Journal of Biomedical Sciences | ISSN: 2960-9356
Research Article Peer-review, Open Access

Validation of Artificial Intelligence in Detection of Indeterminate Pulmonary Nodules in Adults by Chest Radiography

Ahmed Abdullah Mahood*[1], Atheer Adnan Fadel[2]

Abstract

Psoriatic Lung cancer remains the leading cause of cancer-related mortality worldwide. Early detection of indeterminate pulmonary nodules (IPNs) is critical for improving patient outcomes, as timely intervention correlates with higher survival rates. Aim To evaluate the diagnostic performance of the qXR deep-learning algorithm for detecting pulmonary nodules or masses on standard chest radiographs (CXR), using follow-up computed tomography (CT) as the reference standard, and to characterize confirmed nodules according to the Fleischner Society 2017 guidelines. In this single-center, retrospective cohort study, 6,543 CXRs obtained at Baghdad Teaching Hospital between January and December 2023 were screened by the qXR algorithm. Of these, 1,320 images were flagged positive for nodular or mass-like opacities. After applying exclusion criteria—prior thoracic surgery, poor image quality, refusal of follow-up, or nodules < 6 mm—a total of 83 cases underwent CT within two weeks. Algorithm performance was assessed on a per-scan and per-nodule basis, with CT findings serving as the reference. CT confirmed pulmonary nodules in 65 of 83 cases, yielding a per-scan positive predictive value (PPV) of 78.4%. The qXR algorithm detected 116 nodules on CXR versus 94 nodules identified by CT; 73.4% of confirmed nodules were solid. For solid nodules > 8 mm, sensitivity reached 92.5%. Overall, the area under the receiver-operating characteristic curve (AUC) was 0.68, with scan-level sensitivity and specificity of 92.5% and 81.1%, respectively. Subgroup analyses demonstrated variations in performance according to patient demographics (age, sex, smoking history) and nodule characteristics (size, solidity, lobe location). The qXR algorithm exhibits high sensitivity and acceptable specificity for detecting indeterminate pulmonary nodules on CXR, particularly for solid lesions > 8 mm. Integration of AI-driven detection into routine chest radiograph interpretation has the potential to enhance early nodule identification, expedite clinical decision-making, and support lung-cancer risk stratification without replacing radiologists.

Keywords: Artificial Intelligence; Chest Radiography; Pulmonary Nodules; Deep Learning.

[1] M.B.Ch.B., Iraqi Board for Medical Specializations in Diagnostic Radiology, Baghdad Teaching Hospital, Medical City Complex
Email : Ahmedmahood7@gmail.com

[2] M.B.Ch.B - F.I.B.M.S (RAD)., Consultant Radiologist, Department of Radiology, Baghdad Teaching Hospital, Medical City Complex.

Introduction

Lung cancer remains the leading cause of cancer-related mortality worldwide. Early detection of indeterminate pulmonary nodules (IPNs) is critical for improving patient outcomes, as timely intervention correlates with higher survival rates [1].

XR serves as a primary and crucial screening modality in the diagnosis and management of cardiothoracic and pulmonary abnormalities, such as pneumothorax, pleural effusion, atelectasis, cardiac hypertrophy, hyperinflation, and consolidation. CXR plays an important role in the diagnostic domain of medical practice. However, correctly identifying the abnormalities on CXR is often a significant challenge due to the limited number of well-trained radiologists and the heavy workload in extensive healthcare facilities [2].

In recent years, automated CXR screening using CAD systems based on CNNs for the detection of thoracic abnormalities has been an active area of research. The CNN-based CAD system is generally trained on a large-scale database of labeled images. This helps in improving the learning of underlying complex semantic features for superior generalization in disease detection [3].

Chest radiography (CXR) is a widely accessible and cost-effective screening modality; however, interpretation is often subjective and constrained by radiologist shortages and increasing imaging volume. Recent advances in deep learning offer the promise of automated, high-accuracy CXR analysis to assist radiologists in detecting subtle nodular opacities. This study evaluates the Qure.ai qXR algorithm's ability to identify pulmonary nodules on standard CXRs, comparing its performance to CT and classifying nodules per Fleischner Society 2017 guidelines [4].

