

Applications of Artificial Intelligence in Automated Breast Ultrasound

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Automated breast ultrasound (ABUS) is becoming a powerful complementary imaging modality of mammography. Due to its enormous data size, the exploitation of ABUS computer-aided detection and diagnosis (CAD) systems is crucial in the time-consuming screening process. Conventional ABUS-CAD systems containing extensive image processing, hand-crafted feature extraction, and classification modules suffer from low generalization capability. Recently deep learning (DL) has been applied successfully in advanced ABUS-CAD systems given sufficient data and supplementary techniques such as data augmentation and transfer learning. In this study, we investigate underlying artificial intelligence techniques of ABUS-CAD systems with their clinical applications in the literature.

Index words: Breast; Automated Breast Ultrasound; Artificial Intelligence; Computer-Aided Detection; Computer-Aided Diagnosis

Introduction

Breast cancer is the most commonly diagnosed cancer and the leading cause of cancer death in females in 2020 (1). Hence, early detection and treatment of breast cancer are significant and increase the survival rate highly (2). Among several imaging modalities, ultrasound is a powerful screening tool for dense breasts in

specific (3). However, conventional hand-held ultrasound (HHUS) has limitations such as lack of standardization, the requirement for a high level of skill and experience, long acquisition time, and the small field of view (FOV) (4). Recently, automated breast ultrasound (ABUS) has been proposed as a new imaging technique for resolving these limitations. Unlike HHUS, ABUS provides low operator dependency, high reproducibility and resolution, and a wide field of view (4).

Although ABUS is an efficient screening modality with diagnostic performance comparable to HHUS, the time and effort required for interpretation are huge. Therefore, the utilization of computer-aided detection and diagnosis (CAD)

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systems can supplement the limitation of ABUS. Specifically, deep learning (DL) algorithms have been successfully adopted to configure ABUS-CAD systems in medical applications latterly. Figure 1 shows the overview of the conventional and DL-based ABUS-CAD systems. In this study, we present the methodological concerns in ABUS-CAD systems, including the challenges and demands. Furthermore, we provide existing and potential clinical applications of the ABUS-CAD systems.

Methodological Consideration

Developing ABUS-CAD systems has become an attractive research topic due to its impact on efficiency for the time-consuming reviewing process. Those pioneering works at the early phase utilize conventional artificial intelligence methods, which perform a series of image pre-processing, feature extraction, and classification procedures in general. Ikedo et al. (5) adopted a series of techniques such as the Canny edge detector (6), watershed transformation (7), and quadratic discriminant analysis (8) for breast mass detection. They reported a sensitivity of 80.6% with 3.8 false positives (FPs) per case using 109 volumes. Chang et al. (9) proposed to extract a set of features regarding the shape and intensity of a tumorlike region after image enhancement using digital

filters and grey-level slicing (10). They achieved a sensitivity of 92.3% with 1.76 FPs per case on a dataset consisting of 25 ABUS cases.

Moon et al. (11) proposed to estimate tumor likelihoods using a logistic regression model (12) and blobness, internal echo, and morphology features, where sensitivities of 70.0%–100.0% with 2.7–17.4 FPs per case for tumor detection were reported on a dataset consisting of 159 ABUS cases. Similarly, Tan et al. (13) adopted various classifiers such as the support vector machine (14) and artificial neural networks (15) on coronal spiculation patterns, blobness, contrast, and depth features for lesion mass detection. They achieved sensitivities of 64.0%–70.0% with 1.0–2.0 FPs per volume using 348 volumes. These pioneering works at the early stage utilize relatively extensive image pre-processing techniques and extract hand-crafted features. Subsequently, well-known classifiers are adopted to obtain a classification outcome. Hence, the methods show low generalization capability, and the size of the utilized dataset is relatively small.

Recently, DL has been actively adopted in healthcare and medicine (16) due to its high generalization capability. Multi-view convolutional neural networks (CNN) based on a modified Inception-v3 model (17) were proposed for patch-based breast cancer classification (18). A sensitivity of 88.6% and a specificity of 87.6% were reported

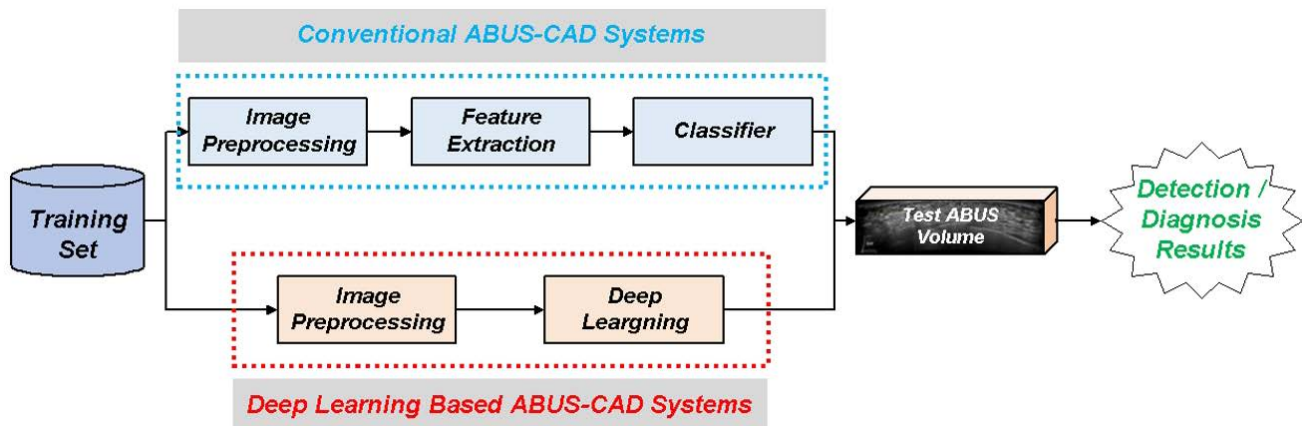


Fig. 1. The overview of the conventional and DL-based ABUS-CAD systems.

