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Review Article | Pregledni rad

Artificial Intelligence in Radiologic Diagnosis of Pulmonary Infection: a PRISMA-Guided Systematic Review

Umjetna inteligencija u radiološkoj dijagnostici plućnih infekcija: sustavni pregled literature prema smjernicama PRISMA

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Summary

Aim: Pulmonary infections, including bacterial and viral pneumonia and tuberculosis (TB), remain major global health concerns. Artificial intelligence (AI), particularly deep learning, has shown strong potential for improving radiologic diagnosis using chest X-rays (CXR) and computed tomography (CT). The aim of this review article is to analyze recent literature on the achievements of artificial intelligence (AI) in the radiological interpretation of imaging studies in patients with pneumonia and tuberculosis.

Methods: A review that was conducted according to PRISMA 2020 guidelines, analysed English-language studies published between January 1st, 2021 and December 31st, 2025 that evaluated AI-based tools for detecting pulmonary infections in adults.

Results: A total of 182 studies were identified, and 20 met inclusion criteria (13 pneumonia and 7 TB studies). Most studies used convolutional neural networks (CNN) trained on large imaging datasets. For pneumonia detection, AI models achieved sensitivities of 80–97% and specificities of 85–95%, with pooled estimates 88% and 90%, respectively. TB models showed high performance, with sensitivities up to 99%.

Conclusion: AI demonstrates high diagnostic accuracy and potential clinical utility in thoracic imaging, but external validation and prospective studies are still needed for routine implementation.

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Sažetak

Cilj: Plućne infekcije, uključujući bakterijske i virusne pneumonije te tuberkulozu (TB), i dalje predstavljaju značajan globalni javnozdravstveni problem. Umjetna inteligencija (UI), posebice metode dubokog učenja pokazale su velik potencijal za unaprjeđenje radiološke dijagnostike primjenom rendgenskih snimki prsnog koša (RTG) i kompjutorizirane tomografije (CT). Cilj ovog preglednog rada bio je analizirati noviju znanstvenu literaturu o postignućima UI u radiološkoj interpretaciji slikovnih pretraga bolesnika s pneumonijom i tuberkulozom.

Metode: Sustavni pregled literature proveden je u skladu sa smjernicama PRISMA 2020. Analizirane su studije na engleskom jeziku objavljene između 1. siječnja 2021. i 31. prosinca 2025. koje su procjenjivale alate UI za otkrivanje plućnih infekcija u odraslih osoba.

Rezultati: Ukupno su identificirane 182 studije, od kojih je dvadeset zadovoljilo kriterije uključivanja (trinaest studija o pneumoniji i sedam o tuberkulozi). Većina istraživanja koristila je konvolucijske neuronske mreže (CNN) trenirane na velikim skupovima slikovnih podataka. Za otkrivanje pneumonije modeli umjetne inteligencije postigli su osjetljivost od 80% do 97% i specifičnost od 85% do 95%, uz objedinjene procjene od 88% odnosno 90%. Modeli za otkrivanje tuberkuloze pokazali su vrlo visoku učinkovitost, s osjetljivošću do 99%.

Zaključak: Umjetna inteligencija pokazuje visoku dijagnostičku točnost i značajan potencijal za primjenu u torakalnoj radiologiji. Međutim, za njezinu rutinsku primjenu u kliničkoj praksi i dalje su potrebne dodatne studije vanjske validacije i prospektivna istraživanja.

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Introduction

Pulmonary infections such as bacterial/viral pneumonia and tuberculosis (TB) remain leading causes of morbidity and mortality worldwide[1]. Advances in artificial intelligence (AI), especially deep learning, have shown promise in improving radiologic detection of these infections on chest imaging[2,3].

Recent evidence demonstrates that AI-based models achieve high diagnostic accuracy, with sensitivities for pneumonia detection typically ranging from 80% to 97% and specificities between 85% and 95%, while meta-analytic data report pooled sensitivity 88% and specificity 90%[4]. For TB, AI systems frequently achieve sensitivities between 90% and 99%, with moderate-to-high specificity depending on clinical setting[5,6]. In several studies, deep learning models demonstrated performance comparable to experienced radiologists, particularly in detecting subtle radiographic findings, and AI-assisted interpretation improved diagnostic sensitivity and clinical workflow efficiency[7,8].

Overall, these findings suggest that AI represents a valuable adjunct in thoracic imaging, with the potential to enhance early detection, improve diagnostic consistency, and support clinical decision-making. However, important limitations remain, including variability in study design, limited external validation, and challenges related to generalizability and integration into routine clinical practice[4,5].

