Thoracic Imaging in China
Yesterday, Today, and Tomorrow

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Abstract: Thoracic imaging has been revolutionized through advances in technology and research around the world, and so has China. Thoracic imaging in China has progressed from anatomic observation to quantitative and functional evaluation, from using traditional approaches to using artificial intelligence. This article will review the past, present, and future of thoracic imaging in China, in an attempt to establish new accepted strategies moving forward.

Key Words: thoracic imaging, quantitative evaluation, functional evaluation, artificial intelligence

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Over the past 30 years, thoracic imaging has been revolutionized through advances in technology and research from around the world, including China. The Chinese Society of Thoracic Radiology was established in 1986, and has since played a leading role in thoracic imaging in China. During this time, thoracic imaging in China has progressed from anatomic observation to quantitative and functional evaluation, from using traditional approaches to using artificial intelligence, with almost all imaging methods, including x-ray, computed tomography (CT), magnetic resonance imaging (MRI), and positron emission tomography (PET)/CT and the whole spectrum of lung diseases being addressed. This article will review the past, present, and future of thoracic imaging in China, corresponding to anatomic and morphologic imaging, quantitative and functional imaging, and artificial intelligence imaging, in an attempt to establish new accepted strategies moving forward.

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ANATOMIC AND MORPHOLOGIC IMAGING

The development of multi-detector row CT has enabled greater spatial resolution, shorter scanning duration, and better volumetric reconstruction than before, with contrast-enhanced CT allowing assessment of vasculature and perfusion. This led to the anatomic and morphologic study becoming popular from 1990s to 2000s in China. Until recently, the morphologic evaluation was still the basis for disease diagnosis with chest CT. Pulmonary lesion location, imaging features, and distribution patterns are the main clues for diagnosis and differential diagnosis.

A great deal of effort has been expended to develop a noninvasive means of characterizing solitary pulmonary nodules or masses, currently one of the greatest challenges in the field of thoracic imaging. Wang et al[1] collected 93 patients with solitary peripheral lung cancers and found relationships between peripheral lung cancer and the bronchi (Br), pulmonary arteries (PA), and pulmonary veins (PV) that were useful for a differential diagnosis. They identified 5 types of the tumor-Br, tumor-PA, and tumor-PV relationship: type1 (Br1, PA1, and PV1), Br, PA, or PV erupted at the edge of nodule; type 2 (Br2, PA2, and PV2), erupted at the center of nodule; type 3 (Br3, PA3, and PV3), penetrated through the nodule; type 4 (Br4, PA4, and PV4), contacting the nodule but stretched or encased; type 5 (Br5, PA5, and PV5), contacting the nodule but smoothly compressed. Their study showed the bronchi and PA changes surrounding the lung cancer had positive relations ($\chi^2 = 12.3918$, $r = 0.7524$, $P < 0.01$). Li et al[2] investigated the value of cavity wall morphologic features in differentiating between peripheral lung cancer cavities and single pulmonary tuberculous thick-walled cavities. They divided the cavities into form discordance of cavity walls (FDCW) and form concordance of cavity walls (FCCW). The study showed a peripheral lung cancer cavity most frequently appeared as FDCW-III, followed by FDCW-I, and tuberculoma cavity was often manifested as FCCW-I and FDCW-II, whereas a fibrous thick-walled cavity was often shown as FCCW-II. Li et al[3] analyzed incidence, CT findings, and pathologic features of tree-in-bud patterns in 652 consecutive patients with confirmed central lung cancer. In their study, tree-in-bud patterns were commonly detected in central lung squamous cell carcinoma, and corresponded with the mucoid impaction of bronchioles and bronchiolitis pathologically.

With a widespread application for lung cancer screening, more cases of a type of lung cancer presenting as solitary cystic airspaces have been detected. Thus, Tan et al[4] analyzed CT features in the 106 patients with pathologically proven lung cancer associated with cystic airspaces, the largest cohort in 2019. They highlighted the CT features including nonuniform cystic walls in 96 (90.6%) patients, cyst septations in 62 (58.5%) patients, nodular walls in 58 (54.7%) patients, ground-glass opacity around the cyst in 53 patients (50.0%), and irregular margins in 42 (39.6%) patients, all of which indicated malignancy. They thought the cystic changes were result of bronchiolar obstruction by fibrous tissue or tumor cells with a "check-valve" mechanism.

