

Research Article

Advances in Artificial Intelligence-Assisted Diagnosis (AI) in Ultrasound

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Abstract

Artificial intelligence-assisted diagnosis (AI) has emerged as a transformative tool in medical imaging, leveraging advanced computational techniques to enhance lesion detection, characterization, and differentiation between benign and malignant conditions. While AI has gained significant traction in CT and MRI, particularly for breast and pulmonary nodule diagnosis, its application in ultrasound remains relatively nascent. Ultrasound, despite its widespread clinical utility, is highly operator-dependent, with diagnostic accuracy influenced by subjective factors. AI-assisted systems aim to mitigate these limitations by providing objective, reproducible analyses. This review explores the fundamental principles of AI-assisted diagnostic systems and their evolving role in ultrasound imaging, with a focus on key clinical applications, challenges, and future directions. The review begins by outlining the historical development and workflow of AI-assisted diagnosis, emphasizing its three core steps: image preprocessing, feature extraction, and data processing. It then delves into specific applications across diverse ultrasound domains: Thyroid Nodules: AI systems demonstrate promise in automating malignancy risk stratification, though challenges persist in real-time performance and regional nodule identification. Breast Nodules: Integration with Breast Imaging Reporting and Data System (BI-RADS) criteria enables improved classification accuracy, particularly for less experienced sonographers. Liver Fibrosis: AI-driven texture analysis of liver parenchyma and capsule geometry offers non-invasive staging tools, albeit with technical complexities due to anatomical variability. Carotid Atherosclerosis: AI aids in plaque detection and stenosis quantification, reducing operator dependence in vascular ultrasound. Myocardial Infarction: Segmentation and acoustic feature analysis enhance echocardiographic assessment of infarcted myocardium, though standardized algorithms remain under development. Additional applications in musculoskeletal imaging, obstetrics, and endoscopic ultrasound are also highlighted. While AI-assisted ultrasound diagnosis holds immense potential to improve diagnostic accuracy, workflow efficiency, and early disease detection, its clinical adoption lags behind other imaging modalities due to challenges in image standardization and algorithm robustness. Future advancements hinge on large-scale validation studies, innovations in deep learning architectures, and interdisciplinary collaboration. With continued refinement, AI is poised to revolutionize ultrasound practice, bridging gaps in precision medicine and expanding access to high-quality diagnostic care.

Keywords

Artificial Intelligence, Ultrasound, Deep Learning, Computer-aided Diagnosis, Medical Imaging

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1. Introduction

In recent years, significant innovations have been made in computer hardware, software, and modern ultrasound equipment, expanding the scope of ultrasound applications. From initial abdominal, vascular, and cardiac ultrasound examinations, it has now extended to superficial organs, contrast-enhanced imaging, musculoskeletal imaging, and prenatal screening, among others. Ultrasound is widely used and serves as an effective tool for auxiliary diagnosis and clinical follow-up of many diseases. As AI has been gradually applied in CT and MRI, especially in breast and pulmonary nodular diseases, its advantages have become evident. Therefore, the application of AI in ultrasound has become a key focus in recent years. Ultrasound examinations are influenced by subjective factors such as the operator's experience and patient-specific conditions, which can lead to misdiagnosis. Some physicians recommend the use of AI in ultrasound to enhance diagnostic objectivity, assist in diagnosis, improve diagnostic specificity, and enable precise detection and differentiation of lesions.

This concept was first proposed half a century ago, but substantial progress has only been made in the last decade.

2. Artificial Intelligence-Assisted Diagnosis

Artificial intelligence-assisted diagnosis (AI), as an intelligent diagnostic aid, was developed by the American R2 Technology, a pioneering company in the field of AI-assisted medical imaging, particularly known for its Computer-Aided Detection (CAD) systems for mammography. The AI system processes and analyzes ultrasound images to identify lesions and determine their nature, providing a "second opinion" for clinicians [1]. This assists ultrasound physicians in improving diagnostic sensitivity and specificity. The practicality, effectiveness, and diagnostic sensitivity of AI have become new research directions for many researchers in medical imaging. It should be regarded as an objective technology aimed at improving lesion detection rates and accuracy [2].

In 1967, a paper published in *Radiology* mentioned the earliest research on AI. Due to limitations in computer system performance, Kunio Doi redefined the AI system in 1985, distinguishing it from traditional "automatic diagnosis." Today, AI has gained recognition from clinicians in both breast cancer and pulmonary nodule diagnosis, particularly for pulmonary and hepatic nodules, where AI has shown significant results [1]. The application of AI in ultrasound has also become a new development direction for many system developers and medical researchers.

Typically, AI-assisted diagnosis in medical imaging involves three steps: Image processing (preprocessing); Feature extraction or quantification of image characteristics; Data processing.

Using AI diagnostic systems, physicians can classify and differentiate lesions, ultimately making a final diagnosis. Methods such as decision trees, rule extraction, and artificial neural networks (ANN) are employed during this process, with ANN being widely used and highly effective.