Chest radiography (CXR) is the most common imaging examination worldwide[2]. It is fast, low-cost, and essential for diagnosing lung infection, but interpretation is error-prone[3]. Missed findings on CXR remain a leading cause of diagnostic error[3]. This diagnostic challenge is compounded by high imaging volumes and workforce limitations in many regions[2]. Computed tomography (CT) is another radiological method used in the diagnosis of pulmonary infections, particularly in cases involving complications.

AI methods (especially convolutional neural networks-CNN) have shown great potential to assist radiologists by automatically detecting disease patterns on images[2,4]. Several recent reviews have highlighted AI's promise in chest X-ray interpretation[4,5]. We conducted a systematic review of studies published in English between from January 1st, 2021 to December 31st, 2025 evaluating deep learning applications for diagnosing pulmonary infections in radiology. We separately analysed studies that evaluated the application of the AI tools in the radiological diagnosis of bacterial and viral pneumonia, as well as separately in pulmonary TB. Given that COVID-19 infection caused a prolonged period of the pandemic and that its imaging features have been extensively analyzed using AI tools, we considered this form of pulmonary infection as a distinct subgroup of viral pneumonia. Our goal is to summarize the latest diagnostic performance findings and assess the readiness of these methods for clinical use.

Methods

We conducted a systematic review according to PRISMA 2020 guidelines[9]. We searched PubMed, Scopus, Embase, and IEEE Xplore for articles (January 1st, 2021 to December 31st, 2025) containing keywords related to "artificial intelligence," "deep learning," "pneumonia," "COVID-19," "tuberculosis," and "chest radiography/CT." Eligible studies were peer-reviewed research papers (English language) that applied machine learning or deep learning models to CXR or thoracic CT for diagnosing bacterial/viral pneumonia and pulmonary TB, in adult cohorts (≥18 years). We excluded editorials, case reports, or studies without explicit diagnostic metrics. Two researchers (one is experienced radiologist and the other is general practitioner) independently screened titles/abstracts, reviewed full texts for inclusion, and resolved discrepancies by consensus.

Data extracted included study design (prospective/retrospective), setting, patient characteristics, imaging modality, AI model type, size of training/testing datasets, and primary diagnostic metrics (sensitivity, specificity, Area Under the Curve-AUC). When reported, we noted comparisons to radiologist performance. Study quality was assessed with Quality Assessment of Diagnostic Accuracy Studies 2 (QUADAS-2) which evaluates studies across four key domains: examining patient selection, index test conduction, reference standard, and flow/timing[10]. Key outcomes were pooled where appropriate (meta-analysis if data allowed) or described narratively. This manuscript was edited for language and clarity using artificial intelligence tools (e.g., OpenAI), with all content reviewed and approved by the authors.

Results

We identified 20 studies meeting inclusion criteria, 13 studies using AI to detect bacterial/viral pneumonia and 7 studies to detect TB, with some studies addressing both conditions.

Out of the total number of sources, 6 studies represent secondary sources, whereas 14 articles constitute primary (original) sources.

Figure 1 shows PRISMA flow diagram of selected studies using AI tools, including deep learning to detect bacterial/viral pneumonia on radiological imaging.

Figure 2 demonstrates PRISMA flow diagram of selected studies using AI tools, including deep learning to detect TB infection on radiological imaging.

During the screening and eligibility phases of the review process, studies were excluded for several predefined reasons to ensure consistency and transparency: irrelevance to the research question or study scope, incorrect population or setting, and inappropriate study design. Additional exclusions were made due to insufficient or unavailable data, lack of full-text access, and duplication of records identified across multiple databases.

Table 1 presents the authors' names, study titles, years of publication, and summaries of the selected papers that analysed the application of AI tools in the radiological diagnosis of bacterial and viral pneumonia (including COVID-19 pneumonia as a subgroup of viral pneumonia).

Table 2 presents the authors' names, study titles, years of publication, and summaries of the selected papers that analysed the application of AI tools in the radiological diagnosis of pulmonary TB.

Table 3 presents imaging findings on computed tomography (CT) scans in bacterial pneumonia, viral pneumonia (including COVID-19 pneumonia), and pulmonary TB.

