REVIEW ARTICLE

Advances in Breast Ultrasound Segmentation and Classification

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Abstract: Breast cancer is one of the most prevalent cancers affecting women worldwide. Ultrasound is extensively utilized for clinical screening and diagnosis due to its affordability, absence of radiation, and rapid imaging capability. To enhance diagnostic accuracy, computer-aided diagnosis (CAD) systems have been developed, with segmentation and classification being key techniques. This review systematically examines 62 recent studies on breast ultrasound segmentation and classification, covering various imaging techniques such as B-mode, elastography, 3D ultrasound, contrast-enhanced ultrasound (CEUS), and color Doppler. specifically, we detail the challenges and deep-learning-based methods associated with these modalities. Comparative analysis reveals that current deep learning approaches typically achieve Dice coefficients ranging from 0.79 to 0.91 for segmentation and classification accuracies exceeding 88.2% in multimodal settings. Finally, this article identifies critical research gaps, including data scarcity and model interpretability, and discusses future directions such as multimodal fusion and explainable AI (XAI) to further improve clinical applicability.

Key words: Breast cancer; Breast ultrasound; Image segmentation; Image classification; Computer-aided diagnosis

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Breast cancer is one of the most prevalent cancers affecting women globally and represents a major public health concern [1,2]. According to a 2015 report by the China Cancer Center, breast cancer has the highest proportion (17.1%) of female cancer patients in China [3].

The primary diagnostic methods for breast cancer in the clinical setting include mammography, magnetic resonance imaging (MRI), and ultrasound (US). Mammography helps radiologists examine lesions such as lumps, cysts, or calcium deposits [4]; however, it is less accurate in screening dense breasts and less sensitive to benign breast cysts, which can be easily misdiagnosed as malignant tumors, leading to unnecessary biopsies from patients [5]. Additionally, X-rays emit radiation, which can harm the human body, especially adversely affecting pregnant women and fetuses.

MRI has been used in clinical diagnosis of breast lesions since 1982. It has clearer imaging, higher resolution, and more detailed tissue information. However, it is expensive and not ideal for early breast cancer screening due to the stringent hospital requirements for its use [6].

Compared to mammography and MRI, ultrasound imaging offers several advantages, including lower cost, no radiation, faster imaging, high sensitivity and accuracy, and higher sensitivity for screening dense breasts, particularly in Asian women [7]. Additionally, it is more

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efficient at detecting cysts and reducing the need for unnecessary biopsies. However, interpreting ultrasound images requires trained and experienced radiologists, and the effectiveness of ultrasound examinations and diagnoses is highly dependent on the operator's experience and proficiency [8]. Recently, numerous researchers have developed computer-aided diagnosis (CAD) systems to help radiologists achieve more reliable and accurate diagnoses. These systems offer an objective second opinion for interpreting and diagnosing medical images, helping radiologists distinguish and classify breast tumors.

Automatic segmentation and classification of breast tumors are vital steps in diagnosis. Prior information can be incorporated to enhance segmentation performance. However, prior knowledge such as intensity, texture, and shape may be inadequate because of the complex nature of breast lesion characteristics. Challenges such as low accuracy, high computational complexity, limited robustness, and poor generalization in medical image segmentation remain unresolved [9]. In breast ultrasound, issues such as scattering noise and low contrast in images can hinder the detection of features that indicate abnormalities. Detecting cancerous areas requires processing each pixel within the breast tissue; however, this pixel-by-pixel classification is time-consuming due to the vast volume of data involved.

In clinical applications, various ultrasound imaging techniques are used to screen and diagnose breast lesions, including B-mode ultrasound, ultrasound elastography, 3D ultrasound, contrast-enhanced ultrasound (CEUS), and color Doppler ultrasound. This paper reviews the latest research progress in intelligent segmentation and classification techniques for breast lesion diagnosis using the ultrasound imaging methods mentioned above.

To provide a comprehensive overview of the research landscape, we present a structured taxonomy of the topics covered in this review, as illustrated in figure 1. This diagram elucidates the relationships between the clinical data sources and the computational analysis tasks. Specifically, the left side outlines the five primary imaging modalities discussed—ranging from anatomical B-mode to functional modalities like Elastography and Color Doppler. The right side maps these inputs to the core diagnostic tasks of segmentation and classification, further branching into the specific methodological evolutions from traditional machine learning to state-of-the-art deep learning and multimodal fusion architectures.

Ultrasound Imaging Techniques Used in Breast Lesion Diagnosis

B-mode ultrasound

The basic principles of B-mode ultrasound imaging are as follows: An ultrasound probe is placed on the skin's surface to emit ultrasound waves. These waves are received by different human body tissues, producing distinct reflected waves. The probe captures these reflections, and the ultrasound imaging equipment processes them into different shades of the grey display, creating a cross-sectional image of the human body. Diagnostic ultrasound devices are classified into various types based on the type of ultrasound modulation, among which B-mode ultrasound is commonly used to detect breast tumors. Figure 2 shows three breast ultrasound

