European Journal of Radiology 139 (2021) 109717

Contents lists available at ScienceDirect

European Journal of Radiology

journal homepage: www.elsevier.com/locate/ejrad

Artificial intelligence in ultrasound

Yu-Ting Shen [a], Liang Chen [b], Wen-Wen Yue [a,*], Hui-Xiong Xu [a,*]

[a] Department of Medical Ultrasound, Shanghai Tenth People's Hospital, Ultrasound Research and Education Institute, Tongji University School of Medicine, Tongji University Cancer Center, Shanghai Engineering Research Center of Ultrasound Diagnosis and Treatment, National Clnical Research Center of Interventional Medicine, Shanghai, 200072, PR China

[b] Department of Gastroenterology, Shanghai Tenth People's Hospital, Tongji University School of Medicine, Shanghai, 200072, PR China

ARTICLE INFO

Keywords:
Ultrasound
Artificial intelligence
Deep learning
Medical imaging

ABSTRACT

Ultrasound (US), a flexible green imaging modality, is expanding globally as a first-line imaging technique in various clinical fields following with the continual emergence of advanced ultrasonic technologies and the well-established US-based digital health system. Actually, in US practice, qualified physicians should manually collect and visually evaluate images for the detection, identification and monitoring of diseases. The diagnostic performance is inevitably reduced due to the intrinsic property of high operator-dependence from US. In contrast, artificial intelligence (AI) excels at automatically recognizing complex patterns and providing quantitative assessment for imaging data, showing high potential to assist physicians in acquiring more accurate and reproducible results. In this article, we will provide a general understanding of AI, machine learning (ML) and deep learning (DL) technologies; We then review the rapidly growing applications of AI-especially DL technology in the field of US-based on the following anatomical regions: thyroid, breast, abdomen and pelvis, obstetrics heart and blood vessels, musculoskeletal system and other organs by covering image quality control, anatomy localization, object detection, lesion segmentation, and computer-aided diagnosis and prognosis evaluation; Finally, we offer our perspective on the challenges and opportunities for the clinical practice of biomedical AI systems in US.

1. Introduction

Nearly two decades into the 21st century, our world has dramatically changed following the application of artificial intelligence (AI) [1], from web search and facial recognition to self-driving vehicles and natural language processing. Although most earlier AI methods have been applied with subhuman performance, recently reported algorithms can match or even exceed humans in some task-specific applications [2–4], owing to the amounts of digital data for training, the development of different algorithms as well as the modern, powerful computational hardware. Computer-based AI is now becoming a leading research focus within scientific community [5–7]. As medical imaging data can be collected during routine clinical practice, large datasets offer an incredibly rich resource for scientific discovery, thus making medical imaging to be a field of research for AI [8,9]. In contrast to qualitative reasoning of physicians, AI excels at identifying complex patterns and can provide quantitative assessment automatically [10], thus enabling the reported results more accurately and reproducibly results.

Ultrasound (US), a flexible green imaging modality, is becoming an indispensable tool for clinical practice throughout the world due to its unique advantages, such as no ionizing radiation, easy to carry out, low-cost, and real-time imaging display. Especially followed with the continual emergence of ultrasonic diagnostic instruments and diagnostic technologies (ie, high-frequency US, shear wave elastography (SWE), contrast-enhanced ultrasound (CEUS), ultrasonic elastography and three/four-dimensional (3D/4D) imaging), US has now been widely preferred as a first-line imaging technique in the fields of obstetrics, cardiovascular, and superficial organs [11–13]. Ultrasonic imaging is globally expanding at an unprecedented rate, AI-related technology for analyzing US imaging has now also been shown to be successful in

Abbreviations: AI, artificial intelligence; ML, machine learning; DL, deep learning; CNNs, convolutional neural networks; ANNs, artificial neural networks; US, ultrasound; CEUS, contrast-enhanced ultrasound; SWE, shear wave elastography; 3D/4D, three/four-dimensional.

* Corresponding authors at: Department of Medical Ultrasound, Shanghai Tenth People's Hospital, Ultrasound Research and Education Institute, Tongji University Cancer Center, Shanghai Engineering Research Center of Ultrasound Diagnosis and Treatment, Tongji University School of Medicine, 301 Yanchang Middle Road, Shanghai 200072, PR China.

E-mail addresses: yuewen0902@163.com (W.-W. Yue), xuhuixiong@126.com (H.-X. Xu).

https://doi.org/10.1016/j.ejrad.2021.109717
Received 27 January 2021; Received in revised form 28 March 2021; Accepted 11 April 2021
Available online 12 April 2021
0720-048X/

oncology for noninvasively identifying cancer patients, evaluating malignant degrees or predicting prognosis [14–16]. Despite tremendous progress has achieved in the last few years, the development of AI approaches specifically associated with US imaging has not yet been timely summarized.

In this review, we will first provide a general understanding of AI and some associated technology methods; We then review the rapidly growing applications of AI-related US imaging analysis based on anatomical regions; Finally, we offer our perspective on the challenges and opportunities for the clinical practice of biomedical AI systems in US.

2. Overview of artificial intelligence technologies

2.1. Artificial intelligence

AI, a branch of computer science that includes machine learning (ML), deep learning (DL) and convolutional neural networks (CNNs), and Fig. 1 present the hierarchical relationships between these terms. Generally speaking, AI can be recognized as using any device to imitate human cognitive process, involves learning, applying and solving complex problems. Nowadays, AI that has ever been called "the fourth industrial revolution" [17] is dramatically reshaping the landscape of our whole life. The long history of AI can be traced back to a conference at Dartmouth in 1956, where the term was first put forward [18] (Fig. 2). Since 2012, the successful development and application of image classifier has contributed to the resurgence of AI recently [7]. Importantly, AI techniques are well suited to the imaging-based fields because the image itself, whose pixel values can be quantified, is the main source of data for training AI algorithms.

2.2. Machine learning

ML is devoted to deploying algorithms without being explicitly programmed. ML algorithms could be viewed as mapping the observed input data variables into the output results [1]. In general, this process is

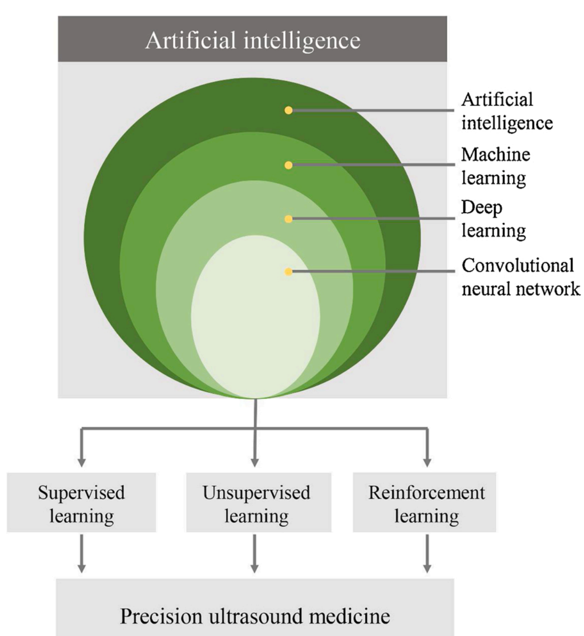

Fig. 1. The hierarchical relationships of artificial intelligence, machine learning, deep learning, and convolutional neural networks. Applying these techniques and three learning methods (supervised learning, unsupervised learning and reinforcement learning) to analyze data will enable precision ultrasound medicine.

developed and improved by using a train-test system [19,20], including training, testing and validation processes. According to the types of learning or task, ML can be roughly divided into three categories: supervised, unsupervised and reinforcement learning. The most common ML method is supervised learning, which is also the most commonly method used in US imaging. In supervised learning, the expected explicit data sets that usually have been labeled by experts called 'ground truth': data labels are determined by experts, and considered to be true. The goal of this algorithm is to minimize error between the known labels and the predicted labels. Supervised learning is useful for classification, characterization and regression of the similarity between instances of similar results labels, but it is very time-consuming because the data need to be labeled by people and that also requires a lot of data sets and experience. Conversely, in unsupervised learning, the algorithms could optimally finds similarities or clusters from data, without corresponding labels, the task of this learning is to find the hidden structure in the data and to categorise it. In reinforcement learning, data labels are acquired by learning from dynamic environment interaction without being explicitly taught. For such dynamic environment, the computer will receive positive or negative reinforcement feedback and, for the predicted results, the reinforcement algorithm will receive reward or penalty feedback. Reinforcement learning can also be regarded as a hybrid of unsupervised learning and supervised learning. Based on whether the predefined features are handcrafted or not, ML can be divided into two types (Fig. 3). The first one is based on predefined handcrafted features from experts, which are considered to be able to effectively differentiate different data classes. Then the most relevant features are selected to fit the data to avoid overfitting. The second one is ML techniques without handcrafted features, that is, it can automatically and directly learn from the navigation data space, optimizing the problem-solving capabilities and reducing prediction errors. The three learning methods and their associated algorithms and applications are summarised in Table 1.

2.3. Deep learning

DL is based on multiple processing layers of artificial neural networks (ANNs). It can automatically learn information representations and accumulate experience from raw data, rather than extracting features by human experts. ANNs, as the name implies, is an artificial network system that simulates the concept of human neurons, and is one of the most successful AI approaches today [21–24]. In contrast to traditional ANNs, DL contains more hidden layers and processes inputs in a layered, non-linear manner. The unprecedented development of DL has benefited from the following factors: (1) the rapid increase in the graphic processing unit and the high-tech central processing unit [25,26]; (2) the development of learning algorithms; (3) the availability of large databases [27]. Therefore, DL techniques have achieved impressive progress in many areas [28–30].

2.4. Convolutional neural networks (CNNs)

CNNs is a subcategory of ANNs, whose input type is explicitly assumed to be images, and has been confirmed to be effective and efficient in performing medical imaging tasks [31]. The typical CNNs architecture comprises a series of layers that can be divided into four types: (1) convolutional layer: the main participant of CNNs, which consists of learnable filters; (2) pooling layer: following the convolutional layer and the function of this layer is to progressively down-sample the feature maps, also to control overfitting; (3) fully-connected layer: serving as a classifier to predict classification labels; (4) non-linearity layer: with activation function and determines whether the neuron is active or not through specific activation conditions or input images. The multiple processing layers of CNNs have been proved to enable CNNs to have the ability to learn hierarchical and abstract features of medical imaging [32].