on 1162 patch images. Chiang et al. (19) proposed simplified three-dimensional (3-D) convolutional neural networks for tumor detection. They achieved sensitivities of 60.0%–100.0% with 1.3–120.0 FPs per case on a dataset consisting of 224 ABUS cases. Furthermore, Moon et al. (20) proposed to utilize an ensemble of the 3-D simplified VGG-16 (21) and 3-D DenseNet (22) for tumor detection. Sensitivities of 84.8%–100.0% with 21.7–126.2 FPs per case were reported on a dataset consisting of 246 ABUS cases. In these works, the authors achieved a certain level of detection and diagnosis performance with sufficient data. Furthermore, additional techniques such as data augmentation and transfer learning (23) are adopted if necessary. Table 1 shows a summary of relevant ABUS-CAD studies.

The DL-based ABUS-CAD systems in the literature perform well on in-house datasets acquired from a small number of institutions. For stable utilization in the clinic, multi-cohort data acquisition and secure data sharing are indispensable. Data transfer via blockchain technology (24) is a potential solution to it. Furthermore, state-of-the-art systems tend to focus on either detection or diagnosis tasks tendentiously. For clinical applications, it is essential to develop reliable end-to-end systems performing detection and diagnosis concurrently.

Simultaneously, explanation and visualization of the decision-making process by neural networks is also an important task to provide the reliability of ABUS-CAD systems in critical applications such as medical diagnosis (25). The class activation map (CAM) is a well-known technique, where the CAM provides the discriminative image regions utilized by the CNN to identify the category (26). These aspects of data quantity and security, generalizability, and interpretation are the main challenges in ABUS-CAD systems development.

Clinical Applications

The ideal roles of ABUS-CAD systems are locating suspicious lesion masses with abnormality scores and providing disease severity levels simultaneously. Exploiting the system outcomes can aid radiologists in improving the performance of the ABUS screening process in terms of time and accuracy. In 2016, QView Medical Inc. announced QVCAD, the first computer-aided detection (CADE) system for ABUS with a US food and drug administration premarket approval. It detects suspicious tissue areas more than 5mm in diameter. Van Zelst et al. (27) compared the breast cancer screening performance with and without QVCAD using 90 ABUS volumes. A statistically significant

Table 1. Summary of ABUS-CAD Studies

Study	Task	Methodology	Dataset	Reported Performance
Ikeda et al. (5)	Detection	Hand-crafted	109 volumes	80.6% sensitivity 3.8 FPs/volume
Chang et al. (9)	Detection	Hand-crafted	25 cases	92.3% sensitivity 1.8 FPs/case
Moon et al. (11)	Detection	Hand-crafted	159 cases	100.0%, 90.0%, 70.% sensitivity 17.4, 8.8, 2.7 FPs/case
Tan et al. (13)	Detection	Hand-crafted	348 volumes	70.0%, 64.0% sensitivity 2.0, 1.0 FPs/volume
Wang et al. (18)	Diagnosis	Deep learning	263 cases	88.6% sensitivity 87.6% specificity 94.7% AUC
Chiang et al. (19)	Detection	Deep learning	187 cases	95.0%, 90.0%, 85.0%, 80.0% sensitivity 14.0, 6.9, 4.9, 3.6 FPs/case
Moon et al. (20)	Detection	Deep learning	246 cases	100.0%, 95.3%, 90.9% sensitivity 126.2, 34.8, 27.1 FPs/case

area under the receiver operating characteristics curve (AUC) performance improvement among six readers was observed using QVCAD (around 0.07 AUC increase, $P=0.001$).

The same research group further showed that utilization of the CAdE system could obtain a significant decrease in reading time (28) for the cancer screening of dense breasts. They randomly selected 375 ABUS volumes with ten repetition times to compare the reading time with and without QVCAD. Without deteriorating the screening accuracy performance, eight radiologists showed a statistically significant decrease in reading time (from 158.3s to 133.4s per case). In (29), they further presented an example of ABUS screening workflow incorporating CAdE validation of reader's findings in a double-reading strategy. In this workflow, the CAdE validation plays a tool for reducing the number of discordant cases to be double-read. Besides the QVCAD, Wang et al. (18) utilized a CNN-based computer-aided diagnosis (CADx) system to enhance the diagnostic performance. The AUC performance using the CADx system improved the AUC performance with statistical significance for three residents and one physician among five human reviewers.

The aforementioned retrospective studies show the successful application of ABUS-CAD systems in breast cancer screening and diagnosis. From a clinical viewpoint, breast cancer prognosis prediction is also an important application. In such an application, the utilization of ABUS-CAD systems can increase the efficiency of benign and malignant lesions follow-up by reducing processing time and error. Developing a reliable CAD system with sufficient interpretation capability for reasoning would be the essential component for accelerating clinical applications of ABUS-CAD systems.

Conclusion

Artificial intelligence and machine learning

technology are effective means of automation in various applications, including medicine. ABUS is a suitable candidate to apply those advanced technologies to aid human experts in saving time and human power in the time-consuming reviewing process. In this study, we reviewed the fundamental methodologies in ABUS-CAD systems and the existing and potential clinical applications. Retaining the generalization, explanation, and visualization capability of the ABUS-CAD systems is the main challenge for their active applications in the field.

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