A SURVEY OF ULTRASONOGRAPHY BREAST CANCER IMAGE SEGMENTATION TECHNIQUES

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ABSTRACT

The most common cause of death among women globally is breast cancer. One of the key strategies to reduce mortality associated with breast cancer is to develop effective early detection techniques. The segmentation of breast ultrasound (BUS) image in Computer-Aided Diagnosis (CAD) systems is critical and challenging. Image segmentation aims to represent the image in a simplified and more meaningful way while retaining crucial features for easier analysis. However, in the field of image processing, image segmentation is a tough task particularly in ultrasound (US) images due to challenges associated with their nature. This paper presents a survey on several techniques of ultrasonography images segmentation including threshold based, region based, watershed, active contour and learning based techniques, their merits, and demerits. This can provide significant insights for CAD developers or researchers to advance this field.

Keywords: Breast cancer, breast ultrasonography images (BUS), computer aided diagnoses (CAD), early detection, segmentation.

1. Introduction

The most common cancer suffered globally by women is breast cancer [1],[2] &[3]. In light of this, mortality attributed to breast cancer could be significantly reduced if its symptoms and signs are detected at an early stage by doctors at clinics [4]. In addition, early treatment and diagnosis would provide the best survival chance for women who are diagnosed with breast cancer. It is thus imperative for procedures developed for early diagnosis to be reliable and accurate, as it will greatly assist doctors to effectively single out malignant breast tumors from benign breast tumors [5],[6],[7] & [8]. Widely used imaging tools to screen breast lesions are sonography and mammography. As complement to imaging tools, ultrasound and the mammography screening may be utilized to feasibly reduce redundant biopsies [9]. In early diagnosis of breast lesions, breast ultrasound (BUS) imaging is the most relied upon technique to perform detection and classification, attributed to its cost-effectiveness, real-time processing, harmless, and non-invasive for patients. However, experienced and well-trained radiologists are needed to interpret ultrasound images produced by BUS. Thus, it is crucial to have computer systems that are able to assist junior radiologists in terms of image processing in the detection of breast cancer.

Computer-aided diagnosis (CAD) systems have been

Academic Journal of Nawroz University
(AJNU) Volume 9, No 1 (2019).
Regular research paper : Published 12 Feb 2020
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doi : 10.25007/ajnu.v9n1a523

developed towards producing non-biased, reliable, and accurate diagnosis as a secondary judgement to form strong reasoning for doctors to single out benign breast tumors from malignant breast tumors [10] & [11]. The most essential yet the most daunting stage in image processing is image segmentation. The stage is a vital element towards successfully analyzing images and recognizing patterns [12]. Image segmentation is a set of procedures used to split a screened image into several regions. In processing medical images, image segmentation plays a key role to segment the representation of tissues of interest from background. As ultrasound (US) images are always crowded with image noises, it becomes practically challenging to segment tumors in BUS images [13]&[14]. Specifically, image noises that pose challenges to segment US images effectively include intensity inhomogeneity, low signal-to-noise ratio, and high speckle noise [15]. In medical examination of image segmentation, the task is typically accomplished by labor-intensive human efforts to perform tracing. Such strategy is laborious, involves specific skillset, requires substantial experience, and consumes a significant amount of time. Therefore, development into the field of CAD systems are deemed highly timely as they would help radiologists to diagnose breast cancer efficiently and effectively [16] & [17]. Existing CAD systems are categorized into two, namely fully-automated and semi-automated systems, depending on the extent of human involvement in the task of segmenting images. In semi-automated systems, the tasks of specifying region of interest (ROI) such as a seed in lesion, an initial boundary, or lesions are accomplished with the expertise of radiologists. Figure 1. shows an example of manually segmented (ROI) by an expert highlighted as red line border of breast tumor in ultrasound image.

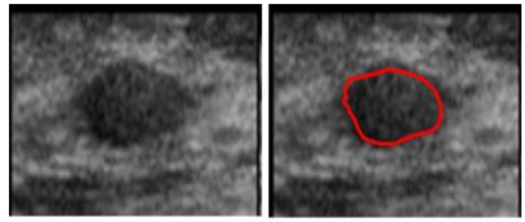

Figure1: illustrates the process of segmentation: a) Original US image b) Segmented US image [67].

