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Artificial intelligence advancements in breast cancer ultrasound screening

ZOU Mingchi*, RAN Haitao, YAO Yanfeng

**Department of Ultrasound, The Affiliated Yongchuan Hospital of Chongqing Medical University, Chongqing 402160, China*

Corresponding author: YAO Yanfeng, E-mail: yaoyanfeng111@163.com

Abstract: Ultrasound is the first-line screening method for breast cancer screening. The application of BI-RADS makes the ultrasound diagnosis of breast diseases relatively consistent, but it is still affected by subjective factors of operators. With the advancement of computer technology and the arrival of the era of big data, artificial intelligence has developed to the stage of deep learning. The performance of computer-aided diagnostic models based on deep learning has been continuously improved from2Dstatic image analysis to dynamic capture of lesions and keyframe analysis to automatic breast volume scanning and multi-modal research. The use of artificial intelligence in ultrasound can ease the strain caused by the lack of sonographers, help sonographers increase the consistency and accuracy of diagnosis, and play an important role in the process of breast cancer screening, diagnosis and treatment.

Keywords: Artificial intelligence; Deep learning; Imaging histology; Breast cancer； Ultrasound; Neoadjuvant chemotherapy; Lymph node metastasis; Sonographer

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Global cancer statistics 2021 showed that there were approximately 2.26 million new cases of breast cancer each year, making it the leading cancer globally [1]. Early detection, diagnosis, and accurate treatment of breast cancer can not only increase patients' survival rates, but also reduce the economic burden on families and healthcare systems [2]. Ultrasound is the primary screening method for breast cancer in China, with convenience, affordability, and safety. However, it lacks consistency and repeatability. With the development of artificial intelligence (AI), utilizing AI systems to assist ultrasound doctors in disease diagnosis has improved the consistency and accuracy of ultrasound diagnosis. This can also alleviate issues such as shortages of sonographer and repetitive image readings, potentially making it an important screening method for breast diseases in the future.

1 Screening Methods for Breast Cancer

Currently, common detection methods for breast cancer include X-ray examination, ultrasound examination, MRI examination, and histopathological biopsy. Among these, X-ray and ultrasound examinations are the most commonly used screening methods.

Ultrasound plays a crucial role in breast cancer screening in China, especially for women with dense breasts. 2D ultrasound is used to assess the nature of breast nodules based on characteristics such as margins, morphology, internal echoes, and microcalcifications. Benign nodules usually exhibit regular shapes and uniform internal echoes, while malignant nodules exhibit irregular shapes, angular margins, spicules, halos, changes in internal low echoes, microcalcifications, posterior acoustic attenuation, increased blood flow signals, high resistance index, and disordered ductal structures [3-4]. Microvascular ultrasound imaging is an emerging and unique Doppler ultrasound technique that provides superior visualization of small blood vessels in tissues, offering more information about vascular structures to doctors [5]. Studies had not found significant difference in diagnostic performance between contrast-enhanced ultrasound and superb microvascular imaging in the diagnosis of breast lesions, but superb microvascular imaging showed potential in the differential diagnosis of breast lesions [6].

Single-mode ultrasound cannot fully reflect the characteristics of breast lesions. With the emergence of new ultrasound technologies such as elastography, contrast-enhanced ultrasound, automated breast ultrasound, and ultrasound-mediated optical tomography, multimodal model can complement each other, providing more comprehensive information for diagnosis. Studies comparing conventional ultrasound with multimodal ultrasound showed that the sensitivity, specificity, positive predictive value, and negative predictive value of multimodal ultrasound were 93.4%, 94.2%, 90.5% and 96.1%, respectively, which were significantly higher than those of conventional ultrasound, contrast-enhanced ultrasonography, and elastography [7].

Breast cancer ultrasound screening in China mainly relies on manual handheld scanning probes, which cannot establish a standardized screening database. The levels of physician expertise vary, resulting in poor consistency and repeatability. Strengthening training to improve physician diagnostic skills and developing AI to replace some sonographers are important strategies to promote universal breast ultrasound screening.

