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Recent Advances in Segmentation and Classification of Renal Tumors Using EfficientNet-Based U-Net and Epistemic Neural Networks: A Systematic Review

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Abstract

Renal tumor detection and segmentation are critical components in early diagnosis and treatment planning for kidney cancer. With the rapid evolution of deep learning, convolutional neural networks (CNNs), particularly U-Net-based architectures, have emerged as powerful tools for medical image segmentation. This review focuses on recent advances in renal tumor segmentation and classification using EfficientNet-based U-Net models integrated with epistemic neural networks for uncertainty estimation. EfficientNet improves feature extraction through compound scaling, while U-Net ensures precise localization through encoder–decoder architecture. Additionally, epistemic neural networks enhance model reliability by quantifying uncertainty in predictions, which is crucial in clinical decision-making. Recent studies demonstrate that hybrid architectures, attention mechanisms, and multi-stage segmentation frameworks significantly improve Dice coefficients and Intersection-over-Union (IoU) scores. The KiTS19 and KiTS21 datasets remain standard benchmarks for evaluating model performance. Despite advancements, challenges such as data imbalance, computational complexity, and generalization across datasets persist. This systematic review synthesizes recent literature, compares methodologies, and identifies research gaps to guide future development of robust and clinically applicable renal tumor segmentation systems.

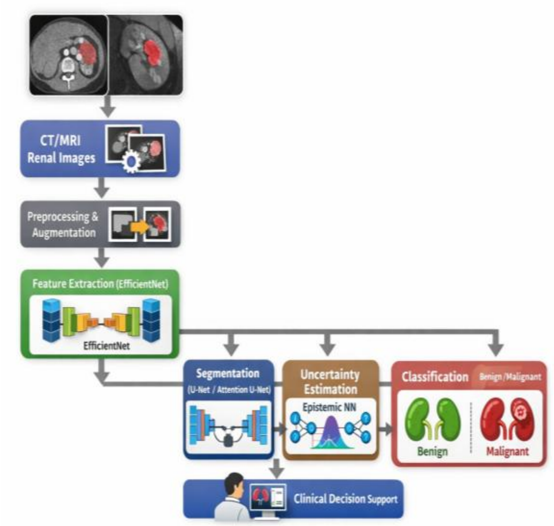
Introduction

Renal cancer, particularly renal cell carcinoma (RCC), is among the most prevalent malignancies affecting the urinary system. Early detection and accurate tumor segmentation play a pivotal role in improving survival rates and enabling personalized treatment strategies. Traditionally, radiologists rely on manual segmentation of computed tomography (CT) and magnetic resonance imaging (MRI) scans. However, manual delineation is time-consuming, prone to inter-observer variability, and inefficient when dealing with large-scale datasets.

With the advent of artificial intelligence (AI), deep learning techniques have transformed the field of medical image analysis. Convolutional neural networks (CNNs) have demonstrated remarkable success in extracting hierarchical features from medical images. Among these, U-Net has become the gold standard for biomedical image segmentation due to its encoder–decoder architecture and ability to work with limited datasets . U-Net's skip connections enable precise