Computer technology has achieved remarkable progress, and AI technology has developed rapidly in countries with advanced healthcare systems, particularly in medical imaging. Practice has shown that AI helps improve clinical accuracy, reduce missed diagnoses, and enhance overall workflow efficiency for medical staff.

3. Applications of AI in Different Ultrasound Fields

3.1. Thyroid AI-Assisted Diagnosis

Thyroid nodules are among the most common endocrine system diseases, with malignant tumors accounting for 3%-10% of cases [3, 4]. The incidence of thyroid cancer has increased 2.4-fold over the past 30 years [5, 6]. Preoperative differentiation between benign and malignant nodules remains challenging. Ultrasound, as the most precise imaging modality, is widely used for preoperative evaluation of fine-needle aspiration (FNA) biopsy [7-9]. Accurate differentiation between benign and malignant lesions is crucial [10, 11].

New AI-assisted diagnostic systems have been developed in recent years for automated and efficient ultrasound image analysis. Some studies report that AI systems have been applied to evaluate breast and lung cancers, providing diagnostic suggestions for radiologists [12, 13]. AI systems typically use deep neural networks to automatically determine the malignancy of thyroid nodules after learning from a large dataset of labeled images. However, their practicality and effectiveness remain debated. The focus of the debate is the time consumption and accuracy of AI compared to experienced sonographers. If AI takes longer than sonographers and cannot achieve real-time performance, its clinical utility is limited. Additionally, regional identification of thyroid nodules [14] and differentiation between benign and malignant nodules [15, 16] are two critical aspects of efficacy evaluation.

Solid nodules with hypoechoic or markedly hypoechoic components are often misinterpreted as partially cystic or partially solid nodules. Therefore, further validation and large-scale studies are needed to improve existing AI systems [17].

3.2. AI-Assisted Diagnosis of Breast Nodules in Ultrasound

Breast cancer is one of the major diseases threatening women's health, with its incidence increasing annually. AI-assisted diagnostic systems for breast ultrasound have been applied to improve diagnostic performance. These systems are based on the Breast Imaging Reporting and Data System (BI-RADS), classifying breast masses as benign or malignant according to BI-RADS-recommended features [18].

Using the BI-RADS-based AI system for breast ultrasound, internal morphology and texture features of breast nodules can be extracted and analyzed, enabling clinicians to make more accurate diagnoses and reducing misdiagnoses caused by subjective interpretation [19]. Combining AI with ultrasound is particularly helpful for junior sonographers.

3.3. AI-Assisted Ultrasound Diagnosis of Liver Fibrosis

Liver fibrosis is a chronic degenerative disease often caused by drug or alcohol-induced liver damage, leading to repeated hepatocyte degeneration, necrosis, fibrous tissue proliferation, and regeneration. This eventually results in cirrhosis, one of the common causes of death reported by the WHO. Some researchers have proposed AI-assisted diagnostic systems for liver fibrosis based on ultrasound images.

Ultrasound, CT, and MRI are conventional methods for diagnosing cirrhosis. As a non-invasive and non-ionizing technique, medical ultrasound is widely used by physicians for cirrhosis diagnosis. AI-assisted diagnostic systems can enable early diagnosis based on ultrasound images, facilitating timely treatment [20]. High-frequency ultrasound provides higher-resolution images of the liver surface, reflecting subtle changes in the liver capsule and parenchyma during early cirrhosis. In normal livers, the parenchyma exhibits uniform echotexture, and the liver capsule is smooth with consistent thickness [21].

Song Jialin et al. [22] proposed an image algorithm suitable for assessing the degree of cirrhosis. The geometric feature parameters of the liver capsule could provide a quantitative method for non-invasive evaluation of cirrhosis, demonstrating significant research value.

AI-assisted cirrhosis diagnosis systems can aid early detection, enabling targeted treatment and saving more lives. However, due to the liver's highly complex structure, automated cirrhosis diagnosis from ultrasound images remains technically challenging.

AI-assisted diagnostic systems supported by quantitative analysis hold considerable clinical value [23]. For example, systems introduced in many hospitals can successfully extract and record fractal features, statistical texture features, spectral features [24-26], or combined features [27, 28] for quantitative analysis of liver parenchymal texture in ultra-

sound images [21].

Overall, analyzing and summarizing multi-source features, designing and establishing multi-classification learning frameworks, and integrating advanced ultrasound technology can build high-precision quantitative evaluation models. These models provide robust technical references for the clinical diagnosis and quantitative analysis of liver fibrosis [29].

3.4. AI-Assisted System for Carotid Atherosclerosis

Carotid atherosclerosis is one of the most important causes of stroke [30]. To date, the degree of carotid stenosis is considered one of the most critical indicators for stroke risk assessment. Ultrasound is a non-invasive, relatively inexpensive, and portable technique with excellent temporal resolution [31]. AI-assisted diagnosis has become a major research area in medical imaging.

