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AI vs radiologists in detecting lung nodules on chest CT- A systematic review

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Abstract

Lung cancer remains one of the leading causes of cancer-related mortality worldwide, and early detection is critical for improving patient outcomes. Traditionally, radiologists have played a pivotal role in diagnosing lung cancer through imaging modalities such as chest computed tomography (CT). However, the recent integration of artificial intelligence (AI) into medical imaging has introduced a promising alternative or adjunct to human interpretation. AI algorithms, particularly those based on deep learning, have demonstrated substantial capability in identifying pulmonary nodules and other lung abnormalities with high sensitivity and specificity.

Several studies have compared the diagnostic accuracy of AI-assisted detection to that of radiologists. A notable study by Wu *et al*. involving over 23,000 patients undergoing low-dose CT screening found that AI systems consistently demonstrated higher positive detection rates across all screening rounds compared to manual readings by radiologists. These findings suggest that AI may reduce the rate of missed diagnoses, particularly in the early stages of lung cancer when lesions are subtle and easily overlooked.

Despite these advancements, AI is not without limitations. Factors such as dataset bias, variability in image quality, and the lack of contextual clinical understanding can affect the performance of AI systems. Moreover, AI cannot replace the nuanced clinical judgment and holistic patient evaluation provided by experienced radiologists.

In conclusion, while AI shows significant promise in augmenting the detection of lung cancer, it is best viewed as a complementary tool to radiologists rather than a replacement. The integration of AI into clinical workflows can enhance diagnostic accuracy, improve screening efficiency, and potentially lead to earlier interventions and better prognoses. Future research should focus on refining AI models, ensuring transparency in algorithm decision-making, and establishing robust clinical validation to fully harness the technology's potential in lung cancer diagnostics.

Keywords: Artificial intelligence, Deep learning, machine learning, radiologist, lung cancer, lung nodules, pulmonary nodules

Introduction

Lung cancer is one of the most threatening malignant tumors to human health and life [1]. Early detection and treatment are essential for lowering the death rate from lung cancer and enhancing quality of life. As thin-layer computed tomography (CT) technology has advanced, the detection rate of lung nodules—an early sign of lung cancer—has grown. But the substantial rise in CT data has also made it more difficult for doctors to interpret the pictures, which could result in lung nodule diagnosis going unnoticed [2]. Computer-aided detection (CAD) systems have become much more useful in a variety of medical examinations, such as mammography, brain CT, and chest radiography or CT, since artificial intelligence (AI) was adopted. These systems can be used for a variety of indications, such as lesion detection, differential diagnosis, prioritizing urgent images, or imaging biomarker extraction [3, 4]. Specifically, in chest radiology, detecting lung nodules has been a classic task. Various AI-based CAD systems have been reported to substantially improve radiologists' performance as a second reader [5].

Artificial intelligence (AI) technology can help doctors reduce their workload and improve diagnostic accuracy by performing preliminary screening of large CT images and marking suspicious lesions [3, 4]. Previous CT studies have reported variable sensitivities (70–83%) and false-positive rates (3–9.6/scan) for evaluation of pulmonary nodules using computer-aided detection (CADe) and computer-aided diagnosis (CADx) algorithms [8, 9]. CADe uses image pattern recognition to detect the presence of specific imaging findings, while CADx analyzes radiographic findings to categorize findings based on their imaging features [10].

There has been a lot of interest in explainable AI as a way to increase the safety and acceptability of AI algorithms in clinical medical imaging diagnosis. Clinician-friendly AI outputs are necessary for integration into daily workflow. Given the possibility of automation bias, it is essential to comprehend how various AI outputs and user interfaces