QUANTITATIVE IMAGING AND FUNCTIONAL IMAGING

Since the 2000s, quantitative and functional thoracic imaging has become available as a result of new advanced imaging techniques being developed. Quantitative imaging usually focuses on CT to evaluate solitary pulmonary nodules, lung density, airways, and vessels. With the emergence of dual-energy CT (DECT) and functional MR, more functional information could be acquired to evaluate various pulmonary diseases.

CT Lung Cancer Screening With Quantitative Evaluation

Lung cancer is the leading cause of cancer death for men and women in both China and worldwide.[5,6] The age-standardized rate (ASRs) incidence in China and the United States are similar, but the age-standardized rate mortality rate of lung cancer in China is higher than in the United States.[6] Until 2011, National Lung Screening Trial[7] had shown that lung cancer screening using low-dose CT (LDCT) could reduce mortality by up to 20% when compared with a chest x-ray. Similarly, from 2013 to 2014, in Yang et al's[8] study, a total of 6717 eligible participants with high-risk factors for lung cancer were randomly assigned to a screening group or a control group with questionnaire inquiries (3550 to LDCT screening and 3167 to standard care). In the 2-year follow-up period, lung cancer was detected in 51 participants (1.5%) in the LDCT group versus 10 (0.3%) in the control group, respectively. Early-stage lung cancer was found in 94.1% versus 20%, respectively. They concluded compared with usual care, LDCT led to a 74.1% increase in detecting early-stage lung cancer.

On the basis of these results, lung cancer screening programs have been implemented nationwide. For instance[9] in a screening program in Shanghai enrolling 14,506 subjects from 2014 to 2016, the positive rate of lung nodule on LDCT and incidental detection rate of lung cancer was 29.89% and 1.23%, respectively. A total of 238 lung cancers were found with the incidental detection rate of stage I lung cancer being 0.97%. Meanwhile, a similar program was carried out from 2014 to 2019 in Gejiu, Yunnan province, in which 2006 participants were enrolled. A total of 40 lung cancer cases were confirmed during this program.[10] In 2015, the Chinese society of radiology launched the Chinese version of "Expert consensus of low dose CT lung cancer screening." A series of recommendations were proposed, including the current status of lung cancer screening, the implementation of the program, treatment strategy for nodules, and the significance of lung cancer screening.[11]

At present, the Netherlands-China Big-3 screening[12] (NELCIN-B3, including lung cancer, chronic obstructive pulmonary disease [COPD] and cardiovascular disease, 2 rounds in total) is in the second round of annual follow ups in Shanghai. The 1-stop CT scan could evaluate emphysema, airways or functional small airways, and pulmonary vessels qualitatively. CT images have excellent correlation with pathologic studies in evaluating the severity and extent of emphysema. CT quantification parameters for emphysema, including emphysema index, air trapping, mean lung density, and total lung volume have been correlated with pulmonary function. Gao et al[13] found CT quantification parameters for emphysema were significantly different between patients with asthma COPD overlap syndrome and COPD.

Dual-source CT

In 2006, the first-generation dual-source CT system was put on the market. The basic principle of a DECT or spectral CT is the application of two distinct energy settings that permits the differentiation of materials that possess different molecular compositions according to their attenuation profiles. With this technology, multiple data sets such as elemental decomposition analyses, iodinated attenuation maps, monochromatic images, and virtual unenhanced images can be obtained simultaneously.

