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.

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 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 (χ² = 12.3918, r = 0.7524, P < 0.01). Li et al 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 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 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 Trial7 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’s8 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 instance9 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 screening12 (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 al13 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 factor17 or microvessel densities (MVDs).18 In the study by Li et al,19 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 al20 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.\(^{28}\) Hyperpolarized \(^{129}\)Xe MRI 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 morphology 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 \(\mu\)m 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 mutation\(^{38}\) 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 radiographs, 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. 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. 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.

**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. proposed a novel tobbogan 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. 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. Xu et al. 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. Zhu et al. 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. 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. Fan et al 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 peri-lesion were included in the region of interest to study. Radiomics, machine learning, and deep learning have been used to predict a variety of gene mutations in lung cancer, such as EGFR, ALK, 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. Song et al 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).

AI in Thoracic MRI

Pulmonary MR mainly focuses on perfusion, ventilation, and pulmonary microstructure using hyperpolarized 129Xe 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 as well as other animal model pulmonary injuries. Zhou et al 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.

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 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 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 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. 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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REFERENCES

1. Wang Y, Liang KR, Liu XG, et al. Relationship between peripheral lung cancer and the surrounding bronchi, pulmonary arteries, pulmonary veins: a multidetector CT observation. Clin Imaging. 2011;35:184–192.
2. Li BG, Ma DQ, Xian ZY, et al. The value of multislice spiral CT features of cavitory walls in differentiating between peripheral lung cancer cavities and single pulmonary tuberculous thick-walled cavities. Br J Radiol. 2012;85:147–152.
3. Li Q, Fan X, Huang XT, et al. Tree-in-bud pattern in central lung cancer: CT findings and pathologic correlation. Lung Cancer. 2015;88:260–266.
4. Tan Y, Gao J, Wu C, et al. CT characteristics and pathologic basis of solitary cystic lung cancer. Radiology. 2019;291:495–501.
5. Chaou M, Wang H, Zeng X, et al. Mortality, morbidity, and risk factors in China and its provinces, 1990-2017: a systematic analysis for the Global Burden of Disease Study 2017. Lancet. 2019;394:1145–1158.
6. Bray F, Ferlay J, Soerjomataram I, et al. Global cancer statistics 2018: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries. CA Cancer J Clin. 2018;68:394–424.
7. National Lung Screening Trial Research Team, Aberle DR, Adams AM, Christine DB, et al. Reduced lung-cancer mortality with low-dose computed tomographic screening. N Engl J Med. 2011;365:395–409.
8. Yang W, Qian F, Teng J, et al. Community-based lung cancer screening with low-dose CT in China: results of the baseline screening. Lancet. 2018;391:20–26.
9. Fan L, Wang Y, Zhou Y, et al. Lung cancer screening with low-dose CT: baseline screening results in Shanghai. Acad Radiol. 2019;26:1283–1291.
10. Wei MN, Su Z, Wang JN, et al. Performance of lung cancer screening with low-dose CT in Gejiu, Yunnan: a population-based, screening cohort study. Thorac Cancer. 2020;11:1224–1232.
11. Cardiothoracic Group of Chinese Medical Association Radiology Branch. Expert consensus of low dose CT lung cancer screening [in Chinese]. Chin J Radiol. 2015;49:328–335.
12. Du YH, Li Q, Sidorenkov G, et al. Computed tomography screening for early lung cancer, COPD and cardiovascular disease in Shanghai: rationale and design of a population-based comparative study. Acad Radiol. 2021;28:36–42.
13. Gao Y, Zhai X, Li K, et al. Asthma COPD overlap syndrome on CT densitometry: a distinct phenotype from COPD. COPD. 2016;13:471–476.
14. Lin LY, Zhang Y, Suo ST, et al. Correlation between dual-energy spectral CT imaging parameters and pathological grades of non-small cell lung cancer. Clin Radiol. 2018;73:412.e1–412.e7.
15. Wu F, Zhou H, Li F, et al. Spectral CT imaging of lung cancer: quantitative analysis of spectral parameters and their correlation with tumor characteristics. Acad Radiol. 2018;25:1398–1404.
16. Xu X, Sui X, Zhong W, et al. Clinical utility of quantitative dual-energy CT iodine maps and CT morphological features in distinguishing small-cell from non-small-cell lung cancer. Clin Radiol. 2019;74:268–278.
17. Li GF, Gao J, Wang GL, et al. Correlation between vascular endothelial growth factor and quantitative dual-energy spectral CT in non-small-cell lung cancer. Clin Radiol. 2016;71:363–368.
18. Li Q, Li X, Li XY, et al. Spectral CT in lung cancer: usefulness of iodine concentration for evaluation of tumor angiogenesis and prognosis. AJR Am J Roentgenol. 2020;215:595–602.
19. Fan L, Liu SY, Sun F, et al. Assessment of pulmonary parenchyma perfusion with FAIR in comparison with DCE-MRI—Initial results. Eur J Radiol. 2009;70:41–48.
20. Fan L, Xia Y, Guan Y, et al. Capability of differentiating smokers with normal pulmonary function from COPD patients: a comparison of CT pulmonary volume analysis and MR perfusion imaging. Eur Radiol. 2013;23:1234–1241.
21. Tang W, Wu N, OuYang H, et al. The presurgical T staging of non-small cell lung cancer: efficacy comparison of 64-MDCT and 3.0 T MRI. Cancer Imaging. 2015;15:14.
22. Chen L, Liu D, Zhang J, et al. Free-breathing dynamic contrast-enhanced MRI for assessment of pulmonary lesions using golden-angle radial sparse parallel imaging. J Magn Reson Imaging. 2018;48:459–468.
23. Xu L, Tian J, Liu Y, et al. Accuracy of diffusion-weighted (DW) MRI with background signal suppression (MR-DWIBS) in diagnosis of mediastinal lymph node metastasis of nonsmall-cell lung cancer (NSCLC). J Magn Reson Imaging. 2014;40:200–205.
24. Yan C, Tan X, Wei Q, et al. Lung MRI of invasive fungal infection at 3 Tesla: evaluation of five different pulse sequences and comparison with multidetector computed tomography (MDCT). Eur Radiol. 2015;25:550–557.
25. Zou Y, Zhang M, Wang Q, et al. Quantitative investigation of solitary pulmonary nodules: dynamic contrast-enhanced MRI and histopathologic analysis. AJR Am J Roentgenol. 2008;191:252–259.
26. Yuan M, Zhang YD, Zhu C, et al. Comparison of intravoxel incoherent motion diffusion-weighted MR imaging with dynamic contrast-enhanced MRI for differentiating lung cancer from benign solitary pulmonary lesions. J Magn Reson Imaging. 2016;43:669–679.
27. Hurd RE, Yen Y-F, Chen A, et al. Hyperpolarized 13C metabolic imaging using dissolution dynamic nuclear polarization. J Magn Reson Imaging. 2012;36:1314–1328.
28. 2 Walker TG, Happer W. Spin-exchange optical pumping of noble-gas nuclei. Rev Mod Phys. 1997;69:629–642.
29. Li H, Zhang Z, Zhao X, et al. Quantitative evaluation of radiation-induced lung injury with hyperpolarized xenon magnetic resonance. Magn Reson Med. 2016;76:408–416.
30. Ruan W, Zhong J, Wang K, et al. Detection of the mild emphysema by quantification of lung respiratory airways with hyperpolarized xenon diffusion MRI. Magn Reson Imaging. 2017;45:879–888.
31. Zhong J, Zhang H, Ruan W, et al. Simultaneous assessment of both lung morphometry and gas exchange function within a
single breath-hold by hyperpolarized 129 Xe MRI. NMR Biomed. 2017;30:e3730.