2 AI Ultrasound-Assisted Breast Cancer Screening

2.1 Development of AI

AI has experienced three research waves since its inception in 1956. Early AI relied on rule-based expert systems, while the second wave relied mainly on machine learning. However, due to the "data hunger" of machine-based learning [8], it is difficult to meet the performance requirements of various clinical fields. The third wave of development benefits from the advancement of computer technology and the advent of the big data era, with deep learning becoming the mainstream of research.

Deep learning, a subset of machine learning, has better performance and greater potential for improvement compared to machine learning. Neural networks resemble brain neurons, consisting of input layers, hidden layers, and output layers. Deep neural networks have multiple hidden layers, with deeper features in the network coming from higher-level features of the previous layer and building more such features. Therefore, deep learning networks can self-train based on given data. Some automated tools based on convolutional neural networks and generative adversarial networks have been applied in oncology research [9-11], such as pathological diagnosis of tumors, elucidating molecular states from pathological data, and standardizing the imaging quality of pathological analysis [12]. Circulating neural networks focusing on the cardiovascular and cerebrovascular fields can achieve disease warning and prediction. Studies based on radiomics and convolutional neural networks have learned and analyzed images to complete basic tasks such as image classification, image segmentation, and object detection [13-16].

2.2 Development Research of AI in Breast Cancer Ultrasound Screening

2.2.1 Deep Learning Models Based on Static Ultrasound Images

The BI-RADS classification based on 2D features has been widely used in clinical practice and plays an important role in the standardized examination of breast ultrasound. The AI-based BI-RADS assessment has become an international standard for assessing malignant tumors [17], and many scholars are committed to developing AI models based on deep learning for the classification of breast tumors to improve diagnostic accuracy and consistency.

Hayashida *et al.* [18] established a deep learning-based AI system, which is capable of distinguishing ultrasound static images, classifying tumors as BI-RADS 3 or lower, BI-RADS 4a or higher, providing important recommendations for the management and treatment of breast patients. The system achieved a classification accuracy with an area under the receiver operating characteristic curve (AUC) of 0.95, which is significantly higher than diagnosis accuracy of sonographers. Gu *et al.* [19] collected 14,043 breast ultrasound images from 32 hospitals to develop a deep learning model. With the model assistance, the accuracy and specificity of sonographers were significantly improved, while sensitivity remained unchanged. Shen *et al.* [20] reported an AI system for breast cancer diagnosis, with higher diagnostic value than the average of diagnoses from 10 breast sonographers (AUC=0.962). With assistance of AI, the false positive rate of breast cancer diagnosis by sonographers decreased by 37.3%, and the rate of required biopsies reduced by 27.8%, while maintaining the same sensitivity. Di *et al.* [21] constructed a hierarchical dense feature aggregation network, a highly accurate classification model for ultrasound breast lesion classification. Results from validation on three datasets indicated that its diagnostic performance exceeded several state-of-the-art deep learning methods. Training deep learning models in a fully supervised manner requires annotation of regions of interest, which consumes time and manpower and is susceptible to human factors. Kim *et al.* [22] developed a weakly supervised deep learning algorithm based on ultrasound images that does not require image annotation. In both internal and external validation sets, the weakly supervised deep learning algorithm showed no statistically significant difference in AUC values compared to fully supervised deep learning algorithms, indicating its good localization and differential diagnostic capabilities for breast masses. Zhu *et al.* [23] developed a deep convolutional neural network-based model for classifying thyroid and breast lesions in ultrasound images and proposed a generic deep convolutional architecture with transfer learning and identical architectural parameter settings. Results showed that both TNet and BNet constructed on this architecture achieved good classification results. When using TNet to classify breast lesions, the model achieved a sensitivity of 86.6% and specificity of 87.1%, demonstrating its ability to learn features commonly shared by thyroid and breast lesions. The AUC for breast cancer classification by the TNet model was 0.875, higher than that of radiologists, indicating that the model had higher accuracy in breast cancer classification than radiologists.

