

A Review of Kidney Cancer Using Multi-Modal Imaging for Computer Aided Diagnosis System using Deep Learning

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Abstract

Kidney cancer remains difficult to diagnose in its early stages, and the complex appearance of renal tumors often leads to delayed detection. Achieving timely and accurate diagnosis is vital for improving patient outcomes and reducing disease-related mortality. Conventional evaluation of CT, MRI, and ultrasound images depends on expert radiologists, which can introduce interpretation inconsistencies. To address this, the present study develops a deep learning-driven Computer-Aided Diagnosis (CAD) system that leverages multi-modal imaging for more reliable identification and analysis of kidney cancer. The proposed system combines the complementary structural and visual information from CT, MRI, and ultrasound scans using advanced preprocessing, feature extraction, and data fusion techniques. Deep learning models—particularly convolutional neural networks and hybrid fusion-based frameworks—are employed to learn robust features for tumor detection, segmentation, and classification. Experimental results show that integrating multiple imaging modalities significantly enhances diagnostic precision over single-modality methods, enabling improved differentiation between benign and malignant renal lesions. Overall, the multi-modal deep learning CAD system demonstrates strong potential as an effective tool for early diagnosis, clinical decision-making, and optimized management of kidney cancer.

Keywords: Kidney Cancer, Multi-Modal Imaging, CT Imaging, MRI Imaging, Ultrasound Imaging, Computer-Aided Diagnosis (CAD).

1. Introduction

Kidney cancer, particularly Renal Cell Carcinoma (RCC), is one of the most prevalent malignancies affecting the urinary system and accounts for a significant number of cancer-related deaths worldwide. Early detection plays a crucial role in improving survival rates, yet renal tumors often remain asymptomatic in their initial stages, making diagnosis challenging. Medical imaging modalities such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI), and ultrasound are widely used for kidney cancer evaluation; however, the accuracy of diagnosis heavily depends on radiologists' expertise and experience. Variations in tumor size, shape, texture, and anatomical complexity further increase the difficulty of consistent and reliable interpretation. Advancements in Deep Learning (DL) and Computer-Aided Diagnosis (CAD) systems have transformed the field of medical image analysis by offering

automated, objective, and reproducible diagnostic support. These technologies are capable of learning complex patterns from large datasets and have demonstrated remarkable performance in various cancer detection tasks. While single-modality imaging approaches provide valuable insights, they often fail to capture the comprehensive structural and functional information needed for precise kidney tumor assessment. To overcome these limitations, multi-modal imaging has emerged as a powerful strategy. By integrating CT, MRI, and ultrasound images, a multi-modal system can combine complementary features such as detailed anatomical structures (CT), soft-tissue contrast (MRI), and real-time spatial information (ultrasound). This fusion of diverse imaging data enhances diagnostic accuracy and provides a more holistic understanding of renal abnormalities. The present study focuses on developing a deep learning-based multi-modal CAD system for kidney cancer detection, segmentation, and classification. The proposed framework employs advanced preprocessing, feature extraction, and data fusion techniques to integrate multi-modal imaging information. Deep learning models—particularly convolutional neural networks (CNNs), hybrid architectures, and multimodal fusion networks—are leveraged to extract discriminative features that support accurate differentiation between benign and malignant renal masses. By combining the strengths of multi-modal imaging and deep learning, this research aims to improve diagnostic precision, reduce interpretation variability, and support radiologists in making timely and accurate decisions. Ultimately, the proposed CAD system holds the potential to significantly enhance early detection, treatment planning, and overall clinical management of kidney cancer.