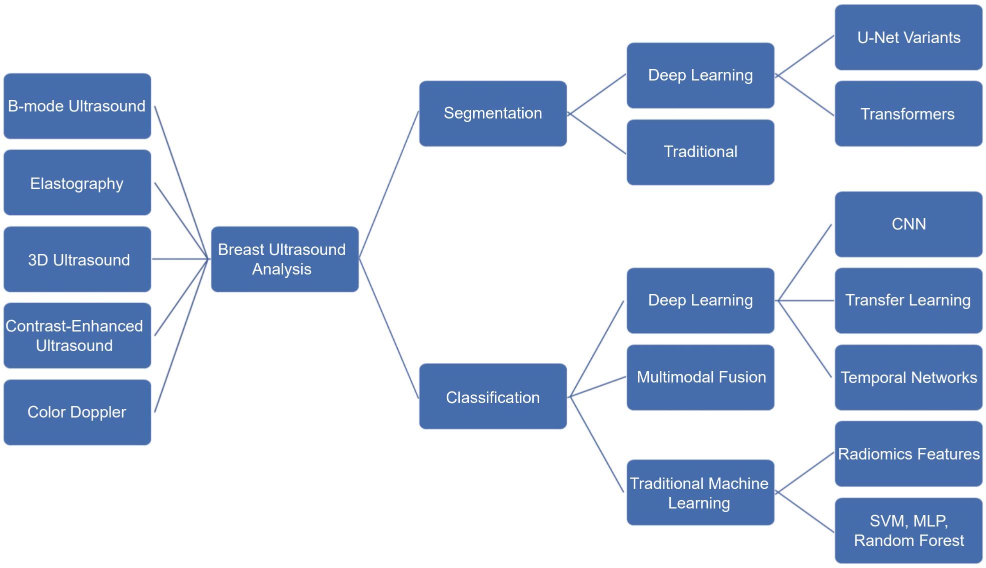
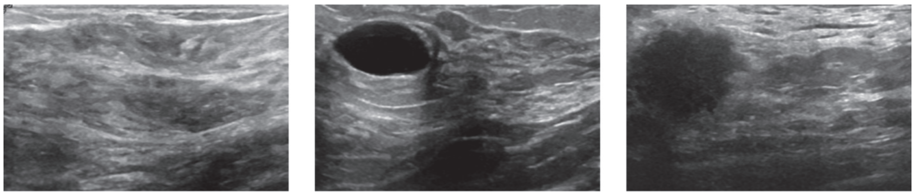


Figure 1 Schematic overview of the review structure. The framework connects the five primary ultrasound modalities (B-mode, Elastography, 3D Ultrasound, CEUS, and Color Doppler) to the downstream tasks of segmentation and classification, categorizing the key technological methodologies applied in recent CAD systems.



Normal Benign Malignant

Figure 2 Three breast ultrasound images from the BUSI dataset [10].

images from the BUSI dataset [10].

Ultrasound elastography

Elastography applies force to the tissue, causing deformation, and the resulting signal changes reflect the tissue's degree of softness or hardness based on its elasticity. Currently, two primary types of elastography are used for breast lesion diagnosis: strain elastography (SE) and shear wave elastography (SWE).

SE was assessed using a 5-point scale, followed by semiquantitative strain or diameter ratios. SWE can be studied quantitatively using metrics such as the maximum, mean, and minimum elastic moduli [11], as shown in figure 3. The combination of SWE and B-mode ultrasound substantially enhances the detection of breast lesions [12].

D ultrasound

3D ultrasound imaging provides continuous dynamic scanning of the entire breast and three-dimensional reconstruction of the region of interest (ROI). This allows for a multi-slice, multidirectional view of the breast and surrounding tissues. On 3D ultrasound, malignant breast masses often exhibit signs such as burr edges, convergence sign, and vascular translucency.

Automated breast ultrasound (ABUS) can visualize the entire breast as a three-dimensional anatomical structure, providing more graphical information about the interior and margins of breast lesions [13]. A set of ABUS images generated by the Somo-V automated 3D breast ultrasound system is shown in figure 4 [14].

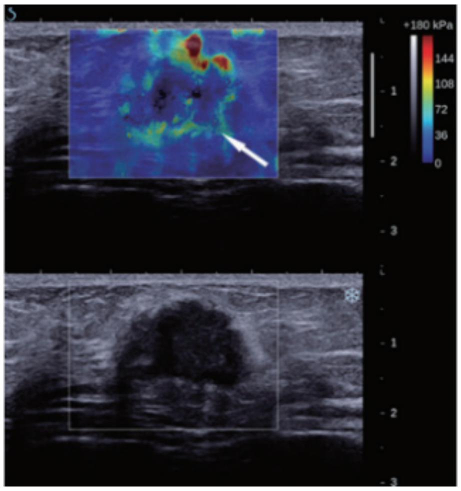


Figure 3 The upper image displays a SWE image indicating increased stiffness in the region surrounding the tumor, and the lower image is the corresponding B-mode ultrasound [11].

Contrasted-enhanced ultrasound

Contrast-enhanced ultrasound (CEUS) is used clinically to observe and measure microvascular growth, distribution, and perfusion at the site of a lesion. This is achieved through the intravenous injection of ultrasound contrast medium, aiding in the diagnosis of breast lesions [15]. Figure 5 shows the uniform enhancement

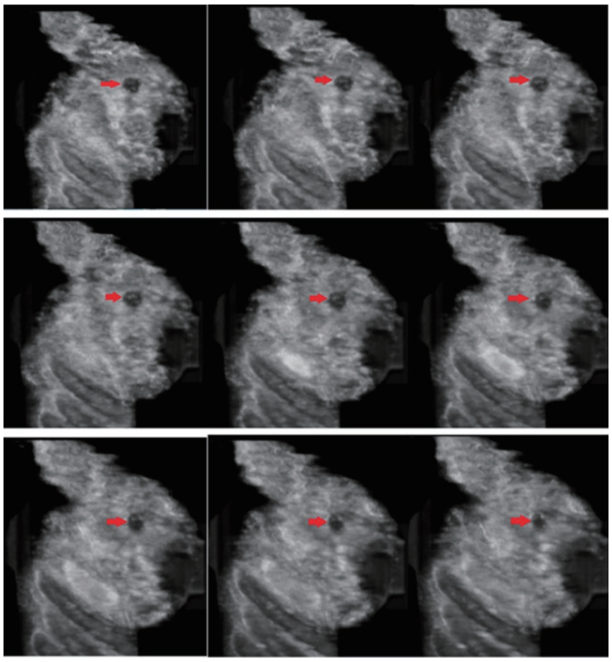


Figure 4 Somo-V generated coronal view of a body mass in 9 consecutive slices. Red arrows indicate the location of the mass [14].

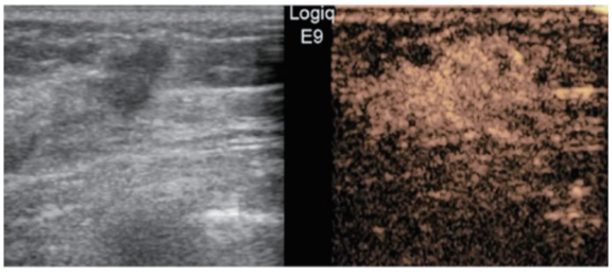


Figure 5 Images of breast tumors. The left image represents the US image and the right image shows the corresponding CEUS image [16].

of the tumor area on CEUS.