(UIs) affect physician decision-making [11]. The majority of AI user interfaces in radiology have been text- and image-based, frequently with an AI confidence score component included. Natural language processing and pretrained transformer models like GPT-3 are used in text-based outputs, such as AI-generated reports, lists of differentials from an image, or brief text outputs [12]. Localization methods like gradient-weighted class activation mapping are used in image-based outputs [13], occlusion maps, local interpretable model-agnostic explanations, and global max pooling [14]. On the premise of maintaining diagnostic performance, it is essential to reduce the radiation dose as much as possible. However, traditional image reconstruction methods, such as filtered back projection (FBP), do not reduce image noise with low-dose acquisitions [15]. Adaptive statistical iterative reconstruction-V (ASIR-V) and advanced modeled iterative reconstruction, or ADMIRE, were developed to reconstruct images and reduce noise [16]. Iterative reconstruction can significantly reduce image noise and improve image quality in low-dose CT settings, with absorbed doses ranging from 1 to 2 mSv [17]. Additional radiation dose reduction for low-dose CT screening may help encourage more use of this method. Ultra–low-dose (ULD) CT reduces the dose level to 0.13–0.49 mSv [18], which is still higher than that of chest radiography (0.03–0.1 mSv) [19]. When using ULD CT at doses similar to those used in chest radiography, iterative reconstruction algorithms affect the display of subtle imaging features, making them less applicable to this task [20]. With these methods, studies have shown significant image quality improvement at coronary CT angiography [22] and thoracic [23], abdominal [24], and cerebral CT [25].

The purpose of this paper is to assess the accuracy of artificial intelligence to detect lung nodules in CT scan in comparison with radiologists.

Methadology

This systematic review was performed with reference to the Cochrane Handbook for Systematic Reviews [26] and the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement guidelines [27]

Eligibility Criteria

Studies were eligible for inclusion if [1] they provided performance outcomes of Artificial intelligence or Radiologist in detecting lung nodules, [2] AI was used for the detection of pulmonary nodules [3] the performance was described in term of accuracy or sensitivity or specificity, Studies were excluded if [1] they did not specify a reference standard (the ground truth with which the radiologist's assessments were compared) [2], they were published before 2015. Studies published between 2015 to 2025 were considered to include adequate up-to-date evidence since the use of AI in lung nodule assessment develops rapidly.

Study Screening

Study selection was conducted independently by two reviewers, each with over five years of experience in conducting systematic review. Articles were first screened by title and abstract (primary screening), followed by full-text review (secondary screening). Exclusions were applied in accordance with the predefined criteria: studies not published in English, those that did not evaluate AI-based detection or classification of lung cancer through chest CT, studies that relied solely on open-source datasets without local or independent test cohorts, and publication types such as case reports, abstracts, guidelines, or consensus statements, and studies that does not provide Free Full text

Search Strategy

An extensive search of the literature was conducted across three major databases: Embase PubMed, and Scopus. The search covered over a 10-years period from 1 January 2015 to July 2025 and was limited to articles published in English.

We employed a combination of controlled vocabulary (e.g., MeSH terms) and free-text keywords, structured using Boolean operators to comprehensively identify relevant studies involving artificial intelligence (AI), lung cancer, and computed tomography (CT) and Radiologist. The terms were applied to the title, abstract, and subject heading fields. The search strings were adapted for syntax differences across databases.

The search string used in PubMed is as follows:

(“Lung Neoplasms” [MeSH] OR “lung cancer” OR “pulmonary neoplasm*” OR “lung nodule*”)

AND

(“Tomography, X-Ray Computed” [MeSH] OR “computed tomography” OR “CT scan” OR “CAT scan”)

AND

(“Artificial Intelligence” [MeSH] OR “deep learning” OR “machine learning” OR “computer vision” OR “neural network*”)

