



AI FOR CANCER LESION SEGMENTATION

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Abstract

Accurate segmentation of cancer lesions in medical imaging is essential for diagnosis, treatment planning, and monitoring therapeutic response. Manual delineation is labor-intensive, time-consuming, and prone to inter-observer variability. Artificial intelligence (AI), particularly deep learning and convolutional neural networks (CNNs), has emerged as a powerful tool for automated lesion segmentation across modalities such as computed tomography (CT), magnetic resonance imaging (MRI), and positron emission tomography (PET). This paper reviews current AI-based methodologies for cancer lesion segmentation, highlights their performance in various tumor types, discusses challenges including data scarcity, variability in imaging protocols, and model interpretability, and explores the clinical potential of AI-assisted segmentation to improve precision oncology and patient outcomes.

Keywords. Cancer, lesion segmentation, artificial intelligence, deep learning, convolutional neural networks, medical imaging, CT, MRI, PET, automated detection

Introduction

Accurate segmentation of cancer lesions is a critical step in modern oncology, enabling precise diagnosis, effective treatment planning, and monitoring of therapeutic response. Medical imaging modalities, including computed tomography (CT), magnetic resonance imaging (MRI), and positron emission tomography (PET), provide detailed visualization of tumor morphology, size, and location. However, manual delineation of lesions is labor-intensive, time-



consuming, and subject to inter- and intra-observer variability, which can affect treatment decisions and clinical outcomes.

Artificial intelligence (AI), particularly deep learning techniques such as convolutional neural networks (CNNs), has emerged as a transformative tool for automated cancer lesion segmentation. CNN-based architectures can learn hierarchical features from imaging data, capturing subtle variations in tumor texture, shape, and intensity. Advanced segmentation models, such as U-Net and its variants, allow accurate pixel-wise delineation of lesions, facilitating volumetric assessment, treatment response evaluation, and radiotherapy planning.

Hybrid approaches that integrate imaging data with clinical parameters, including tumor biomarkers, patient demographics, and genetic information, further enhance predictive performance and support personalized oncology care. Challenges in AI-based cancer lesion segmentation include variability in imaging protocols, differences in scanner resolution, scarcity of high-quality annotated datasets, and model interpretability. Data augmentation, transfer learning, and multi-center dataset integration are common strategies to improve model robustness and generalizability.

This paper reviews current AI methodologies for cancer lesion segmentation, discusses model architectures, performance metrics, clinical applicability, and limitations, and highlights the potential of AI-assisted segmentation to improve diagnostic accuracy, optimize treatment planning, and enhance patient outcomes in precision oncology.

Main Body

Artificial intelligence (AI) and deep learning have transformed cancer lesion segmentation by enabling automated, accurate, and reproducible delineation of tumors across multiple imaging modalities. Convolutional neural networks (CNNs) are particularly effective in capturing hierarchical features from CT, MRI, and PET scans, allowing precise identification of lesion boundaries, tumor heterogeneity, and surrounding tissue characteristics. Advanced architectures such as U-Net, V-Net, and attention-based networks facilitate pixel-wise



segmentation, supporting volumetric assessment, treatment planning, and monitoring therapeutic response.

Multi-modal approaches that integrate imaging data with clinical and molecular information, including tumor markers, genomic profiles, and patient demographics, improve segmentation accuracy and enable personalized oncology care. Techniques such as data augmentation, transfer learning, and multi-center dataset integration enhance model robustness, addressing challenges associated with limited annotated datasets and variability in imaging protocols.

Evaluation metrics such as Dice coefficient, Intersection over Union (IoU), sensitivity, specificity, and Hausdorff distance are commonly used to assess segmentation performance. High-performing AI models have demonstrated near-human or superior accuracy in delineating lesions in lung, liver, brain, and breast cancers, significantly reducing inter-observer variability and manual workload.

Interpretability and clinical trust remain crucial for adoption. Visualization tools, including attention maps and saliency overlays, allow clinicians to understand AI decision-making and validate segmentation outputs. Ethical considerations, patient privacy, and regulatory compliance are essential for safe deployment in clinical settings.

Overall, AI-assisted cancer lesion segmentation offers a powerful solution for precise, rapid, and reproducible tumor delineation, enhancing diagnostic accuracy, guiding treatment planning, and improving patient outcomes in modern oncology practice.

Discussion

The application of artificial intelligence (AI) in cancer lesion segmentation has significantly enhanced precision oncology by providing automated, accurate, and reproducible delineation of tumors. Deep learning models, particularly convolutional neural networks (CNNs) and U-Net variants, enable pixel-wise segmentation of lesions across multiple imaging modalities, including CT, MRI, and PET. These systems allow volumetric assessment of tumor size, shape, and heterogeneity, facilitating treatment planning, radiotherapy targeting, and monitoring therapeutic response.



Multi-modal approaches that integrate imaging with clinical and molecular data, such as tumor biomarkers, genetic profiles, and patient demographics, improve segmentation performance and support personalized treatment strategies. Challenges such as variability in imaging protocols, limited annotated datasets, and model interpretability are being addressed through techniques like data augmentation, transfer learning, and multi-center dataset integration.

Interpretability is critical for clinical adoption. Visualization methods, including attention maps and saliency overlays, help clinicians understand AI predictions, validate outputs, and build trust in automated systems. Ethical considerations, patient privacy, and adherence to regulatory standards are essential to ensure safe and equitable deployment.

Overall, AI-assisted cancer lesion segmentation has the potential to reduce manual workload, minimize inter-observer variability, enhance diagnostic accuracy, and improve patient outcomes, demonstrating a transformative impact on modern oncology practice.

Conclusion

In conclusion, artificial intelligence and deep learning provide powerful tools for automated cancer lesion segmentation across CT, MRI, and PET imaging. CNN-based architectures, including U-Net and attention-based models, enable accurate and reproducible delineation of tumors, supporting precise diagnosis, treatment planning, and monitoring of therapeutic response.

Although challenges such as imaging variability, limited annotated datasets, and the need for interpretability persist, ongoing methodological innovations and integration of multi-modal data continue to enhance model performance. The clinical implementation of AI-assisted segmentation systems can improve workflow efficiency, reduce diagnostic errors, and advance personalized oncology care, highlighting the transformative potential of AI in modern cancer diagnostics.



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