Radiologists worldwide routinely interpret a large number of CT examinations related to bacterial and viral pneumonias, as well as signs of pulmonary TB. Given the significant shortage of radiologists and the time-consuming nature of image interpretation, a growing body of research is focused on developing practical, accurate, and user-friendly AI tools to assist radiologists in detecting the opacities described in Table 3, thereby facilitating and expediting the reporting process. To create large databases used for training AI tools, many radiologists are involved in research projects. Their role as experts is to annotate listed opacities on a large number of CT images.

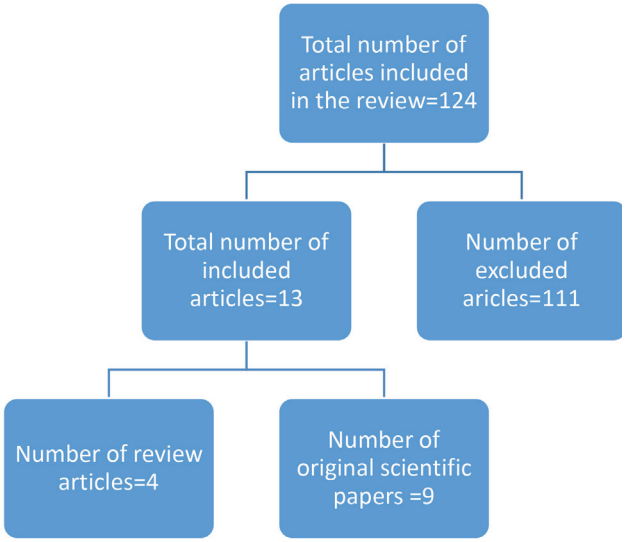


Figure 1. PRISMA diagram of articles using AI tools in diagnostics of bacterial/viral pneumonia (including COVID-19 pneumonia) included in the study

Slika 1. PRISMA dijagram postupka pretraživanja, odabira i uključivanja radova o primjeni alata umjetne inteligencije u dijagnostici bakterijske i virusne pneumonije (uključujući pneumoniju uzrokovanu bolešću COVID-19)

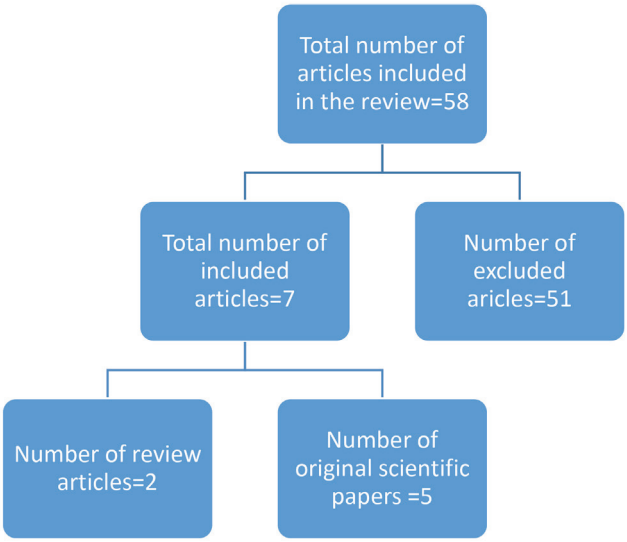


Figure 2. PRISMA diagram of articles using AI tools in diagnostics of pulmonary TB included in the study

Slika 2. PRISMA dijagram postupka pretraživanja, odabira i uključivanja radova o primjeni alata umjetne inteligencije u dijagnostici plućne tuberkuloze

Deep learning models were predominantly based on CNN trained on large chest imaging datasets. For pneumonia detection on chest radiographs, most AI algorithms achieved high diagnostic accuracy. In our review, reported sensitivities ranged from 80% to 97%, with specificities between 85% and 95%, comparable to or exceeding the performance of human radiologists[4]. A recent meta-analysis reported a pooled sensitivity of 88% and specificity of 90% for AI-based chest X-ray interpretation in pneumonia detection[11].

Several studies demonstrated excellent performance. For example, the "Pneumonia-Plus" deep learning mod-

el, designed to differentiate bacterial, viral, and fungal pneumonia on CT imaging, achieved AUC values ranging from 0.82 to 0.93 and performed comparably to experienced radiologists[12]. On chest radiographs, novel deep learning architectures, including EfficientNet-based models and transformer-CNN hybrids, demonstrated classification accuracies between 90% and 95% in independent test datasets[12,13,14]. In emergency settings, AI has also shown clinical utility. For instance, one study demonstrated that an AI system could accurately differentiate pneumonia from other lung pathologies on chest X-ray, facilitating rapid triage and decision-making[11]. Notably, AI-assisted interpretation can significantly improve radiologist performance, with