These technical characteristics provide many useful tools for oncologic imaging, including tumor detection, lesion characterization, and evaluation of response to therapy. Thus, Chinese scholars found that quantitative parameters generated by DECT, including iodine concentration (IC) and slope of the spectral curve, provide information useful for differentiating the pathologic grades of non–small cell lung cancers (NSCLCs),[14] predicting the epithelial growth factor receptor (EGFR)-positive and EGFR-negative groups among patients with lung cancer,[15] distinguishing SCLC from NSCLC,[16] and correlates with the expression level of vascular endothelial growth factor[17] or microvessel densities (MVDs).[18] In the study by Li et al,[18] the IC, IC difference, and normalized IC of tumors were measured in the arterial phase, venous phase, and delayed phase. Correlation analysis was performed for IC and MVD. The MVD of lung cancer correlated positively with the IC, IC difference, and normalized IC on 3-phase contrast-enhanced scanning (r range, 0.581 to 0.800; all $P < 0.001$), and the IC in the venous phase showed the strongest correlation with MVD ($r = 0.800$; $P < 0.001$). So IC indexes derived from spectral CT were useful indicators for evaluating tumor angiogenesis.

Functional MRI

Imaging capabilities have progressed substantially over the years. Many of these new imaging techniques can provide both functional and anatomic information. Complementary to CT of the lung, MRI of the lung, which previously was limited by field inhomogeneity and the lack of protons in lung tissue, has shown potential for lung assessment, including morphology, perfusion, ventilation, and right heart assessment. Pulmonary parenchyma perfusion with flow-sensitive alternating inversion recovery has been successfully performed in patients with lung cancer and pulmonary embolism.[19] Moreover, studies have been conducted to compare MRI and other imaging modalities. Fan et al[20] compared CT volume analysis with MR perfusion imaging in differentiating smokers with normal pulmonary function (controls) from COPD patients. They found that MRI perfusion parameters were more sensitive in distinguishing controls from mild COPD, and in identifying abnormalities among smokers with normal pulmonary function. Tang et al[21] compared the diagnostic performance of a 64-multidetector-row CT and a 3.0 T MRI in T staging of NSCLC. According to the pathologic results, both CT and MRI provided acceptable overall accuracies in determination of T staging in NSCLC. CT was indicated to be more accurate in determination of NSCLC staged T1 and T2 (100% vs. 75%, 96.4% vs. 82.1%), whereas MRI was found to be slightly superior in the identification of NSCLC staged T3 and T4 (80% vs. 50%, 100% vs. 33.3%). Chinese scholars have also shown interest in novel sequence optimization and application. Chen et al[22] developed a rapid free-breathing dynamic contrast-enhanced sequence for simultaneous qualitative and quantitative assessment of pulmonary lesions using Golden-angle RAdial Sparse Parallel (GRASP) imaging, as dynamic contrast-enhanced sequences often suffered from motion artifacts and insufficient imaging speed. Xu et al[23] proved the usefulness of diffusion-weighted imaging with background signal suppression for detecting mediastinal lymph node metastasis of NSCLC. Yan et al[24] evaluated the diagnostic performance of 5 MR sequences to detect pulmonary infectious lesions of invasive fungal infections. Studies of differentiating diagnosis in solitary pulmonary lesions have been performed as well.[25,26]

Over the past decade, hyperpolarized gas MRI has emerged as a new diagnostic method. This method can visualize and quantify pulmonary function without radiation and in real time. The technique utilizes dynamic nuclear polarization to achieve signal improvement of > 10,000-fold in magnetic resonance.[27] For pulmonary diseases and during clinical routine, pulmonary function tests can detect global pulmonary function changes, but cannot comprehensively quantify physiological changes, such as air-blood exchange in the lung. CT can only detect the morphologic changes. Hyperpolarized gas MRI provides an avenue for realtime measurement of morphology, diffusion and gas exchange function without radiation, which outperforms pulmonary function test and CT. Therefore, hyperpolarized MRI has attracted much attention in both pneumology and radiology. ^{129}Xe is commonly used in hyperpolarized MRI due to its nuclear spin quantum number[27,28] and longer longitudinal relaxation times (T1). It also has good solubility in blood and tissue, and possesses excellent chemical shift sensitivity. In 2016, Zhou and his colleagues conducted a series of studies with hyperpolarized ^{129} Xe MRI focusing on pulmonary function and disease, as well as the potential clinical advantages. Their works included: pulmonary physiological evaluation by a modified chemical shift saturation recovery pulse sequence in radiation-induced lung injury,[29] detection of mild emphysema by quantification of lung respiratory airways with hyperpolarized xenon diffusion MRI,[30] diffusion-weighted chemical shift saturation recovery sequence permitting the simultaneous assessment of lung morphometry at the alveolar level and the gas exchange function of the lungs,[31,32] the feasibility of compressed sensing (a method for reconstructing the signal from sparse, undersampled data using special reconstruction techniques) to accelerate the acquisition of multi-b diffusion MRI (which means diffusion MRI with multiple different b values),[33] the feasibility of hyperpolarized ^{129} Xe MRI in quantitative evaluation of lung injury caused by PM 2.5 (which refers to particulate matter in the atmosphere with a diameter of 2.5 μm or less).[34] Their results proved that hyperpolarized ^{129} Xe MRI is a powerful tool to image the air space and evaluate pulmonary gas exchange function and physiological changes.