Color Doppler ultrasound

Doppler ultrasound provides insights into the overall tumor and its physiopathological features. It can be used for preoperative assessment of tumor angiogenesis and anti-angiogenesis, as well as for predicting postoperative prognosis. Color Doppler ultrasound uses the Doppler principle to extract the Doppler frequency shift for color coding. Blood flow in the direction of the transducer is usually shown in red, whereas blood flow away from the transducer is shown in blue.

Breast Ultrasound Segmentation

Breast ultrasound segmentation is a crucial step in differentiating between benign and malignant tumors. US image segmentation usually requires pre-processing and extracting suspicious regions as regions of interest (ROI). Tumor region or border segmentation is performed to help clinicians focus their analysis on the tumor area. Therefore, the segmentation accuracy directly affects the effectiveness of tumor detection.

However, challenges in breast ultrasound segmentation and classification arise from factors such as the homogeneity of breast tissue, tissue overlap, speckle noise, artifacts, and low image quality, among other complexities. At one point, many researchers proposed various segmentation methods, including thresholding, morphology-based techniques, watershed, clustering, Markov random fields, level sets, texture-based approaches, and combinations of different algorithms [17-19]. Each method has corresponding limitations and does not solve the difficulties of breast segmentation. Most of the leading segmentation methods currently in use have been developed using artificial intelligence and deep learning methods.

B-mode Ultrasound

Lesion segmentation methods utilizing B-mode ultrasound represent the majority of the research on breast ultrasound segmentation.

Ning et al. [20] proposed a saliency-guided, morphology-aware U-net (SMU-Net). Initially, the method introduced the generation of saliency maps that capture image structures for the foreground and background. These saliency maps were utilized to guide the primary and auxiliary networks in learning the representations of foreground and background saliency, respectively, effectively leveraging the abundant texture information in the background to aid foreground segmentation. Similarly, Chen et al. [21] introduced an innovative cascaded convolutional neural network (CNN) designed for lesion segmentation in breast ultrasound images by combining a U-net, a Bidirectional Attention-Guided Network (BAGNet), and a Refined Residual Network (RFNet). Saliency maps were created for this study. However, it enhances the U-Net core architecture by developing an improved residual network to produce a more comprehensive lesion mask.

Huang et al. [22] developed a semantic segmentation algorithm based on breast anatomical constraints. This algorithm uses a fuzzy, fully convolutional network for contrast-enhanced pre-processing and initial image segmentation. It then applies fine post-processing of the segmentation results using breast anatomical constrained random fields (CRFs) and positional relationship information between the breast anatomical layers to improve segmentation performance.

In addition, some researchers explored the segmentation of breast ultrasound images in a weakly supervised setting by incorporating anatomical constraints related to the breast. To achieve breast tumor segmentation using image-level labels, Li et al. [23] deconstructed the breast anatomy into several anatomical structures within a semi-supervised learning framework and utilized fat and mammary layers as constraint regions. They used class activation mapping and a deep-level set (CAM-DLS) method based on anatomical constraints to perform breast tumor segmentation. This framework requires only small manual labeling and can efficiently identify and segment breast tumors simultaneously in a weakly supervised setting.

Zou et al. [24] developed the Noisy Annotation Tolerance Network (NAT-Net), which identifies noise using a proposed noise index and dynamically corrects noise labeling during the training phase. Zhai et al. [25] proposed an asymmetric semi-supervised generative adversarial network (ASSGAN), which employs two mutually supervised generators and a discriminator for adversarial learning. It successfully uses unlabeled cases to facilitate model training. Huang et al. [26] employed a network architecture with a boundary selection module to automatically concentrate on regions with blurred boundaries and a graph convolution-based boundary drawing module to assess global contour information.

Wu et al. [27] introduced a novel deep network called Breast Ultrasound Segmentation (BUSSeg), equipped with intra- and inter-image remote dependency modeling. This method proposes a cross-image dependency module (CDM) that enhances the ability of BUSSeg to capture remote dependencies in images to capture more representative features by fully utilizing limited training data.

Convolutional operations in a CNN typically concentrate on localized areas, resulting in a limited capacity to capture remote dependencies in the input images. Xue et al. [28] designed a global guidance network (GG-Net) based on a global guidance block (GGB) and a breast lesion boundary detection module (BD). A schematic representation of the network is shown in figure 6. The algorithm employs multilayer integrated feature mapping to provide guidance information for learning remote nonlocal dependencies within spatial and channel domains. The boundary detection module also generates supplementary breast lesion boundary maps to improve the segmentation performance. In addition, Chen et al. [29] introduced a new hybrid adaptive attention module (HAAM) to replace traditional convolutional operations. They utilized it to develop an Adaptive Attention U-net (AAU-net). HAAM is capable of capturing additional features across various sensory fields, guiding the network to adaptively choose more robust features in the spatial dimension, thus improving generalization performance.

Lou et al. [30] constructed a new multilayer context refinement network (MCRNet). This method enhances the contextual relationship between the encoder and decoder using two lightweight context optimization blocks, which significantly improves the semantic segmentation performance with only a small amount of computation.

Inspired by the classical U-Net, Iqbal et al. [31] proposed a multiscale dual-attention network (MDA-Net) based on the classical fixed receptive field problem by introducing a multiscale fusion (MF) block that helps extract more semantic features. Based on the classical U-net network, Chen et al. [32] constructed a plain nested U-net (NU-net) that employs U-Nets of varying depths with shared weights to ensure a robust characterization of breast tumors.

Most traditional methods rely on a single network architecture, which often results in a high number of false positives when tested using normal images. To address this dilemma, Cho et al. proposed a multistage segmentation technique [33]. In the first stage, a Breast Tumor Ensemble Classification Network (BTEC-Net) was designed to classify the input images as normal and abnormal. In the second stage, Residual Feature Selection UNet (RFS-UNet) was designed to segment only abnormal images. This multistage segmentation approach can decrease false positive results and enhance the segmentation accuracy.