32. Xie J, Li H, Zhang H, et al. Single breath-hold measurement of pulmonary gas exchange and diffusion in humans with hyperpolarized 129 Xe MR. NMR Biomed. 2019;32:e4908.

33. Zhang H, Xie J, Xiao S, et al. Lung morphometry using hyperpolarized 129 Xe multi-b diffusion MRI with compressed sensing in healthy subjects and patients with COPD. Med Phys. 2018;45:3097–3108.

34. Zhang M, Li H, Li H, et al. Quantitative evaluation of lung injury caused by PM2.5 using hyperpolarized gas magnetic resonance imaging. Magn Reson Med. 2020;84:569–578.

35. Zhou XL, Deng HY, Wu WL, et al. Prognostic value of 18F-FDG PET/CT imaging and VEGF expression in non-small cell lung cancer. J Chin Clin Med Imaging. 2019;30:174–178.

36. Wang ZF, Li P, Yang YY, et al. Application of 18F-FDG PET-CT combined with chest breath-hold spiral CT in preoperative TNM staging of NSCLC [in Chinese]. Chin J CT MRI. 2018;16:75–77; 118.

37. Guo CM, Wang D, Huang SS, et al. The value of 18F-FDG PET/CT in Predicting distant metastasis of non-small cell lung cancer [in Chinese]. J Clin Radiol. 2021;40:1920–1924.