Ultrasound imaging not only displays the anatomy of stenosis but also functional aspects. Non-invasive vascular ultrasound can assess arterial morphology and dynamic parameters such as diameter, distensibility, or intima-media thickness. AI-assisted diagnosis has become a primary research direction in medical imaging. AI should be regarded as an objective technology aimed at reducing costs and improving efficiency.

Lilla Bonanno et al. [32] developed an AI system capable of differentiating plaques from non-plaques and identifying the location and size of each plaque. Clinicians can use the AI system's output as a "second opinion" to assist in clinical diagnosis.

Vascular ultrasound is operator-dependent, and image interpretation requires high expertise. To reduce operator dependence and improve diagnostic accuracy, many researchers have focused on developing AI systems for plaque detection and classification. These systems can identify and differentiate plaques while avoiding subjective clinical judgments in plaque morphology and localization. In the future, AI-assisted diagnostic systems for automated carotid atherosclerosis detection will be promising auxiliary tools [32].

3.5. AI-Assisted Ultrasound Diagnosis of Myocardial Infarction

The incidence and mortality of myocardial infarction (MI) are increasing annually. MI causes irreversible changes in cardiac function, leading to late-stage left ventricular remodeling, scar formation in the infarcted myocardium, and subsequent heart failure [33-38].

Echocardiography is convenient, non-invasive, cost-effective, and real-time. However, due to operator experience limitations, traditional echocardiography has suboptimal clinical diagnostic rates, with significant subjective variability. AI-assisted echocardiography for MI diagnosis can

reduce human error, ensure scientific and reliable results, and provide valuable diagnostic information for sonographers. It also reduces time and labor costs, benefiting early MI diagnosis.

The process involves two steps: Myocardial segmentation: Distinguishing infarcted from normal myocardium [39].

Acoustic feature extraction and analysis: Texture features intuitively reflect image regularity, roughness, and smoothness. Structural and statistical analyses are common texture analysis methods [40, 41].

Accurate myocardial segmentation enables calculation of ejection fraction (EF), wall motion, and wall thickening rate, facilitating cardiac function assessment [4]. Ultrasound findings include hypokinesis or paradoxical motion in the infarcted myocardial wall [37].

The application of machine learning in echocardiography remains in its early stages. Given the significant variability in myocardial tissue and image interference from multiple factors, no definitive acoustic feature model or algorithm for MI diagnosis has been established. Current approaches often combine multiple algorithms. In the AI era, AI-assisted ultrasound technology is expected to provide greater clinical diagnostic support [42].

3.6. Other Applications

AI systems based on ultrasound images have been explored in other fields, such as endoscopic ultrasound for pancreatic cancer diagnosis [34]. High-frequency ultrasound has also been applied in musculoskeletal imaging, where researchers use AI to improve the diagnosis of skeletal muscle injuries. Zhao Jiaqi et al. [35] achieved segmentation of blurred edges in muscle injury regions after contrast-enhanced ultrasound using computer vision for quantitative texture recognition [19].

In obstetrics, AI can intelligently identify standard fetal cranial and cardiac views, automatically capture optimal images, and measure basic parameters without manual adjustment. Intelligent 3D ultrasound imaging is now widely used in obstetric ultrasound examinations across hospitals. Based on regression analysis and spatiotemporal regression models, current computer technology enables automated grading of bladder prolapse [36].

4. Summary

AI-assisted diagnosis offers advantages such as repeatability and objectivity, pointing to new directions for clinical practice. However, it is important to recognize that AI is still in its early stages, and large-scale studies are needed for further development. AI systems are gradually being commercialized and applied clinically. In CT, MRI, and X-ray imaging, AI-assisted systems for breast and pulmonary nodules

are widely used. However, larger-scale clinical studies and improvements are required for other diseases to ensure stable diagnostic performance.

In ultrasound, AI development is in its infancy, lagging far behind CT, MRI, and X-ray AI. The challenges are greater due to the difficulty in obtaining high-quality images, which depend on operator skill, patient factors, and equipment. Therefore, AI in ultrasound faces significant hurdles.

Nevertheless, with standardized image acquisition, innovations in image processing, machine learning methods, and ongoing research, AI-assisted ultrasound diagnostic systems will advance rapidly. They will be applied to more diseases, meeting current and future demands for fast and accurate ultrasound diagnosis, improving clinical services, and enhancing patient care. The future of AI in ultrasound holds broad innovation and bright prospects.

Abbreviations

AI	Artificial Intelligence-assisted Diagnosis
BI-RADS	Breast Imaging Reporting and Data System
CAD	Computer-Aided Detection
ANN	Artificial Neural Networks
FNA	Fine-needle Aspiration
MI	Myocardial Infarction
EF	Ejection Fraction

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Data Availability Statement

Not applicable.

Conflicts of Interest

The authors declare no conflicts of interest.

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