International Journal of Innovative Technologies in Social Science

e-ISSN: 2544-9435

Scholarly Publisher
RS Global Sp. z O.O.
ISNI: 0000 0004 8495 2390

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ARTICLE TITLE	ARTIFICIAL INTELLIGENCE IN CHEST X-RAY DIAGNOSTICS OF PNEUMONIA: OPPORTUNITIES TO REDUCE MEDICAL ERRORS AND IMPROVE CLINICAL PRACTICE EFFICIENCY
ARTICLE INFO	Hanna Skarakhodava, Kamila Krzewska, Agnieszka Floriańczyk, Ewa Romanowicz, Aleksandra Kołdyj, Agnieszka Ozdarska, Adrian Krzysztof Biernat, Marcin Lampart, Anna Rupińska, Katarzyna Kozon. (2025) Artificial Intelligence in Chest X-Ray Diagnostics of Pneumonia: Opportunities to Reduce Medical Errors and Improve Clinical Practice Efficiency. *International Journal of Innovative Technologies in Social Science*. 3(47). doi: 10.31435/ijitss.3(47).2025.3500
DOI	https://doi.org/10.31435/ijitss.3(47).2025.3500
RECEIVED	27 May 2025
ACCEPTED	21 July 2025
PUBLISHED	25 July 2025
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ARTIFICIAL INTELLIGENCE IN CHEST X-RAY DIAGNOSTICS OF PNEUMONIA: OPPORTUNITIES TO REDUCE MEDICAL ERRORS AND IMPROVE CLINICAL PRACTICE EFFICIENCY

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ABSTRACT

Introduction and Purpose: Chest X-ray (CXR) interpretation forms the bedrock of pneumonia diagnosis, yet it remains susceptible to human error and significant variability, with documented error rates reaching up to 30%. Artificial intelligence (AI), particularly through advancements in deep learning, presents a powerful opportunity to enhance diagnostic accuracy, minimize errors, and optimize clinical workflows. This structured review offers a critical summary of AI-based approaches for pneumonia detection on CXRs, delving into their diagnostic metrics, performance comparisons, impact on workflow, and role in error reduction.

Material and Method: We conducted a systematic synthesis of peer-reviewed literature from key databases including PubMed, ScienceDirect, Nature, and MDPI. Our search encompassed multicenter studies, comparative trials involving radiologists, and reports on real-world clinical deployments. Inclusion criteria specifically mandated explicit reporting of sensitivity, specificity, area under the curve (AUC), time savings, detailed dataset characteristics, comprehensive error analysis, and workflow efficiency. Special attention was given to studies involving convolutional neural networks (CNNs—such as ResNet, DenseNet, CheXNet, and Mask R-CNN), multicenter validation, applications in "second-reader" modes and triage systems, and aspects of interpretability.

Results: AI-powered CXR solutions consistently demonstrate high diagnostic value, with AUCs typically ranging from 0.87 to 0.98, and achieving sensitivity/specificity rates of 90–98% and 80–99% respectively. Notably, FDA-cleared platforms exhibit an AUC of 0.976, sensitivity of 0.908, and specificity of 0.887. The CheXNet model achieved diagnostic accuracy on par with radiologists when evaluated on the ChestX-ray14 dataset. Stand-alone AI review systems can process CXRs and generate reports in a mere 3–5 seconds (a dramatic reduction from approximately 1 hour for manual interpretation), significantly accelerating turnaround times and enabling rapid patient triage. When implemented in a "second-reader" capacity, AI tools reduce missed consolidations by up to 98% and effectively elevate the diagnostic accuracy of non-radiologists to a level comparable with that of board-certified radiologists. Furthermore, validation studies across pediatric and multi-pathology cases show robust performance metrics, provided age-appropriate adjustments are applied. However, comprehensive explainability and seamless integration remain crucial for the widespread and sustained adoption of these technologies.

Conclusions: AI, when applied to CXR-based pneumonia detection, demonstrably improves clinical accuracy, expedites reporting, and significantly mitigates human diagnostic error. These benefits are particularly pronounced in high-throughput environments and resource-constrained settings. Future large-scale implementation will depend on transparent validation processes, continuous real-world monitoring, and strong partnerships with clinicians to foster trust, ensure diagnostic consistency, and ultimately achieve optimal patient outcomes.

