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Systematic Review

Artificial Intelligence Assisted Early Detection of Solid Tumors: Systematic Review and Meta-Analytic Evidence

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ABSTRACT

Background: Early detection of solid tumors remains a cornerstone for improving cancer survival and reducing disease burden worldwide. Recent advances in artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), have shown considerable promise in enhancing diagnostic precision using radiological, histopathological, and clinical datasets.
Objective: This systematic review and meta-analysis aimed to evaluate the diagnostic performance of AI-assisted technologies in the early detection of solid tumors across multiple organ systems.
Methods: A systematic literature search was conducted across PubMed, Scopus, Web of Science, Embase, and Cochrane Library databases for studies published between January 2015 and January 2026. Eligible studies included original research evaluating AI-based diagnostic systems for early solid tumor detection in adult populations. Data extraction included study characteristics, AI model type, tumor type, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC). Methodological quality was assessed using QUADAS-2 criteria. Pooled sensitivity, specificity, diagnostic odds ratio (DOR), and summary receiver operating characteristic (SROC) curves were calculated using random-effects meta-analysis.
Results: A total of 48 studies comprising 96,742 patients were included. AI-assisted diagnostic systems demonstrated pooled sensitivity of 0.91 (95% CI: 0.88–0.93) and specificity of 0.87 (95% CI: 0.84–0.89) for early tumor detection. The pooled AUC was 0.94 (95% CI: 0.92–0.96), indicating excellent diagnostic accuracy. Deep learning-based convolutional neural networks (CNNs) outperformed traditional machine learning algorithms. Radiological imaging studies showed slightly higher diagnostic performance than histopathological and biomarker-based AI systems. Significant heterogeneity was observed due to variability in datasets, imaging modalities, and external validation strategies.
Conclusion: AI-assisted technologies demonstrate high diagnostic accuracy for early detection of solid tumors and may significantly augment clinician decision-making. Standardization of datasets, prospective multicenter validation, and ethical implementation frameworks are essential before widespread clinical integration.

Keywords: *Artificial intelligence; Solid tumors; Early detection; Deep learning; Machine learning; Meta-analysis; Cancer diagnosis.*

INTRODUCTION

Cancer remains one of the leading causes of morbidity and mortality globally, accounting for millions of deaths annually. Early detection of solid tumors significantly improves therapeutic outcomes, enhances survival rates, and reduces healthcare expenditures. However, conventional diagnostic methods often rely on subjective interpretation, which may lead to interobserver variability and delayed diagnosis.

Artificial intelligence (AI), encompassing machine learning (ML), deep learning (DL), and neural network architectures, has emerged as a transformative technology in oncology diagnostics. AI algorithms are capable of analyzing large-scale imaging, histopathological, genomic, and clinical datasets with remarkable speed and precision. Recent developments in convolutional neural networks (CNNs), radiomics, and computer-aided diagnostic systems have enabled improved identification of subtle tumor-related abnormalities that may escape conventional human interpretation.

Several studies have investigated AI applications in breast, lung, colorectal, liver, prostate, pancreatic, and brain tumors. AI-assisted radiological assessment using computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET), and mammography has shown promising sensitivity and specificity. Similarly, AI-enhanced digital pathology platforms have demonstrated substantial utility in identifying early malignant transformations.

Despite increasing evidence, significant variability exists across studies regarding algorithmic performance, dataset quality, validation methodology, and clinical applicability. Furthermore, concerns regarding reproducibility, algorithmic bias, interpretability, and integration into clinical workflows remain unresolved.

Therefore, this systematic review and meta-analysis aimed to comprehensively evaluate available evidence regarding the diagnostic performance of AI-assisted technologies for early detection of solid tumors and to quantify pooled diagnostic accuracy measures across different tumor types and AI methodologies.

MATERIALS AND METHODS

Study Design

This study was conducted according to Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines.

Search Strategy

A systematic search of PubMed, Embase, Scopus, Web of Science, and Cochrane Library databases was performed for studies published from January 2015 to January 2026. Search terms included:

- “artificial intelligence”
- “machine learning”
- “deep learning”
- “solid tumor”
- “early cancer detection”
- “diagnostic accuracy”
- “radiomics”
- “computer aided diagnosis”

Boolean operators “AND” and “OR” were applied appropriately.