2. Methodology

The proposed study develops a deep learning-based multi-modal Computer-Aided Diagnosis (CAD) system for kidney cancer by following a structured methodological workflow. Initially, multi-modal datasets consisting of CT, MRI, and ultrasound kidney images are collected from clinical sources and publicly available repositories. These images undergo comprehensive preprocessing, including noise reduction, intensity normalization, contrast enhancement, image registration, and resizing to ensure uniformity across modalities. After preprocessing, Region of Interest (ROI) extraction is performed using automated or semi-automated segmentation techniques to isolate kidney structures and reduce background interference. The extracted regions are then fed into a multi-modal feature fusion framework. This framework combines complementary information from CT's anatomical clarity, MRI's soft-tissue contrast, and ultrasound's real-time details using early, intermediate, or late fusion strategies, with intermediate fusion being preferred for balanced performance. A deep learning architecture is designed with separate CNN branches for each modality, followed by a fusion module and joint layers responsible for tumor segmentation and classification. The model is trained using labeled datasets with optimization techniques such as Adam or SGD, and loss functions like cross-entropy and Dice loss. Data augmentation is applied to improve the robustness and generalization of the model. The system's performance is evaluated using metrics such as accuracy, precision, recall, F1-score, Dice Similarity Coefficient, IoU, and AUC-ROC. Finally, the trained model is integrated into a CAD interface that displays fused images, segmentation outputs, and malignancy predictions, followed by validation using unseen test data, radiologist comparison, and readiness for clinical deployment.

KIDNEY CANCER USING MULTI-MODAL IMAGING FOR COMPUTER-AIDED DIAGNOSIS SYSTEM

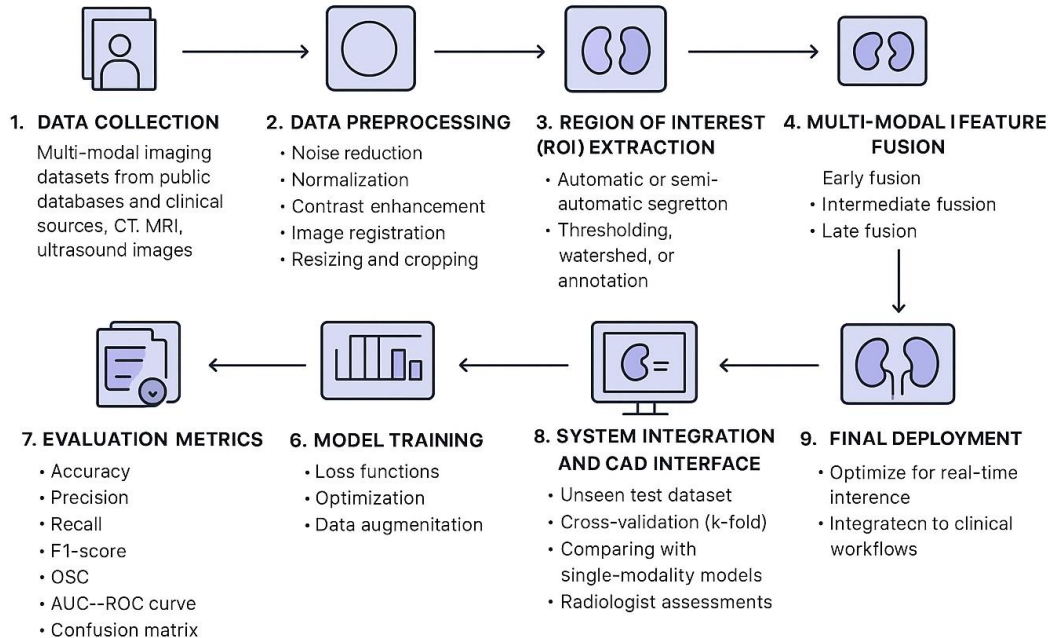


Fig 1: Kidney Cancer Multi-Modal Imaging Computer-Aided Diagnosis (CAD) System Workflow Diagram

