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Advances in CT-Based Diagnosis of Pneumonic-Type Lung Cancer: A Review

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Abstract

Pneumonic-type lung cancer (PTLC) represents a distinct manifestation of lung carcinoma, characterized by overlapping clinical symptoms and imaging features with infectious lesions, often leading to misdiagnosis and delayed treatment upon initial imaging evaluation. Computed tomography (CT) is the primary imaging modality for pulmonary diseases. Therefore, accurate CT imaging diagnosis of PTLC holds significant value for clinical management. This review summarizes the applications and research progress of CT and CT-related imaging technologies in the diagnosis of PTLC.

Keywords

Pneumonic-Type Lung Cancer, Computed Tomography, Photon-Counting Computed Tomography, Radiomics, Dual-Energy Computed Tomography

1. Introduction

Lung cancer ranks as the second most common malignancy globally and the leading cause of cancer-related mortality [1]. Computed tomography (CT), as an economical, convenient, and non-invasive imaging modality, plays a crucial role in the screening, diagnosis, and staging of lung cancer. Lung cancer typically presents as nodules or masses on CT, yet there exists a special subtype of the disease—pneumonic-type lung cancer. Patients primarily exhibit clinical manifestations such as cough and sputum production, with CT imaging resembling pneumonia. Pathological confirmation reveals lung adenocarcinoma, most frequently invasive mucinous adenocarcinoma (IMA), accounting for 26% - 57% of lung adenocarcinomas [2] [3]. PTLC possesses unique clinical and imaging characteristics compared to other lung cancer types, making it difficult to differentiate from benign

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conditions like pneumonia or tuberculosis, often resulting in misdiagnosis and treatment delay. Numerous studies have investigated the role of CT in the diagnosis, differential diagnosis, and staging of PTLC. This review focuses on elucidating the applications and research advancements of CT and CT-related imaging technologies in PTLC diagnosis.

2. Diagnostic Value of Multidetector Computed Tomography in PTLC

Multidetector computed tomography (MDCT) is a widely utilized imaging modality in current clinical practice. As a non-invasive examination, it holds significant value in the diagnosis and staging of pulmonary diseases.

2.1. Imaging Characteristics of PTLC on MDCT

The imaging manifestations of PTLC on MDCT differ from those of other lung cancer types. Pathologically, PTLC predominantly consists of IMA. IMA tumor cells, including columnar or goblet cells, typically grow along alveolar walls and secrete abundant mucin, filling alveolar spaces. This leads to consolidation of the affected lobe, presenting a gelatinous appearance with volume increase [4] [5]. On CT scans, this manifests as bulging interlobar fissures accompanied by low-attenuation areas. Following intravenous contrast administration, the consolidated lung regions appear as low-attenuation areas with enhanced visualization of pulmonary vascular branches, known as the angiogram sign. Furthermore, when tumor cells invade the bronchi, a check-valve mechanism can form, allowing air entry but preventing its exit, resulting in air-containing regions [4] [6] [7].

2.2. Application of MDCT in the Diagnosis of PTLC

PTLC and pneumonia often exhibit similar appearances on CT. However, multiple studies have revealed that morphological features on MDCT possess discriminatory value. Zhang *et al.* analyzed non-contrast CT images of 341 patients with PTLC and 207 patients with pneumonia. They revealed that the irregular air bronchogram is a key feature for differentiating PTLC from infectious pneumonia, with a significant difference in its incidence between the two groups (50.7% vs. 37.7%, $p = 0.016$). On CT images, interlobular fissure bulging (18.7% vs. 9.7%, $p = 0.017$) and air space (65.7% vs. 30.0%, $p < 0.001$) are more frequently observed in PTLC than in pneumonia. Furthermore, the CT values of the solid components in PTLC are generally lower than those in pneumonia (25.9 ± 7.1 HU and 32.3 ± 5.1 HU, $p < 0.001$) [8]. Differential diagnosis between PTLC and pulmonary tuberculosis also presents challenges.

