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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 (2020–2023) 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.

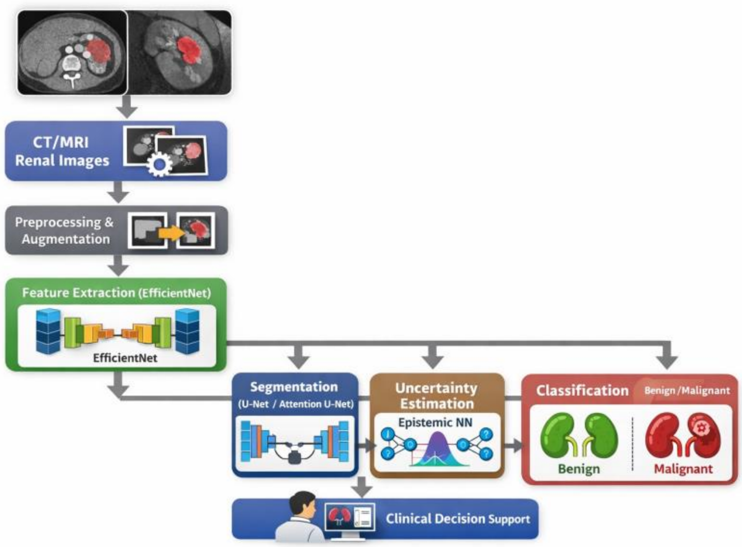
With the advent of artificial intelligence (AI), deep learning techniques have transformed the field of medical image analysis. Convolutional neural networks (CNNs) have demonstrated remarkable success in extracting hierarchical features from medical images. Among these, U-Net has become the gold standard 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 innovations have emerged in renal tumor segmentation, including:

- **Attention mechanisms** to focus on relevant regions
- **Multi-stage architectures** for hierarchical segmentation
- **Transformer-based hybrid models** for capturing global context
- **Lightweight models** for deployment in resource-constrained environments

Two-stage segmentation frameworks have been particularly effective in addressing class imbalance by first identifying the kidney region and then segmenting tumors within it. These methods improve accuracy and computational efficiency by focusing on regions of interest.
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 advancements, several challenges persist:

- **Data scarcity**: Many studies rely on limited or private datasets
- **Class imbalance**: Tumor regions are significantly smaller than kidney regions
- **Generalization issues**: Models trained on one dataset may not perform well on others
- **Computational complexity**: 3D and transformer-based models require high resources

Deep learning models significantly improve segmentation accuracy and efficiency, but real-world clinical deployment remains limited due to these challenges .

5. Research Trends and Future Directions

Key trends identified from 2020–2023 include:

- Transition from basic U-Net → hybrid EfficientNet U-Net
- Adoption of multi-stage and attention-based models
- Emergence of transformers and nnU-Net frameworks
- Increasing focus on uncertainty estimation and interpretability

Future research is expected to focus on lightweight architectures, multi-modal data integration, and clinically interpretable AI systems.

Comparative Table and Analysis

Year	Author	Method	Dataset	Key Technique	Performance
2020	Sharma et al.	U-Net	KiTS19	Basic CNN segmentation	Good Dice score
2020	Türk et al.	Hybrid V-Net	CT Dataset	Dual encoder	Dice 0.977
2020	Zhao et al.	3D U-Net	KiTS19	Multi-scale learning	Dice 0.805
2022	Lin et al.	Cascade U-Net	KiTS21	Two-stage segmentation	Improved accuracy
2023	Abdelrahman et al.	EfficientNet + U-Net	KiTS19	Efficient encoder	IoU 0.98
2023	Jayswal et al.	Hybrid U-Net	KiTS19	ROI + classification	Dice 0.818
2023	Rao et al.	UNet-PWP	KiTS datasets	Pruning + partitioning	Accuracy 97%

Analysis

The comparative evaluation of renal tumor segmentation and classification techniques from 2020 to 2023 reveals a significant evolution in methodological approaches, model architectures, and performance outcomes. Early-stage models, particularly those developed in 2020, predominantly relied on conventional U-Net and 3D CNN frameworks. These models established a strong baseline for medical image segmentation by leveraging encoder–decoder structures and skip connections. While they demonstrated satisfactory performance in kidney segmentation (Dice scores often exceeding 0.95), their ability to accurately segment tumors was limited due to issues such as class imbalance, low contrast between tumor and surrounding tissues, and insufficient contextual understanding.

