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Review Article

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Transformative Role of Artificial Intelligence in Cancer Detection, Diagnosis, and Treatment Planning: A Narrative Review

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ABSTRACT

Background: Even with the current breakthroughs in detection and treatment, cancer continues to be a leading source of disease and mortality across the world. Conventional approaches face limitations such as late detection, misdiagnosis, high treatment costs, and treatment resistance.

Objective: To examine the role of artificial intelligence in diagnosing cancer, determining its type, developing treatments, and improving the personalization of cancer treatment through advanced models and technologies.

Methods: This narrative review draws on a search conducted across major databases, including PubMed, Scopus, Web of Science, IEEE Xplore, and Google Scholar, using keywords like "Artificial Intelligence," "Deep Learning," "Oncology," "Radiomics," and "Explainable AI." Reference lists of key papers were also manually checked to catch any relevant studies the database search might have missed. Only studies published between January 2015 and July 2026 were considered, covering both the foundational AI-in-oncology literature and the most recent developments in explainable AI. Studies published in peer-reviewed journals or conference proceedings, those focusing on AI, ML, or DL applications in cancer detection, diagnosis, prognosis, or treatment planning, reporting diagnostic performance, model architecture, or clinical validation outcomes, or having articles published in English were included. Studies unrelated to oncology or cancer-specific applications, conference abstracts, editorials, or opinion pieces without substantive data, duplicate publications, and studies with insufficient methodological details were excluded.

Results: This review indicates that artificial intelligence acts as a crucial aspect for the detection, classification, diagnosis, and treatment planning of cancer. Deep learning approaches, including Convolutional neural networks, and machine learning approaches such as random forests and support vector machines performed outstandingly in analyzing complex data such as imaging, pathological, clinical, and genomic data. Artificial intelligence-driven systems have the potential to improve diagnostic accuracy, enable early cancer detection, streamline radiology and pathology workflows, and support personalized medicine.

Conclusion: It can be seen that artificial intelligence has emerged as an extremely powerful tool in modern-day oncology and possesses the potential to bring about revolutionary changes in the way we identify, diagnose, and treat cancers. The use of artificial intelligence in combination with clinical expertise can help deliver much more accurate and customized treatment of cancer.

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INTRODUCTION

Cancer is the leading cause of death worldwide. It has been estimated by GLOBOCAN 2020 that nearly 10 million deaths from cancer were recorded globally, while about 19.3 million new cases of cancer have been reported.[1] According to WHO, cancer occurs due to the conversion of normal cells to cancerous cells. It has many causes that range from genetic factors, environmental factors, viruses, and lifestyle-related factors.[2] Breast Cancer is mainly caused by mutations in genes such as BRCA1 and BRCA2. The diagnosis of breast cancer usually involves mammography, biopsy, and several genetic tests.[3]

Lung cancer can be genetic, and several environmental factors can trigger mutations. The genetic mutations in several genes such as EGFR, KRAS, ALK, and TP53 contribute to the development and progression of lung cancer.[4] Blood cancer, or leukemia, is a complex type of cancer that involves leukemia, lymphomas, and Myeloma. Changes in some genes that help regulate blood cell growth can lead to abnormal production of white blood cells, severely affecting our immune system.[5] Gastric Cancer is actually a series of malignant tumors that arise in the different organs of the digestive system, including the stomach, colon, rectum, esophagus, and rectum. Mutations in genes like APC, KRAS, and TP53 lead to cancer. Dysfunction of the mismatch repair mechanism also causes this cancer. Not only genetic but lifestyle factors like diet, smoking, and use of alcohol may also have a worse impact on gastric cancers.[6]

Prostate Cancer: One of the common types of cancer affecting men is prostate cancer, developing in the prostate gland. The symptoms of this illness are difficulties with urination and increased urination frequency, as well as pelvic pain. In addition, some of the genes involved in the process of developing breast and ovarian cancer, namely BRCA1, BRCA2, and TP53, were found to be related to certain forms of prostate cancer.[7] Brain Cancer Mainly in the mutations of TP53 gene, EGFR, and IDH1 trigger Brain cancer. Each of these genes plays a role in tumor formation and progression.[8] Skin cancer can mostly develop due to genetic mutations and environmental factors like exposure to UV rays. Mutations in genes like BRAF, TP53, and CDKN2A can cause skin cancer.[9]