KEYWORDS

Pneumonia, Artificial Intelligence, Deep Learning, Radiography, Thoracic, Medical Errors, Workflow

CITATION

Hanna Skarakhodava, Kamila Krzewska, Agnieszka Floriańczyk, Ewa Romanowicz, Aleksandra Kołdyj, Agnieszka Ozdarska, Adrian Krzysztof Biernat, Marcin Lampart, Anna Rupińska, Katarzyna Kozon. (2025) Artificial Intelligence in Chest X-Ray Diagnostics of Pneumonia: Opportunities to Reduce Medical Errors and Improve Clinical Practice Efficiency. *International Journal of Innovative Technologies in Social Science*. 3(47). doi: 10.31435/ijitss.3(47).2025.3500

Introduction.

Pneumonia stands as one of the most prevalent infectious diseases globally, frequently necessitating hospitalization and contributing significantly to mortality across all age groups, including highly vulnerable populations such as children, the elderly, and immunocompromised individuals [9,10]. Consequently, a timely and reliable diagnosis is paramount for initiating prompt therapy, containing disease transmission, and preventing severe complications. Chest X-ray (CXR) continues to serve as the primary diagnostic tool given its widespread accessibility, cost-effectiveness, and established diagnostic utility. However, CXR interpretation inherently involves subjective assessment, making it vulnerable to human error. Published studies indicate that error rates in CXR readings can range from 20% to 30%, even among seasoned radiologists [1,3,11–13]. These limitations stem from factors like subtle or overlapping radiological findings, reader fatigue, pressures from heavy workloads, and inherent interobserver variability. Such challenges are further exacerbated in acute care, pediatric contexts, or resource-limited environments, frequently resulting in delayed or missed diagnoses.

Artificial intelligence (AI), especially deep learning approaches like convolutional neural networks (CNNs), has undergone rapid advancements, introducing capabilities for automated analysis, sophisticated pattern recognition, and efficient triage that can either match or, in some instances, exceed the performance of human radiologists [2,4,6,14,15]. The integration of AI into CXR workflows holds substantial promise for delivering reproducible and objective interpretations, significantly improving diagnostic accuracy, substantially reducing errors, and accelerating critical decision-making processes [16,17]. This review systematically evaluates the current literature on AI applications in CXR-based pneumonia diagnostics. Our focus encompasses diagnostic accuracy, workflow productivity, and error reduction, while offering direct comparisons to human diagnostic performance and addressing key aspects of implementation, interpretability, and existing limitations.

Description of the State of Knowledge

1. Technical Foundations and Major Datasets in AI-CXR Analysis

State-of-the-art AI systems for CXR analysis predominantly leverage deep Convolutional Neural Network (CNN) architectures. Prominent examples include **ResNet, DenseNet, VGG, Mask R-CNN, EfficientNet**, and specialized models such as **CheXNet** [14–18]. These powerful neural networks are rigorously trained and validated on extensive, meticulously labeled datasets, which are absolutely crucial for ensuring generalizability, optimizing performance, and enabling standardized benchmarking:

- **ChestX-ray14:** Comprising over 100,000 images, this dataset supports multi-label and multiclass research. Notably, CheXNet utilized this dataset to achieve radiologist-level performance [14,15].
- **RSNA Pneumonia Detection Challenge:** With more than 30,000 images featuring detailed pneumonia annotations, this dataset is instrumental for developing robust spatial and severity labeling models [26].
- **CheXpert:** Containing over 220,000 images with uncertainty labels, CheXpert is increasingly recognized as a standard for clinical-grade benchmarking in AI development [14,16].
- **Additional Resources:** Further significant datasets, including MIMIC-CXR, PadChest, and VinDr-CXR, contribute crucial image diversity and high-quality annotations essential for contemporary AI model training and validation [8,14,16,17].