Table1. Articles included in analysis of studies using artificial intelligence (AI) tools (including deep learning) to detect bacterial and viral pneumonia (including COVID-19 pneumonia) on radiological imaging

Tablica 1. Radovi uključeni u analizu studija koje su koristile alate umjetne inteligencije (UI), uključujući duboko učenje, za otkrivanje bakterijske i virusne pneumonije (uključujući pneumoniju uzrokovanu bolešću COVID-19) na radiološkim slikovnim prikazima

No.	First author's name (ref)	Study title	Type of study	Study design	Year of publication	Study overview
1.	Akhter Y et al. [2]	AI-based radiodiagnosis using chest X-rays: A review	review	retrospective	2023	This review summarizes artificial intelligence and machine learning–based approaches for chest X-ray analysis, highlighting available datasets and performance metrics. It identifies major challenges, including data limitations, privacy concerns, and model interpretability, and outlines current research gaps and open problems in artificial intelligence–assisted chest X-ray diagnosis.
2.	Sharma S et al. [4]	A systematic literature review on deep learning approaches for pneumonia detection using chest X-ray images	systematic review	retrospective	2024	This systematic review surveys deep learning methods for pneumonia detection on chest X-rays, covering common model architectures, datasets, and reported accuracies. It discusses challenges like limited training data and suggests directions for future research.
3.	Essa MEA [11]	Diagnostic accuracy of AI in chest radiography for pneumonia and lung cancer: a meta-analysis	meta-analysis	retrospective	2025	A meta-analysis of AI for chest X-ray diagnosis (pneumonia and lung cancer). The study reports pooled sensitivity ≈88% and specificity ≈90% for pneumonia, indicating high overall accuracy. It highlights that deep learning models perform comparably to radiologists and calls for standardized evaluation protocols.
4.	Wang F et al. [12]	Pneumonia-Plus: a deep learning model for the classification of bacterial, fungal, and viral pneumonia based on CT	original research	prospective	2023	This study developed Pneumonia-Plus, a deep learning algorithm for CT-based classification of bacterial, fungal, and viral pneumonia, trained on 2,763 patients and prospectively tested on 173 cases. The model showed high diagnostic performance, with the best results in bacterial pneumonia (AUC 0.934), and performed comparably to experienced radiologists while outperforming less experienced readers in key comparisons. Pneumonia-Plus may support more accurate pneumonia differentiation and improve clinical decision-making.
5.	Ali M et al. [13]	Pneumonia detection using chest radiographs with a novel EfficientNetV2L model	original research	prospective	2024	Presented an EfficientNetV2-L CNN for pneumonia detection on chest X-rays. Trained on a large dataset, the model achieved ~94.0% accuracy on an independent test set, outperforming baseline Convolutional neural networks. The study emphasizes improved performance of advanced architectures.

6.	Wu L et al. [14]	Pneumonia detection based on RSNA dataset and anchor-free deep learning detector	original research	prospective	2024	Proposed an anchor-free object-detection network for pneumonia on X-rays, using the RSNA Pneumonia dataset. The model achieved mean Average Precision ~51.5% (IoU=0.1), demonstrating the feasibility of localizing infiltrates via deep learning.
7.	Hofmeister J et al. [8]	Validating the accuracy of deep learning for the diagnosis of pneumonia on chest x-ray against a robust multimodal reference diagnosis: a post hoc analysis of two prospective studies	original research	prospective	2024	Prospective validation study of a convolutional neural network for pneumonia diagnosis on chest X-ray using a robust multimodal expert reference standard rather than radiologist report alone. The validation cohorts included 430 patients. Reported convolutional neural network accuracy was 71.0% in one cohort and 72.6% in the other, comparable to senior radiologists; the study also reports a receiver operating characteristic area under the curve of 0.74 and concludes that prior artificial intelligence performance for pneumonia on chest X-ray may have been overestimated when weaker reference standards were used.
8.	Miyazaki A et al. [15]	Computer-aided diagnosis of chest X-ray for COVID-19 diagnosis in external validation study by radiologists with and without deep learning system	original research	prospective	2023	External validation study of a deep learning system for three-class chest X-ray classification (normal, non-COVID-19 pneumonia, and COVID-19 pneumonia) using 26,393 chest X-rays from public and multicenter private datasets. The deep learning model achieved an overall accuracy of 0.733, compared with 0.696 ± 0.031 for radiologists without deep learning support, and radiologist performance for COVID-19 versus all other findings improved significantly with deep learning assistance (difference in area under the receiver operating characteristic curve, p = 0.0038).
9.	Altan G et al. [16]	DeepCOVIDNet-CXR: deep learning strategies for identifying COVID-19 on enhanced chest X-rays	original research	prospective	2024	COVID-19 CXR classification study using transfer learning with several ConvNet architectures after adaptive histogram equalization preprocessing. The authors report 98.26% accuracy on a balanced small-scale dataset and 95.04% accuracy on a large-scale dataset; the work included 3,615 COVID-19 cases and emphasizes model generalization across different training strategies.
10.	Wang T et al. [17]	PneuNet: deep learning for COVID-19 pneumonia diagnosis on chest X-ray image analysis using Vision Transformer	original research	prospective	2023	Vision Transformer–based CXR model for COVID-19/pneumonia classification. The study reports 94.96% test accuracy for three-class classification, 95.16% overall prediction accuracy, and for the COVID-19 class precision 96.95%, recall 98.45%, and F1-score 97.69%. The model also achieved approximately 99.3% accuracy in binary COVID-versus-nonpneumonia classification.
11.	Liu X et al. [18]	A Deep Learning Model for Diagnosing COVID-19 and Pneumonia through X-ray	original research	prospective	2023	Transfer-learning and ensemble-learning study proposing a COVID-ensemble model for CXR diagnosis. Reported performance was 91.5% accuracy for binary classification (no finding vs pneumonia) and 91.11% accuracy for multi-class classification (COVID-19 / no findings / pneumonia). The paper positions the model as a rapid screening tool for both pneumonia and COVID-19.