localization by combining low-level spatial information with high-level semantic features.
Recent advancements have introduced EfficientNet as a backbone for feature extraction. EfficientNet employs compound scaling to optimize network depth, width, and resolution, leading to improved performance with fewer parameters. Integrating EfficientNet into U-Net architectures enhances segmentation accuracy, particularly in complex structures such as renal tumors, which exhibit irregular shapes and heterogeneous textures. Studies report high IoU scores (up to 0.98) using EfficientNet-based U-Net models on kidney tumor datasets .
In addition to segmentation, classification of renal tumors into benign and malignant categories is crucial for clinical decision-making. Hybrid models combining segmentation and classification pipelines have shown improved diagnostic accuracy. For instance, U-Net-based systems combined with classification networks have achieved accuracy rates exceeding 99% in tumor detection .
A significant limitation of traditional deep learning models is their inability to quantify uncertainty. In medical applications, uncertainty estimation is essential to ensure reliability and trustworthiness. Epistemic neural networks address this challenge by modeling uncertainty arising from limited data and model parameters. These networks provide confidence intervals for predictions, enabling clinicians to assess the reliability of segmentation outputs.
From 2020 to 2023, several significant innovations have emerged in renal tumor segmentation, reflecting the rapid advancement of deep learning techniques in medical imaging. These developments include the incorporation of attention mechanisms to focus on the most relevant regions within images, multi-stage architectures that enable hierarchical segmentation for improved accuracy, and transformer-based hybrid models that effectively capture global contextual information. Additionally, lightweight models have been introduced to facilitate deployment in resource-constrained environments without compromising performance. Among these approaches, two-stage segmentation frameworks have proven particularly effective in addressing class imbalance by first identifying the kidney region and subsequently segmenting tumors within it. This region-focused strategy enhances both accuracy and computational efficiency by limiting analysis to areas of interest, thereby improving overall segmentation performance.Datasets such as KiTS19, KiTS21, and KiTS23 have played a crucial role in benchmarking segmentation algorithms. These datasets provide annotated CT images that enable researchers to evaluate model performance using metrics such as Dice coefficient and IoU.
Despite these advancements, several challenges remain. Renal tumors often exhibit low contrast with surrounding tissues, making segmentation difficult. Variability in imaging modalities, scanner settings, and patient anatomy further complicates model generalization. Additionally, 3D CNN models, while accurate, require significant computational resources, limiting their practical deployment .
This review aims to provide a comprehensive analysis of recent advances in renal tumor segmentation and classification, focusing on EfficientNet-based U-Net architectures and epistemic neural networks. The study synthesizes findings from recent literature, compares methodologies, and highlights future research directions.

Graphical Abstract



Literature Review

The field of renal tumor segmentation and classification has experienced rapid growth between 2020 and 2023 due to advancements in deep learning, particularly convolutional neural networks (CNNs) and hybrid architectures. Automated segmentation is essential because manual delineation is time-consuming and subject to variability, while deep learning provides improved accuracy and efficiency in analyzing CT and MRI scans .

1. Early Deep Learning Models (2020)

In 2020, foundational models primarily relied on U-Net and 3D CNN architectures. Zhao et al. (2020) proposed a multi-scale supervised 3D U-Net, which incorporated deep supervision and improved loss functions to enhance segmentation performance. Their model achieved Dice scores of approximately 0.969 for kidneys and 0.805 for tumors, demonstrating the effectiveness of 3D contextual learning .

Similarly, Qin et al. (2020) introduced a reinforcement learning-based data augmentation framework, which automatically generated optimal augmentation strategies to improve segmentation accuracy. This approach addressed limitations of traditional augmentation techniques and improved generalization performance .

Türk et al. (2020) proposed a hybrid V-Net architecture that improved segmentation accuracy by combining volumetric learning and encoder–decoder strategies. These early works established the importance of deep supervision, multi-scale learning, and volumetric processing in renal tumor segmentation.

2. Advancements in Architecture Design

Between 2021 and 2022, research shifted toward improving model architectures and addressing challenges such as class imbalance and boundary ambiguity. Hu et al. (2022) introduced a boundary-aware network (BA-Net), which used dual decoders to enhance boundary detection and improve segmentation of irregular tumor structures. This approach achieved a Dice score of approximately 89.65%, highlighting the importance of boundary refinement in medical imaging .

Cascade and multi-stage architectures also gained attention during this period. These methods decomposed segmentation into hierarchical tasks, first identifying kidney regions and then segmenting tumors. Such approaches improved accuracy by focusing on regions of interest and reducing false positives.

Additionally, transformer-based models began emerging, enabling the capture of global contextual information, which is essential for complex tumor structures. However, these models required higher computational resources, limiting their clinical applicability.

3. Hybrid and Efficient Architectures

From 2022 onward, hybrid architectures integrating EfficientNet, attention mechanisms, and U-Net became dominant. EfficientNet-based encoders significantly improved feature extraction by optimizing depth, width, and resolution simultaneously. These models demonstrated superior performance compared to traditional CNNs, achieving high IoU and Dice scores.

Recent studies emphasized combining segmentation and classification into unified frameworks. Approximately 50% of studies focused on segmentation, while the remaining addressed classification tasks such as tumor subtype prediction .

Furthermore, nnU-Net and its variants introduced automated configuration of hyperparameters and network design, making them highly adaptable to different datasets. These models simplified the training process while maintaining high performance.