On the other hand, fully automated systems are independent of human involvement, and are capable of modelling breast ultrasound and oncology knowledge as preceding constraints autonomously. Primary advantages of fully-automated systems include reproducibility and independency from operators [18]. In a typical CAD system, four main tasks are performed as shown in figure 2. encompassing: 1) pre-processing, 2) segmentation, 3) feature selection, and 4) classification. Accuracy of segmentation task greatly affects the results of CAD systems as numerous critical features used for distinguishing malignant and benign tumors rely on texture, contour, and shape of lesions. The features may only be effectively extracted if segmentation of tumors is performed with great accuracy [19], [20], [21] & [22].

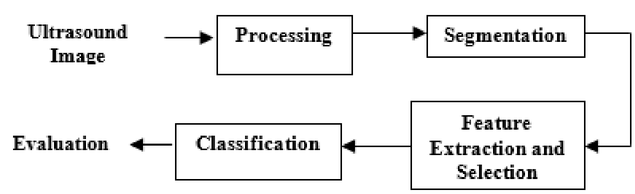

Figure 2: CAD system for breast cancer detection and classification

The remainder of the paper is structured as following: Section2 briefly described the role of preprocessing operations. Section3 presents five BUS image segmentation techniques. Section4 expresses relevant performance evaluations that are commonly used in evaluating segmentation techniques. Finally, Section5

doi : 10.25007/ajnu.v9n1a523

concludes the survey.

2. Preprocessing

An image produced by ultrasound is typically filled with speckle noise scattered in random regions within the image that are grainy in form. In order for segmentation to produce better outcomes, reduction of speckle noise is thus necessary. This is typically performed during pre-processing phase. In this phase, specifically for medical images, image enhancement and speckle reduction steps are undertaken to improve from various medical image artefacts (i.e. signal dropout, shadow, speckle, attenuation) [23] & [72]. Primary goal of this phase is to enhance image quality prior to proceeding with subsequent image processing phases.

3. Bus Image Segmentation Techniques

BUS CAD systems face challenges to produce desirable outcomes in processing BUS image segmentation. This is attributed to inherent noise in BUS images, in addition to poor image quality and shadow regions within the images. This has led to difficulty in the task of segmenting tumor from the processed images. The task of image segmentation involves separating background and objects that are present in the images, and to split image I into several subsets named regions Ri [24], [25]. In image segmentation, several techniques are in existence. These techniques are broadly categorized into discontinuity based and similarity-based techniques which are critical in their own merits [26] [27].

a. **Discontinuity based technique:** Segmentation using discontinuity based technique involves partitioning images, which is governed by an image's grey intensity levels. Discovery of lines, edges, and isolated points in images are primary characterization of discontinuity based technique [28].

b. **Similarity based technique :**Segmentation using similarity based technique results in an image being segmented into several regions depending on their extent of similarity. The technique would cover steps including region growing, thresholding, and region split and merge. All these steps would eventually produce segmented image into regions based on pixel similarity [29]. Figure 3. shows the categories of image segmentation techniques.

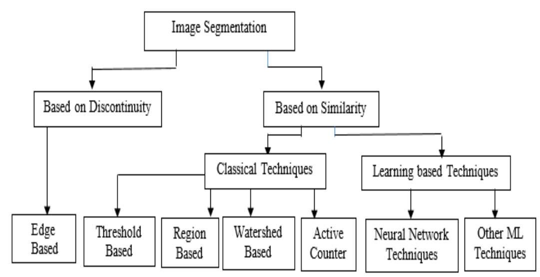

Figure 3: Categories of image segmentation techniques

3.1 Classical segmentation Techniques

Several classical techniques of segmentation used in BUS are discussed in this section. These techniques are sometimes combined (or hybridized) in segmentation to obtain better implementations.

