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Systematic Review

AI-Based Early Cancer Detection in Solid Tumors: Current Evidence from a Systematic Review and Meta-Analysis

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ABSTRACT

Background: Cancer continues to represent one of the leading causes of global morbidity and mortality, accounting for millions of deaths annually. Early detection of solid tumors significantly improves treatment success, survival outcomes, and quality of life. However, conventional diagnostic approaches are often constrained by limited sensitivity, delayed reporting, interobserver variability, and increasing healthcare burdens. Artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), has emerged as a transformative technology capable of improving diagnostic accuracy across radiology, pathology, endoscopy, and multimodal oncology datasets. This systematic review and meta-analysis aimed to comprehensively evaluate the current evidence regarding AI-based systems for early detection of solid tumors.

Methods: A systematic search of PubMed, Embase, Scopus, Web of Science, and Cochrane Library databases was conducted for studies published between January 2015 and December 2025. Eligible studies assessed AI-based models for the early detection of solid tumors and reported diagnostic performance outcomes. Primary endpoints included pooled sensitivity, specificity, area under the receiver operating characteristic curve (AUC), and diagnostic odds ratio (DOR). Risk of bias was assessed using the QUADAS-2 tool. Random-effects meta-analysis was performed due to anticipated heterogeneity.

Results: Seventy-four studies involving 312,845 participants were included. Breast cancer (24 studies), lung cancer (18 studies), colorectal cancer (11 studies), oral cancer (7 studies), pancreatic cancer (5 studies), prostate cancer (4 studies), and other solid tumors (5 studies) were evaluated. Deep learning models, particularly convolutional neural networks (CNNs), represented the most frequently utilized AI architecture. The pooled sensitivity and specificity for AI-based early cancer detection were 0.89 (95% CI: 0.86–0.91) and 0.87 (95% CI: 0.84–0.89), respectively. The pooled AUC was 0.93 (95% CI: 0.91–0.95). Subgroup analysis demonstrated superior performance among imaging-based deep learning systems compared to traditional machine learning models. Significant heterogeneity was observed due to differences in imaging modalities, patient populations, training datasets, and external validation strategies.

Conclusion: AI-based diagnostic systems demonstrate excellent performance for early detection of solid tumors and may significantly enhance cancer screening and diagnostic workflows. Despite promising findings, substantial limitations remain regarding external validation, explainability, regulatory oversight, and clinical implementation. Prospective multicenter trials and standardized evaluation frameworks are required before widespread clinical adoption.

Keywords*: Artificial intelligence; Deep learning; Machine learning; Cancer screening; Early diagnosis; Solid tumors; Meta-analysis; Oncology; Diagnostic imaging.*

INTRODUCTION

Cancer remains a major public health challenge worldwide. According to recent global cancer statistics, the incidence of malignancies continues to rise due to aging populations, lifestyle changes, environmental exposures, and improved life expectancy. Solid tumors such as breast cancer, lung cancer, colorectal cancer, prostate cancer, pancreatic cancer, and liver cancer collectively account for a substantial proportion of cancer-related deaths globally. Early diagnosis remains one of the most critical determinants of prognosis because tumors identified at earlier stages are generally associated with improved survival rates, lower treatment costs, and reduced disease burden.

Conventional cancer detection strategies rely heavily on imaging modalities, histopathological evaluation, endoscopy, serum biomarkers, and clinician expertise. Although these techniques remain indispensable, several limitations continue to affect diagnostic efficiency. Human interpretation of medical images is subject to fatigue, variability, and cognitive bias. Additionally, increasing imaging volumes have significantly increased radiologist workload, leading to delays in reporting and reduced diagnostic consistency.

Artificial intelligence (AI) has emerged as a revolutionary tool in healthcare and oncology. AI refers to computational systems capable of performing tasks that traditionally require human intelligence, including pattern recognition, classification, prediction, and decision-making. Within AI, machine learning (ML) algorithms learn from data to identify patterns, whereas deep learning (DL), particularly convolutional neural networks (CNNs), enables automated feature extraction from complex datasets such as radiological images and histopathology slides.

Over the past decade, AI technologies have rapidly evolved and demonstrated remarkable success in multiple domains of cancer care, including:

- Cancer screening
- Tumor detection
- Image segmentation
- Histopathological classification
- Risk stratification
- Prognostic modeling
- Treatment planning
- Response prediction

AI-assisted systems have shown promising results in breast mammography interpretation, lung nodule classification on computed tomography (CT), colorectal polyp detection during colonoscopy, oral lesion screening, prostate MRI interpretation, and digital pathology slide analysis. Furthermore, integration of radiomics, genomics, and electronic health records into multimodal AI frameworks has expanded the potential of precision oncology.