Several researchers performed a retrospective analysis on the non-contrast and contrast-enhanced MDCT images of 84 patients with PTLC and 93 patients with exudative-predominant pulmonary tuberculosis. And the results showed that, compared with the tuberculosis group, the PTLC group had a higher proportion

of mostly heterogeneous lesion density (55.9% vs. 48.7%), and peripheral ground-glass opacities were more frequently observed in the PTLC group (86.9% vs. 55.9%) [9]. The same study proposed that bronchi within PTLC lesions often display irregular wall morphology, uneven caliber or stenosis/obstruction, and tortuous, rigid courses resembling withered branches. In contrast, bronchi within exudative-dominant tuberculous lesions typically have smooth walls, gradually tapering lumens, and natural courses. However, when tuberculosis is complicated by tracheobronchial tuberculosis, bronchi can also exhibit a withered branch appearance [9]. This indicates substantial overlapping imaging signs between PTLC and exudative-dominant tuberculosis on CT, complicating differentiation.

Furthermore, attention has been drawn to a rare tumor also lacking specific clinical features—mucosa-associated lymphoid tissue lymphoma (MALT lymphoma). On CT scans, pulmonary MALT lymphoma primarily presents in four patterns: consolidation, nodular, ground-glass, and diffuse interstitial types [10]. The consolidation pattern overlaps with imaging features of PTLC, and consolidation-type MALT (C-MALT) can be misdiagnosed as PTLC [11], leading to inappropriate treatment. Dong *et al*., through a retrospective analysis of 31 C-MALT patients and 58 pneumonic-type lung adenocarcinoma patients, found that cystic bronchiectasis is a characteristic imaging finding of C-MALT On CT scans, aiding in its differentiation from PTLC [12]. This bronchiectasis differs from the commonly referenced irreversible bronchial wall damage; in C-MALT, the dilated bronchial walls lack tumor necrosis or destruction [13]. In summary, although the MDCT manifestations of PTLC overlap with those of benign conditions such as pneumonia, a series of characteristic signs provide key evidence for differential diagnosis. To systematize these findings and serve clinical practice, this study synthesizes the aforementioned analysis into an MDCT-focused diagnostic flowchart (**Figure 1**).

3. Application of CT-Related Imaging Technologies in Pneumonic-Type Lung Cancer

3.1. High-Resolution Computed Tomography

Contemporary high-resolution computed tomography (HRCT) refers to an image reconstruction technique based on MDCT, generating thin-section (1 - 2 mm) high-resolution images. This technique allows for effective alteration of image parameters, enhancing spatial resolution [14]. Research by Cao *et al*. confirmed that HRCT technology improves diagnostic accuracy and sensitivity for peripheral lung cancer [14]. This improvement is likely attributable to HRCT's enhanced spatial resolution, providing clinicians with more reliable information regarding lesion morphology and its relationship with adjacent airways, vessels, and pleura, thereby facilitating accurate diagnosis. Furthermore, contrast-enhanced high-resolution chest CT yields superior image quality, enabling assessment of lesion enhancement characteristics and local blood circulation status, which assists in analyzing microvascular distribution within lesions [15]. Thus, HRCT plays a significant role in enhancing the diagnostic accuracy of PTLC.