- **Thresholding-based technique:**

  Attributed to effectiveness and simplicity, thresholding technique is highly favored to distinguish objects from background in an image. In image segmentation, thresholding technique is dubbed as the most simplistic strategy where thresholding is performed based on threshold value or clip level towards producing a binary image from a grayscale image. Strategy most commonly employed to execute thresholding is through performing searching for valleys or local minima of an image's gray-level histogram. Alternative strategy employed is to perform

doi : 10.25007/ajnu.v9n1a523

searching for threshold value, dependent on certain information measure's maximization or entropy [30][31]. Ultimate characteristic of thresholding technique is reliant on an image's characteristics. The technique selects suitable thresholds, Tn, and subsequently performs pixel splitting into a number of classes and lastly performs separation of objects from background. Formally, thresholding is expressed as following:

At a single threshold T, a point in an image is known as an object if it is located at position (x, y) for as long as $f(x,y)>T$, while a point is known as a background if it is located at position (x, y) for as long as $f(x,y)<T$. T is expressed as:

$$T = M[x, y, p(x,y), f(x,y)] \quad (1)$$

Referring to "(1)", thresholding techniques can be categorized into local and global. Conventional thresholding technique is simplistic and rudimentary and may produce sub-par outcomes in processing unimodal histogram images. This is because conventional thresholding technique overlooks spatial location statistics and only considers the statistics of gray levels. In addition, in certain images, overlapping of distribution of gray levels among background and objects could occur. This is a challenge posed to thresholding technique, which necessitates the selection of appropriate threshold value (or several values when more than one level is chosen). In real-time applications, several techniques have been used including k-means clustering, Otsu's technique (maximum variance), and maximum entropy technique [32].

Sahar et al. [33] put forth adaptive median filter and adaptive thresholding strategies in segmenting images at pre-processing stage, and finally followed by morphological steps to detect lesions. More recently, Liu et al. [34] introduced a computational framework capable of detecting and segmenting lesions autonomously in medical images. Liu et al. executed a non-local low-rank-(NLLR) filtering strategy towards minimizing speckle noise in images. In initialization of contour, Liu et al. utilized Otsu-based adaptive thresholding (OBAT) algorithm coupled with morphologic steps to successfully identify regions with tumor and perform tumor contour initialization. Finally, upon initializing the contours of tumor, an enhanced Chan-Vese model with derivation of ratio of exponentially weighted averages (CV-ROEWA) was used. Zebari et al. [71] focused on the enhancement stage based on wavelet to produce image with quality that can help to improve the segmentation and features extraction stage. In literature, various combinations of thresholding-based techniques have been pursued towards improving segmentation outcomes including combining ant colony optimization and regulation parameters with k-means algorithm [35].

- **Region-based technique**

In region-based technique, an image is segmented into different regions. The regions are differentiated based on several criteria including object, intensity, or color. A region growing algorithm may be used to segment an image into different regions. The algorithm begins with a chosen seed point or seed area and gradually assesses and either discards or adds neighbors to a region depending on their similarity value. The algorithm will halt once a stopping condition is satisfied. In region-based technique, two predominant techniques may be used encompassing region splitting and merging and region growing [36] & [37]. Li et al. [38] put forth an automated technique to partition BUS images

doi : 10.25007/ajnu.v9n1a523

where in initial selection of contours, BUS images are pre-processed covering several steps. The steps include setting iterative threshold, separating potential tumor locations, and rearranging the ranks of left over areas towards confirming ROI. Upon identifying ROI, a seed point may be selected. From this seed point, region growing algorithm moves to attain initial contour as the initial result. Li et al. further introduced a new level set algorithm to enable the confirmation of the ultimate contour, incorporated with region-based energy restrictions, local statistics, and global statistics. In the most recent work, Lal et al. [39] presented a fully-automated seed point selection technique on B-Mode BUS images. In this technique, initial seed point is calculated based on input image's texture and spatial information. The technique is capable of locating seed point for images with shadows with great accuracy. Despite this, in images containing malignant tumor, the technique has performed with poor accuracy in the selection of seed point, thus necessitating for further improvements to be pursued in this area. In improving BUS images' contrast and discarding speckle noise in neutrosophic set (NS) domain, Jiang et al. [40] proposed an adaptive OBTA and morphology steps to choose seed area. Jiang et al. then utilized an adaptive region growing technique to identify potential tumor in the NS domain. Region growing direction is governed by several constraints including distance between candidate growing points and seed region, value of texture homogeneity, and similarity value differences.