Materials and Methods

1. Study Design and Population

A prospective cohort of adult patients (≥ 18 years) who underwent routine CXR at Baghdad Teaching Hospital from January through December 2023 was assembled. The Institutional Review Board of the Iraqi Board of Diagnostic Radiology approved the study, and informed consent was obtained. High-risk patients—defined by respiratory symptoms, smoking history, prior malignancy, or chronic lung disease—received follow-up CT within two weeks when CXR findings were positive for nodules or masses.

2. Inclusion and Exclusion Criteria

- **Inclusion:** Adults with respiratory complaints or known cancer undergoing standard, posteroanterior and/or lateral CXR.
- **Exclusion:** Recent thoracic surgery, acute pulmonary infection, refusal of CT follow-up, poor radiograph quality (e.g., rotation, under- or overexposure), or nodules < 6 mm in greatest dimension.

3. Image Analysis

All CXRs were processed by the qXR algorithm, which flags nodular or mass-like opacities and assigns a probability score. Radiologists blinded to CT results reviewed CT scans, identifying and sizing nodules in accordance with Fleischner guidelines (solid, subsolid, part-solid)

4. Statistical Analysis

Performance metrics at the scan and nodule levels included sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), and AUC of the receiver-operating characteristic (ROC) curve. Subgroup analyses examined algorithm performance by patient age, sex, smoking history, and nodule characteristics (size categories: 6–8 mm, > 8 mm; solidity; lobe location). Statistical significance was defined as $p < 0.05$.

Results

1. Demographic Variables of Participants

Regarding the demographic characteristics of patients with pulmonary nodules: Their age ranged from 18 to 83 years, with a mean of 50.6 ± 16.5 S/D years.

Table 1. Patient Demographics and Baseline Characteristics.

Characteristic	Category	Value
Total Participants		**100** (Total CXR Cohort n=6,543; CT Cohort n=83)
Age (Years)	Mean ± SD	50.6 ± 16.5
	Range	18 – 83
Sex	Male	58 (58%)
	Female	42 (42%)
Ratio	Male : Female	1.3 : 1

2. Characteristics of Pulmonary Nodules

Regarding characteristics of pulmonary nodules (Table 2), the median nodule size was 11.2 mm, and most nodules detected were solid nodules (about 74.4%). Regarding nodule location, the most common site is seen in the right upper lobe at about 30.8%, and fewer sites for nodules show in both lower lobes. About 50% of nodules are in the RT upper and middle lobe as shown in (Table 2).

Table 2. Characteristics of Pulmonary Nodules by CT (n = 94) 44.

Variable	Category	Number (n)	Percentage (%)
Total Nodules		**94**	**100%**
Nodule Size	Median Diameter	11.2 mm	—
Nodule Type	Solid	69	73.4%
	Ground Glass (GGN)	19	20.2%
	Part-Solid (PSN)	7	7.4%
Location	Right Upper Lobe (RUL)	29	30.8%
	Right Middle Lobe (RML)	19	20.2%
	Right Lower Lobe (RLL)	7	7.4%
	Left Upper Lobe (LUL)	8	8.5%
	Left Middle Lobe (lingula)	11	11.7%
	Left Lower Lobe (LLL)	7	7.4%

3. Diagnostic Performance of AI in the Detection of Nodule

Regarding the lung nodule malignancy score shown in Table 3:

- When nodule size is more than 8mm and the nodule texture is solid, the SP was 92.50 (80.13 – 97.416) and AUC was 0.680 (0.54 – 0.81).
- When nodule size is more than 8 mm and nodule texture was GGN, the SP was 73.33 (48.04 – 89.10) and AUC was 0.315 (0.171– 0.459).
- This shows the SP and AUC decrease as compared to when the nodule texture was solid.
- The highest SP and NPV were seen when the patient had a previous cancer history and the nodule texture was solid and multiple: SP 90.163 (80.15 – 95.41), NPV 98.214 (90.55 – 99.68).

Table 3. The diagnostic performance of the different parameters of CXR analysis 50.