12.	Sasaki K et al. [19]	Artificial Intelligence Assessment of Chest Radiographs for COVID-19	original research	prospective	2025	Deep CNN model for identifying COVID-19 pneumonia on chest radiographs. Training data included 8,851 normal, 6,045 pneumonia, and 200 COVID-19 pneumonia radiographs, with the cohort split into 13,586 training and 1,510 test images. The AI assessment achieved 96.8% sensitivity and 90.9% positive predictive value on the test dataset; in one external validation, it correctly identified 174/204 radiographs (85%) and 97/107 patients (91%) as COVID-19 pneumonia.
13.	Tzeng IS et al. [20]	Artificial Intelligence-Assisted Chest X-ray for the Diagnosis of COVID-19: A Systematic Review and Meta-Analysis	systematic review and meta-analysis	retrospective	2023	Systematic review and meta-analysis of AI-assisted CXR for COVID-19 detection including 9 studies and 39,603 subjects. The pooled sensitivity was 94.72%, pooled specificity 96.10%, and AUC 0.98, supporting strong diagnostic potential for COVID-19 detection on chest radiographs while still requiring attention to heterogeneity and bias.

Table2. Articles included in analysis of studies using AI tools (deep learning) to detect pulmonary TB on radiological imaging

Tablica 2. Radovi uključeni u analizu studija koje su koristile alate umjetne inteligencije (UI) temeljene na dubokom učenju za otkrivanje plućne tuberkuloze na radiološkim slikovnim prikazima

No.	First author (ref)	Study title	Type of study	Study design	Year of publication	Study overview
1.	Hansun S [5]	Diagnostic Performance of AI-Based Methods for Tuberculosis Detection: Systematic Review	systematic review	retrospective	2025	Systematic review showing CNN-based approaches dominate TB detection with high performance; highlights lack of generalizability and real-world validation.
2.	Tavaziva G et al. [6]	Diagnostic accuracy of a commercially available deep learning-based chest X-ray interpretation software for detecting culture-confirmed pulmonary tuberculosis	original research	prospective	2022	Commercial AI (Lunit) achieved 87.7% sensitivity and 64.3% specificity; higher sensitivity than radiologists but more false positives.
3.	Kolhar M et al. [21]	Augmenting radiological diagnostics with AI for tuberculosis and COVID-19 disease detection: deep learning detection of chest radiographs	original research	prospective	2024	ResNet50 and VGG16 used; ResNet50 achieved ~99% precision/recall for TB; demonstrates multi-disease screening potential.
4.	Qin ZZ et al. [22]	Tuberculosis detection from chest X-rays for triaging in a high tuberculosis-burden setting: an evaluation of five artificial intelligence algorithms	original research	prospective	2023	CAD systems achieved >90% sensitivity and 70–85% specificity; useful for screening programs.
5.	Devasia J et al. [23]	Deep learning classification of active tuberculosis lung zones-wise manifestations using chest X-rays: a multi-label approach	original research	prospective	2023	Multi-label DL model for regional TB detection; high sensitivity but reduced specificity in complex cases.
6.	Chen CF et al. [24]	A deep learning-based algorithm for pulmonary tuberculosis detection in chest radiography	original research	prospective	2024	CNN achieved AUC ~0.90–0.94 with good external validation performance.
7.	Han ZL et al. [25]	A systematic review and meta-analysis of artificial intelligence software for tuberculosis diagnosis using chest X-ray imaging	systematic review	retrospective	2025	Across 21 studies, AI showed high sensitivity but variable specificity; strong screening potential but needs optimization.