Inspired by raw ultrasound shape data, several researchers have attempted to use “radiofrequency” (RF) data. Gare et al. [34] developed a new CNN framework called W-Net to semantically segment and classify breast tissues using raw ultrasound shapes and grayscale ultrasound images. This study is the first CNN segmentation network to analyze raw ultrasound RF data and greyscale images.

3D ultrasound

Regarding 3D ultrasound image segmentation, most researchers currently focus on breast lesion segmentation using ABUS.

Lee et al. [35] proposed an automatic lesion-segmentation algorithm. The first step is to automatically select the volume of interest (VOI) using a 3D-level set. The second step is to process the scattering noise on the image using anisotropic diffusion to eliminate shadow artifacts. The third step automatically segments the image using the adaptive distance regularized level set method (DRLSE). Finally, 3D reconstruction is performed on the 2D segmented image. Lei et al. [36] created a deep-learning codec segmentation method utilizing a self-attention mechanism, as illustrated in figure 7. This method introduces a spatial and channel attention block (SC) that incorporates a nonlocal context block (NCB) to explore nonlocal cues. In addition, the weighted upsampling block (WUB) is developed in this study to improve the upscaling quality of the decoder path.

Zhou et al. [37] constructed a new cross-model atten-

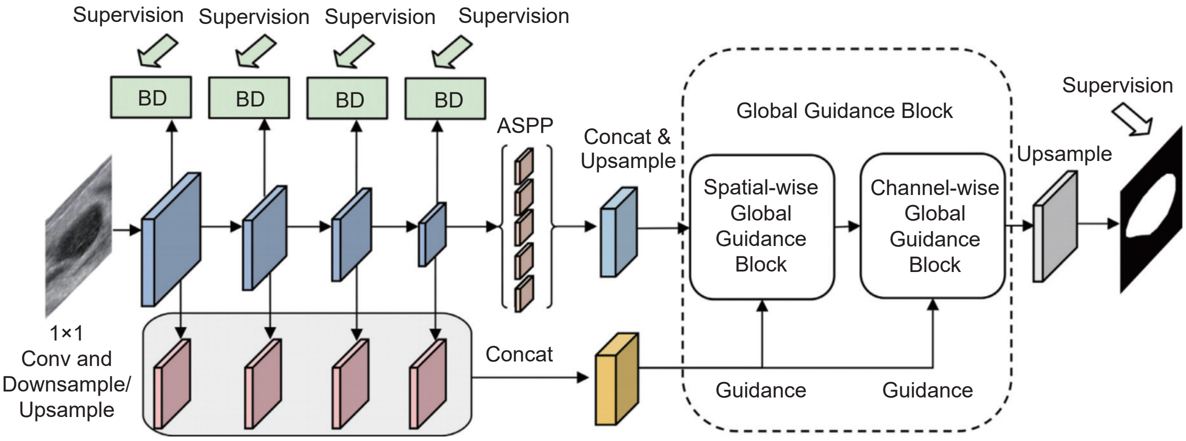


Figure 6 Schematic diagram of GG-Net [28].

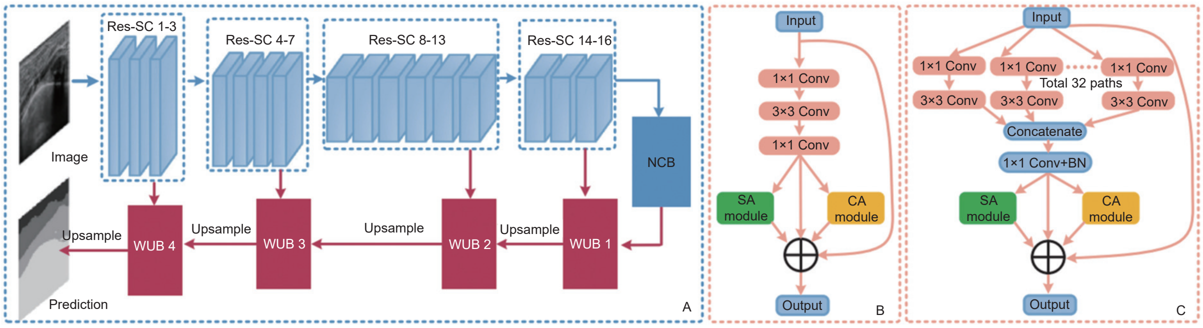


Figure 7 Schematic representation of the framework for the segmentation method utilizing a self-attention mechanism. (A) Network structure; (B) SC module integrated with ResNet; (C) SC module integrated with ResNeXt [36].

tion-guided tumor segmentation network for mixed-loss 3D ABUS images by combining an improved 3D Mask R-CNN head into the V-Net, thereby establishing a cross-model attention mechanism in multilevel segmentation features and aggregating the segmentation probability maps into the V-Net. Lei et al. [38] proposed a mask-scoring region-based convolutional neural network (R-CNN) that integrates network blocks to construct mask qualities directly related to region classes into a mask-scoring-based R-CNN framework for segmenting new ABUS images with fuzzy regions of interest.

Other ultrasound imaging techniques

SWE images are commonly used for the screening and auxiliary diagnosis of breast lesions. However, shear wave elastography methods suffer from poor imaging quality in regions far from the thrust position, particularly those that rely on a single focused ultrasound thrust beam to generate shear waves. Ahmed et al. [39] proposed a DSWE-Net network structure to construct Young's modulus maps from ultrasound-tracked tissue velocity data generated by a single acoustic radiant force (ARF) push. The algorithm features an innovative 3D encoder and dual 2D decoder structure integrated with a Convolutional Long Short-Term Memory (ConvLSTM) layer to effectively leverage the spatial and temporal information present in the input data, enabling inclusion segmentation through the generation of a binary mask. This study provides a broader perspective on the applicability of combining high-quality SWE imaging with breast lesion segmentation.