- **Watershed-based technique**

Image segmentation could also be performed through mathematical morphology known as watershed transformation technique. Beucher and Lantue' joul [41] first conceived a novel watershed technique which was later implemented through various algorithms put forth by researchers. Watershed technique is inspired by mathematical morphology which analyzes an image's topography structures [42]. Figure 4. shows a topographic view of watershed. Mathematical morphology in watershed transformation for image segmentation involves thresholding, region growing, and detection of edges. The technique improves stability of segmentation outcomes and offers a simplistic framework [43]. In image segmentation via watershed technique, regional minimum is a term used to signify a region having pixels with the least regional elevation. An image's minima objects are pixels clusters having grey level that is inferior to their regional neighbors (pixels). A simulation of rainfalls models the flow of rain drops upon reaching a surface, descending from a steep elevation to a low surface point. A catchment basin refers to the converging pixel paths of rain drops as they fall towards the low surface point. Several catchment basins normally exist which are segmented by watershed's elevated areas. Catchment basins represent segments of an image which is the goal of an image segmentation while segments' boundaries represent watersheds [44]. Objects present in an image may be analyzed based on their forms and shapes utilizing the capability of mathematical morphology.

Gomez et al. [45] introduced a technique which segments BUS tumors' image semi-automatically incorporating average radial derivative function or minima imposition, watershed transformation, and mathematical morphology. The incorporation of several techniques produced promising segmentation capability for segmenting complex

doi : 10.25007/ajnu.v9n1a523

US images. The proposed technique was able to outline lesions almost accurately in real-time implementation. Meanwhile, Zhang et al. [11] introduced an automated detection of BUS tumors by exploiting the power of fuzzy logic where a US image is treated as a fuzzy problem. In the technique, iteration is utilized to discover a suitable threshold value. Subsequently, a watershed technique is executed on binary images produced by the fuzzy logic theory to obtain the resulting boundaries of tumors.

In a recent study, Nugroho et al. [46] & [47] introduced breast nodule characteristics classification technique that allows differentiation into non-circumscribed and circumscribed categories to be accomplished. The technique employs marker removal via adaptive median filter, image normalization and speckle reduction anisotropic diffusion (SRAD) filter using pre-processing, neutrosophic, and finally segmentation using watershed technique. Hopeful outcomes were produced as the technique was capable of classifying breast nodule through exploiting characteristics of margin, which is crucial to assist accurate interpretation of US images by radiologists. Meanwhile, Bafna et al. [48] perform tumors' contours extraction utilizing watershed algorithm in BUS images. Through the technique, image noise is lessened using preprocessing filter while retaining critical features of tumor lesion such as edges. Calculation of foreground and background area is performed with dependency on threshold values. Difference of area between foreground and background signifies focused region which is calculated through referring to a connected component graph. Finally, tumor's contours are determined by implementing a watershed algorithm. Automation of segmentation of breast lesions is highly beneficial as it is effortless and efficient to assist radiologists in making analysis and forming decisions.

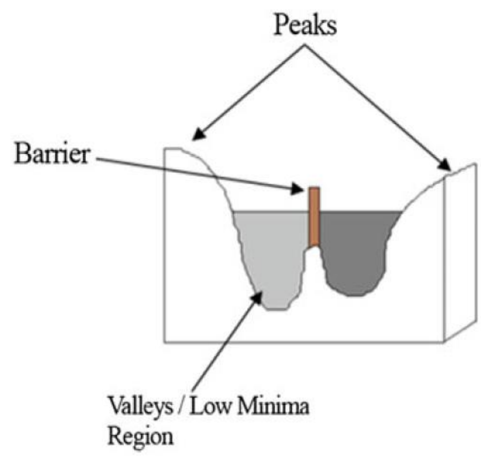

Figure 4: Topographic view of watershed

- **Active contour-based technique**

Research on image segmentation utilizing active contour models is gaining traction [49]. Active contour technique has also been termed as snake [50], attributed to its adaptability and autonomous property in distinguishing object's boundary via manipulating contour dynamically. Active contour technique may be broadly divided into two categories namely region-based and edge-based technique. Active contour governed by edge-based technique, also known as gradient-based technique, is commonly utilized to perform segmentation on images having uniform edges with low noises [38]. On the other hand, active contour driven by region-based technique exploits intensities' statistics and assesses boundary's geometry. Despite underperformance in performing segmentation on images possessing heterogenous features, region-based technique primarily relies on an image's global statistical information. There is a growing

