Review

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Application of Artificial Intelligence to Ultrasonography

Xaira Elena Santacruz-Yaah*
Avenida Universidad, Universidad Autonoma del Estado de Morelos, 62210 Cuernavaca, Mor., Mexico
*: All correspondence should be sent to: Ms. Xaira Elena Santacruz-Yaah.
Author's Contact: Xaira Elena Santacruz-Yaah, MSc, E-mail: xesantazruzyaah@gmail.com
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The use of artificial intelligence (AI) technology in medicine has gained considerable attention, although its application in ultrasound medicine is still in its infancy. Deep learning, the main algorithm of AI technology, can be applied to intelligent ultrasound picture detection and classification. Describe the application status of AI in ultrasound imaging, including thyroid, breast, and liver disease applications. The merging of AI and ultrasound imaging can increase the accuracy and specificity of ultrasound diagnosis and decrease the percentage of incorrect diagnoses.

Keywords: Ultrasonography; Artificial Intelligence; Convolutional Neural Network; Diagnostics

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JOHN MCCARTHY first presented the concept of artificial intelligence (AI) at the Dartmouth Conference in 1956 (1), and it has a history of more than 60 years. The goal is to teach computers to replicate human thought and cognitive functions and to develop human-like thought. There will be three stages of development for artificial intelligence: weak artificial intelligence, strong artificial intelligence, and super AI (2). The advancement of AI technologies relies heavily on deep learning algorithms. Convolutional neural network (CNN)-based learning systems have become one of the most rapidly expanding areas of deep learning algorithms in recent years, mostly utilized for image recognition and classification (3). Deep learning is the automatic extraction of image features, the fusion of basic features into complex features, and the application of complex features to problem solving (4). Presently, AI technology is employed extensively in numerous industries, and its relationship with the medical industry, particularly in conjunction with medical imaging, is growing (CT, X-ray, MRI, and PET). Ultrasound has been widely used in the inspection and diagnosis of the liver, heart, blood vessels, thyroid, breast, muscle, and other internal organs and superficial structures due to the fact that it is painless, non-invasive, non-ionizing radiation, simple, fast, capable of real-time imaging, and has high repeatability (5, 6). However, there are subjective variances in ultrasound examinations, and extensive training and education are required to become a certified sonographer. In contrast, the coupling of AI and ultrasound imaging simplifies operating stages, eliminates subjectivity, conserves physician resources, reduces reporting time, and enhances diagnostic efficacy. Its primary research topics are the detection of abnormalities in the thyroid, breast, and liver.

Intelligent Application of Ultrasound Imaging to the Thyroid

Ultrasound is essential for the diagnosis of thyroid disorders. Nodule location, size, and number; echo intensity; whether the boundary is clear and regular; calcification; cystic degeneration; aspect ratio, and color Doppler blood flow signals can be used to identify worrisome lesions. Acharya et al. employed the K-nearest neighbor algorithm to detect three-dimensional contrast-enhanced ultrasound thyroid pictures with an accuracy of

98.9%, a sensitivity of 98.0%, and a specificity of 99.8%, based on the image texture and discrete wavelet transform (7). Deep convolutional neural networks (DCNN) paved the way for this advancement in computer-based diagnostics. Nguyen et al. extracted picture features from ultrasound thyroid images in two domains: the spatial domain using deep learning and the frequency domain using Fast Fourier transform and confirmed that the combination of AI and ultrasound imaging is beneficial for the detection of benign and malignant thyroid nodules (8). Wang et al. used a device combining ultrasound and AI to identify 600 images of thyroid nodules with a sensitivity of 86.20% and a specificity of 85.48%, indicating that AI ultrasound plays a significant role in the clinical diagnosis of thyroid disease (9). Chi et al. preprocessed ultrasound pictures of the thyroid to eliminate artifacts and then fine-tuned the preprocessed GoogleNet model to extract features. Their results indicated that the model has good classification performance with a classification accuracy of 98.29% and a sensitivity of 98.29% (10). However, the images of the thyroid lesions were not discovered by a computer-aided diagnostic (CAD) system, but rather by clinicians. Ma et al. utilized two CNN fusion methods for the gathered 15,000 images, and this method's accuracy was 83.02%, indicating that deep learning may considerably increase the diagnostic accuracy of thyroid nodules by ultrasound (11).

In addition, Ma et al. used a CNN cascade model to detect thyroid lesions in 21,532 ultrasound pictures. Their method involved two CNN systems with varying depths, and the results revealed an AUC of 98.51%, which was higher than the conventional model. based on machine learning, but the physician must manually manipulate the ultrasound picture detection area (12). The AICAD system was used by Zhang et al. to distinguish between benign and malignant thyroid nodules (13). Its diagnostic sensitivity and negative predictive value for malignant thyroid nodules were comparable to those of experienced sonographers, whereas its specificity and accuracy rate were lower. Using the DCNN model, Li and colleagues enhanced the detection accuracy of thyroid cancer compared to professional sonographers (14).