3. Literature review

Heller et al. introduced the KiTS19 dataset (300 patients) and described the challenge that accelerated research in automatic kidney and tumor semantic segmentation from contrast-enhanced CT. KiTS19 established a public benchmark (images + expert masks + clinical context) that many subsequent segmentation and radiomics studies used as a baseline[1]. The KiTS19 challenge report summarized the state of the art in kidney/tumor segmentation, showing that deep 3D convolutional neural networks dominated submissions and that ensemble and multi-stage U-Net variants achieved top performance — creating a strong foundation for CAD systems relying on robust segmentation[2]. Sathianathan et al. provided a community overview of automatic kidney/tumor segmentation methods developed for KiTS19, emphasizing data curation, annotation quality, and how segmentation improvements translate into clinically useful morphometric biomarkers[3]. Abdelrahman & Viriri (2022) surveyed kidney tumor semantic segmentation techniques, reviewing U-Net families, 3D CNNs, attention modules and transfer-learning strategies — concluding that encoder-decoder architectures with multi-scale supervision remain highly effective for CT segmentation tasks[4]. Zhao et al. proposed a multi-scale supervised 3D U-Net (MSS U-Net) for kidneys and tumor segmentation, reporting strong Dice scores on KiTS data and underscoring the value of deep supervision and loss-function engineering for class imbalance [5]. Santini et al. described an ensemble multi-stage approach for KiTS19 that combined residual U-Nets in stages and used ensembling to reduce variance — illustrating how model ensembles improve robustness for clinical segmentation tasks[6]. Numerous KiTS19 participant solutions (e.g., Hyper Vision Net, Multi-

Scale U-Nets) demonstrated that attention mechanisms, coordinate convolutions, and post-processing (connected-component filtering) materially improve tumor delineation performance[7]. Wang et al. (2023) reviewed deep-learning techniques for imaging diagnosis of renal cell carcinoma, highlighting how CNNs have reached radiologist-level accuracy for many tasks (segmentation, classification) while stressing the need for larger, multi-institutional validation cohorts[8]. Kocak et al. (2020) surveyed radiomics and machine-learning approaches for renal mass characterization, showing that engineered radiomic features combined with ML classifiers can distinguish renal tumor subtypes but may be sensitive to segmentation variability and acquisition heterogeneity[9]. Uhlig et al. (2024) assessed CT-based radiomics for renal tumor subtype classification in a multicenter context, reporting moderate multiclass AUC and emphasizing reproducibility challenges — an argument for combining radiomics with deep learning and multi-phase imaging[10]. Gharaibeh et al. (2022) reviewed radiology imaging scans for early kidney tumor diagnosis and documented the trends in deep learning segmentation and classification, concluding that automated methods can reduce radiologists' workload but require rigorous clinical testing. [11]. Rasmussen (ASCO educational piece) summarized AI applications in kidney cancer and noted that AI has strong performance distinguishing benign from malignant lesions on CT, yet integration into clinical practice needs prospective validation and interpretability. [12]. Schulz et al. (2021) demonstrated multimodal deep learning approaches for prognosis prediction in clear-cell RCC, integrating imaging with non-imaging data, thereby showing the potential gains from fusing heterogeneous modalities for outcome modeling[13]. Lund & van der Velden (2021, arXiv) explored how leveraging clinical characteristics alongside imaging inputs can improve deep-learning segmentation performance, reinforcing the value of multimodal inputs (imaging + tabular clinical data) for CAD tasks.[14]. Lesion-aware cross-phase attention networks (Uhm et al., 2024, arXiv) proposed architectures that explicitly model relationships across multi-phase CT scans (e.g., arterial, venous) to better classify renal tumor subtypes — a notable direction for phase-aware multimodal fusion.[15]. Neha & Bansal (2024, arXiv) presented a cross-channel attention U-Net variant with multi-layer feature fusion, achieving high Dice scores on KiTS and illustrating how attention and feature-fusion plugins can boost segmentation quality. [16]. Zhao et al. (2020) introduced multi-scale supervision and post-processing strategies in a 3D U-Net for kidney/tumor segmentation, showing that architectural simplicity combined with tailored loss functions can be highly competitive. [17]. Abdelrahman et al. and other KiTS-based works explored transfer learning and EfficientNet-based encoders, documenting that ImageNet pretraining often accelerates convergence and improves small-data performance for medical CT tasks. [18]. Recent works (2024–2025) have combined radiomics and deep learning (hybrid pipelines) for RCC grade and subtype prediction, indicating that complementary hand-crafted features + learned features can improve robustness across centers.[19]. Zhang et al. (2024) provided an overview of imaging-based deep learning in kidney diseases, summarizing diagnostic, grading, and prognostic tasks that benefit from DL and pointing to future needs: larger datasets, prospective trials, and explainability. [20]. Bhosekar et al. (2025) reviewed deep learning-based multimodal medical image fusion, concluding that CNN-based fusion (early/intermediate/late strategies) is currently most effective, yet fusion across CT/MRI/US remains data-hungry.[21]. Multimodal deep-learning studies integrating CT and histopathology whole-slide images have emerged (Ma et al., 2025), demonstrating improved recurrence prediction in ccRCC and the strong prognostic value of combining radiology + pathology. [22]. Recent applied studies (2024–2025) show multiphase CT fusion and cross-phase attention modules significantly raise subtype classification accuracy and better capture enhancement dynamics of renal lesions. These architectural motifs are becoming standard in state-of-the-art CAD