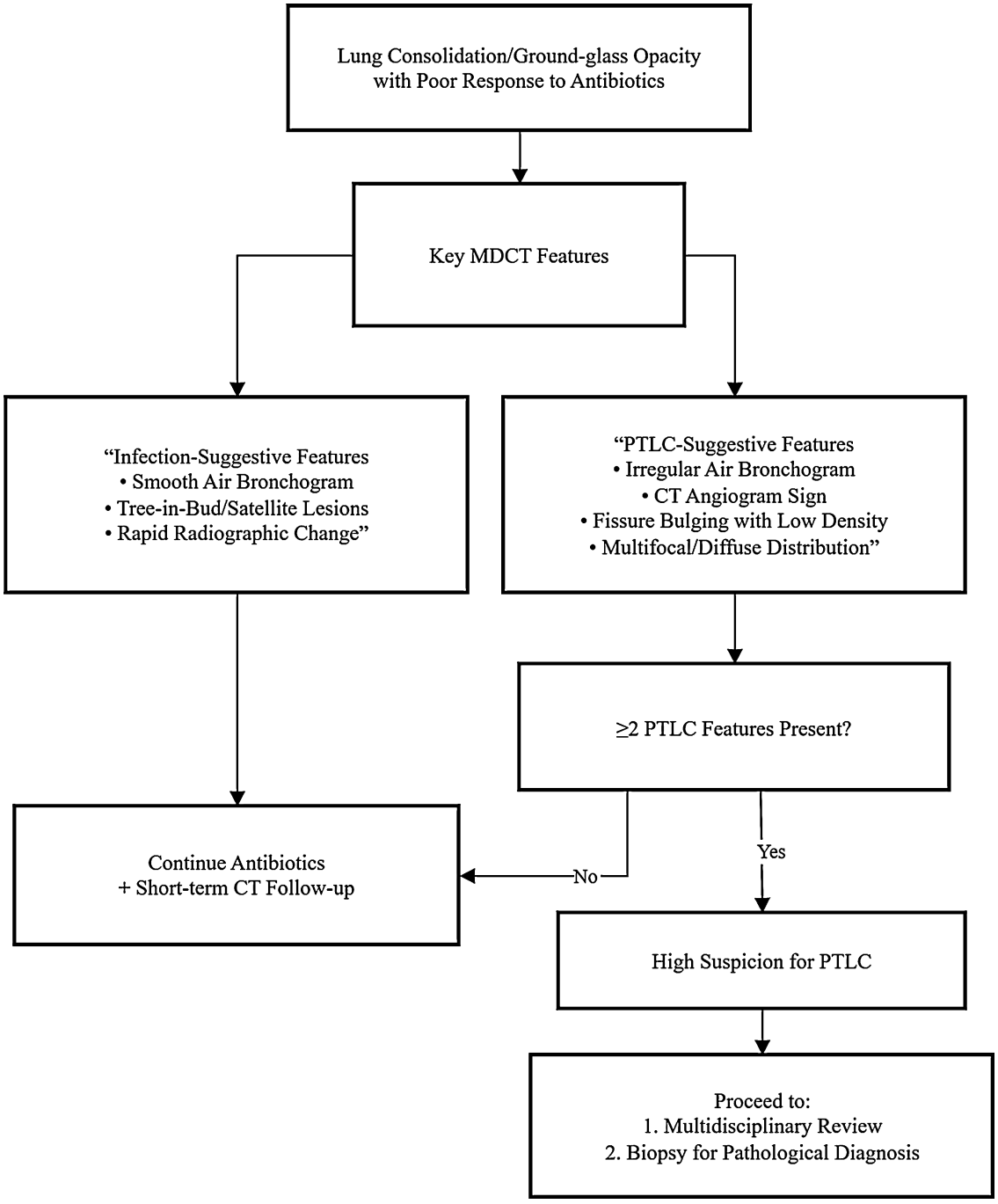

Figure 1. Diagnostic and clinical decision-making flowchart for PTLC based on MDCT imaging features.

3.2. Dual-Energy Computed Tomography

Dual-energy computed tomography (DECT) enables post-processing reconstruction to generate virtual monoenergetic images and material decomposition images [16], allowing for quantitative analysis of lesions to aid disease diagnosis. Although research on spectral CT in PTLC is limited, its value in qualitative diagnosis of pulmonary diseases, differentiation of lung cancer subtypes, and prediction of genetic mutation status has been demonstrated [17]-[19]. Several researchers per-