Variable / Subgroup	Sensitivity (SN)95% CI	Specificity (SP)95% CI	NPV95% CI	PPV95% CI	AUC95% CI
Solid Nodules > 8mm	**92.50%**	**26.08%**	**66.66%**	**68.51%**	**0.680**
(Smoker)	(80.13 – 97.41)	(12.54 – 46.47)	(35.42 – 87.94)	(55.25 – 79.32)	(0.54 – 0.81)
GGN or PSN > 8mm	**73.33%**	**20.37%**	**55.55%**	**20.37%**	**0.315**
(Non-smoker)	(48.04 – 89.10)	(11.77 – 32.90)	(26.66 – 81.12)	(11.77 – 32.90)	(0.171 – 0.459)
Multiple Nodules > 8mm	**50.00%**	**90.16%**	**98.21%**	**14.28%**	**0.573**
(History of CA)	(9.45 – 90.54)	(80.15 – 95.41)	(90.55 – 99.68)	(2.56 – 51.31)	(0.15 – 0.99)

4. Variables Analysis

Cancer history also influences the detection outcomes of positive nodules. Individuals with a positive cancer history had fewer positive nodules detected by both AI and CT than those with a negative cancer history: 9 (AI) vs 8 (CT) for those with a positive cancer history, and 74 (AI) vs 57 (CT) for those with a negative cancer history (Table 4). However, the PPV for those with a positive cancer history was higher than those with a negative cancer history: 81.82% vs 72.97%.

Table 4. PPV of AI positive nodule compared to the CT scan 54.

Variable	Subgroup	AI Positive Nodules (n)	CT Confirmed Nodules (n)	PPV (95% CI)
Age	≥ 45 years	54	47	**87.04%** (75.57 – 93.57)
	< 45 years	29	18	**62.07%** (44.00 – 77.31)
Sex	Male	48	42	**87.50%** (75.29 – 94.14)
	Female	35	23	**65.71%** (49.15 – 79.16)
Smoking History	Smoker / Ex-smoker	52	45	**86.67%** (70.31 – 94.69)
	Non-Smoker	31	20	**64.71%** (47.91 – 78.51)
Cancer History	Positive	11	9	**81.82%** (52.30 – 94.86)
	Negative	72	56	**76.47%** (65.14 – 84.96)

5. cases from study:

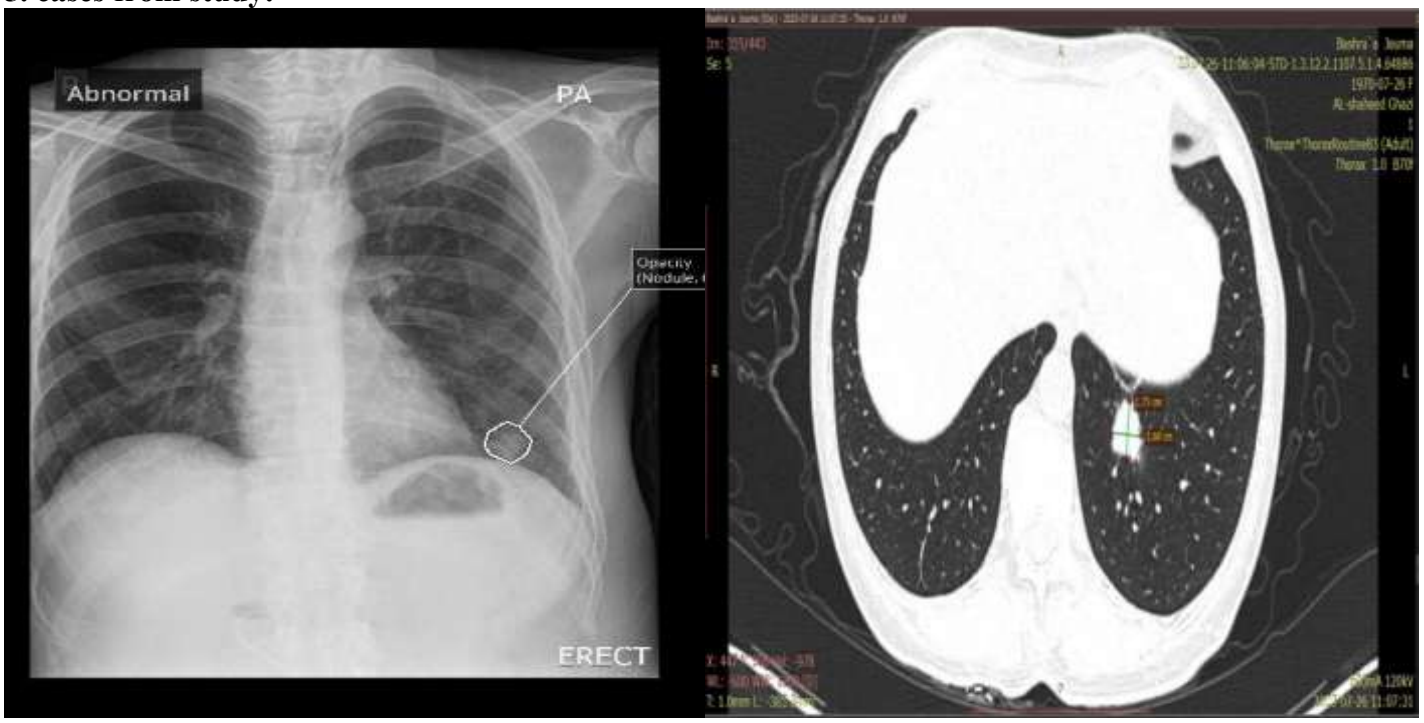


Figure 3.1. a case of 53-year-old man found in CXR during a health check-up. (a) AI software detected a small lung nodule in the LLL with an abnormality score of .26 MR % on CXR. (b) A corresponding CT revealed a 17 mm non-calcified solid lung nodule with a speculated margin.



Figure 3.2. a case of 57-year-old man found in CXR during a health check-up. (a) AI-software detected a small lung nodule in the RML with an abnormality score of .34 MR % on CXR. (b) A corresponding CT revealed a 26 mm non-calcified solid lung nodule with a speculated margin.