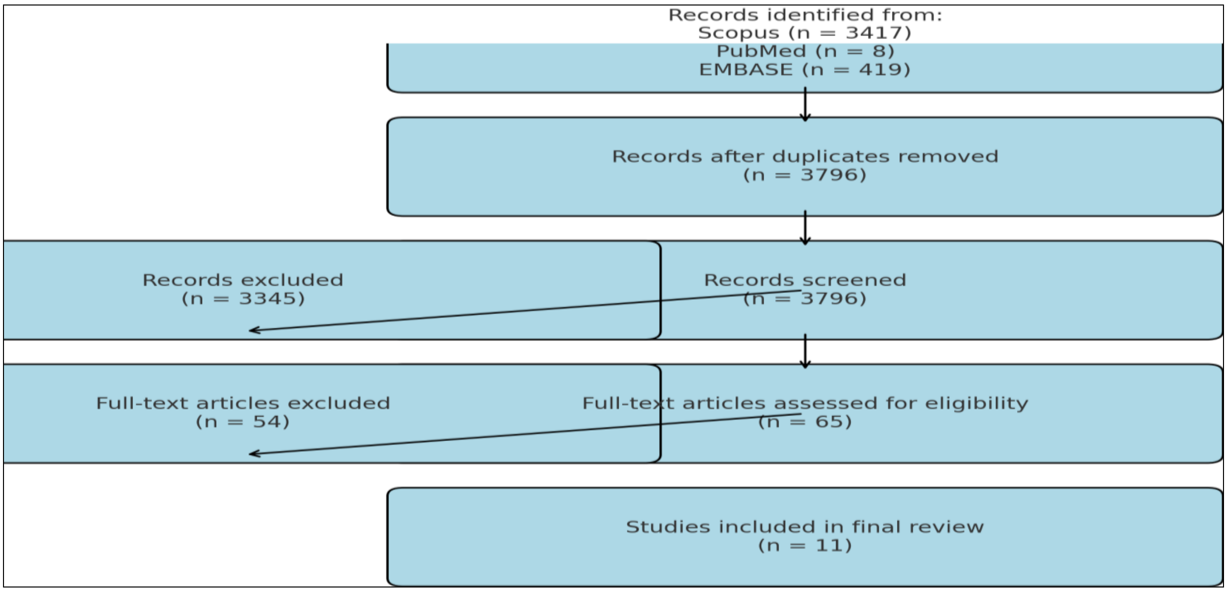
This strategy ensured the comprehensive retrieval of studies evaluating the AI-based detection or classification of lung cancer using chest CT. The full list of search strings for each database is available upon request.

comprehensive search was developed iteratively and undertaken in a range of relevant bibliographic databases. Searches combined keywords and, where appropriate, thesaurus (MeSH/EMTREE) terms relating to AI, ‘lung nodules/lung cancer’ and CT or screening’. Searches were limited to studies published in English as studies published in other languages were likely to be difficult to assess. No date limits were applied. An information specialist not otherwise involved in the project checked the draft MEDLINE search strategy for any omissions or errors

Results

Study Selection

The selection process is presented in the PRISMA flow diagram in Figure 1. 3844 studies have been selected from databases (pubmed, scopus and EMBASE, 48 were duplicated, 3731 were excluded in the primary screening(title/abstract), and 54 studies have been excluded in the secondary screening (full text screening). The remaining eligible studies were Eleven studies.



PRISMA Flowchart 2020

Data extraction

The main sources of information for the gathered material included the text, tables, figures, and additional web resources present in the articles. The initial stage of the selection process involved the elimination of duplicate submissions, followed by a thorough examination of each abstract and, ultimately, a complete review of the entire text. Additionally, the reference lists of the collected papers were meticulously inspected to identify relevant content.

In the context of our review, we considered the following variables to be considered for reporting: [1] study characteristics: study number and author, country of the study, the year of study development, study design, and population; [2] the indexed or comparator, reference standard [3] intervention and outcome

Quality assessment

two investigators independently evaluated the published material and documented their findings. These tools are tailored to specific study designs, enabling the detection of methodological or design concerns.

For the remaining studies, the Quality Assessment Tool for Observational Cohort and Clinical trials Investigations was employed. Each question within the tool received a score of 1 point for "Yes" answers and 0 points for "No" and "Other" responses. Subsequently, the final performance score was calculated. Accordingly, studies with scores ranging from 0 to 4 were considered to be of fair quality, those with scores between 5 and 9 were deemed to be of good quality, and those with a score of 10 or higher were classified as excellent quality. To mitigate inherent biases in the included studies, two researchers were assigned to evaluate the quality of the chosen articles. This approach minimized the risks associated with selection bias, missing data, and measurement bias.