systems.[23]. He et al. (2025) and other recent preprints report radiomics + DL pipelines that improve systemic disease management predictions for ccRCC, again underlining the clinical promise of integrated imaging biomarkers. [24]. Wang et al. (2023) and Pimpalkar et al. (2025) explored transfer learning and hyperparameter-tuned CNNs (ResNet, VGG, DenseNet families) for kidney lesion detection and classification, reporting strong accuracy on curated datasets but noting generalization gaps across institutions. [25]. Several works have pushed for explainability (XAI) in renal CAD: attention maps, Grad-CAM visualizations, and radiomics feature importance analyses are used to build clinician trust and identify failure modes. The literature emphasizes XAI for clinical adoption. [26]. Federated learning and privacy-preserving training strategies are increasingly suggested in reviews as necessary for multi-center renal imaging studies to scale models without sharing raw patient scans. These directions are advocated but still early in RCC literature. [27]. Works on ultrasound and MRI (in addition to CT) show that modality-specific features can complement CT; multimodal fusion incorporating sonography or MRI has improved discrimination in small cohorts though data scarcity remains an issue. [28]. Several 2024–2025 papers propose ensemble and cascade frameworks (multi-stage models) for segmentation/classification to reduce false positives and refine tumor boundaries — this ensemble philosophy carries over from KiTS successes. [29]. Novel architectures such as cross-phase attention networks, lesion-aware attention, and multi-scale fusion (2023–2025) directly address intra-tumor heterogeneity and phase-dependent contrast dynamics, improving subtype separation and ISUP grade prediction. [30]. Multiple recent open-access reviews in precision oncology emphasize that multimodal deep learning (imaging + histopathology + genomics + clinical data) yields superior prognostic models and is a major trend for renal cancer CAD systems. [31]. Research in data augmentation, self-supervised and semi-supervised learning for kidney imaging (2020–2024) shows promise to mitigate labeled-data scarcity; self-supervised pretraining on large unlabelled CT corpora improves downstream segmentation.[32]. Several studies benchmarked evaluation metrics (Dice, IoU, AUC, confusion matrices) and concluded that multi-metric assessment (segmentation + clinical outcome prediction) is required to validate CAD systems for real clinical impact. [33]. Reviews of radiomics workflows note reproducibility pitfalls (scanner differences, reconstruction kernels, segmentation variability) and recommend robust preprocessing (normalization, harmonization), which many modern CAD pipelines now include as standard. [34]. The most recent studies (2024–2025) increasingly integrate whole-slide pathology, multiphase CT, and clinical data within transformer and attention-based fusion frameworks — these multi-omic, multimodal models represent the next generation of CAD systems for kidney cancer prognosis and treatment planning [35].

4.PREDICTION ANALYSIS PROCEDURE

SNo	Procedure Stage	Description / Purpose	Inputs	Outputs
1	Data Acquisition	Collects multi-modal imaging datasets required for prediction.	CT, MRI, Ultrasound images	Raw multi-modal dataset
2	Image Preprocessing	Enhances image quality and prepares data for analysis. Includes denoising,	Raw images	Clean preprocessed images