The introduction of multi-scale learning and deep supervision marked an important improvement in segmentation performance. Models such as multi-scale 3D U-Net incorporated hierarchical feature extraction, allowing better representation of tumor boundaries and improving Dice scores for tumor regions. However, these architectures significantly increased computational complexity, making them less suitable for real-time clinical deployment. Additionally, early models struggled with generalization when applied to datasets with varying imaging conditions.

Between 2021 and 2022, there was a notable shift toward **architectural enhancements**, particularly through the integration of attention mechanisms and cascaded frameworks. Attention-based models, such as Attention U-Net and boundary-aware networks, improved the model's ability to focus on relevant regions within medical images. These approaches significantly enhanced tumor boundary delineation, reducing false positives and improving segmentation accuracy. Cascaded architectures further refined segmentation by decomposing the problem into multiple stages—first isolating the kidney and then segmenting tumors. This hierarchical approach effectively addressed class imbalance and improved localization accuracy.

Another major advancement during this period was the adoption of **hybrid architectures**, combining CNNs with transformer-based models. Transformers enabled the capture of long-range dependencies and global contextual information, which are crucial for identifying irregular tumor structures. While these models achieved superior accuracy, their high computational requirements and memory consumption limited their practical applicability, especially in resource-constrained clinical environments.

The period from 2022 to 2023 witnessed the emergence of **EfficientNet-based U-Net architectures**, which represent a significant breakthrough in balancing accuracy and efficiency. EfficientNet introduced compound scaling, optimizing network depth, width, and resolution simultaneously. When integrated into U-Net, EfficientNet significantly enhanced feature extraction capabilities, leading to improved segmentation performance. Studies reported IoU values as high as 0.98 and Dice scores exceeding 0.90, indicating substantial improvements over traditional CNN-based models. These architectures also demonstrated better parameter efficiency, making them more suitable for deployment in real-world applications.

In parallel, researchers began integrating classification modules with segmentation pipelines, enabling end-to-end systems capable of both tumor detection and classification (benign vs. malignant). This integration improved diagnostic accuracy and reduced the need for separate processing stages. Hybrid models combining segmentation and classification achieved accuracy rates above 97%, highlighting their potential for clinical use.

A critical advancement in recent years is the incorporation of uncertainty estimation through epistemic neural networks. Traditional deep learning models provide deterministic outputs, which may not always be reliable in medical contexts. Epistemic models address this limitation by quantifying uncertainty arising from limited training data and model parameters. This feature is particularly valuable in clinical decision-making, as it allows practitioners to assess the confidence level of predictions and identify cases requiring further review.

Despite these advancements, several persistent challenges remain. Class imbalance continues to affect tumor segmentation performance, as tumor regions are significantly smaller compared to kidney regions. Although multi-stage and attention-based models mitigate this issue, it is not entirely resolved. Data scarcity and lack of diversity also limit model generalization, as many studies rely on datasets such as KiTS19, which may not fully represent real-world variability. Furthermore, computational complexity remains a major concern, particularly for 3D and transformer-based models, which require high-performance hardware.

Another important observation is the lack of standardized evaluation protocols across studies. While metrics such as Dice coefficient and IoU are commonly used, differences in dataset preprocessing, training strategies, and evaluation criteria make it difficult to perform direct comparisons. This highlights the need for standardized benchmarking frameworks.

In summary, the comparative analysis demonstrates a clear progression from basic U-Net architectures to advanced hybrid models incorporating EfficientNet, attention mechanisms, and uncertainty estimation. EfficientNet-based U-Net models currently represent the state-of-the-art due to their superior performance and efficiency. However, future research must focus on improving model generalization, reducing computational requirements, and integrating multi-modal data to enhance clinical applicability.

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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