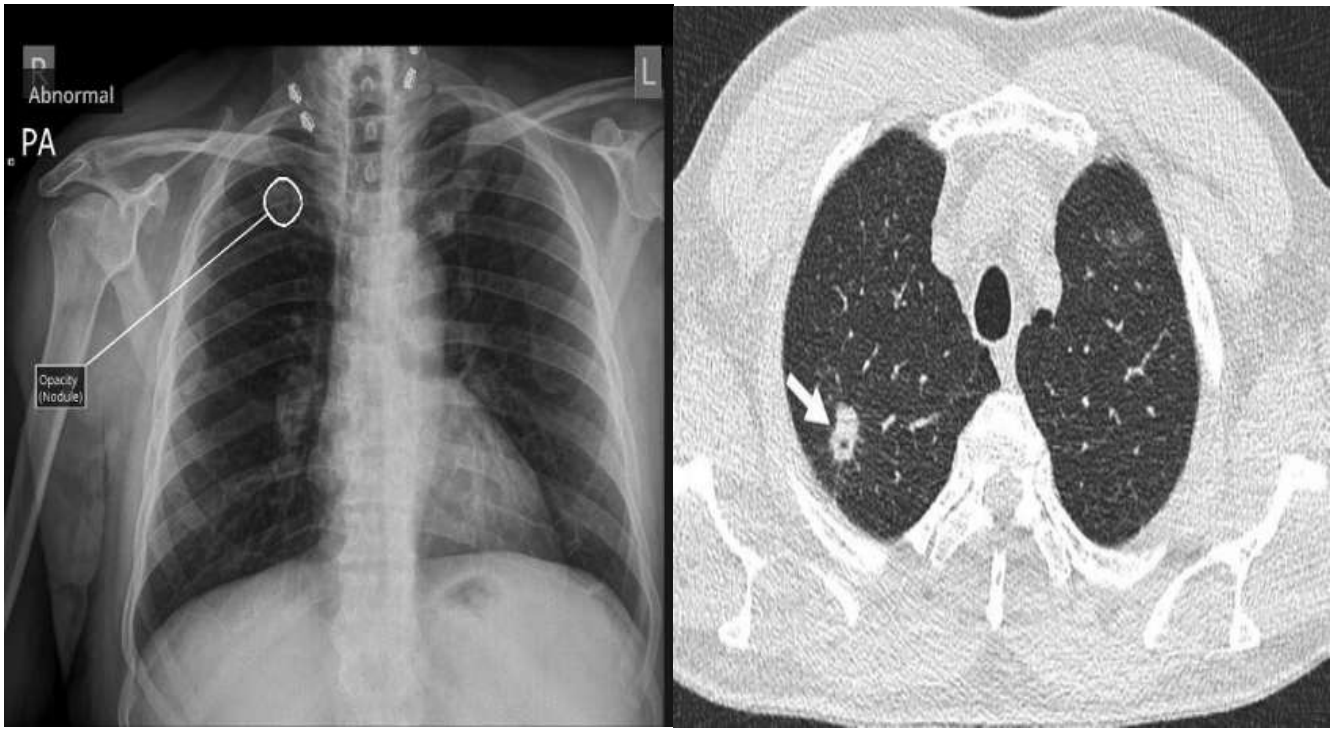


Figure 3.3. a case of a 64-year-old man found in CXR during a health check-up. (a) AI-software detected a small lung nodule in the right upper lung with an abnormality score of 0.19 MR % on CXR. (b) A corresponding CT revealed a 1.7-cm non-calcified solid lung nodule with a speculated margin and internal bubble-like air lucencies.

Discussion

It has been observed that using artificial intelligence to analyze abnormalities in chest X-rays can assist in distinguishing malignant lesions from those that don't require further evaluation. While there's no established size threshold for the detection of lung nodules on AI-assisted CXR, a study has shown that AI-assisted nodule detection has led to the early detection of incidental pulmonary malignancies [5].

AI-based detection resulted in a higher false positive rate in comparison to radiologists. Sometimes, AI software detects lung nodules that are not noticed by humans. However, such nodules may not be clinically significant and do not require any additional workup or treatment, which may avoid unnecessary CT scans. A study by Jang et al. [6] conducted on a healthy control group found no significant difference in the rate of unnecessary chest CT recommendations due to false positive detection, irrespective of the use of AI software.

The use of deep learning has led to significant improvements in computer-aided lung nodule detection over the past few decades. The sensitivity and specificity of AI software in detecting lung nodules in CXR range from 44.1% to 95.7% and 71.9% to 97.5%, respectively.

During the study, the AI software detected lung nodules incidentally on CXR in 1.0% of patients (65 out of 6543). The PPV for qXR in detecting nodules from CXR when compared with CT ground truth was 78.31 (68.30 - 85.81). [64]Out of the total, there were 65 true positives and 18 false positives. Associated lesions could help differentiate true positive nodules. For instance, associated consolidation and pleural effusion could suggest active inflammation and infection, whereas associated fibrosis indicates post-inflammatory sequelae. An AI-detected isolated lung nodule without associated abnormalities on CXR could indicate malignancy [7].

In this study, patients with a pulmonary nodule were detected across a wide range of age groups spanning from 18 to 83 years old. The mean age of the patients was found to be 50.6 ± 10.17 years. This is different from the findings of Hendrix et al. 2023 [8], who reported that the mean age of patients who underwent a chest CT scan in 2019 was 58.1 ± 15.2 years. This difference may be due to our population age group being younger than that study's, and similar to the age group studied by Farouk et al. 2023 [9].

In the studied population with pulmonary nodules, the number of males was 1.3:1 to that of females (58 males vs 42 females). However, it is important to note that sex is not the only factor that affects the risk and prognosis of lung nodules. Other factors such as smoking history, exposure to carcinogens, family history, and symptoms that have no definite sex predominance also play a role.

In this study, the mean diameter of the nodules was found to be 11.2 mm (ranging from 8mm to 28mm). These findings agree with the results of Farouk et al. (2023) [9] who also reported a median nodule diameter of 10mm. However, Liang et al. [10] detected pulmonary nodules with an average diameter of 18 mm. This difference in results could be due to the use of different AI algorithms in the studies, with the present study potentially having a better ability to detect smaller lesions.