Author	year of pubication/ country
Jiaxuan Wu	2024 [29] \China
Zhong-Yan Ma	2024 / China
Ya Yang	2025 [30] / China
Atilla P. Kiraly	2024 [32] / United States \ Japan
Jinhua Wang	2025 [38]/ China
Jiasen Zhang,	2024 / United States
Jianing Liu	2023 [31]/ China
Dennis Robert	2025 [37] / USA
Weiqi Liu,	2025 [35] / China
A.A. Abe	2025 [36] / South Africa
Julia Geppert	2024 [33]/ UK

Study design / setting	Sampling methods
prospective cohort\Health Management Center of	convenience non-probability sampling
Retrospective, diagnostic cohort study conducted	Continuous collection of non-enhanced chest SD
comparative diagnostic performance study	convenience sample
Retrospective randomized multireader multicase	The study cases were collected from four
Prospective comparative study conducted at a	Prospective convenience sampling
A methodological study focused on developing an	The study used two datasets: LUNA16 dataset: Used for pre-training. This is a
Retrospective comparative diagnostic performance	Retrospective convenience sampling.
A fully-crossed Multi-Reader Multi-Case (MRM	C Retrospective random sampling.
Retrospective observational study (before-	Convenience sampling with systematic
A methodological study focused on developing an	convenience sample
Systematic review of test accuracy studies.	A systematic search was conducted across

sample size	Population
23 336 patients	patients who underwent chest low-dose
130 patients with 130 GGNs.	Patients with pulmonary ground-glass nodules (G
200 cases (patients) with a total of 231 nodules.	Patients with pulmonary nodules, where the nodul
627 cases (141 cancer-positive cases).	Patients undergoing low-dose chest CT (LDCT) f
84 participants were initially enrolled, and 79 part	Patients over 18 years old with incidental or suspe
LUNA16: 888 CT scans, 2523 nodules (for pre-training).	Lung nodules in CT images. The study acknowled
200 SSPNs (100 benign, 100 malignant). These w	Patients with subcentimeter (≤10 mm) solid pulm
9000 readings (4500 without AI, 4500 with AI).	Patients (mean age, 64 ± 15 years; 174 women) u
12,889 patients (6450 from Hospital A, 6439 fro	m Patients undergoing chest CT scans in two tertiar
Total CT images: 1097 Total cases: 110	Individuals represented by the IQ-OTH/NCCD da
11 studies evaluating 6 different AI-based softwar	Individuals undergoing CT lung cancer screening

Study Aim	Intervention
to explore the value and diag nostic accuracy of	manual reading of scans
To assess the performance of an established AI al	A commercial deep learning-based computer-aide
To integrate a medical imaging-aided diagnosis sy	An AI-based medical imaging diagnosis assistant
To evaluate the impact of an artificial intelligence	AI assistant for lung cancer screening (a cloud-ba
To compare the image quality, pulmonary nodule	Ultra-low-dose CT (ULDCT) scans
To introduce a novel deep learning model for seg	The proposed "Detection-Guided Deep Learning-
To assess the diagnostic performance of a deep le	A deep learning (DL)-based AI software, "Dr. Wi
To assess the effect of artificial intelligence (AI) a	AI assistance as a second reader. After interpreting the CXR without AI, readers were
To evaluate the impact of an AI-assisted diagnosti	Implementation of an AI-assisted diagnostic system for lung nodules.
To propose and evaluate a deep learning (DL) alg	The proposed deep learning model, "DeepNodule
To examine the accuracy and impact of artificial i	AI-based software for automated detection and an

Comparator	Outcomes
artificial intelligence (AI) image-assisted diagnosi	AI-assisted diagnosis system significantly outperf
Conventional polychromatic computed tomograph	The AI algorithm trained on CPIs showed consistent diagnostic performance on VMIs for
Radiologists (manual interpretation).	The AI software detected 881 true nodules with a sensitivity of 99.10% (881/889).
Manual interpretation by experienced thoracic rad	Radiologists' Level of Suspicion (LoS) AUC:
Standard-dose CT (SDCT) images reconstructed	Radiation Dose: ULDCT effective dose (0.16 ±
Other commonly used segmentation models: U-Net Ronneberger *et al.* (2015)	The proposed model (without transfer learning) outperformed other classic models on the CCF
Radiologists with 10 and 15 years of experience i	Overall Diagnostic Accuracy (regarding indeterminate results as errors):
Readers interpreting CXRs without AI assistance.	Mean AFROC (primary outcome for localization

