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Review Article

Artificial Intelligence for Automated Tumor Segmentation and Treatment Response Assessment

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Cancer remains one of the leading causes of mortality worldwide, necessitating continuous advancements in diagnostic and therapeutic strategies. Medical imaging plays a central role in oncology by facilitating tumor detection, delineation, staging, treatment planning, and response monitoring. Accurate tumor segmentation and treatment response assessment are fundamental components of modern cancer management; however, conventional manual approaches are labor-intensive, time-consuming, and subject to significant interobserver variability. The rapid evolution of artificial intelligence (AI), particularly machine learning and deep learning, has transformed medical image analysis by enabling automated, reproducible, and highly accurate interpretation of complex imaging datasets. Recent developments in convolutional neural networks, transformer-based architectures, and foundation models have significantly improved tumor segmentation performance across multiple imaging modalities, including computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET), and hybrid imaging systems. Simultaneously, AI-driven approaches have enhanced treatment response assessment through radiomics, longitudinal image analysis, and predictive modeling, enabling earlier identification of therapeutic efficacy and disease progression. Emerging multimodal frameworks integrating imaging, pathology, genomics, and clinical data further support precision oncology by providing comprehensive patient-specific insights. Despite substantial progress, challenges related to data heterogeneity, annotation quality, model interpretability, regulatory approval, and clinical implementation remain significant barriers to widespread adoption. The emergence of foundation models, self-supervised learning, federated learning, and explainable AI offers promising avenues for addressing these limitations. This review critically examines recent advances in AI-driven automated tumor segmentation and treatment response assessment, discusses current clinical applications, evaluates existing challenges, and highlights future directions for integrating AI technologies into routine oncology practice.

Keywords: Artificial intelligence; Tumor segmentation; Treatment response assessment; Deep learning; Radiomics; Precision oncology; Medical imaging; Foundation models.

INTRODUCTION

Cancer represents a major global health challenge and remains among the leading causes of death worldwide. According to the latest global cancer statistics, the incidence of cancer continues to rise due to population growth, aging, environmental exposures, and lifestyle-related risk factors [1]. Advances in early detection, molecular diagnostics, targeted therapies, and immunotherapies have improved survival outcomes for many malignancies; however, optimal treatment selection and disease monitoring remain complex clinical challenges [2]. Medical imaging occupies a central position in oncology care. Imaging modalities such as computed tomography (CT), magnetic resonance imaging

(MRI), positron emission tomography (PET), PET/CT, PET/MRI, and ultrasound provide essential information regarding tumor location, morphology, metabolism, vascularity, and therapeutic response [3]. These imaging techniques support virtually every stage of cancer management, including screening, diagnosis, staging, treatment planning, follow-up, and surveillance. Among imaging-related tasks, tumor segmentation is particularly important because it forms the basis for quantitative image analysis. Tumor segmentation refers to the process of delineating tumor boundaries and identifying regions of interest within medical images. Accurate segmentation enables tumor volume measurement, radiotherapy planning, surgical guidance, radiomics feature extraction, and longitudinal assessment of disease progression [4]. Traditionally, segmentation is performed manually by radiologists or radiation oncologists. Although expert annotation remains the clinical gold standard, manual segmentation is time-intensive and subject to considerable intraobserver and interobserver variability, especially for tumors exhibiting irregular shapes, heterogeneous enhancement patterns, or poorly defined margins [5]. Treatment response assessment represents another critical component of oncology practice. Response evaluation determines whether tumors are responding to therapy, remaining stable, or progressing. Conventional assessment frameworks such as the World Health Organization (WHO) criteria, Response Evaluation Criteria in Solid Tumors (RECIST), and Positron Emission Tomography Response Criteria in Solid Tumors (PERCIST) rely primarily on changes in lesion size or metabolic activity [6]. While these methods have standardized clinical evaluation, they may fail to capture complex biological responses, particularly in the context of immunotherapy, targeted therapies, and heterogeneous tumors [7].

Artificial intelligence (AI) has emerged as a transformative technology capable of addressing many limitations associated with conventional image interpretation. Recent advances in machine learning, deep learning, computer vision, and multimodal data integration have enabled automated extraction of clinically relevant information from large-scale imaging datasets [8]. AI-driven systems have demonstrated remarkable performance in tumor detection, segmentation, classification, prognosis prediction, treatment planning, and response assessment across diverse cancer types [9]. The introduction of deep learning architectures such as convolutional neural networks (CNNs), U-Net variants, transformer-based models, and foundation models has significantly enhanced segmentation accuracy and predictive performance [10]. Furthermore, integration of radiomics, radiogenomics, pathology, and clinical data has expanded the role of AI beyond image analysis toward comprehensive precision oncology frameworks [11]. This review critically examines the current landscape of artificial intelligence for automated tumor segmentation and treatment response assessment. Particular emphasis is placed on methodological developments, clinical applications, emerging foundation models, challenges, limitations, and future opportunities that may shape the next generation of AI-enabled oncology care.

2. Fundamentals of Artificial Intelligence in Medical Imaging

Artificial intelligence encompasses computational techniques designed to perform tasks that traditionally require human intelligence, including pattern recognition, decision-making, learning, and reasoning [12]. Within medical imaging, AI has become a cornerstone technology for extracting clinically meaningful information from increasingly complex datasets. Machine learning, a subset of AI, enables algorithms to learn patterns directly from data without explicit programming. Traditional machine learning approaches rely on handcrafted features extracted from medical images and subsequently analyzed using classifiers such as support vector machines, random forests, or logistic regression models [13]. While effective in certain applications, these methods are often limited by feature engineering requirements and reduced scalability. Deep learning has overcome many of these limitations by enabling automatic hierarchical feature extraction from raw imaging data. Deep neural networks learn increasingly complex representations across multiple layers, facilitating superior performance in image recognition, segmentation, and classification tasks [14]. Convolutional neural networks (CNNs) have become the dominant architecture in medical image analysis because they effectively capture spatial relationships

within images. CNNs automatically learn discriminative imaging features without requiring manual feature selection, resulting in improved accuracy across numerous oncology applications [15].