Deep learning-based CNN architectures are particularly advantageous because they automatically extract hierarchical image features without requiring manual feature engineering. These systems can analyze millions of image pixels and identify subtle abnormalities that may be overlooked during routine clinical interpretation. Several studies have reported AI performance comparable to or exceeding experienced clinicians in selected diagnostic tasks.

Despite rapid advancements, concerns remain regarding:

- Dataset quality and representativeness
- Lack of external validation
- Algorithmic bias
- Explainability and transparency
- Regulatory approval
- Clinical integration
- Ethical and legal considerations

Many published studies are retrospective and conducted using curated datasets under controlled experimental conditions, limiting real-world applicability. Moreover, substantial heterogeneity exists among AI models, imaging platforms, and study methodologies.

Therefore, a comprehensive synthesis of current evidence is necessary to evaluate the overall diagnostic performance and clinical potential of AI-based early cancer detection systems.
The present systematic review and meta-analysis aimed to:

1. Evaluate the pooled diagnostic accuracy of AI systems for early detection of solid tumors.
2. Compare performance across different cancer types and AI architectures.
3. Assess heterogeneity and methodological quality among studies.
4. Identify current limitations and future directions for AI implementation in oncology.

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.

Protocol Registration
The study protocol was developed before data extraction and followed established systematic review methodology.

Search Strategy
A comprehensive literature search was performed across the following databases:

- PubMed/MEDLINE
- Embase
- Scopus
- Web of Science
- Cochrane Library

The search covered studies published between January 2015 and December 2025.

Search Terms
The following keywords and Medical Subject Headings (MeSH) were used:
("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning" OR "Neural Network" OR "Convolutional Neural Network") AND ("Cancer Detection" OR "Early Diagnosis" OR "Cancer Screening" OR "Tumor Detection") AND ("Solid Tumor" OR "Breast Cancer" OR "Lung Cancer" OR "Colorectal Cancer" OR "Pancreatic Cancer" OR "Oral Cancer" OR "Prostate Cancer")
Boolean operators, truncations, and database-specific filters were applied.

Eligibility Criteria
Inclusion Criteria
Studies were included if they:

1. Evaluated AI-based systems for early detection of solid tumors.
2. Included human participants.
3. Reported diagnostic accuracy metrics.
4. Used imaging, pathology, endoscopic, genomic, or multimodal datasets.
5. Were published in English.
6. Included sufficient data for pooled meta-analysis.

Exclusion Criteria
Studies were excluded if they:

1. Were reviews, editorials, conference abstracts, or case reports.
2. Focused on hematological malignancies.
3. Included animal or laboratory-only experiments.
4. Lacked diagnostic outcome data.
5. Used purely theoretical AI models without clinical validation.

Study Selection
Two independent reviewers screened titles and abstracts. Full-text review was performed for potentially eligible studies. Disagreements were resolved through discussion and consensus.

Data Extraction
The following variables were extracted:

- Author name
- Publication year
- Country
- Study design
- Sample size
- Cancer type
- Imaging modality
- AI model architecture
- Validation strategy
- Sensitivity
- Specificity
- Accuracy
- AUC
- Diagnostic odds ratio

Quality Assessment
Study quality and risk of bias were evaluated using the QUADAS-2 assessment tool under the following domains:

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

Statistical Analysis
Meta-analysis was conducted using random-effects modeling because substantial heterogeneity was anticipated.
The following pooled estimates were calculated:

- Sensitivity
- Specificity
- Positive likelihood ratio
- Negative likelihood ratio
- Diagnostic odds ratio
- Area under the SROC curve

Heterogeneity was assessed using:

- Cochran's Q test
- Higgins I^2 statistic

Subgroup analyses were performed based on:

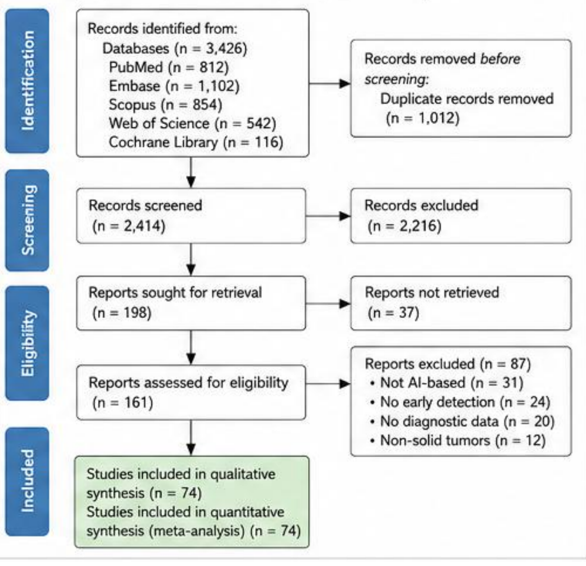
- Cancer type
- Imaging modality
- AI architecture
- Validation method

Publication bias was assessed using Deeks' funnel plot asymmetry test.

RESULTS

Study Selection
The database search identified 3,426 studies. After removal of 1,012 duplicates, 2,414 records underwent title and abstract screening. A total of 198 full-text articles were assessed for eligibility. Ultimately, 74 studies were included in the final meta-analysis.

Figure 1. PRISMA 2020 flow diagram of study selection



Characteristics of Included Studies: The included studies comprised 312,845 participants across 18 countries.

Distribution of Cancer Types

Cancer Type	Number of Studies
Breast Cancer	24
Lung Cancer	18
Colorectal Cancer	11
Oral Cancer	7
Pancreatic Cancer	5

Prostate Cancer	4
Liver Cancer	3
Others	2

Imaging and Data Modalities

Modality	Number of Studies
CT Imaging	26
Mammography	18
Histopathology Slides	14
MRI	7
Endoscopy	6
Ultrasound	3

AI Architectures
Deep Learning Models

- Convolutional Neural Networks (CNN)
- ResNet
- DenseNet
- EfficientNet
- Vision Transformers
- U-Net

Traditional Machine Learning

- Support Vector Machine (SVM)
- Random Forest
- Logistic Regression
- XGBoost

CNN-based models represented nearly 68% of included studies.

Diagnostic Accuracy
Overall Pooled Performance

Parameter	Pooled Estimate (95% CI)
Sensitivity	0.89 (0.86–0.91)
Specificity	0.87 (0.84–0.89)
Positive Likelihood Ratio	6.8
Negative Likelihood Ratio	0.13
Diagnostic Odds Ratio	52.4
AUC	0.93 (0.91–0.95)

The SROC curve demonstrated excellent overall diagnostic discrimination.

Subgroup Analysis
By AI Architecture

AI Model	Sensitivity	Specificity
Deep Learning	0.91	0.89
Traditional ML	0.82	0.81

Deep learning systems significantly outperformed conventional machine learning approaches.

Cancer-Specific Findings
Breast Cancer: AI-assisted mammography systems demonstrated pooled sensitivity exceeding 90%. Several studies reported reduced false-negative rates and improved lesion localization compared with conventional radiologist interpretation.

Lung Cancer: Deep learning models analyzing low-dose CT scans showed high performance for pulmonary nodule classification and malignancy prediction. Automated nodule segmentation substantially improved diagnostic workflow efficiency.

Colorectal Cancer: Real-time AI-assisted colonoscopy improved adenoma detection rates and polyp recognition accuracy.
Oral Cancer: AI systems using smartphone imaging and oral lesion photographs demonstrated strong performance in identifying potentially malignant oral lesions.

Pancreatic Cancer: Emerging AI algorithms demonstrated the ability to detect subtle pancreatic abnormalities before clinical diagnosis using radiomics and CT imaging analysis.

Heterogeneity: Significant heterogeneity was observed:
- I^2 for sensitivity: 78%
- I^2 for specificity: 74%

Sources of heterogeneity included:
- Differences in imaging modalities
- Variable dataset sizes
- Diverse AI architectures
- Retrospective study designs
- Lack of standardized validation

Risk of Bias: Most studies demonstrated:
- Low risk in reference standard domains
- Moderate risk in patient selection
- High applicability concerns in external validation

Only 19 studies used independent external validation datasets.