In segmentation using multimodal ultrasound images, recent research has emphasized the integration of two modalities: CEUS and standard grayscale ultrasound images. Meng et al. [40] constructed a U-shaped network with dual top-down branches and residual connections called CEUSegNet. The network utilizes the ultrasound and CEUS images from the dual CEUS image section as inputs. It incorporates two modules, cross-modal segmentation attention (CSA) and cross-modal feature fusion (CFF), to combine US and CEUS features at multiple scales, achieving a segmentation performance comparable to that of clinicians. Xie et al. [41] constructed a multimodal segmentation network called IMAN (Iterative Mutual Assistance network). The IMAN architecture features an innovative hourglass shape comprising two branches that separately process CEUS and US data, with each branch producing segmentation results for its corresponding modality. This structure effectively facilitates the mutual support of the two image modalities, making the IMAN network more robust and generalizable.

As shown in table 1, we created a table comparing the segmentation performance of various methods across different ultrasound imaging modalities. The four aspects of this study are summarized as follows: image types, methods used, datasets, and performance. The performance is evaluated in terms of Dice coefficients. Since different methods use different optimization methods, the datasets used are not the same between the various methods, but we can see that most of the segmentation studies on ultrasound use public breast datasets, such as BUSI and UDIAT, so the performance comparison is informative. Most segmentation models using BUSI have a performance above 82%, while most of the segmentation models using UDIAT have a performance above 86%. The latter is higher than the former, but the size of the BUSI dataset is much larger, which may be due to differences in image clarity, morphological distribution, and differences in the quality of annotation between the two datasets.

Classification of Breast Ultrasound Images

Beyond the challenges associated with breast ultrasound segmentation, several complex issues have arisen, including the absence of standardized image datasets for multiple imaging modalities, limited scalability of clinical datasets, small training sample sizes, and imbalances in category distribution, all of which create significant obstacles for breast tumor classification. Currently,

Table 1 Comparison of different breast ultrasound segmentation models.

Author	Image type	Year	Method	Dataset	Performance (Dice)
Xue C et al. [28]	B-mode	2021	GG-Net	BUSI/Private	87.10%/82.10%
Ning Z et al. [20]	B-mode	2021	SMU-Net	BUSI/UDIAT	88.27%/87.03%
Chen G et al. [21]	B-mode	2022	U-net + BAGNet + RFNet	BUSI	79.35%
Zhai D et al. [25]	B-mode	2022	ASSGAN	DBUI/SPDBUI/ADBUI	86.90%/93.91%/76.44%
Chen G et al. [29]	B-mode	2022	AAU-net	BUSI/UDIAT	77.51%/78.14%
Huang R et al. [26]	B-mode	2022	boundary-rendering	UDIAT	89.40%
Li Y et al. [23]	B-mode	2022	CAM-DLS	Private	77.30%
Cho S W et al. [33]	B-mode	2022	BTEC-Net + RFS-UNet	BUSI/UDIAT	84.86%/85.37%
Lou M et al. [30]	B-mode	2022	MCRNet	BUSI/UDIAT	82.31%/90.05%
Iqbal A et al. [31]	B-mode	2022	MDA-Net	UDIAT/BUSIS	87.68%/91.85%
Wu H et al. [27]	B-mode	2023	BUSSeg	BUSI/UDIAT	85.77%/88.11%
Chen G et al. [32]	B-mode	2023	NU-net	BUSI/UDIAT	78.62%/80.80%
Lei B et al. [36]	ABUS	2020	Self-attention + Res-SC + NCB	Private	86.60%
Lei Y et al. [38]	ABUS	2021	Mask scoring R-CNN	BUSI/UDIAT	82.31%/90.05%
Meng Z et al. [40]	US+CEUS	2022	CEUSegNet	Private	US: 91.05%, CEUS: 89.97%
Xie X et al. [41]	US+CEUS	2023	IMAN	Private	US: 83.96%, CEUS: 81.16%

machine learning methods are widely used to classify suspicious regions as normal, benign, or malignant [42]. The commonly used classification methods are Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), k-nearest neighbors (KNN), Random Forests (RF), and Extreme Learning Machine (ELM). In addition to this, researchers are currently proposing a variety of classification methods based on deep learning.

B-mode ultrasound

Numerous studies have focused on utilizing breast ultrasound images to assist in classifying the benign or malignant characteristics of breast tumors using CAD systems. To address the difficulty of confirming overfitting in conventional CAD systems, Moon et al. [43] developed a multi-image fusion breast tumor CAD diagnostic system based on a CNN architecture. The system employs an image fusion algorithm that uses operators to extract the tumor region image and tumor shape image (TSI) separately, generate a 3-channel fusion image using different images, and integrate the results generated from different underlying models.

To incorporate the guidance information provided by the Breast Imaging Reporting and Data System (BI-RADS) into deep-learning-based classification, Xing et al. [44] designed a BI-RADS Vector Attention Network (BVA Net), which is a model that is trained using both the texture and decoding information of the BI-RADS hierarchy, and its network schematic is shown in figure 8. Considering the BI-RADS as a routine evaluation method for clinical diagnosis, a method combining BVA Net binary classification with BI-RADS hierarchical estimation was designed to improve the sensitivity and specificity of the overall classification model.

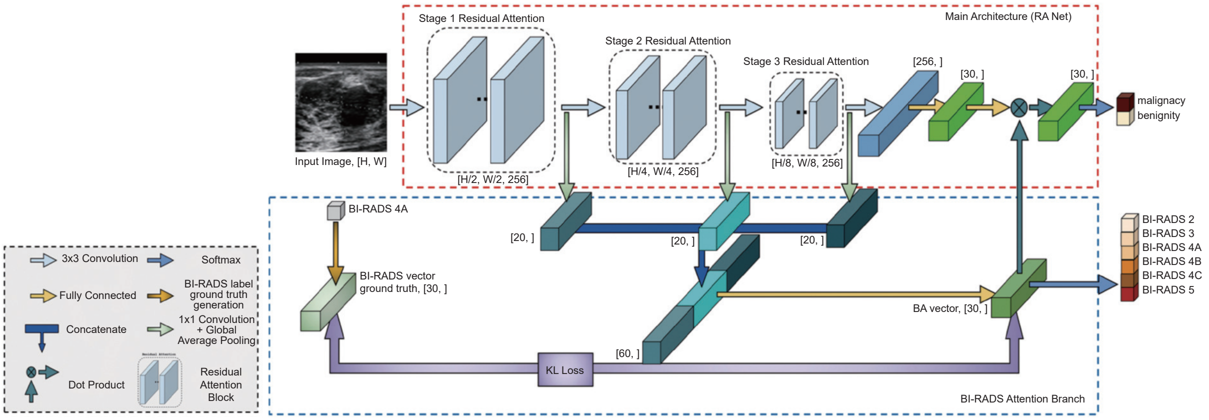


Figure 8 General schematic of the BVA Net. The BVA network consists of two parts, a main architecture (RA net) that applies spatial residual attention, and a BI-RADS attention branch that applies channel smart attention using BI-RADS hierarchy [44].