Diagnosis, supported by radiology, pathology, and biopsy, relies on physicians' interpretation; therefore, different specialists may interpret the same results differently, and early-stage changes may go unnoticed. Many Screening methods miss small and hidden tumors until the disease has already progressed, making further treatment more difficult.[10] False positives and negatives are not uncommon. False positives will cause additional stress and cost for the patient, and false negatives mean no treatment for cancer although it exists.

It is challenging for precision medicine to be scalable because each patient will have their own genetic and molecular makeup, and so two patients suffering from the same form of cancer can react completely differently to the same treatment, but personalization is costly. Resistance to drugs occurs because of the changes that take place in cancer cells due to the effects of chemotherapy, targeted therapy, and hormonal therapy.[11] The technology of artificial intelligence has become increasingly innovative in the field of oncology. With an increase in the amount of available imaging, computing power, and data, AI allows physicians to deal with complicated clinical data more quickly and systematically and identify patterns that facilitate early detection.

Machine Learning enables algorithms to learn from data, thereby identifying patterns that can be used to predict the progression and choose the most effective treatment.[12] Deep Learning is one of the branches of ML based on neural networks and is especially efficient at analyzing visual medical data (CT, MRI, mammography, and pathologic slides). Convolutional Neural Networks have proven their high efficiency, being able to achieve up to 99% accuracy in the classification of brain, breast, lung, and cervical cancers based on large public data sets.[13]

Computer Vision enables the analysis of visual medical data, thus locating tumors and assisting in surgery. Computer-aided diagnosis (CADx) systems in gastroenterological oncology have managed to achieve a higher level of accuracy from 78% to almost 90%.[14] Natural language Processing (NLP) is used to derive insights from unstructured text-based data, including pathology reports and medical papers. Radiomics involves deriving quantitative information (including size, shape, and texture) using imaging data such as CT, MRI, and PET scans. The approach provides insight into tumor staging as well as treatment response prediction. Digital pathology involves the use of AI to analyze whole-slide images (WSIs) to determine the tumor subtype and mutation, and make prognosis predictions based on tissue morphology.[15] This review is not exhaustive but aims to produce representative, high-impact studies across major cancer types and AI modalities. It examines the role of artificial intelligence in diagnosing cancer, determining its type, developing

treatments, and improving the personalization of cancer treatment through advanced models and technologies.

METHODS

This review draws on a search conducted across major databases, including PubMed, Scopus, Web of Science, IEEE Xplore, and Google Scholar, using keywords like "Artificial Intelligence," "Deep Learning," "Oncology," "Radiomics," and "Explainable AI." Reference lists of key papers were also manually checked to catch any relevant studies the database search might have missed. Only studies published between January 2015 and July 2026 were considered, covering both the foundational AI-in-oncology literature and the most recent developments in explainable AI.

Studies published in peer-reviewed journals or conference proceedings, those focusing on AI, ML, or DL applications in cancer detection, diagnosis, prognosis, or treatment planning, reporting diagnostic performance, model architecture, or clinical validation outcomes, or having articles published in English were included in the review. Studies unrelated to oncology or cancer-specific applications, conference abstracts, editorials, or opinion pieces without substantive data, duplicate publications or studies with insufficient methodological detail, and non-English language articles without available translation were excluded.

Title and abstract screening were conducted to determine relevance, followed by full-text assessment of shortlisted papers. In cases of any disagreement regarding eligibility criteria, discussion among the authors took place, while the review process was informed by systematic-review conventions where practical. Since this is a review of already published literature and not a study involving actual patients, the quality of each included paper was judged based on how clearly its methodology was explained, how reliable and well-sourced its dataset was, and whether its results were properly validated. This helped maintain a fair and consistent comparison across the different types of studies covered in this review.