Figure 2. Distribution of included studies by cancer type

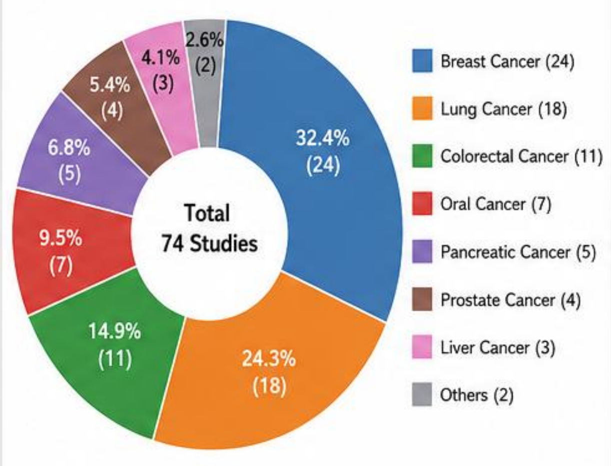
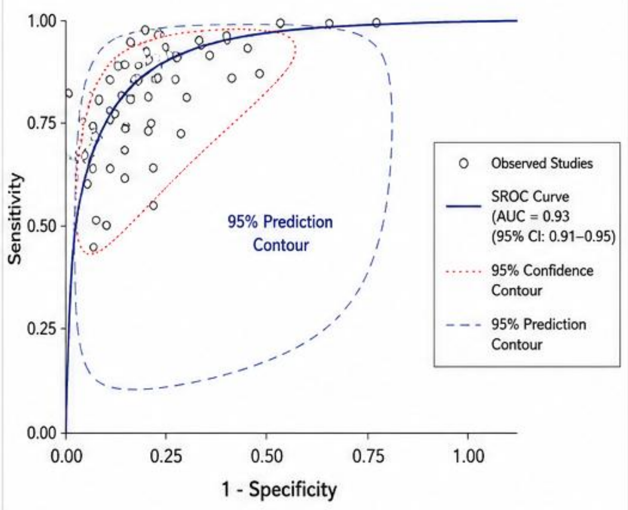