38. Chang C, Sun X, Wang G, et al. A machine learning model based on PET/CT radiomics and clinical characteristics predicts ALK rearrangement status in lung adenocarcinoma. Front Oncol. 2021;11:603882.

39. Chen L, Zhou Y, Tang X, et al. EGFR mutation decreases FDG uptake in non-small cell lung cancer via the NOX4/ROS/GLUT1 axis. Int J Oncol. 2019;54:370–380.

40. Lambin P, Rios-Velazquez E, Leijenaar R, et al. Radiomics: extracting more information from medical images using advanced feature analysis. Eur J Cancer. 2012;48:441–446.

41. Tan J, Li Z, Pan N, et al. Study on dual protection value of the AI based vVision technology combined with low mAs in patients with chest CT screening for COVID-19. Chin Med Devices. 2020;35:44+48+58; [in Chinese].

42. Liu K, Zhang RG, Tu WT, et al. A preliminary investigation on pulmonary subsolid nodule detection using deep learning methods from chest X-rays [in Chinese]. Chin J Radiol. 2017;51:88–921.

43. Wei YJ, Pan N, Chen Y, et al. A study using deep learning-based computer aided diagnostic system with chest radiographs-pneumothorax and pulmonary nodules detection. J Clin Radiol. 2021;40:252–257; in chinese.

44. Nijjati M, Zhang Z, Abulzi A, et al. Deep learning assistance for tuberculosis diagnosis with chest radiography in low-resource countries. Sci Technol Med. 2021;9:706.

45. Jin C, Chen W, Cao Y, et al. Development and evaluation of an artificial intelligence system for COVID-19 diagnosis. Nat Commun. 2020;11:5088.

46. Wang Z, Xiao Y, Li Y, et al. Automatically discriminating and localizing COVID-19 from community-acquired pneumonia on chest X-rays. Pattern Recognit. 2021;110:107613.

47. Wang G, Liu X, Shen J, et al. A deep-learning pipeline for the diagnosis and discrimination of viral, non-viral and COVID-19 pneumonia from chest X-ray images. Nat Biomed Eng. 2021; 5:509–521.

48. Liu H, Wang L, Nan Y, et al. SDFN: segmentation-based deep fusion network for thoracic disease classification in chest X-ray images. Comput Med Imaging Graph. 2019;75:66–73.

49. Wang H, Wang S, Qin Z, et al. Triple attention learning for classification of 14 thoracic diseases using chest radiography. Med Image Anal. 2021;67:101846.

50. Song J, Yang C, Fan L, et al. Lung lesion extraction using a tobaggon based growing automatic segmentation approach. IEEE Trans Med Imaging. 2016;35:337–353.

51. Su Y, Li D, Chen X. Lung nodule detection based on faster R-CNN framework. Comput Methods Programs Biomed. 2021;200:105866.

52. Xu X, Wang C, Guo J, et al. MSCS-DeepLN: evaluating lung nodule malignancy using multi-scale cost-sensitive neural networks. Med Image Anal. 2020;65:101772.

53. Lv W, Wang Y, Zhou C, et al. Development and validation of a clinically applicable deep learning strategy (HONORS) for pulmonary nodule classification at CT: a retrospective multi-centre study. Lung Cancer. 2021;155:78–86.

54. Xie Y, Zhang J, Xia Y. Semi-supervised adversarial model for benign-malignant lung nodule classification on chest CT. Med Image Anal. 2019;57:237–248.

55. Zhu X, Dong D, Chen Z, et al. Radiomic signature as a diagnostic factor for histologic subtype classification of non-small cell lung cancer. Eur Radiol. 2018;28:2772–2778.

56. Li H, Gao L, Ma H, et al. Radiomics-based features for prediction of histological subtypes in central lung cancer. Front Oncol. 2021;11:658887.

57. Fu Y, Xue P, Li N, et al. Fusion of 3D lung CT and serum biomarkers for diagnosis of multiple pathological types on pulmonary nodules. Comput Methods Programs Biomed. 2021;210:106381.

58. Fan L, Fang MJ, Li ZB, et al. Radiomics signature: a biomarker for the preoperative discrimination of lung invasive adenocarcinoma manifesting as a ground-glass nodule. Eur Radiol. 2018;29:1–9.

59. Xu F, Zhu W, Shen Y, et al. Radiomic-based quantitative CT analysis of pure ground-glass nodules to predict the invasiveness of lung adenocarcinoma. Front Oncol. 2020; 10:872.