Junior radiologists' diagnostic reports without AI assistance (before AI implementation).	accuracy). dification Rate (by senior radiologists Report Mo for junior radiologists' reports on lung nodule
Individual CNN models (Model 1, Model 2, Model 3) within the ensemble.	The performance of the DeepNodule-Detect ensemble model with data augmentation and lung
Unaided reading by trained human readers (radiol	Speed: AI-assisted reading was generally faster. Sensitivity: Generally improved.

area-under the curve (AUC), sensitivity,	**Reference standar**
None	manual interpretation
Total mass: Convention (CPIs): AUC = 0.862 (95% CI	Established by a reading from the attending radiol
Overall Performance (AI vs. Radiologists for true nodules):	For the clinical portion of this study, the reference
Radiologist Performance (with AI assistance):	Positive cases: Pathology-confirmed lung cancer
The study primarily reports detection rates and	For image quality and nodule
Metrics reported for Segmentation (on CCF dataset):	For the LUNA16 dataset, the annotations were derived from the LIDC-IDRI dataset, which
ROC Curve (for differentiating benign vs. malignant/indeterminate):	Malignancy: Confirmed by surgical pathology. Benignity: Confirmed by surgical pathology OR
Area-under the curve (AUC), Sensitivity, Specificity:	Established by a consensus of five independent th
Sensitivity: The study defines "Sensitivity was defined as a junior radiologist’s ability to	The diagnostic results of senior radiologists (those
For "DeepNodule-Detect" with data augmentation and lung ROI segmentation:	The pathologically defined diagnosis provided wit
The review notes that reference standards varied across the included primary studies, but	he reviews synthesizes results across studies, providing ranges for changes in sensitivity and

Discussion

The present study aimed to compare the diagnostic accuracy of machine learning and deep learning AI architectures in detecting and classifying lung cancer with trained radiologists. Various machine learning AI architectures have the potential to improve the diagnostic accuracy of lung cancer detection and classification [28].

The selected 11 studies confirm the effectiveness of AI-assisted diagnosis for lung cancer. All these studies have confirmed that AI can enhance the diagnosis and treatment of lung nodules and lung cancer, thereby improving the efficiency of medical professionals to some extent.

The study by Jiaxuan Wu, which included 23,336 patients undergoing six rounds of low-dose spiral chest CT screening for lung cancer, demonstrates compelling evidence that AI-assisted reading significantly outperforms manual CT interpretation by radiologists [29]. Across all six screening rounds (T0–T5), the AI-assisted system consistently showed a significantly higher positive rate compared to manual reading, with detection rates increasing from 64.9% to 72.2% in the AI group versus only 15.3% to 36.6% in the manual group (all $p < 0.001$). Additionally, AI identified a greater proportion of malignant pulmonary nodules across all rounds, with percentages ranging from 4.9% to 6.8% compared to just 0.5% to 1.5% for manual readings (all $p < 0.001$). Importantly, AI detected 97.2% of the malignant nodules compared to 86.4% by manual reading, missing only 2.8% versus 13.6%, respectively. The nodules missed by manual reading were slightly larger (6.38 ± 1.47 mm) than those missed by AI (5.64 ± 1.13 mm), and the time until eventual diagnosis was also slightly longer for manual reading (3.00 ± 1.47 years vs. 2.90 ± 1.45 years). This indicates not only a lower detection rate with manual interpretation but also a longer delay in identifying missed nodules, which could lead to worse clinical outcomes. AI-assisted CT interpretation significantly improves the detection rate of malignant pulmonary nodules compared to manual reading by radiologists [29].