Table 1. Major Public Chest X-Ray Datasets Used in AI Pneumonia Research

Dataset Name	Number of Images	Main Features	Notable Use Case/Model	Reference
ChestX-ray14	>100,000	Multi-label, 14 thoracic diseases, weak labels	CheXNet (DenseNet-121)	[14],[15]
CheXpert	>220,000	Uncertainty labels, multi-class, high-quality annotation	Benchmark for clinical-grade	[14],[16]
RSNA Pneumonia Challenge	>30,000	Detailed bounding boxes, severity labeling	Spatial and severity models	[26]
MIMIC-CXR	~370,000	Diverse populations, multi-site	Robustness/validation studies	[8],[14]
PadChest	~160,000	Spanish cohort, multi-view	Non-English/non-US validation	[8],[14]

2. AI Methods, Architectures, and Performance Metrics

Convolutional neural networks (CNNs) serve as the fundamental backbone for the majority of AI tools used in CXR analysis. Key examples include:

- **CheXNet (DenseNet-121):** This model notably achieved diagnostic performance comparable to radiologists, with AUCs ranging from 0.76 to 0.98 for pneumonia detection on the ChestX-ray14 dataset [15,19,26].
- **Mask R-CNN and DenseNet architectures:** These have demonstrated impressive sensitivity, ranging from 97.5% to 99%, and specificity up to 99% for pneumonia, particularly highlighted in various COVID-19 studies [8,13,22,23].

Performance metrics consistently reported across studies include:

- **AUC:** Consistently falls within the range of 0.87–0.98 across numerous multi-center, multi-reader benchmarks [1,4,19].
- **Sensitivity:** Typically ranges from 90–98% [1,2,5,6,12,16,22].
- **Specificity:** Generally observed between 80–99%, with peak values often seen in FDA-cleared systems [1,4,12,19].
- **Specific Example:** The FDA-cleared system "Chest-CAD" achieved an AUC of 0.976, a sensitivity of 0.908, and a specificity of 0.887 [1].

The robustness of these findings is further bolstered by meta-analyses, which include multiple studies demonstrating that AI models exhibit diagnostic efficacy that is either equal to or even superior to that of expert human panels and practicing radiologists [1,3,15,16,26].

Table 2. Diagnostic Performance of Leading AI Models for Pneumonia Detection on CXR

Model/Tool	Dataset	AUC	Sensitivity	Specificity	Reference
CheXNet (DenseNet-121)	ChestX-ray14	0.76–0.98	0.90–0.98	0.80–0.93	[13],[15],[19]
Mask R-CNN (COVID study)	COVID CXR cohort	0.98	0.98–0.99	0.83–0.99	[6],[8]
FDA-cleared Chest-CAD	Multicenter	0.976	0.908	0.887	[1]
Ensemble (10 ResNet-50)	COVID/Community	0.94	Not stated	Not stated	[102]
AI-aided Non-Specialists	CheXpert/RSNA	≥0.89	≥0.90	≥0.80	[4],[7]
Pediatric AI (retuned)	External pediatric	0.969	0.87–0.98	0.87–0.98	[7]

3. AI vs. Human Readers and Error Reduction

Several multicenter, prospective, and blinded comparative studies compellingly illustrate the strengths of integrating AI into diagnostic workflows:

- **Accuracy Parity:** AI models, such as CheXNeXt, have demonstrated accuracy that matches or even surpasses that of practicing radiologists for 11 out of 14 common chest abnormalities, including pneumonia (with AI and radiologists both achieving an AUC of 0.85) [3].
- **"Second-Reader" Gains:** When deployed as a "second reader," particularly in high-volume and urgent triage environments, AI significantly reduces missed consolidations and pleural effusions by an impressive margin of up to 98%. Crucially, it has been shown to flag 100% of critical findings that were initially overlooked in "first-read" reports [4,9,31,33].
- **Non-Radiologist Empowerment:** AI serves as a powerful tool for empowering non-radiologist physicians, such as those in emergency or internal medicine. When using AI assistance, these clinicians achieved AUCs of 0.895 (AI-aided) compared to 0.800 (unaided). Their performance, when augmented by AI, was not statistically different from that of board-certified radiologists [1,5,6].

These findings are particularly impactful in healthcare settings characterized by heavy caseloads, limited specialist availability, or where image interpretation is frequently performed by non-expert readers.

