2.1 million new cases of breast cancer were identified in 2018. The eight malignancies with the highest global incidence are depicted in Fig. 1 along with an estimation of the total number and percentage of newly diagnosed cases. The biggest cause of death for women worldwide today is breast cancer, [3]. In 2018, there were about 627,000 breast cancer fatalities reported. Based on an IARC study [4], [5], and Fig. 2, the total number of cancer-related fatalities worldwide is depicted.

Techniques for breast screening are crucial for cancer detection. The chances that a breast cancer patient would survive are considerably increased by precise segmentation for suspected tumors utilizing computer algorithms. To limit the amount of false-positive results, image processing techniques are required to aid radiologists in deciphering the images and segmenting tumor regions [6].

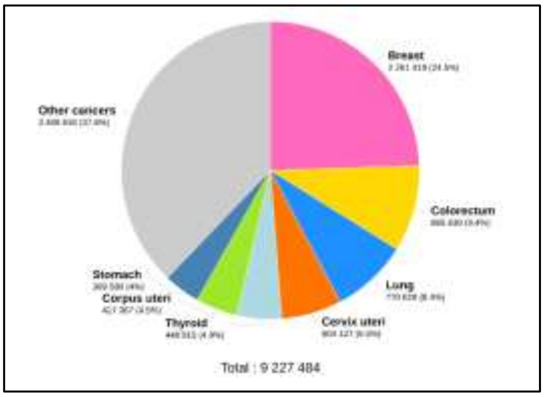

Fig. 1: Based on an IARC investigation, an estimated number of cancer cases have been diagnosed worldwide [4].

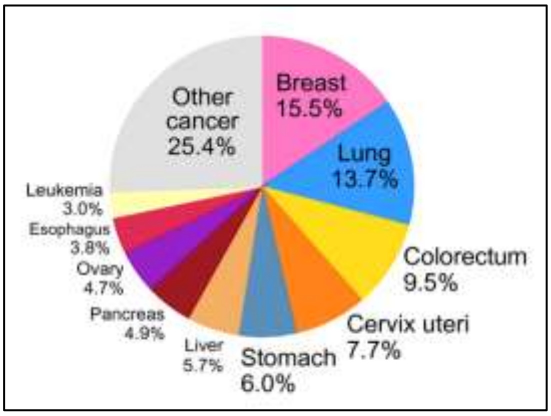

Fig. 2: Based on an IARC study, the number of cancer deaths worldwide is estimated to be [4].

2 Breast Screening Mechanisms

Different screening procedures are employed for a more thorough evaluation in addition to self-checking and physical inspection for probable breast cancers. The most popular breast screening methods in medical settings are; Mammography, ultrasonography, and magnetic resonance imaging (MRI).

2.1 Mammography

Mass screening programs frequently employ the non-invasive X-ray method known as mammography. To obtain the image's details, this method includes subjecting the breast to a little quantity of ionizing radiation [7]. Due to its ability to create an acceptable image of abnormalities and its capacity to reveal indirect calcifications, mammography is frequently used as an image screening modality [8], [9].

Mammography does, however, have several flaws and restrictions. These flaws can be seen in recognizing very small tumors, contrast characteristics, and narrow dynamic range [10]. Fig. 3 displays a few Mammogram image samples [11].

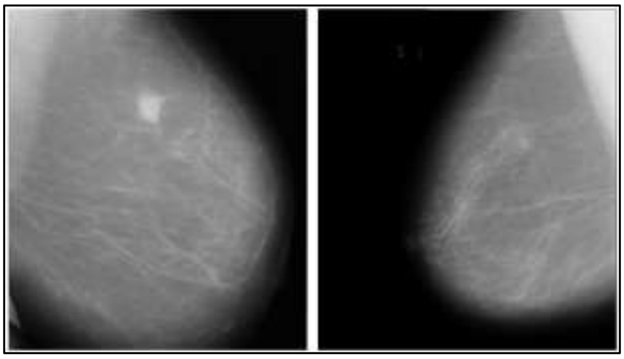

Fig. 3: Mammogram image examples [11].