doi : 10.25007/ajnu.v9n1a523

number of researches on active contour based on local region, which is used to offset global statistical information's limitations. Malignant BUS images are complex images as they are often discontinuous and contain a high intensity of noise, in which local region-based technique is superior than global region-based in performing mass segmentation effectively [51]&[52]. Dinesh et al. [53] put forth a CAD system exploiting anisotropic diffusion filtering in eliminating speckle noise (multiplicative noise) and Gaussian smoothing in eliminating additive noise in images. Active contour technique has also been utilized on images which have been filtered to extract their closed contour, which signifies the outline of a spiculated mass. Irregularity in breast mass is attributed to spiculations. In image segmentation, spiculations are identified through quantifying curvature angle of individual pixel at mass' outline (boundary). Menon et al. [51] proposed simplistic filters to lessen speckle noise and enhance images. The technique exhibited superior capabilities when compared against conventional SRAD technique in yielding preprocessed images. Active contour local region-based technique may then be used to effectively identify ROI on the preprocessed images. The work of Menon et al. performed BUS images' classification through implementing histogram-based, morphological-based, and textural-based feature metrics. Incorporation of combination of feature metrics and active contour local region-based technique managed to efficiently perform image segmentation. Extending a previous work of Selvan et al. [55], Panigrahi et al. [54] exploited the capability of pixel-based k-means segmentation which is able to resolve the issue of energy reduction in active contour technique. Panigrahi et al. also performed a comparison of active contour, Ostu's technique, and k-means in detecting boundaries. Despite superior capabilities, active contour failed to accurately perform detection on various images' boundaries. More recently, Prabhakar et al. [56] put forth automation algorithm for breast lesions' classification and segmentation in US images. The proposed work reduced speckle noise by implementing Tetrolet filtering. The technique also allowed automatic segmentation of breast lesions to be achieved via active contour governed by features' statistics. Neutrosophy is a study of paradoxes and contractions and dissects scope, nature and origin of neutralities. In the branch of computer science, neutrosophy simplifies fuzzy theory and is capable of unravelling problems that fuzzy logic fails to resolve [57]. In this light, Lotfollahi et al. [58] proposed a BUS image segmentation technique that exploits the capabilities of neutrosophic theory and active contour driven by region-based technique. The technique reduces inherent noises in US images' properties such as textures related to tissues and speckle noise. Attributed to such versatile capabilities, the technique may be applied on US images of other organs, and not just restricted to BUS images.

3.2 Learning-based technique

Segmentation of images may be treated as a classification challenge such as to categorize super pixels and pixels into different classes. Application of machine learning in segmenting images via classification technique is highly favored among researchers. Specifically, techniques including unsupervised and supervised learning have been utilized to perform segmentation of BUS images [59]. Machine learning technique has been popularized in

