Advancing Deep Learning Techniques for Early Detection and Classification of Renal Cell Carcinoma : A review

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Abstract: Kidney cancer, particularly renal cell carcinoma (RCC), poses a significant global health threat, exhibiting a higher mortality rate in men. Accurate and timely diagnosis is paramount for effective treatment. This research explores the application of artificial intelligence (AI), specifically deep learning and machine learning, in the detection and classification of kidney tumors. We systematically examine existing literature to assess current advancements in AI-driven kidney tumor detection, primarily using computed tomography (CT) scans, the standard imaging modality. Analysis of various deep learning and machine learning models employed for this purpose, detailing the datasets used and evaluating the advantages and limitations of each approach. A key focus is on segmentation techniques, which isolate the tumor from surrounding tissue, and classification methods, which differentiate between benign, malignant, and indolent tumors. We also address the challenges hindering the widespread adoption of AI-based diagnostic tools, including variations in tumor appearance, limitations in dataset size and quality, computational demands, and the need for expertly annotated data. By identifying these challenges, this review aims to pinpoint gaps in current research and inform future development. The review also examines the datasets used in AI-based kidney tumor detection and their influence on model training and evaluation. Ultimately, this work seeks to lay the groundwork for developing improved deep learning models that enhance the accuracy and efficiency of kidney tumor diagnosis, leading to more reliable, automated systems and better patient outcomes.

Keywords: Kidney Tumor, Renal Cell Carcinoma, Deep Learning, Machine Learning, Segmentation, Classification, Computed Tomography, CT Scan, Artificial Intelligence, Medical Image Analysis, Diagnosis.

Introduction

Kidneys are vital organs responsible for filtering waste products and toxins from the bloodstream. Kidney cancer ranks among the seven most prevalent cancer types globally, affecting both men and women. [1]. Kidney tumors are classified into three main categories: benign, malignant, and indolent. Benign tumors are characterized by slow growth and do not spread to other tissues. Malignant and indolent tumors are both cancerous. However, indolent tumors are generally slow-growing and have a lower tendency to spread to distant sites within the body compared to malignant tumors [2]. Kidney tumor development begins with changes in healthy cells or the rapid proliferation of abnormal cells. Renal cell carcinoma (RCC) is the most common type of kidney cancer, with subtypes including clear cell RCC, papillary RCC, and chromophobe RCC. RCC is often linked to genetic abnormalities.

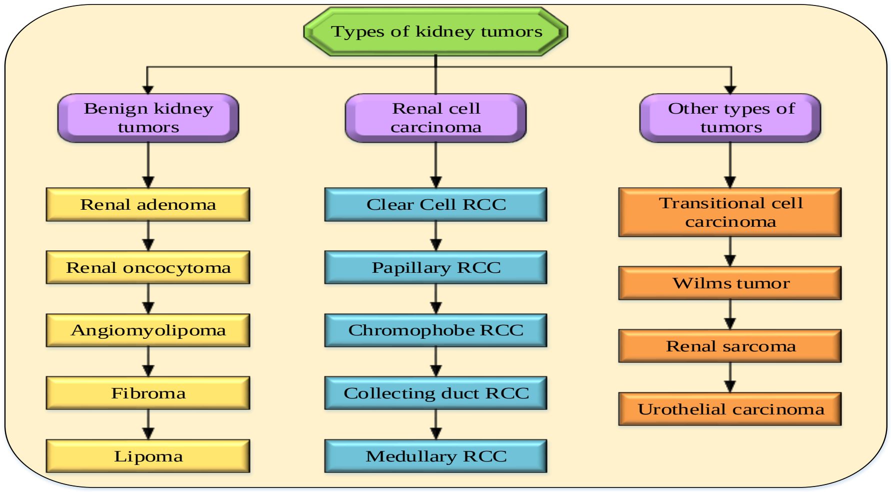


Figure 1. various types of kidney tumors.

