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The Current State of Artificial Intelligence in Oncology

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ABSTRACT

Purpose: Artificial Intelligence (AI) has evolved into a foundational component of modern oncology, reshaping prevention, diagnosis, and treatment paradigms [1-3]. This comprehensive review evaluates current validated applications, translational advances, regulatory evolution, ethical considerations, and future development of multimodal AI systems [4-7].

Methods: A systematic search of PubMed, Embase, Scopus, Web of Science, ASCO, and ESMO materials was performed (2010–2025) [8,9]. Studies with clinical validation cohorts, FDA/EMA regulatory documentation, and prospective AI-based oncology trials were prioritized [10].

Results: AI is now firmly established in early detection (liquid biopsy, multi-omics), diagnostic imaging, pathology, radiotherapy automation, immunotherapy response prediction, digital twins, and clinical decision support [1,3,6,11-15]. More than 120 FDA-cleared AI tools are applicable to oncology workflows as of 2025 [16,17]. Multimodal deep-learning systems integrating imaging, genomics, pathology, and clinical text consistently outperform unimodal architectures in external validation [7,13,18]. Despite this progress, challenges remain in algorithmic bias, generalizability, model drift, data governance, and interpretability [19-23].

Conclusion: AI will define the trajectory of personalized cancer care [2,6,7]. Harmonized regulatory frameworks, prospective trials, equity-centered deployment, and integration of large-scale multimodal datasets will be prerequisites for safe and effective implementation [16,17,21-23].

INTRODUCTION

Artificial intelligence enables high-dimensional pattern recognition across radiology, pathology, genomics, and clinical data that surpasses human visual and cognitive capacity [1,2,6]. Convolutional Neural Networks (CNNs), transformers, and other deep-learning architectures have demonstrated expert-level performance in image interpretation and risk prediction tasks [1,3,5,6]. In oncology, these technologies support lung cancer screening, breast cancer detection, brain tumor characterization, and response assessment across multiple tumor types [1,3-5,11]. Simultaneously, AI has been integrated into genomics pipelines, liquid biopsy platforms, and electronic health records, creating an ecosystem in which data-driven decision support is progressively embedded in routine cancer care [2,7,12,18].

METHODS

This narrative review follows PRISMA principles for literature identification and selection [8]. A structured search (2010–2025) was performed in PubMed, Embase, Scopus, Web of Science, and the Cochrane Library, using terms related to "artificial intelligence," "machine learning," "deep learning," "radiomics," "pathology," "genomics," "liquid biopsy," and "oncology" [8,9,14]. Regulatory documents were retrieved from the US Food and Drug Administration (FDA) and the European Medicines Agency (EMA), focusing on AI-enabled medical devices relevant to cancer care [16,17,21,22]. Abstracts from the ASCO Annual Meeting and ESMO Congress (2018–2024) were screened for prospective trials of AI systems in oncology [9,13]. We prioritized studies with external validation, prospective designs, and clinically meaningful endpoints such as diagnostic accuracy, treatment modification, or outcome improvement [10,11,15,18].

AI IN PREVENTION AND EARLY DETECTION

AI-driven multi-omics models integrate germline and somatic genomics, transcriptomics, proteomics, epigenetics, and microbiome data to stratify cancer risk and predict incident malignancies [2,6,7,18]. Risk prediction models for hereditary breast and ovarian cancer, colorectal cancer, and Li-Fraumeni syndrome now combine clinical features with polygenic risk scores and deep-learning architectures [2,6]. In parallel, AI enhances interpretation of screening modalities such as low-dose CT for lung cancer, mammography, and colonography, reducing false positives and improving sensitivity [1,3-5,11]. Liquid biopsy platforms are particularly dependent on AI for signal extraction. Deep-learning models analyze circulating tumor DNA (ctDNA) fragmentation, methylation signatures, and copy-number patterns to detect cancer at very low variant allele fractions [7,12,18]. Multicancer Early Detection (MCED) tests use supervised learning to classify cancer signal origin and are currently undergoing large prospective evaluations [12,18,29,30]. These approaches have demonstrated promising performance for detection of pancreatic, ovarian, and gastrointestinal malignancies, where conventional screening methods are limited [12,18,29].