Ciritsis et al. [45] utilized a deep convolutional neural network (dCNN) for fully automated classification of breast ultrasound lesions. The method employs a hierarchical classification strategy that analyzes each region of the entire image step-by-step using a sliding window algorithm and classifies them according to the ACR BI-RADS catalog, which mimics the human decision-making process and obtains reliable and robust performance.

Traditional data enhancement methods are limited to medical image datasets with strict standards. In this regard, Dhabyani et al. [46] combined traditional enhancement methods with Generative Adversarial Network (GAN) enhancement methods and used CNN-based and migration learning methods for classification.

To address the limitations of many current artificial neural networks for breast cancer diagnosis, such as slow convergence and long training times, Bourouis et al. [47] proposed a CAD technique for breast lesions detection combining wavelet neural network (WNN) and gray wolf optimization (GWO) algorithms. The use of the GWO to correct the wavelet neural network parameters reduces the computational cost and training time, enhances the robustness of the GWO-WNN method, requires less training data, and achieves faster convergence.

Some integration work was performed by Ragab et al. [48], who developed a clinical decision support system for breast cancer diagnosis and classification (EDL-CDS-BCDC) by integrating various deep learning methods. The system uses a combination of the Chaotic Krill Herd Algorithm (CKHA) and the Kapur Entropy (KE) algorithm for image segmentation, integrates three models (VGG-16, VGG-19, and SqueezeNet) for feature extraction, and finally utilizes the Multilayer Perceptron (MLP) model for classification. Although the algorithmic structure is complex, this integration achieves excellent classification accuracy.

Ultrasound elastography

The application of ultrasound elastography faces many challenges, such as susceptibility to subjective manipulation and echo signal attenuation, leading to the formation of ultrasound artifacts. The miniaturization trend for ultrasound equipment is limited by hardware requirements. To enhance the imaging quality of ultrasound elastography and facilitate its acquisition, Yao et al. [49] proposed a generative adversarial Network (GAN)-based image synthesis model to directly convert conventional B-mode ultrasound images into virtual ultrasound elastography (V-EUS) images, which avoids artifacts resulting from the attenuation of actual ultrasound signals from deep tumors. This study experimentally verified that virtual EUS performs better than real EUS.

To evaluate the effectiveness of CNN-based deep learning approaches for differential breast tumor diagnosis in ultrasound SWE, Fujioka et al. [50] used several CNN architectures (Xception, InceptionV3, InceptionResNetV2, DenseNet121, DenseNet169, and NASNetMobile) to build and test deep learning models. The results showed that the CNN models performed just as well, or better than, the radiologists in diagnostic performance.

Shao et al. [51] introduced a new processing pipeline to classify breast tumor features based on S-wave data, which calculates bispectral features from RF time series, combines texture and spectral features of US and ultrasound elasticity images, reduces the feature dimensions using Random Forest Alignment Importance Sorting and Quadratic Mutual Information methods, and finally completes the classification using Support Vector Machines and Random Forest Classifier.

Xie et al. [52] developed a bimodal CNN architecture that combined US images surrounding the tumor with SWE images. The approach first automatically segmented the region based on the optimal width around the tumor on the SWE image and then integrated this segmentation model into the CNN-based classification model, enhancing the accuracy of SWE in diagnosing breast cancer.

Contrasted-enhanced ultrasound（*CEUS*）

CEUS is frequently used to diagnose breast tumors. Compared to static US images, CEUS videos offer more comprehensive information regarding tumor blood supply.

Researchers have observed that radiologists typically concentrate on specific time series when reviewing CEUS videos, while also noting the differences between CEUS frames and ultrasound images from that period. Inspired by this, Chen et al. [53] designed a 3D convolutional diagnostic model based on CEUS images, as shown in figure 9. The research team designed a domain knowledge-guided time-attention module (DKG-TAM) and a channel-attention module (DKG-CAM) to focus on time-domain information and feature-based domain information, respectively, allowing the model to concentrate on critical segments of CEUS videos.

Yang et al. [54] proposed a new network structure, the time-series dual branching network (TSDBN), to classify breast lesions for the first time by combining US and CEUS images. In the US branch, the features were extracted using the conventional ResNeXt network. In the CEUS branch, a time-series regression mechanism (TSRM) was developed to extract the enhanced features of CEUS videos, and a time-series shuffling mechanism