Another study done by Ya Yang [30] detected 231 nodules with pathology or no change in follow-up for more than two years were also tested in 200 cases. The results showed that the AI software detected a total of 881 true nodules with a sensitivity of 99.10% (881/889). The radiologists detected 385 true nodules with a sensitivity of 43.31% (385/889). The sensitivity of AI software in detecting non-calcified nodules was significantly higher than that of radiologists (99.01% vs 43.30%, P<0.001), and the difference was statistically significant.

A study done by Jianing Liu [31] analyzing accuracy of the DL model, in differentiating malignant and benign SSPNs, was significantly higher than that of the radiologists (71.5% vs. 38.5%, P<0.001). The DL model reported more benign or malignant deterministic results and fewer indeterminate results. In subgroup analysis of nodule size, the DL model also yielded higher performance in comparison with that of the radiologists, providing fewer indeterminate results. The accuracy of the two methods in the 3–6-, 6–8-, and 8–10-mm subgroups was 75.5% vs. 28.3% (P<0.001), 62.0% vs. 28.2% (P<0.001), and 77.6% vs. 55.3% (P=0.001), respectively, and the indeterminate results were 3.8% vs. 66.0%, 8.5% vs. 66.2%, and 2.6% vs. 35.5% (all P<0.001), respectively. Comparing and contrasting the results from the nine studies, it is evident that the ML architectures demonstrated promising results in the detection and classification of lung cancer, with generally high true positive and true negative rates and low false positive and false negative rates, and high sensitivity and specificity. However, the performance varied across studies, with some achieving higher overall accuracy than others. The studies employed various types of imaging, including CT, HRCT, LDCT, and RADS, indicating that AI can potentially be effective across a range of imaging modalities.

And in study done by Attila [32] in US and Japan comparing accuracy of each system reported that With AI assistance, the radiologists’ AUC (receiver operating characteristic curveincreased by 0.023 (0.70 to 0.72; P = .02) for the U.S. study and by 0.023 (0.93 to 0.96; P = .18) for the Japan study. Scoring system specificity for actionable findings increased 5.5% (57% to 63%; P < .001) for the U.S. study and 6.7% (23% to 30%; P < .001) for the Japan study. There was no evidence of a difference in corresponding sensitivity between unassisted and AI-assisted reads for the U.S. (67.3% to 67.5%; P = .88) and Japan (98% to 100%; P > .99) studies. Corresponding stand-alone AI AUC system performance was 0.75 (95% CI: 0.70, 0.81) and 0.88 (95% CI: 0.78, 0.97) for the U.S.- and Japan-based datasets, respectively.

A study done by Julia [33] in eleven studies evaluating six different AI-based software and reporting on 19 770 patients were eligible. All were at high risk of bias with multiple applicability concerns. Compared with unaided reading, AI-assisted reading was faster and generally improved sensitivity (+5% to +20% for detecting/categorising actionable nodules; +3% to +15% for detecting/categorising malignant nodules), with lower specificity (−7% to −3% for correctly detecting/categorising people without actionable nodules; −8% to −6% for correctly detecting/ categorising people without malignant nodules). AI assistance tended to increase the proportion of nodules allocated to higher risk categories. Assuming 0.5% cancer prevalence, these results would translate into additional 150–750 cancers detected per million people attending screening but lead to an additional 59 700 to 79 600 people attending screening without cancer receiving unnecessary CT surveillance.