2.2.2 Model Research Based on Dynamic Ultrasound Videos

Static AI analysis mainly relies on sonographers manually detecting lesions and selecting key frames, which cannot truly capture and comprehensively analyze images and overlooks the influence of key frame selection. Therefore, it is necessary to develop an analysis model based on real-time dynamic videos to address the problem of single-angle plane wave ultrasound. Huang *et al.* [24] proposed a framework based on deep learning that can automatically extract key frames from variable-length breast ultrasound videos. It is equipped with a nodules-based filtering module and feedback mechanism, integrating the anatomical and diagnostic features of lesions into key frame search. It also designed a simple and effective loss function to alleviate the imbalance in nodule classification. Experiments with these two innovative designs showed that the framework could generate representative key frame sequences under various screening conditions, effectively addressing the problem of AI key frame capture.

Contrast-enhanced ultrasound can display dynamically microcirculation of organ perfusion in real-time. Its application in the breast has gradually matured, and the detection of microvessels can improve the diagnostic accuracy of breast diseases [25-26]. In 2021, Chen *et al.* [27] proposed a novel diagnostic model based on breast contrast-enhanced ultrasound videos. The backbone of this model is a 3D convolutional neural network. Sonographers usually focus on two specific patterns when reviewing contrast-enhanced videos: the time difference of contrast-agent-based perfusion and the difference between contrast-enhanced ultrasound and conventional ultrasound images. These two patterns were integrated into an AI deep learning model, which included a domain knowledge-guided temporal attention module and a channel attention module. Validated on a dataset consisting of 221 cases, the model achieved a sensitivity of 97.2% and an accuracy of 86.3% for breast cancer diagnosis. The establishment of this model further opened up research into multimodal ultrasound-guided AI.

2.2.3 3D Automated Breast Ultrasound Imaging

3D automated breast ultrasound does not rely excessively on operators and has advantages such as preserving standardized images and providing more comprehensive scans for multiple nodules and non-mass lesions. Comparing the diagnostic performance of automated breast volume ultrasound systems and handheld ultrasound in detecting and classifying dense breast lesions, it was found that they exhibited good consistency (kappa=0.66, $P<0.01$), indicating that 3D automated breast volume ultrasound is a reliable method for detecting malignant tumors in dense breasts. The fusion of 3D ultrasound and AI has become an inevitable trend. Hejduk *et al.* [28] developed a deep learning network for automatic classification of automated breast ultrasound (ABUS) volume images according to the BI-RADS. In a comparative study with two radiologists, the deep learning model exhibited similar sensitivity and higher specificity, positive predictive value, and negative predictive value, and achieved an AUC of 0.91, comparable to the radiologists' AUCs of 0.82 and 0.91. This indicates that the developed deep learning model can detect and classify breast lesions in ABUS, achieving classification accuracy similar to that of sonographers. Scholars have found that computer-assisted automatic breast volume imaging systems can help sonographers shorten reading time, improve reading efficiency, and achieve high detection sensitivity and low false positivity [29-30]. The fully automatic breast ultrasound scanning robot (artificial intelligence breast ultrasound diagnosis system, AIBUS) is used for breast examination without the need for sonographers. The robot automatically scans based on breast morphology, with short scanning time. The images obtained can be transmitted to the cloud in real time and can achieve multi-terminal remote reading. Yu *et al.* [31] compared AIBUS with handheld ultrasound in terms of the detection rate, coincidence rate, misdiagnosis rate, and examination time for breast cancer. The results showed that AIBUS had a higher ultrasound detection rate and shorter examination time, enabling rapid completion of screening work. It can be used in conjunction with handheld ultrasound to achieve complementary advantages. AIBUS can be operated by general technical personnel, which can alleviate the shortage of physicians in breast cancer screening. AIBUS can scan multiple planes, permanently save standard images, and establish a database with good repeatability and consistency, making it a good means of breast cancer screening in the future.