doi : 10.25007/ajnu.v9n1a523

segmenting images such as neural network (NN) based technique. In NN, the challenge of segmentation is solved via treating it as a classification challenge where classifying of image segments into different classes are achieved via referring to their set of input features [60]. Region growing and thresholding techniques, unlike machine learning, are straightforward techniques as they are fast and easy [61]. Yet, the former techniques are incapable of dealing with complex tumor images [62]. Literary evidence indicates that deep learning is a growing field with promising capabilities across various domains. In the task of segmenting BUS images, deep learning may prove to be a scalable technique that is able to scale to large BUS dataset size in learning various representations of compact images [63] [64] & [65]. In the work of Almajalid et al. [66], segmentation framework incorporating deep learning u-net was introduced for segmenting BUS images. In theory, U-net comprises convolutional neural network that is constructed for solving segmentation on biological images on a constraint training data. U-net was initially used to segment neuronal structures that are present on microscopy images. However, Almajalid et al. utilized the technique with improvement to perform segmentation on BUS images. In their work, firstly, speckle noise was reduced, and contrast was improved at pre-processing phase to enhance the quality of the image. Secondly, a two-fold cross validation was performed to test and train the u-net model. The authors implemented elastic deformation and rotation which are a part of data augmentation technique to augment the size of training data. Lastly, regions with noises are removed at post-processing phase. The proposed work exhibited greater accuracy and robustness in segmenting BUS images containing tumors. In the most recent development in the field of image segmentation, Zeebaree et al. [67] proposed a two-step technique to extract breast ROI utilizing neural network and local pixel information with the aim of diminishing the amount of false positives (FP). The proposed two-step technique involves testing and training. During training, batches are extracted from background and ROI to build a trained model. Meanwhile, in testing, an image is scanned with a preset size of window to distinguish background and ROI. Subsequently, removal of non-ROI and identification of ROI are performed using a distance transform technique. In a related work, Zeebaree et al. [68] introduced a descriptor that is capable of implementing identification of breast abnormality through improving local binary pattern (LBP) descriptor and LBP texture's features. This was achieved through using a different threshold that is able to perform identification of critical information towards detecting abnormal cases.

4. Performance Evaluation of Segmentation Techniques

Experiment results of segmentation techniques can be quantified through adopting several criteria. Most commonly utilized evaluation metrics to assess the performance of segmentation techniques are expressed as follows:

$$TP\ Rate = TP / (TP + FN) \quad (2)$$

$$Accuracy = (TP + TN) / (TP + TN + FP + FN) \quad (3)$$

$$Sensitivity = TP / (TP + FN) \quad (4)$$

Where FP (false positives) and FN (false negatives) are incorrect diagnoses of benign and malignant cases. Whereas TP (true positives) and TN (true negatives) are correct diagnoses of benign and malignant cases [69]. Meanwhile, coincidence percentage (CP) is an evaluation metric used to quantify similarity value between manually delineated and a proposed segmentation technique, expressed as follows:

$$CP = \frac{\text{Area}(S1 \cap S2)}{\text{Area}(S1 \cup S2)} \times 100 \quad (5)$$

doi : 10.25007/ajnu.v9n1a523

Where $S1$ and $S2$ denote the segments of interest where comparison will be performed. Whereas, symbol ∩ denotes intersection while ∪ denotes union (in pixels). CP value will be 100% in the event of $S1$=$S2$ [45].

5. Conclusion

A summary from what has been reviewed in this survey, a comparison between five different segmentation techniques is presented in Table 1. Meanwhile, five techniques and recent advancements accomplished in the field of image segmentation are summarized in Table 2. Upon analysis of several image segmentation techniques, the following points are observed:

- Segmentation of BUS images remains a growing research field attributed to challenges of US artefacts in image processing. Some of the challenges of US artefacts include blurry boundaries, intensity in-homogeneity, low signal-to-noise ratio, low contrast, and high speckle noise. In addition, manifestations of malignant and benign tumors are varied in medical BUS images. The procedures undertaken by radiologists in analyzing image segmentation also vary, which only aggravate the difficulty in performing BUS segmentation.
- Application of different ultrasonic devices yields varied BUS images' qualities. Meanwhile, segmentation is largely affected by various aspects including spatial characteristics, image homogeneity, image content, and textures. As the field of image segmentation is continuously advanced, various novel techniques are birthed to improve existing works and to obtain better efficiency.
- Image segmentation utilizes two or more techniques as a hybrid solution towards obtaining superior performance in solving the problem of image segmentation.
- Utilizing neutrosophic theory with some segmentation techniques is an effective way to overcome the natural properties of ultrasound images towards removing speckle noise, enhancing contrast in BUS images, and getting better results.
- Sometimes a post-processing phase is carried out for enhancing images due to the nature of BUS images and the segmentation techniques themselves. However, candidate image regions have only been generated using unsupervised