Diagnosis relies on various methods, including physical examinations and imaging techniques like CT scans, MRI, and ultrasound. However, these methods can have limitations in accurately detecting kidney tumors. Traditional diagnostic approaches are often time-consuming and can yield inconsistent results. Recent research has explored the application of machine learning and deep learning algorithms, such as Convolutional Neural Networks (CNNs), U-net, and Deep Neural Networks (DNNs), to improve kidney tumor detection. This review paper examines existing machine learning and deep learning models, identifying their limitations. Furthermore, it analyzes segmentation and classification approaches for kidney tumor detection. By highlighting the challenges inherent in current machine learning and deep learning models, this review aims to inform the development of more effective diagnostic tools. Deep learning has become a crucial tool in kidney tumor diagnosis, segmentation, and classification Computational techniques have progressively improved, aiming to enhance the accuracy of medical image analysis and support clinical decisions. Figure 1 illustrates the various types of kidney tumors.
Figure classifies various kidney tumors into three primary categories: Benign, Renal Cell Carcinoma (RCC), and Other Tumor Types. Within each category, specific tumor subtypes are listed.

Key Contribution

This review thoroughly investigates key research questions about kidney tumor detection and deep learning, aiming to provide comprehensive insights into the roles of medical imaging, machine learning, and datasets in accurate kidney tumor diagnosis and classification.

Article selection and search strategy

This review surveys kidney tumor detection techniques, offering a distinct perspective from existing literature by focusing on deep learning and machine learning models, and analyzing their respective advantages and disadvantages. A systematic search process, using keywords like "kidney tumor," "kidney tumor detection," "kidney tumor classification," and "diagnosis of kidney tumor," was conducted across prominent journals such as IEEE, Elsevier, and Springer. This review serves as a valuable resource for researchers exploring machine learning and deep learning approaches for kidney tumor detection.

Related work – Existing reviews

Several reviews have explored various aspects of kidney tumor detection and diagnosis. Abdelrahman et al. [3] surveyed deep learning for kidney tumor *segmentation*, focusing on CNNs and datasets like KITS19 and KITS21. Pandey et al. [4] reviewed automated kidney *segmentation* techniques in abdominal images, using PRISMA guidelines and evaluating metrics like the Dice coefficient. Qezelbash-Chamak et al.[5] examined machine learning for kidney *disease* diagnosis, including classification frameworks and datasets like RD-UCI. Ursprung et al. [6] analyzed CT and MRI for renal cell carcinoma (*RCC*) detection, assessing methodological quality and bias.

Imaging modalities employed in the visualization and assessment of kidney tumors

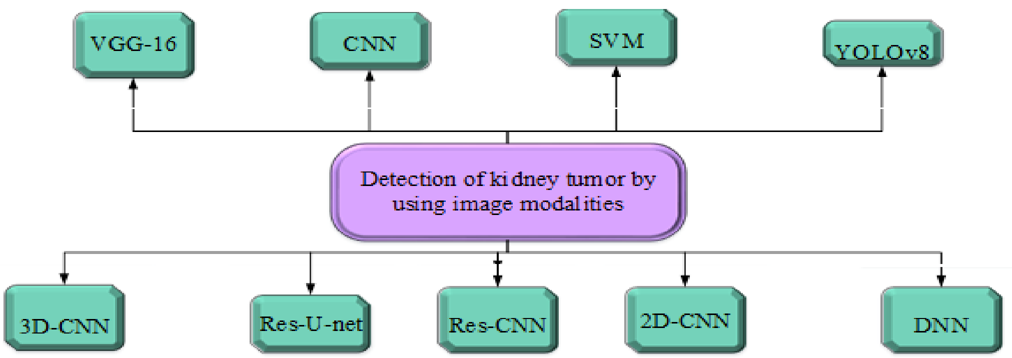


Figure 2. Imaging modalities employed in the visualization and assessment of kidney tumors

Visualizing and evaluating kidney tumors depends significantly on sophisticated imaging methods. Medical imaging is essential for tumor detection, distinguishing benign from malignant growths, cancer staging, and informing treatment strategies. Several imaging modalities, each with unique strengths and weaknesses, are used in kidney tumor assessment. CT scans are frequently used for kidney tumor detection, providing high-resolution images for detailed tumor characterization.