Table 3. Imaging findings on computed tomography (CT) scans in bacterial pneumonia, viral pneumonia (including COVID-19 pneumonia), and pulmonary TB

Tablica 3. Prikaz slikovnih nalaza na kompjutoriziranoj tomografiji (CT) kod bakterijske pneumonije, virusne pneumonije (uključujući pneumoniju uzrokovanu bolešću COVID-19) i plućne tuberkuloze

Type of pulmonary infection	Most common computed tomography (CT) imaging patterns	CT imaging pattern description
Bacterial pneumonia [26, 27]	Airspace consolidation	An area of increased pulmonary opacity resulting in complete obscuration of the underlying bronchovascular structures.
	Air bronchograms	Patent bronchi within consolidation
	Bronchopneumonia pattern	Patchy, ill-defined opacities
Viral pneumonia [26, 27]	„Ground glass opacity“ (GGO)	Pulmonary opacity with increased attenuation that allows preservation of visualization of the underlying bronchovascular structures.
	„Crazy paving“	Thicken interlobular septa on a background of GGO
	Centrilobular nodules	Ill-defined nodules scattered through the lung
COVID-19 pneumonia (subgroup of viral pneumonia) [26, 27]		Bilateral, peripheral GGO, often superimposed consolidation and „crazy paving“ pattern
Tuberculosis [5, 26, 27]	„Tree-in-bud“ pattern	Branching micronodular opacities due to infectious endobronchial filling.
	Milliary pattern	Multiple tiny pulmonary nodules with a random bilateral distribution.
	Cavitations	Thick walled cavities
	Lymphadenopathy	Enlarged lymph nodes, sometimes filled with caseous necrotic material

evidence suggesting an increase in sensitivity of approximately 10 percentage points for detecting subtle pneumonic infiltrates[2].

For TB, AI algorithms similarly demonstrated high diagnostic performance. A recent systematic review by Hansun et al. reported that deep learning-based chest X-ray interpretation achieved sensitivities ranging from 90% to 99%, with moderate-to-high specificity depending on the clinical setting[5]. Several studies evaluated commercially available AI tools for TB screening[5,6]. For example, Tavaziva et al. reported that a deep learning-based software achieved a sensitivity of 87.7% and specificity of 64.3% for detecting culture-confirmed pulmonary TB[6].

In addition to commercial tools, multiple studies have developed custom deep learning models for TB detection, often achieving expert-level accuracy on chest radiographs, particularly in high-burden and resource-limited settings[23]. Furthermore, recent work has explored multi-disease classification systems; for example, one study demonstrated that a deep learning model could simultaneously classify chest X-rays as normal or indicative of TB, COVID-19 pneumonia, or other pulmonary infections, achieving overall accuracy exceeding 95%[21].

Overall, deep learning approaches consistently demonstrated high performance for both bacterial/viral pneumonia and TB detection, with diagnostic accuracy comparable to experienced radiologists and substantially higher than that of less experienced readers in most studies[5,8].

Bacterial/viral pneumonia detection

Most pneumonia studies focused on chest X-ray. Across studies, AI models achieved high diagnostic accuracy. In aggregate, individual AI algorithms reached sensitivity 80–97% and specificity 85–95% for pneumonia detection, values comparable to radiologist benchmarks[4,11]. Essa et al.'s meta-analysis (2025) of 15 CXR studies (~12,000 films) reported a pooled AI sensitivity of 88% and specificity 90% for pneumonia[11].