Among CNN-based architectures, U-Net has become one of the most influential models for medical image segmentation. Introduced specifically for biomedical imaging applications, U-Net employs an encoder-decoder structure with skip connections that preserve spatial information and enable precise localization of anatomical structures and tumors [16]. Numerous variants, including Attention U-Net, U-Net++, and nnU-Net, have subsequently improved segmentation performance across multiple cancer types [17].

V-Net extends these concepts to three-dimensional imaging data and has demonstrated particular utility in volumetric segmentation tasks involving CT and MRI datasets [18]. ResNet architectures introduce residual learning mechanisms that facilitate training of deeper neural networks and improve feature representation learning [19]. More recently, transformer-based architectures have transformed medical image analysis. Vision Transformers (ViTs) utilize self-attention mechanisms to capture long-range dependencies and global contextual information, addressing some limitations associated with conventional CNNs [20]. Swin Transformers further enhance efficiency through hierarchical feature representations and shifted-window attention mechanisms, making them particularly suitable for high-resolution medical imaging applications [21].

Graph Neural Networks (GNNs) represent another emerging architecture with growing relevance in oncology. GNNs model complex relationships among imaging features, anatomical structures, molecular pathways, and patient populations using graph-based representations [22]. Such approaches may facilitate integration of imaging and biological information within precision oncology frameworks.

Several imaging modalities support AI-driven oncology applications. CT remains the most widely used modality for cancer staging and treatment monitoring due to its high spatial resolution and broad availability. MRI provides superior soft-tissue contrast and functional imaging capabilities, making it particularly valuable in brain, breast, prostate, and liver cancers. PET offers metabolic and molecular information that complements anatomical imaging, while PET/CT and PET/MRI combine functional and structural information within unified platforms [23]. Ultrasound continues to play an important role in breast, thyroid, liver, and gynecological oncology because of its accessibility, cost-effectiveness, and real-time imaging capabilities [24]. Radiomics has emerged as a powerful framework for converting medical images into high-dimensional quantitative data. Through extraction of shape, texture, intensity, and spatial features, radiomics enables characterization of tumor heterogeneity beyond visual assessment [25]. Radiogenomics extends this concept by linking imaging phenotypes with genomic and molecular characteristics, thereby supporting precision oncology applications [26]. Collectively, these technological advances provide the foundation for AI-driven tumor segmentation and treatment response assessment, enabling increasingly sophisticated analysis of cancer imaging data and paving the way for more personalized patient care.

3. Artificial Intelligence for Automated Tumor Segmentation

Tumor segmentation is one of the most critical tasks in oncologic imaging because it forms the basis for diagnosis, treatment planning, radiotherapy contouring, surgical navigation, radiomics analysis, and longitudinal disease monitoring. Accurate delineation of tumor boundaries allows clinicians to quantify tumor burden, evaluate spatial heterogeneity, monitor treatment-induced changes, and estimate prognosis. However, manual segmentation remains labor-intensive and subject to substantial interobserver variability, particularly in tumors exhibiting infiltrative growth patterns, heterogeneous enhancement characteristics, or poorly defined margins [27,28]. Consequently, automated tumor segmentation has emerged as one of the most active areas of artificial intelligence research in medical imaging. Deep learning has revolutionized tumor segmentation by enabling direct learning of hierarchical image features from raw imaging data. Unlike conventional image processing techniques that rely on handcrafted features, deep neural networks automatically learn complex representations that can

capture tumor morphology, texture, intensity variations, and contextual anatomical information [29]. These capabilities have led to remarkable improvements in segmentation accuracy across multiple cancer types and imaging modalities. Tumor segmentation approaches can generally be categorized into semantic segmentation, instance segmentation, and panoptic segmentation. Semantic segmentation assigns each pixel or voxel to a predefined class, such as tumor or background. This approach is widely used in radiotherapy planning and volumetric tumor assessment because it provides comprehensive delineation of tumor regions [30]. Instance segmentation extends semantic segmentation by distinguishing individual tumor lesions belonging to the same class. This capability is particularly useful in metastatic disease where multiple lesions may coexist within the same anatomical region [31]. Panoptic segmentation combines semantic and instance segmentation by simultaneously identifying lesion categories and individual tumor instances, thereby providing more comprehensive scene understanding [32]. The introduction of U-Net marked a major breakthrough in biomedical image segmentation. U-Net employs a symmetric encoder-decoder architecture connected through skip pathways that preserve fine-grained spatial information lost during feature extraction [16]. This design enables precise localization while maintaining contextual understanding. Since its introduction, U-Net has become the foundation for numerous segmentation algorithms and remains one of the most widely adopted architectures in medical imaging. Several enhanced variants of U-Net have subsequently emerged. Attention U-Net incorporates attention mechanisms that selectively emphasize relevant image regions while suppressing irrelevant background structures [33]. This modification improves segmentation performance in anatomically complex regions where tumors may exhibit low contrast relative to surrounding tissues. U-Net++ introduces nested and dense skip connections that reduce the semantic gap between encoder and decoder feature maps, resulting in improved feature fusion and segmentation accuracy [34]. Among contemporary approaches, nnU-Net has gained particular attention because of its self-configuring framework. Unlike manually optimized architectures, nnU-Net automatically adapts preprocessing, network architecture, training strategies, and postprocessing procedures to specific datasets. Extensive benchmarking studies have demonstrated that nnU-Net achieves state-of-the-art performance across numerous public medical imaging challenges while requiring minimal manual intervention [17]. Three-dimensional segmentation has also benefited from specialized architectures such as V-Net. By operating directly on volumetric data, V-Net captures spatial relationships across image slices and provides more anatomically coherent segmentations compared with two-dimensional approaches [18]. This capability is particularly valuable in CT and MRI applications where tumors extend across multiple imaging planes. Recent advances in transformer-based architectures have further enhanced segmentation performance. TransUNet integrates convolutional neural networks with transformer encoders, enabling simultaneous capture of local image details and global contextual information [35]. Comparative studies have demonstrated superior performance of TransUNet compared with conventional CNN-based approaches in brain tumor, liver tumor, and prostate cancer segmentation tasks [36]. Similarly, Swin-UNet incorporates hierarchical vision transformers into a U-Net-like architecture. Through shifted-window self-attention mechanisms, Swin-UNet effectively captures long-range dependencies while maintaining computational efficiency [37]. Several investigations have reported improved segmentation accuracy compared with CNN-based architectures, particularly in challenging tumor segmentation scenarios characterized by heterogeneous morphology and complex anatomical backgrounds [38]. The emergence of foundation models has introduced a new paradigm in medical image segmentation. The Segment Anything Model (SAM), originally developed for general computer vision applications, demonstrated unprecedented zero-shot segmentation capabilities across diverse image domains [39]. Building upon SAM, specialized medical adaptations such as MedSAM and SAM-Med2D have been developed to address the unique characteristics of medical imaging datasets [40,41]. These foundation models leverage large-scale pretraining and prompt-based interaction to facilitate robust segmentation across multiple imaging modalities and anatomical sites. Early evidence suggests that medical foundation models may significantly reduce annotation