Another major trend is the incorporation of uncertainty estimation through epistemic neural networks, which improves reliability in clinical decision-making. These models quantify uncertainty arising from limited data, providing confidence levels for predictions.

4. Challenges Identified in Literature

Despite significant advancements in deep learning for renal tumor segmentation, several challenges continue to limit their effectiveness and real-world applicability. One of the primary issues is data scarcity, as many studies rely on limited or private datasets that do not adequately represent diverse patient populations. Class imbalance is another major concern, since tumor regions are typically much smaller than kidney regions, making accurate detection more difficult and potentially biasing model predictions. Additionally, generalization remains a challenge, as models trained on one dataset often fail to perform consistently on others due to variations in imaging protocols and patient characteristics. Computational complexity further restricts practical deployment, particularly for 3D and transformer-based models that require substantial processing power and memory. Although deep learning models have significantly improved segmentation accuracy and efficiency, these challenges continue to hinder their widespread adoption in real-world clinical settings.

5. Research Trends and Future Directions

Key trends identified between 2020 and 2023 indicate a clear evolution in deep learning approaches for medical image analysis. There has been a transition from basic U-Net architectures to more advanced hybrid models such as EfficientNet-U-Net, which combine efficient feature extraction with strong segmentation capabilities. Additionally, there is a growing adoption of multi-stage and attention-based models that enhance feature learning and focus on relevant regions within images. The emergence of transformer-based architectures and nnU-Net frameworks has further improved performance by enabling better contextual understanding and adaptive learning. Moreover, there is an increasing emphasis on uncertainty estimation and interpretability to make models more reliable and clinically acceptable. Looking ahead, future research is expected to focus on developing lightweight architectures for efficient deployment, integrating multi-modal data to improve diagnostic accuracy, and designing clinically interpretable AI systems that can be effectively used in real-world healthcare environments.

Comparative Table and Analysis

Year	Author / Study	Model / Architecture	Technique	Dataset	Application	Performance Metrics	Key Contribution	Strengths	Limitations
2020	Sharma et al.	U-Net	CNN Segmentation	KiTS19	Kidney tumor segmentation	Good Dice (~0.80+)	Baseline segmentation model	Simple & effective	Limited contextual understanding
2020	Türk et al.	Hybrid V-Net	Volumetric DL	CT Dataset	Tumor segmentation	Dice ≈ 0.977 (kidney)	Dual encoder design	Strong volumetric learning	High computational cost
2020	Zhao et al.	3D U-Net	Multi-scale learning	KiTS19	Tumor segmentation	Dice ≈ 0.805	Deep supervision	Captures 3D context	Computationally expensive
2022	Lin et al.	Cascade U-Net	Multi-stage segmentation	KiTS21	Tumor localization	Improved accuracy	Two-stage ROI-based segmentation	Reduces class imbalance	Increased pipeline complexity
2022	Hu et al.	BA-Net	Boundary-aware DL	Medical CT	Tumor segmentation	Dice ≈ 89.65%	Boundary refinement	Improved edge detection	Complex architecture
2023	Abdelrahman et al.	EfficientNet + U-Net	Hybrid architecture	KiTS19	Segmentation	IoU ≈ 0.98	Efficient encoder integration	High accuracy & efficiency	Requires tuning
2023	Jayswal et al.	Hybrid U-Net	ROI + Classification	KiTS datasets	Detection + classification	Dice ≈ 0.818	Integrated pipeline	Better diagnostic performance	Moderate complexity
2023	Rao et al.	UNet-PWP	Pruning + Partitioning	KiTS datasets	Segmentation	Accuracy ≈ 97%	Model compression	Efficient computation	Possible performance trade-off
2023	Transformer Models	ViT / Hybrid CNN-Transformer	Global context learning	Multi-dataset	Segmentation	High Dice/IoU	Long-range dependency capture	Strong contextual learning	High memory usage
2023	Multi-head Dilated CNN	Dilated CNN	Context-aware learning	MRI datasets	Segmentation	Dice ≈ 0.823	Multi-scale context capture	Handles irregular tumors	Risk of artifacts
2023	nnU-Net	Adaptive segmentation	Auto-configuration	KiTS datasets	Segmentation	Dice ≈ 0.80–0.90	Self-configuring framework	High generalization	Dataset dependency