CT scans can be performed with or without contrast enhancement, aiding in both initial assessment and differentiation of benign/malignant tumors. While offering excellent anatomical detail and RCC staging capabilities, CT scans involve radiation exposure and potential nephrotoxicity from contrast agents. MRI provides superior soft-tissue contrast without radiation, making it useful when CT results are unclear or detailed tissue analysis is needed. Ultrasound is a readily accessible and non-invasive imaging method used for initial kidney tumor screening, especially for distinguishing cystic from solid masses. PET scans, often combined with CT (PET/CT), offer functional imaging by detecting metabolic activity, particularly useful for identifying metastases. Dual-Energy CT (DECT) uses two X-ray energy levels to improve tissue characterization and differentiate tumor types. Contrast-Enhanced Spectral Mammography (CESM), primarily used for breast imaging, is being investigated for kidney tumor assessment due to its vascular highlighting capabilities.

Figure 2 illustrates Imaging modalities employed in the visualization and assessment of kidney tumors.Klontzas et al. [7] used a CNN with transfer learning (InceptionV3, Inception-ResNetV2, and

VGG-16) on CT images from a multi-center dataset to distinguish between benign and malignant kidney tumors, achieving a high AUC of 0.918. Yang et al. [8] developed a weakly supervised CNN using bounding box annotations for kidney tumor segmentation in CTA images, achieving a Dice coefficient of 0.826. Pande et al [9] used YOLOv8 to automatically detect kidney abnormalities (tumors, cysts, stones) in CT and urogram images, achieving high accuracy, precision, and specificity. While promising, the system's computational complexity hinders real-time use, and the recall rate suggests room for improvement, pointing towards future optimization and expanded datasets. Liang et al. [10] developed a 2D CNN framework with a spatial transformer network and residual U-Net for kidney cancer staging and segmentation, achieving high Dice coefficients.

Machine learning and deep learning techniques for kidney tumor analysis.

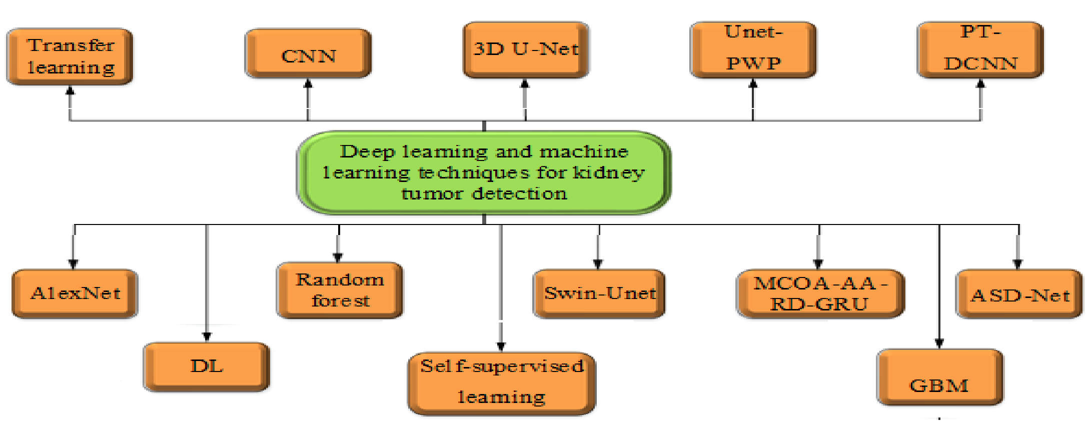


Figure 3. Deep learning and machine learning techniques for kidney tumor detection