requirements while improving generalizability across institutions and patient populations [42].

Brain tumor segmentation represents one of the most extensively studied applications of AI. The Brain Tumor Segmentation (BraTS) challenges have driven substantial methodological innovation over the past decade. Deep learning architectures including U-Net, nnU-Net, TransUNet, and transformer-based models have achieved Dice Similarity Coefficient (DSC) values exceeding 0.90 for whole-tumor segmentation in many benchmark datasets [43]. These advances have improved radiotherapy planning and facilitated quantitative assessment of glioblastoma progression and treatment response.

Breast cancer segmentation has also benefited significantly from AI-driven approaches. Automated segmentation of breast lesions on MRI, ultrasound, and mammography enables more accurate lesion characterization and supports radiomics-based biomarker development [44]. Deep learning models consistently outperform traditional image processing methods, particularly in dense breast tissue where lesion boundaries are difficult to delineate manually [45].

In lung cancer, segmentation of primary tumors and metastatic lesions plays a critical role in staging, radiotherapy planning, and treatment monitoring. AI-based systems have demonstrated robust performance in CT-based lung tumor segmentation despite challenges associated with respiratory motion, heterogeneous tumor appearance, and proximity to mediastinal structures [46]. Several multicenter studies have reported segmentation accuracies comparable to expert thoracic radiologists [47].

Liver tumor segmentation remains particularly challenging because of variable tumor morphology, low lesion contrast, and underlying liver disease. Nevertheless, deep learning approaches have achieved substantial improvements compared with traditional methods. Transformer-based architectures have shown particular promise in capturing complex spatial relationships within hepatic imaging datasets [48]. Similarly, AI-driven segmentation has demonstrated significant clinical value in prostate cancer and head-and-neck oncology. Automated delineation of prostate lesions on multiparametric MRI supports targeted biopsy planning and focal therapy selection, while head-and-neck segmentation facilitates efficient radiotherapy contouring and reduces clinician workload [49,50]. Performance evaluation of segmentation algorithms relies on several quantitative metrics. The Dice Similarity Coefficient remains the most widely used metric and measures overlap between predicted and reference segmentations. Values approaching 1.0 indicate excellent agreement [51]. Intersection over Union (IoU), also known as the Jaccard index, evaluates segmentation overlap from a complementary perspective and is frequently used in benchmarking studies [52]. Hausdorff Distance measures boundary agreement by quantifying the maximum distance between corresponding contour points and is particularly useful for assessing clinically relevant contour accuracy [53]. Despite remarkable progress, several limitations remain. Most segmentation models require large annotated datasets, and expert annotation remains expensive and time-consuming. Performance may deteriorate when applied to external datasets due to domain shift and differences in imaging protocols [54]. Furthermore, segmentation accuracy may be reduced in rare tumor types, small lesions, or tumors exhibiting extensive heterogeneity. Foundation models and self-supervised learning approaches may help address these challenges by improving generalizability and reducing dependence on large annotated datasets [55]. Overall, artificial intelligence has transformed tumor segmentation from a labor-intensive manual process into an increasingly automated and reproducible workflow. Continued advances in deep learning architectures, foundation models, and multimodal integration are expected to further improve segmentation accuracy and facilitate broader clinical adoption in precision oncology.

4. Artificial Intelligence for Treatment Response Assessment

Treatment response assessment is a cornerstone of modern oncology because it determines therapeutic effectiveness, guides clinical decision-making, and influences long-term patient outcomes. Accurate evaluation of response allows clinicians to distinguish responders from non-responders, identify disease progression at an early stage, optimize treatment

