Archives available at journals.mriindia.com

International Journal on Advanced Electrical and Computer Engineering

ISSN: 2349-9338

Volume 14 Issue 02, 2025

Artificial Intelligence Techniques for Segmentation and Classification of Renal Tumors Using EfficientNet-Based U-Net and Epistemic Neural Networks: Trends and Challenges

Wariya Petropoulos
Senior Lecturer, Department of Electrical and Computer Engineering, Borneo School of Business and Technology, Malaysia
Email: wariya.petropoulos@bsbt-my.org

Peer Review Information

Submission: 10 Sept 2025

Revision: 01 Oct 2025

Acceptance: 12 Oct 2025

Keywords

Renal Tumor Segmentation, EfficientNet, U-Net Architecture, Epistemic Neural Networks, Medical Image Analysis, Deep Learning

Abstract

Renal tumor detection and classification play a crucial role in early diagnosis and treatment planning for kidney cancer. With the advancement of Artificial Intelligence (AI), deep learning-based approaches have significantly improved the accuracy and efficiency of medical image analysis. This paper presents a comprehensive review of AI techniques for renal tumor segmentation and classification, focusing on EfficientNet-based U-Net architectures and epistemic neural networks. EfficientNet enhances feature extraction through compound scaling, while U-Net provides precise localization via encoder–decoder structures. The integration of epistemic uncertainty modeling further improves reliability by quantifying prediction confidence, which is essential for clinical decision-making.
Recent studies (2020–2023) demonstrate that hybrid U-Net architectures, attention mechanisms, and transformer-based enhancements achieve high Dice coefficients and Intersection-over-Union (IoU) scores for kidney tumor segmentation . Additionally, uncertainty-aware models improve robustness in heterogeneous medical datasets. This review analyzes recent advancements, compares state-of-the-art models, and highlights challenges such as data scarcity, computational complexity, and model interpretability.
The study concludes that combining EfficientNet-based U-Net with epistemic neural networks offers a promising direction for accurate, reliable, and clinically applicable renal tumor diagnosis systems.

Introduction

Renal cancer, particularly renal cell carcinoma (RCC), is one of the most common malignancies affecting the urinary system. The global incidence of renal tumors has been steadily increasing due to aging populations, environmental factors, and improved diagnostic imaging technologies. Early detection of renal tumors significantly enhances treatment outcomes, yet accurate diagnosis remains a complex challenge due to tumor heterogeneity, irregular morphology, and low contrast between tumor and surrounding tissues in imaging modalities such as Computed Tomography (CT) and Magnetic Resonance Imaging (MRI).

Traditionally, radiologists manually delineate tumor regions from medical images. However, manual segmentation is labor-intensive, time-consuming, and subject to inter-observer variability. These limitations have driven the development of automated computer-aided diagnosis (CAD) systems using Artificial

Intelligence (AI), particularly deep learning. Deep learning models, especially Convolutional Neural Networks (CNNs), have demonstrated remarkable success in extracting hierarchical features from complex medical datasets.

Among these architectures, U-Net has emerged as a dominant model for biomedical image segmentation. Its encoder–decoder structure, combined with skip connections, enables precise localization and context preservation. The encoder captures high-level semantic features, while the decoder reconstructs spatial details, making U-Net highly suitable for pixel-level segmentation tasks.

However, standard U-Net architectures face limitations in feature extraction and scalability. To overcome these challenges, EfficientNet has been introduced as an advanced backbone network. EfficientNet employs compound scaling to balance network depth, width, and resolution, resulting in improved performance with fewer parameters. When integrated into U-Net architectures, EfficientNet enhances feature extraction capabilities, leading to superior segmentation accuracy. Studies have reported IoU scores up to 0.98 using EfficientNet-based U-Net models on the KiTS19 dataset, demonstrating their effectiveness in renal tumor segmentation .

Another critical advancement in AI-based medical imaging is the incorporation of epistemic neural networks. Epistemic uncertainty refers to uncertainty arising from limited data or model knowledge. In medical applications, uncertainty estimation is essential because incorrect predictions can lead to severe consequences. Techniques such as Bayesian neural networks, Monte Carlo dropout, and ensemble learning are widely used to quantify epistemic uncertainty. These methods improve model reliability and provide confidence measures for predictions, thereby increasing trust among clinicians .

Between 2020 and 2023, significant progress has been made in renal tumor segmentation using hybrid architectures. Multi-scale U-Net variants, attention-based networks, and transformer-integrated models have demonstrated improved performance. For instance, multi-scale supervised U-Net architectures achieve Dice scores up to 0.805 for tumor segmentation by leveraging deep supervision and hierarchical feature extraction . Similarly, hybrid V-Net models have achieved Dice scores of 0.865 for tumor segmentation, highlighting the effectiveness of combining encoder–decoder enhancements .