Deep learning has become a crucial tool in kidney tumor diagnosis, segmentation, and classification Computational techniques have progressively improved, aiming to enhance the accuracy of medical image analysis and support clinical decisions. Several studies have explored machine and deep learning for kidney tumor analysis. Nasir et al. [11] combined transfer learning, blockchain, and deep learning for kidney cancer prediction, achieving high accuracy but lacking interpretability. Nikpanah et al. [12] used AlexNet for RCC subtype differentiation. Erdim et al. [13] applied machine learning algorithms for tumor classification, and Rehman et al. utilized multi-model transfer learning for kidney carcinoma prediction. Patel et al. [14] developed an adaptive deep learning framework for tumor segmentation and classification, while Ji et al. [15] created a U-Net-based network for enhanced segmentation. *Figure 3.* illustrates *deep learning and machine learning techniques for kidney tumor detection .*

kidney and renal tumor segmentation methods

Deep learning has been widely explored for kidney and renal tumor segmentation. Various deep learning architectures have been investigated for kidney and renal tumor segmentation. Hybrid V-Nets, combinations of MSS and 3D U-Net, and 3D residual networks with SE blocks have been explored. Additionally, networks combining convolutions and transformers, pretrained reconstruction networks

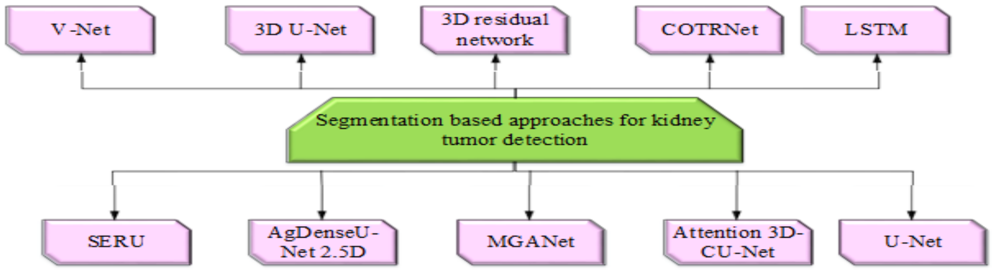


Figure 4. kidney and renal tumor segmentation methods

with convolutional LSTMs, and variations of U-Net with attention mechanisms or grayscale adaptation have been developed. These studies demonstrate varying levels of success, often achieving high Dice coefficients, but also highlight persistent challenges including computational cost, overfitting, feature extraction, interpretability, data requirements, and handling grayscale variations. Turk et al. [16] used a hybrid V-Net, Zhao et al. [17] combined MSS and 3D U-Net , and Qayyum et al. [18] employed a 3D residual network with SE blocks. Figure 4 illustrates kidney and renal tumor segmentation methods.