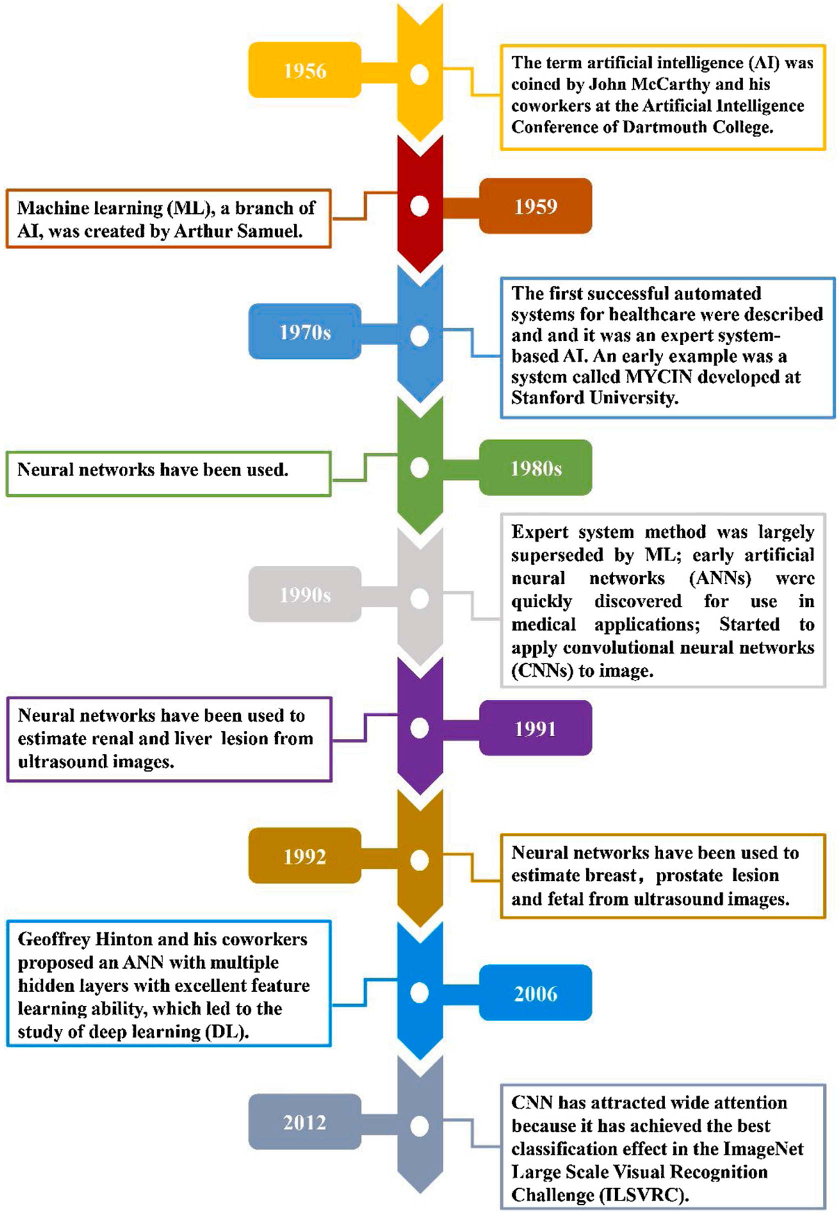

Fig. 2. Timeline of artificial intelligence technology development.

3. Overview of anatomical region-based deep learning in ultrasonic image analysis

Ultrasonic imaging analysis has entered a new era, assisted by the development of AI, the advancement of ML and the penetration of DL. Supported by these technologies, the status of US image variation factors such as operator-, scanner-, patient-dependent can be significantly improved. Computer-aided systems in US have already been recognized by the industry and benefited a lot from some principal applications, such as (Fig. 4): (1) detection: automatically identifying organ structures, lesions and other objects of interest; (2) diagnosis or classification: analyzing US imaging to assess disease status or classify it into a specific category; (3) segmentation: implemented to delineation the precise boundaries for lesions; (4) other applications including regression that involves the prediction of a continuous, approximating variable; image registration and content retrieval. In this article, we collect more influential literature on the use of AI technology in US imaging in recent years. DL, as the state-of-the-art ML approach, is particularly prominent in the field of medical imaging (including US and radiology) thanks to increased computational power and the availability of a large number of new datasets. The power of DL in terms of image recognition and raw data processing makes it a potential tool for ultrasonic image analysis. And since the corresponding studies report that DL outperforms traditional techniques and even better than radiologists in certain tasks, we then summarize the rapidly growing applications of DL in US (Tables 2–4) based on the anatomical regions (Fig. 5).

3.1. Thyroid

Nowadays, US has been endorsed as the first-line imaging modality in identifying thyroid diseases, by many guidelines including the American Thyroid Association [33] and American Association of Clinical Endocrinologists, Associazione Medici Endocrinologi and European Thyroid Association [34]. As a result, over the last years several US-image based Thyroid Imaging Reporting and Data Systems [35,36] have been established. With the advent of well-performed AI-related technologies, DL involved with thyroid US imaging has been increasingly focused on detecting and diagnosing thyroid nodules [16,37–55]

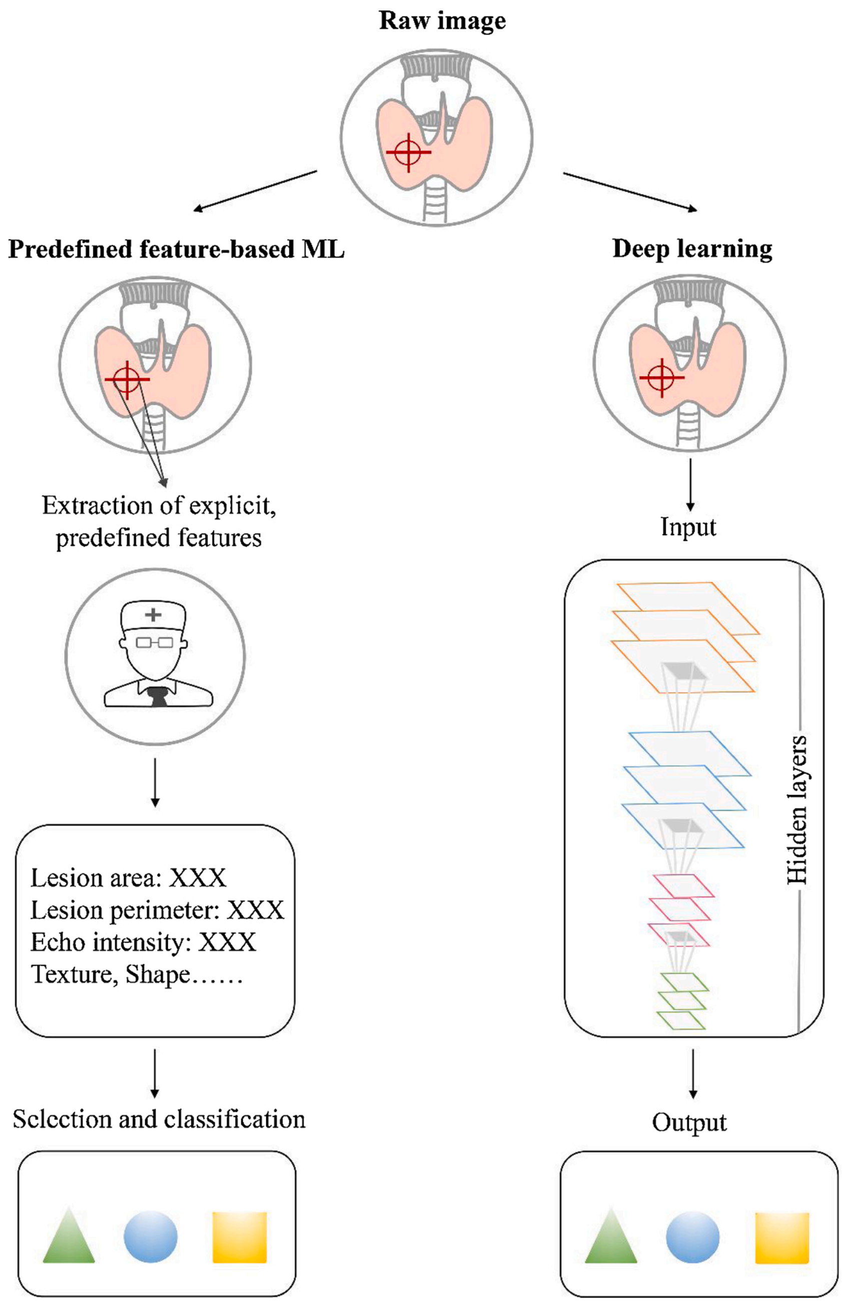

Fig. 3. A predefined handcrafted feature-based machine learning method versus a deep learning method applied to ultrasound image. The former method relies on the predefined manual features of experts, and classifies the images extracting these explicit features from the regions of interest. In contrast, the latter deep learning method automatically learns and extracts features on the basis of the raw image.

(Table 2). For instance, Liu and coworkers [47] presented a multi-scale CNNs-based method for thyroid nodule detection and classification and achieved significantly better sensitivity (0.964 vs 0.928), specificity (0.780 vs 0.366) and accuracy (0.928 vs 0.816) than those of radiologists. While in an interesting study [44] Zhu Y and coworkers created six ML models to further classify suspicious thyroid nodules undergoing fine needle aspiration using the Bethesda System for Report Thyroid Cytology. Among these, the deep neural networks performed better than other five models to help radiologists to distinguish Bethesda class III from class IV, V, VI lesions, providing effective and efficient management for those nodules. Besides, in thyroid US images, effective delineation of the nodular boundaries plays an important part in characterizing thyroid diseases [57–60]. Ma et al., proposed a CNN-based method to segment thyroid nodules automatically and accurately. And their research achieved an average of 0.915, 0.9224, 0.8683, 0.6228, 0.0669 for the true positive rate, dice ratio, overlap metric, modified Hausdorff distance, and false positive rate, respectively, on overall folds. These parameters were used to quantitatively measure the accuracy of segmentation, and indicated that this approach was really efficient and accurate. In addition, Buda et al. [37], developed a DL-based learning algorithm to assess the prognosis of thyroid nodules and the need to evaluate them for further processing by biopsy, and the algorithm achieved performance similar to that of expert radiologists adhering to the American College of Radiology's Thyroid Imaging Reporting and Data System. AI in thyroid US is also used to diagnose follicular carcinoma [49], detect papillary cancer [54], and detect lymph node metastases in the neck [56], which are useful in the evaluation of the thyroid lesions.

Table 1
Summary of three learning methods and their related algorithms and application.

Types of learning	Types of algorithm	Main application
Supervised learning	1 support vector machines [126]	This algorithm maps training data into space and finds the hyperplane where feature separation is maximized, and then applies it to classification or regression tasks.
	2 logistic regression [127]	This algorithm is a ML method for solving bicategorical problems to estimate the probability of an event. The dependent variable of a logistic regression is subject to a Bernoulli distribution.
	3 Naïve Bayes classifier [128]	This algorithm is a simple probabilistic classification method based on Bayes' theorem, which has the advantage that a small amount of training data can be used to estimate the parameters required for classification.
	4 Random forest [129]	This algorithm is a classifier with multiple decision trees, and its output is determined by the common value of the categories output from the individual trees.
	5 Decision tree [130]	This algorithm uses a flowchart-like tree model with multiple branch nodes to determine a target value from the input. It can be used to perform classification (classification trees) or regression tasks (regression trees).
	6 K-nearest neighbor algorithms	This algorithm trains the data for geometric evaluation and then determines whether the input data belongs to the same category based on the training examples obtained.
Unsupervised learning	1 Clustering methods [131]	This algorithm is designed to achieve the goal of reducing the amount of data and performing classification by categorizing or grouping similar data items.
	2 self-organizing maps [132]	A neural network-based clustering algorithm that is a single-layer neural network containing only input and output layers.
	3 Principal component analysis [133]	This algorithm is a technique for analyzing and simplifying datasets. It reduces the number of dimensions of the dataset while maintaining the features that contribute the most to the variance of the dataset
	4 K-means [134]	This algorithm measures the distance between each pair of data points and the specified clustering centroid to classify the data, and optimizes the allocation by comparing intra- and inter-family data point distances.
Reinforcement learning [2]	/	Data labels are acquired by learning from dynamic environment interaction (the computer will receive positive or negative reinforcement feedback) without being explicitly taught.

Note. ML: machine learning.

3.2. Breast

Breast cancer is considered as one of the most common cancer types in women worldwide and remains the second leading cause of cancer-related death [61,62]. Among the surveyed articles, the most common application of DL in breast US is diagnosis and classification of breast masses [63–80] (Table 2). For example, Qi et al. [68] proposed a novel model that consisted of two networks with skip connections and multi-scale kernels to overcome shortcomings of traditional one and expressed better performance in diagnosing breast cancers.