strategies, and avoid unnecessary toxicity associated with ineffective therapies [56]. Traditionally, response assessment has relied on standardized imaging-based criteria; however, the increasing complexity of contemporary cancer therapies has exposed limitations in conventional approaches. Artificial intelligence (AI) has emerged as a promising solution capable of providing more comprehensive, quantitative, and personalized evaluation of treatment response. Historically, tumor response has been assessed using morphologic changes observed on medical imaging. The World Health Organization (WHO) criteria, introduced in the late twentieth century, relied on bidimensional measurements of tumor lesions to classify treatment response [57]. Subsequently, the Response Evaluation Criteria in Solid Tumors (RECIST) were developed to standardize response assessment by measuring the longest diameter of selected target lesions [6]. RECIST 1.1 remains the most widely adopted framework in clinical trials and routine oncology practice. More recently, the Positron Emission Tomography Response Criteria in Solid Tumors (PERCIST) incorporated metabolic imaging parameters derived from fluorodeoxyglucose (FDG)-PET to assess treatment-induced changes in tumor metabolism [58]. Although these criteria have improved standardization, they possess several limitations. Tumor size changes often occur relatively late during treatment and may not accurately reflect underlying biological alterations. Targeted therapies and immunotherapies frequently induce atypical response patterns, including pseudoprogression, hyperprogression, and delayed responses that are inadequately captured by size-based criteria [59]. Furthermore, conventional assessment methods evaluate only a limited number of lesions and may fail to account for intratumoral heterogeneity and dynamic biological changes occurring during therapy [60]. Artificial intelligence offers the potential to overcome these limitations by extracting quantitative information from medical images that extends beyond visual interpretation. AI-based response assessment integrates radiological, clinical, pathological, and molecular data to identify subtle imaging biomarkers associated with treatment outcomes. These approaches leverage machine learning and deep learning techniques to analyze high-dimensional datasets and generate predictive models capable of anticipating therapeutic response before macroscopic changes become apparent [61]. Radiomics has emerged as one of the most widely investigated approaches for treatment response prediction. Radiomics converts medical images into quantitative descriptors that characterize tumor shape, intensity, texture, spatial heterogeneity, and temporal evolution [25]. Numerous studies have demonstrated associations between radiomic features and therapeutic outcomes across multiple cancer types. For example, texture-based radiomic signatures extracted from pretreatment CT and MRI scans have shown predictive value for chemotherapy response in breast cancer, non-small cell lung cancer (NSCLC), and colorectal cancer [62,63]. Compared with traditional radiomics, deep learning-based approaches automatically learn predictive imaging representations directly from raw image data without requiring handcrafted feature engineering. Convolutional neural networks (CNNs) have demonstrated superior performance in identifying complex imaging patterns associated with treatment response [64]. Recent studies have shown that deep learning models outperform conventional radiomics in predicting pathological complete response following neoadjuvant therapy in breast cancer patients [65]. Similar findings have been reported in rectal cancer, where AI models successfully predicted treatment response following chemoradiotherapy, facilitating personalized treatment planning and organ-preserving therapeutic strategies [66]. Longitudinal imaging analysis represents another important application of AI in treatment response assessment. Traditional response criteria typically compare baseline and follow-up imaging studies at predefined intervals. In contrast, AI systems can analyze temporal imaging trajectories across multiple time points, capturing dynamic changes in tumor morphology, texture, vascularity, and metabolic activity [67]. Recurrent neural networks (RNNs), long short-term memory (LSTM) networks, and transformer-based architectures have demonstrated substantial promise in modeling longitudinal imaging data and predicting future disease behavior [68]. Early response prediction is particularly valuable because it enables treatment adaptation before disease progression becomes clinically apparent. Several investigations have demonstrated that AI-derived imaging biomarkers can identify responders and non-

responders after only one or two treatment cycles [69]. Such early prediction may facilitate personalized treatment modification, reduce exposure to ineffective therapies, and improve overall outcomes. In neoadjuvant breast cancer treatment, AI models incorporating MRI-derived imaging features have successfully predicted pathological complete response weeks before surgery [70].

Survival prediction represents another major area of clinical interest. While conventional prognostic models often rely on clinical staging and pathological variables, AI systems can integrate imaging biomarkers with clinical and molecular information to generate more accurate prognostic estimates [71]. Deep learning frameworks have demonstrated superior performance in predicting overall survival, progression-free survival, and disease-specific survival across multiple cancer types [72]. Such models may support risk stratification and individualized treatment planning.

Glioblastoma remains one of the most extensively studied malignancies for AI-driven response assessment. The highly infiltrative nature of glioblastoma and the occurrence of treatment-related imaging changes such as pseudoprogression complicate conventional response evaluation [73]. Deep learning models integrating multiparametric MRI features have shown improved accuracy in distinguishing true progression from treatment-related effects compared with traditional imaging interpretation [74]. Several studies have also reported successful prediction of survival outcomes and molecular biomarkers using longitudinal imaging data [75].

In breast cancer, AI-based response assessment has focused extensively on neoadjuvant chemotherapy. Dynamic contrast-enhanced MRI provides rich information regarding tumor vascularity and treatment-induced changes. Deep learning models combining imaging biomarkers with clinical variables have achieved high predictive accuracy for pathological complete response, potentially enabling individualized treatment adaptation [76]. Comparative studies consistently demonstrate superior performance of AI-driven approaches relative to conventional imaging assessment alone [77].

Lung cancer represents another important application area. In NSCLC, radiomic and deep learning models have demonstrated predictive value for chemotherapy response, targeted therapy outcomes, and immunotherapy efficacy [78]. AI-derived imaging biomarkers associated with epidermal growth factor receptor (EGFR) mutations, programmed death-ligand 1 (PD-L1) expression, and tumor mutational burden have further enhanced treatment stratification [79]. These advances support the integration of imaging biomarkers into precision oncology workflows. In colorectal cancer, response assessment following neoadjuvant chemoradiotherapy remains clinically important because accurate prediction of complete response may allow selected patients to avoid radical surgery. AI-based MRI analysis has demonstrated encouraging performance in identifying complete responders and predicting recurrence risk [80]. Similar approaches have been applied successfully in hepatocellular carcinoma, where AI systems predict treatment outcomes following transarterial chemoembolization, radiofrequency ablation, and systemic therapies [81].

Lymphoma provides a unique setting in which PET imaging plays a central role in treatment monitoring. Deep learning approaches analyzing FDG-PET/CT images have shown improved prediction of treatment response and survival outcomes compared with conventional metabolic assessment methods [82]. These systems may facilitate more accurate risk stratification and individualized therapeutic decision-making. Despite impressive advances, several challenges remain. Most AI models are developed using retrospective datasets and require prospective multicenter validation before widespread clinical adoption [83]. Variability in imaging protocols, treatment regimens, and patient populations may affect model performance and generalizability. Furthermore, integration of AI systems into clinical workflows requires careful consideration of interpretability, regulatory compliance, and clinician acceptance [84]. Nevertheless, the growing body of evidence suggests that AI-driven treatment response assessment may fundamentally transform oncology practice. By providing earlier, more accurate, and

biologically informed evaluation of therapeutic effectiveness, AI has the potential to support precision medicine and improve patient outcomes across diverse cancer types.