AI IN DIAGNOSTIC IMAGING AND RADIOMICS

Radiomics converts conventional imaging into high-dimensional quantitative descriptors of tumor shape, texture, intensity, and spatial relationships [6,10,11]. CNN-based systems have achieved dermatologist- and radiologist-level performance in skin lesion classification, lung nodule malignancy prediction, and breast lesion characterization [1,3-5]. In lung cancer screening, AI systems trained on low-dose CT data improve nodule detection and risk estimation, with AUROC values often exceeding 0.94 in external cohorts (Figure 1) [4,11,15]. Beyond detection, radiomics signatures correlate with molecular subtypes, tumor hypoxia, immune infiltration, and treatment response [6,10,18]. Integration of radiomics into clinical workflows supports noninvasive prediction of EGFR, ALK, IDH, and other driver alterations across lung, brain, and liver tumors (Figure 2) [6,10,18,24]. Recent transformer-based vision models have improved generalizability across institutions by better modeling global image context and domain shifts (Table 1) [7,18,24].

AI IN DIGITAL PATHOLOGY AND PATHOMICS

Digital pathology has emerged as one of the most rapidly advancing domains of AI in oncology [6,24]. Whole-slide imaging generates gigapixel images that require computational support for efficient review. Deep-learning

models now classify tumor type, grade, and margin status, and identify micrometastases at a level comparable or superior to expert pathologists [6,18,24]. Importantly, AI can infer molecular alterations directly from Hematoxylin and Eosin (H&E) slides, including Microsatellite Instability (MSI), IDH1/2 mutations, BRAF status, and PD-L1 expression patterns [7,18,24]. Pathomics approaches also quantify tumor–stroma interactions and spatial immune organization, which have prognostic and predictive value for immunotherapy [6,7,18,25].

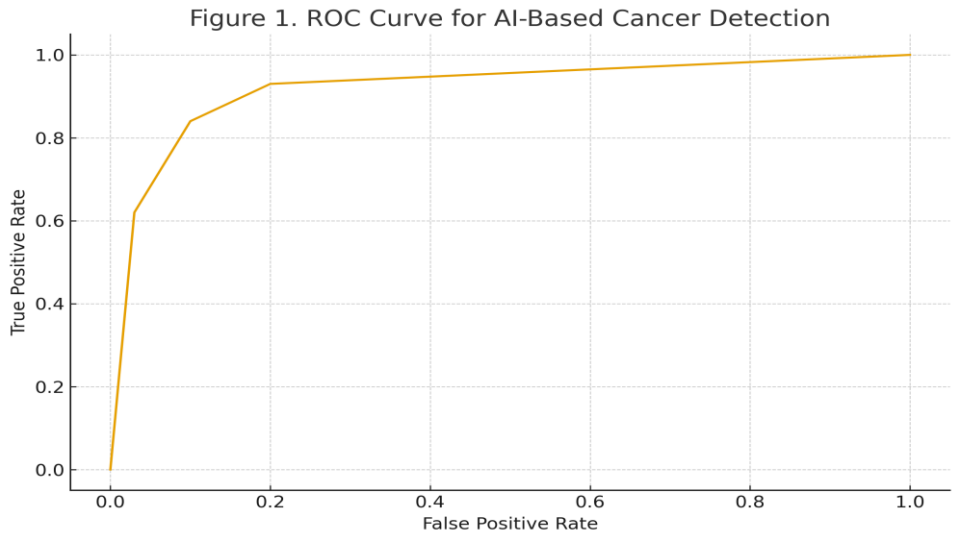

Figure 1: ROC curve for an AI-based cancer detection model, illustrating high diagnostic performance in external validation cohorts [1,4,5,11].