Several studies exemplified this performance: Wang et al. (2023) developed "Pneumonia-Plus," a deep CNN on chest CT, which differentiated viral, bacterial, and fungal pneumonia[12]. This model achieved AUCs of 0.816–0.934 across classes [(e.g. 0.816 for viral, 0.934 for bacterial pneumonia) –equivalent with experienced radiologists[12]. On plain CXR, Ali et al. (2024) reported 94.0% accuracy using an EfficientNetV2-L network[13]. Wu et al. (2024) used an anchor-free de-

tection CNN on the RSNA dataset and found similarly high accuracy[14]. In an ED triage context, Ippolito et al. (2023) tested an AI classifier on CXR and found it achieved 95% sensitivity and 84% specificity for pneumonia, assisting in distinguishing pneumonia from other lung conditions[11].

Notably, AI as a second reader markedly improved human performance. Essa et al. found that adding AI to radiologist reads increased sensitivity by ~10 percentage points[11]. This parallels findings in chest radiography for other diseases: Nam et al. (2023) showed in a large RCT that AI-assisted reporting significantly increased lung nodule detection on CXR[7]. By extension, integrating AI may help catch subtle pneumonic infiltrates that might otherwise be overlooked.

Pulmonary tuberculosis detection

All TB studies in this review used CXR. Hansun et al. (2025) systematically reviewed deep learning for TB CXR interpretation, finding extremely high performance: mean AI sensitivity was 92.8% and specificity 92.4 %[5]. Many individual algorithms surpassed 90% sensitivity in detecting radiographically evident TB. Commercial TB screening software (often trained on World Health Organisation-WHO TB prevalence datasets) demonstrated similar trends. For example, Tavaziva et al. (2022) evaluated a commercial AI tool for culture-confirmed TB and reported sensitivity ~88% (at a moderate threshold) but only 64–70% specificity[6]. This gap suggests that these tools are optimized for high sensitivity to ensure case detection, potentially at the expense of increased false-positive rates.

Recent models can also screen multiple diseases. Kolhar et al. (2024) described a CNN that classified CXR into normal, TB, COVID-19, or other pneumonia, achieving 0.99 precision and recall for TB detection[21].

Overall, TB AI systems often reach expert-level accuracy. Hansun et al. noted that many studies report sensitivities in the 90–99% range[5]. When compared to radiologists, deep learning tools frequently matched or outperformed unassisted junior readers in detecting TB, though variability in specificity was noted[22-25].

Discussion

Our review demonstrates that by 2021, deep learning has become highly effective for detecting bacterial/viral pneumonia and TB on chest imaging. As noted in Table 3, when interpreting and reporting pulmonary infections on CT, radiologist analyse the distribution of various opacities, consolidations and other lesions. The final conclusion is made in the context of patient's medical history, clinical presentation and laboratory findings. Therefore, it is important that AI tools integrate all elements of radiological reasoning, rather than focusing solely on lesion description. Across independent studies, AI algorithms consistently achieved high accuracy and AUCs (often ≥0.90), matching or exceeding expert radiologist performance[6]. These findings are in accordance with previous overviews: Sharma and Guleria (2024) similarly reported very high deep learning accuracy for pneumonia on CXR, and Hansun et al. (2025) concluded that TB detection sensitivity is now at the same value of quality with experts[4,5]. Importantly, the ability of AI to highlight subtle findings – faint consolidations or small cavitation – can augment human readers. For example, one multi-reader trial (although in lung nodule detection) showed radiologist sensitivity increasing by 10% when aided by AI[7]. In the context of infection, an AI-generated flag identifying an otherwise overlooked area of pneumonia could facilitate timely clinical intervention and treatment.

Our results suggest that AI is especially valuable in high-volume or low-resource settings, where a "second look" is needed or expert interpretation is scarce.

Recent studies also explored more complex tasks. Wang et al. Pneumonia-Plus model partly differentiated pneumonia etiology (viral vs. bacterial) on CT[12]. During COVID-19 peaks, AI tools were piloted to triage viral pneumonia on CXR[20]. Kolhar et al. have built multi-class classifiers for normal vs. TB vs. COVID-19 vs. other pneumonia[21]. These multi-disease models highlight AI's versatility: a single AI platform could flag any of several pathologies on a single CXR, streamlining screening programs (e.g. combined TB/COVID screening in endemic regions).

Despite the excitement, important challenges remain. Many models were trained on specific datasets (e.g. a particular hospital's X-rays or a public repository) and may not generalize to all populations or imaging protocols. Several authors noted performance drops when testing on external data[8,11]. This underscores the need for diverse training cohorts and external validation. Deep learning is also sensitive to image quality: suboptimal CXR (motion artifacts, poor exposure) or coexisting pathologies (e.g. severe pulmonary edema) could confound the algorithm if such cases were under-represented in training. Explainability is another concern; clinicians may hesitate to trust a "black box." Some newer studies used attention maps or saliency mapping to show which lung regions drove the AI's prediction, which can build trust by verifying that AI focusses on plausible abnormalities[8,11].

