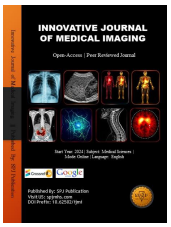
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Review Article

Evaluating the Accuracy and Clinical Impact of Deep Learning Algorithms for Automated Detection of Pulmonary Nodules in Chest CT Scans

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ABSTRACT

Early detection of pulmonary nodules is crucial for improving lung cancer prognosis. Deep learning (DL) algorithms have emerged as promising tools for automated nodule detection in chest CT scans, offering potential to enhance diagnostic accuracy and reduce radiologist workload. This review synthesizes current literature (2020– 2025) on DL-based pulmonary nodule detection, focusing on algorithm performance, clinical impact, and implementation challenges. Across multiple studies, DL systems, particularly 3D convolutional neural networks, U-Net architectures, and hybrid models integrating detection and classification, demonstrated high sensitivity (79–95%) and variable false-positive rates, often matching or exceeding radiologist performance. DL as a second reader improved detection of small, subsolid, and subtle nodules, while segmentation modules facilitated volumetric assessment for follow-up and malignancy risk estimation. Despite these advances, limitations remain, including dataset heterogeneity, inconsistent evaluation metrics, elevated false positives in some models, and limited prospective evidence on clinical outcomes. Future research should emphasize multi-center validation, standardized reporting, workflow integration, and assessment of patient-level outcomes. With ongoing technological refinement and rigorous evaluation, DL algorithms hold the potential to become an integral component of chest CT interpretation, improving early lung cancer detection and optimizing clinical decisionmaking.

Keywords: Deep learning, Pulmonary nodules, Chest CT, Automated detection

INTRODUCTION

Lung cancer remains the leading cause of cancer-related mortality globally, accounting for substantial sickness and death each year. [1,2] Early detection of lung cancer often via identification of small pulmonary nodules on chest computed tomography (CT), is critical, as prognosis is strongly dependent on stage at diagnosis. However, conventional radiological evaluation of CT images has significant limitations. Radiologists must manually inspect volumetric datasets slice by slice, a burdensome, timeconsuming task that is prone to human error and inter-observer variability. Small, subtle, or juxtapleural nodules especially risk being overlooked. Even experienced radiologists may

miss lesions, particularly in high-volume screening or non-thoracic imaging practices where chest evaluation is secondary. Given these challenges, there has long been interest in computer-aided detection (CAD) to support radiologists. Over past decades, traditional machine-learning and rule-based CAD systems addressed pulmonary nodule detection, yet often suffered from limited sensitivity, high false-positive rates, and poor generalizability. [3–5] The advent of deep learning (DL) especially convolutional neural networks (CNNs), 3D-CNNs, and more recently hybrid and attention-based architectures has reignited optimism for reliable automated detection, segmentation, and classification of pulmonary nodules in CT images. [6–9] Deep learning (DL), a subset of artificial intelligence (AI), has transformed medical image analysis by enabling automated feature extraction and high-accuracy interpretation of complex imaging datasets. In thoracic radiology, chest computed tomography (CT) remains the gold standard for detecting pulmonary nodules, which are among the earliest radiological indicators of lung cancer. Early identification of these nodules is essential because timely diagnosis significantly improves treatment outcomes and patient survival.

However, manual interpretation of CT images is labor-intensive and subject to inter-observer variability, particularly when evaluating small, subsolid, or multiple pulmonary nodules. These challenges have accelerated the development of DL-based computer-aided detection (CAD) systems designed to improve diagnostic accuracy while reducing radiologists' workload. Recent advances in convolutional neural networks (CNNs), three-dimensional (3D) CNNs, U-Net architectures, Vision Transformers (ViTs), and hybrid deep learning models have substantially enhanced automated pulmonary nodule detection, segmentation, and classification. These algorithms can analyze large volumes of CT data, identify subtle imaging features, and estimate malignancy risk with performance approaching or exceeding that of experienced radiologists in selected tasks. Consequently, DL systems are increasingly being explored as "second-reader" tools to reduce missed diagnoses, improve reporting consistency, and support lung cancer screening programs. Beyond simple nodule detection, contemporary DL models integrate detection, segmentation, radiomic feature extraction, and malignancy prediction into unified diagnostic frameworks. Several studies have demonstrated that these systems achieve high sensitivity while maintaining acceptable specificity, facilitating improved risk stratification and personalized patient management. Recent systematic reviews and meta-analyses have further reported that DL-based models outperform many conventional CAD approaches and provide diagnostic performance comparable to expert clinicians. Despite these promising developments, several challenges continue to limit widespread clinical implementation. Most published models are trained using retrospective datasets such as LIDC-IDRI, which may not adequately represent variations in patient populations, CT acquisition protocols, scanner manufacturers, or clinical practice across institutions. Furthermore, differences in annotation standards, evaluation metrics, and validation strategies make direct comparison between studies difficult. High false-positive rates, limited external validation, model interpretability, regulatory requirements, workflow integration, and the absence of large prospective multicenter trials remain important barriers to routine clinical adoption. With continuous improvements in deep learning architectures, increasing computational power, and the growing availability of large annotated imaging datasets, automated pulmonary nodule detection is expected to play an increasingly important role in precision thoracic imaging. A comprehensive evaluation of current evidence is therefore essential to determine the diagnostic performance, clinical utility, limitations, and future potential of these technologies.