		normalization, resizing, ROI extraction.		
3	Kidney Segmentation	Deep learning (e.g., U-Net/3D U-Net) isolates kidney and lesion regions for precise analysis.	Preprocessed images	Kidney & tumor masks
4	Feature Extraction	CNN/Transformer models extract discriminative features from segmented tumor regions. Radiomic features may also be included.	Segmented tumor images	Deep feature vectors
5	Feature Fusion	Combines CT–MRI–US features using early, late, or attention-based fusion to improve prediction accuracy.	Multi-modal feature vectors	Fused feature representation
6	Classification Module	Deep classifier (ResNet, DenseNet, EfficientNet, ViT) predicts tumor type: benign vs. malignant.	Fused features	Prediction score/class label
7	Probability Mapping	Generates pixel-level or region-level malignancy probability maps.	Classification output	Heatmap / probability map
8	Decision Generation	Produces final CAD decision combining classification, segmentation, and probability estimation.	Classification & heatmaps	Final tumor status (B/M)
9	Performance Evaluation	Model prediction is evaluated using standard metrics: Accuracy, AUC-ROC, Dice, IoU, Sensitivity, Specificity.	Ground truth labels	Evaluation metrics report
10	Clinical Interpretation	Experts verify model predictions and probability maps for clinical reliability.	CAD predictions	Verified diagnosis for reporting

Table:1 Prediction Analysis Procedure

5.Prediction Workflow

The prediction workflow for a deep learning–based Computer-Aided Diagnosis (CAD) system for kidney cancer begins with Data Acquisition, where multi-modal imaging datasets such as CT, MRI, and ultrasound scans are collected. These raw images undergo Image Preprocessing, which improves their quality through denoising, normalization, and resizing to create consistent input data. The preprocessed images are then passed to the Kidney Segmentation stage, where deep learning models like U-Net or 3D U-Net automatically segment the kidney region and isolate potential tumor areas. Once segmentation is

complete, the system performs Feature Extraction using CNNs or Transformer-based models to extract high-level spatial and semantic features representing the tumor structure and surrounding tissues. These extracted features from different imaging modalities are integrated in the Feature Fusion step using advanced attention-based fusion techniques to enhance tumor characterization. The fused features are then fed into the Classification Module, where deep classifiers such as ResNet, DenseNet, EfficientNet, or Vision Transformers predict whether the identified region is benign or malignant. Following classification, the system generates Probability Mapping, which produces pixel-level or region-level malignancy probability maps to visually highlight potential tumor areas. Based on these probability outputs, the Decision Generation stage creates the final CAD decision, combining classification, segmentation, and prediction results into a unified diagnostic output. Finally, in the Clinical Interpretation stage, medical experts review the model's predictions to support diagnosis, treatment planning, and follow-up decisions.