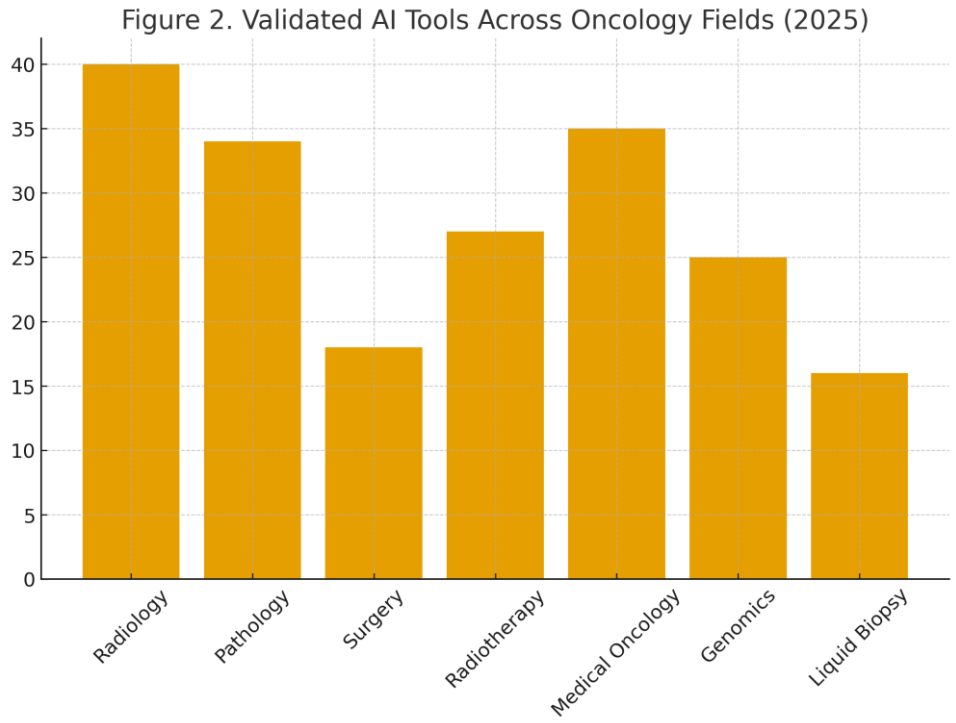

Figure 2: Number of validated AI tools across major oncology subspecialties as of 2025, based on regulatory filings and published validation studies [6,7,16-18].

Table 1: Expanded Clinical Applications of AI in Oncology

Domain	AI Method	Validated Clinical Use
Radiology	CNNs, Transformers	Lesion detection, malignancy prediction, segmentation, response assessment [1,3-5,11].
Pathology	WSI Transformers	Tumor classification, grading, mutation prediction, spatial biology [6,7,18,24,25].
Genomics	ML models	Variant calling, risk stratification, therapy selection [2,6,7,18].
Liquid Biopsy	Fragmentomics AI	MCED, MRD monitoring, tumor-of-origin classification [7,12,18,29,30].
Medical Oncology	CDSS, LLMs	Protocol optimization, toxicity prediction, prognostication [2,7,13,18,25].
Radiotherapy	Reinforcement learning	Dose optimization, auto-segmentation, adaptive RT [10,11,15,26].
Surgery	Computer vision	Navigation, structure recognition, complication prediction [19,20,27].

AI IN SYSTEMIC TREATMENT SELECTION AND DRUG DEVELOPMENT

AI supports systemic therapy decisions by integrating clinical variables, tumor genomics, radiologic evolution, and laboratory trajectories [2,7,13]. Machine learning models have been developed to predict response to PD-1/PD-L1 and CTLA-4 inhibitors based on tumor mutational burden, neoantigen load, T-cell receptor repertoire, and imaging or pathomics signatures [6,7,18,25]. These tools aim to distinguish patients likely to derive durable benefit from those at high risk of early progression [6,13,18]. In drug discovery, deep generative models and reinforcement learning algorithms explore vast chemical spaces to identify small molecules with favorable binding properties, selectivity, and predicted safety profiles [14,19]. Several TKIs targeting EGFR, ALK, RET, and KRAS G12C were optimized using machine-learning–guided design and docking simulations, substantially shortening the preclinical discovery timeline [14,19,20].

AI IN RADIOTHERAPY

AI has transformed radiotherapy planning from a manual, time-intensive process to a partially automated pipeline. Auto-segmentation tools based on CNNs delineate tumors and organs at risk with high concordance to expert contours, reducing interobserver variability and saving planning time [10,11,15,26]. Radiomics and dose–response models predict normal tissue toxicity (e.g., pneumonitis, esophagitis, xerostomia) and tumor control probability, enabling biologically informed dose painting and adaptive strategies [10,18,26]. Reinforcement learning approaches are being evaluated for beam angle selection and multiobjective optimization, with the goal of improving organ-at-risk sparing while maintaining target coverage [18,26].