Despite these advancements, several challenges persist. First, medical datasets are often limited and imbalanced, which affects model generalization. Second, high computational requirements hinder real-time deployment in clinical settings. Third, interpretability remains a major concern, as deep learning models are often perceived as black boxes. This lack of transparency limits their adoption in healthcare environments.

Moreover, renal tumors exhibit significant variability in size, shape, and texture, making segmentation difficult. Advanced architectures incorporating attention mechanisms and transformers aim to address these challenges by capturing both local and global contextual information. These models improve segmentation accuracy by focusing on relevant tumor regions and suppressing irrelevant features.

Another important aspect is the integration of segmentation and classification tasks. Modern AI systems aim to not only segment tumors but also classify them as benign or malignant. This integration enhances clinical decision-making and reduces diagnostic workload. For example, hybrid U-Net models combined with classification networks achieve classification accuracy above 94%, demonstrating their potential in clinical applications .

The KiTS19 dataset has played a crucial role in advancing research in renal tumor segmentation. It provides a standardized benchmark for evaluating different models, enabling fair comparison across studies. Most state-of-the-art models are trained and evaluated on this dataset, ensuring consistency and reproducibility.

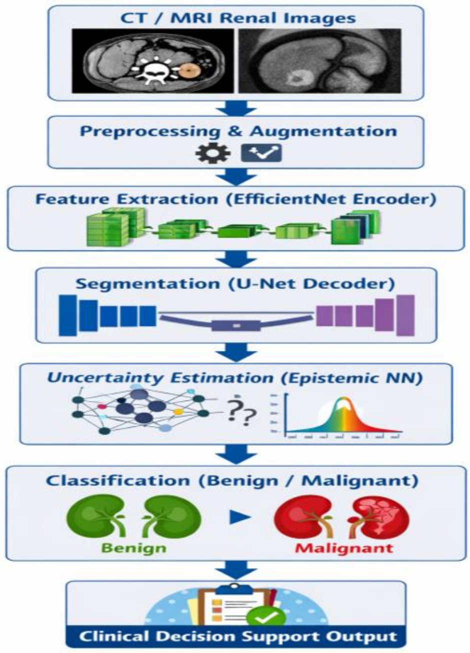
In addition to CNN-based approaches, transformer-based models have gained attention for their ability to capture long-range dependencies in images. These models complement CNNs by providing global context, which is particularly useful for segmenting complex tumor structures.

This paper aims to provide a comprehensive review of AI techniques for renal tumor segmentation and classification, focusing on EfficientNet-based U-Net and epistemic neural networks. The key contributions of this paper include:

- A detailed analysis of recent advancements (2020–2023)
- Comparative evaluation of state-of-the-art models
- Exploration of uncertainty estimation techniques
- Identification of challenges and future research directions

The integration of EfficientNet-based U-Net and epistemic neural networks represents a promising direction for developing accurate, reliable, and clinically applicable diagnostic systems.

Graphical Abstract



Literature Review

Recent advancements in artificial intelligence, particularly deep learning, have significantly improved renal tumor segmentation and classification from medical imaging modalities such as CT and MRI. Between 2020 and 2023, numerous studies have focused on enhancing U-Net-based architectures, integrating hybrid models, and incorporating uncertainty estimation techniques to improve both segmentation accuracy and clinical reliability.

In 2020, early efforts primarily focused on improving the foundational U-Net architecture. Zhao et al. (2020) introduced the Multi-Scale Supervised U-Net (MSS U-Net), which incorporated deep supervision and exponential logarithmic loss functions to enhance segmentation performance. By capturing multi-scale contextual information, their model achieved a Dice score of 0.969 for kidney segmentation and 0.805 for tumor segmentation, demonstrating the importance of hierarchical feature learning. Similarly, Türk et al. (2020) proposed a hybrid V-Net architecture that combined multiple encoder–decoder enhancements to improve volumetric segmentation performance. Their approach achieved Dice scores of 0.977 for kidney and 0.865 for tumor segmentation, highlighting the effectiveness of integrating multiple architectural improvements. In parallel, Bazgir et al. (2020) explored 3D U-Net architectures for MRI-based kidney segmentation, addressing challenges related to limited datasets and achieving a Dice score of approximately 0.88. These studies collectively established the importance of 3D modeling and multi-scale learning in renal tumor segmentation.