1. Fundamentals of AI in Oncology

A huge amount of data is produced by cancer treatment every day, including radiological images, pathology images, sequencing data, laboratory tests, and years of medical history of the patients. There is no way for a doctor to analyze that much data within the time frame needed to recognize all patterns and connections. It is in this very gap that artificial intelligence came into play, and in the last ten years, it has quietly evolved from a research tool to a technology that is actively changing the face of cancer diagnostics, staging, and treatment. The development was accurately depicted by Elemento et al.; AI has now become a part of the routine work in oncology with improved prediction models and increased precision of treatment.[16]

Similar ideas were put forward by Eric Topol, who emphasized that the real potential of AI in medicine does not lie in having a computer instead of a doctor, but in collaboration between the two parties, resulting in what he called "high-performance medicine," with a computer making decisions based on pattern recognition and a doctor having final decision-making ability.[17] Table 1 summarizes major AI techniques used in oncology.

Machine Learning in Cancer Research

Machine learning (ML) forms the foundation of everything else; ML models learn patterns from the data without having to be explicitly programmed. In the context of cancer research, it implies the prediction of risk, classification of cancers, prognosis prediction, and the discovery of biomarkers. There are certain algorithms that learn from labeled data sets (supervised learning), such as Support Vector Machines, Random Forests, and XGBoost, since genomics/radiomics has labeled outcomes and hence they fit well here. Then some algorithms uncover underlying structures in the unlabeled data sets (unsupervised learning), which have proven to be beneficial in the case of finding novel cancer subtypes and stratification of cases not belonging to the already defined subtypes. The same benefits have been observed in radiation oncology.[18]

Deep Learning

This is further enhanced by deep learning (DL), which learns its own features from unprocessed data without the need for human hand-engineering. This matters enormously for medical images, pathology slides, and multi-omics datasets, which are too complex for manual feature extraction to capture everything relevant. Convolutional Neural Networks (CNNs) are the workhorse here; they're what allow a computer to look at an MRI, CT scan, mammogram, or a whole-slide pathology image and pick out the spatial patterns that indicate malignancy. This strategy beats previous methods because deep networks create their own hierarchy of features rather than depending on manually created ones, as detailed by LeCun, Bengio, and Hinton's seminal review of the area.[19] The clearest oncology demonstration of this came when Esteva and colleagues trained a deep neural network to classify skin lesions at a level matching board-certified

dermatologists, a result that reframed what many thought was possible for AI in visual diagnosis.[20]

Computer Vision

Computer vision is the applied layer that sits on top of deep learning for anything image-based: detecting tumors, outlining lesion boundaries, and tracking how a disease progresses over serial scans. Segmentation, precisely marking where a tumor starts and stops, is one of its most clinically important jobs, since accurate boundaries are essential for radiotherapy planning.

Isensee et al. introduced nnU-Net, a self-configuring segmentation framework that has become something of a benchmark here, achieving state-of-the-art results across a wide range of biomedical imaging tasks with essentially no manual tuning. Similar improvements have been made in digital pathology with the direct application of weakly supervised deep learning to whole-slide images, which allows systems to achieve near-pathologist accuracy while significantly reducing the effort required to scan each slide individually.[21]

Natural Language Processing

A huge share of oncology information pathology reports, radiology notes, clinical narratives exists only as free text, which is where natural language processing (NLP) comes in. Specialized language models such as BioBERT and ClinicalBERT were built specifically to parse dense biomedical terminology, and more recently, general-purpose large language models have entered the conversation. Lee et al. discussed the emerging role of GPT -4 in medicine, as it can play a potential role in clinical documentation, and it might significantly reduce the administrative load. Similarly, Singhal et al. introduced Med-PaLM, which is a large language model and can achieve high performance in medical Assessment and clinical interpretation tasks.[22]

Radiomics, Pathomics, and Multi-Omics

Radiomics extracts huge amounts of quantitative data on texture, shape, and heterogeneity from medical images that may highlight information on tumor characteristics not visible to the naked eye. Radiomics has been called the link between imaging and personalized medicine and has proven itself in its prognostic and predictive utility. The pathology counterpart – pathomics – extracts similar data from tissue samples. The combination of radiomics and pathomics data together with genomic (multi-omic) data gives a much better view of a tumor compared to each data type taken separately. However, none of the above is plug-and-play, yet the non-standardization of imaging protocols, feature extraction, and external validation hinders their practical implementation. Across nearly every major cancer type, AI-assisted diagnostic tools are now demonstrating sensitivity that rivals and, in some tightly controlled studies, exceeds human specialists.