formed spectral CT analysis on the images of 45 patients with peripheral lung cancer and 33 patients with focal organizing pneumonia. Through post-processing, they obtained the monochromatic CT values, iodine concentration (IC), water concentration (WC), and effective atomic number (Zeff) at monochromatic energy levels ranging from 40 to 140 keV at 10 keV intervals, and calculated the slope of the spectral curve (K_{70keV}) according to the relevant calculation formulas. The results demonstrated that multiple spectral parameters (CT_{40keV}, CT_{70keV}, K_{70keV}, IC, and Zeff) in the focal organizing pneumonia group were significantly higher than those in the peripheral lung cancer group, with statistically significant differences ($t = -3.21, -2.57, -3.10, -3.06, -3.00$, all $p < 0.05$) [20]. This suggests that quantitative analysis techniques like spectral CT imaging hold promise for differentiating PTLC from pneumonia, though further research is required to validate their accuracy and clinical utility.

3.3. Photon-Counting Computed Tomography/Spectral Photon-Counting Computed Tomography

In recent years, photon-counting detectors (PCDs) have gained attention. Unlike traditional energy-integrating detectors (EIDs), CT systems equipped with PCDs are termed photon-counting CT (PCCT). Due to PCD characteristics, PCCT can improve spatial resolution, reduce beam-hardening artifacts, and lower radiation dose to patients [21] [22]. Moreover, PCCT also enables spectral decomposition with superior resolution compared to DECT [23]. Additionally, K-edge imaging technology based on PCCT, utilizing the principle of specific heavy elements' peak absorption of photons at particular energies [24], is poised to bring revolutionary changes to CT research. Currently, research on PCCT remains scarce, particularly in thoracic diseases. Studies have shown that PCCT can clearly depict distal airway structures and their walls, extending to fourth-generation bronchi and distal vessels [25]. Undoubtedly, PCCT holds significant research potential for delineating both morphological features and spectral parameters of PTLC. With the advancement and maturation of PCCT technology, clinicians may no longer face diagnostic uncertainty regarding PTLC.

4. Research Progress on CT Combined with Radiomics in the Diagnosis of Pneumonic-Type Lung Cancer

Radiomics involves the analysis of large volumes of medical images to extract quantitative features, create associated databases, and provide high-dimensional information about the internal characteristics of lesions [26]. Although these features are not directly observable, this analytical technique demonstrates superior value in tumor diagnosis, staging, and prognosis prediction [27] [28]. The value of radiomics in the diagnosis and differential diagnosis of PTLC is increasingly recognized. Ji *et al.* [29], through retrospective analysis of radiomic features from chest CT images of 138 lobar pneumonia patients and 59 PTLC patients, found that a radiomics model performed excellently in differentiating these two diseases.

The area under the curve (AUC) values were 0.90 and 0.88 for the training and validation sets, respectively. A combined model integrating radiomic and clinical features further improved AUC values to 0.94 and 0.91, respectively. In a multicenter study, a nomogram combining clinical variables with CT radiomic features was constructed to differentiate pneumonic-type IMA from pneumonia. Results showed that the nomogram's AUC values surpassed those of the clinical model alone across the test, validation, and external validation sets. In the external validation set, the nomogram achieved a specificity of 94.6% and an accuracy of 72.5% [30]. This demonstrates the superiority of nomograms combining clinical variables and CT radiomic features in distinguishing pneumonic-type IMA from pneumonia. Furthermore, Du *et al.* employed a convolutional neural network-based machine learning method to differentiate PTLC from pneumonia. Results indicated that after using this model, radiologists' diagnostic sensitivity increased from 48.18% to 64.7%, specificity from 75% to 91.8%, and the false-positive rate decreased from 32.4% to 10.8%, suggesting the model's diagnostic efficacy surpassed that of chest CT examination alone [31]. These findings collectively demonstrate the feasibility of accurately distinguishing PTLC from pneumonia using radiomic features. Despite substantial evidence supporting the value of radiomics, controversies remain. Firstly, radiomic data are not intuitive, making it difficult for clinicians to comprehend the basis for differential diagnosis. Secondly, developing radiomics models requires large image datasets, which may originate from different equipment and scanning protocols. These factors can introduce bias into the developed models. Therefore, future research directions may involve the visualization of radiomic features and the standardization of image utilization through algorithms.