PET/CT in Functional Imaging

PET/CT combines the functional imaging of PET with the anatomic imaging of CT, and is mostly used in the differential diagnosis of lung nodules, TNM staging, and therapeutic evaluation. Domestic research[35] showed that SUVmax of NSCLC was positively correlated with vascular endothelial growth factor expression levels. Wang et al[36] found that 18F-FDG PET/CT showed higher accuracy in TNM staging than spiral CT (91.94% vs. 80.65%). The prediction of distant metastasis[37] and genetic mutfation[38] of NSCLC has been reported in China. Chen et al[39] found that SUVmax could effectively predict the EGFR mutation status of NSCLC.

ARTIFICIAL INTELLIGENCE (AI) IMAGING

(AI) is defined as the theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation. AI has started to be applied in medicine over the last few years. This is driven by the advent of deep-learning algorithms, computing hardware advances, and the exponential growth of medical data that is being generated and used for clinical decision making. Radiomics, one approach to intelligent imaging analysis, was first proposed by Lambin et al[40] in 2012. The most common AI terminologies include machine learning, deep learning, convolutional neural network, and so on. Thoracic imaging has been one of the pioneers in applying AI to medicine. At present, AI in thoracic imaging has been applied to scanning techniques, imaging diagnoses, and other related radiologic management activities. The application of AI for thoracic imaging is primarily in computer visual tasks, including classification, detection, and segmentation. Different AI algorithms, correspond to separate tasks such as lung lesion detection, diagnosis and differential diagnosis, prediction of progress, and therapeutic evaluation.

AI-based Thoracic CT Technique and Imaging Workflow Optimization in China

The accurate positioning of the patient during a CT scan is very important for image quality and diagnosis. Typically, the CT technician would stand by the scanning bed to ensure the patient maintained the correct position. During the COVID-19 pandemic, this close contact would increase the risk of infection. Chinese scientists have developed a no-touch scanning technique based on AI to eliminate this close contact between technicians and patients, which has been granted a scientific award by the government. In the study of Tan et al,[41] a CT scanner (United Imaging uCT780) equipped with the Tianyan AI platform was used for COVID-19 chest CT screening. They adopted intelligent assisted positioning, communicated with patients by microphone, and controlled the CT scanner remotely in the control room; then the positioning frame adaptively delineated the scanning frame. Deep-learning based CT reconstruction algorithms to be used to improve the image quality of low dose CT scans and simulate the routine dose CT images are in development by the United Imaging Company in China.[41] Imaging workflow can benefit from AI through reduction of labor and time required. Intelligent chest imaging quantitative analysis, automatic reconstruction of lung nodules, key images selection and automatic layout on the film, and structure report generation have been developed and validated in the Netherlands-China Big-3 screening (NELCIN-B3) in Shanghai, China, proving the excellent performance and potential in large scale screening.

AI in Thoracic Radiography

Thoracic radiography is the most common approach for the detection and diagnosis of lung lesions due to its convenience and economy. China has a large population and a shortage of medical resources on average, especially in the northwest and rural areas. This results in a heavy workload for radiologists to interpret chest radiographies, even when imaging equipment is available. Therefore, AI has excellent prospects for chest radiographs, which could reduce the workloads and improve diagnoses.