From a clinical perspective, integrating AI requires workflow adjustments. Early evidence (such as the emergency department-ED and screening trials) suggests this could yield faster diagnoses and reduce misses. In TB control programs, AI-driven triage could quickly rule out normals and refer likely TB cases for confirmatory testing, thereby improving case finding. However, care must be taken to avoid over-reliance: any AI alert should be interpreted in clinical context (symptoms, labs, epidemiology).

Compared to prior reviews, our focused 2021–2025 overview captures the very latest developments. Sharma and Guleria's 2024 review of pneumonia detection emphasized large datasets and robust validation[4]; we extend that by including CT-based models and citing actual performance ranges and multi-class results. Hansun et al. 2025 TB review found pooled sensitivity ~92–99% and noted specificity variability[5]. Our findings are consistent with previous reports indicating that many TB AI tools are optimized for maximal sensitivity.

A novel addition is the evaluation of large language models: Chetla et al. (2025) directly tested ChatGPT-4 on pediatric CXRs and found it vastly underperformed CNNs (ChatGPT accuracy ~61% vs. CNN ~93%; specificity only 38% vs. 90%)[11]. This underscores that general large language models-LLMs, without image training, are not yet reliable for radiologic diagnosis, and domain-specific vision models remain superior.

Several limitations of the evidence base should be acknowledged.

Most studies were retrospective and single-center; only a few were prospective or randomized trials[4,5,8,11]. Thus real-world workflow impact and user acceptance were seldom measured. Publication bias may inflate reported accuracies; as negative or modest results often go unpublished. Also, nearly all research came from high-resource settings; the performance of these AI tools in low-resource clinics (with different patient populations and equipment) is largely untested. Training data differences may limit transfer: a model trained on adult CXRs might not work well for pediatrics and vice versa. We also note some redundancy in our findings (e.g. similar "risk of bias" concerns repeated), reflecting that multiple reviews have pointed out the same issues (retrospective design, lack of external validation). Finally, our review period excluded pre-2021 studies and non-English publications, which may miss some innovations.

Clinically, these results suggest that AI could soon become a valuable "second pair of eyes" for infection detection on CXR/CT. For example, in TB-endemic regions, AI screening could accelerate identification of potential cases for isolation and treatment. In emergency or pandemic situations, AI triage might expedite care when radiologist resources are stretched. However, deployment must be accompanied by training and guidelines: clinicians should know AI's limitations (e.g. what kinds of cases it tends to miss) and use it as an aid, not a replacement. Regulatory bodies and institutions will need to validate any AI tool to ensure non-inferiority to standard care.

Future research should emphasize prospective, real-world evaluations. A key question is whether AI assistance improves patient outcomes (faster diagnosis, reduced morbidity) in practice, beyond just accuracy metrics. Ongoing trials are exploring AI integration into radiology workflows and tracking outcomes. There is also interest in hybrid AI systems that combine imaging with clinical data (symptoms, labs, genomics) to improve diagnostic precision. Continual learning methods – allowing AI to update on new cases – could help maintain performance over time. Lastly, ethical and equity considerations must be addressed: AI should be tested across diverse populations to avoid exacerbating disparities, and transparency in algorithms (open models, performance reporting) will be important for trust.

Conclusion

This systematic review of 2021–2025 studies demonstrates that deep learning has matured into a highly accurate tool for radiologic diagnosis of pulmonary infections [bacterial/viral pneumonia (including COVID-19 pneumonia) and TB] on chest X-rays and CT with sensitivity and specificity comparable to experienced radiologists. They are particularly effective at identifying subtle or early disease and can significantly augment human readers when used as a second opinion. Challenges remain in generalizability and clinical integration. With proper validation and implementation, AI-assisted chest imaging of pulmonary infection may help streamline workflows, reduce diagnostic errors, and ultimately improve patient care.

Conflict of interest:

The authors declare no conflict of interest.

List of Abbreviations:

Artificial Intelligence (AI)
Area Under the Curve (AUC)
Chest X-ray (CXR)
Computed Tomography (CT)

Convolutional Neural Network (CNN)
Deep Learning (DL)
Emergency Department (ED)
Large Language Models (LLMs)
Quality Assessment of Diagnostic Accuracy Studies 2 (QUADAS-2)
Tuberculosis (TB)
World Health Organisation (WHO)

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