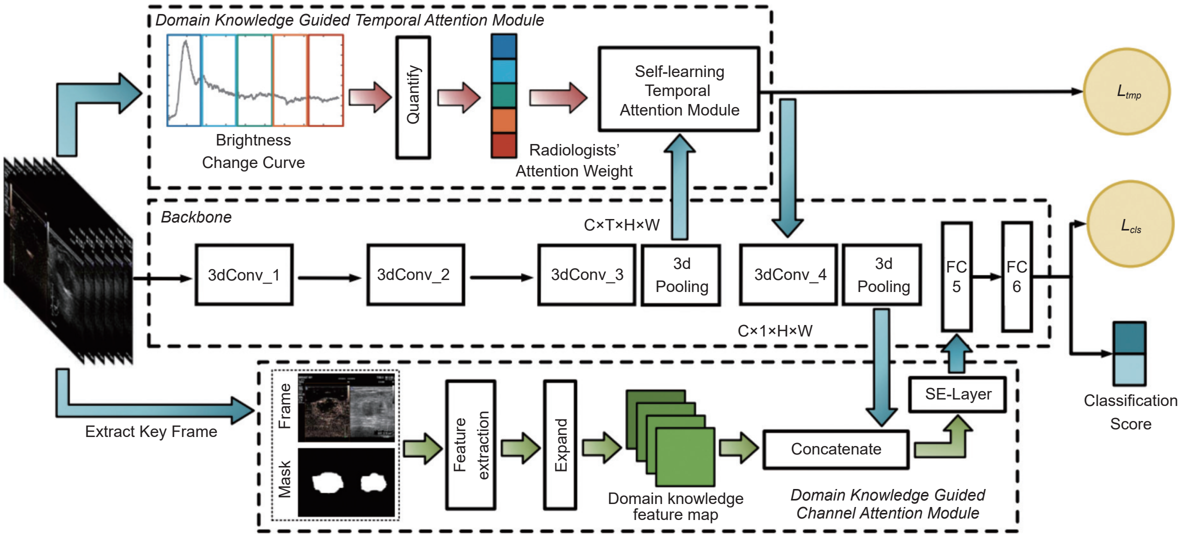


Figure 9 Schematic diagram of the architecture of the CEUS video-based diagnostic model by Chen et al. [53].

(STSM) was designed to shuffle the time series to further enhance inter-frame temporal information.

Li et al. [55] used a radiomics approach with attribute bagging to classify breast tumors using US and CEUS images. This study used an attribute bagging method for feature selection and classification, which enhanced the efficiency of radiomics feature utilization.

Gong et al. [56] designed a bimodal ultrasound network (BUS-Net) capable of simultaneously processing B-mode ultrasound and CEUS videos. The network adopted a two-branch structure using seven ultrasound pathology features as multiple labels in the CEUS branch; in the US branch, a set of shape descriptors was used to enhance the recognition of samples with morphological abnormalities.

To align with the radiologist's approach for analyzing CEUS images and directing the model's attention to keyframes while simulating the physician's spatial attention to the images, Guo et al. [57] designed a knowledge-enhanced multimodal breast cancer diagnostic method based on KAMnet, which introduced three types of a priori knowledge in the model. This method uses a period selection strategy based on Gaussian sampling, achieves feature fusion through decision-level integration, and directs spatial attention by synthesizing a spatial attention loss function.

Other ultrasound imaging techniques

In 3D ultrasound, Zhou et al. [58] proposed a 3D multiview tumor detection method for ABUS volume. To enhance the capability of the model to capture local texture features of small tumor images, a Faster R-CNN-based layer connectivity feature extraction network was designed, and the improved Faster R-CNN was used to reconstruct and detect orthogonal multiview slices, extract key 2D images, and fuse them with 3D multiview localization to obtain the final 3D detection results.

Hejduk et al. [59] also utilized ABUS images, performed data augmentation to train a deep convolutional neural network, and used a 3D sliding window approach to progressively evaluate regions of interest and accurately classify lesions based on BI-RADS mapping. This method achieved accuracy comparable to that achieved by an experienced radiologist.

In a related multimodal study, Qian et al. [60] constructed a bimodal neural network classification model for a joint B-mode ultrasound and color Doppler. In this study, US and color Doppler images were segmented separately to extract multimodal features, which were evaluated according to the BI-RADS catalog, quantified into BI-RADS category information, and added to the classification network to improve classification accuracy. Wang et al. [61] proposed the first method for automatically identifying breast tumors by combining four types of US: B-mode ultrasound, color Doppler, strain, and shear wave elastography. This study developed a novel multimodal framework that employs a weight-sharing strategy to promote interactions among various modalities. Clinically, radiologists usually complete the final diagnosis based on ultrasonography and the corresponding mammograms. Inspired by this, Atrey et al. [62] proposed a multimodal automatic classification system that combined features from mammograms and ultrasound images. The algorithm extracts 42 grayscale features from the multimodal images, and after evaluating several different machine learning classifiers, the classification is performed using a cubic support vector machine to obtain the optimal performance of this multimodal classification method.

As presented in table 2, we summarized the classifi-

Table 2 Comparison of breast ultrasound classification models.

Author	Image type	Year	Method	Dataset	Performance
Ciritsis A et al. [45]	B-mode US	2019	dCNN	Private	AUC: 0.838 (Internal)/ 0.967 (External)
Al-Dhabyani W et al. [46]	B-mode US	2019	NASNet + DAGAN	BUSI; UDIAT	ACC: 94% (BUSI); 99% (Combined)
Fujioka T et al. [50]	SWE	2020	DenseNet169	Private	AUC: 0.898; Sens: 85.7%
Li Y et al. [55]	B-mode + SWE + CEUS	2020	RAB (Radiomics + Attribute Bagging)	Private	ACC: 84.1%; AUC: 0.919
Moon W K et al. [43]	B-mode US	2020	Ensemble CNN (VGG, ResNet, DenseNet)	Private; BUSI	ACC: 94.6%; (BUSI); AUC: 0.97
Qian X et al. [60]	B-mode + Color Doppler	2020	CNN	Private	AUC: 0.982; Spec: 88.7%
Wang J et al. [61]	B-mode + Doppler + SWE + SE	2020	ResNet-18	Private	ACC: 95.4%; Sens: 96.1%
Yang Z et al. [54]	B-mode + CEUS	2020	TSDBN	Private	ACC: 90.2%; F1: 93.2%
Chen C et al. [53]	CEUS	2021	DKG-C3D (3D-CNN + Attention)	Private	ACC: 86.3%; Sens: 97.2%
Xing J et al. [44]	B-mode US	2021	BVA Net (ResNet-50 + Attention)	Private; UDIAT; BUSI	AUC: 0.91 (Private); AUC: 0.89 (BUSI)
Zhou Y et al. [51]	3D ABUS	2021	Faster R-CNN + Multi-view Analysis	Private	Sens: 95.1%
Bourouis S et al. [47]	B-mode US	2022	GWO-WNN	Public	ACC: 98.0%; Sens: 98.8%
Gong X et al. [56]	B-mode + CEUS	2022	BUS-Net (ResNet/R(2+1)D)	Private	ACC: 89.7%; AUC: 0.93
Hejduk P et al. [59]	3D ABUS	2022	dCNN + Sliding Window	Private	ACC: 90.9%
Ragab M et al. [48]	B-mode US	2022	Ensemble DL + CSO-MLP	BUSI	ACC: 97.1%; Spec: 97.7%
Shao Y et al. [51]	S-WAVE (RF Data)	2022	SVM/Random Forest	Private	AUC: 95%; Sens: 95%
Xie L et al. [52]	US + Peritumoral SWE	2023	EfficientNet-B0	Private	AUC: 0.93; ACC: 91%
Yao Z et al. [49]	Virtual EUS	2023	GAN (U-Net + Discriminator)	Private	V-EUS AUC: 0.75
Atrey K et al. [62]	US + Mammogram	2024	SVM (Cubic kernel)	Private	ACC: 98.8%; Spec: 99.3%
Guo D et al. [57]	B-mode + CEUS	2024	KAMnet (Knowledge-Augmented)	Private	ACC: 88.2%; Sens: 90.9%