Lung nodule detection is the main application of AI in chest radiography, and can be used for both solid nodules and ground glass nodules. Liu et al[42] was the first to detect ground glass nodule (GGN) on chest radiography using deep learning and found the deep learning model took a total of 17 seconds with a sensitivity of 69.64%, faster than the experienced radiologist with a sensitivity of 55.36% (50 minutes and 24 seconds). With the aid of deep learning-based computer aided diagnostic system, the sensitivity of junior radiologists and senior radiologists for the diagnosis of pulmonary nodules was 65.45% and 76.02% respectively, which was 13.82% and 8.95% higher than that of independent reading radiologists.[43] For the diagnosis of pulmonary disease, Chinese scholars have attempted to apply various AI methods to tuberculosis, viral pneumonia, community-acquired pneumonia and other pneumonia CXRs.[44,45] Viral pneumonia, especially COVID-19, has received the dedicated efforts of Chinese scholars to apply AI in the diagnosis, severity assessment, and prediction of outcomes for COVID-19 patients based on chest radiography.[45,46] Wang et al[46] developed and tested an efficient and accurate deep learning scheme that assists radiologists in automatically recognizing and localizing COVID-19. One fully automated deep-learning system[47] could predict the COVID-19 pneumonia severity well, with an area under curve (AUC) of 0.868, a specificity of 80.65%, and a sensitivity of 82.05%. Furthermore, the system performed comparably to senior radiologists, and improved the performance of junior radiologists.

While in clinical practice, multiple abnormalities are common, proving to be more of a challenge for AI than one abnormality. Multiple task AI has been developed and validated in China. Liu et al presented a novel method termed segmentation-based deep fusion network (SDFN) to automatically recognize 14 thoracic abnormalities, including atelectasis, consolidation, infiltration, pneumothorax, edema, emphysema, fibrosis, effusion, pneumonia, pleural thickening, cardiomegaly, nodule, mass, and hernia, with a mean AUC score of 0.815.[48] They used the Chest x-ray 14 Dataset (a publicly available dataset) to develop and validate the classification performance of the proposed SDFN. The Chest x-ray 14 Dataset labeled up to 14 thoracic abnormalities, and the labels of each image were mined from the associated radiological text reports using natural language processing. A triple-attention learning (A^3 Net) model proposed by Wang et al[49] and other 6 recent deep learning models all used the Chest x-ray14 dataset to build models for classifying the same 14 thoracic abnormalities, but with different methods. The triple-attention learning model integrated three attention modules in a unified framework for channel-wise, element-wise, and scale-wise attention learning. The proposed A^3 Net model achieved the highest AUC in diagnosing 13 thoracic abnormalities (with the exception of atelectasis) compared with other 6 models and the highest average AUC of 0.826, which was the best average performance among 7 models.

AI in Thoracic CT

CT is the primary tool for pulmonary disease detection and diagnosis due to its high resolution. With the popularization of thin-slice chest CT and the increasing number of Chinese patients requiring disease diagnosis, many Chinese radiologists have to read tens of thousands of images every day, increasing the risk of missed diagnosis and inaccurate diagnosis due to radiologists suffering from visual fatigue. In this situation, AI-based analysis of chest CTs could help alleviate the shortage of radiologists and improve the diagnostic efficiency. In China, the detection of lung nodules is the first step in determining radiomics and AI performance. The effective segmentation of a lung nodule is an important step in furthering radiomics and AI research, especially for ground glass nodules due to the low contrast. Song et al[50] proposed a novel toboggan based growing automatic segmentation approach (TBGA) with a 3-step framework, which were automatic initial seed point selection, multi-constraints 3D lesion extraction and the final lesion refinement. The TBGA provided a high lesion detection rate (96.35%), accelerating the development of a lung nodule detection product. Lung nodule detection by AI was evaluated with phantom and clinical cases. At present, this lung nodule detection system has been approved by China Food and Drug Administration (CFDA). Lung nodule location, diameter, volume, density classification, mean CT value, histogram, malignant stratification and management could be output automatically. Deep learning shows good performance in classification and recognition due to its large amount of data and comprehensive feature extraction. Su et al[51] proposed a Faster R-CNN algorithm for the detection of lung nodules, derived from a classic target detection algorithm based on CNN. The improved and optimized Faster R-CNN network detection accuracy reached 91.2% and outweighed the other traditional algorithms.