2.2 Ultrasonography

Another non-invasive screening method that makes use of sound waves to visualize the breast is ultrasound. If a mass contains solid or fluid, the ultrasound image could be helpful [7], [12].

One benefit of ultrasonography is that it may find cancers that mammography may not be able to identify as solid or liquid. Additionally, the method results in less discomfort, costs less money and has no negative health repercussions [13].

On the other side, misleading positive results from ultrasound images may result in misdiagnosis [14]. Additionally, ultrasonography is not frequently used in clinical settings, and using the equipment requires highly qualified professionals [14], [15]. Fig. 4 displays some breast ultrasound imaging samples [16].

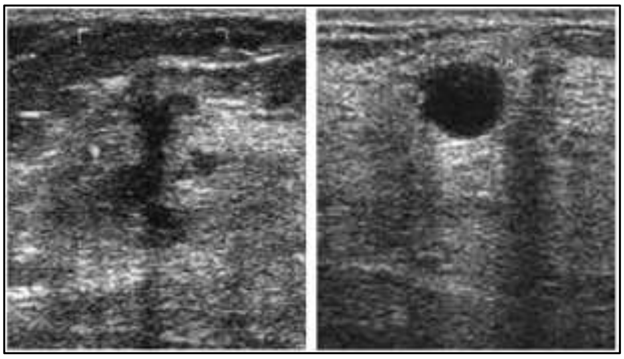

Fig. 4: Breast ultrasound image examples [16]

2.3 MRI Screening

A non-invasive imaging method is MRI screening. It has been extensively utilized for medical imaging, including breast screening and imaging of the brain, spine, bones, and joints. It is based on magnetic and radio frequency fields. A discernible signal is created as a result of how the radio frequency pulses affect how the resonant nuclei are arranged [17]. Fig. 5 displays some breast MRI image samples [18].

MRI, on the other hand, offers bright, sharp images that provide an improved contrast between various types of soft tissues, whereas mammogram images show the contrast between soft tissue and bone density. Because of this, MRI is employed in breast screening to examine the minute intricacies within breast tissues. Although this is important knowledge, the radiologist still needs to analyze the supplied data [19]. MRI radiologists employ CAD algorithms to analyze breast MRIs and to lessen the incidence of false-positive diagnoses [6].

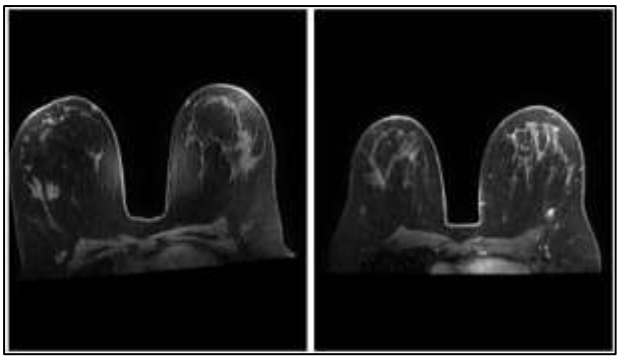

Fig. 5: Breast MRI picture examples [18]

3 Breast MRI with CAD

To aid MRI radiologists in enhancing the accuracy of breast MRIs, detecting tumor masses, and lowering the incidence of false-positive detection, CAD systems are utilized in conjunction with image processing algorithms [6].

To find malignancies inside bodily organs, CAD algorithms are created [20], [21]. For the various modalities of medical pictures, including X-Ray and Ultrasound, a variety of segmentation and classification approaches are used. Wavelets, fractals, statistical techniques, and vision-based techniques have all been presented recently for breast mass identification [22], [23], [24]. Additionally, approaches based on artificial intelligence, such as Fuzzy Logic and Artificial Neural Networks (ANN), have been developed for classification [22], [25], [26].

Studies [10], [20], [27], [28] have established the benefits of adopting CAD systems for breast tumor identification in screening technologies. Fast detection, accuracy, and helping radiologists locate dense breasts that could be missed are some of the benefits of CAD. However, to overcome the drawbacks of present systems, CAD systems still require upgrades.