kidney and renal tumor classification methods

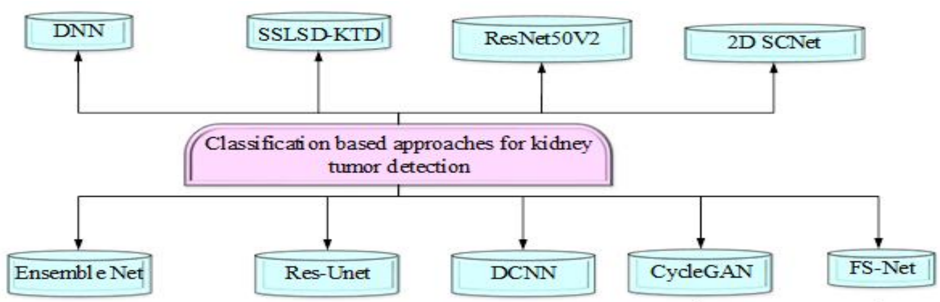


Figure 6. kidney and renal tumor classification methods

Various classification methods have been investigated for kidney tumor analysis. Transfer learning and ensemble learning with SVMs and DNNs have been used for ultrasound image classification, achieving high accuracy but with significant computational costs. Self-supervised learning with masked autoencoders has been applied to CT image classification, yielding even higher accuracy but demanding extensive computation. CNNs have been utilized for renal tumor classification and oncocytoma detection, reaching good accuracy with limited datasets. Dual-task CNNs have been developed for simultaneous classification and segmentation, achieving high classification accuracy but with substantial computational requirements. Ensemble networks combining CNNs and probabilistic classifiers have shown high accuracy but with limited generalizability due to dataset size. These studies demonstrate the potential of deep learning for kidney tumor classification, while highlighting challenges related to computational resources, dataset size, and model complexity. Illustrates

Furthermore, AI systems employing 3D Res-UNets have been developed for segmentation and classification, achieving high accuracy and Dice coefficients on multi-institutional datasets, though generalization remains a challenge. Conditional CycleGANs have been utilized to generate synthetic kidney tumor images, addressing data scarcity and improving classification accuracy, albeit with limited adaptability. Transfer learning with CNNs has been employed to enhance segmentation and classification, achieving good Dice similarity scores, but with limited transferability to other tasks. Several studies have explored classification-based approaches for kidney tumor analysis. Gong et al. [19] developed a dual-task CNN (2D SCNet) for classification and segmentation, achieving 99.5% classification accuracy, but with high computational demands. Pedersen et al. [20] used a CNN for renal tumor classification and oncocytoma detection, achieving 90% accuracy, but with a limited sample size. Figure 6. illustrates kidney and renal tumor classification methods.

Datasets in Kidney Tumor Research

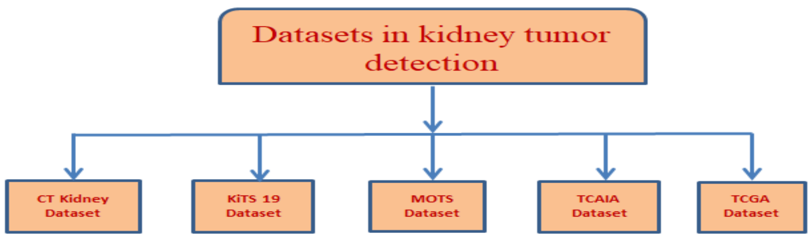


Figure 7. Datasets in Kidney Tumor Research

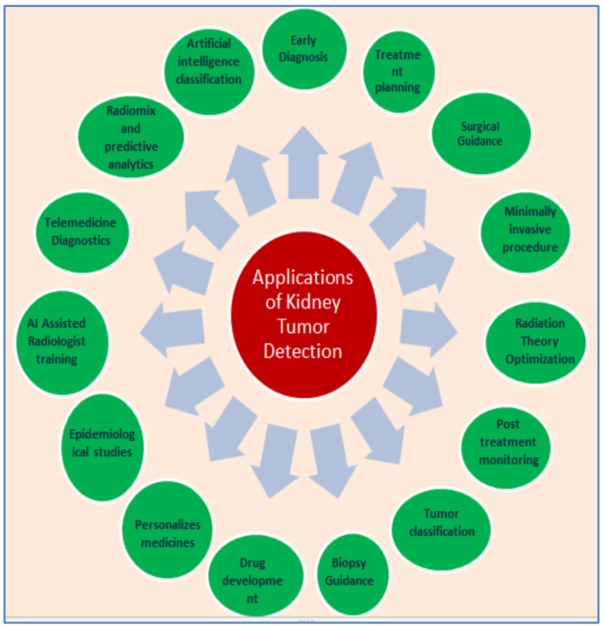
Various datasets have been investigated for kidney tumor analysis. The CT Kidney dataset contains 12,446 normal kidney images, 2,283 tumor images, 5,077 cyst images, and 3,709 kidney stone images, derived from various CT scans and urograms (coronal and axial views). These images, each with defined pixel dimensions, represent diverse kidney conditions. The KiTS19 (Kidney Tumor Segmentation 2019) dataset is a public benchmark for medical image segmentation algorithms, offering high-quality labeled annotations and diverse kidney tumor images with standardized pixel size and resolution. The Multi-Organ and Tumor Segmentation (MOTS) dataset contains seven sub-datasets for organ and tumor segmentation, comprising 1,155 CT scan volumes (920 for training, 235 for testing). The 235 test volumes are excluded from training, which uses only the 920 designated training volumes. The Cancer Imaging Archive (TCAIA) dataset contains arterial phase CT scans from 210 patients who had nephrectomies. It includes analysis of 225 radiomic features and 59 clinical features, offering valuable data for medical research and diagnostics. The Cancer Genome Atlas (TCGA) provides extensive genetic data for about 20,000 primary cancer cases across 33 cancer types, including normal samples. This collaborative project by the NCI and NHGRI offers publicly available data to advance cancer research, diagnosis, treatment, and prevention. *Figure 7* illustrates *Datasets in Kidney Tumor Research*