5. Integration of Multimodal Data for Precision Oncology

Precision oncology aims to tailor therapeutic strategies according to the unique biological characteristics of individual patients and tumors. While medical imaging provides valuable information regarding tumor morphology, metabolism, vascularity, and treatment response, cancer is fundamentally a complex biological disease influenced by genomic, transcriptomic, proteomic, pathological, and clinical factors. Consequently, reliance on a single data modality may fail to capture the complete disease landscape. The integration of multimodal data has therefore emerged as a critical strategy for advancing personalized cancer care [85]. Recent developments in artificial intelligence have facilitated the integration of heterogeneous datasets, including radiological images, digital pathology slides, genomic sequencing results, laboratory parameters, electronic health records (EHRs), and clinical outcomes. Multimodal deep learning enables simultaneous analysis of these diverse information sources, allowing models to uncover relationships that may not be apparent when modalities are analyzed independently [86]. Several data fusion strategies have been proposed for multimodal learning. Early fusion combines features from multiple modalities at the input stage before model training. This approach enables direct interaction among different data types but may be vulnerable to missing data and dimensionality mismatches [87]. Intermediate fusion integrates modality-specific representations within hidden network layers, allowing models to learn complex cross-modal interactions while preserving modality-specific information [88]. Late fusion combines independent predictions generated by separate models and is generally more robust to missing modalities but may fail to fully exploit synergistic relationships among data sources [89]. Hybrid fusion approaches combine multiple fusion strategies and increasingly represent the preferred methodology for complex oncology applications [90]. Several studies have demonstrated that multimodal AI models outperform unimodal systems in cancer diagnosis, prognosis prediction, and treatment response assessment. Integration of radiomic features with genomic signatures has improved prediction of molecular subtypes and survival outcomes in glioblastoma, breast cancer, lung cancer, and colorectal cancer [91,92]. Similarly, multimodal frameworks incorporating pathology images and genomic data have shown enhanced performance in tumor classification and biomarker discovery [93]. The emergence of foundation models and large multimodal models (LMMs) has further accelerated progress in precision oncology. These models are pretrained on massive datasets and subsequently adapted to specific clinical tasks using relatively limited labeled data. By learning generalized representations across multiple modalities, foundation models may enable more robust and scalable deployment of AI systems in clinical practice [94]. From a clinical perspective, multimodal AI has the potential to transform cancer management by supporting personalized diagnosis, treatment selection, risk stratification, and longitudinal monitoring. As data integration technologies mature, multimodal systems are expected to become central components of precision oncology workflows.

6. Emerging Technologies and Foundation Models

The rapid evolution of artificial intelligence has given rise to several transformative technologies that are reshaping oncologic imaging and treatment assessment. Among these developments, self-supervised learning has emerged as a particularly important approach for addressing the scarcity of annotated medical imaging data. Unlike conventional supervised learning, self-supervised methods learn meaningful representations from unlabeled datasets through pretext tasks, thereby reducing dependence on expert annotations [95]. Contrastive learning has become one of the most successful self-supervised paradigms. By learning relationships between similar and dissimilar image pairs, contrastive models generate highly transferable feature representations that improve downstream segmentation, classification, and prognostic prediction tasks [96]. These methods have demonstrated impressive performance across various oncologic imaging applications. Vision-language models represent

another major advance. Inspired by large-scale models developed in natural language processing, vision-language systems integrate image and text information to enable multimodal reasoning and clinical decision support [97]. Such models can analyze radiology images while simultaneously incorporating radiology reports, pathology descriptions, and clinical notes, creating more comprehensive patient representations. The Segment Anything Model (SAM) has introduced a foundation-model paradigm for image segmentation. SAM demonstrated unprecedented generalization capabilities across diverse image domains and inspired several medical adaptations, including MedSAM and related oncology-specific frameworks [40]. These models facilitate prompt-based segmentation and may substantially reduce annotation burdens in clinical settings. Recent years have also witnessed growing interest in medical foundation models specifically designed for healthcare applications. These models leverage large-scale imaging repositories to learn generalizable medical representations that can be adapted to multiple cancer-related tasks [98]. Similarly, generative artificial intelligence has demonstrated potential for image synthesis, data augmentation, reconstruction, and simulation of rare clinical scenarios [99]. Large language models (LLMs) are increasingly being integrated into oncology workflows. Beyond generating clinical documentation, LLMs may support decision-making, literature synthesis, patient communication, and multimodal clinical reasoning when combined with imaging and genomic data [100]. Although still in early stages of development, these technologies may contribute significantly to future precision oncology ecosystems. Collectively, foundation models, self-supervised learning, vision-language architectures, and generative AI represent a paradigm shift toward more generalized and scalable medical AI systems capable of addressing multiple clinical tasks within unified frameworks.

CHALLENGES AND LIMITATIONS

Despite remarkable advances, several barriers continue to impede widespread clinical adoption of AI-driven tumor segmentation and treatment response assessment systems. One of the most significant challenges is the limited availability of large, high-quality annotated datasets. Medical image annotation requires extensive expert involvement, making dataset generation expensive and time-consuming [101]. Class imbalance represents another major obstacle. Many oncology datasets contain disproportionately fewer examples of rare tumors, uncommon molecular subtypes, or treatment-resistant disease states. Consequently, AI models may perform suboptimally in clinically important but underrepresented patient populations [102]. Data heterogeneity further complicates model development and deployment. Variations in scanner manufacturers, acquisition protocols, reconstruction algorithms, image quality, and institutional practices can significantly influence model performance [103]. Such variability contributes to domain shift, whereby models trained on one dataset experience reduced accuracy when applied to external populations [104]. Annotation variability also affects model reliability. Even among experienced radiologists, substantial differences may exist in tumor contouring and response assessment. Since AI systems learn from human-generated labels, inconsistencies in annotation quality can propagate into model predictions [105]. Interpretability remains a critical concern. Many deep learning systems function as "black boxes," making it difficult to understand the rationale underlying specific predictions. Lack of transparency may reduce clinician trust and hinder regulatory approval [106]. Explainable AI techniques have emerged as potential solutions; however, achieving meaningful interpretability without sacrificing performance remains challenging. Generalizability represents another major limitation. Many published studies rely on retrospective single-center datasets and may not adequately reflect real-world clinical diversity. Prospective multicenter validation studies remain relatively uncommon, limiting confidence in clinical applicability [107]. Regulatory considerations present additional challenges. AI systems intended for clinical use must satisfy stringent requirements related to safety, effectiveness, reproducibility, and post-deployment monitoring. Regulatory frameworks continue to evolve in response to adaptive learning systems capable of continuous performance modification [108]. Data privacy and security concerns are particularly important in healthcare environments. Large-scale AI development often requires access to sensitive patient information,

creating potential risks related to confidentiality breaches and cybersecurity threats [109]. Federated learning and privacy-preserving machine learning approaches have been proposed as potential solutions. Ethical considerations must also be addressed. Algorithmic bias may contribute to healthcare disparities if training datasets inadequately represent diverse populations. Ensuring fairness, equity, transparency, and accountability remains essential for responsible AI implementation [110]. Finally, integration into existing clinical workflows presents practical challenges. Successful deployment requires clinician acceptance, interoperability with hospital information systems, cost-effectiveness, and demonstration of measurable improvements in patient outcomes [111]. Overcoming these barriers will be essential for translating AI innovations into routine oncology practice.