Intelligent Application of Breast Ultrasound Imaging

Breast cancer is one of the most prevalent cancers and the major cause of cancer-related mortality in women. The screening and detection of benign and malignant breast nodules are greatly facilitated by artificial intelligence. The distinguishing characteristics between benign and malignant breast nodules can begin with the following: whether the mass has a regular shape, whether the edge is smooth, internal echo (hypoechoic, anechoic), posterior echo attenuation, capsule integrity, presence or absence of calcification, longitudinal and transverse ratio, color Doppler blood flow signal, and so on. Wu et al. reviewed breast ultrasound AI technology to detect breast nodule (15). Using a deep learning model (GoogleNet model of CNN), Kalafi et al. analyzed ultrasound breast images to identify benign and malignant tumors with an accuracy of 93% (16). This method can classify malignant lesions in a short amount of time and aids the radiologists' diagnosis of malignant lesions. Lei et al. employed 3D CNN-based detection system for 3D automatic whole breast ultrasonography tumor diagnosis, obtaining good sensitivity but low specificity when the sensitivity was > 98% (17). Park et al. performed CAD detection on breast masses and evaluated the differences between physicians (18). They discovered that when CAD was paired with ultrasonography, the diagnostic abilities of all physicians were greatly enhanced.

A general deep learning software was developed to identify and differentiate ultrasound breast cancer images and discovered that deep learning software can aid in diagnosing breast cancer images similarly to sonographers and novice academics. improved acceptance and accelerated learning (19). Kim et al. investigated the diagnostic effectiveness of the deep learning algorithm-based smart detect (S-Detect) technology in breast ultrasound examinations and employed the Kappa test to determine the consistency between sonographers and S-Detect (20). When the BI-RADS grade was above grade 4a, their results indicated that the specificity, positive predictive value, and accuracy of S-Detect technology were considerably higher than those of sonographers. Alzubaidi and coworkers established a deep learning architecture, which is a 2-layer deep learning model: the first layer is a fully connected neural network for feature extraction, and the second layer is a constrained Boltzmann machine to provide better features (21). This architecture can automatically extract the features of shear wave elastography and distinguish between benign and malignant tumors. Ghosh et al. identified breast ultrasonography lesions using stacked denoising autoencoders, which is superior to conventional machine learning techniques (22). Yap et al. employed three deep learning approaches (patch-based Lenet, U-net, and pre-trained FCN-AlexNet transfer learning method) for the detection of breast lesions by ultrasound, and then compared their performance to that of four cutting-edge algorithms, and their findings indicated that transfer learning has a superior learning effect (23).

Xiao et al. gathered ultrasound pictures consisting of 1,370 benign and 688 malignant lesions and compared the differential diagnosis of benign and malignant tumors using the transfer model, CNN model, and conventional machine learning (24). Their results indicated that the transfer model is valid. Among the models, InceptionV3 performed the best, with an accuracy of 85.13% and an AUC of 91%; additionally, a model based on deep feature classification retrieved from the transfer model also achieved good performance, with an accuracy of 89.44% and an AUC of 93%. Di Segni et al. investigated the diagnostic performance of S-Detect for breast lesions, demonstrating a sensitivity of 90% and a specificity of 70.8%, supporting its increased specificity (25). Using a deep learning-based transfer learning CNN model, Zahoor and coworkers identified benign and malignant breast lesions with an AUC of 93.6%, which could assist sonographers in classifying breast masses (26).

Intelligent Application of Ultrasound Imaging to the Liver

Sonography is the imaging method of choice for evaluating liver disorders. The application of AI in liver ultrasound is primarily for fat detection and fibrosis evaluation. Byra et al. used a DCNN model with transfer learning for pre-training on the

ImageNet dataset for the ultrasound assessment of non-alcoholic fatty liver disease for the assessment of liver steatosis on liver ultrasound, and then applied the support vector machine (SVM) algorithm (27). For picture classification, the sensitivity was 100%, the specificity was 88.2%, the accuracy was 96.3%, and the AUC was 97.7%, demonstrating that this method can assist doctors in determining the fat content of the liver. Biswas et al. employed a deep learning approach (DL-CNN model) to evaluate fatty liver. Compared with SVM and extreme learning machines (ELM), the diagnosis accuracy was 100%, 82%, and 92%, respectively, showing that ultrasonography utilizing deep learning can better distinguish fatty liver (28). A stacked sparse autoencoder based on deep learning approaches extracted high-level features from segmented liver images with 97.2% accuracy and was compared to multi-support vector machine (multi-SVM) and K-nearest neighbor classification (29).