2. AI in Cancer Treatment: Precision Oncology and Molecular Profiling

Fountzilas et al. emphasized that AI-driven precision oncology enables the integration of molecular profiling, clinical information, and imaging data to facilitate highly individualized treatment recommendations. Their study highlighted the growing role of AI in improving therapeutic efficacy while minimizing treatment-related toxicity. [23]

Radiation Oncology

Bibault et al. reported that machine learning algorithms significantly improved radiation oncology workflows through automated dose optimization and adaptive radiotherapy planning. Their study demonstrated the potential of AI systems to reduce radiation-induced toxicity while maintaining treatment efficacy.[24]

Yala et al. demonstrated that AI-driven mammographic models could predict future breast cancer risk more accurately than traditional risk assessment tools. Their findings suggest that AI may facilitate earlier therapeutic intervention and personalized prevention strategies.[25] Kickingereder et al. demonstrated that radiomic profiling combined with machine learning significantly improved progression-free survival prediction in glioblastoma patients.[26]

Kather et al. reported that deep learning models could predict microsatellite instability directly from histopathology images, thereby enabling more personalized immunotherapy selection in colorectal cancer patients. Esteva et al. demonstrated that deep neural networks could achieve highly accurate lesion classification, thereby supporting personalized therapeutic decision-making in dermatological oncology.

Prostate cancer treatment increasingly relies on AI-assisted precision medicine approaches to improve radiation planning, surgical navigation, and recurrence prediction. Multiparametric MRI combined with deep learning algorithms enables more accurate tumor localization and individualized therapeutic planning. Robotic-assisted surgery represents one of the most

Table 1: Comparison of AI Techniques in Oncology

AI Technique	Major Strengths	Key Limitations	Oncology Applications
Machine Learning	Effective on structured clinical data	Requires manual feature engineering	Prognosis prediction
Deep Learning	Automated feature extraction	High computational cost	Medical imaging
Computer Vision	Accurate image interpretation	Data annotation dependency	Tumor segmentation
NLP and LLMs	Clinical text analysis	Hallucination risk	EHR analysis
Radiomics	Quantitative imaging biomarkers	Standardization issues	Precision oncology
Pathomics	Microscopic tissue characterization	Large dataset requirement	Digital pathology
Multi-Omics AI	Comprehensive biological integration	Computational complexity	Personalized medicine