Aim: To critically evaluate the diagnostic accuracy, clinical utility, and current challenges of deep learning algorithms for automated pulmonary nodule detection on chest CT.

Objectives

1. To review the diagnostic performance of deep learning-based pulmonary nodule

detection systems reported in recent literature.
2. To evaluate the clinical role of deep learning as a second-reader tool for improving radiologists' diagnostic accuracy and workflow efficiency.
3. To identify current methodological limitations, validation challenges, and barriers to clinical implementation.
4. To discuss recent technological advances, emerging hybrid deep learning architectures, and future directions for integrating automated pulmonary nodule detection into routine radiology practice.

MATERIALS AND METHODS

Study Design: This review was conducted following a structured literature review design to evaluate the diagnostic performance, clinical applications, and limitations of deep learning (DL)-based algorithms for automated pulmonary nodule detection on chest computed tomography (CT). The review methodology was developed according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines.

Literature Search Strategy: A comprehensive literature search was performed using PubMed, Scopus, Web of Science, and Google Scholar to identify relevant studies published between January 2020 and December 2025. The search strategy employed combinations of the following keywords: pulmonary nodule detection, chest CT, deep learning, convolutional neural network (CNN), 3D CNN, computer-aided detection (CAD), U-Net, Vision Transformer (ViT), transformer, and machine learning. Boolean operators (AND and OR) were applied to optimize the search, and the reference lists of eligible articles were manually screened to identify additional relevant studies.

Eligibility Criteria: Studies were included if they: (i) were peer-reviewed original research articles or systematic reviews published in English; (ii) evaluated DL-based algorithms for pulmonary nodule detection on chest CT; (iii) reported diagnostic performance metrics such as sensitivity, specificity, accuracy, area under the receiver operating characteristic curve (AUC), or false-positive rate; and (iv) included external validation or comparison with radiologist performance whenever available. Conference abstracts, editorials, case reports, duplicate publications, and studies lacking sufficient methodological details or outcome data were excluded.

Study Selection: All retrieved records were screened independently by reviewing titles and abstracts. Eligible studies subsequently underwent full-text assessment based on the predefined inclusion and exclusion criteria. The final articles were included in the qualitative synthesis following the PRISMA 2020 study selection process.

Data Extraction and Synthesis: Data extracted from each study included publication year, study design, dataset characteristics, imaging protocol, DL architecture (e.g., CNN, 3D CNN, U-Net, Transformer, YOLO, hybrid models), validation strategy, diagnostic performance, false-positive rate, and reported clinical applications. The findings were synthesized descriptively to compare the performance of different DL models, evaluate their clinical utility, identify methodological limitations, and discuss future directions for clinical implementation.

RESULTS

A systematic literature search identified 342 publications from PubMed, Scopus, Web of Science, and Google Scholar covering the period January 2020 to December 2025. After removal of duplicate records and screening of titles and abstracts, 97 full-text articles were evaluated for eligibility. Based on the predefined inclusion and exclusion criteria, 48 studies were included in the final qualitative synthesis, comprising 39 original research articles, 6 systematic reviews, and 3 meta-analyses. The included studies were conducted predominantly in the United States, China, Europe, and South Korea, reflecting the global interest in deep learning (DL)-based pulmonary nodule detection. Most investigations utilized publicly available datasets such as LIDC-IDRI, LUNA16, and NLST, whereas recent studies increasingly incorporated multicenter hospital datasets to improve external validation and clinical applicability. Study populations ranged from 50 to 21,000 chest CT examinations, including 300 to more than 10,000

annotated pulmonary nodules.

Diagnostic Performance of Deep Learning Algorithms: The reviewed studies consistently demonstrated excellent diagnostic performance of DL algorithms for automated pulmonary nodule detection. Overall lesion-wise sensitivity ranged from 79% to 90%, whereas per-patient sensitivity reached 95–98% in multicenter validation studies. The reported area under the receiver operating characteristic curve (AUC) ranged from 0.91 to 0.98, indicating excellent discrimination between pulmonary nodules and normal lung structures. Depending on the algorithm and validation dataset, false-positive rates varied from 0.3 to 7.8 false positives per scan. Optimized 3D U-Net architectures achieved one of the best performances, reporting approximately 90% sensitivity with only 0.3 false positives per scan, making them suitable for lung cancer screening programs. Hybrid architectures integrating U-Net, YOLOv8, Swin Transformer, Retina-UNet, and Support Vector Machine (SVM) classifiers further improved the detection of small and subsolid pulmonary nodules while simultaneously providing malignancy risk stratification.