Transfer learning is a kind of ML method that could use pre-trained models to solve problems in a different application domain. When the involved dataset is relatively small, it is also an effective way to improve accuracy while reducing training time. Byra et al., [64] and Xiao et al. [67], both presented their transfer learning models for classifying breast lesions by sonography. The former [64] adopted a VGG19 neural network (a CNN model), and pre-trained it on the ImageNet as a fixed feature extraction model. Then the model of the original VGG19 CNN was modified, and the new data set was used for fine-tuning. And a highest value of 0.936 was achieved for area under curve with the fine-tuned VGG19 CNN model. The latter [65] had developed a traditional ML-based model, a CNN model as well as three transferred models. Both of them achieved the highest values of area under the curve for the classification of breast lesions compared to other methods. Automatically delineating breast tumour from US image is crucial for computer-aided diagnosis. Some studies [81–83] have already presented efficient approaches for automatically segmenting breast US imaging. Gu and coworkers [82] proposed an automated 3D segmentation approach to demarcate major tissue types in 3D breast ultrasonic volumes to assist radiologist in explaining and diagnosing breast cancer. This method included three main stages: the first step was morphological reconstruction, which can prevent false contours that caused by filtering operations; the second step was image segmentation, a 3D Sobel operators were used to extract edge information; the third step was region classification, which mainly divided images into two regions, small and big, and then further classify the tissues. Finally, this method exhibited great potential of automatic segmentation of 3D whole breast US images. And the DL model applied by Zhou et al., [14] can effectively predict clinically negative lymph node metastases, providing an early prediction strategy for patients with lymph node metastases.

3.3. Abdomen and pelvis

Abdominopelvic imaging analysis using DL has different applications in US (Table 3), many of which were focused on liver. Wang et al., [84] and Rousselet et al. [85], developed their DL modes based on elastography, and they found that this strategy was more accurate than two-dimensional SWE and some biomarkers in assessing advanced fibrosis and cirrhosis for HBV-infected patients. Lee et al. [86], also developed a deep CNN method to predict the METAVIR score (semi--quantitatively evaluate liver fibrosis), using a total of 13,608 US images from the two tertiary academic referral centers as training database. And their method showed high accuracy for predicting the METAVIR score, and was superior to radiologists in diagnosing liver fibrosis. Also, Ta et al., [87] established a computer-aided diagnosis system to classify malignant and benign focal liver lesions from CEUS cine recordings, and the accuracy of this method is similar to that of an expert reader.

Nowadays, US-guided thermal ablation is increasingly used in clinical treatment of various diseases, [88–90], including tumors, thanks to its minimally invasive property and well therapeutic effect. The real-time monitoring and evaluation of the thermal ablation process is critical to improve the clinical practice, accurate treatment and reduce thermal damage to surrounding tissues. Recently, Zhang and his/her team [91] proposed to evaluate the performance of a US-CNNs architecture in detecting and monitoring of microwave ablation-induced thermal lesions in porcine liver, widely broadening the potential clinical application of DL. Lei et al. [92], provided a multidirectional DL-based method that integrating deep supervision into 3D patch-based V-Net for the segmentation of transrectal ultrasound prostate images. And it proved to be a promising tool for the diagnosis of prostate cancer and US-guided therapy.

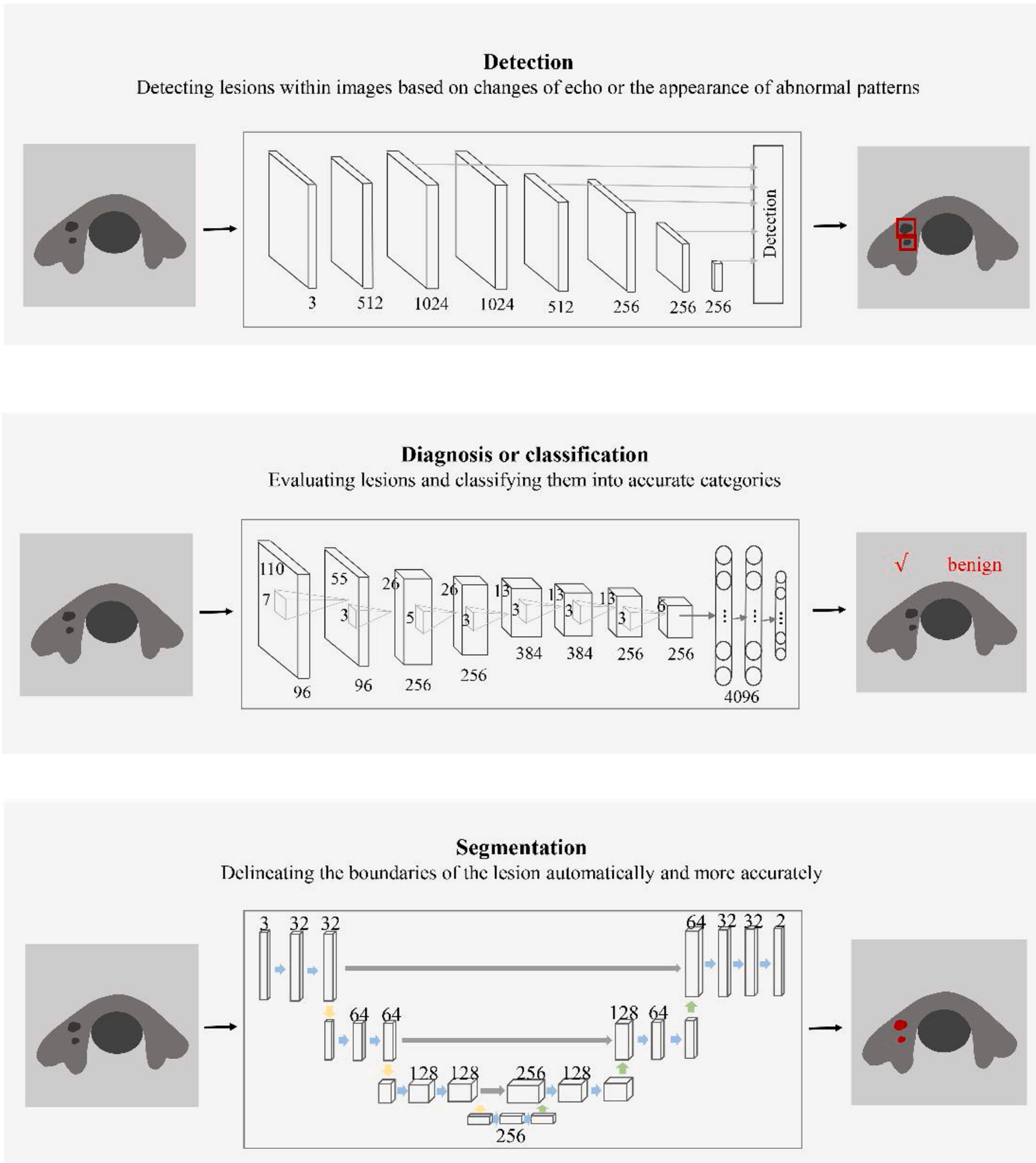

Fig. 4. The three main applications of artificial intelligence in ultrasonic image analysis include detection, diagnosis or classification and segmentation, which helps radiologists to analyze images more accurately.

3.4. Obstetrics and gynecology

For decades, US has been the main imaging modality in diagnosis of fetal anomalies. The application of DL based on obstetric US imaging is increasing and maturing (Table 3). For example, Burgos-Artizzu et al., [93] provided a new Fetal Lung Maturity estimator software (quantusFLM®) version 3.0 (Transmural Biotech, Barcelona, Spain), which incorporated DL-based techniques for the delineation of the fetal lung. This method significantly improved the prediction rate of neonatal respiratory morbidity with fully automated identification, delineation and segmentation of the fetal lung US images. In a recent study, Xie H et al. [152] used CNN-based DL algorithms to classify fetal brain sonographic images. The DL algorithms were trained in three steps: firstly, segmenting the craniocerebral region; secondly, classifying fetal US brain images as normal or abnormal; thirdly, locating lesions using heat maps. Then the performance of this classification system was evaluated with accuracy, sensitivity and specificity, which were 96.3 %, 96.9 and 95.9 % respectively. This method obtained well classification performance, but the average time needed for the whole process of one image was about 1.08 s, which was a small limitation.

During the obstetric examination, accurately obtaining a standard fetal plane with critical anatomical structures is pivotal for diagnosis and biometric measurement. Chen et al., [94] and Yu et al. [95], proposed their CNNs approaches that could extract in- and between-plane spatial features from fetal US with specialized convolutional and recurrent neural networks to identify and classify fetal standard planes. Besides, the fetal abdominal circumference or other structures are difficult to assess accurately due to their particular environment. As Drukker et al. [96], showed: when training computer models to perform tasks, try to reduce the generation of artificially trained bias models, which can

Table 2
Summarize the machine learning applications in thyroid and breast ultrasonic image analysis in the papers surveyed.

Organ system and body location	Disease classification	Object detection	Image segmentation	Prognosis evaluation
Thyroid	Diagnosis of thyroid malignancy [16,38,39,40, 42,43,45,46, 47,50,51,52]	Detection of thyroid nodules [47, 48,53,55]	Segmentation of thyroid nodules [57, 58]	Management of thyroid nodules [37]
	Diagnose benign nodules and avoid unnecessary fine-needle aspiration [41]	Detection of thyroid papillary cancer [54]	Segmentation of thyroid US images [59]	
	Differentiate Bethesda class III versus class IV/V/VI [44]	Detection of neck metastatic lymph nodes [56]	Segmentation of leukocyte in papillary thyroid carcinoma [60]	
	Classification of the follicular neoplasm [49]	Detection and extraction of calcification in thyroid US images [135]		
	Diagnosis of neck metastatic lymph nodes [56]			
Breast	Distinction between benign and malignant breast masses [63,64,65,66, 67,68,69,70, 71,74,75,78]	Detection of breast lesions [74,136,137]	Segmentation of breast nodules [71, 138]	Assessment of the prognosis of breast cancer and prediction of lymph node metastasis [14]
	Classification of focal breast lesions [72,76]	Detection and Recognize solid nodules [68]	Segmentation of breast region of interest [81]	Prediction of response to neoadjuvant chemotherapy in breast cancer sonography [139]
	Classification of breast cancer [73,77, 79,80]			
	Assessment of axillary lymph node metastasis [14, 15,140]			

reduce the detection of deviations expected measurement values in the third trimester of pregnancy. In addition, for applications in prognostic assessment, Liang et al. [155], based on the DL model CR-Unet used in a previous study to predict follicle maturation during the reproductive cycle, the intraobserver variability was expressed as intra-class correlation coefficients, which was 0.973 and 0.982 for senior and junior sonographers, respectively, and 0.979 and 0.920 for multiple follicle cycles, respectively, during the measurement. However, the DL model CR-Unet has no intra-group variation and requires significantly less measurement time. This demonstrates the potential of the model for clinical application in predicting follicular maturation during the reproductive cycle.

While the application of AI in US obstetrics has gradually increased, there are still some shortcomings in the application of AI in this field. For example, the AI technology designed for the second trimester is not suitable for the first trimester scans. Besides, the estimation of gestational age and the diagnosis of placenta previa need continuous involvement and breakthroughs [97].

3.5. Heart and blood vessels

Since echocardiography is a real-time imaging technology for evaluating the status of heart and blood vessels, it plays a central role in the management of cardiovascular diseases. Accurate and reliable echocardiographic evaluation is essential for clinical diagnosis and treatment. A landmark article published by Zhang et al., [98], used the DL model to fully automate the processing of echocardiography, including disease detection, image segmentation, structure and function quantification, enabling numbers of cardiologists aware of the potential role of AI in this field. DL related to echocardiography involves the classification of images such as Madani and coworkers [99] trained a CNN for echocardiographic view classification with an overall accuracy of 97.8 % and no overfitting. The accuracy of 91.7 % on individual low-resolution images was much higher than that of 70.2–84.0 % for echocardiographers. This demonstrates the potential of the model for clinical applications. And ventricular wall motion [100–102], the detection of heart diseases [103,104], and the segmentation of ventricles [105,106] (Table 4).