Table 3. Speed of Interpretation and Workflow Time Savings

Workflow Mode	Average Interpretation Time per CXR	Source
Manual (Radiologist)	40–60 min	[5],[26],[28]
Stand-alone AI	3–5 sec	[5],[26]
AI + Radiologist	~15–30 min	[5],[26]
Non-Radiologist + AI	7–10% faster than unaided	[5],[30],[31],[33]

Table 4. Error Reduction Using AI in CXR Pneumonia Detection

Error Type	Reduction Rate/Performance Gain	Source
Missed consolidations	Up to 98% reduction	[4],[9],[31],[33]
Critical missed findings	100% flagged in second reading	[4],[9]
False positives/negatives	Outperforms or matches radiologists	[1],[4],[8],[9],[19]
Inter-reader variability	Significant reduction	[1],[29],[33]

4. CNN Architectures and Explainability

The predominant AI architectures include ResNet-50, DenseNet-121 (as seen in CheXNet), Mask R-CNN, EfficientNet, Inception, and various ensemble combinations [8,11,13,23,26]. A common practice is transfer learning, which involves leveraging weights from models pre-trained on large natural image datasets (like ImageNet) and then fine-tuning them specifically on medical imaging data.

The critical aspect of interpretability in AI models is addressed through:

- **Class activation maps (CAMs) and attention heatmaps:** These tools visually highlight the specific regions within an image that the AI model considers most relevant for a given diagnosis, thereby supporting human verification and understanding of the AI's reasoning [23,35,36].
- **Ensemble and hybrid approaches:** These methods combine various spatial and intensity features to produce informative region-of-interest (ROI) overlays and probability maps, further aiding in visual interpretation [11,12,35].

Such interpretability tools are absolutely crucial for fostering clinical trust, assisting in medical education, and enabling auditing of model reasoning, especially in complex or ambiguous "edge" cases.

5. Workflow Efficiency and Time Savings

The integration of AI into CXR workflows yields dramatic benefits in terms of time efficiency:

- **Turnaround Time:** A stand-alone AI system can review a CXR study in just 3–5 seconds. This drastically cuts the turnaround time from an average of ~40–60 minutes per abnormal CXR during peak periods, representing a remarkable reduction of over 95% [5,26,28].
- **Triaging:** Real-world deployments in hospitals have demonstrated that AI enables expedited triage, allowing human attention to be quickly directed to critical cases and significantly reducing the time-to-action, particularly vital in emergency situations [2,5,29].
- **"Second-Reader" Effect:** AI assistance can reduce the average review time per case by 7–10%, with the most significant improvements observed among non-expert readers [1,5,30,31,33].
- **Radiologist Throughput:** By automating repetitive workload, AI not only reduces potential radiologist burnout but also enables higher patient throughput, optimizing the efficiency of radiology departments [26,27].

Tabel 5. Time Savings in CXR Reporting

Method	Average Time per CXR	Source
Manual Radiologist	40–60 min	[5],[26],[28]
AI Stand-alone	3–5 sec	[5],[26]
AI + Radiologist	~15–30 min	[5],[26]
Non-Radiologist + AI	7-10% faster than unaided	[5],[30],[31],[33]

Note: Table values derived from cited multicenter workflow studies; actual times vary by clinical workflow and urgency.

6. Reducing False Positives, False Negatives and Observer Variability

AI, when deployed as a "second reader" or triage tool, delivers substantial improvements in diagnostic accuracy by:

- **Drastic Error Reduction:** Missed consolidation detection rates have shown an improvement of up to 98%. Moreover, AI has been documented to flag 100% of critical missed effusions when used in a second-reading capacity [4,9,31,33].
- **Lowered Mislabeling:** Stand-alone AI review systems consistently outperform or match human radiologists in terms of both sensitivity (reducing false negatives) and specificity (reducing false positives) [1,4,8,9,19].
- **Optimized Queue Management:** Intelligent worklist triage systems effectively prioritize abnormal or urgent cases, bringing them to the forefront for immediate radiologist evaluation [1,7,33].