The most frequent drawbacks of breast CAD systems include the production of false-positive results in many breast images, the failure to detect tiny tumors, and the requirement for human user engagement [10]. In contrast to another human anatomy, there haven't been many studies on breast MRI CAD systems

4 Breast MRI Tumour Segmentation Methods

Supervised and unsupervised techniques are the two primary subcategories of image segmentation systems. Similar classification algorithms are used in breast MRI tumor segmentation systems. Additionally, some researchers have suggested mixed systems or semi-supervised methods, which will be discussed later in this section.

4.1 Supervised Methods

The analyst knows in advance the numerical features, such as mean and variance, of the classes in the image and uses them in the training stage when using the supervised approach [29]. Learning the individual items to be detected is done during the training phase. The system must then be ready to recognize and categorize new input images based on the occurrence or nonappearance of comparable items. Examples with and without the item are covered in the training step [30]. Popular supervised algorithms include the Bayesian Method, Support Vector Machine, and K-Nearest Neighbours (KNN).

Support vector machine classifier-based supervised technique for breast MRI cancer segmentation was proposed by Jianhua et al. [31]. The chest and out-of-body portions are first segregated in this approach, leaving only the breast region for subsequent processing. The texture features are extracted for each pixel. To extract frequency features, the wavelet transform is used. In the training stage, a committee of Support Vector Machines is created as the classifier after a progressive feature selection is carried out to pick useful features. To classify new data at the pixel level, this classifier is applied. Various picture protocols can be addressed using this technique. It also lowers the number of features that are chosen. To get the desired results, it must, however, be trained on at least ten different cases.

Rabiei [32] uses the K-Nearest Neighbours (KNN) classifier. They employed contextual data based on the temporal kinetic signal and the geometry of the items of interest in their work. The method is illustrated by utilizing machine learning to divide breast diseases into four categories using a KNN classifier. In complex backdrops, the system achieved high tumor segmentation results. The fundamental drawback of this approach is that the user must manually detect a binary window to begin the initial segmentation, pick the breast region, and ignore the remaining parts of the images that are related to the tissues of the chest and heart.

Another supervised technique was put forth by Wu et al. [33] and is based on the Bayesian method and Markov random field model. With this method, the characteristics of the breast MRI images were analyzed and classified as tumor or non-tumor regions. The Iterative Conditional Mode (ICM) approach is used to estimate class membership. Modeling the prior distribution of the class's membership as a multi-level logistic model using a Markov Random Field assumes that the class's composition depends only on its immediate neighbors. It is assumed that the likelihood distribution is gaussian. This method could be successfully used for real-time segmentation in healthcare facilities. However, each Gaussian distribution's parameters are explicitly chosen as an approximation of its class representative.

4.2 Unsupervised Methods

Unsupervised segmentation is the process of dividing an image into a collection of sections that are distinct and constant in terms of certain properties, such as intensity level, size, or texture [30], [34], [35]. The unsupervised segmentation family includes clustering, region-based approaches, thresholding, and contour methods.

Compared to supervised approaches, unsupervised methods have several advantages. With supervised approaches, the segmentation must begin with the analyst determining the features of the images in the dataset beforehand. Contrarily, unsupervised algorithms automatically identify unique classes, significantly reducing the analyst's workload. Additionally, for the supervised approaches, some object attributes might not be known beforehand. Unsupervised algorithms, however, automatically identify these features in the image [35], [36].

A fuzzy c-means (FCM) clustering-based technique for the segmentation of breast tumors in MRI images was presented by Chen et al. [37]. The suggested tumor segmentation approach requires input from a person to choose the ROI, then picture enhancement within the chosen ROI. The increased ROI is then classified using FCM. By implementing thresholding to the tumor membership map, connected component labeling, and hole filling to the chosen object, the tumor is finally segmented. The technique can segment breast MRI tumors in a precise, effective, and reliable manner. This method's fundamental flaw is that it requires manual input to identify the ROI as a rectangular shape before segmentation can begin.