2.2.4 Imaging Omics Prediction of Pathological Classification Based on Ultrasound Deep Learning

With the further development of AI, scholars are no longer satisfied with capturing lesions through AI and diagnosing them based on BI-RADS classification. They also hope to use AI to propose molecular subtyping or histopathological subtyping of breast cancer. The molecular subtypes of breast cancer are mainly determined by immunohistochemistry and genetics, and biopsy-based pathological detection has false negative results. Ultrasonic radiomics is expected to become a new guide for the histopathological subtyping of breast cancer [32]. Zhou *et al.* [33] constructed a convolutional neural network model for preoperatively predicting molecular subtypes using multimodal ultrasound images, with pathological results as the gold standard. The model achieved satisfactory predictive performance in predicting 4-class and 5-class molecular subtypes and identifying triple-negative subtypes from non-triple-negative subtypes. A multicenter retrospective study showed that a deep convolutional neural network based on preprocessed ultrasound images had an accuracy of 97.02% in predicting the four molecular subtypes of breast cancer, and also had good diagnostic performance in distinguishing intraductal from extralobular diseases [34].

3 AI Ultrasound Prediction of Neoadjuvant Chemotherapy (NAC) Prognosis

NAC shows significant individual differences in the treatment of breast cancer patients, so timely adjustment of treatment plans is crucial. Liu *et al.* [35] developed a multitask Siamese network to predict the efficacy of HER2-positive breast cancer patients in the early stage of NAC. The results showed that the AUC value of the network in the internal and external validation sets was significantly higher than that of the clinical model, which helps clinical physicians adjust treatment plans in a timely manner. Jiang *et al.* [36] developed radiotherapy nomogram based on deep learning ultrasound, which can provide valuable information for individualized treatment. Gu *et al.* [37] developed two deep learning radiomic models for predicting the response after the second and fourth cycles of NAC, and combined these two models to propose a deep learning radiomic pipeline (DLRP) for gradually predicting responses at different times of NAC. The results showed that the predictive accuracy of the two models reached 0.81 and 0.94, respectively. The pipeline model can predict early response to NAC to determine further personalized treatment plans.

4 AI Ultrasound Prediction of Lymph Node Metastasis in Breast Cancer

Axillary lymph nodes are a common site of metastasis of breast cancer. The status of axillary lymph nodes is a key indicator for evaluating the tumor staging of breast cancer patients and determining treatment strategies. In order to better understand their status and reduce the incidence of postoperative complications, a non-invasive and effective method is needed to assess the status of axillary lymph nodes [38]. A multicenter study showed that deep learning models can effectively predict clinically negative axillary lymph node metastasis, providing an early diagnostic strategy for lymph node metastasis in breast cancer patients with lymph node-negative [39]. AI can be used to predict whether there is metastasis in axillary lymph nodes, with a sensitivity of 77.1%, a positive predictive value of 77.1%, and an AUC value of 0.78, comparable to trained radiologists [40]. NAC can reduce the staging of tumor and axillary lymph nodes in breast cancer patients. However, the response of tumors and axillary lymph nodes to NAC is not parallel and varies from patient to patient. Scholars have studied the feasibility of independently predicting lymph node metastasis using deep learning radiotherapy nomogram, and the AUC values in the validation and test sets were 0.853 and 0.863, respectively, with specificities of 82.0% and 81.8%, and negative predictive values of 81.3% and 87.2%, achieving satisfactory predictive performance [41].

5 Summary and Outlook

Most deep learning models based on neural networks have demonstrate superior diagnostic performance. The field of AI has evolved from the analysis of static ultrasound images to capturing and analyzing dynamic video key frames, as well as the development of fully automatic AIBUS scanning and analysis. Monomodal AI ultrasound has achieved significant progress. In the future, there is potential to integrate examination techniques such as elastography and contrast-enhanced ultrasound into the research on multimodal AI ultrasound, apart from increasing international large-sample multicenter studies to optimize AI models. In China, the coverage of early breast cancer screening is very limited. AI ultrasound has the potential to partially alleviate the shortage of sonographers, reduce human biases, improve screening efficiency, and enhance diagnostic efficacy. However, as AI has not yet achieved algorithmic breakthroughs, it is primary used to assist sonographers in refining diagnoses. Scholars need to develop and explore further, aiming to enable the widespread application of fully automated AI ultrasound in breast disease screening. Additionally, AI ultrasound based on radiomics, holds promise for predicting pathological subtypes, forecasting outcomes of NAC, and predicting lymph node metastasis in breast cancer, all of which require further in-depth research.