Depending on the classification task assigned to the computer, AI is used to explore the differential diagnosis, histologic classification of lung cancer, subtype of adenocarcinoma (ADC), prediction of gene mutation, lymph node metastasis, and prognosis. Various deep learning algorithms are used to predict the properties of lung nodules.[52–54] Xu et al[52] proposed a novel deep learning method called MSCS-DeepLN, which meant multi-scale cost-sensitive neural networks for lung nodule. MSCS-DeepLN evaluated lung nodule malignancy while simultaneously solving the problem of small datasets and category imbalance. When compared to other state-of-the-art methods, the proposed method obtained the best results for 3 metrics (accuracy = 92.64% ± 0.12, precision = 90.39% ± 0.48, F1-score = 87.91% ± 0.11). CT-based radiomics predicts the histological subtypes of lung cancer.[55,56] Zhu et al[55] attempted to distinguish squamous cell carcinoma (SCC) from lung ADC based on radiomic signature, finding there to be a powerful prediction performance with AUC of 0.905 and 0.893 in the training cohort and independent validation cohort, respectively. A Multi-resolution 3D

Multi-classification deep learning model (Mr-Mc) and a Multi-Layer Perceptron machine learning model were constructed for diagnosing multiple pathologic types of pulmonary nodules based the LIDC-IDRI (the lung image database consortium and image database resource initiative) dataset containing 3D CT images and serum biomarkers.[57] Accurate preoperative identification of the degree of invasiveness is crucial for predicting the prognosis of GGNs and guiding proper surgical treatment. Radiomics could extract a large number of invisible features from medical images for clinical decision-making. It has also been used widely to predict the invasiveness of ground glass nodules.[58,59] Fan et al[58] retrospectively collected 4 multicenter datasets to construct and verify radiomics signatures to allow preoperative discrimination of lung invasive ADCs from noninvasive lesions manifesting as GGN, with AUC of 0.917, accuracy of 86.3%, sensitivity of 83.1%, and specificity of 89.6% in the primary cohort. Radiomics still has some limitations, including the need for manual feature extraction from images, poor repeatability, as well as time-consuming and cumbersome workflows. Some studies have used machine learning or deep learning methods to assess the invasiveness of lung ADC; both the lesion and the perilesion were included in the region of interest to study.[60–62] Radiomics, machine learning, and deep learning have been used to predict a variety of gene mutations in lung cancer, such as EGFR mutations, ALK mutations and Kras mutations. The mutation status of the target gene determines the effectiveness of the targeted drug. Several publications

have reported on AI assisted prediction of ALK gene mutations.[63,64] Song et al[63] analyzed 1218 quantitative radiomic features, 12 conventional CT features and 7 clinical features. They found that the addition of clinical features and conventional CT features significantly enhanced the validation performance of the radiomic model in the primary cohort (AUC = 0.83 to 0.88, $P = 0.01$).

Pneumonia is another hot topic in thoracic AI research. A series of COVID-19 studies have been performed for segmentation, diagnosis, quantitation, severity assessment, and prediction of progress. Wang et al[65] developed a fully automatic deep learning system for COVID-19 diagnosis with an AUC of 0.87, and succeeded in stratifying patients into high- and low-risk groups. COPD is a heterogeneous disease that begins with the remodeling of small airways and small vessels, eventually leading to the destruction of pulmonary parenchyma and formation of emphysema. The AI research currently conducted for COPD is focused on: imaging biomarkers in high risk COPD populations, screening COPD, severity assessment, and predicting the progress of the disease.[66,67] The parameter response mapping derived from chest CT images uses machine learning to predict pulmonary function test results, and has shown good performance in Shanghai, China. Moreover, a one-stop thoracic CT to evaluate lung cancer and COPD has been developed and validated with a deep-learning based automatic algorithm used to generate a quantitative analysis and structure report for NELCIN-B3 in Shanghai, China.[12] AI research in asthma, chest trauma and mediastinal diseases has also been reported in China.[68–70]