US plays an important role in the evaluation of superficial blood vessel diseases because of its unique advantages including short examination time, non-invasiveness, and good practicability. DL-based assessment of vascular US images has been applied to the measurement and classification of carotid artery intima-media thickness [107], classification of vascular plaque components [108], detection of the vascular lumen [109], and segmentation of vascular images [110–113] (Table 4). For example, Zhou et al., [110] proposed a DL-based semi-automatic segmentation method to segment the media-adventitia and lumen-intima from carotid 3-D images. with dynamic CNN model and an improved U-Net model, respectively. And it showed better performance with average Dice similarity coefficients (DSC) of 96.46 ± 2.22 % and 92.84 ± 4.46 % for media-adventitia and lumen-intima, respectively, compared with other methods. Lo Vercio et al. [111], and Yang et al. [112], proposed their DL-based automatic segmentation methods for dividing the lumen-intima and media-adventitia and showed excellent performance, demonstrating great potential in monitoring atherosclerosis.

3.6. Musculoskeletal system

In recent years, the improved resolution of US for soft tissue by US has contributed to its increasing use in musculoskeletal system (Table 4). For example, DL-based US is used for the diagnosis of muscle diseases [114,115], cone positioning [116,117], and segmentation of muscle imageing [118,119]. A CNN-based method proposed by Burlina et al., [114] was used for the assessment and classification of inflammatory muscle diseases, which improved the accuracy of diagnosis of neuromuscular diseases. The accuracy of applying this CNN-based method compared to conventional ML method for the classification of the three conditions of myositis was 76.2 % ± 3.1 % vs 72.3 % ± 3.3 % (normal vs affected (inclusion body myositis, dermatomyositis, polymyositis)); 86.6 % ± 2.4 % vs 84.3 ± 2.3 % (normal vs inclusion body myositis); 74.8 % ± 3.9 % vs 68.9 % ± 2.5 % (inclusion body myositis vs dermatomyositis or polymyositis). The correct identification of the vertebral level is crucial for neuroanesthesia and analgesia. However, current clinical practice usually uses manual palpation of the spine to blindly identify the position of the vertebrae with an accuracy of only 30 %. Hetherington and coworkers have developed a CNN approach to automatically identify vertebrae levels in real time in US images and their images can

Table 3
Summarize the machine learning applications in abdomen and pelvis and obstetrics ultrasonic image analysis in the papers surveyed.

Organ system and body location	Disease classification	Object detection	Image segmentation	Prognosis evaluation
Abdomen and pelvis	Classification of liver fibrosis [84,86] Classification of benign and malignant focal liver lesions [87,144] Risk stratification of fatty liver disease [141] Classification and Prediction of kidney function or disease [148,149] Classification of three classes of kidney ultrasound images [126]	Detection of fatty liver disease [141] Detection of thermal lesions induced by microwave ablation [91] Detection of image registration for prostate radiotherapy [147] Detection of prostate image registration [150] Detection of prostate cancer [151]	Segmentation of US prostate [92,142,143] Segmentation of US kidney [145]	Monitoring of thermal lesions induced by microwave ablation [91] Prediction of responses to TACE for hepatocellular carcinoma patients [146]
Obstetrics and gynecology	Classification of fetal brain US images [152] Classification of fetal standard planes [94,95] Estimation of fetal abdominal circumference [158,159] Diagnosis of ovarian cancer [160]	Detection and localization of fetal brain structures [153,154] Detection and assessment of fetal ultrasound image quality [156] Detection of expected value bias in routine third-trimester growth scans [96]	Segmentation of fetal lung [93] Segmentation of placenta [157]	Monitoring of US follicle to reduce diameter variability [155]

Note. US: ultrasound, TACE: transarterial chemoembolization.

Table 4
Summarize the machine learning applications in heart and blood vessels and musculoskeletal system as well as other organ systems ultrasonic image analysis in the papers surveyed.

Organ system and body location	Disease classification	Object detection	Image segmentation	Prognosis evaluation
Heart	View classification of echocardiograms [99,100] Classification of myocardial wall motion [101,102] Diagnosis of ventricular volume [161]	Detection of heart disease [98,103, 104]	Segmentation of the ventricle of the heart [105] Segmentation of left ventricle and left atrium [106]	
Blood vessels	Classification of carotid artery intima-media thickness [107] Characterization of plaque composition in vascular [108]	Detection of vascular lumen [109]	Segmentation of lumen-intima and media-adventitia [110,111,112] Segmentation of vascular structure [113]	
Musculoskeletal system	Diagnosis of myositis from muscle US [114] Estimation of skeletal muscle status [115]	US-assisted vertebral body positioning [116] Detection and identification of spine level [117]	Segmentation of rectus femoris muscle [118] Segmentation of puborectalis muscle and urogenital hiatus [119]	
Other organ systems or body location	Classification of pediatric pneumonia [120] Assessment and diagnosis of lung US [122,123]	Improve US imaging contrast and detection rate [124]	Segmentation of subpleural pulmonary lesions [121]	

Note. US: ultrasound.

be integrated into the 3D Slicer and achieve a 20-fold cross-validation accuracy of up to 88 %. Chen et al., [118] developed a method for automatic segmentation of rectus femoris using CNN method, which only required 0.2 s. Real-time ultrasonic images of the rectus femoris muscle were obtained during the contraction of the muscle, followed by feature extraction and fractional map reconstruction to build a CNN segmentation of the rectus femoris muscle. In addition, Van den Noort et al., [119] developed a CNN model for the segmentation of the urogenital hiatus and puborectalis muscle in the plane of the minimal hiatal dimensions with transperineal US imaging.

3.7. Other organs

In addition to the applications of DL-related US in the above-mentioned organs, other aspects have also been explored, such as lung applications [120–123] and image processing applications [124] (Table 4).

4. Conclusions and outlook

For decades, US has been applied extensively in disease diagnosis because of its high safety and efficiency. Especially with recent well-implemented advances in the establishment of US-based digital health system—Picture Archiving and Communication System, US images can be electronically organized systematically, allowing for their rapid expansion in different medical fields. Optimizing AI-related technology in US can bring three domains of benefits:(a) effective: providing reliable diagnosis guidance, assist radiologists in making clinical diagnostic decisions;(b) efficient: reducing the workload of radiologists and saving time for patients and providers;(c) equitable: as medical resources in many urban and rural areas of some countries are unbalanced, the AI-based US system could contribute to reducing barriers and offering a convenient method to provide US services. However, there still some critical issues that should be addressed before their widely clinical application.

On the one hand, it is the data that contribute to the most central and critical component of AI learning systems, and thus both the quantity and quality of database will directly affect performance of the AI-related technologies. As we all know, compared with computed tomography and magnetic resonance imaging, US is a type of imaging modality with high operator dependence, and there inevitably exists high internal and external variabilities in the manual acquisition and evaluation of US images. Such US image data are usually not curated in “real-world” clinical practice, representing a major bottleneck for learning any AI

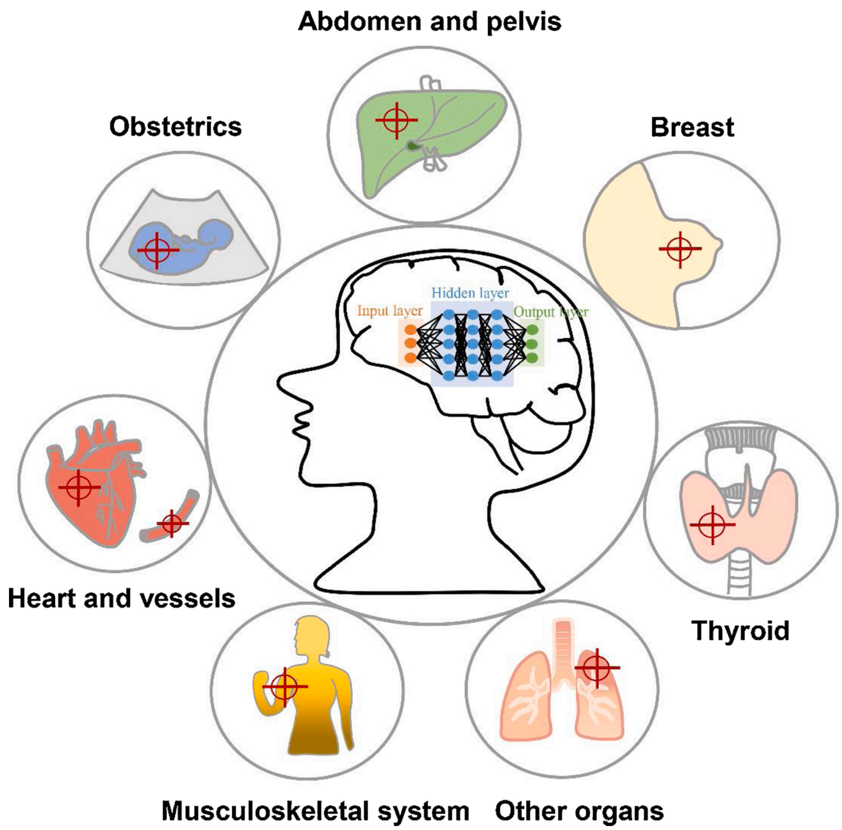

Fig. 5. Artificial intelligence (especially deep learning)-related ultrasound imaging analysis has been applied in the field of thyroid, breast, abdomen and pelvis, obstetrics and gynecology, heart and blood vessels and musculoskeletal system as well as other organs in the papers surveyed.

model. Curation ensures that all the training data could adhere to a predefined set of quality criteria, and thus to avoid the unwanted variance within US imaging data owing to differences in acquisition processes or imaging protocols. Therefore, a standard of US image collecting and processing should be constructed, especially across institutions, to better improve quality of the database. Besides, based on the fifth-generation (5 G) wireless transmission and cloud servers, tele-ultrasound can be operated with a "cloud-based data transmission and management" mode. This advanced technology can provide powerful network services to support "real-time" interaction of Digital Imaging and Communications in Medicine (DICOM) Data, and it can serve as a "DICOM Data bank", DICOM has revolutionised radiology practice, offering a great opportunity for the development of AI technology.

On the other hand, AI-model technology synthesizing the two-dimensional, 3D, SWE and CEUS images–called ultrasonic radiomics, can provide high-throughput medical features of the detected diseases. Also, clinical parameters can help to provide some complementary information for the image features. In addition, "black box" medicine is an unavoidable challenge. AI algorithms lack transparency. For example, we cannot know the internal structure of the multiple hidden layers between the DL input layer and the output layer. If there is an error in the hidden layer of the algorithm, there is no way to know which layer it is, making it difficult to find a solution to the question [125]. Another ethical issue concerning AI in US involves patient privacy and data security. The handling of patient data is closely related to computer programmers, and the protection of data is critical when training, validating and sharing data.

In conclusion, AI technology, driven by the considerable demand for US imaging from clinical practice and the advanced technologies, will undoubtedly have broad prospects in US. However, we should give an entire and exact understanding of this novel issue. AI-based US diagnosis fails to make top-down associations like a human brain and is lack of humanistic care and logical reasoning advocated in the medical process, so radiologists cannot be entirely replaced by machines. With the construction of large shared US standard-datasets and the exploration of AI technology and its hidden information, we believe that AI-based US will gradually evolve into an important educational resource, explaining its diagnostic basis, facilitating US clinical workflow, and ultimately, benefit both patients and doctors.