Cui et al. [38] suggest using a marker-controlled watershed technique to separate malignant tumors from breast MRI images. The semi-automatically method begins by manually defining the ROI ellipse. Then, using Gaussian mixture modeling, the internal and exterior markers for the tumor's watershed segmentation are found. The results demonstrate good segmentation outcomes that are consistent with the radiologist's manual tumor volume description. The use of a mouse to line an ROI in the shape of an ellipse on a chosen area that contains the suspected tumor is the main weakness of this method.
Militello et al. [39] investigated and compared four unsupervised segmentation algorithms. These include k-means, fuzzy c-means, spatial fuzzy c-means, split-and-merge combined with region growing (SMRG), and (sFCM). The observed experimental results support the use of unsupervised pattern recognition methods for segmenting medical images using area- and distance-based metrics. In particular, clustering-based segmentation approaches outperformed the SMRG. Therefore, for medical pictures that are characterized by uncertainty/variability (sometimes connected to noise), crisp segmentation techniques—such as k-means and SMRG—are not well-suited, producing erroneous borders and poorly defined details. Fuzzy modeling, which has inherent flexibility, was used in both FCM and sFCM clustering techniques to greatly improve performance. Breast images are characterized by essential variability, which underperforms in complex cases and may cause unsupervised methods to fail to identify borders or anatomical details. Additionally, noise tampers with digital photos, changing some aspects of the original image. Dealing with noisy or low-contrast images is typical. Lesion segmentation in these kinds of images is not a simple task that can be done without user input. This is because it is important to get accurate results.

4.3 Semi-Supervised Methods

The area of machine learning known as semi-supervised learning is focused on employing both labeled and unlabeled data to carry out certain learning tasks. It allows using the substantial amounts of unlabeled data accessible in several use cases in blending with smaller sets of labeled data. It is conceptually located between supervised and unsupervised learning.

Semi-supervised learning is frequently utilized to decrease time-consuming and expensive manual pixel-level annotation. Consistency regularisation places restrictions on the consistency of predictions made using perturbations to inputs, features, and networks [40].

Oh et al. [40] proposed a semi-supervised breast MRI segmentation approach that can be trained with small amounts of annotation. A time difference map is also proposed to incorporate the distinct time-varying enhancement pattern of the tumor. In their work, they also presented a novel loss function that efficiently distinguishes breast tumors from those without tumors based on triple loss. This loss reduces the potential for false positives. The proposed method produces better segmentation results with fewer annotations, particularly for boundary-based metrics relevant to spatially continuous breast tumors.

To obtain a high performance, Azmi et al. [41] offer a semi-supervised classification method to segment breast tumors in MRI based on texture analysis. The Improved Self-Training (IMPST) classifier is trained solely with a labeled image in the first stage of this two-stage procedure. The classifier is then retrained to achieve high accuracy using nondeterministic unlabeled data that is obtained in the subsequent stage using a straightforward thresholding method. The drawback of this method appears in the requirement for the user to create a small window to identify the cancer ROI region, even though the accuracy and precision of segmented images have increased based on reported results.

In the work by Azmi et al., the supervised, unsupervised, and semi-supervised approaches are examined [41]. The supervised segmentation methods, such as K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Bayesian, as well as the semi-supervised methods, such as self-training and improved self-training (IMPST), lead to high accuracy, according to their comparison study on the MRI Breast RIDER dataset [18]. But prior knowledge is necessary. As a result, the procedure becomes challenging, costly, and time-consuming. Contrarily, unsupervised techniques like fuzzy C-means (FCM) do not require prior information, yet they perform poorly [41].

5 Discussion

The methods under the supervised category use the training phase to learn the system before segmenting the tumors. This phase requires previous knowledge. Among the advantages of using supervised methods are that they can be applied to several image protocols. Also fixable in terms of choosing features ranging from few to many, with the choice based on the needs of the system and the type of images used. Furthermore, these methods produced excellent tumor segmentation results in complex systems. However, the drawbacks of using supervised methods consist of the requirement of training in at least ten different situations to produce the desired results. In addition, in most of the supervised applications, a window must be manually created to choose the breast area while ignoring the other areas of the image that contain heart and chest tissue. Also, the parameters should be calculated carefully and chosen so that they are typical of the class.