Conflicts of interest: None

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· 研究进展 ·

人工智能在乳腺癌超声筛查中的应用进展

邹明池[1]，　冉海涛[2]，　姚延峰[1,2]

1. 重庆医科大学附属永川医院超声科，重庆 402160；

2. 重庆医科大学超声影像学研究所，重庆 400010

摘要： 超声是乳腺癌筛查的一线检查方法，BI-RADS 的应用使超声对乳腺疾病的诊断具有相对一致性，但仍不同程度受操作者主观因素影响。随着计算机技术的发展和大数据时代的到来，人工智能乳腺超声从基于二维静态图像分析、到动态捕获病灶和关键帧分析、到全自动乳腺容积扫查和多模态研究，基于深度学习建立的计算机辅助诊断模型性能不断提升和完善。人工智能超声的应用可辅助超声医师提高诊断的准确性和一致性，在乳腺癌的筛查和诊疗过程中具有重要价值。

关键词： 人工智能；深度学习；影像组学；乳腺癌；超声；新辅助化疗；淋巴结转移；超声医师

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ZOU Mingchi*, RAN Haitao, YAO Yanfeng

** Department of Ultrasound, The Affiliated Yongchuan Hospital of Chongqing Medical University, Chongqing 402160, China*

Corresponding author: YAO Yanfeng, E-mail: yaoyanfeng111@163.com

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Keywords: Artificial intelligence; Deep learning; Imaging histology; Breast cancer; Ultrasound; Neoadjuvant chemotherapy; Lymph node metastasis; Sonographer

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2021 年全球癌症统计数据显示乳腺癌每年新增达 226 万例，已成为全球第一大癌症[1]。对乳腺癌进行早期发现、早期诊断、提高诊断的准确性、早期治疗，既能增加患者的生存机会又能降低疾病给家庭和卫生系统带来的经济负担[2]。超声是我国乳腺癌的主要筛查方法，具有便捷、便宜、安全的特点，但一致性和重复性欠佳。随着人工智能技术（artificial intelligence, AI）的发展，由 AI 系统辅助超声医生进行疾病诊断提高了超声诊断的一致性和准确性，可缓解超声医师短缺、重复读片等问题，未来有望成为乳腺疾病的重要筛查方式。

1　乳腺癌的筛查手段

目前临床上乳腺癌常用检出方式主要有 X 线检查、超声检查、MRI 检查、组织学活检等，其中 X 线和超声检查是最常用的筛查手段。

超声在我国乳腺癌筛查中起着重要作用，特别是对于致密型乳腺的女性。二维超声判断乳腺结节性质的依据主要为边缘、形态、内部回声、微钙化等。良性结节多表现为形态规则，内部回声均匀；恶性结节的征象主要包括形状不规则、边缘成角、毛刺、晕、内部低回声改变、微钙化、后方回声衰减、血流信号增多及阻力指数高、导管结构紊乱等[3-4]。微血管超声成像是新兴和独特的多普勒超声技术。它使用先进的杂波滤波器，去除杂波伪影并保留低速微血管流动信号。微血管超声检查的优点是其在检测和可视化组织中小血管方面的优越性，为医生提供了有关血管结构的更多信息[5]。Xiao 等[6]通过比较造影剂增强超声微血管成像和精湛微血管成像在乳

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通信作者： 姚延峰，E-mail：yaoyanfeng111@163.com

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QR code for English version

腺病变中的诊断性能,得出两者的诊断性能没有显著差异,但精湛微血管成像在乳腺病变的鉴别诊断方面具有潜力。

单模态超声并不能全面反应乳腺病变特征,随着弹性成像、超声造影、自动乳腺全容积成像、超声光散射断层成像等超声新技术的出现,多模态联合使用可以相互补充,为诊断提供更全面的信息。任少杰等[7]对比常规超声与多模态超声的诊断性能,发现多模态超声联合诊断的敏感度为 93.4%,特异度为 94.2%,阳性预测值为 90.5%,阴性预测值为 96.1%,均显著高于单独使用常规超声、超声造影及弹性成像。

