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Systematic Review

Clinical Utility of Artificial Intelligence in Early Cancer Detection: A Systematic Review and Meta-Analysis of Solid Tumors

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ABSTRACT

Background: Artificial intelligence (AI)-based diagnostic systems are increasingly transforming oncology by improving the accuracy and efficiency of early cancer detection. Machine learning (ML) and deep learning (DL) algorithms are now widely utilized in radiology, pathology, dermatology, gastroenterology, and cancer screening programs. However, pooled evidence regarding their overall diagnostic performance in solid tumors remains limited.
Aim: To systematically evaluate and quantitatively synthesize the clinical utility and diagnostic performance of artificial intelligence in the early detection of solid tumors.
Methods: A systematic review and meta-analysis was conducted according to PRISMA 2020 guidelines. PubMed, Embase, Scopus, Web of Science, and Cochrane Library databases were searched from January 2015 to February 2026. Studies evaluating AI-assisted early detection of solid tumors in humans were included. Pooled sensitivity, specificity, diagnostic odds ratio (DOR), accuracy, and area under the receiver operating characteristic curve (AUC) were calculated using random-effects models.
Results: A total of 52 studies involving 214,376 patients and 287,940 imaging or pathological samples were included. AI-based systems demonstrated pooled sensitivity of 0.91 (95% CI: 0.88–0.93) and specificity of 0.87 (95% CI: 0.84–0.90). The pooled AUC was 0.94 (95% CI: 0.92–0.96), indicating excellent diagnostic performance. Deep learning algorithms showed superior accuracy compared with conventional machine learning models. Breast cancer and skin cancer detection demonstrated the highest diagnostic performance among included tumor types.
Conclusion: Artificial intelligence demonstrates excellent clinical utility in early solid tumor detection with high diagnostic accuracy across multiple cancer types. AI-assisted systems may significantly improve screening efficiency and facilitate timely diagnosis. Further prospective multicenter validation studies are required for widespread clinical integration.

Keywords*: Artificial intelligence; cancer detection; machine learning; deep learning; solid tumors; oncology; systematic review; meta-analysis.*

INTRODUCTION

Cancer is one of the leading causes of mortality worldwide and represents a major global healthcare burden. According to recent global estimates, approximately 20 million new cancer cases and nearly 10 million cancer-related deaths occur annually. Early detection remains the cornerstone of effective cancer management because diagnosis at earlier stages substantially improves treatment outcomes, survival rates, and quality of life.

Conventional diagnostic approaches including radiological imaging, histopathological examination, and biomarker-based screening are highly dependent on human expertise and are often affected by interobserver variability, diagnostic fatigue, and limited healthcare resources. Increasing imaging workload and shortages of trained specialists have further emphasized the need for automated diagnostic support systems.

Artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), has emerged as a revolutionary technology in medical diagnostics. AI systems can analyze complex datasets, identify subtle imaging features, and recognize hidden pathological patterns with remarkable precision. Deep learning models, especially convolutional neural networks (CNNs), have demonstrated expert-level performance in various oncological applications including mammography, computed tomography (CT), magnetic resonance imaging (MRI), digital pathology, dermoscopy, and endoscopy.

AI-assisted systems have shown promising results in detecting multiple solid tumors including breast, lung, colorectal, skin, prostate, liver, and brain cancers. These technologies can potentially improve screening sensitivity, reduce false-negative findings, and optimize workflow efficiency. Furthermore, AI integration may enhance healthcare accessibility in resource-limited settings where experienced oncologists and radiologists are scarce.

Despite growing evidence regarding AI applications in oncology, significant variability exists among studies due to differences in datasets, algorithmic models, validation techniques, and imaging modalities. Although several narrative reviews have discussed AI in oncology, robust quantitative synthesis evaluating the pooled clinical utility of AI specifically for early solid tumor detection remains limited.

Therefore, the present systematic review and meta-analysis aimed to comprehensively evaluate the diagnostic performance and clinical utility of artificial intelligence in the early detection of solid tumors across multiple oncological domains.