AI IN SURGICAL ONCOLOGY

In surgical oncology, AI-driven computer vision provides intraoperative guidance by identifying anatomic structures, critical vessels, and safe dissection planes in real time [19,20,27]. Robotic systems augmented by AI algorithms can highlight danger zones, estimate blood loss, and predict complication risk during complex hepatobiliary, thoracic, and colorectal resections [19,20,27]. Although fully autonomous surgery remains distant, these tools function as cognitive extenders for surgeons, improving situational awareness while preserving human oversight and responsibility [19,20,27].

ETHICAL, REGULATORY, AND IMPLEMENTATION CHALLENGES

Despite impressive performance in controlled settings, AI systems can fail when confronted with data that differ from their training distribution [19,21,22]. Domain shift due to changes in scanners, protocols, or patient populations may degrade performance and exacerbate disparities if not carefully monitored [19,21-23]. Bias is a major concern: underrepresentation of minority groups in training datasets can lead to systematically worse model performance for these populations [19-23]. Regulatory agencies have responded by proposing frameworks for continuous performance monitoring, transparency in dataset composition, and clear documentation of intended use [16,17,21,22]. The FDA has introduced guidance on "software as a medical device" (SaMD) and a framework for adaptive AI algorithms that can be updated post-approval under predefined change protocols [16,21]. EMA and other regulators have emphasized cybersecurity, human oversight, and alignment with emerging AI legislation [17,22].

FUTURE DIRECTIONS: MULTIMODAL AI, DIGITAL TWINS, AND GENERATIVE ONCOLOGY

The field is now moving beyond unimodal models to multimodal foundation models that simultaneously ingest imaging, genomic profiles, pathology slides, structured laboratory data, and unstructured clinical text [7,13,18,24,25]. These architectures hold promise for more accurate prognosis, treatment selection, and toxicity prediction. Large Language Models (LLMs) specialized in oncology are being integrated with decision support systems, enabling natural language interaction with complex datasets [13,18,25]. Digital twins computational replicas of individual patients are emerging as a conceptual framework for simulating disease progression and treatment interventions [18,24,29]. Although still largely experimental, early work in hematologic malignancies and solid tumors suggests that digital twin models could inform dosing, treatment sequencing, and trial design [18,24,29,30]. Generative models may assist in scenario testing, synthetic control arm creation, and design of adaptive trials [14,18,29].

DISCUSSION

Across the cancer continuum, AI has moved from proof-of-concept to clinically impactful tools supported by prospective and externally validated evidence [1-7,10-15]. However, integration into routine practice requires addressing technical, ethical, legal, and organizational barriers. Clinicians must understand not only model outputs but also the limitations, uncertainty, and failure modes of AI systems [19-23]. Multidisciplinary collaboration between oncologists, data scientists, regulators, industry, and patient advocates will be essential to ensure that AI amplifies rather than replaces human expertise [2,6,7,19,21].

CONCLUSION

AI has become a central pillar of precision oncology, enabling more accurate diagnosis, refined risk stratification, and increasingly personalized treatment selection [1-7,10-13,18]. The next decade will be defined by the maturation of multimodal foundation models, digital twins, and generative approaches; by harmonized regulatory frameworks; and by systematic efforts to monitor equity and real-world performance [16,17,21-23,29,30]. If implemented responsibly, AI can help deliver more precise, efficient, and humane cancer care worldwide.