我国乳腺癌超声筛查主要基于人工手持式探头扫查,无法建立标准筛查数据库,医师水平参差不齐,一致性和重复性差,加强培训提高医师诊断水平、发展 AI 辅助超声医师是解决全民乳腺超声筛查的重要方案。

2　AI 超声辅助乳腺癌筛查

2.1　*AI 的发展进程*　AI 自 1956 年诞生至今经历了三次研究热潮。早期 AI 基于规则的专家系统,而第二次研究热潮主要基于机器学习,但机器学习存在“数据饥渴”[8],很难达到临床各领域的性能要求。第三波发展热潮则得益于计算机技术的发展和大数据时代的到来,深度学习成为研究的主流。

深度学习是机器学习的子集,相比机器学习具有更好的性能以及更大的提升空间。神经网络类似于大脑神经元,由输入层、隐藏层、输出层构成,深度神经网络有多个隐藏层,网络的特征来自前一层的高级特征并构建更多此类特征,因此,深度学习网络可以根据给定的数据进行自我训练。一些基于卷积神经网络、生成对抗网络的自动化工具被应用于肿瘤学的研究[9-11],例如肿瘤的病理诊断,从病理数据中阐明分子状态,标准化病理分析的成像质量[12];聚焦于心脑血管领域的循环神经网络,可以实现对疾病的预警和预测;基于影像组学、卷积神经网络等的研究,对图像进行学习和分析,进而完成图像分类、图像分割[13-14]和目标检测[15-16]等基本任务。

2.2　*AI 在乳腺癌超声筛查中的开发研究*

2.2.1　基于超声静态图像的深度学习模型　基于二维特征的 BI-RADS 分类已广泛应用于临床,对乳腺超声的规范化检查起到了重要作用。结合 AI 的 BI-RADS 评估方法在国际上已经成为衡量恶性肿瘤的标准[17],诸多学者致力于开发基于深度学习的 AI 模型用于乳腺肿瘤的分类以提高诊断的准确性和一致性。

Hayashida 等[18]建立了一套基于深度学习的 AI 系统,AI 可以区分超声静态图像,将肿瘤分类为 BI-RADS 3 级或更低、BI-RADS 4a 级或更高,为乳腺患者管理和治疗提供重要建议。该系统实现了 ROC 曲线下面积(area under curve, AUC)为0.95 的分类精度,其诊断的准确性明显优于影像医生。Gu 等[19]使用大型数据集从 32 家医院收集了 14 043 张乳腺超声图像开发了一个深度学习模型,在模型辅助后,医师的准确性和特异性得到了显著提高,而敏感性没有降低。Shen 等[20]的 AI 系统用于乳腺癌的诊断,该系统诊断乳腺癌的价值高于十位乳腺超声医师的平均值(AUC=0.962)。在 AI 的帮助下,超声医生诊断乳腺癌的假阳性率降低了 37.3%,并将要求的活检减少了 27.8%,同时保持了相同的灵敏度水平。Di 等[21]构建了一种显著图引导的分层密集特征聚合框架,即一种高精度的分类模型,用于超声乳腺病变分类,在三个数据集上验证后结果表明,它的诊断性能优于几种最先进的深度学习方法。使用全监督方式训练深度学习模型时需要注解兴趣区,这样会消耗时间和人力,而且会受到人为因素的影响。Kim 等[22]基于超声图像开发了一种无需图像注释的弱监督深度学习算法,在内外部验证集中,弱监督深度学习算法与全监督深度学习算法 AUC 值差异无统计学意义,这表明这种弱监督算法对乳腺肿块有良好的定位和鉴别诊断功能。Zhu 等[23]开发了一种基于深度卷积神经网络对超声图像中的甲状腺和乳腺病变进行分类的模型,并提出了一种具有迁移学习和相同架构参数设置的通用深度卷积架构,结果表明,在该架构上构建的 TNet 和 BNet 都取得了良好的分类结果,在使用 TNet 对乳房病变进行分类时,该模型的灵敏度达到86.6%,特异性达到87.1%,表明其学习甲状腺和乳房病变通常共享的特征的能力。其中 TNet 模型的乳腺癌分类 AUC 为0.875 高于放射医生的 AUC,表明该模型在乳腺癌分类方面具有比放射科医生更高的精度。