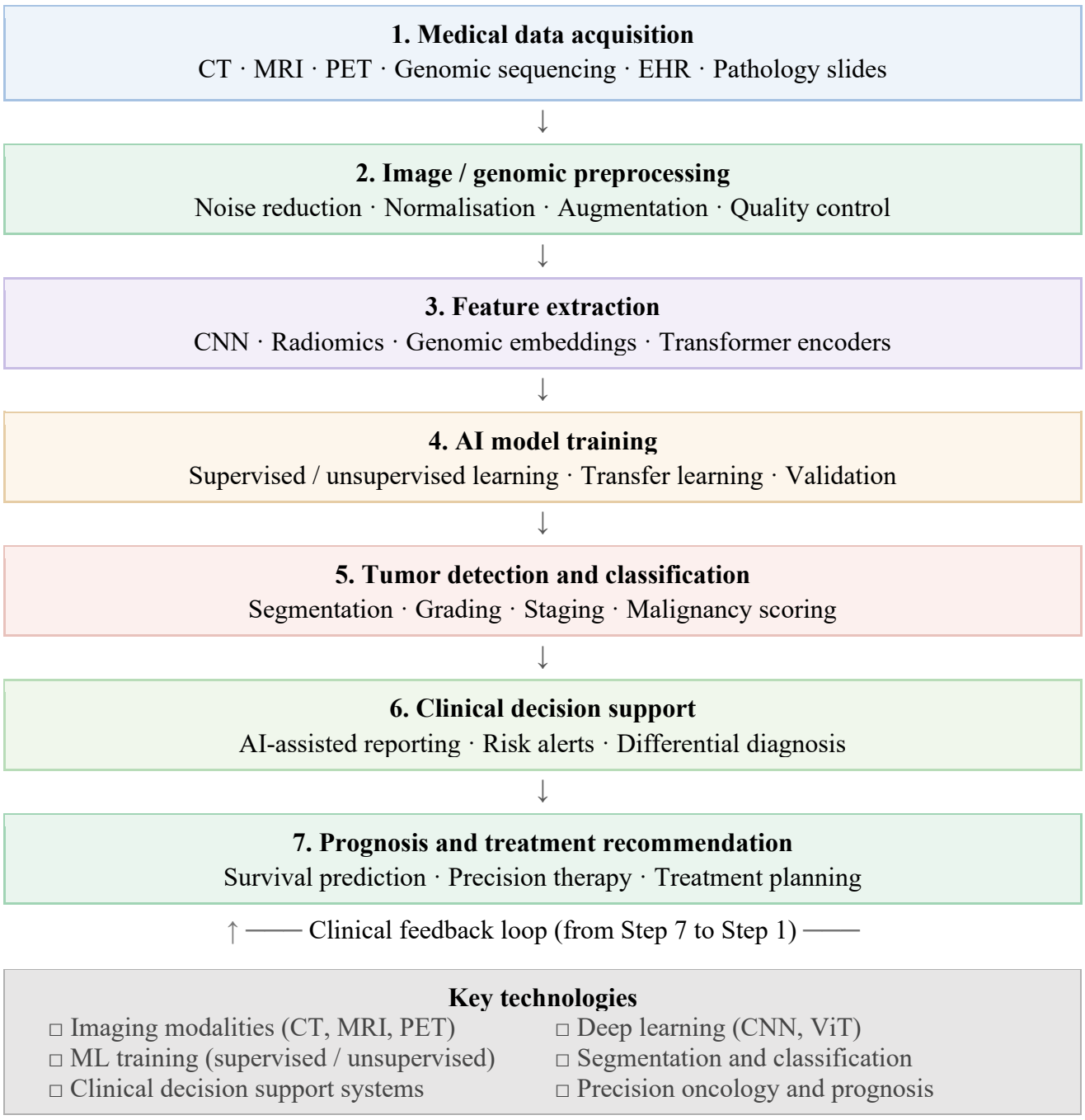
Table 2: AI Diagnostic Performance across different Cancer types

Cancer Type	AI Model	Imaging / Data Type	Key Application	Major Limitation
Lung Cancer	CNNs, Radiomics	CT scans	Pulmonary nodule detection	False positives
Breast Cancer	Deep CNNs	Mammography, MRI	Tumor classification	Explainability
Brain Tumors	U-Net, Transformers	MRI	Tumor segmentation	Dataset variability
Colorectal Cancer	Computer Vision AI	Colonoscopy	Polyp detection	Imaging inconsistency
Skin Cancer	CNNs	Dermoscopy Images	Melanoma classification	Dataset bias
Prostate Cancer	Deep Learning	mpMRI, Pathology	Lesion localization	Annotation variability
Leukemia	CNNs	Blood Smear Images	Blast cell recognition	Limited datasets

clinically mature AI applications in prostate cancer management. AI-enhanced robotic systems improve surgical precision, reduce operative complications, and enhance postoperative recovery outcomes. The robotic surgical platform developed by Intuitive Surgical has substantially transformed minimally invasive prostate cancer surgery by integrating computer-assisted visualization and precision instrumentation. Matek et al. demonstrated that deep learning systems could accurately classify leukemia blast cells, thereby supporting diagnostic standardization and personalized therapeutic strategies.[27]