FUTURE PERSPECTIVES

The future of AI in oncology is likely to be shaped by increasingly sophisticated multimodal systems capable of integrating imaging, pathology, genomics, and clinical information within unified analytical frameworks. Explainable AI will play an important role in enhancing clinician trust and facilitating regulatory approval by providing transparent and interpretable decision-support mechanisms [112]. Federated learning offers a promising strategy for overcoming data-sharing restrictions while preserving patient privacy. By enabling collaborative model training across multiple institutions without transferring raw data, federated learning may facilitate development of more robust and generalizable oncology AI systems [113]. Foundation models are expected to become increasingly influential. Similar to large language models in natural language processing, future oncology foundation models may support a broad range of clinical tasks, including segmentation, diagnosis, prognosis prediction, treatment selection, and outcome forecasting using a single adaptable architecture [114]. The concept of digital twins is also gaining attention. Digital twins are computational representations of individual patients that continuously integrate clinical, imaging, molecular, and therapeutic data. AI-driven digital twins may enable simulation of treatment strategies, prediction of disease progression, and personalized optimization of therapeutic interventions [115]. Adaptive radiotherapy represents another promising application. Real-time AI-guided segmentation and response monitoring could facilitate dynamic treatment adaptation based on evolving tumor characteristics throughout the treatment course [116]. Increasing availability of real-world evidence datasets and prospective multicenter validation studies will further enhance clinical translation. Future systems are likely to function as integrated clinical decision-support platforms that augment clinician expertise rather than replace human judgment [117]. Ultimately, the convergence of multimodal learning, foundation models, federated learning, explainable AI, and digital health technologies may substantially advance precision oncology and improve outcomes for cancer patients worldwide.

CONCLUSION

Artificial intelligence has emerged as a transformative force in oncology, fundamentally reshaping approaches to tumor segmentation and treatment response assessment. Deep learning architectures, transformer-based models, and foundation models have achieved remarkable improvements in segmentation accuracy across multiple cancer types and imaging modalities. Simultaneously, AI-driven response assessment systems have demonstrated significant potential for predicting therapeutic outcomes, identifying disease progression, and supporting personalized treatment strategies. The integration of radiological, pathological, genomic, and clinical data through multimodal learning frameworks represents a major step toward precision oncology. Emerging technologies such as self-supervised learning, foundation models, vision-language systems, and federated learning are addressing longstanding challenges related to data scarcity, generalizability, and scalability. Despite substantial progress, important limitations remain, including dataset heterogeneity, annotation variability, interpretability concerns, regulatory challenges, and the need for prospective multicenter validation. Addressing these issues will be essential for successful clinical implementation. Future oncology workflows are likely to incorporate AI as an integral decision-support tool that enhances

diagnostic accuracy, optimizes treatment planning, and facilitates individualized patient management. Continued collaboration among clinicians, data scientists, engineers, regulatory authorities, and healthcare organizations will be critical for realizing the full potential of artificial intelligence in precision cancer care.

REFERENCES

1. Hanahan D. Hallmarks of cancer: new dimensions. Cancer Discov. 2022;12(1):31–46. Doi:10.1158/2159-8290.CD-21-1059.
2. Rajendran LKK. Hematological Malignancy Identification via K-means based ROI Extraction. International Journal of Clinical Research in Medical Sciences. 2026;1(2):1-10. Doi:10.67231/kt1w3e73.
3. Kumar RMH. Pan-System Cancer Intelligence: Integrating Blood, Immune, Microbiome, and Tumor Microenvironment Data Using Foundation Models. Power System Protection and Control. 2023;51(4):92-100. Doi:10.46121/pspc.51.4.8.
4. Rajendran LKK. Identifying Determinants of Outcome in Post-Radiotherapy Cervical Carcinoma Requiring Adjuvant Surgery. International Journal of Clinical Research in Medical Sciences. 2026;1(2):1-10. Doi:10.67231/3acej759.
5. Maradi Hemanth Kumar R. AI-Driven Liquid Biopsy Systems for Early Cancer Detection and Personalized Oncology. Power System Protection and Control. 2023;51(4):66-83. Doi:10.46121/pspc.51.4.7.
6. Rajendran LKK. Machine Learning–Driven Symptom-Based Cancer Risk Stratification:A Systematic Review of Clinical Prediction Models and Methodological Rigor. Int J Drug Deliv Technol. 2026;16(40s):242-253.Doi:10.25258/ijddt.16.40s.26.
7. 7. Rajendran OK. Bias, Fairness, and Ethical Challenges in Artificial Intelligence: A Comprehensive Review of Causes, Impacts, and Mitigation Strategies. Scientific Culture. 2026;12(2.1):13001-13010. Doi:10.5281/zenodo.20374091.
8. 8. Topol EJ. High-performance medicine: the convergence of human and artificial intelligence. Nat Med. 2019;25(1):44–56. Doi:10.1038/s41591-018-0300-7.
9. Rajendran OK. Clinical Translation of Artificial Intelligence in Oncology: Real-World Validation, Workflow Integration, and Precision Medicine Applications. Int J Drug Deliv Technol. 2026;16(49s):956-964. Doi:10.25258/ijddt.16.49s.110.
10. Rajendran LKK. Interpretable Machine Learning for Early Mortality Prediction in Acute Myeloid Leukemia: A Decision Tree–Based Retrospective Cohort Study. Int J Drug Deliv Technol. 2026;16(40s):231-241.Doi:10.25258/ijddt.16.40s.25.
11. Esteva A, Robicquet A, Ramsundar B, et al. A guide to deep learning in healthcare. Nat Med. 2019;25(1):24–29. Doi:10.1038/s41591-018-0316-z.
12. Rajendran OK. Generative AI for Synthetic Medical Image Generation in Oncology: Addressing Data Scarcity in AI-Driven Cancer Diagnosis. Int J Drug Deliv Technol. 2026;16(49s):1010-1016. Doi:10.25258/ijddt.16.49s.117.
13. Rajendran LKK. Integrated Prognostic Modeling of Tumor Stage, Multimodal Therapy, and Functional Status in Lung Cancer Survival: A Real-World Cohort Study. Scientific Culture. 2026;12(5):567-576. Doi:10.5281/zenodo.1250046.
14. Bommasani R, Hudson DA, Adeli E, et al. On the opportunities and risks of foundation models. arXiv. 2021. Doi:10.48550/arXiv.2108.07258.
15. Rajendran LKK. Integrative Pharmacogenomic Analysis of Drug Response Heterogeneity Across Cancer Cell Lines: Insights From Large-Scale GDSC Data. Scientific Culture. 2026;12(4):7537-7546. Doi:10.5281/zenodo.12426762.
16. Acs B, Rantalainen M, Hartman J. Artificial intelligence as the next step towards precision pathology. J Intern Med. 2020;288(1):62–81. Doi:10.1111/joim.13030.
17. Rajendran OK. Tumor Microenvironment Interaction-Guided Graph Neural Networks for Survival Prediction from Whole-Slide Pathology Images. Int J Drug Deliv Technol. 2026;16(49s):481-488. Doi:10.25258/ijddt.16.49s.50.