2.2.2　基于超声动态视频的模型研究　AI 静态分析主要依靠超声医生手动检出病灶和选择关键帧,不能让 AI 真正捕获和全面分析图像,也忽略了关键帧选择的影响,因此需要研发基于实时动态视频的分析模型以改善静态超声单一切面的问题。Huang 等[24]提出的基于深度强化学习的框架可以自动从非固定长度的乳腺超声视频中提取关键帧,它配备了基于检测结节的过滤模块和反馈机制,可以将病变的解剖和诊断特征整合到关键帧搜索中,它还设计了一个简单有效的损失函数来缓解结节分类不平衡问题,通过这两种创新设计后实验表明,该框架能够在各种筛选条件下生成具有代表性的关键帧序列,有效解决了 AI 捕获关键帧图像问题。

超声造影能实时动态显示脏器微循环灌注,在乳腺的应用逐渐成熟,肿瘤的生长和转移离不开新生血管的形成,因此微细血管的检出能提高乳腺疾病的诊断准确性[25-26]。2021 年,Chen 等[27]提出了基于乳腺超声造影视频的新型诊断模型,该模型的主干是一个 3D 卷积神经网络,研究者注意到超声医生在浏览造影视频时通常关注两种特定模式,一是造影剂灌注的时间差异,二是超声造影和常规超声图像之间的差异,研究将这两种模式整合到 AI 深度学习模型中,设计了一个领域知识引导的时间注意模块和一个通道注意模块,在由 221 个病例组成数据集上验证,该模型对于乳腺癌的诊断可以达到 97.2%的灵敏度和 86.3%的准确率,这种模型的建立也进一步开启了多模态 AI 超声的研究。

2.2.3　基于三维成像的 AI 乳腺超声扫查　三维自动乳腺容积超声不需过度依赖操作人员,具有保存标准化图像、对多发结节和非肿块型癌扫查更全面等优势,通过比较自动乳腺超声系统与手持超声在致密乳房病变检测与分类方面的诊断性能,得出自动乳腺超声系统与手持超声具有良好的一致性(kappa=0.66, $P<0.01$),这表明三维自动乳腺容积超声是

检测致密乳房恶性肿瘤的可靠方法。三维超声与 AI 的融合成为必然的发展趋势。Hejduk 等[28]开发了基于深度学习网络根据 BI-RADS 对自动乳腺容积成像的图像进行全自动分类的后处理技术,在该模型和两位放射科医生的比较研究中,深度学习模型产生的 AUC 为 0.91,与放射科医生 AUC 0.82、0.91 相当。该模型显示出相似的敏感性以及更高的特异性,阳性预测值和阴性预测值。这表明,开发的深度学习模型可以检测并分类 ABUS 中的乳腺病变,实现了与超声科医师相似的分类精度。有学者研究发现计算机辅助的自动乳腺容积成像系统能帮助超声医生缩短阅片时间,提高阅片效率,同时获得高检测灵敏度和低假阳性[29-30]。人工智能乳腺超声诊断系统(artificial intelligence breast ultrasound diagnosis system, AIBUS)可根据乳房形态实现自动扫查,扫查时间短,获取的图像可以实时传输到云端,并可实现多终端远程读片。于馨等[31]比较了 AIBUS 和手持超声对乳腺癌的检出率、符合率、误诊率以及检查时间的差异,结果表明 AIBUS 有较高的超声检出率和较短的检查时间,能快速完成筛查工作,并可联合手持超声实现优势互补。AIBUS 可由一般技术人员操作,在乳腺癌筛查工作中可缓解医师短缺问题,且 AIBUS 可多个切面扫查、永久保存标准图像和建立数据库,重复性和一致性较好,未来将是乳腺筛查的良好检查手段。