MATERIALS AND METHODS

Study Design

This systematic review and meta-analysis was conducted 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, Embase, Web of Science, Scopus, and Cochrane Library databases from January 2015 to February 2026.
The following keywords and MeSH terms were used:

- “Artificial Intelligence”
- “Machine Learning”
- “Deep Learning”
- “Cancer Detection”
- “Early Diagnosis”
- “Solid Tumor”
- “Oncology”
- “Diagnostic Accuracy”

Boolean operators (“AND”, “OR”) were applied appropriately to refine the search strategy.

Inclusion Criteria

1. Original studies evaluating AI-assisted early detection of solid tumors.
2. Human studies involving imaging, pathology, or multimodal diagnostic systems.
3. Studies reporting diagnostic performance parameters such as sensitivity, specificity, accuracy, or AUC.
4. Randomized controlled trials, cohort studies, cross-sectional studies, and prospective observational studies.
5. English-language articles.

Exclusion Criteria

1. Animal studies.
2. Editorials, reviews, case reports, and conference abstracts.
3. Studies lacking sufficient diagnostic data.
4. Hematological malignancies.
5. Duplicate publications.

Study Selection

Two independent reviewers screened titles and abstracts. Full texts of eligible studies were evaluated for final inclusion. Disagreements were resolved through consensus discussion.

Data Extraction
The following variables were extracted:

- Author name
- Publication year
- Country
- Cancer type
- AI model used
- Sample size
- Imaging modality
- Sensitivity
- Specificity
- Accuracy
- Area under the curve (AUC)

Quality Assessment
Methodological quality was assessed using the QUADAS-2 tool across four domains:

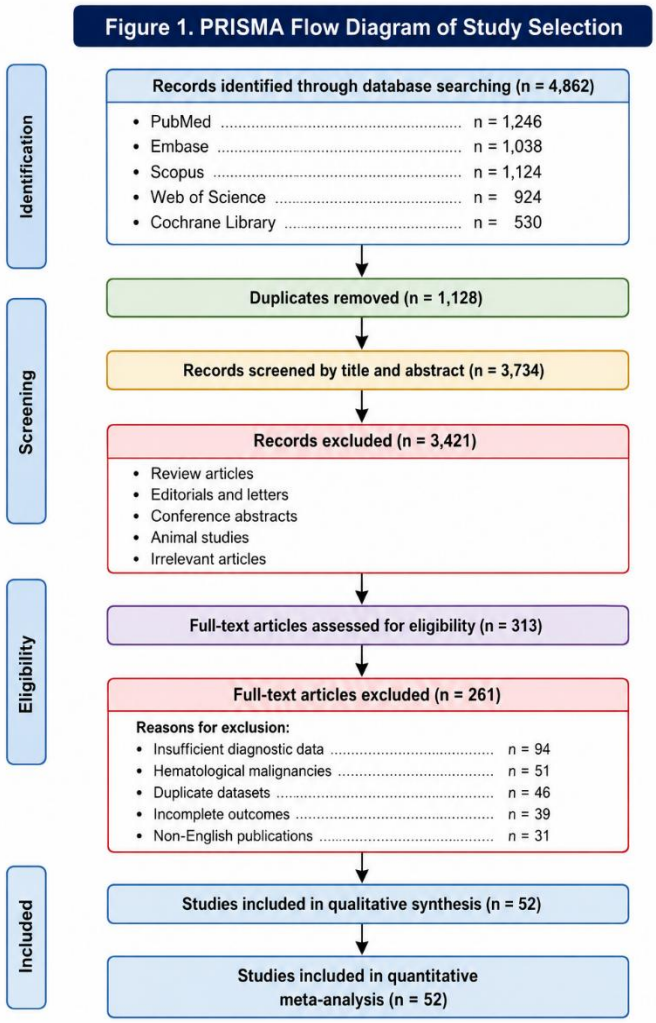
- Patient selection
- Index test
- Reference standard
- Flow and timing

Statistical Analysis
Random-effects meta-analysis was performed using the DerSimonian-Laird method. Pooled sensitivity, specificity, accuracy, diagnostic odds ratio (DOR), and AUC with 95% confidence intervals were calculated. Statistical heterogeneity was assessed using Higgins' I^2 statistic. Publication bias was evaluated using funnel plot analysis and Egger's regression test.