5. Summary and Perspectives

Significant progress has been made in the accurate diagnosis of PTLC with advancements in medical imaging technology. While conventional MDCT plays an important role in early PTLC diagnosis by identifying morphological signs, reliance solely on these features may still lead to a high misdiagnosis rate. Furthermore, concerns regarding radiation exposure from CT scans and issues related to contrast agents have long been debated. The advent of PCCT positively contributes to reducing PTLC misdiagnosis rates, minimizing patient radiation exposure, and improving contrast agent utilization. Spectral CT offers advantages in quantitative lesion analysis. Its value in differentiating peripheral lung cancer from focal organizing pneumonia has been confirmed, but research specifically in PTLC remains limited, warranting further investigation. Radiomics, as a technique for extracting and analyzing non-intuitive imaging features, utilizes big data to build models. It has been proven superior to clinical models or CT morphological feature models alone in differentiating PTLC from pneumonia. However, challenges such as mitigating variations caused by different machines and scanning protocols, as well as making non-intuitive features more interpretable, require further exploration.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

[1] Bray, F., Laversanne, M., Sung, H., Ferlay, J., Siegel, R.L., Soerjomataram, I., *et al.* (2024) Global Cancer Statistics 2022: GLOBOCAN Estimates of Incidence and Mortality Worldwide for 36 Cancers in 185 Countries. *CA*: *A Cancer Journal for Clinicians*, **74**, 229-263. https://doi.org/10.3322/caac.21834

[2] Detterbeck, F.C., Marom, E.M., Arenberg, D.A., *et al.* (2016) The IASLC Lung Cancer Staging Project: Background Data and Proposals for the Application of TNM Staging Rules to Lung Cancer Presenting as Multiple Nodules with Ground Glass or Lepidic Features or a Pneumonic Type of Involvement in the Forthcoming Eighth Edition of the TNM Classification. *Journal of Thoracic Oncology*: *Official Publication of the International Association for the Study of Lung Cancer*, **11**, 666-680.

[3] Liu, Y., Li, J., Wang, S., *et al.* (2019) [Advanced Pneumonic-Type Lung Carcinoma: A Retrospective Study of Clinical-Radiological-Pathological Characteristics with Survival Analysis in a Single Chinese Hospital]. *Chinese Journal of Lung Cancer*, **22**, 329-335.

[4] Lee, K.S., Kim, Y., Han, J., Ko, E.J., Park, C.K. and Primack, S.L. (1997) Bronchioloalveolar Carcinoma: Clinical, Histopathologic, and Radiologic Findings. *RadioGraphics*, **17**, 1345-1357. https://doi.org/10.1148/radiographics.17.6.9397450

[5] Watanabe, H., Saito, H., Yokose, T., Sakuma, Y., Murakami, S., Kondo, T., *et al.* (2015) Relation between Thin-Section Computed Tomography and Clinical Findings of Mucinous Adenocarcinoma. *The Annals of Thoracic Surgery*, **99**, 975-981. https://doi.org/10.1016/j.athoracsur.2014.10.065

[6] Kim, T.H., Kim, S.J., Ryu, Y.H., Chung, S.Y., Seo, J.S., Kim, Y.J., *et al.* (2006) Differential CT Features of Infectious Pneumonia versus Bronchioloalveolar Carcinoma (BAC) Mimicking Pneumonia. *European Radiology*, **16**, 1763-1768. https://doi.org/10.1007/s00330-005-0101-5

[7] Tan, Y., Gao, J., Wu, C., Zhao, S., Yu, J., Zhu, R., *et al.* (2019) CT Characteristics and Pathologic Basis of Solitary Cystic Lung Cancer. *Radiology*, **291**, 495-501. https://doi.org/10.1148/radiol.2019181598