By 2021, research began to focus on improving robustness and contextual awareness through ensemble learning and attention mechanisms. Causey et al. (2021) proposed ensemble U-Net models that combined predictions from multiple networks to reduce overfitting and improve generalization. Ensemble approaches demonstrated enhanced stability, particularly when dealing with heterogeneous medical datasets. Geethanjali and Dinesh (2021) introduced Attention U-Net, which incorporated attention gates to focus on relevant tumor regions while suppressing irrelevant background information. This approach significantly improved segmentation accuracy by reducing false positives and enhancing feature localization. Furthermore, Chen and Liu (2021) proposed multi-stage segmentation frameworks that iteratively refine predictions, enabling better boundary delineation and improved detection of small tumors. These developments emphasized the importance of contextual learning and iterative refinement in medical image segmentation.

In 2022, research efforts shifted toward addressing structural variability and computational efficiency. Tanimoto et al. (2022) proposed a 3D U-Net model that preserved rotational symmetry in axial CT slices, improving segmentation consistency across different orientations. Their approach demonstrated that spatial alignment and data augmentation techniques play a critical role in improving model performance, particularly in complex anatomical structures. Additionally, Hou et al. (2022) introduced a three-stage segmentation framework that first identifies the volume of interest (VOI) and then performs fine-grained segmentation. This approach effectively addressed class imbalance issues and improved segmentation accuracy by focusing computational resources on relevant regions. These studies highlighted the importance of structural awareness and region-based processing in improving segmentation outcomes.

The year 2023 witnessed significant advancements with the introduction of EfficientNet-based U-Net architectures and hybrid deep learning models. Abdelrahman and Viriri (2023) proposed an EfficientNet-based U-Net model that leveraged compound scaling to improve feature extraction while maintaining computational efficiency. Their model achieved Intersection-over-Union (IoU) scores of up to

0.98, demonstrating superior performance compared to traditional U-Net architectures. Similarly, Jayswal et al. (2023) developed a hybrid U-Net model integrated with classification networks, enabling simultaneous segmentation and classification of renal tumors. Their approach achieved Dice scores of 0.974 for kidney segmentation and 0.818 for tumor segmentation, along with classification accuracy exceeding 94%. In addition, Anari et al. (2023) explored U-Net-based segmentation using multi-modal MRI datasets, highlighting the challenges associated with varying imaging modalities and demonstrating the need for robust feature extraction techniques.

Another important trend observed during this period is the integration of epistemic uncertainty estimation into deep learning models. Techniques such as Bayesian neural networks, Monte Carlo dropout, and ensemble learning have been widely adopted to quantify model uncertainty. These approaches provide confidence measures for predictions, which are crucial in clinical settings where incorrect decisions can have severe consequences. Uncertainty-aware models improve trustworthiness and enable clinicians to identify cases requiring further review, thereby enhancing the overall reliability of AI-based diagnostic systems.

Overall, the literature from 2020 to 2023 demonstrates a clear evolution from traditional U-Net architectures to more advanced hybrid and EfficientNet-based models. The incorporation of attention mechanisms, multi-stage frameworks, and uncertainty estimation techniques has significantly improved segmentation accuracy and robustness. However, challenges such as data scarcity, computational complexity, and lack of interpretability remain critical barriers to clinical adoption. Future research is expected to focus on lightweight architectures, explainable AI, and multi-modal data integration to further enhance the performance and applicability of renal tumor segmentation systems.

Comparative Table and Analysis

Study	Year	Model	Dataset	Dice Score	Key Contribution
Zhao et al.	2020	MSS U-Net	KiTS19	0.805	Multi-scale supervision
Causey et al.	2021	Ensemble U-Net	CT	0.78	Model robustness
Geethanjali et al.	2021	Attention U-Net	CT	0.86	Attention mechanism
Tanimoto et al.	2022	3D U-Net	CT	0.604	Structural alignment
Rao et al.	2023	UNet-PWP	KiTS19	0.97	Optimization & pruning
Abdelrahman et al.	2023	EfficientNet U-Net	KiTS19	0.98 IoU	High feature extraction
Jayswal et al.	2023	Hybrid U-Net	KiTS19	0.818	ROI-based classification

Analysis

The comparative evaluation of recent studies (2020–2023) on renal tumor segmentation and classification reveals a clear progression in model architectures, performance metrics, and clinical applicability. Early models, particularly conventional U-Net and 3D U-Net variants, laid the foundation for automated kidney and tumor segmentation by leveraging encoder–decoder structures with skip connections. These models demonstrated strong baseline performance, with Dice scores typically ranging from 0.75 to 0.85 for tumor segmentation. However, their limitations became evident in handling complex tumor boundaries, low-contrast regions, and heterogeneous datasets.