Declaration of Competing Interest

The authors declare no conflict of interest.

Acknowledgements

This work was supported in part by the National Natural Science Foundation of China (Grants 81601502, 81900491, 81671695 and 81927801), the Science and Technology Commission of Shanghai Municipality (Grants 19441903200) and Shanghai Pujiang Program (2019PJD039).

References

[1] S.L. Goldenberg, G. Nir, S.E. Salcudean, A new era: artificial intelligence and machine learning in prostate cancer, Nat. Rev. Urol. 16 (7) (2019) 391–403.
[2] V. Mnih, K. Kavukcuoglu, D. Silver, A.A. Rusu, J. Veness, M.G. Bellemare, A. Graves, M. Riedmiller, A.K. Fidjeland, G. Ostrovski, S. Petersen, C. Beattie, A. Sadik, I. Antonoglou, H. King, D. Kumaran, D. Wierstra, S. Legg, D. Hassabis, Human-level control through deep reinforcement learning, Nature 518 (7540) (2015) 529–533.
[3] S.D. Pendleton, H. Andersen, X.X. Du, X.T. Shen, M. Meghjani, Y.H. Eng, D. Rus, M.H. Ang, Perception, Planning, Control, and Coordination for Autonomous Vehicles, Machines 5 (1) (2017) 6.
[4] M. Moravcik, M. Schmid, N. Burch, V. Lisy, D. Morrill, N. Bard, T. Davis, K. Waugh, M. Johanson, M. Bowling, DeepStack: Expert-level artificial intelligence in heads-up no-limit poker, Science 356 (6337) (2017) 508–513.

[5] J.H. Chen, S.M. Asch, Machine learning and prediction in medicine - beyond the peak of inflated expectations, N. Engl. J. Med. 376 (26) (2017) 2507–2509.
[6] E.J. Topol, High-performance medicine: the convergence of human and artificial intelligence, Nat. Med. 25 (1) (2019) 44–56.
[7] K.H. Yu, A.L. Beam, I.S. Kohane, Artificial intelligence in healthcare, Nat. Biomed. Eng. 2 (10) (2018) 719–731.
[8] H.J. Aerts, The potential of radiomic-based phenotyping in precision medicine: a review, JAMA Oncol. 2 (12) (2016) 1636–1642.
[9] P. Lambin, E. Rios-Velazquez, R. Leijenaar, S. Carvalho, R.G.P.M. van Stiphout, P. Granton, C.M.L. Zegers, R. Gillies, R. Boellard, A. Dekker, H.J.W.L. Aerts, Q. C. Consortium, Radiomics: extracting more information from medical images using advanced feature analysis, Eur. J. Cancer 48 (4) (2012) 441–446.
[10] W.L. Bi, A. Hosny, M.B. Schabath, M.L. Giger, N.J. Birkbak, A. Mehrtash, T. Allison, O. Arnaout, C. Abbosh, I.F. Dunn, R.H. Mak, R.M. Tamimi, C. M. Tempany, C. Swanton, U. Hoffmann, L.H. Schwartz, R.J. Gillies, R.Y. Huang, H. Aerts, Artificial intelligence in cancer imaging: clinical challenges and applications, CA Cancer J. Clin. 69 (2) (2019) 127–157.
[11] G.R. Kim, J.S. Choi, B.K. Han, J.E. Lee, S.J. Nam, E.Y. Ko, E.S. Ko, S.K. Lee, Preoperative axillary US in early-stage breast Cancer: potential to prevent unnecessary axillary lymph node dissection, Radiology 288 (1) (2018) 55–63.
[12] E.A. Sadowski, V. Paroder, K. Patel-Lippmann, J.B. Robbins, L. Barroilhet, E. Maddox, T. McMahon, E. Sampene, A.P. Wasnik, A.D. Blaty, K.E. Maturen, Indeterminate adnexal cysts at US: prevalence and characteristics of ovarian Cancer, Radiology 287 (3) (2018) 1041–1049.
[13] J.R. van Nagell Jr., P.D. DePriest, F.R. Ueland, C.P. DeSimone, A.L. Cooper, J. M. McDonald, E.J. Pavlik, R.J. Kryscio, Ovarian cancer screening with annual transvaginal sonography: findings of 25,000 women screened, Cancer 109 (9) (2007) 1887–1896.
[14] L.Q. Zhou, X.L. Wu, S.Y. Huang, G.G. Wu, H.R. Ye, Q. Wei, L.Y. Bao, Y.B. Deng, X. R. Li, X.W. Cui, C.F. Dietrich, Lymph node metastasis prediction from primary breast Cancer us images using deep learning, Radiology 294 (1) (2020) 19–28.
[15] X.Y. Zheng, Z. Yao, Y.N. Huang, Y.Y. Yu, Y. Wang, Y.B. Liu, R.S. Mao, F. Li, Y. Xiao, Y. Wang, Y.X. Hu, J.H. Yu, J.H. Zhou, Deep learning radiomics can predict axillary lymph node status in early-stage breast cancer, Nat. Commun. 11 (1) (2020) 1236.
[16] X.C. Li, S. Zhang, Q. Zhang, X. Wei, Y. Pan, J. Zhao, X.J. Xin, C.X. Qin, X.Q. Wang, J.X. Li, F. Yang, Y.H. Zhao, M. Yang, Q.H. Wang, M. Zheng, X.Q. Zheng, X. M. Yang, C.T. Whitlow, M.N. Gurcan, L. Zhang, X.D. Wang, B.C. Pasche, M. Gao, W. Zhang, K.X. Chen, Diagnosis of thyroid cancer using deep convolutional neural network models applied to sonographic images: a retrospective, multicohort, diagnostic study, Lancet Oncol. 20 (2) (2019) 193–201.
[17] D. Yoon, What we need to prepare for the fourth industrial revolution, Healthc. Inform. Res. 23 (2) (2017) 75–76.
[18] Russell, J. Stuart, Artificial Intelligence: A Modern Approach, 2002.
[19] R.C. Deo, Machine learning in medicine, Circulation 132 (20) (2015) 1920–1930.
[20] G. Choy, O. Khalilzadeh, M. Michalski, S. Do, A.E. Samir, O.S. Pianykh, J.R. Geis, P.V. Pandharipande, J.A. Brink, K.J. Dreyer, Current applications and future impact of machine learning in radiology, Radiology 288 (2) (2018) 318–328.
[21] D. Hassabis, D. Kumaran, C. Summerfield, M. Botvinick, Neuroscience-inspired artificial intelligence, Neuron 95 (2) (2017) 245–258.
[22] A.M. Zador, A critique of pure learning and what artificial neural networks can learn from animal brains, Nat. Commun. 10 (1) (2019) 3770.
[23] D.C. Mocanu, E. Mocanu, P. Stone, P.H. Nguyen, M. Gibescu, A. Liotta, Scalable training of artificial neural networks with adaptive sparse connectivity inspired by network science, Nat. Commun. 9 (1) (2018) 2383.
[24] G. Hinton, Deep Learning-A technology with the potential to transform health care, Jama-J Am Med Assoc 320 (11) (2018) 1101–1102.
[25] K.Y. Ngiam, I.W. Khor, Big data and machine learning algorithms for health-care delivery, Lancet Oncol. 20 (5) (2019) e262–e273.
[26] E. Gawehn, J.A. Hiss, J.B. Brown, G. Schneider, Advancing drug discovery via GPU-based deep learning, Expert Opin. Drug Discov. 13 (7) (2018) 579–582.
[27] S. Zhang, D. Metaxas, Large-Scale medical image analytics: recent methodologies, applications and Future directions, Med. Image Anal. 33 (2016) 98–101.
[28] D. Lin, A.V. Vasilakos, Y. Tang, Y.Z. Yao, Neural networks for computer-aided diagnosis in medicine: a review, Neurocomputing 216 (2016) 700–708.
[29] Z. Akkus, J. Cai, A. Boonrod, A. Zeinoddini, A.D. Weston, K.A. Philbrick, B. J. Erickson, A survey of deep-learning applications in ultrasound: artificial intelligence-powered ultrasound for improving clinical workflow, J. Am. Coll. Radiol. 16 (9) (2019) 1318–1328.
[30] F. Verburg, C. Reiners, Sonographic diagnosis of thyroid cancer with support of AI, Nat. Rev. Endocrinol. 15 (6) (2019) 319–321.
[31] S. Soffer, A. Ben-Cohen, O. Shimon, M.M. Amitai, H. Greenspan, E. Klang, Convolutional neural networks for radiologic images: a radiologist's guide, Radiology 290 (3) (2019) 590–606.
[32] Y. LeCun, Y. Bengio, G. Hinton, Deep learning, Nature 521 (7553) (2015) 436–444.