cation performance of various deep learning and machine learning models across different ultrasound imaging modalities. This comparison encompasses five dimensions: image type (modality), method (backbone/classifier), key contributions, datasets, and quantitative performance. The performance is comprehensively assessed using indices including accuracy (ACC), sensitivity (Sens), specificity (Spec), and the area under the ROC curve (AUC).

Unlike the segmentation tasks in table 1 which frequently utilize public datasets, classification studies involving advanced modalities—such as Elastography, CEUS, and 3D ABUS—predominantly rely on private datasets due to the scarcity of open-source multi-modal data. The table illustrates a clear trend: while B-mode-based methods continue to evolve through attention mechanisms and auxiliary supervision (e.g., BI-RADS), multi-modal fusion strategies generally yield superior diagnostic accuracy. Specifically, models integrating temporal information from CEUS videos or stiffness data from Elastography consistently outperform single-modality baselines. Notably, several multi-modal fusion frameworks and 3D analysis methods achieve AUCs and sensitivities exceeding 95%, demonstrating the significant value of integrating complementary clinical information and domain knowledge into deep learning architectures.

Conclusion

This paper introduces ultrasound imaging techniques, such as B-mode ultrasound, ultrasound elastography, three-dimensional ultrasound, contrast-enhanced ultrasound, and color Doppler ultrasound, which are widely used in clinics at present, and reviews the latest research progress on the above types of ultrasound used for breast lesion diagnosis from the aspect of intelligent image segmentation and classification.

In breast ultrasound segmentation, many excellent segmentation studies have been inspired by the classical U-Net structure to improve performance by proposing new algorithmic modules and optimizing the network structure. Influenced by the Transformer architecture, which has yielded significant results in computer vision tasks recently, researchers have gradually made progress by introducing the attention mechanism into the segmentation network, designing various attention modules based on temporal relations and image space relations, and attempting to optimize the network's versatility and robustness while guaranteeing model segmentation accuracy. There are also different research ideas that innovatively propose various effective segmentation methods from new perspectives, such as the anatomical positional relationship of the breast, image morphology principles, ultrasound prototype image data, and imaging principles of different ultrasound imaging techniques.

Similarly, in breast ultrasound image classification, many classification models study algorithmic modules and network structures and introduce attention mechanisms to improve classification performance. However, compared to the various studies on segmentation mentioned above, the research ideas on classification are broader, such as extracting image features, introducing classification information with reference to the BI-RADS scoring method, and designing multistage image processing methods to assist classification. In addition, research on breast ultrasound classification has paid more attention to the fusion of multi-morphological information, including the feature fusion between different ultrasound imaging techniques and the feature fusion between multiple morphologies, such as ultrasound, X-ray, and MRI, and better research progress has been made.

However, in current research on breast ultrasound images, several critical challenges and research gaps remain. Common problems of medical image networks are still prevalent in both segmentation and classification, such as poor model generalization ability and poor training ability on small datasets. Although some studies have aimed to improve the generalizability of networks or have used data enhancement means and weak supervision methods to alleviate the problem of the small size of medical image datasets, these remain areas that require further attention in future research. Furthermore, the "black box" nature of deep learning models poses a significant barrier to clinical adoption, as radiologists often require transparent reasoning behind a diagnosis. The lack of standardized datasets and evaluation protocols across different ultrasound vendors also hinders the objective comparison of different CAD systems.

Looking forward, future research should focus on bridging the gap between algorithmic performance and clinical applicability. Most researchers are currently focusing on the segmentation and classification of one type of image, B-mode ultrasound, with relatively little attention being paid to other ultrasound imaging techniques. Considering that color Doppler, ultrasonography, and ultrasound elastography have been widely used in the clinical screening and diagnosis of breast lesions and that some studies have already achieved preliminary results, researchers can pay more attention to combining multimodal information from ultrasound and other ultrasound imaging techniques. Specifically, developing Explainable AI (XAI) techniques to visualize decision-making processes, and designing lightweight models for real-time deployment on portable devices, will be key directions. Simultaneously, more innovative segmentation and classification methods can be proposed based on the characteristics and principles of one or more of these imaging techniques as well as prior knowledge introduced by referring to the way radiologists read and analyze ultrasound images. In addition, clinical screening and diagnosis of breast lesions not only rely on reading medical images, but also need to pay attention to other aspects of the patient's basic information, so it is possible to consider that the relevant research based on multiple types of ultrasound images and other medical imaging, combined with other modal information such as clinical information and risk factors for breast cancer to help diagnose breast lesions, is of great potential.

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Authors' Contributions

LF, LYP, LZJ, and FLJ contributed to the conceptualization and design of the review. FLJ and LYP developed the methodology. FLJ and LN, LZL performed the investigation (literature search and data collection) and prepared the visualization (figures and tables). FLJ was responsible for writing the original draft. LYP and LF, LZJ provided supervision and contributed to funding acquisition. All authors contributed to editorial changes in the manuscript. All authors read and approved the final manuscript. All authors have participated sufficiently in the work and agreed to be accountable for all aspects of the work.

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Data Availability

Not applicable.

Declarations

Ethics approval and consent to participate

Not applicable.

Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Consent for publication

All authors approve the final manuscript for publication.

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