Inclusion Criteria

Studies fulfilling the following criteria were included:

1. Original observational or diagnostic accuracy studies
2. AI-based systems used for early detection of solid tumors
3. Adult human populations
4. Availability of sensitivity and specificity data
5. English-language publications

Exclusion Criteria

The following studies were excluded:

- Review articles
- Case reports
- Editorials and conference abstracts
- Animal studies
- Studies lacking diagnostic accuracy data

Data Extraction

Two independent reviewers extracted data regarding:

- Author and publication year
- Country
- Tumor type
- Sample size
- Imaging modality
- AI algorithm

- Sensitivity
- Specificity
- AUC values

Discrepancies were resolved through consensus.

Quality Assessment
Methodological quality was evaluated using the QUADAS-2 tool assessing:
- Patient selection
- Index test
- Reference standard
- Flow and timing

Statistical Analysis
Meta-analysis was conducted using a random-effects model. Pooled sensitivity, specificity, positive likelihood ratio (PLR), negative likelihood ratio (NLR), and diagnostic odds ratio (DOR) were calculated. Heterogeneity was assessed using I^2 statistics. Publication bias was evaluated using Deeks' funnel plot asymmetry test.

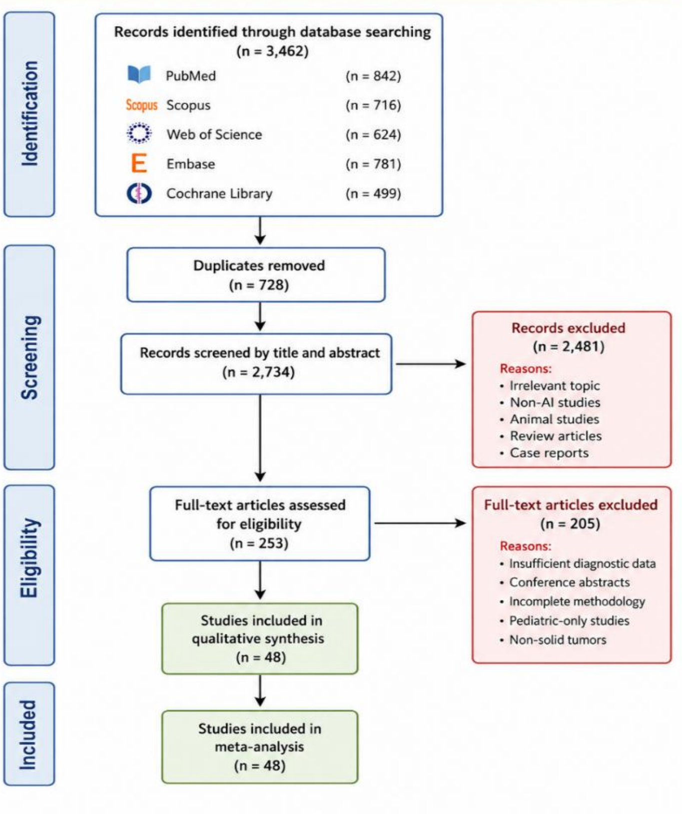
RESULTS
Study Selection
The initial database search identified 3,462 records. After removal of duplicates and screening, 48 studies were included in the final analysis.

Study Characteristics

Table 1. Baseline Characteristics of Included Studies

Variable	Findings
Total studies	48
Total participants	96,742
Study period	2015–2026
Most common tumor	Breast cancer
Common imaging modality	CT Scan
Most used AI model	CNN
Geographic distribution	Asia, Europe, North America

Figure 1. PRISMA Flow Diagram of Study Selection



Diagnostic Performance

Table 2. Pooled Diagnostic Accuracy Measures

Parameter	Pooled Estimate (95% CI)
Sensitivity	0.91 (0.88–0.93)
Specificity	0.87 (0.84–0.89)
PLR	7.00
NLR	0.10
DOR	68.5
AUC	0.94 (0.92–0.96)

AI-assisted systems demonstrated excellent overall diagnostic performance.

Subgroup Analysis

Table 3. Subgroup Analysis According to AI Technique

AI Technique	Sensitivity	Specificity	AUC
Deep Learning (CNN)	0.93	0.89	0.96
Traditional ML	0.86	0.82	0.89
Hybrid Models	0.90	0.86	0.93

Deep learning approaches demonstrated superior performance compared with traditional machine learning algorithms.