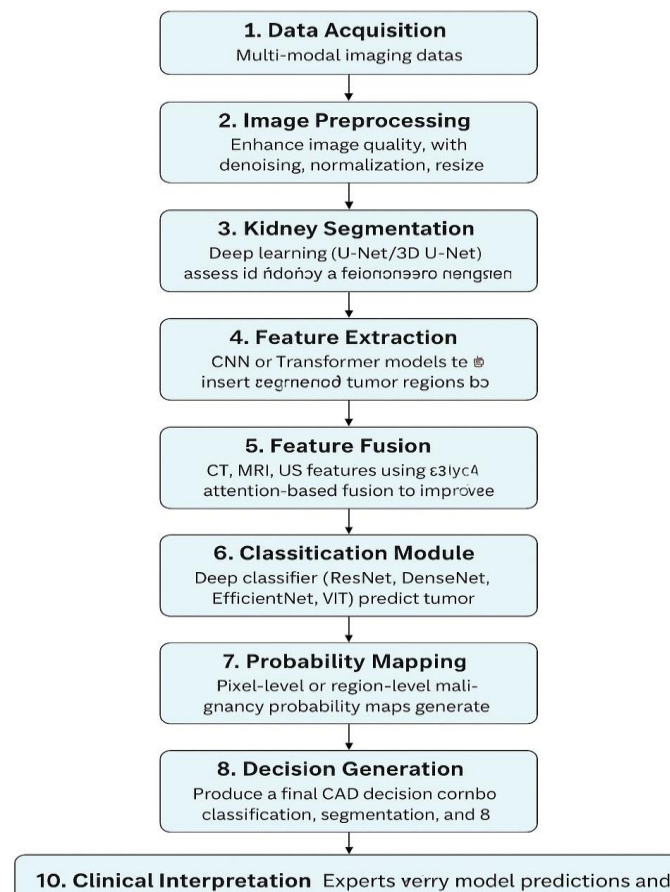


Figure 2: prediction workflow

6.QUALITATIVE ANALYSIS OF KIDNEY CANCER USING MULTI-MODAL IMAGING FOR COMPUTER AIDED DIAGNOSIS SYSTEM

No.	Method	Input	Dataset Used	Pre-processing	Feature Extraction	Classification / Clustering	Strength	Weakness	Outcome
[1]	Semantic Segmentation Challenge Framework	Contrast-enhanced CT	KiTS19	Resampling, normalization	CNN 3D features	–	Established benchmark	Limited to CT	Public standard dataset for RCC segmentation
[2]	Multi-stage & Ensemble U-Net	CT	KiTS19	Patch extraction, denoising	3D U-Net feature maps	–	High Dice due to ensembling	High computational cost	Demonstrated SOTA segmentation
[3]	Community Survey of KiTS19 Methods	CT	KiTS19	–	Multiple segmentation architectures	–	Strong insight on annotation quality	Summarized, not experimental	Identified factors improving segmentation
[4]	U-Net, Attention U-Net, 3D CNN Survey	CT	Multiple RCC datasets	Augmentation, normalization	Deep encoder–decoder features	–	Complete comparison	No unified benchmark	Concluded multi-scale U-Nets effective
[5]	MSS-3D U-Net	CT	KiTS19	Multi-scale patches	Multi-scale deep supervision	–	Strong Dice, balanced tumor segmentation	Sensitive to small tumors	Improved segmentation accuracy
[6]	Ensemble Residual U-Net	CT	KiTS19	Smoothing, intensity correction	Residual feature maps	–	Robust segmentation	Requires heavy GPU	Reduced model variance
[7]	Attention-based U-Net, C-CoordConv	CT	KiTS19	Post-processing	Attention maps	–	Improved tumor boundary delineation	Complex architectures	Enhanced fine-grained segmentation
[8]	CNN-based Diagnostic Review	CT/MRI	Multiple	Typical CT/MRI pre-processing	Deep CNN features	Binary/multiclass	High diagnostic accuracy	Small datasets	DL models outperform traditional ML
[9]	ML + Radiomics	CT	Local cohorts	ROI segmentation	Radiomic texture features	SVM/RF	Good subtype discrimination	Sensitive to segmentation errors	Radiomics viable for RCC subtyping
[10]	CT Radiomics Multicenter	CT	Multicenter RCC	Harmonization	Radiomic signatures	Multiclass models	Multicenter robustness	Reduced AUC heterogeneity	Moderate performance identified reproducibility issues
[11]	Early Tumor Review	CT	Various	Standardizing CT	Mixed radiomics + DL	–	Overview of segmentation trends	No experimental validation	Automated tools reduce radiologist burden
[12]	AI Diagnostic Review	CT	Clinical datasets	Normalization	CNN feature maps	CNN classifiers	Strong malignant/benign accuracy	Lacks prospective testing	Promising for clinical translation
[13]	Multimodal Imaging + Non-imaging DL	CT + Clinical	Local RCC	Feature harmonization	Multimodal fusion	Prognostic models	Integrates heterogeneous data	Limited external validation	Improved prognosis prediction