In this study, the AI model was more successful in detecting solid nodules than other types of nodules: 73.4% for solid nodules, 20.2% for GGN, and 7.4% for PSN. These findings are consistent with a study conducted by Liang et al. [10] in 2020. Out of 47 pulmonary nodules, 39 (82.97%) were solid nodules and eight (17.02%) were part-solid nodules. Another study conducted by Nam et al. [11] showed that out of 187 nodules, 80% were solid nodules (149 out of 187), 14% were subsolid nodules (26 out of 187), and 6.4% were cystic.

About nodule location, the right upper lung zone has the highest occurrence of lung nodules. This is because the airflow during breathing has the greatest impact on the right upper lobe bronchi. As a result, particles from tobacco smoke tend to accumulate at this location, which can have carcinogenic effects. On the other hand, the left lower lung zone has the lowest prevalence of nodules. However, a study by Nam et al. [11] conducted in 2023 found that the right lower lung had the highest number of nodules, while the right middle lung had the lowest. Despite this difference, both studies agree on the effectiveness of AI in detecting obscured nodules, as well as the success of using AI-assisted detection to identify hilar and apical nodules. The algorithm was able to help readers detect more than 10% additional nodules.

In this study, when nodule size was above 8 mm and the texture was solid, the sensitivity was 92.50 (80.13 – 97.416) and AUC was 0.680 (0.54 –0.81). But when nodule size was above 8 mm and nodule texture was GGN or PSN, the sensitivity was 73.33 (48.04 – 89.10) and AUC was 0.315 (0.171– 0.459). Thus, the sensitivity and AUC decrease when nodule texture is ground glass or partially solid. These findings are consistent with a study conducted by Farouk et al. [9] 2023, who found the sensitivity for solid nodules was 91.4 and for ground glass nodules was 70.6.

In this study, we found the specificity and NPV for lung nodules when the patients have a nodule size more than 8 mm, a solid nodule texture, and have a history of carcinoma, the specificity was 90.163 (80.15 – 95.41) and NPV 98.214 (90.55 – 99.68). These findings are consistent with a study conducted by Yoo et al. [12] that found for malignant pulmonary nodule detection the specificity was (90.9% [95% CI, 89.6%-92.1%]) and negative predictive value was (100.0% [95% CI, 100.0%-100.0%]).

AI software performs similarly or better than physicians and radiologists in detecting lung nodules or malignancies [13,14] . When used in conjunction with doctor judgment, AI software can improve lung nodule detection [15]. However, it's worth noting that some nodules were found only by either a radiologist or AI-based detection software.

Limitations of the Study

- We conducted a study at a single center, focusing solely on pulmonary nodules and ignoring other pulmonary abnormalities.
- The aim of the study did not include the characterization of nodules as either benign or malignant. Our study did not consider pneumonia and interstitial lung disease.
- The retrocardiac region and subdiaphragmatic regions presented challenges during lung segmentation and might have been neglected due to our study only dealing with chest radiographs obtained at posterior-anterior projections. However, including the lateral view images, bone suppressed and bone view images, or dual-energy chest radiographs by using deep learning technology might further enhance the performance.

Conclusions

- AI-powered machine learning models can speed up lung nodule detection and identify incidental cases. These models analyze medical records to calculate lung cancer risk and help physicians make accurate decisions.
- AI can increase diagnostic accuracy and performance for abnormalities on chest X-rays.
- Although AI will not replace radiologists, it can enhance their performance.
- AI-based lesion-detection software on CXRs could help identify incidental findings.

Reference

[1] P. S. Paul, A. J. Isaacs, T. Treasure, N. K. Altorki, and A. Sedrakyan, "Long term survival with thoracoscopic versus open lobectomy: Propensity matched comparative analysis using SEER-Medicare database," BMJ, vol. 349, 2014.