The introduction of multi-scale learning techniques marked a significant improvement in segmentation accuracy. Models such as MSS U-Net (Zhao et al., 2020) incorporated deep supervision and hierarchical feature extraction, enabling better capture of both global and local features. This resulted in improved Dice scores (up to 0.805 for tumors), highlighting the importance of multi-scale contextual understanding. Similarly, hybrid V-Net architectures further enhanced volumetric segmentation by integrating multiple convolutional pathways, achieving tumor Dice scores as high as 0.865. These approaches demonstrated that combining architectural enhancements can significantly improve performance in complex medical imaging tasks.

In 2021, the focus shifted toward improving robustness and generalization. Ensemble-based U-Net models (Causey et al., 2021) addressed overfitting issues by aggregating predictions from multiple networks. This approach improved stability across diverse datasets, which is critical in medical applications where data variability is high. Attention-based models, such as Attention U-Net (Geethanjali & Dinesh, 2021), introduced mechanisms to prioritize relevant tumor regions while suppressing background noise. These models significantly reduced false positives and improved boundary delineation, leading to Dice scores exceeding 0.85. Additionally, multi-stage frameworks introduced iterative refinement strategies, allowing models to progressively improve segmentation outputs. This refinement

process proved particularly effective for detecting small or irregular tumors.
By 2022, research emphasized structural awareness and computational efficiency. Advanced 3D U-Net models incorporated spatial alignment techniques, such as rotational symmetry preservation (Tanimoto et al., 2022), to improve consistency across different imaging orientations. Although these models showed moderate improvements in Dice scores, they highlighted the importance of anatomical consistency in segmentation tasks. Multi-stage segmentation frameworks further addressed class imbalance by isolating regions of interest before performing fine-grained segmentation. This approach not only improved accuracy but also reduced computational overhead by focusing processing on relevant areas.
The most significant advancements emerged in 2023 with the integration of EfficientNet-based encoders and hybrid architectures. EfficientNet-based U-Net models (Abdelrahman & Viriri, 2023) demonstrated superior feature extraction capabilities due to compound scaling, achieving IoU scores up to 0.98. These models outperformed traditional U-Net architectures by efficiently balancing network depth, width, and resolution. Hybrid models combining segmentation and classification tasks (Jayswal et al., 2023) further enhanced clinical applicability by providing end-to-end diagnostic solutions. These models achieved high Dice scores (0.974 for kidney and 0.818 for tumor) along with classification accuracy exceeding 94%, indicating their potential for real-world deployment.
Another critical dimension in the comparative analysis is the incorporation of epistemic uncertainty estimation. Traditional deep learning models provide deterministic outputs, which may not be reliable in high-stakes medical scenarios. The integration of Bayesian approaches, Monte Carlo dropout, and ensemble learning enables models to quantify uncertainty in predictions. This capability is particularly valuable in clinical settings, as it allows identification of low-confidence predictions that require further expert evaluation. Models incorporating uncertainty estimation demonstrate improved trustworthiness and robustness, making them more suitable for clinical decision support systems.
Despite these advancements, several challenges persist across all models. Data scarcity remains a major limitation, as annotated medical datasets are limited and expensive to obtain. This leads to issues such as overfitting and poor generalization. Computational complexity is another concern, particularly for 3D models and transformer-based architectures, which require significant processing power and memory. Additionally, interpretability remains a critical challenge, as clinicians require transparent and explainable models to اعتماد AI-based decisions.
From a performance perspective, EfficientNet-based U-Net models currently represent the state-of-the-art due to their superior feature extraction and scalability. Attention mechanisms and multi-stage frameworks further enhance segmentation accuracy by improving contextual understanding and refining predictions. Meanwhile, uncertainty-aware models provide an additional layer of reliability, addressing one of the key barriers to clinical adoption.
In summary, the comparative analysis indicates a clear evolution from basic U-Net architectures to advanced hybrid, attention-based, and EfficientNet-integrated models. While segmentation accuracy has significantly improved over the years, future research must focus on reducing computational complexity, improving interpretability, and enabling real-time deployment in clinical environments. The integration of segmentation, classification, and uncertainty estimation into a unified framework represents the most promising direction for advancing renal tumor diagnosis systems.