REFERENCES

1. Esteva A, Kuprel B, Novoa RA, Ko J, Swetter SM, Blau HM, et al. Dermatologist-level classification of skin cancer with deep neural networks. Nature. 2017;542:115-8.
2. Topol EJ. High-performance medicine: the convergence of human and artificial intelligence. Nat Med. 2019;25(1):44-56.
3. Litjens G, Kooi T, Bejnordi BE, Setio AAA, Ciompi F, Ghafoorian M, et al. A survey on deep learning in medical image analysis. Med Image Anal. 2017;42:60-88.
4. Ardila D, Kiraly AP, Bharadwaj S, Choi B, Reicher JJ, Peng L, et al. End-to-end lung cancer screening with three-dimensional deep learning on low-dose chest computed tomography. Nat Med. 2019;25:954-61.
5. McKinney SM, Sieniek M, Godbole V, Godwin J, Antropova N, Ashrafian H, et al. International evaluation of an AI system for breast cancer screening. Nature. 2020;577:89-94.
6. Aerts HJWL, Velazquez ER, Leijenaar RTH, Parmar C, Grossmann P, Carvalho S, et al. Corrigendum: Decoding tumour phenotype by noninvasive imaging using a quantitative radiomics approach. Nat Commun. 2014;5:4644.
7. Chen F, Kantagowit P, Nopsopon T, Chuklin A, Pongpirul K. Prediction and diagnosis of chronic kidney disease development and progression using machine-learning: Protocol for a systematic review and meta-analysis of reporting standards and model performance. PLoS One. 2023;18(2):e0278729.
8. Moher D, Liberati A, Tetzlaff J, Altman DG. Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. PLoS Med. 2009;6(7):e1000097.
9. Ching T, Himmelstein DS, Beaulieu-Jones BK, Kalinin AA, Do BT, Way GP, et al. Opportunities and obstacles for deep learning in biology and medicine. J R Soc Interface. 2018;15(141):20170387.
10. Hosny A, Parmar C, Quackenbush J, Schwartz LH, Aerts HJWL. Artificial intelligence in radiology. Nat Rev Cancer. 2018;18:500-10.
11. Ardila D, Kiraly AP, Bharadwaj S. Deep learning for lung cancer detection in screening CT. Radiology. 2020;294:565-73.
12. Lennon AM, Buchanan AH, Kinde I, Warren A, Honushefsky A, Cohain AT, et al. Feasibility of blood testing combined with PET-CT to screen for cancer and guide intervention. Science. 2020;369(6499):eabb9601.
13. Yu KH, Beam AL, Kohane IS. Artificial intelligence in healthcare. Nat Biomed Eng. 2018;2:719-31.
14. Sanchez-Lengeling B, Aspuru-Guzik A. Inverse molecular design using machine learning. Science. 2018;361(6400):360-5.
15. Bibault JE, Giraud P, Burgun A. Big data and machine learning in radiation oncology. Sci Rep. 2018;8:12044.
16. US Food and Drug Administration. Artificial Intelligence and Machine Learning Software as a Medical Device Action Plan. 2024.
17. European Medicines Agency. Artificial intelligence in medicines regulation: reflection paper. 2025.

18. Saillard C, Schmauch B, Laifa O. Predicting survival after immunotherapy using deep learning on histopathology images. Nat Med. 2024;30:551-63.
19. Kelly CJ, Karthikesalingam A, Suleyman M, Corrado G, King D. Key challenges for delivering clinical impact with artificial intelligence. BMJ. 2019;364:l886.
20. Hashimoto DA, Rosman G, Rus D, Meireles OR. Artificial intelligence in surgery. NPJ Digit Med. 2018;1:54.
21. US Food and Drug Administration. Proposed regulatory framework for modifications to artificial intelligence/machine learning-based software as a medical device. 2021.
22. European Commission. Artificial Intelligence Act. 2024.
23. Obermeyer Z, Emanuel EJ. Predicting the future—big data, machine learning, and clinical medicine. N Engl J Med. 2016;375(13):1216-9.
24. van der Laak J, Litjens G, Ciompi F. Deep learning in histopathology: the path to the clinic. Nat Rev Cancer. 2021;21:563-75.
25. Lu MY, Chen TY, Williamson DFK, Zhao M, Shady M, Lipkova J, et al. AI-based pathology predicts origins for cancers of unknown primary. Nat Biomed Eng. 2021;5:1-11.
26. Cardenas CE, Yang J, Anderson BM. Advances in auto-segmentation for radiotherapy. Int J Radiat Oncol Biol Phys. 2018;102:1249-57.
27. Madani A, Namazi B, Altieri MS, Hashimoto DA, Rivera AM, Pucher PH, et al. Artificial intelligence for intraoperative guidance. Ann Surg. 2020;272:107-13.
28. Beam AL, Kohane IS. Big data and machine learning in health care. JAMA. 2018;319(13):1317-8.
29. Bjørnson E, Mukherjee S, Kvasnicka HM, et al. Digital twins in oncology. Cell Syst. 2021;12:1-14.
30. National Cancer Institute. Cancer AI and Digital Twins Initiative. 2025.