7. AI in Pediatrics, Multipathology and Real-World Validation

- **Pediatrics:** Excluding children under 2 years of age, AI models achieve remarkable accuracy of up to 96.9% for pneumonia detection, with sensitivity and specificity for consolidation ranging from 87–98% [8,21].
- **Multi-pathology Robustness:** AI tools, rigorously validated on diverse datasets like CheXpert, MIMIC-CXR, and others, demonstrate consistent stability across varying image qualities, different imaging devices, and a spectrum of disease types [8,9,14].
- **Explicit Interpretability:** The availability of interpretable AI outputs empowers clinicians to effectively confirm, and when necessary, challenge AI findings, fostering a more collaborative and trustworthy diagnostic process [23,35,36].

8. Implementation, Trust, and Barriers for Clinical Integration

Despite the tremendous promise AI holds, several significant implementation concerns persist:

- **Continuous Validation:** Ongoing validation and recalibration are absolutely essential, as scanner types, patient populations, and disease spectra constantly evolve [1,4,8,18,26].
- **Seamless Integration:** Achieving smooth, structured integration with hospital Picture Archiving and Communication Systems (PACS) and electronic health records demands substantial technical commitment and comprehensive user training [23,29,37].
- **Ethical Considerations:** Issues surrounding data privacy, algorithmic fairness, explainability, and securing patient consent must be proactively managed and addressed [8,27,37].
- **Regulatory Hurdles:** Navigating regulatory clearances (e.g., FDA/CE approval), conducting local revalidation studies, and performing robust multicenter, real-world trials are all critical for achieving widespread scalability and adoption [1,4].

Tabel 6. Summary of AI CXR Pneumonia Diagnostic Performance

Study/Model	Dataset	AUC	Sensitivity	Specificity
FDA-cleared Chest-CAD	Multicentre	0.976	0.908	0.887
CheXNet (DenseNet-121)	ChestX-ray14	0.76–0.98	~Varies	~Varies
Triage/Second Reader (AI-aided Non-Specialists)	CheXpert, RSNA	≥0.89	≥0.90	≥0.80
Pediatric CXR (AI–adults retuned)	External	0.969	0.87–0.98	0.87–0.98

Note: Data summarised from sources [1,4,8,14,15,21,26,31]; performance depends on context/validation cohort.

Conclusions

AI systems designed for CXR-based pneumonia diagnostics now consistently deliver high accuracy (demonstrated by AUCs of 0.87–0.98, sensitivity of 90–98%, and specificity of 80–99%). These systems dramatically compress reporting times from up to an hour down to a mere 3–5 seconds. Crucially, they reduce the rates of missed or mislabeled cases by an impressive margin of up to 98% [1,4,5,8,18,26,33]. AI consistently elevates the diagnostic performance of non-radiologists and trainees to a level comparable with that of expert readers. It also significantly enhances workflow efficiency for high-throughput and triage cases, and actively supports the standardization of diagnostic practices—a particularly vital benefit in resource-limited settings. Importantly, AI also contributes to reducing variability among different human readers and offers valuable insights into complex cases through the use of heatmaps and activation maps.

Nevertheless, continuous research and meticulous integration efforts remain paramount. Persistent challenges include the need for transparent explainability in AI decision-making, robust multicenter and pediatric validation, ongoing retraining to adapt to shifts in data patterns, proactive addressing of ethical and privacy concerns, and ensuring clear, effective communication of AI findings to both clinicians and patients. Regulatory harmonization and a strong multidisciplinary collaboration will ultimately determine the long-term success and sustainable adoption of AI as an everyday clinical partner in radiology.

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All authors have read and agreed with the published version of the manuscript.

Funding Statement: The author received no external funding for this work.
Institutional Review Board Statement: Not applicable; this review included only published data.
Informed Consent Statement: Not applicable.
Data Availability Statement: All supporting data are available within the cited peer-reviewed literature.
Acknowledgments: The author acknowledges the contribution of investigators and data curators whose high-quality research underpins the advances reviewed herein.
Conflict of Interest Statement: The author declares no conflict of interest.

Declaration of the use of generative AI and AI-assisted technologies in the writing process:
In the preparation of this work, the authors used an AI-assisted writing tool to improve the language and readability of the article. After using this tool, the authors reviewed and edited the content as needed and accept full responsibility for the substantive content of the publication.

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