Meng et al. used a transfer learning-based VGGNet and a fully connected network (FCNet) model to stage liver fibrosis, and the results showed a 93.9% accuracy on a 30% test set (30). Liu et al. proposed using the DCNN model of liver pictures to extract the image features of the liver capsule, and the AUC was 96.8%, showing that this technique can effectively extract the image characteristics of the liver capsule and diagnose liver cirrhosis properly (31). Yeom et al. presented a high-frequency ultrasound imaging algorithm for liver cirrhosis, which primarily analyzed the continuity and smoothness of the liver capsule and extracted the image's form or texture features for quantitative analysis. The results demonstrate that this method can be used to assess liver cirrhosis (32). The AUC of this method was 97% for liver cirrhosis (F4 stage), 98% for advanced liver fibrosis (F3 stage), and statistically significant for liver fibrosis (F3 stage). The F2 AUC was reduced from 99% to 85%, demonstrating that this method is more accurate than two-dimensional shear wave elastography for assessing liver cirrhosis and advanced liver fibrosis. In addition, Oezdemir et al. used AI to quantitatively analyze the response of CEUS to transarterial chemoembolization in order to predict the effect of transarterial chemoembolization in patients with hepatocellular carcinoma and established a deep learning radiomics-based CEUS model, machine-based on radiomics and deep learning (33). Contrast was drawn between the contrast-enhanced ultrasound model for machine learning radiomics and the B-Mode image model based on machine learning radiomics. According to their findings, contrast-enhanced ultrasonography was capable of accurately predicting the AUC of 93%.

Other Intelligent Applications for Ultrasound Imaging

Wilkinson et al. investigated the use of computer texture analysis technology to quantitatively identify the texture features of skeletal muscle ultrasound images under vision, and their self-developed intensity interface multilevel decomposition method for quantitative analysis of skeletal muscle injury ultrasound images was demonstrated to be effective (34). Yu et al. proposed a DCNN to identify fetal facial standard planes. It consists of 16 convolutional layers with 3 kernels and 3 fully connected layers, and it can classify fetal ultrasound planes with an accuracy of up to 93.03%, which is higher than the accuracy of the conventional method, making it useful for clinical diagnosis (35).

Wu et al. proposed evaluating the quality of fetal ultrasound images using two DCNN models (36). The L-type CNN model was used to detect the ROI of the abdomen in the ultrasound picture; the C-type CNN model was used to evaluate the gastric vesicles and umbilical veins of important structures in the images; and the model was used to evaluate the ROI of the abdomen. The outcomes were comparable to the subjective image quality evaluations of three physicians. Chen et al. investigated a composite neural network framework of DCNN and recurrent neural networks that can explore intra-and inter-plane features and classify fetal standard planes from ultrasound images of fetal organs (37). This neural network is referred to as T-RNN. The test demonstrated the model's validity, and its AUC for recognizing fetus standard plane was achieved at 95%.

The research of Hetherington et al. helped anesthesiologists perform anesthesia procedures by automatically identifying the spinal level from ultrasound pictures (38). A CNN model with four convolutional layers of 3 x 3 size and three completely linked layers can categorize atherosclerotic plaques, including lipid content. The Pearson's correlation coefficients for the number of cores, fibrous tissue, and calcified tissue were 0.92 for lipid cores, 0.87 for fibrous tissue, and 0.93 for calcified tissue, indicating that automatic measurement can be utilized for clinical prediction of carotid ultrasound plaques.

Currently, in the medical industry, 90% of the data sources rely on medical images, and each piece of data is inseparable from manual analysis, which wastes medical resources and inevitably leads to subjective errors in doctors' judgment (39). Intelligent ultrasound imaging can compensate for personnel shortages and human error, hence enhancing the accuracy of disease diagnosis. However, the capture of large volumes of ultrasound data is frequently dependent on the physician's actions, which raises the bar for the identification and extraction of ultrasound images. In addition, a quantitative standard can be defined for the obtained ultrasound pictures to promote industry standardization. Using AI technology, during an ultrasound examination, images can be automatically classified to ensure the continuity and integrity of image acquisition (40, 41).

Conclusion

The advancement of AI has facilitated the growth of ultrasound imaging. It is believed that as scientific and technological strength continues to grow, the combination of ultrasound imaging and AI will become more in-depth, and AI will be utilized in a wider variety of fields. It can increase the accuracy of ultrasound diagnostics and decrease the number of incorrect diagnoses.■

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