A result from a study done by Jiasen shows that our proposed model can capture the target nodules more accurately compared to other commonly used models. By applying transfer learning, the performance can be further improved, achieving a sensitivity score of 0.885 and a Dice score of 0.814 [34]. There is a noted substantial improvement in the detection rate of lung nodules following the implementation of the AI system. This improvement can be attributed to the AI's capability to augment radiologists' ability to spot small nodules that might indicate an underlying disease. AI algorithms are designed to methodically examine a wide range of medical images, thereby highlighting potential abnormalities that the human eye might miss. Furthermore, small lung nodules are often linked to early-stage diseases, which provide additional time for effective interventions, thus increasing the value of AI diagnostic systems in improving the detection of lung nodules in CT scans as well as the overall outcome of such patients [35] Deep learning algorithms can effectively detect pulmonary nodules from patient chest computed tomography scans when trained on relatively small dataset [36] A study done in US [37] utilized chest radio-raph ima-es from multiple sites in the US and readers from specialties of radiolo-y, pulmonolo-y, and emer-ency departments to investi-ate if AI can improve the performance of readers in lun- nodule detection and localization. We found that AI-assisted readin- improved the lun- nodule localization accuracy of readers as demonstrated by unutilized chest radio-raph ima-es from multiple sites in the US and readers from specialties of radiolo-y, pulmonolo-y, and emer-ency departments to investi-ate if AI can improve the performance of readers in lun- nodule detection and localization. They found that AI-assisted readin- improved the lun- nodule localization accuracy of readers as demonstrated by an AFROC of 0.73 without AI and 0.81 with AI (difference: 0.08, P < .001). One can improve the true positive rate by marking any suspicious regions, but this could increase the false positive rate which may end up harmful for the patients. In our study, we found that the false positive rate of the readers did not differ significantly in non-diseased cases (95% CI of difference in specificity, −0.8–2.6, P = .31), although an ideal result would have been a simultaneous significant decrease in false positive rate (37) By this we stated that AI assistance holds great promise for lung nodule assessment, maintaining consistent performance to provide radiologists with decision support. With DLR providing images with lower noise and higher quality, AI-assisted systems have the potential to enhance nodule detection sensitivity, thereby reducing radiologists' workload. By pre-screening CT images and flagging suspicious nodules, AI systems help to ease the increasing burden associated with the growing number of CT examinations. This enables radiologists to focus on reviewing AI-detected findings, enhancing diagnostic efficiency. Nonetheless, optimizing AI-assisted detection systems specifically for ULDCT images remains essential to improve nodule detection performance [38].

Limitation

This systematic review has several limitations. First, the heterogeneity in study designs, AI model architectures, dataset compositions, and outcome reporting limited our ability to conduct a formal meta-analysis. Instead, we used descriptive summaries to synthesise findings across diverse studies, which may limit statistical precision. Second, although we employed a comprehensive multi-database search strategy, we restricted inclusion to English language articles, potentially omitting relevant non-English studies. Third, our exclusion of studies using only open-source datasets—while justified to reduce bias—may have excluded some well-performing algorithms that lacked access to local data. Fourth, the limited number of included studies (n = 11) reflects the strict quality and inclusion criteria but may reduce the breadth of generalisability.

Conclusion

In conclusion, the comparison between artificial intelligence (AI) and radiologists in detecting lung nodules reveals a significant advantage in favor of AI, especially in terms of sensitivity, specificity, and overall diagnostic accuracy. Numerous studies and clinical trials have demonstrated that AI algorithms, particularly those based on deep learning and convolutional neural networks (CNNs), can detect pulmonary nodules with a higher degree of precision than human radiologists. AI systems are capable of analyzing thousands of CT images in seconds, recognizing subtle patterns that might be missed by the human eye, especially in early-stage or small-sized nodules. AI's superior sensitivity allows it to detect more true positive cases, reducing the likelihood of missed lung nodules, which is critical in the early detection of lung cancer. At the same time, its higher specificity minimizes false positives, thereby reducing unnecessary biopsies, follow-up scans, and patient anxiety. These benefits contribute to more efficient workflows, lower healthcare costs, and improved patient outcomes. Moreover, AI does not suffer from fatigue or variability in interpretation, unlike human radiologists whose performance may vary based on experience, workload, or other human factors. When integrated into clinical practice as a supportive tool, AI can enhance radiologists' decision-making, reduce diagnostic errors, and ensure consistent quality across institutions. However, it is important to emphasize that AI should not be viewed as a replacement for radiologists but rather as a complementary tool that augments their expertise. The combination of AI's computational power with the clinical judgment of experienced radiologists offers the most promising approach to improving diagnostic accuracy in lung cancer screening. In summary, AI has proven to be more accurate than radiologists in detecting lung nodules, demonstrating higher sensitivity and specificity. Its integration into diagnostic workflows represents a transformative step forward in early lung cancer detection and patient care.

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