[2] R. Singh, M. K. Kalra, C. Nitiwarangkul, J. A. Patti, F. Homayounieh, A. Padole, et al., "Deep learning in chest radiography: Detection of findings and presence of change," PLoS One, vol. 13, no. 10, p. e0204155, 2018.

[3] U. Avni, H. Greenspan, E. Konen, M. Sharon, and J. Goldberger, "X-ray categorization and retrieval on the organ and pathology level, using patch-based visual words," IEEE Trans. Med. Imaging, vol. 30, no. 3, pp. 733–746, 2010.

[4] J. T. Wu, K. C. L. Wong, Y. Gur, N. Ansari, A. Karargyris, A. Sharma, et al., "Comparison of chest radiograph interpretations by artificial intelligence algorithm vs radiology residents," JAMA Netw. Open, vol. 3, no. 10, p. e2022779, 2020.

[5] S. H. Kwak, E. K. Kim, M. H. Kim, E. H. Lee, and H. J. Shin, "Incidentally found resectable lung cancer with the usage of artificial intelligence on chest radiographs," PLoS One, vol. 18, no. 3, p. e0281690, 2023.

[6] S. Jang, H. Song, Y. J. Shin, J. Kim, J. Kim, K. W. Lee, et al., "Deep learning-based automatic detection algorithm for reducing overlooked lung cancers on chest radiographs," Radiology, vol. 296, no. 3, pp. 652–661, 2020.

[7] E. J. Hwang, S. Park, K. N. Jin, J. Im Kim, S. Y. Choi, J. H. Lee, et al., "Development and validation of a deep learning-based automated detection algorithm for major thoracic diseases on chest radiographs," JAMA Netw. Open, vol. 2, no. 3, p. e191095, 2019.

[8] W. Hendrix, M. Rutten, N. Hendrix, B. van Ginneken, C. Schaefer-Prokop, E. T. Scholten, et al., "Trends in the incidence of pulmonary nodules in chest computed tomography: 10-year results from two Dutch hospitals," Eur. Radiol., vol. 33, no. 11, pp. 8279–8288, 2023.

[9] S. Farouk, A. M. Osman, S. M. Awadallah, and A. S. Abdelrahman, "The added value of using artificial intelligence in adult chest X-rays for nodules and masses detection in daily radiology practice," Egypt. J. Radiol. Nucl. Med., vol. 54, no. 1, p. 142, 2023.

[10] C. H. Liang, Y. C. Liu, M. T. Wu, F. Garcia-Castro, A. Alberich-Bayarri, and F. Z. Wu, "Identifying pulmonary nodules or masses on chest radiography using deep learning: External validation and strategies to improve clinical practice," Clin. Radiol., vol. 75, no. 1, pp. 38–45, 2020

[11] J. G. Nam, E. J. Hwang, J. Kim, N. Park, E. H. Lee, H. J. Kim, et al., "AI improves nodule detection on chest radiographs in a health screening population: A randomized controlled trial," Radiology, vol. 307, no. 2, p. e221894, 2023.

[12] H. Yoo, K. H. Kim, R. Singh, S. R. Digumarthy, and M. K. Kalra, "Validation of a deep learning algorithm for the detection of malignant pulmonary nodules in chest radiographs," JAMA Netw. Open, vol. 3, no. 9, p. e2017135, 2020.

[13] A. A. Peters, A. Decasper, J. Munz, J. Klaus, L. I. Loebelenz, M. K. M. Hoffner, et al., "Performance of an AI based CAD system in solid lung nodule detection on chest phantom radiographs compared to radiology residents and fellow radiologists," J. Thorac. Dis., vol. 13, no. 5, pp. 2728–2739, 2021.

[14] Y. Sim, et al., "Deep convolutional neural network-based software improves radiologist detection of malignant lung nodules on chest radiographs," Radiology, vol. 294, no. 1, pp. 199–209, 2020.

[15] C. Yang, H. Jin, X. Yu, Z. Wang, Y. Liu, F. Fan, et al., "LungNoduleAgent: A collaborative multi-agent system for precision diagnosis of lung nodules," in Proc. AAAI Conf. Artif. Intell., vol. 40, no. 35, pp. 29793–29801, Mar. 2026.