60. Wang X, Chen K, Wang W, et al. Can peritumoral regions increase the efficiency of machine-learning prediction of pathological invasiveness in lung adenocarcinoma manifesting as ground-glass nodules? Journal of Thoracic Disease. 2021;13:1327–1337.

61. Wang X, Li Q, Cai J, et al. Predicting the invasiveness of lung adenocarcinomas appearing as ground-glass nodule on CT scan using multi-task learning and deep radiomics. Transl Lung Cancer Res. 2020;9:1397–1406.

62. Shen T, Hou R, Ye X, et al. Predicting malignancy and invasiveness of pulmonary subsolid nodules on CT images using deep learning. Front Oncol. 2021;11:700158.

63. Song L, Zhu Z, Mao L, et al. Clinical, conventional ct and radiomic feature-based machine learning models for predicting ALK rearrangement status in lung adenocarcinoma patients. Front Oncol. 2020;10:369.

64. Song Z, Liu T, Shi L, et al. The deep learning model combining CT image and clinicopathological information for predicting ALK fusion status and response to ALK-TKI therapy in non-small cell lung cancer patients. Eur J Nucl Med Mol Imaging. 2021;48:361–371.

65. Wang S, Zha X, Li W, et al. A fully automatic deep learning system for COVID-19 diagnostic and prognostic analysis. Eur Respir J. 2020;56:2000775.

66. Sun J, Liao X, Yan Y, et al. Detection and staging of chronic obstructive pulmonary disease using a computed tomography-based weakly supervised deep learning approach. Eur Radiol. 2022;32:5319–5329.

67. Zhang L, Jiang B, Wisselink HJJ, et al. COPD identification and grading based on deep learning of lung parenchyma and bronchial wall in chest CT images. Br J Radiol. 2022;95:20210637.

68. Qin Y, Wang J, Han Y, et al. Deep learning algorithms-based CT images in glucocorticoid therapy in asthma children with small airway obstruction. J Healthc Eng. 2021:2021;9:547043.

69. Zhang B, Jia C, Wu R, et al. Improving rib fracture detection accuracy and reading efficiency with deep learning-based detection software: a clinical evaluation. Br J Radiol. 2021; 94:20200870.

70. Liu J, Yin P, Wang S, et al. CT-based radiomics signatures for predicting the risk categorization of thymic epithelial tumors. Front Oncol. 2021;11:628534.

71. Li P, Han J, Zhang D, et al. Effects of dexamethasone on oxidative stress and inflammatory response in lungs during mechanical ventilation in COPD rats. Exp Ther Med. 2020; 19:1219–1224.
72. Duan C, Deng H, Xiao S, et al. Fast and accurate reconstruction of human lung gas MRI with deep learning. *Magn Reson Med*. 2019;82:2273–2285.

73. Duan C, Deng H, Xiao S, et al. Accelerate gas diffusion-weighted MRI for lung morphometry with deep learning. *Eur Radiol*. 2021;32:702–713.

74. Wang X, Wan Q, Chen H, et al. Classification of pulmonary lesion based on multiparametric MRI: utility of radiomics and comparison of machine learning methods. *Eur Radiol*. 2020;30:4595–4605.

75. Guo YB, Dang S, Duan HF, et al. The value of MR-based radiomics signature for differentiating small cell lung cancer from non-small cell lung cancer [in Chinese]. *J Clin Radiol*. 2020;39:1776–1779.

76. Xiao G, Hu YC, Ren JL, et al. MR imaging of thymomas: a combined radiomics nomogram to predict histologic subtypes. *Eur Radiol*. 2021;31:447–457.

77. Yang B, Zhong J, Zhong J, et al. Development and validation of a radiomics nomogram based on (18)F-fluorodeoxyglucose positron emission tomography/computed tomography and clinicopathological factors to predict the survival outcomes of patients with non-small cell lung cancer. *Front Oncol*. 2020;10:1042.

78. Li L, Zhao X, Lu W, et al. Deep learning for variational multimodality tumor segmentation in PET/CT. *Neurocomputing*. 2020;392:277–295.

79. National Institutes for Food and Drug Control, Cardiothoracic Group of Chinese Medical Association Radiology Branch. Expert consensus on the rule and quality control of pulmonary nodule annotation based on thoracic CT [in Chinese]. *J Clin Radiol*. 2019;53:9–15.

80. Radiology Society of Chinese Medical Association, National Institutes for Food and Drug Control, National Health Commission Capacity Building and Continuing Education Center. Expert consensus on the construction and quality control of thoracic CT datasets for pulmonary nodules [in Chinese]. *J Clin Radiol*. 2021;55:104–110.