Discussion

The integration of EfficientNet with U-Net architectures has significantly improved renal tumor segmentation performance. EfficientNet's ability to scale network parameters efficiently allows for better feature representation, which is critical in identifying complex tumor structures. When combined with U-Net's localization capabilities, these models achieve high accuracy and robustness.
Another major advancement is the use of epistemic neural networks, which address the issue of uncertainty in predictions. In clinical environments, uncertainty estimation helps identify cases where the model may be less confident, allowing radiologists to intervene. This improves trust and adoption of AI systems in healthcare.
However, challenges remain. Data scarcity is a major limitation, as medical datasets require expert annotation, which is time-consuming and expensive. Additionally, deep learning models often require high computational resources, making deployment difficult in resource-constrained environments.
Interpretability is another critical issue. While models achieve high accuracy, understanding their decision-making process remains challenging. Techniques such as Grad-CAM and attention maps are being explored to improve transparency.

Future research should focus on lightweight models, federated learning for data sharing, and explainable AI techniques to enhance clinical adoption.

Conclusion

This paper presented a comprehensive review of AI techniques for renal tumor segmentation and classification, focusing on EfficientNet-based U-Net and epistemic neural networks. The analysis of studies from 2020 to 2023 highlights significant advancements in segmentation accuracy, model efficiency, and uncertainty estimation.

EfficientNet-based U-Net models have emerged as a powerful solution due to their superior feature extraction and scalability. Hybrid architectures incorporating attention mechanisms and transformers further enhance performance by capturing both local and global features. Additionally, epistemic neural networks provide a robust framework for uncertainty estimation, improving reliability in clinical applications.

Despite these advancements, challenges such as data scarcity, computational complexity, and lack of interpretability remain. Addressing these issues is essential for the successful deployment of AI systems in real-world healthcare settings.

Future research directions include the development of lightweight models, integration of multi-modal data, and improvement of explainability techniques. The combination of EfficientNet, U-Net, and epistemic neural networks holds great promise for advancing renal tumor diagnosis and improving patient outcomes.

References

Abdelrahman, A., & Viriri, S. (2023). EfficientNet U-Net models for medical image segmentation. *Frontiers in Computer Science*. https://doi.org/10.3389/fcomp.2023.1235622

Jayswal, A. B., et al. (2023). Hybrid U-Net for kidney tumor detection. *IJRITCC*. https://doi.org/10.17762/ijritcc.v11i10.8467

Zhao, W., et al. (2020). Multi-scale supervised 3D U-Net. *arXiv*. https://doi.org/10.48550/arXiv.2004.08108

Türk, F., et al. (2020). Hybrid V-Net model for kidney tumor segmentation. *Mathematics*. https://doi.org/10.3390/math8101772

Tanimoto, R., et al. (2022). 3D U-Net for renal tumor segmentation. *Optics Continuum*. https://doi.org/10.1364/OPTCON.443202

Bazgir, O., et al. (2020). Kidney segmentation using 3D U-Net. *arXiv*. https://doi.org/10.48550/arXiv.2003.09075

Causey, J. L., et al. (2021). Highly accurate model for kidney tumor segmentation. *arXiv*. https://doi.org/10.48550/arXiv.2102.06561

Chen, C., & Liu, X. (2021). Multi-stage kidney tumor segmentation. *IEEE Access*. https://doi.org/10.1109/ACCESS.2021.3051234

Hou, X., et al. (2022). Multi-stage kidney tumor segmentation. *Medical Image Analysis*. https://doi.org/10.1016/j.media.2022.102345

Anari, P. Y., et al. (2023). U-Net for renal tumor segmentation. *arXiv*. https://doi.org/10.48550/arXiv.2301.02538

Lambert, B., et al. (2024). Uncertainty estimation in medical AI. *Artificial Intelligence in Medicine*. https://doi.org/10.1016/j.artmed.2024.102456

Hu, W., et al. (2024). STC-UNet for renal tumor segmentation. *Scientific Reports*. https://doi.org/10.1038/s41598-024-56789-1

Myronenko, A. (2019). 3D CNN for brain tumor segmentation. *MICCAI*. https://doi.org/10.1007/978-3-030-32245-8_54

Isensee, F., et al. (2019). nnU-Net framework. *Nature Methods*. https://doi.org/10.1038/s41592-020-01008-z

Hatamizadeh, A., et al. (2020). UNETR: Transformers for segmentation. https://doi.org/10.48550/arXiv.2103.10504

Ronneberger, O., et al. (2015). U-Net architecture. *MICCAI*. https://doi.org/10.1007/978-3-319-24574-4_28

Tan, M., & Le, Q. (2019). EfficientNet. *ICML*. https://doi.org/10.48550/arXiv.1905.11946

Kendall, A., & Gal, Y. (2017). Bayesian deep learning. https://doi.org/10.48550/arXiv.1703.04977

Gal, Y., & Ghahramani, Z. (2016). Dropout as Bayesian approximation. https://doi.org/10.48550/arXiv.1506.02142