[33] B.R. Haugen, E.K. Alexander, K.C. Bible, G.M. Doherty, S.J. Mandel, Y. E. Nikiforov, F. Pacini, G.W. Randolph, A.M. Sawka, M. Schlumberger, K. G. Schuff, S.I. Sherman, J.A. Sosa, D.L. Steward, R.M. Tuttle, L. Wartofsky, 2015 American Thyroid Association Management Guidelines for Adult Patients with Thyroid Nodules and Differentiated Thyroid Cancer: The American Thyroid Association Guidelines Task Force on Thyroid Nodules and Differentiated Thyroid Cancer, Thyroid 26 (1) (2016) 1–133.
[34] H. Gharib, E. Papini, R. Paschke, D.S. Duick, R. Valcavi, L. Hegedus, P. Vitti, A.A. E.T.F.o.T. Nodules, American Association of Clinical Endocrinologists, Associazione Medici Endocrinologi, and European Thyroid Association medical guidelines for clinical practice for the diagnosis and management of thyroid nodules: executive summary of recommendations, J. Endocrinol. Invest. 33 (5 Suppl) (2010) 51–56.
[35] J.Y. Kwak, K.H. Han, J.H. Yoon, H.J. Moon, E.J. Son, S.H. Park, H.K. Jung, J. S. Choi, B.M. Kim, E.K. Kim, Thyroid imaging reporting and data system for US features of nodules: a step in establishing better stratification of cancer risk, Radiology 260 (3) (2011) 892–899.
[36] J.Y. Park, H.J. Lee, H.W. Jang, H.K. Kim, J.H. Yi, W. Lee, S.H. Kim, A proposal for a thyroid imaging reporting and data system for ultrasound features of thyroid carcinoma, Thyroid 19 (11) (2009) 1257–1264.
[37] M. Buda, B. Wildman-Tobriner, J.K. Hoang, D. Thayer, F.N. Tessler, W. D. Middleton, M.A. Mazurowski, Management thyroid nodules seen on US images: deep learning may match performance of radiologists, Radiology 292 (3) (2019) 695–701.
[38] S.Y. Ko, J.H. Lee, J.H. Yoon, H. Na, E. Hong, K. Han, I. Jung, E.K. Kim, H.J. Moon, V.Y. Park, E. Lee, J.Y. Kwak, Deep convolutional neural network for the diagnosis of thyroid nodules on ultrasound, Head Neck 41 (4) (2019) 885–891.
[39] Y.J. Choi, J.H. Baek, H.S. Park, W.H. Shim, T.Y. Kim, Y.K. Shong, J.H. Lee, A computer-aided diagnosis system using artificial intelligence for the diagnosis and characterization of thyroid nodules on ultrasound: initial clinical assessment, Thyroid 27 (4) (2017) 546–552.
[40] Y.J. Yoo, E.J. Ha, Y.J. Cho, H.L. Kim, M. Han, S.Y. Kang, Computer-aided diagnosis of thyroid nodules via ultrasonography: initial clinical experience, Korean J. Radiol. 19 (4) (2018) 665–672.
[41] J. Song, Y.J. Chai, H. Masuoka, S.W. Park, S.J. Kim, J.Y. Choi, H.J. Kong, K.E. Lee, J. Lee, N. Kwak, K.H. Yi, A. Miyauchi, Ultrasound image analysis using deep learning algorithm for the diagnosis of thyroid nodules, Medicine 98 (15) (2019).
[42] E. Lee, H. Ha, H.J. Kim, H.J. Moon, J.H. Byon, S. Huh, J. Son, J. Yoon, K. Han, J. Y. Kwak, Differentiation of thyroid nodules on US using features learned and extracted from various convolutional neural networks, Sci Rep-Uk 9 (1) (2019) 19854.
[43] V.Y. Park, K. Han, Y.K. Seong, M.H. Park, E.K. Kim, H.J. Moon, J.H. Yoon, J. Y. Kwak, Diagnosis of thyroid nodules: performance of a deep learning convolutional neural network model vs, Radiol. Sci. Rep. 9 (1) (2019) 17843.
[44] Y. Zhu, Q. Sang, S.J. Jia, Y. Wang, T. Deyer, Deep neural networks could differentiate Bethesda class III versus class IV/V/VI, Ann. Transl. Med. 7 (11) (2019) 231.
[45] L. Wang, S.J. Yang, S. Yang, C. Zhao, G.Y. Tian, Y.X. Gao, Y.J. Chen, Y. Lu, Automatic thyroid nodule recognition and diagnosis in ultrasound imaging with the YOLOv2 neural network, World J. Surg. Oncol. 17 (1) (2019) 12.
[46] J.L. Ma, F. Wu, J. Zhu, D. Xu, D.X. Kong, A pre-trained convolutional neural network based method for thyroid nodule diagnosis, Ultrasonics 73 (2017) 221–230.
[47] T.J. Liu, Q.Q. Guo, C.F. Lian, X.H. Ren, S.J. Liang, J. Yu, L.J. Niu, W.D. Sun, D. G. Shen, Automated detection and classification of thyroid nodules in ultrasound images using clinical-knowledge-guided convolutional neural networks, Med. Image Anal. 58 (2019), 101555.
[48] W. Song, S. Li, J. Liu, H. Qin, B. Zhang, S. Zhang, A. Hao, Multitask cascade convolution neural networks for automatic thyroid nodule detection and recognition, IEEE J. Biomed. Health Inform. 23 (3) (2019) 1215–1224.
[49] J.K. Seo, Y.J. Kim, K.G. Kim, I. Shin, J.H. Shin, J.Y. Kwak, Differentiation of the follicular neoplasm on the gray-scale US by image selection subsampling along with the marginal outline using convolutional neural network, Biomed Res. Int. 2017 (2017), 3098293.
[50] D.T. Nguyen, T.D. Pham, G. Batchuluun, H.S. Yoon, K.R. Park, Artificial intelligence-based thyroid nodule classification using information from spatial and frequency domains, J. Clin. Med. 8 (11) (2019) 1976.
[51] J.N. Chi, E. Walia, P. Babyn, J. Wang, G. Groot, M. Eramian, Thyroid nodule classification in ultrasound images by fine-tuning deep convolutional neural network, J. Digit. Imaging 30 (4) (2017) 477–486.
[52] Q. Guan, Y.J. Wang, J.J. Du, Y. Qin, H.T. Lu, J. Xiang, F. Wang, Deep learning based classification of ultrasound images for thyroid nodules: a large scale of pilot study, Ann. Transl. Med. 7 (7) (2019) 137.
[53] J. Ma, F. Wu, T. Jiang, J. Zhu, D. Kong, Cascade convolutional neural networks for automatic detection of thyroid nodules in ultrasound images, Med. Phys. 44 (5) (2017) 1678–1691.
[54] H. Li, J. Weng, Y. Shi, W. Gu, Y. Mao, Y. Wang, W. Liu, J. Zhang, An improved deep learning approach for detection of thyroid papillary cancer in ultrasound images, Sci. Rep. 8 (1) (2018) 6600.
[55] J. Ma, S. Duan, Y. Zhang, J. Wang, Z. Wang, R. Li, Y. Li, L. Zhang, H. Ma, Efficient deep learning architecture for detection and recognition of thyroid nodules, Comput. Intell. Neurosci. 2020 (2020), 1242781.
[56] J.H. Lee, J.H. Baek, J.H. Kim, W.H. Shim, S.R. Chung, Y.J. Choi, J.H. Lee, Deep learning-based computer-aided diagnosis system for localization and diagnosis of metastatic lymph nodes on ultrasound: a pilot study, Thyroid 28 (10) (2018) 1332–1338.
[57] J.L. Ma, F. Wu, T.A. Jiang, Q.Y. Zhao, D.X. Kong, Ultrasound image-based thyroid nodule automatic segmentation using convolutional neural networks, Int. J. Comput. Assist. Radiol. Surg. 12 (11) (2017) 1895–1910.
[58] M. Buda, B. Wildman-Tobriner, K. Castor, J.K. Hoang, M.A. Mazurowski, Deep learning-based segmentation of nodules in thyroid ultrasound: improving performance by utilizing markers present in the images, Ultrasound Med. Biol. 46 (2) (2020) 415–421.
[59] P. Poudel, A. Illanes, D. Sheet, M. Friebe, Evaluation of commonly used algorithms for thyroid ultrasound images segmentation and improvement using machine learning approaches, J. Healthc. Eng. 2018 (2018), 8087624.