Performance evaluation metrics

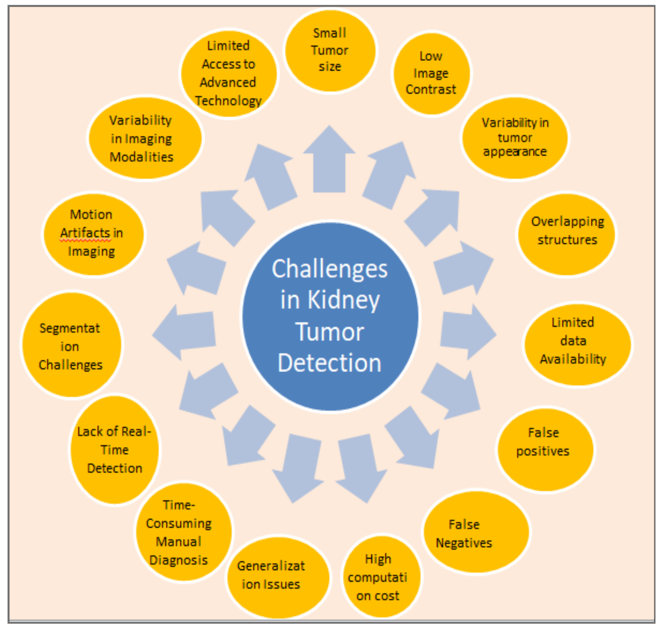
Performance evaluation of deep learning models for kidney tumor detection heavily relies on metrics such as accuracy, precision, F1-score, AUC-ROC, Dice coefficient, IoU, MAE, and MSE, often derived from a confusion matrix[21-22]. These metrics are crucial for assessing the model's effectiveness [23].

Kidney tumor detection applications

Kidney tumor detection has diverse applications, it Improves treatment outcomes and survival rates by detecting kidney tumors in their early stages. Enables personalized treatment strategies, including surgery, chemotherapy, or radiation therapy. Assists surgeons in precisely locating and removing tumors while preserving kidney function. Facilitates robotic and laparoscopic surgeries, reducing recovery time and improving patient comfort. Allows for precise targeting of tumors, minimizing damage to healthy tissues. Tracks treatment effectiveness and detects potential tumor recurrence. In Figure 8 a) Kidney tumor detection applications illustrated.



a)



b)

Figure 8. a) Kidney tumor detection applications b) Kidney tumor detection Challenges

Kidney tumor detection challenges

Kidney tumor detection faces numerous challenges Early-stage tumors can be difficult to visualize due to their small size. Poor contrast between tumors and surrounding tissue makes differentiation challenging. Diverse tumor shapes, sizes, and textures complicate consistent detection.Adjacent organs and tissues can obscure tumors in images.High-quality, labeled datasets for AI training are scarce. Benign conditions can be misidentified as tumors. Malignant tumors can be missed, delaying diagnosis .Advanced AI models often require substantial computing resources. AI models may not perform reliably across different datasets. Radiologist analysis of scans is often time-intensive. In Figure 8 (b) Kidney tumor detection challengess illustrated. *Comparison of kidney tumor detection works with respect to technique used, performance and limitation* illustrated *in table 1* .