TABLE 1. COMPARISON OF DIFFIDENT SEGMENTATION TECHNIQUES

Segmentation technique	Characterization	Merit	Demerit
Threshold	Finds threshold values depending on an image's histogram peaks.	• Acts well with images having prominent edges. • Simple method, previous information are not required.	• Inappropriate for images having many or smooth edges. • Unsuitable for images with unimodal histograms.
Region based	Divides an image into homogenous regions.	• Works well when it is easy to define the criteria of similarity. • Has good immunity to noise where edges are difficult to identify.	• Time and memory consuming. • It gives different results when different seeds selected.
Watershed	Depends on topographical representations.	• Intuitive method, simple and fast. • Attain stable results even if the contrast is poor.	• Gradients need complex calculation. • Sensitive to noise. • Over segmentation.
Active contour	Uses snake deformation mode.	• Lesion extraction could be done in a diversity of shapes while correctly keeping accurate boundaries.	• The speed of iteration is slow. • It gives low accuracy with images having noise and week boundary
Learning based	Decision making relies on the simulation of learning process.	• Robust against noise utilizing an architecture of enormous connections • Easy to implement.	• Sometimes image's prior information is needed to achieve high performance. • Takes time for training.

doi : 10.25007/ajnu.v9n1a523

techniques at pre-processing phase attributed to modest simplicity. This is because final segmentation commonly utilizes more complex techniques to achieve desirable results.

- Learning based techniques are more effective than classical techniques in dealing with complex ultrasound images of tumors.

doi : 10.25007/ajnu.v9n1a523

TABLE 2. SUMMARY OF THE SURVEY

Ref.	Year	Author (s)	No. of images	Preprocessing	Segmentation technique	Metrics	F/S
[33]	2016	Sahar et al.	30 Total 20 Benign 10Malignant	Adaptive median filter	Threshold Based	Accuracy= 95.19%	F
[34]	2018	Liu et al.	61Total 29 Benign 32Malignant	NLLR	Threshold Based	Accuracy= 95.96	F
[38]	2016	X. Li et al.	44Total	Iterative threshold	Region growing	TP= 93.06%	S
[39]	2018	Lal et al.	108Total 57Benign 51Malignant	SRAD filter	Region growing	Accuracy= 95.37%	F
[40]	2019	Jiang et al.	121Total 35Without tumor 36Benign 50Malignant	Neutrosophic set	Region growing and CNN	TP= 90%	F
[45]	2009	Gomez et al.	Total=36	Morographical Operator Mathematical morphology	Watershed transform	CP ≥ 80 %	S
[11]	2011	Zhang et al.	____	____	Watershed	___	F
[46]	2017	Nugroho et al.	102Total 57Non-circumscribed 45 circumscribed	SRAD	Watershed	Accuracy= 94.12%	S
[47]	2017	Nugroho et al.	102Total 57Noncircumscribed 45 Circumscribed margins	SRAD	Watershed	Accuracy= 95.10%	S
[48]	2018	Bafna et al.	127Total 52 Benign 75Malignant	Gaussian smoothing technique	Watershed	Accuracy= 90%	F
[70]	2017	Raha et al.	85Total 30Benign 54Malignant	Median filtering Boost filter Sobel filter	Watershed	Accuracy= 96.4%	F
[53]	2012	Dinesh et al.	100Total 60 Benign 40Malignant	Gaussian and anisotropic diffusion filters	Active contour	Sensitivity= 92.7%	S
[51]	2015	Menon et. al	___	SRAD	Active contour	Accuracy= 95.7 %	F
[54]	2016	Panigrahi et. al	116 Total 45 Benign 71 Malignant	Median filter	Active contour	Accuracy= 89.65 %	F
[58]	2017	Lotfollahi et. al	36 Total	Non-local means filter and fuzzy logic	Active contour	Accuracy= 95%	S
[56]	2017	Prabhakar et. al	___	Tetrolet filter	Active contour	Accuracy= 87.27%	F
[66]	2017	Almajalid et al.	221 Total	SRAD	U-net	TP=78.66%	F
[64]	2018	Wang et al.	196 Patients 661 Cancer regions	______	U-net	sensitivity = 93%	F
[67]	2019	Zeebaree et al.	120 Total 150 Benign 100 Malignant	LBP	ML& Region Growing	Accuracy= 95.4%	F
[68]	2019	Zeebaree et al.	250 Total 150 Benign 100 Malignant	Enhanced LBP	RCNN	Accuracy= 96%	F

doi : 10.25007/ajnu.v9n1a523

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