[60] S.E. Stenman, D. Bychkov, H. Kucukel, N. Linder, C. Haglund, J. Arola, L. Johan, Antibody supervised training of a deep learning based algorithm for leukocyte segmentation in papillary thyroid carcinoma, IEEE J Biomed Health Inform PP (2020).
[61] C.E. DeSantis, J. Ma, A. Goding Sauer, L.A. Newman, A. Jemal, Breast cancer statistics, 2017, racial disparity in mortality by state, CA Cancer J. Clin. 67 (6) (2017) 439–448.
[62] R.L. Siegel, K.D. Miller, A. Jemal, Cancer Statistics, 2018, Ca-Cancer J Clin 68 (1) (2018) 7–30.
[63] T. Fujioka, K. Kubota, M. Mori, Y. Kikuchi, L. Katsuta, M. Kasahara, G. Oda, T. Ishiba, T. Nakagawa, U. Tateishi, Distinction between benign and malignant breast masses at breast ultrasound using deep learning method with convolutional neural network, J. Radiol. 37 (6) (2019) 466–472.
[64] M. Byra, M. Galperin, H. Ojeda-Fournier, L. Olson, M. O'Boyle, C. Comstock, M. Andre, Breast mass classification in sonography with transfer learning using a deep convolutional neural network and color conversion, Med. Phys. 46 (2) (2019) 746–755.
[65] L. Bing, W. Wang, Sparse representation based multi-instance learning for breast ultrasound image classification, Comput Math Method M 2017 (2017), 7894705.
[66] S. Han, H.K. Kang, J.Y. Jeong, M.H. Park, W. Kim, W.C. Bang, Y.K. Seong, A deep learning framework for supporting the classification of breast lesions in ultrasound images, Phys. Med. Biol. 62 (19) (2017) 7714–7728.
[67] T. Xiao, L. Liu, K. Li, W.J. Qin, S.D. Yu, Z.C. Li, Comparison of transferred deep neural networks in ultrasonic breast masses discrimination, Biomed Res. Int. 2018 (2018), 4605191.
[68] X.F. Qi, L. Zhang, Y. Chen, Y. Pi, Y. Chen, Q. Lv, Z. Yi, Automated diagnosis of breast ultrasonography images using deep neural networks, Med. Image Anal. 52 (2019) 185–198.
[69] J.Z. Cheng, D. Ni, Y.H. Chou, J. Qin, C.M. Tiu, Y.C. Chang, C.S. Huang, D. Shen, C. M. Chen, Computer-aided diagnosis with deep learning architecture: applications to breast lesions in US images and pulmonary nodules in CT scans, Sci Rep-Uk 6 (2016) 24454.
[70] K. Kim, M.K. Song, E.K. Kim, J.H. Yoon, Clinical application of S-Detect to breast masses on ultrasonography: a study evaluating the diagnostic performance and agreement with a dedicated breast radiologist, Ultrasonography 36 (1) (2017) 3–9.
[71] K.D. Marcomini, A.A.O. Carneiro, H. Schiabel, Application of artificial neural network models in segmentation and classification of nodules in breast ultrasound digital images, Int. J. Biomed. Imaging 2016 (2016), 7987212.
[72] M. Di Segni, V. de Soccio, V. Cantisani, G. Bonito, A. Rubini, G. Di Segni, S. Lamorte, V. Magri, C. De Vito, G. Migliara, T.V. Bartolotta, A. Metere, L. Giacomelli, C. de Felice, F. D'Ambrosio, Automated classification of focal breast lesions according to S-detect: validation and role as a clinical and teaching tool, J. Ultrasound 21 (2) (2018) 105–118.
[73] A.S. Becker, M. Mueller, E. Stofel, M. Marcon, S. Ghafoor, A. Boss, Classification of breast cancer in ultrasound imaging using a generic deep learning analysis software: a pilot study, Brit J Radiol 91 (1083) (2018).
[74] Z.T. Cao, L.X. Duan, G.W. Yang, T. Yue, Q. Chen, An experimental study on breast lesion detection and classification from ultrasound images using deep learning architectures, BMC Med. Imaging 19 (1) (2019) 51.
[75] J.S. Choi, B.K. Han, E.S. Ko, J.M. Bae, E.Y. Ko, S.H. Song, M.R. Kwon, J.H. Shin, S. Y. Hahn, Effect of a Deep Learning Framework-Based Computer- Aided Diagnosis System on the Diagnostic Performance of Radiologists in Differentiating between Malignant and Benign Masses on Breast Ultrasonography, Korean J. Radiol. 20 (5) (2019) 749–758.
[76] A. Ciritsis, C. Rossi, M. Eberhard, M. Marcon, A.S. Becker, A. Boss, Automatic classification of ultrasound breast lesions using a deep convolutional neural network mimicking human decision-making, Eur. Radiol. 29 (10) (2019) 5458–5468.
[77] J. Shi, S.C. Zhou, X. Liu, Q. Zhang, M.H. Lu, T.F. Wang, Stacked deep polynomial network based representation learning for tumor classification with small ultrasound image dataset, Neurocomputing 194 (2016) 87–94.
[78] W.J. Wu, S.W. Lin, W.K. Moon, An artificial immune system-based support vector machine approach for classifying ultrasound breast tumor images, J. Digit. Imaging 28 (5) (2015) 576–585.
[79] Q. Zhang, Y. Xiao, W. Dai, J.F. Suo, C.Z. Wang, J. Shi, H.R. Zheng, Deep learning based classification of breast tumors with shear-wave elastography, Ultrasonics 72 (2016) 150–157.
[80] Y.J. Zhou, J.X. Xu, Q.G. Liu, C. Li, Z.Y. Liu, M.Y. Wang, H.R. Zheng, S.S. Wang, A radiomics approach with CNN for shear-wave elastography breast tumor classification, Ieee T Bio. Med. Eng. 65 (9) (2018) 1935–1942.
[81] J. Shan, H.D. Cheng, Y.X. Wang, Completely automated segmentation approach for breast ultrasound images using multiple-domain features, Ultrasound Med. Biol. 38 (2) (2012) 262–275.
[82] P. Gu, W.M. Lee, M.A. Roubidoux, J. Yuan, X.D. Wang, P.L. Carson, Automated 3D ultrasound image segmentation to aid breast cancer image interpretation, Ultrasonics 65 (2016) 51–58.
[83] Y. Feng, F. Dong, X. Xia, C.H. Hu, Q. Fan, Y. Hu, M. Gao, S. Mutic, An adaptive Fuzzy C-means method utilizing neighboring information for breast tumor segmentation in ultrasound images, Med. Phys. 44 (7) (2017) 3752–3760.
[84] K. Wang, X. Lu, H. Zhou, Y.Y. Gao, J. Zheng, M.H. Tong, C.J. Wu, C.Z. Liu, L. P. Huang, T. Jiang, F.K. Meng, Y.P. Lu, H. Ai, X.Y. Xie, L.P. Yin, P. Liang, J. Tian, R.Q. Zheng, Deep learning Radiomics of shear wave elastography significantly improved diagnostic performance for assessing liver fibrosis in chronic hepatitis B: a prospective multicentre study, Gut 68 (4) (2019) 729–741.
[85] M.C. Rousselet, S. Michalak, F. Dupre, A. Croue, P. Bedossa, J.P. Saint-Andre, P. Cales, H.N. 49, Sources of variability in histological scoring of chronic viral hepatitis, Hepatology 41 (2) (2005) 257–264.
[86] J.H. Lee, I. Joo, T.W. Kang, Y.H. Paik, D.H. Sinn, S.Y. Ha, K. Kim, C. Choi, G. W. Lee, J.H. Yi, W.C. Bang, Deep learning with ultrasonography: automated classification of liver fibrosis using a deep convolutional neural network, Eur. Radiol. 30 (2) (2020) 1264–1273.
[87] C.N. Ta, Y. Kono, M. Eghtedari, Y.T. Oh, M.L. Robbin, R.G. Barr, A.C. Kummel, R. F. Mattrey, Focal liver lesions: computer-aided diagnosis by using contrast-enhanced US cine recordings, Radiology 286 (3) (2018) 1062–1071.
[88] W.W. Yue, L. Qi, D.D. Wang, S.J. Yu, X.J. Wang, H.X. Xu, S.R. Wang, US-guided microwave ablation of low-risk papillary thyroid microcarcinoma: longer-term results of a prospective study, J. Clin. Endocrinol. Metab. 105 (6) (2020).
[89] W.W. Yue, S.R. Wang, F. Lu, L.P. Sun, L.H. Guo, Y.L. Zhang, X.L. Li, H.X. Xu, Radiofrequency ablation vs. Microwave ablation for patients with benign thyroid nodules: a propensity score matching study, Endocrine 55 (2) (2017) 485–495.
[90] W. Yue, S. Wang, B. Wang, Q. Xu, S. Yu, Z. Yonglin, X. Wang, Ultrasound guided percutaneous microwave ablation of benign thyroid nodules: safety and imaging follow-up in 222 patients, Eur. J. Radiol. 82 (1) (2013) e11–e16.
[91] S.Y. Zhang, S. Wu, S.Q. Shang, X.W. Qin, X. Jia, D.P. Li, Z.W. Cui, T.Q. Xu, G. Niu, A. Bouakaz, M.X. Wan, Detection and monitoring of thermal lesions induced by microwave ablation using ultrasound imaging and convolutional neural networks, Ieee J. Biomed. Health 24 (4) (2020) 965–973.
[92] Y. Lei, S. Tian, X. He, T. Wang, B. Wang, P. Patel, A.B. Jani, H. Mao, W.J. Curran, T. Liu, X. Yang, Ultrasound prostate segmentation based on multidirectional deeply supervised V-Net, Med. Phys. 46 (7) (2019) 3194–3206.
[93] X.P. Burgos-Artizzu, A. Perez-Moreno, D. Coronado-Gutierrez, E. Gratacos, M. Palacio, Evaluation of an improved tool for non-invasive prediction of neonatal respiratory morbidity based on fully automated fetal lung ultrasound analysis, Sci. Rep. 9 (1) (2019) 1950.
[94] H. Chen, L.Y. Wu, Q. Dou, J. Qin, S.L. Li, J.Z. Cheng, D. Ni, P.A. Heng, Ultrasound standard plane detection using a composite neural network framework, Ieee T Cybernetics 47 (6) (2017) 1576–1586.
[95] Z. Yu, E.L. Tan, D. Ni, J. Qin, S. Chen, S. Li, B. Lei, T. Wang, A deep convolutional neural network-based framework for automatic fetal facial standard plane recognition, IEEE J. Biomed. Health Inform. 22 (3) (2018) 874–885.
[96] L. Drukker, R. Droste, P. Chatelain, J.A. Noble, A.T. Papageorghiou, Expected-value bias in routine third-trimester growth scans, Ultrasound Obstet. Gynecol. 55 (3) (2020) 375–382.
[97] L. Drukker, J.A. Noble, A.T. Papageorghiou, Introduction to artificial intelligence in ultrasound imaging in obstetrics and gynecology, Ultrasound Obstet. Gynecol. 56 (4) (2020) 498–505.
[98] J. Zhang, S. Gajjala, P. Agrawal, G.H. Tison, L.A. Hallock, L. Beussink-Nelson, M. H. Lassen, E. Fan, M.A. Aras, C. Jordan, K.E. Fleischmann, M. Melisko, A. Qasim, S.J. Shah, R. Bajcsy, R.C. Deo, Fully automated echocardiogram interpretation in clinical practice: feasibility and diagnostic accuracy, Circulation 138 (16) (2018) 1623–1635.
[99] A. Madani, R. Arnaout, M. Mofrad, R. Arnaout, Fast and accurate view classification of echocardiograms using deep learning, Npj Digit Med 1 (2018) 6.
[100] H. Khamis, G. Zurakhov, V. Azar, A. Raz, Z. Friedman, D. Adam, Automatic apical view classification of echocardiograms using a discriminative learning dictionary, Med. Image Anal. 36 (2017) 15–21.
[101] H.A. Omar, J.S. Domingos, A. Patra, R. Upton, P. Leeson, J.A. Noble, Quantification of cardiac bull`s-Eye map based on principal strain analysis for myocardial wall motion assessment in stress echocardiography, I S Biomed Imaging (2018) 1195–1198.
[102] K. Kusunose, T. Abe, A. Haga, D. Fukuda, H. Yamada, M. Harada, M. Sata, A deep learning approach for assessment of regional wall motion abnormality from echocardiographic images, JACC Cardiovasc. Imaging 13 (2 Pt 1) (2020) 374–381.
[103] M. Alsharqi, R. Upton, A. Mumith, P. Leeson, Artificial intelligence: a new clinical support tool for stress echocardiography, Expert Rev. Med. Devices 15 (8) (2018) 513–515.
[104] A. Madani, J.R. Ong, A. Tibrewal, M.R.K. Mofrad, Deep echocardiography: data-efficient supervised and semi-supervised deep learning towards automated diagnosis of cardiac disease, Npj Digit Med 1 (2018) 59.
[105] G. Carneiro, J.C. Nascimento, A. Freitas, The segmentation of the left ventricle of the heart from ultrasound data using deep learning architectures and derivative-based search methods, IEEE Trans. Image Process. 21 (3) (2012) 968–982.
[106] Y. Hu, L. Guo, B. Lei, M. Mao, Z. Jin, A. Elazab, B. Xia, T. Wang, Fully automatic pediatric echocardiography segmentation using deep convolutional networks based on BiSeNet, Conf. Proc. IEEE Eng. Med. Biol. Soc. 2019 (2019) 6561–6564.
[107] S. Savas, N. Topaloglu, O. Kazci, P.N. Kosar, Classification of carotid artery intima media thickness ultrasound images with deep learning, J. Med. Syst. 43 (8) (2019) 273.
[108] K. Lekadir, A. Galimzianova, A. Betriu, M. Del Mar Vila, L. Igual, D.L. Rubin, E. Fernandez, P. Radeva, S. Napel, A convolutional neural network for automatic characterization of plaque composition in carotid ultrasound, IEEE J. Biomed. Health Inform. 21 (1) (2017) 48–55.
[109] M. Biswas, V. Kuppili, L. Saba, D.R. Edla, H.S. Suri, A. Sharma, E. Cuadrado-Godia, J.R. Laird, A. Nicolaides, J.S. Suri, Deep learning fully convolution network for lumen characterization in diabetic patients using carotid ultrasound: a tool for stroke risk, Med. Biol. Eng. Comput. 57 (2) (2019) 543–564.
[110] R. Zhou, A. Fenster, Y. Xia, J.D. Spence, M. Ding, Deep learning-based carotid media-adventitia and lumen-intima boundary segmentation from three-dimensional ultrasound images, Med. Phys. 46 (7) (2019) 3180–3193.