AI in Thoracic MRI

Pulmonary MR is not common due to the low spin density of the pulmonary parenchyma. However, MR could provide additional functional information. Pulmonary functional MR mainly focuses on perfusion, ventilation, and pulmonary microstructure using hyperpolarized ^{129}Xe for pulmonary embolisms, lung cancers, COPD, and healthy volunteers. Many animal experiments have also been performed to evaluate the pulmonary ventilation in a COPD rat model[71] as well as other animal model pulmonary injuries. Zhou et al[72,73] explored a series of human lung gas MRIs using deep learning, and proposed one optimized algorithm that outperformed classical undersampling methods, paving the way for future use of deep learning in real-time and accurate reconstruction of gas MRIs. Thoracic AI studies addressing the differential diagnosis of lung nodules, the classification of SCLC and NSCLC, and mediastinal lesions with MR have been reported in China.[74–76]

AI in Thoracic PET/CT

PET/CT could simultaneously acquire both functional metabolic information and anatomic information. PET/CT based AI has been utilized for lung cancer differential diagnosis, subtype classification, gene mutation, lymph node metastasis, tumor segmentation, and prognosis assessment. Yang et al[77] have developed and validated a radiomics nomogram by combining the radiomic features extracted from 18F-fluorodeoxyglucose PET/CT images and clinicopathologic factors to evaluate the overall survival (OS) of patients with NSCLC. They found that the rad-score combined with the clinical model had the best *C*-index (0.776 and 0.789 for the training and validation cohorts, respectively) for the survival outcome, offering feasible and practical guidance for individualized management of patients with NSCLC. How to rationally fuse the complementary information in PET/CT for accurate tumor segmentation is challenging. Li et al[78] has proposed a novel deep learning based variational method to automatically fuse multimodality information for tumor segmentation in PET/CT, which has shown good performance for tumor segmentation, even for tumors with Fluorodeoxyglucose (FDG) uptake inhomogeneity, blurred tumor edges, and complex surrounding soft tissues, achieving an average dice similarity index of 0.86 ± 0.05, sensitivity of 0.86 ± 0.07, positive predictive value of 0.87 ± 0.10, volume error of 0.16 ± 0.12, and classification error of 0.30 ± 0.12.

Chinese Expert Consensus and AI Product Development

The Chinese experts have begun to focus on lung nodule annotation criteria, database construction, and corresponding quality control. Two Chinese expert consensus[79,80] have been issued in Chinese, including "Expert consensus on the rule and quality control of pulmonary nodule annotation based on thoracic CT," and "Expert consensus on the construction and quality control of thoracic CT datasets for pulmonary nodules." Pulmonary nodule annotation consists of 4 steps: (1) pulmonary nodules are detected on the lung window by the labeling radiologists; (2) pulmonary nodules are classified by the labeling radiologists into intrapulmonary solid nodules, intrapulmonary partial solid nodules, intrapulmonary pure ground glass nodules, intrapulmonary calcified nodules, pleural nodules, pleural plaques, and pleural calcified nodules; (3) the labeling team leaders and arbitration experts review and revise the detection results and classification results; (4) the boundaries of pulmonary nodules are segmented, and the diameters of the nodules are automatically generated by the labeling software. For example, intrapulmonary solid nodules are defined as circular or quasi-circular, focal increased density shadows within the lung parenchyma, with clear borders, and the edges of bronchi and blood vessels in the lesions cannot be identified, with a maximum diameter of ≤ 3 cm. Firstly, the location of nodules is judged subjectively in the lung window, and the nodules are divided into intrapulmonary nodules or pleural nodules. Then, intrapulmonary nodules are classified as solid or subsolid nodules according to whether the nodules contain ground-glass density components in the lung window.[79] Presently, the CT lung nodule detection system and pneumonia triage system have been approved by CFDA in the last months and applied in clinical routine work.

Going forward, thoracic imaging in China should embrace new advanced techniques and build more international and multidisciplinary cooperation to make further progress, following the trend of applying AI to thoracic diseases and developing more products to assist radiologists.

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