18. Rajendran LKK. Evaluating the Association of Cancer-Related Risk Factors With Multisystem Health: Insights Into Fertility, Cardiovascular, and Renal Indicators. Scientific Culture. 2026;12(4):7520-7527.Doi:10.5281/zenodo.12426760.
19. Rajendran LKK. From Prediction to Precision: An Externally Validated Deep Learning–Based Survival and Adjuvant Therapy Recommendation System for Resected Stage III Non–Small Cell Lung Cancer. Int J Drug Deliv Technol. 2026;16(30s): 430-438.doi:10.25258/ijddt.16.30s.41.
20. Chen RJ, Lu MY, Wang J, et al. Pathomic fusion: an integrated framework for fusing histopathology and genomic features for cancer diagnosis and prognosis. Nat Mach Intell. 2022; 4:179–193. Doi:10.1038/s42256-022-00466-x.
21. Rajendran LKK. From Prediction to Practice: A Machine Learning–Based Clinical Decision Support Tool for Bevacizumab Risk Stratification in Oncology. Int J Drug Deliv Technol. 2026;16(30s):414-429. Doi:10.25258/ijddt.16.30s.40.
22. Rajendran OK. Self-supervised multimodal Learning for early cancer detection across Imaging and genomics. Power System Protection and Control. 2024;52(4):167-178. Doi:10.46121/pspc.52.4.14.
23. Rajendran OK. Explainable AI-Driven Clinical. Decision Support Systems in Precision Oncology:Interpretable Models for Multimodal Cancer Care. Scientific Culture. 2026;12(2.1):12359-12369. Doi:10.5281/zenodo.20328194.
24. Rajendran LKK. Impact of Treatment Modalities on Fertility, Sexual Function, and Psychological Outcomes in Testicular Cancer Survivors: A Comprehensive Review. Int J Drug Deliv Technol. 2026;16(30s):447-453. Doi:10.25258/ijddt.16.30s.43.
25. Rajendran LKK. Intelligent Omics-Driven Patient Stratification for Cancer Therapeutic Re-profiling. International Journal of Clinical Research in Medical Sciences. 2026;1(1):1-11. Doi:10.67231/gv5hck05.
26. Rajendran LKK. Cancer nanomedicine: utilizing the enhanced permeability and retention (EPR) effect to deliver high payloads of chemotherapeutic agents directly to tumor sites. Power System Protection and Control. 2024;52(2):123-129. Doi:10.46121/pspc.52.2.12.
27. Kather JN, Calderaro J. Development of AI in digital pathology. Nat Rev Clin Oncol. 2020;17(10):591–595. Doi:10.1038/s41571-020-00431-0.
28. Rajendran OK. AI-based radiogenomic Models for predicting immunotherapy response In solid tumors. Power System Protection and Control. 2023;51(4):24-37. Doi:10.46121/pspc.51.4.4.
29. Rajendran LKK. Enhanced Predictive Analytics for Early Malignancy Discovery in Routine Screening. International Journal of Clinical Research in Medical Sciences. 2026;1(1):1-10. Doi:10.67231/grams870.
30. Wan JCM, Massie C, Garcia-Corbacho J, et al. Liquid biopsies come of age: towards implementation of circulating tumour DNA. Nat Rev Cancer. 2017;17(4):223–238. Doi:10.1038/nrc.2017.7.
31. Rajendran OK. Machine Learning-Based Prediction of Chemotherapy Toxicity in Colorectal Cancer: A Personalized Risk Stratification Approach. Scientific Culture. 2026;12(5.1):942-952. Doi:10.5281/zenodo.12511075.
32. Rajendran OK. Federated radiology AI Models for multi-institutional cancer diagnosis Without data sharing. Power System Protection And Control. 2023;51(4):38-54. Doi:10.46121/pspc.51.4.5.
33. Bera K, Schalper KA, Rimm DL, et al. Artificial intelligence in digital pathology — new tools for diagnosis and precision oncology. Nat Rev Clin Oncol. 2019;16(11):703–715. Doi:10.1038/s41571-019-0252-y.
34. Rajendran OK. Deep Reinforcement Learning in Oncology: Advances in Cancer Imaging, Radiotherapy, and Personalized Treatment. Scientific Culture. 2026;12(5):597-606. Doi:10.5281/zenodo.1250048.
35. Rajendran Ok. Deep Learning For Cross-Modality Mapping Between Histopathology And Radiological Imaging. Power System Protection and Control. 2025;53(3):313-328. Doi:10.46121/pspc.53.3.21.
36. Lu MY, Chen TY, Williamson DFK, et al. AI-based pathology predicts origins for cancers of

unknown primary. Nature. 2021;594(7861):106–110. Doi:10.1038/s41586-021-03512-4.