In the unsupervised category, methods do not require a training phase; they divide the images into a collection of classes that are distinct and constant in terms of certain properties, such as intensity level, size, or texture. Unsupervised methods can segment breast MRI tumors in a precise, effective, and reliable manner. Also, results demonstrate good segmentation outcomes that are consistent with the radiologist's manual tumor volume description. On the other hand, the drawbacks of unsupervised approaches are that the segmentation procedure cannot begin unless the user recognizes ROI areas. The methods underperform in complex cases and may cause unsupervised methods to fail to identify borders or anatomical details. Segmenting noisy images or low-contrast images is challenging, and it might need user input.

The methods under the semi-supervised category employ both labeled and unlabeled data to carry out certain learning tasks. They are a hybrid of supervised and unsupervised learning methods. Based on recorded findings, the accuracy and precision of segmented images have improved. Most of their systems require user input to either create windows to identify the tumor regions and/or select parameters to start the process.

The three categories' descriptions, benefits, and drawbacks are summarised in Table 1.

6 Conclusion

This paper reviewed earlier research on MRI breast tumor segmentation systems along with associated image processing methods and algorithms. The study included several topics, including the history of breast cancer, breast screening, CAD systems, and methods for breast MRI tumor segmentation.

The various breast screening methods, such as mammography, ultrasonography, and MRI, are discussed. Previous research revealed that CAD algorithms are crucial for assisting radiologists in reading images and lowering the incidence of false-positive diagnoses.

Approaches for segmenting breast MRI tumors have been discovered; they are divided into supervised, unsupervised, and semi-supervised approaches. High accuracy is achieved during supervised segmentation. However, due to the need for prior knowledge, the procedure becomes challenging, expensive, and time-consuming. Unsupervised methods, on the other hand, do not require prior information, although they do less well than other approaches. The exclusion of other parts of the breast is a crucial pre-process in tumor segmentation systems. This procedure is crucial because, in the majority of MRI breast cases, the feature levels between the tumor regions and other regions are comparable. Several methods have been developed to exclude these unwanted regions from breast images. Even though these methods typically succeeded in their aim of exclusion. The approaches suffered from the fact of creating them for a specific type of image solely or the requirement for user input are still their primary drawbacks. It is advised to look at the potential for developing new CAD systems using a combination of supervised and unsupervised techniques to get highly accurate segmentation results without the requirement for prior knowledge. Fully automatic systems that do not require user inputs might also be regarded as potential study topics in the future.

Table 1. Summary of MRI breast tumors segmentation approaches

Method	**Description**	**Benefits**	**Drawbacks**
Supervised methods [31], [32], [33]	Methods that use the training phase to learn the system before segmenting the tumors.	● They can be applied to several image protocols. ● Fixable in terms of selecting features ranging from few to many. ● In complex systems, they achieved high tumor segmentation results.	● The system must be trained in at least ten different situations to produce the desired results. ● In most of their applications, a window must be manually created to choose the breast area while ignoring the other areas of the image that contain heart and chest tissue. ● The parameters should be carefully computed and chosen as being typical of the class.
Unsupervised methods [37, [38], [39]	Methods do not require a training phase, and they divide the images into a collection of sections that are distinct and constant in terms of certain properties, such as intensity level, size, or texture.	● The ability to segment breast MRI tumors in a precise, effective, and reliable manner. ● Results demonstrate good segmentation outcomes that are consistent with the radiologist's manual tumor volume description.	● The segmentation procedure cannot begin unless the user recognizes ROI areas. ● The methods underperform in complex cases and may cause unsupervised methods to fail to identify borders or anatomical details. ● Segmenting noisy images or low-contrast images is challenging, and it might need user input.
Semi-supervised methods [40], [41]	The methods employ both labeled and unlabeled data to carry out certain learning tasks. They are a hybrid of supervised and unsupervised learning methods.	Based on recorded findings, the accuracy and precision of segmented images have improved.	Most of their systems require user input to either create windows to identify the tumor regions and/or select parameters to start the process.