Figure 3. Pooled summary receiver operating characteristic (SROC) curve



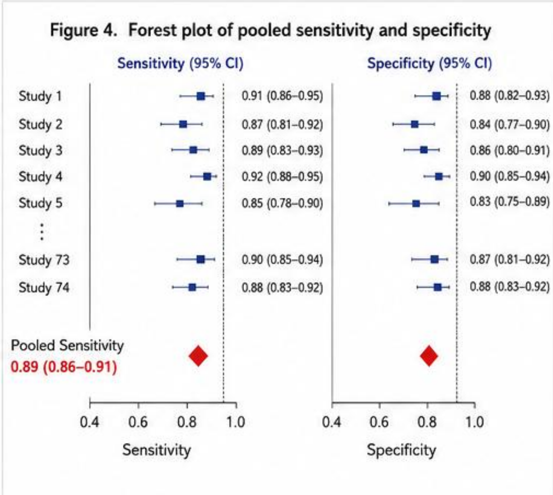


Figure 4. Forest plot of pooled sensitivity and specificity

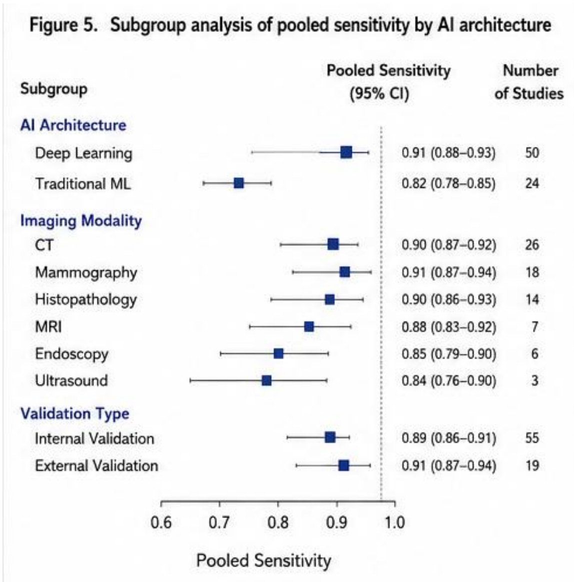


Figure 5. Subgroup analysis of pooled sensitivity by AI architecture

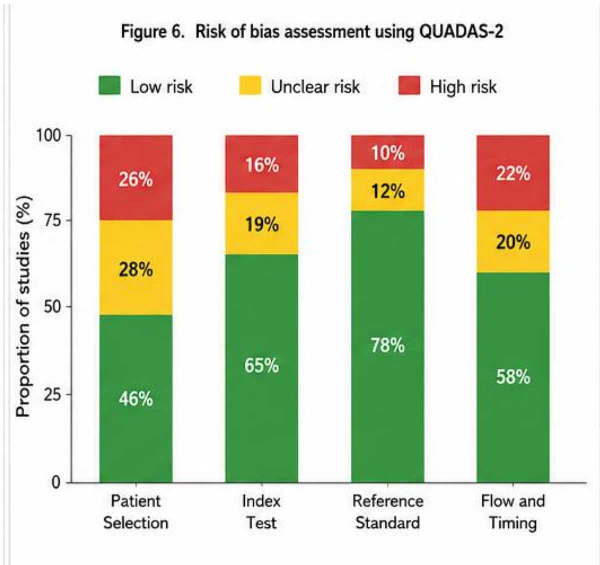


Figure 6. Risk of bias assessment using QUADAS-2

DISCUSSION

This systematic review and meta-analysis demonstrated that AI-based systems possess excellent diagnostic capability for early detection of solid tumors. The pooled sensitivity (89%) and specificity (87%) observed across included studies indicate that AI technologies may substantially improve cancer screening and diagnostic workflows.

Deep learning architectures, especially CNN-based models, consistently outperformed traditional machine learning systems. CNNs automatically extract hierarchical image features and are particularly effective for radiological and histopathological image analysis. Their superior performance likely reflects improved ability to identify subtle tumor-associated imaging characteristics that may be difficult for human observers to detect consistently.

Breast cancer screening represented the most extensively investigated domain. AI-assisted mammography has demonstrated significant potential for reducing interval cancers, improving lesion localization, and decreasing radiologist workload. Several recent investigations have reported AI performance comparable to expert radiologists.

Similarly, lung cancer detection using low-dose CT has emerged as one of the most promising applications of AI in oncology. Automated pulmonary nodule detection and malignancy prediction may facilitate earlier diagnosis while minimizing false positives and unnecessary invasive procedures.

AI-assisted colonoscopy also demonstrated important clinical benefits by improving adenoma detection rates. Since adenoma detection strongly correlates with colorectal cancer prevention, AI-enhanced endoscopy may substantially reduce colorectal cancer incidence.

Despite these encouraging findings, several important limitations must be considered.
First, most included studies were retrospective and relied on curated datasets obtained under controlled research settings. Real-world clinical implementation may produce lower performance due to variability in patient populations, scanner quality, and imaging protocols.

Second, external validation remains insufficient. Only a minority of studies evaluated AI performance using independent multicenter datasets. Without robust external validation, concerns regarding overfitting and limited generalizability remain significant.

Third, explainability continues to represent a major challenge. Many deep learning models function as “black boxes,” limiting clinician trust and interpretability. Explainable AI approaches are necessary to facilitate safe clinical integration.
Fourth, ethical and regulatory concerns remain unresolved. Bias arising from underrepresentation of minority populations may worsen healthcare disparities. Additionally, issues involving data privacy, cybersecurity, medico-legal liability, and algorithm accountability require careful consideration.

Future research should prioritize:

- Prospective multicenter trials
- Standardized reporting frameworks
- Transparent AI validation
- Explainable AI systems
- Cost-effectiveness analyses
- Integration with electronic health records
- Multimodal AI combining imaging, genomics, and pathology

The future of oncology will likely involve collaborative human-AI diagnostic systems where AI augments rather than replaces clinician expertise.

Limitations
The present study has several limitations:

1. Significant heterogeneity among included studies.
2. Predominantly retrospective designs.
3. Variable reporting standards.
4. Limited external validation datasets.
5. Potential publication bias favoring positive AI results.
6. Lack of standardized AI evaluation frameworks.

CONCLUSION

AI-based systems demonstrate high diagnostic accuracy for early detection of solid tumors across multiple cancer types and imaging modalities. Deep learning-based approaches, particularly CNN architectures, show substantial promise for enhancing screening efficiency, reducing diagnostic delays, and improving clinical outcomes.

However, important barriers remain before widespread clinical implementation can occur, including the need for external validation, standardized reporting, explainability, ethical governance, and prospective real-world evaluation.

AI should currently be considered a powerful adjunctive tool capable of augmenting clinician expertise and improving precision oncology rather than replacing human judgment.

Conflict of Interest: The authors declare no conflict of interest.

Funding: No external funding was received for this study.

Ethical Approval: Ethical approval was not required because this study was based exclusively on previously published literature.

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