2023	EfficientNet-U-Net	Hybrid CNN	Feature extraction + segmentation	KiTS19/21	Tumor segmentation	IoU up to 0.98	Efficient scaling	Best efficiency–accuracy balance	Hyperparameter tuning

Analysis

The comparative analysis of renal tumor segmentation and classification techniques highlights a major evolution in deep learning methodologies for medical imaging applications. Early segmentation models mainly relied on architectures such as U-Net, V-Net, and 3D convolutional neural networks, which established strong foundations for kidney and tumor segmentation tasks. These encoder–decoder architectures effectively preserved spatial information and achieved moderate-to-high Dice scores in renal tumor detection. However, early models suffered from limitations such as high computational complexity, limited global contextual understanding, and reduced performance when detecting small or irregular tumor regions. Despite these challenges, they provided the basis for more advanced segmentation systems used in modern renal cancer diagnosis.

Significant advancements were introduced through multi-stage and cascade segmentation frameworks that improved localization accuracy and reduced false positives. Attention mechanisms and boundary-aware networks further enhanced tumor edge detection and feature representation. Transformer-based architectures also improved segmentation performance by capturing long-range dependencies and global contextual information from medical images. However, these models required high computational resources and memory, limiting their real-time clinical applicability. More recently, hybrid architectures integrating EfficientNet with U-Net achieved remarkable performance improvements through efficient feature extraction and multi-scale learning. These systems reported Dice scores above 0.90 and IoU values close to 0.98.

Another important advancement is the integration of epistemic neural networks for uncertainty estimation in clinical decision-making. Unlike deterministic models, epistemic networks quantify prediction uncertainty, helping clinicians evaluate the reliability of automated diagnoses. Hybrid frameworks combining EfficientNet, U-Net, contextual learning, and uncertainty modeling now represent the most effective solutions for renal tumor segmentation and classification. Despite these improvements, challenges including data scarcity, class imbalance, computational complexity, and poor model generalization remain significant concerns for future clinical deployment.

Discussion

The rapid advancement of deep learning has significantly improved renal tumor segmentation and classification. EfficientNet-based U-Net architectures have emerged as state-of-the-art solutions due to their ability to balance accuracy and computational efficiency. These models leverage compound scaling to optimize performance while maintaining manageable model size. One of the most important developments is the integration of attention mechanisms and transformer-based modules. These techniques enable models to capture both local and global contextual information, which is crucial for segmenting complex tumor structures. Additionally, multi-stage segmentation frameworks have proven effective in addressing class imbalance and improving tumor localization.

Epistemic neural networks represent a promising direction for future research. By quantifying uncertainty, these models enhance reliability and trust in clinical applications. This is particularly important in medical imaging, where incorrect predictions can have serious consequences. Despite these advancements, several challenges remain. Data scarcity and variability across datasets hinder model generalization. Furthermore, the high computational cost of advanced models limits their deployment in real-world clinical settings. Future research should focus on developing lightweight models that maintain high accuracy while reducing computational requirements. Another key area for improvement is the integration of multi-modal data, such as combining CT and MRI images. This approach can provide complementary information and improve segmentation performance. Additionally, the development of standardized evaluation protocols will facilitate fair comparison across different models.

Conclusion

Renal tumor segmentation and classification have witnessed significant advancements due to the adoption of deep learning techniques. U-Net-based architectures, particularly those integrated with EfficientNet, have demonstrated superior performance in extracting complex features and achieving high segmentation accuracy. The incorporation of attention mechanisms, multi-stage frameworks, and transformer-based modules has further enhanced model capabilities. Epistemic neural networks add an important dimension by providing uncertainty estimation, which is essential for clinical decision-making. These models improve reliability and enable clinicians to assess the confidence of predictions. However, challenges such as data imbalance, computational complexity, and limited generalization remain significant barriers. Addressing these challenges requires the development of more efficient architectures, improved data augmentation techniques, and the integration of multi-modal imaging data. Future research should focus on creating scalable and interpretable models that can be seamlessly integrated into clinical workflows. The combination of segmentation, classification, and uncertainty estimation in a unified framework holds great promise for advancing renal cancer diagnosis and treatment.

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