References:

[1] B. Stewart and C. P. Wild, "World Cancer Report," in "International Agency for Research on Cancer," 2018.
[2] Z. Sultana, M. A. R. Khan, and N. Jahan, "Early Breast Cancer Detection Utilizing Artificial Neural Network," *WSEAS Transactions on Biology and Biomedicine*, vol. 18, pp. 32-42, 2021.
[3] C. E. DeSantis, S. A. Fedewa, A. G. Sauer, J. L. Kramer, R. A. Smith, and A. Jemal, "Breast cancer statistics 2015," *Cancer Journal for Clinicians*, vol. 66, no. 1, pp. 31-42, 2016.
[4] J. Ferlay *et al.*, "Estimating the global cancer incidence and mortality in 2018: GLOBOCAN sources and methods," *Int J Cancer*, vol. 144, no. 8, pp. 1941-1953, Apr 15, 2019, doi: 10.1002/ijc.31937.
[5] F. Bray, J. Ferlay, I. Soerjomataram, R. L. Siegel, L. A. Torre, and A. Jemal, "Global cancer statistics 2018: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries," *CA Cancer J Clin*, vol. 68, no. 6, pp. 394-424, Nov 2018, doi: 10.3322/caac.21492.
[6] C. D. Lehman, S. Peacock, W. B. DeMartini, and X. Chen, "A New Automated Software System to Evaluate Breast MR Examinations: Improved Specificity Without Decreased Sensitivity," *Am. J. Roentgenol.*, vol. 187, no. 1, pp. 51-56, July 1, 2006 2006, doi: 10.2214/ajr.05.0269.
[7] R. Hussain, S. Arif, M. A. Sikander, and A. R. Memon, "Fuzzy Clustering Based Malignant Areas Detection In Noisy Breast Magnetic Resonant (MR) Images," *International Journal of Academic Research*, vol. 3, no. 2, March, 2011 2011.
[8] R. Croshaw, H. Shapiro-Wright, E. Svensson, K. Erb, and T. Julian, "Accuracy of Clinical Examination, Digital Mammogram, Ultrasound, and MRI in Determining Postneoadjuvant Pathologic Tumor Response in Operable Breast Cancer Patients," *Annals of Surgical Oncology*, vol. 18, no. 11, pp. 3160-3163, 2011.
[9] R. Bronstein, D. Reyes, and T. Kaufman, "Breast Imaging," in *Clinician's Guide to Diagnostic Imaging*, W. R. Reinus Ed. New York, NY: Springer New York, 2014, pp. 83-95.
[10] G. I. Andreea, R. Pegza, L. C. Lascu, S. Bondari, Z. Stoica, and A. Bondari, "The Role of Imaging Techniques in Diagnosis of Breast Cancer," 2012.
[11] J. Suckling *et al. Mammographic Image Analysis Society (MIAS) database*,
[12] S. P. Foroozandehasl, M. W. Marashdeh, M. S. Jaafar, and L. Ghasemi, "Assessment of an Anthropomorphic Ultrasound Breast Phantom," *WSEAS Transactions on International Journal of Electrical Engineering and Computer Science*, vol. 1, pp. 56-60, 2019.
[13] C. H. Lee *et al.*, "Breast cancer screening with imaging: recommendations from the Society of Breast Imaging and the ACR on the use of mammography, breast MRI, breast ultrasound, and other technologies for the detection of clinically occult breast cancer," (in eng), *J Am Coll Radiol*, vol. 7, no. 1, pp. 18-27, Jan 2010, doi: 10.1016/j.jacr.2009.09.022.
[14] S. Li and P. H. Wu, "Magnetic resonance image-guided versus ultrasound-guided high-intensity focused ultrasound in the treatment of breast cancer," (in eng), *Chin J Cancer*, vol. 32, no. 8, pp. 441-52, Aug 2013, doi: 10.5732/cjc.012.10104.
[15] J. G. Elmore, K. Armstrong, C. D. Lehman, and S. W. Fletcher, "Screening for Breast cancer," (in 0098-7484), *JAMA, the journal of the American Medical Association*, vol. 293, no. 10, p. 12, 2005.
[16] S. Prapavesis *et al.*, "Breast ultrasound and ultrasound-guided interventional procedures in the breast: A CD-ROM multimedia teaching file," 2003: European Congress of Radiology-ECR 2003.
[17] J. B. Weaver, Y. Xu, D. M. Healy, and L. D. Cromwell, "Filtering Noise From Images With Wavelet Transforms," *Magnetic Resonance in Medicine*, vol. 21, no. 2, pp. 288-295, 1991, doi: 10.1002/mrm.1910210213.
[18] U.S. National Cancer Institute. Reference Image Database to Evaluate Therapy Response (RIDER) MRI Breast [Online] Available: from National Biomedical Imaging Archive (NBIA) Web site https://imaging.nci.nih.gov/ncia,
[19] I. Gardiner. (2010, February 4, 2010) CAD Improves Breast MRI Workflow: Increasing Throughput While Maintaining Accuracy in Breast MRI Reads Requires Powerful Workflow Tools. *Imaging Technology News*. Available:

http://www.itnonline.com/article/cad-improves-breast-mri-workflow
[20] L. Li, R. A. Clark, and J. A. Thomas, "Computer-Aided Diagnosis of Masses with Full-Field Digital Mammography," *Academic Radiology*, vol. 9, no. 1, pp. 4-12, 2002.
[21] B. Verma and J. Zakos, "A Computer-Aided Diagnosis System For Digital Mammograms Based on Fuzzy-Neural and Feature Extraction Techniques," *IEEE Transactions on Information Technology in Biomedicine*, vol. 5, no. 1, pp. 46-54, 2001.
[22] D. R. Chen, R. F. Chang, W. J. Kuo, M. C. Chen, and Y. L. Huang, "Diagnosis of breast tumors with sonographic texture analysis using wavelet transform and neural networks," (in eng), *Ultrasound Med Biol*, vol. 28, no. 10, pp. 1301-10, Oct 2002, doi: 10.1016/s0301-5629(02)00620-8.
[23] D. R. Chen *et al.*, "Classification of breast ultrasound images using fractal feature," (in eng), *Clin Imaging*, vol. 29, no. 4, pp. 235-45, Jul-Aug 2005, doi: 10.1016/j.clinimag.2004.11.024.
[24] W.-J. Kuo, R.-F. Chang, D.-R. Chen, and C. C. Lee, "Data mining with decision trees for diagnosis of breast tumor in medical ultrasonic images," *Breast Cancer Research and Treatment*, vol. 66, no. 1, pp. 51-57, 2001/03/01 2001, doi: 10.1023/A:1010676701382.
[25] R. Mousa, Q. Munib, and A. Moussa, "Breast cancer diagnosis system based on wavelet analysis and fuzzy-neural," *Expert Systems with Applications*, vol. 28, no. 4, pp. 713-723, 2005/05/01/ 2005, doi: https://doi.org/10.1016/j.eswa.2004.12.028.
[26] H. D. Cheng and M. Cui, "Mass lesion detection with a fuzzy neural network," *Pattern Recognition*, vol. 37, no. 6, pp. 1189-1200, 2004/06/01/ 2004, doi: https://doi.org/10.1016/j.patcog.2003.11.002.
[27] I. Leichter, S. Buchbinder, P. Bamberger, B. Novak, S. Fields, and R. Lederman, "Quantitative characterization of mass lesions on digitized mammograms for computer-assisted diagnosis," (in eng), *Invest Radiol*, vol. 35, no. 6, pp. 366-72, Jun 2000, doi: 10.1097/00004424-200006000-00005.
[28] S. Arora, J. Acharya, A. Verma, and P. K. Panigrahi, "Multilevel thresholding for image segmentation through a fast statistical recursive algorithm," *Pattern Recognition Letters*, vol. 29, no. 2, pp. 119-125, 2008/01/15/ 2008, doi: https://doi.org/10.1016/j.patrec.2007.09.005.
[29] C. K. Narayanappa, G. R. Poornima, and B. V. Hiremath, "Estimation of the Ambit of Breast Cancer with a Modified Resnet Analysis Using Machine Learning Approach," *WSEAS Transactions on Biology and Biomedicine*, vol. 18, pp. 183-190, 2021.