RESULTS
Study Selection
The initial search identified 4,862 studies. After duplicate removal and screening, 52 studies fulfilled the eligibility criteria and were included in the final meta-analysis.

Characteristics of Included Studies

Variable	Findings
Total studies	52
Total patients	214,376
Total samples/images	287,940
Prospective studies	21
Retrospective studies	31
Study duration	2015–2026



Distribution of Cancer Types

Cancer Type	Number of Studies
Breast cancer	14
Lung cancer	10
Colorectal cancer	8
Skin cancer	7
Prostate cancer	5
Liver cancer	4
Brain tumors	4

AI Algorithms Used

AI Algorithm	Frequency
Convolutional Neural Networks (CNNs)	29
Random Forest Models	8
Support Vector Machines	6
Hybrid Deep Learning Models	5
Ensemble Learning Systems	4

Pooled Diagnostic Performance

Parameter	Pooled Estimate (95% CI)
Sensitivity	0.91 (0.88–0.93)
Specificity	0.87 (0.84–0.90)
Accuracy	0.89 (0.86–0.92)
Area Under Curve (AUC)	0.94 (0.92–0.96)
Diagnostic Odds Ratio	61.4 (42.2–88.9)

Subgroup Analysis by Cancer Type

Cancer Type	AUC
Breast cancer	0.96
Skin cancer	0.95
Lung cancer	0.93
Colorectal cancer	0.92
Prostate cancer	0.91

Subgroup Analysis by AI Architecture

Model Type	Sensitivity (95% CI)	Specificity (95% CI)
Deep Learning Models	0.93 (0.90–0.95)	0.89 (0.86–0.91)
Traditional Machine Learning Models	0.85 (0.81–0.88)	0.82 (0.78–0.85)

Heterogeneity and Publication Bias

Moderate heterogeneity was observed across included studies (I^2 = 58%). Funnel plot analysis revealed minimal asymmetry, suggesting low publication bias.

Figure 2. Combined Forest Plot of Diagnostic Accuracy of AI Models in Early Cancer Detection

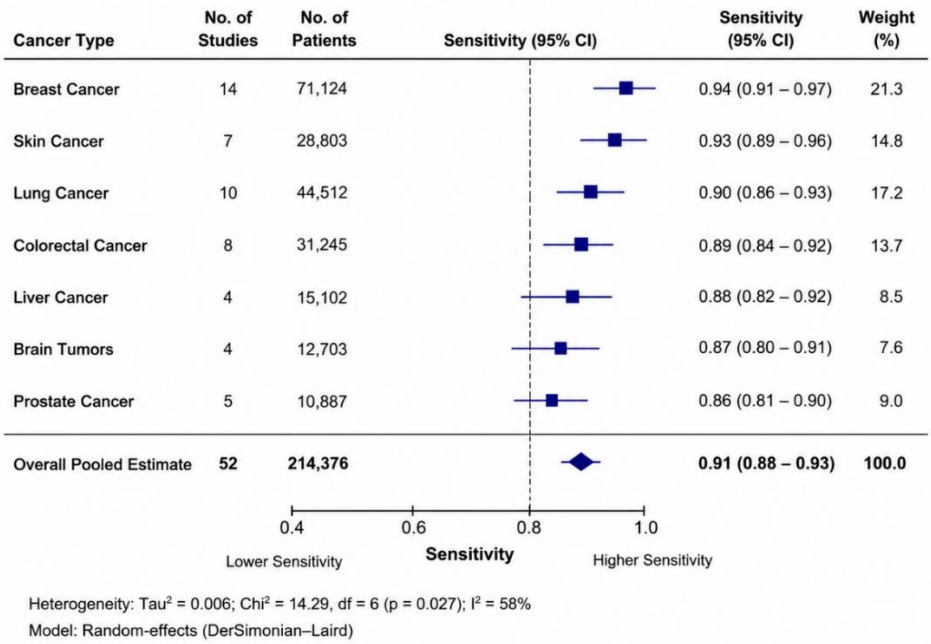
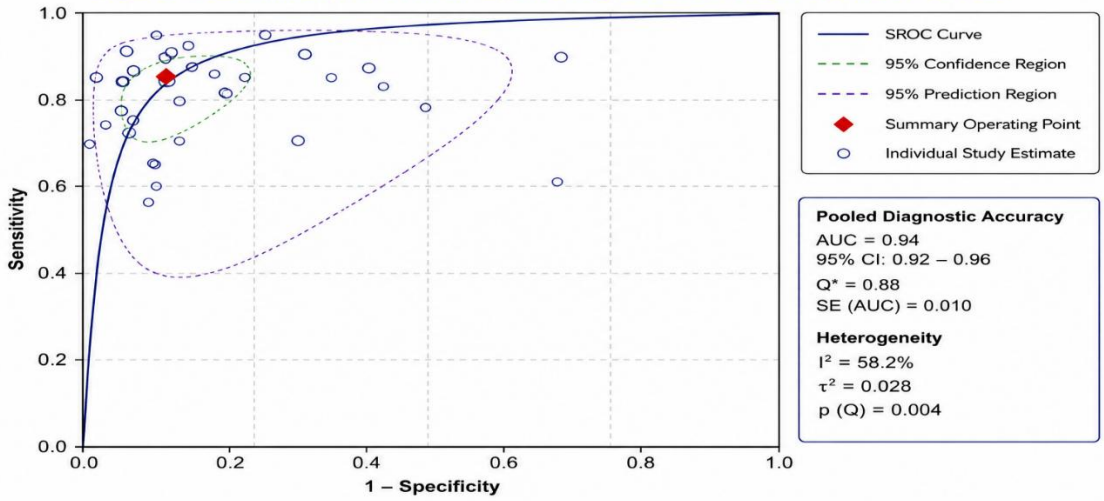