[111] L. Lo Vercio, M. del Fresno, I. Larrabide, Lumen-intima and media-adventitia segmentation in IVUS images using supervised classifications of arterial layers and morphological structures, Comput Meth Prog Bio 177 (2019) 113–121.
[112] J. Yang, M. Faraji, A. Basu, Robust segmentation of arterial walls in intravascular ultrasound images using Dual Path U-Net, Ultrasonics 96 (2019) 24–33.
[113] J. Jaworek-Korjakowska, A deep learning approach to vascular structure segmentation in dermoscopy colour images, Biomed Res. Int. 2018 (2018), 5049390.
[114] P. Burlina, S. Billings, N. Joshi, J. Albayda, Automated diagnosis of myositis from muscle ultrasound: exploring the use of machine learning and deep learning methods, PLoS One 12 (8) (2017), e0184059.
[115] R.J. Cunningham, I.D. Loram, Estimation of absolute states of human skeletal muscle via standard B-mode ultrasound imaging and deep convolutional neural networks, J. R. Soc. Interface 17 (162) (2020), 20190715.
[116] N. Baka, S. Leenstra, T. van Walsum, Ultrasound aided vertebral level localization for lumbar surgery, IEEE Trans. Med. Imaging 36 (10) (2017) 2138–2147.
[117] J. Hetherington, V. Lessoway, V. Gunka, P. Abolmaesumi, R. Rohling, SLIDE: automatic spine level identification system using a deep convolutional neural network, Int J Comput Ass Rad 12 (7) (2017) 1189–1198.
[118] X. Chen, C.X. Xie, Z.W. Chen, Q.L. Li, Automatic tracking of muscle cross-sectional area using convolutional neural networks with ultrasound, J Ultras Med 38 (11) (2019) 2901–2908.
[119] F. van den Noort, C.H. van der Vaart, A.T.M. Grob, M.K. van de Waarsenburg, C. H. Slump, M. van Stralen, Deep learning enables automatic quantitative assessment of puborectalis muscle and urogenital hiatus in plane of minimal hiatal dimensions, Ultrasound Obstet. Gynecol. 54 (2) (2019) 270–275.
[120] M. Correa, M. Zimic, F. Barrientos, R. Barrientos, A. Roman-Gonzalez, M. J. Pajuelo, C. Anticona, H. Mayta, A. Alva, L. Solis-Vasquez, D.A. Figueroa, M. A. Chavez, R. Lavarello, B. Castaneda, V.A. Paz-Soldan, W. Checkley, R. H. Gilman, R. Oberhelman, Automatic classification of pediatric pneumonia based on lung ultrasound pattern recognition, PLoS One 13 (12) (2018), e0206410.
[121] Y. Xu, Y. Zhang, K. Bi, Z. Ning, L. Xu, M. Shen, G. Deng, Y. Wang, Boundary restored network for subpleural pulmonary lesion segmentation on ultrasound images at local and global scales, J. Digit. Imaging 33 (5) (2020) 1155–1166.
[122] B. Cristiana, T. Grzegorz, K. Seungsoo, M. Katelyn, L. Rachel, M. Shaw, R. L. McNamara, R. Balasundar, C.L. Moore, Automated lung ultrasound B-line assessment using a deep learning algorithm, IEEE Trans. Ultrason. Ferroelectr. Freq. Control 67 (11) (2020) 2312–2320.
[123] S.A. Qureshi, A.U. Rehman, Optical techniques, computed tomography and deep learning role in the diagnosis of COVID-19 pandemic towards increasing the survival rate of vulnerable populations, Photodiagnosis Photodyn. Ther. (2020), 101880.
[124] M. Dai, S. Li, Y. Wang, Q. Zhang, J. Yu, Post-processing radio-frequency signal based on deep learning method for ultrasonic microbubble imaging, Biomed. Eng. Online 18 (1) (2019) 95.
[125] F. Wang, R. Kaushal, D. Khullar, Should Health Care Demand Interpretable Artificial Intelligence or Accept "Black Box" Medicine? Ann. Intern. Med. 172 (1) (2020) 59–60.
[126] M.B. Subramanya, V. Kumar, S. Mukherjee, M. Saini, SVM-based CAC system for B-Mode kidney ultrasound images, J. Digit. Imaging 28 (4) (2015) 448–458.
[127] T. Pang, L. Huang, Y. Deng, T. Wang, S. Chen, X. Gong, W. Liu, Logistic regression analysis of conventional ultrasonography, strain elastosonography, and contrast-enhanced ultrasound characteristics for the differentiation of benign and malignant thyroid nodules, PLoS One 12 (12) (2017), e0188987.
[128] J. Fernandes, L. Sannachi, W.T. Tran, A. Koven, E. Watkins, F. Hadizad, S. Gandhi, F. Wright, B. Curpen, A. El Kaffas, J. Faltyn, A. Sadeghi-Naini, G. Czarnota, Monitoring breast Cancer response to neoadjuvant chemotherapy using ultrasound strain elastography, Transl. Oncol. 12 (9) (2019) 1177–1184.
[129] K. Shameer, G. Pugalenthi, K.K. Kandaswamy, R. Sowdhamini, 3dswap-pred: prediction of 3D domain swapping from protein sequence using random forest approach, Protein Peptide Lett 18 (10) (2011) 1010–1020.
[130] P. Doupe, J. Faghmous, S. Basu, Machine learning for health services researchers, Value Health 22 (7) (2019) 808–815.
[131] J. Henrichs, V. Verfaille, P. Jellema, L. Viester, E. Pajkrt, J. Wilschut, H.E. van der Horst, A. Franx, A. de Jonge, I.s. group, Effectiveness of routine third trimester ultrasonography to reduce adverse perinatal outcomes in low risk pregnancy (the IRIS study): nationwide, pragmatic, multicentre, stepped wedge cluster randomised trial, BMJ 367 (2019) l5517.
[132] D.R. Chen, R.F. Chang, Y.L. Huang, Breast cancer diagnosis using self-organizing map for sonography, Ultrasound Med. Biol. 26 (3) (2000) 405–411.
[133] A. Dall'Asta, S. Schievano, J.L. Bruse, G. Paramasivam, C.T. Kaihura, D. Dunaway, C.C. Lees, Quantitative analysis of fetal facial morphology using 3D ultrasound and statistical shape modeling: a feasibility study, Am. J. Obstet. Gynecol. 217 (1) (2017), 76.e1-76.e8.
[134] S. P, M. M, An effective two way classification of breast Cancer images: a detailed review, Asian Pac. J. Cancer Prev. 19 (12) (2018) 3335–3339.
[135] D. Zuo, L. Han, K. Chen, C. Li, Z. Hua, J. Lin, [Extraction of calcification in ultrasonic images based on convolution neural network], Sheng Wu Yi Xue Gong Cheng Xue Za Zhi 35 (5) (2018) 679–687.
[136] M.H. Yap, G. Pons, J. Marti, S. Ganau, M. Sentis, R. Zwiggelaar, A.K. Davison, R. Marti, Automated breast ultrasound lesions detection using convolutional neural networks, IEEE J. Biomed. Health Inform. 22 (4) (2018) 1218–1226.
[137] Y. Ikedo, D. Fukuoka, T. Hara, H. Fujita, E. Takada, T. Endo, T. Morita, Development of a fully automatic scheme for detection of masses in whole breast ultrasound images, Med. Phys. 34 (11) (2007) 4378–4388.
[138] H. Lee, J. Park, J.Y. Hwang, Channel attention module with multiscale grid average pooling for breast Cancer segmentation in an ultrasound image, IEEE Trans. Ultrason. Ferroelectr. Freq. Control 67 (7) (2020) 1344–1353.
[139] M. Byra, K. Dobruch-Sobczak, Z. Klimonda, H. Piotrzkowska-Wroblewska, J. Litniewski, Early prediction of response to neoadjuvant chemotherapy in breast cancer sonography using Siamese convolutional neural networks, IEEE J Biomed Health Inform PP (2020).
[140] Q.C. Sun, X.N. Lin, Y.S. Zhao, L. Li, K. Yan, D. Liang, D.S. Sun, Z.C. Li, Deep learning vs. Radiomics for predicting axillary lymph node metastasis of breast Cancer Using ultrasound images: don't forget the peritumoral region, Front. Oncol. 10 (2020) 53.
[141] M. Biswas, V. Kuppili, D.R. Edla, H.S. Suri, L. Saba, R.T. Marinhoe, J.M. Sanches, J.S. Suri, Symtosis: A liver ultrasound tissue characterization and risk stratification in optimized deep learning paradigm, Comput. Methods Programs Biomed. 155 (2018) 165–177.
[142] N. Orlando, D.J. Gillies, I. Gyacskov, C. Romagnoli, D. D'Souza, A. Fenster, Automatic prostate segmentation using deep learning on clinically diverse 3D transrectal ultrasound images, Med. Phys. 47 (6) (2020) 2413–2426.
[143] D. Karimi, Q. Zeng, P. Mathur, A. Avinash, S. Mahdavi, I. Spadinger, P. Abolmaesumi, S.E. Salcudean, Accurate and robust deep learning-based segmentation of the prostate clinical target volume in ultrasound images, Med. Image Anal. 57 (2019) 186–196.
[144] I.L. Xi, J. Wu, J. Guan, P.J. Zhang, S.C. Horii, M.C. Soulen, Z. Zhang, H.X. Bai, Deep learning for differentiation of benign and malignant solid liver lesions on ultrasonography, Abdom. Radiol. (NY) (2020).
[145] S. Yin, Z. Zhang, H. Li, Q. Peng, X. You, S.L. Furth, G.E. Tasian, Y. Fan, Fully-Automatic Segmentation of Kidneys in Clinical Ultrasound Images Using a Boundary Distance Regression Network, Proc. IEEE Int. Symp. Biomed. Imaging 2019 (2019) 1741–1744.
[146] D. Liu, F. Liu, X. Xie, L. Su, M. Liu, X. Xie, M. Kuang, G. Huang, Y. Wang, H. Zhou, K. Wang, M. Lin, J. Tian, Accurate prediction of responses to transarterial chemoembolization for patients with hepatocellular carcinoma by using artificial intelligence in contrast-enhanced ultrasound, Eur. Radiol. 30 (4) (2020) 2365–2376.
[147] N. Zhu, M. Najafi, B. Han, S. Hancock, D. Hristov, Feasibility of Image Registration for Ultrasound-Guided Prostate Radiotherapy Based on Similarity Measurement by a Convolutional Neural Network, Technol Cancer Res T 18 (2019), 1533033818821964.
[148] C.C. Kuo, C.M. Chang, K.T. Liu, W.K. Lin, H.Y. Chiang, C.W. Chung, M.R. Ho, P. R. Sun, R.L. Yang, K.T. Chen, Automation of the kidney function prediction and classification through ultrasound-based kidney imaging using deep learning, Npj Digit Med 2 (2019) 29.
[149] S. Yin, Q. Peng, H. Li, Z. Zhang, X. You, H. Liu, K. Fischer, S.L. Furth, G.E. Tasian, Y. Fan, Multi-instance deep learning with graph convolutional neural networks for diagnosis of kidney diseases using ultrasound imaging, Uncert. Safe Util Mach. Learn Med. Imag. Clin. Image Based Proc. 11840 (2019) 146–154.
[150] H. Guo, M. Kruger, S. Xu, B.J. Wood, P. Yan, Deep adaptive registration of multi-modal prostate images, Comput. Med. Imaging Graph. 84 (2020), 101769.
[151] S. Azizi, S. Bayat, P. Yan, A. Tahmasebi, J.T. Kwak, S. Xu, B. Turkbey, P. Choyke, P. Pinto, B. Wood, P. Mousavi, P. Abolmaesumi, Deep Recurrent Neural Networks for Prostate Cancer Detection: Analysis of Temporal Enhanced Ultrasound, IEEE Trans. Med. Imaging 37 (12) (2018) 2695–2703.
[152] H. Xie, N. Wang, M. He, L. Zhang, H. Cai, J. Xian, M. Lin, J. Zheng, Y. Yang, Using deep learning algorithms to classify fetal brain ultrasound images as normal or abnormal, Ultrasound Obstet. Gynecol. 56 (4) (2020) 579–587.
[153] R. Huang, W. Xie, J. Alison Noble, VP-Nets : efficient automatic localization of key brain structures in 3D fetal neurosonography, Med. Image Anal. 47 (2018) 127–139.
[154] A.I.L. Namburete, W.D. Xie, M. Yaqub, A. Zisserman, J.A. Noble, Fully-automated alignment of 3D fetal brain ultrasound to a canonical reference space using multi-task learning, Med. Image Anal. 46 (2018) 1–14.
[155] X. Liang, J. Fang, H. Li, X. Yang, D. Ni, F. Zeng, Z. Chen, CR-unet-Based ultrasonic follicle monitoring to reduce diameter variability and generate area automatically as a novel biomarker for follicular maturity, Ultrasound Med. Biol. 46 (11) (2020) 3125–3134.
[156] L. Wu, J.Z. Cheng, S. Li, B. Lei, T. Wang, D. Ni, FUIQA: fetal ultrasound image quality assessment with deep convolutional networks, IEEE Trans. Cybern. 47 (5) (2017) 1336–1349.
[157] P. Looney, G.N. Stevenson, K.H. Nicolaides, W. Plasencia, M. Molloholli, S. Natsis, S.L. Collins, Fully automated, real-time 3D ultrasound segmentation to estimate first trimester placental volume using deep learning, JCI Insight 3 (11) (2018), e120178.
[158] J. Jang, Y. Park, B. Kim, S.M. Lee, J.Y. Kwon, J.K. Seo, Automatic estimation of fetal abdominal circumference from ultrasound images, IEEE J. Biomed. Health Inform. 22 (5) (2018) 1512–1520.
[159] B. Kim, K.C. Kim, Y. Park, J.Y. Kwon, J. Jang, J.K. Seo, Machine-learning-based automatic identification of fetal abdominal circumference from ultrasound images, Physiol. Meas. 39 (10) (2018), 105007.
[160] L. Zhang, J. Huang, L. Liu, Improved deep learning network based in combination with cost-sensitive learning for early detection of ovarian Cancer in color ultrasound detecting system, J. Med. Syst. 43 (8) (2019) 251.
[161] A. Narang, V. Mor-Avi, A. Prado, V. Volpato, D. Prater, G. Tamborini, L. Fusini, M. Pepi, N. Goyal, K. Addetia, A. Goncalves, A.R. Patel, R.M. Lang, Machine learning based automated dynamic quantification of left heart chamber volumes, Eur. Heart J. Cardiovasc. Imaging 20 (5) (2019) 541–549.