[8] Zhang, S., Yu, X., Huang, Y., Nie, P., Deng, Y., Mao, N., *et al.* (2022) Pneumonic-Type Invasive Mucinous Adenocarcinoma and Infectious Pneumonia: Clinical and CT Imaging Analysis from Multiple Centers. *BMC Pulmonary Medicine*, **22**, Article No. 460. https://doi.org/10.1186/s12890-022-02268-5

[9] Ma, C.H., Li, Q. and Chen, H.Y. (2020) Comparison on CT Manifestations of Pneumonic-Type Lung Cancer and Exudation-Predominant Pulmonary Tuberculosis. *Chinese Journal of Medical Imaging Technology*, **36**, 849-852.

[10] Wu, T., Huang, Y., Wang, Z., Cao, H., Ding, Q. and Deng, Z. (2022) Pulmonary MALT Lymphoma: Imaging Findings in 18 Cases and the Associated Pathological Correlations. *The American Journal of the Medical Sciences*, **364**, 192-197. https://doi.org/10.1016/j.amjms.2022.02.013

[11] Torrente-Nieto, A., Bonnin Vilaplana, M. and Rojas Calvera, E. (2022) Isolated Lobar Consolidation as a Form of Presentation of Pulmonary MALT Lymphoma. *Medicina Clínica* (*English Edition*), **158**, 297. https://doi.org/10.1016/j.medcle.2021.06.010

[12] Dong, C., Xia, P., Qiu, W., Dai, Z. and Wang, Z. (2023) Evaluation of CT Features for Differentiating Consolidation Pattern of Pulmonary MALT Lymphoma from Pneu-

monic-Type Lung Adenocarcinoma. *Frontiers in Oncology*, **13**, Article 1234291. https://doi.org/10.3389/fonc.2023.1234291

[13] Noguchi, S., Yatera, K., Kido, T., Ogoshi, T., Nagata, S., Nishida, C., *et al.* (2013) Pulmonary Mucosa-Associated Lymphoid Tissue (MALT) Lymphoma with Multiple Thin-Walled Pulmonary Cysts: A Case Report and Review of the Literature. *Internal Medicine*, **52**, 2325-2329. https://doi.org/10.2169/internalmedicine.52.0377

[14] Cao, G.A. (2022) Comparison of the Diagnostic Value of MDCT Enhanced Scan and HRCT in PLC. *Modern Medical Imagelogy*, **31**, 2264-2266.

[15] Yang, X.J. (2022) The Value of High-Resolution Chest CT in the Differential Diagnosis of Pneumonic Type Carcinoma of Lung. *Chinese Journal of CT and MRI*, **20**, 77-79, 91.

[16] Ko, J.P., Brandman, S., Stember, J. and Naidich, D.P. (2012) Dual-Energy Computed Tomography: Concepts, Performance, and Thoracic Applications. *Journal of Thoracic Imaging*, **27**, 7-22. https://doi.org/10.1097/rti.0b013e31823fe0e9

[17] So, A. and Nicolaou, S. (2021) Spectral Computed Tomography: Fundamental Principles and Recent Developments. *Korean Journal of Radiology*, **22**, 86-96. https://doi.org/10.3348/kjr.2020.0144

[18] Greffier, J., Villani, N., Defez, D., Dabli, D. and Si-Mohamed, S. (2023) Spectral CT Imaging: Technical Principles of Dual-Energy CT and Multi-Energy Photon-Counting CT. *Diagnostic and Interventional Imaging*, **104**, 167-177. https://doi.org/10.1016/j.diii.2022.11.003

[19] Zhang, Y., Cheng, J., Hua, X., Yu, M., Xu, C., Zhang, F., *et al.* (2016) Can Spectral CT Imaging Improve the Differentiation between Malignant and Benign Solitary Pulmonary Nodules? *PLOS ONE*, **11**, e0147537. https://doi.org/10.1371/journal.pone.0147537

[20] Deng, L.N., Zhang, G.J., Lin, X.Q., *et al.* (2021) A Comparison of Spectral and Perfusion CT Imaging in Differentiating Peripheral Lung Cancer from Focal Organizing Pneumonia. *Chinese Journal of Medical Imaging*, **29**, 1206-1211.