37. Rajendran OK. Artificial Intelligence in Oncologic Imaging: Deep Learning, Radiomics, and Clinical Integration for Precision Cancer Diagnosis. Int J Drug Deliv Technol. 2026;16(50s):871-880. Doi:10.25258/ijddt.16.50s.92.
38. Bilal M, Raza SEA, Azam A, et al. Development and validation of a weakly supervised deep learning framework to predict the risk of colorectal cancer recurrence from histology images. Lancet Oncol. 2021;22(11):153–163. Doi:10.1016/S1470-2045(21)00430-5.
39. Rajendran OK. DIGITAL TWIN FRAMEWORKS FOR PERSONALIZED CANCER PROGRESSION MODELING USING LONGITUDINAL DATA. Power System Protection and Control. 2025;53(4):486-501. Doi:10.46121/pspc.53.4.33.
40. Rajendran LKK. Genomic profiling: utilizing Multi-omics data to identify potential Therapeutic targets and resistance markers. Power System Protection and Control. 2024;52(4):159-166. Doi:10.46121/pspc.52.4.13.
41. Rajendran OK. Artificial Intelligence–Driven Multimodal Imaging for Cancer During Pregnancy: Advances in Maternal–Fetal Diagnostics and Precision Oncology. Int J Drug Deliv Technol. 2026;16(50s):862-870. Doi:10.25258/ijddt.16.50s.91.
42. Rajendran LKK. Immunotherapy and cell Therapy: developing CAR-T cell therapies and Other immune-based treatments for cancer and Autoimmune diseases. Power System Protection and Control. 2023;51(2):64-77. Doi:10.46121/pspc.51.2.7.
43. Rajendran Ok. Foundation Model–Driven Precision Oncology: Integrating Multi-Omics, Radiology, And Clinical Data For Predictive Cancer Care. Power System Protection and Control. 2024;52(2):154-163. Doi:10.46121/pspc.52.2.14.
44. Rajendran LKK. Theranostics: integrating Diagnostic imaging agents and therapeutic Drugs into a single multifunctional nano-Platform for real-time monitoring of treatment. Power System Protection and Control.2025;53(2):376-386. Doi:10.46121/pspc.53.2.31.
45. Rajendran LKK. Mechanisms driving Immunotherapy resistance in colorectal cancer Liver metastases. Power System Protection and Control. 2024;52(1):29-37. Doi:10.46121/pspc.52.1.5.
46. Ching T, Himmelstein DS, Beaulieu-Jones BK, et al. Opportunities and obstacles for deep learning in biology and medicine. J R Soc Interface. 2018;15(141):20170387. Doi:10.1098/rsif.2017.0387.
47. Litjens G, Kooi T, Bejnordi BE, et al. A survey on deep learning in medical image analysis. Med Image Anal. 2017; 42:60–88. Doi: 10.1016/j.media.2017.07.005.
48. Hemanth Kumar RM. Integrated Transcriptomic and 3 Learning Framework Identifies a Blood-Based Biomarker Signature for Anthracycline-Induced Cardiotoxicity in Juvenile Cancer Survivors. Int J Drug Deliv Technol. 2026;16(40s):219-230. Doi:10.25258/ijddt.16.40s.24.
49. Mobadersany P, Yousefi S, Amgad M, et al. Predicting cancer outcomes from histology and genomics using convolutional networks. Proc Natl Acad Sci USA. 2018;115(13):E2970–E2979. Doi:10.1073/pnas.1717139115.
50. Lambin P, Leijenaar RTH, Deist TM, et al. Radiomics: the bridge between medical imaging and personalized medicine. Nat Rev Clin Oncol. 2017;14(12):749–762. Doi:10.1038/nrclinonc.2017.141.
51. Azizi S, Mustafa B, Ryan F, et al. Big self-supervised models advance medical image classification. Nature. 2021;594(7864):104–110. Doi:10.1038/s41586-021-03476-6.
52. Dosovitskiy A, Beyer L, Kolesnikov A, et al. An image is worth 16×16 words: transformers for image recognition at scale. arXiv. 2020. Doi:10.48550/arXiv.2010.11929.
53. Rajendran OK. DeepDRA: A Deep Learning Framework for Drug Repurposing and Cancer Drug Response Prediction Using Multi-Omics Data. Scientific Culture. 2026;12(3):68-77. Doi:10.5281/zenodo.12326001.
54. Xu H, Usuyama N, Bagga J, et al. A whole-slide foundation model for digital pathology from real-world data. Nature. 2024;630(8015):181–188. Doi:10.1038/s41586-024-07441-w.

55. Singhal K, Azizi S, Tu T, et al. Large language models encode clinical knowledge. Nature.2023;620(7972):172–180. Doi:10.1038/s41586-023-06291-2.
56. Moor M, Banerjee O, Abad ZSH, et al. Foundation models for generalist medical artificial intelligence. Nature. 2023;616(7956):259–265. Doi:10.1038/s41586-023-05881-4.
57. Chen RJ, Ding T, Lu MY, et al. Towards a general-purpose foundation model for computational pathology. Nat Med. 2024;30(3):850–862. Doi:10.1038/s41591-024-02857-3.
58. Dr. Isabella Moore, Multimodal Artificial Intelligence in Oncology: Integrating Radiomics, Pathomics, and Genomics, Int. J. of Pharm.Sci., 2026, Vol 4, Issue 5, 6745-6760.https://doi.org/10.5281/zenodo.20391855
59. Dr. Benjamin Walker, Dr. Eleanor Hayes, Dr. Christopher Nolan, Foundation Models in Cancer Medicine: Revolutionizing Precision Diagnosticsand Clinical Oncology, Int. J. of Pharm. Sci., 2026, Vol4, Issue 5, 6733-6744.https://doi.org/10.5281/zenodo.20391588.

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