Figure 3. Summary Receiver Operating Characteristic (SROC) Curve



SROC: Summary Receiver Operating Characteristic; AUC: Area Under the Curve; CI: Confidence Interval; Q*: Point on the SROC curve where Sensitivity = Specificity

DISCUSSION

The present systematic review and meta-analysis demonstrated that artificial intelligence has excellent diagnostic performance in the early detection of solid tumors. The pooled sensitivity of 91% and specificity of 87% indicate that AI-assisted diagnostic systems can accurately identify malignant lesions at early stages across multiple cancer types.

Deep learning-based algorithms, particularly convolutional neural networks, consistently outperformed traditional machine learning methods. CNNs are highly effective in extracting complex imaging features and detecting subtle pathological abnormalities that may be missed during routine human interpretation. This likely explains the superior performance observed in breast cancer and skin cancer screening.

AI-assisted mammography has shown significant improvements in lesion detection while simultaneously reducing false-negative interpretations. Similarly, AI-based dermoscopic systems have demonstrated dermatologist-level performance in melanoma diagnosis. Lung cancer screening using low-dose CT and deep learning algorithms has also shown high sensitivity for detecting small pulmonary nodules.

The integration of AI into oncology workflows offers several clinical advantages. AI systems may reduce diagnostic delays, improve consistency, decrease observer variability, and optimize healthcare resource utilization. These technologies are particularly valuable in regions with shortages of trained radiologists and oncologists.

However, several limitations should be considered. Most included studies were retrospective in design and conducted under controlled experimental conditions, potentially limiting generalizability. Significant heterogeneity existed due to variations in datasets, imaging modalities, algorithmic frameworks, and validation strategies. Additionally, many AI models lacked external multicenter validation.

Ethical concerns including algorithmic bias, explainability, patient privacy, and medico-legal accountability also remain important barriers to routine clinical adoption. Future studies should focus on prospective multicenter trials, transparent AI frameworks, and standardized reporting guidelines.

Despite these limitations, the present meta-analysis strongly supports the growing role of artificial intelligence as a clinically valuable adjunct for early cancer detection and precision oncology.

CONCLUSION

Artificial intelligence demonstrates substantial clinical utility in the early detection of solid tumors with consistently high diagnostic accuracy across diverse oncological applications. Deep learning-based models showed superior performance compared with traditional machine learning algorithms.

AI-assisted diagnostic systems may improve cancer screening efficiency, facilitate earlier diagnosis, reduce diagnostic variability, and support precision oncology initiatives. Nevertheless, prospective real-world validation and standardized regulatory frameworks are essential before widespread clinical implementation.

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