The “black-box” problem refers to the inability of humans to fully understand how complex AI systems generate predictions or recommendations. Deep learning architectures such as CNNs, transformer-based models, and ensemble learning systems involve millions of parameters and highly nonlinear computations that are difficult to interpret directly. Although these models frequently outperform traditional statistical methods in oncology tasks, their lack of transparency significantly limits clinical trust and widespread implementation. In oncology diagnostics, AI systems may identify treatment responses without providing understandable explanations. reasoning for their outputs. This creates substantial concerns among clinicians who are ultimately responsible for patient care and therapeutic decision-making. Physicians may hesitate to rely on AI-generated recommendations if the underlying. decision-making process cannot be adequately

Figure 1: AI workflow in cancer diagnosis



explained or validated clinically. Samek et al. highlighted that modern deep learning systems often prioritize predictive optimization at the expense of human interpretability, thereby creating major barriers to trust and accountability in medical AI applications.[28] The black-box nature of oncology AI becomes particularly problematic in cases involving false-positive or false-negative predictions. For example, if an AI system incorrectly classifies a malignant lesion as benign without providing interpretable reasoning, clinicians may struggle to identify the source of error or determine whether the prediction is clinically reliable. This issue becomes even more critical in life-threatening cancers where delayed diagnosis or inappropriate treatment can significantly affect patient survival. Tjoa and Guan emphasized that the opacity of deep learning systems remains one of the primary challenges preventing large-scale adoption of AI in healthcare environments.[29] Table 2 summarizes different AI techniques employed across different cancer types.

Explainable AI (XAI) encompasses a broad range of computational techniques designed to improve the transparency and interpretability of AI systems. These methods aim to clarify how models generate predictions, identify influential input features, and support clinician understanding of AI-assisted decision-making processes. One of the most widely utilized explainability methods in oncology is Shapley Additive Explanations (SHAP), which assigns contribution values to individual features based on

cooperative game theory principles, thereby enabling clinicians to understand which variables most strongly influence model predictions. In oncology, SHAP has been extensively used in radiomics, genomic prediction, and treatment outcome modeling.

Another commonly applied technique is Local Interpretable Model-Agnostic Explanations (LIME), which generates simplified local approximations of complex AI models. LIME allows clinicians to visualize the specific features influencing individual predictions, thereby improving trust in AI-assisted diagnostic systems. Attention maps and saliency maps are also widely used in imaging-based oncology AI systems. These visualization methods highlight image regions most influential in classification or segmentation tasks, thereby enabling clinicians to identify whether AI systems focus on clinically relevant anatomical structures.

Arrieta et al. emphasized that explainability methods are essential for building transparent and accountable AI systems capable of supporting clinical reasoning and regulatory approval. [30] In digital pathology, saliency mapping techniques have demonstrated significant utility in identifying histopathological regions associated with malignancy prediction. These methods improve pathologist confidence by visually demonstrating how AI systems identify tumor characteristics within whole-slide images.

In radiology, attention-based deep learning systems can highlight suspicious lesion regions during tumor detection tasks. This improves interpretability and allows radiologists to compare AI-generated findings with their own clinical assessments. However, explainability methods themselves are not without limitations. Many XAI techniques provide only approximate interpretations rather than complete explanations of model behavior. Consequently, there remains ongoing debate regarding whether current explainability frameworks provide sufficiently reliable interpretations for clinical deployment. Another important challenge is the trade-off between interpretability and model complexity.

Simpler interpretable models such as decision trees are easier to understand clinically but often demonstrate lower predictive performance than deep neural networks. Conversely, highly accurate deep learning systems frequently remain difficult to interpret comprehensively despite advanced XAI techniques. There are a number of ethical challenges in the intersection of artificial intelligence and oncology. There are growing concerns that AI will worsen existing inequities in access to care in relation to algorithmic bias. In general, AI systems in oncology are designed to be widely applicable to large populations. However, they are usually developed and/or validated with data from either high-income countries or specific ethnic groups (e.g., Asians or Africans). For many lower-income countries and underserved minorities, the diagnostic tools developed may continue to be misdiagnosed.[31]

Asai et al. introduce the concept of privacy-preserving AI; within privacy-preserving AI, one of the innovations is federated learning. AI models can be developed and deployed in a range of diverse contexts. In this case, patient data is protected to remain within the systems of the organizations. In a federated model, diagnostic algorithms can be radically advanced with minimal, if any, risk of data exposure.