[30] A. Oliver *et al.*, "A review of automatic mass detection and segmentation in mammographic images," *Medical Image Analysis*, vol. 14, no. 2, pp. 87-110, 2010/04/01/ 2010, doi: https://doi.org/10.1016/j.media.2009.12.005.
[31] J. Yao, J. Chen, and C. Chow, "Breast Tumor Analysis in Dynamic Contrast Enhanced MRI Using Texture Features and Wavelet Transform," *Selected Topics in Signal Processing, IEEE Journal of*, vol. 3, no. 1, pp. 94-100, 2009, doi: 10.1109/jstsp.2008.2011110.
[32] H. Rabiei, A. Mahloojifar, and M. E. Farmer, "PROVIDING CONTEXT FOR TUMOR RECOGNITION USING THE WRAPPER FRAMEWORK," in *Biomedical Imaging: From Nano to Macro, 2007. ISBI 2007. 4th IEEE International Symposium on*, 12-15 April 2007 2007, pp. 1252-1255, doi: 10.1109/isbi.2007.357086.
[33] Q. Wu, M. Salganicoff, A. Krishnan, D. S. Fussell, and M. K. Markey, "Interactive lesion segmentation on dynamic contrast enhanced breast MRI using a Markov model," 2006, vol. 6144, pp. 61444M-61444M-8. [Online]. Available: http://dx.doi.org/10.1117/12.654308
[34] K. S. Fu and J. K. Mui, "A survey on image segmentation," *Pattern Recognition*, vol. 13, no. 1, pp. 3-16, 1981/01/01/ 1981, doi: https://doi.org/10.1016/0031-3203(81)90028-5.
[35] M. G. H. Omran, "A PSO-based Clustering Algorithm with Application to Unsupervised Image Classification," University of Pretoria etd, 2005.
[36] R. W. Bogue, "Machine Vision Theory, Algorithms, Practicalities," *Assembly Automation*, vol. 25, no. 3, 2005, doi: 10.1108/aa.2005.03325cae.001.
[37] W. Chen, M. L. Giger, and U. Bick, "A Fuzzy C-Means (FCM)-Based Approach for Computerized Segmentation of Breast Lesions in Dynamic Contrast-Enhanced MR Images1," *Academic radiology*, vol. 13, no. 1, pp. 63-72, 2006.

[38] Y. Cui *et al.*, "Malignant lesion segmentation in contrast-enhanced breast MR images based on the marker-controlled watershed," *Medical Physics*, vol. 36, no. 10, pp. 4359-4369, 2009, doi: doi:http://dx.doi.org/10.1118/1.3213514.

[39] C. Militello *et al.*, "On Unsupervised Methods for Medical Image Segmentation: Investigating Classic Approaches in Breast Cancer DCE-MRI," vol. 12, no. 1, p. 162, 2022.

[40] Y.-T. Oh, E. S. Ko, and H. Park, "Semi-supervised Breast Lesion Segmentation using Local Cross Triplet Loss for Ultrafast Dynamic Contrast-Enhanced MRI," in *Asian Conference on Computer Vision (ACCV)*, 2022, pp. 2713-2728.

[41] R. Azmi, R. Anbiaee, N. Norozi, L. Salehi, and A. Amirzadi, "IMPST: A New Interactive Self-Training Approach to Segmentation Suspicious Lesions in Breast MRI," *J Med Signals Sens*, vol. 1, no. 2, pp. 138-48, 2011.

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