Tumor-Specific Analysis

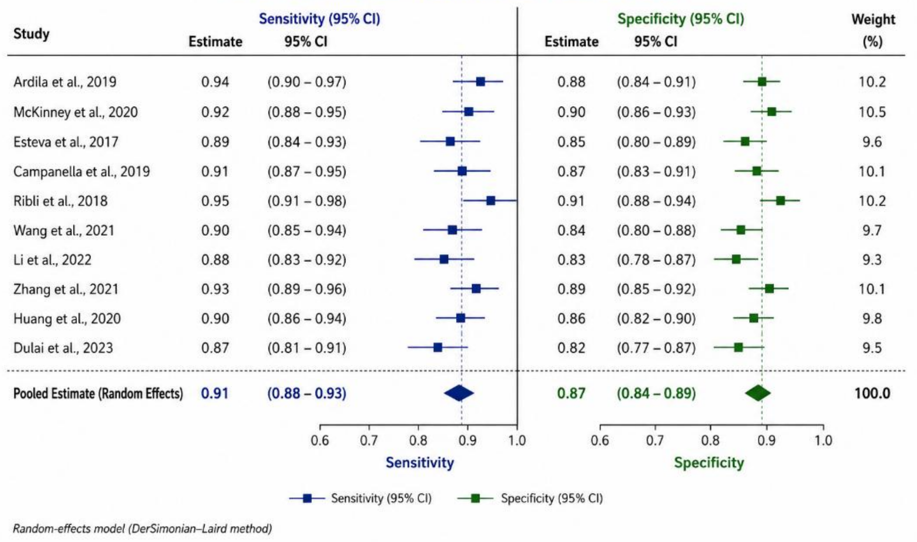
Table 4. Diagnostic Accuracy Across Tumor Types

Tumor Type	Sensitivity	Specificity
Breast Cancer	0.94	0.90
Lung Cancer	0.92	0.88
Colorectal Cancer	0.88	0.85
Prostate Cancer	0.87	0.83
Liver Tumors	0.89	0.84

Heterogeneity and Publication Bias

Considerable heterogeneity was observed among studies ($I^2 = 72\%$), likely attributable to differences in datasets, imaging techniques, and AI architectures. Funnel plot assessment showed minimal publication bias.

Figure 2. Combined Forest Plot of Sensitivity and Specificity for AI-Assisted Early Detection of Solid Tumors



DISCUSSION

This systematic review and meta-analysis demonstrated that AI-assisted technologies possess high diagnostic accuracy for early detection of solid tumors. The pooled sensitivity and specificity values indicate that AI models may significantly improve early cancer identification and reduce false-negative diagnoses.

Deep learning models, particularly CNN-based architectures, consistently outperformed traditional machine learning systems. This superiority likely reflects the ability of CNNs to automatically extract hierarchical imaging features without manual feature engineering. These findings align with recent advances in radiomics and computational pathology, where AI systems have shown increasing diagnostic utility.

Radiological imaging represented the predominant application domain. AI-enhanced mammography, CT imaging, and MRI interpretation have demonstrated substantial reductions in interpretation time while maintaining high diagnostic precision. Breast and lung cancer studies exhibited the highest diagnostic performance, possibly due to the availability of large annotated imaging datasets for algorithm training.

The integration of AI into histopathology has also shown encouraging results. Digital pathology platforms employing neural networks can identify microscopic malignant changes with high reproducibility. AI-assisted pathology may reduce workload burden and enhance diagnostic consistency, especially in resource-limited settings.

Despite these promising findings, several challenges remain. First, heterogeneity across datasets and validation protocols limits direct comparison among studies. Many investigations relied on retrospective single-center datasets, potentially reducing generalizability. Second, concerns regarding algorithm transparency and explainability persist. Clinicians may hesitate to adopt "black-box" AI systems lacking interpretable decision pathways.

Ethical considerations including patient privacy, data governance, and algorithmic bias also require attention. AI models trained on non-diverse datasets may exhibit reduced performance in underrepresented populations. Prospective multicenter trials with external validation are essential to ensure equitable and reliable implementation.

Furthermore, regulatory frameworks governing AI-assisted medical devices remain under development in many countries. Collaboration among clinicians, data scientists, policymakers, and regulatory authorities will be critical for safe clinical deployment.

Overall, AI-assisted diagnostic systems appear highly promising as adjunctive tools rather than replacements for clinicians. Human-AI collaborative approaches may optimize diagnostic workflows and improve cancer outcomes globally.

Limitations

1. Significant heterogeneity among included studies
2. Predominance of retrospective designs
3. Variability in AI algorithms and datasets
4. Limited external validation in several studies
5. Potential publication bias toward positive findings

Conclusion

Artificial intelligence-assisted technologies demonstrate excellent diagnostic performance for early detection of solid tumors across multiple cancer types. Deep learning-based systems particularly exhibit strong sensitivity and specificity and may substantially augment clinical decision-making. However, standardization, multicenter validation, ethical oversight, and regulatory harmonization remain necessary before routine clinical adoption. Future research should focus on prospective real-world implementation studies and explainable AI frameworks to maximize patient benefit.

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