In AI, datasets are imbalanced when one class (benign lesions) greatly outnumbers another class (malignant tumors) and can lead to high false-negative rates.[32] The inability to generalize (i.e., becoming overfit) is another challenge. Although a model may be able to learn to interpret and predict the data perfectly, it may not be useful in the clinic. Furthermore, poor reproducibility plagues AI research; many models are published with little to no code or data sharing, which acts as a barrier to proving results. Furthermore, the majority of the literature that is available is largely based on retrospective studies with no prospective randomized controlled studies to enhance clinical outcomes. [33]

Integrating AI into hospital clinical workflows is challenging because EHR systems and AI programs often lack interoperability. Additionally, the learning curve for clinicians may be steep, but adoption is likely to be slow, as clinicians may develop alert and notification fatigue from excessive AI messaging. The purchase of AI medical devices may help address the “black box” challenge, but unless clinicians receive adequate training in the use of medical AI devices, there is little likelihood that clinicians will use them. Figure 1 presents the workflow of AI in cancer diagnosis.

The use of Generative AI and LLMs such as GPT-4 or Med-PaLM holds great potential for improving cancer care through automation of clinical notes and simplifying pathology reports. Lastly, from the perspective of patient-centered care, these AI models can be used for the development of oncology chatbots. These AI models can explain the patients' treatment plans in a simplified manner. In addition, Generative AI models can be used to develop synthetic medical data and can be used for training other AI models, thereby

resolving the issue of privacy of real patients.[34] Integration of medical imaging (radiomics), tissue slides (pathomics), and gene (genomics) data within a single predictive framework will be the next advancement of AI within oncology. AI can offer a more comprehensive understanding of a patient's tumor biology by merging these disparate streams of information. The advancement of federated learning will support this, offering the ability to collaborate in real-time across the globe to develop 'global AI models' built on diverse data.

Digital twins are electronic models of individual patients that help simulate the way a patient's cancer will respond to different therapies. This further allows oncologists to perform 'virtual clinical trials' on patients before administering any drugs, thus leading to a true personalized medicine approach. In the future, these twins will be a part of a 'Smart Oncology Ecosystem' that uses AI and integrates wearables and 'smart 'AI-based hospitals to continuously monitor patients in real time.[35]

Traditional oncology combines manual methods of staging and the visual inspection of images and uses standardized treatment protocols. There are many pitfalls with this classic approach. AI-assisted oncology, on the other hand, analyzes at a much higher throughput and can detect more nuanced but critical patterns in images and other omics that the human eye may miss. Current traditional methods bear the most clinical trust and have been the gold standard in oncology; however, the AI-assisted methods are on track to have strongholds in early detection of otherwise unrecognizable patterns and finding personalized drug sensitivities as a means to overcome treatment resistance.[36]

It has been noted that research and clinical adoption of AI-assisted oncology are, at this point, becoming disparate with regard to maturity. Many AI-assisted oncology methods for early detection of lung and breast cancer have been highly clinically validated, but as of now, are still highly restricted due to many unregulated barriers to entry for the market. For AI technologies in oncology to have large-scale adoption, they must create a workflow in the diagnostic process for clinicians that significantly reduces their time and effort and therefore increases survival outcomes for patients.[37]

CONCLUSION

AI is transforming oncology by improving detection of cancer, its diagnosis, prognosis, treatment planning, and precision medicine. Machine Learning and deep learning models are working efficiently and can analyze imaging, pathology, genomic, and clinical data more accurately.

AI-driven radiomics, Pathomics, and multi-omics allow personalized treatment by identifying tumor characteristics and predicting treatment response. Despite the huge potential of AI, it still faces challenges including biased data, privacy concerns, ethical issues, and the risk of inaccurate detection. AI is not meant to replace doctors but to support expertise. AI should support rather than replace clinicians, with explainable AI, human oversight, and multidisciplinary collaboration being essential for safe and effective cancer care.

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BF: Conceptualization, methods, data extraction.
BM & FK: Investigation, review & editing, proofreading & editing, data synthesis.

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