Table 1. Comparison of kidney tumor detection works with respect to technique used, performance and limitation

Author & Reference	Techniques used	Performance	Limitations
Klontzas et al. [7]	VGG-16	Achieved high level of AUC as 0.918	Complexity in implementation

Yang et al. [8]	CNN	Achieved the dice coefficient as 0.826	Interpretability challenges.
Pande et al. [9]	YOLOv8	Yields the accuracy level as 82.52%, 85.76% as precision, 75.72% as F1 score, 75.28% recall and the specificity level as 93.12%	Computationally intensive.
Liang et al. [10]	2D-CNN	Attains the Dice coefficients as 97.89% and 92.54% for the kidney and kidney cancer segmentation	Data heterogeneity issues.
Nasir et al. [11]	Transfer learning	Achieved high training and prediction accuracy as 99.8% and 99.20%.	Interpretability issues
Nikpanah et al. [12]	AlexNet	Obtained the accuracy level as 91%.	Low number of lesions are used.
Erdim et al. [13]	Random forest	Reached the accuracy level as 90.5% and AUC as 0.915	Interpretation complexity & needs more resources.
Patel et al. [14]	MCOA-AA-RD-GRU	Reached the accuracy level as 97.02%, recall as 97.008%, and precision as 96.134%, then the specificity as 97.032%	Quality of data is reduced for the large scale datasets
Ji et al. [15]	ASD-Net	Attains the recall as 88.55%, precision as 84.19%, DSC score as 85.22% and IoU value as 75.46%.	Difficulties due to the overlapping structures
Turk et al. [16]	V-Net	Achieved the dice coefficients as 97.7% and segmentation of kidney tumor as 86.5%.	Computational cost and issues in fusion of feature
Zhao et al. [17]	3D U-Net	Attained dice coefficient score for segmentation of kidney and kidney tumor as 0.969 and 0.805	overfitting issues
Qayyum et al. [18]	3D residual network	Attains the DSC score for kidney tumor as 0.868 and 0.825 for liver tumor	Feature extraction challenges
Gong et al [19]	2D SCNet	Reached the accuracy level as 99.5% for classification and dice coefficients for the segmentation achieved 0.946 and 0.846	Obtained high time consumption for training
Pedersen et al [20]	ResNet50V 2	Yields the accuracy level as 90.0% and specificity as 93.5%	Only low number of patient sample is included

Conclusion

This review emphasizes the crucial role of early kidney tumor detection and examines diverse methodologies employed in previous research. While imaging modalities like CT scans, MRIs, and ultrasounds are standard tools, they possess inherent limitations. This work analyzes numerous studies focused on tumor detection, critically evaluating existing deep learning and machine learning approaches. Previous models have encountered challenges related to dataset diversity, interpretability, computational expense, and sensitivity to initialization. Furthermore, this review examines different segmentation and classification techniques used in past kidney tumor detection studies. By identifying weaknesses in current methodologies, this paper emphasizes the necessity for enhanced models that offer greater accuracy and reliability. The identified limitations within current deep learning frameworks suggest avenues for improvement, potentially leading to more effective tumor detection systems. Addressing these challenges not only stands to improve kidney tumor identification but may also contribute to broader cancer detection advancements. Future research will prioritize developing a more precise and efficient model that overcomes these limitations and significantly improves the accuracy of kidney tumor detection.

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