2.2.4　基于超声深度学习的影像组学预测病理分型　随着 AI 进一步发展,学者们已不满足于仅通过 AI 捕获病灶和基于 BI-RADS 分类的诊断,又期望通过 AI 提出对乳腺癌进行分子分型或组织学病理分型的可能。乳腺癌的分子亚型主要通过免疫组化来确定,而基于活检的病理检测存在假阴性的结果,超声放射组学有望成为乳腺癌病理分型的新指导[32]。Zhou 等[33]构建的卷积神经网络模型,用于使用多模态超声图像进行分子亚型的术前预测,以病理结果为金标准,该模型在预测 4 类和 5 类分子亚型以及从非三阴性亚型中识别三阴性乳腺癌获得了令人满意的预测性能。一项多中心回顾性研究表明,源自预处理超声图像的深度卷积神经网络对乳腺癌四种分子亚型的预测准确率可达 97.02%,且在区分导管内和导管外疾病方面也具有良好的诊断效能[34]。

3　AI 超声预测新辅助化疗预后

新辅助化疗对乳腺癌患者的治疗存在较大的个体差异,因此,及时调整治疗方案是至关重要的。Liu 等[35]开发了一种孪生多任务网络模型,用于预测 HER-2 阳性乳腺癌患者在新辅助化疗早期阶段疗效,结果表明该网络在内外部验证集中的 AUC 值均显著高于临床模型,有助于临床医生及时调整治疗方案。Jiang 等[36]开发了基于超声深度学习放射组列线图,可为个体化治疗提供有价值的信息。Gu 等[37]开发了两个深度学习放射组学模型,可用于预测新辅助化疗第二和第四疗程后的反应,并结合这两个模型提出了深度学习放射组学管道(DLRP),用于逐步预测新辅助化疗给药不同时间点的反应,结果表明两种模型的预测精度分别达到了 0.81 和 0.94,管道模型可用于预测早期对新辅助化疗的反应以助医生确定进一步的治疗方案。

4　AI 超声预测乳腺癌淋巴结转移

腋窝淋巴结是乳腺癌常见的转移部位,腋窝淋巴结状态是评估乳腺癌患者癌症分期和决定治疗策略的关键指标,为了更好地了解其状态并减少术后并发症的发生率,需要一种无创且有效的方法来评估腋窝淋巴结状态[38]。一项多中心研究表明,深度学习模型可有效预测临床阴性腋窝淋巴结转移,为临床淋巴结阴性的乳腺癌患者的淋巴结转移提供早期诊断策略[39]。AI 可用于预测腋窝淋巴结是否存在转移,其灵敏度为 77.1%,阳性预测值为 77.1%,AUC=0.78,具有与训练有素的放射科医生相当的性能[40]。新辅助化疗可以降低乳腺癌患者的肿瘤和腋窝淋巴结分期。然而,肿瘤和腋窝淋巴结对新辅助化疗的反应并不平行,并且因患者而异。有学者通过研究深度学习影像组学列线图独立预测淋巴结转移的可行性,得出在验证和测试队列中的 AUC 分别为 0.853 和 0.863,特异性为 82.0%和 81.8%,阴性预测值分别为 81.3%和 87.2%,取得了令人满意的预测性能[41]。

5　总结与展望

国内外学者基于神经网络构建各种深度学习模型,大都显示出优越的诊断性能,AI 从聚焦静态超声图像分析,到动态视频关键帧的捕获和分析,到 AIBUS 全自动扫查和分析,单模态 AI 超声取得了长足的发展,未来除了增加国际化大样本多中心的研究来优化 AI 模型外,还可融合弹性成像、超声造影等检查技术,对多模态 AI 超声进一步研究。我国乳腺癌的早期筛查工作覆盖面非常有限,AI 超声能部分缓解医师短缺、减少人为影响、提高筛查效率和诊断效能,但由于 AI 尚未实现算法突破,目前 AI 主要用于辅助超声医师校正诊断,有待更多学者去开发和探索,让全自动 AI 超声早日广泛应用于乳腺疾病筛查。另外,AI 超声基于影像组学预测病理分型、预测新辅助化疗预后、预测乳腺癌淋巴结转移均有待进一步深入研究。

利益冲突　无

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