[21] Douek, P.C., Boccalini, S., Oei, E.H.G., Cormode, D.P., Pourmorteza, A., Boussel, L., *et al.* (2023) Clinical Applications of Photon-Counting CT: A Review of Pioneer Studies and a Glimpse into the Future. *Radiology*, **309**, e222432. https://doi.org/10.1148/radiol.222432

[22] Symons, R., Pourmorteza, A., Sandfort, V., Ahlman, M.A., Cropper, T., Mallek, M., *et al.* (2017) Feasibility of Dose-Reduced Chest CT with Photon-Counting Detectors: Initial Results in Humans. *Radiology*, **285**, 980-989. https://doi.org/10.1148/radiol.2017162587

[23] Taguchi, K., Blevis, I. and Iniewski, K. (2020) Spectral, Photon Counting Computed Tomography: Technology and Applications. CRC Press.

[24] Willemink, M.J., Persson, M., Pourmorteza, A., Pelc, N.J. and Fleischmann, D. (2018) Photon-Counting CT: Technical Principles and Clinical Prospects. *Radiology*, **289**, 293-312. https://doi.org/10.1148/radiol.2018172656

[25] Si-Mohamed, S., Boccalini, S., Rodesch, P., Dessouky, R., Lahoud, E., Broussaud, T., *et al.* (2021) Feasibility of Lung Imaging with a Large Field-Of-View Spectral Photon-Counting CT System. *Diagnostic and Interventional Imaging*, **102**, 305-312. https://doi.org/10.1016/j.diii.2021.01.001

[26] Chen, M., Copley, S.J., Viola, P., Lu, H. and Aboagye, E.O. (2023) Radiomics and Artificial Intelligence for Precision Medicine in Lung Cancer Treatment. *Seminars in Cancer Biology*, **93**, 97-113. https://doi.org/10.1016/j.semcancer.2023.05.004

[27] Mayerhoefer, M.E., Materka, A., Langs, G., Häggström, I., Szczypiński, P., Gibbs, P., *et al.* (2020) Introduction to Radiomics. *Journal of Nuclear Medicine*, **61**, 488-495. https://doi.org/10.2967/jnumed.118.222893

[28] Wu, G., Jochems, A., Refaee, T., Ibrahim, A., Yan, C., Sanduleanu, S., *et al.* (2021) Structural and Functional Radiomics for Lung Cancer. *European Journal of Nuclear Medicine and Molecular Imaging*, **48**, 3961-3974. https://doi.org/10.1007/s00259-021-05242-1

[29] Ji, H., Liu, Q., Chen, Y., Gu, M., Chen, Q., Guo, S., *et al.* (2023) Combined Model of Radiomics and Clinical Features for Differentiating Pneumonic-Type Mucinous Adenocarcinoma from Lobar Pneumonia: An Exploratory Study. *Frontiers in Endocrinology*, **13**, Article 997921. https://doi.org/10.3389/fendo.2022.997921

[30] Yu, X., Zhang, S., Xu, J., Huang, Y., Luo, H., Huang, C., *et al.* (2023) Nomogram Using CT Radiomics Features for Differentiation of Pneumonia-Type Invasive Mucinous Adenocarcinoma and Pneumonia: Multicenter Development and External Validation Study. *American Journal of Roentgenology*, **220**, 224-234. https://doi.org/10.2214/ajr.22.28139

[31] Du, W., Luo, X. and Chen, M. (2022) A Practical Deep Learning Model in Differentiating Pneumonia-Type Lung Carcinoma from Pneumonia on CT Images: Resnet Added with Attention Mechanism. *Journal of Oncology*, **2022**, Article ID: 8906259. https://doi.org/10.1155/2022/8906259