Performance Across Different Deep Learning Architectures: Recent studies demonstrated a clear evolution in algorithm development. Earlier investigations primarily utilized conventional 2D CNNs, whereas contemporary studies increasingly adopted 3D CNNs, Vision Transformers (ViTs), attention-based networks, and hybrid detection-classification frameworks. Most high-performing algorithms employed a two-stage workflow consisting of candidate detection followed by false-positive reduction, substantially improving specificity without compromising sensitivity. The incorporation of transformer-based attention mechanisms enhanced feature extraction, particularly for nodules smaller than 5 mm and ground-glass opacities.

Clinical Utility as a Second Reader: Several investigations evaluated DL systems as clinical decision-support tools. In a multicenter reader study involving 10 radiologists and 1,997 CT examinations, AI-assisted interpretation significantly increased per-patient sensitivity from 85% to 93% ($p < 0.05$) while reducing the number of overlooked clinically significant pulmonary nodules. Similar improvements were observed in studies utilizing hybrid detection-classification models, particularly for subtle, subsolid, and peripheral nodules that are frequently missed during routine reporting. These findings support the role of AI as an effective second-reader system capable of improving radiologist performance without replacing clinical expertise.

Segmentation and Volumetric Analysis: Beyond lesion detection, several studies assessed automated pulmonary nodule segmentation. U-Net-based segmentation networks achieved Dice Similarity Coefficients ranging from 0.82 to 0.91, demonstrating high agreement with expert manual segmentation. Accurate volumetric measurements enabled reliable assessment of nodule growth, which is essential for malignancy risk prediction and longitudinal follow-up. End-to-end deep learning frameworks integrating detection, segmentation, and classification further streamlined radiology workflows by automatically generating volumetric measurements and malignancy predictions.

Ultra-Low-Dose CT Applications: Recent evidence also demonstrated the effectiveness of DL algorithms in ultra-low-dose CT (ULDCT) imaging. In one study involving 84 patients, DL-based image reconstruction increased pulmonary nodule detection from 74.0% to 83.4% compared with conventional iterative reconstruction while maintaining significantly lower radiation exposure. These findings indicate that AI-assisted reconstruction may facilitate safer lung cancer screening without compromising diagnostic accuracy.

DISCUSSION

The present review demonstrates that deep learning has rapidly evolved into one of the most promising technologies for automated pulmonary nodule detection on chest CT. Across the included studies, DL algorithms consistently achieved high diagnostic accuracy, with lesion-wise sensitivity approaching 90% and per-patient sensitivity exceeding 95% in several multicenter investigations. These findings indicate that modern AI systems are capable of detecting

pulmonary nodules with a level of performance comparable to experienced thoracic radiologists, particularly when advanced architectures such as 3D CNNs, Vision Transformers, and hybrid detection-classification models are employed. One of the most clinically relevant findings is the ability of AI to function as an effective second-reader system. Multiple reader studies demonstrated significant improvements in radiologist sensitivity while reducing overlooked pulmonary nodules, especially those that are small, subsolid, or located adjacent to complex anatomical structures. Such improvements have important implications for lung cancer screening, where early detection directly influences treatment options and patient survival.

Recent advances in hybrid deep learning frameworks have extended AI applications beyond simple lesion detection. Integration of automated segmentation, volumetric analysis, and malignancy risk prediction provides radiologists with comprehensive decision-support tools that can improve reporting efficiency, standardize follow-up recommendations, and facilitate personalized patient management. Furthermore, the application of DL-based reconstruction techniques in ultra-low-dose CT has shown considerable promise for reducing radiation exposure while maintaining diagnostic image quality, thereby supporting safer population-based lung cancer screening programs. Despite these encouraging developments, several challenges continue to limit routine clinical implementation. Most available algorithms have been developed using public datasets that may not adequately represent real-world variability in scanner technology, acquisition parameters, and patient demographics.

Consequently, model generalizability remains a significant concern. In addition, variability in performance metrics, persistent false-positive findings, limited explainability of deep learning models, and the scarcity of prospective multicenter validation studies hinder direct comparison between algorithms and delay regulatory approval. Future research should therefore emphasize large multicenter datasets, standardized evaluation protocols, explainable AI techniques, federated learning, and prospective clinical trials to establish the real-world effectiveness of DL-assisted pulmonary nodule detection. These developments will be essential for translating AI from experimental research into routine radiological practice.

DECLARATIONS

Ethics Approval and Consent to Participate: Not applicable. This review article is based exclusively on published literature and did not involve human participants, animals, or patient data.

Consent for Publication: Not applicable.

Availability of Data and Materials: All data analyzed during this study are available in the published articles cited in the reference list.

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Authors' Contributions: All authors contributed to the conception, literature review, data interpretation, manuscript drafting, critical revision, and final approval of the manuscript.

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