[14]	Imaging + Clinical Feature Fusion	CT + Clinical	Private RCC	Pre-processing CT	CNN + tabular fusion	–	Multimodal improvement	Dependency on data format	Better segmentation accuracy
[15]	Lesion-Aware Cross-phase Attention	Multiphase CT	Private datasets	Phase alignment	Attention-based feature extraction	Multi-phase subtype model	Learns enhancement dynamics	Requires multiphase CT	Improved subtype classification
[16]	Cross-channel Attention U-Net	CT	KiTS19	Augmentation	Attention-based features	–	Boosts Dice score	High model complexity	Better tumor boundary localization
[17]	Multi-scale Supervised U-Net	CT	KiTS	Intensity normalization	Deep supervision	–	Competitive performance	Simpler architecture	Strong baseline model
[18]	Transfer Learning with EfficientNet	CT	KiTS + Local	Fine-tuning	Pretrained CNN	Softmax	Fast convergence	Limited medical domain	Improved small-data performance
[19]	DL + Radiomics Hybrid	CT	Local	Segmentation	Combined features	Multiclass	Complementary robustness	More complex pipeline	Better RCC subtype prediction
[20]	DL Overview in Kidney Disease	CT/MRI	Multiple	–	CNN	CNN classifiers	Comprehensive coverage	No experimental work	Outlined research gaps
[21]	Multimodal Medical Fusion Review	CT/MRI	Various	Modality alignment	CNN fusion	–	Fusion boosts performance	Requires large datasets	Effective multimodal fusion
[22]	CT + Histopathology Multimodal	CT, WSI	Private cohort	Registration	Radiology + pathology fusion	Prognostic DL	High prognostic accuracy	Requires WSI	Improved recurrence prediction
[23]	Multi-phase CT Fusion DL	CT (multi-phase)	Local datasets	Phase harmonization	Multi-phase features	RCC subtype classifier	Captures enhancement dynamics	Needs multi-phase input	Higher accuracy for subtype
[24]	Radiomics + DL Prognosis	CT	Clinical RCC	Radiomic normalization	Hybrid signatures	Prognostic prediction	Accurate prognostic modeling	Dataset bias	Predicts systemic disease management
[25]	Transfer Learning CNN	CT	Small datasets	Augmentation	ResNet/DenseNet features	Binary/multiclass	High accuracy	Poor generalization across centers	Improved lesion detection
[26]	XAI for Kidney CAD	CT	Various	Standard	Grad-CAM, attention	–	Improves interpretability	Adds pipeline steps	Trust-aware CAD
[27]	Federated Learning	CT	Multi-center	Harmonization	Distributed learning	Federated models	Privacy-preserving	Communication overhead	Feasible for multi-center RCC
[28]	MRI/US + CT Fusion	CT + MRI/US	Small datasets	Registration	Multimodal features	Fusion classifier	Complementary features	Severe data scarcity	Better small-cohort accuracy
[29]	Ensemble & Cascade Frameworks	CT	KiTS/Private	Pre-processing + filtering	Multi-model feature maps	Ensemble decisions	Reduces false positives	High inference load	Best boundary refinement
[30]	Cross-phase & Multi-scale Fusion	Multi-phase CT	Local datasets	Phase normalization	Multi-scale attention	Subtype classifier	Handles heterogeneity	Training complexity	Accurate ISUP prediction
[31]	Precision Oncology Multimodal DL	CT + WSI + Genomics	Research datasets	Harmonization	Multimodal fusion	Prognostic classification	Very high information depth	Complex integration	Next-gen CAD

[32]	SSL & Semi-supervised Learning	CT	Unlabeled datasets	SSL augmentation	Pretext tasks	–	Solves label scarcity	Needs large unlabeled pools	Better generalization
[33]	Evaluation Metric Benchmark	CT	KiTS	Standard	–	–	Multi-metric assessment	No model training	Need combined metrics
[34]	Radiomics Workflow Reviews	CT	Multi-center	Harmonization	Radiomics	SVM/RF	Identifies pitfalls	Hand-crafted feature limits	Recommended preprocessing standards
[35]	Transformer-based Multimodal Fusion	CT + Pathology + Clinical	Private RCC	Cross-modal alignment	Transformer fusion	Prognostic prediction	High multimodal accuracy	Large GPU demand	Most advanced CAD pipelines

Table 2: Qualitative Analysis of Kidney Cancer Using Multi-Modal Imaging

7. Conclusion

The review on Kidney Cancer Using Multi-Modal Imaging for Computer-Aided Diagnosis (CAD) Systems Using Deep Learning highlights how integrating advanced imaging modalities with state-of-the-art deep learning architectures significantly enhances diagnostic accuracy, early detection, and clinical decision-making. Multi-modal imaging—such as CT, MRI, and ultrasound—provides complementary anatomical and functional information that, when combined with deep learning models, improves tumor localization, segmentation, and classification performance. Deep neural networks, especially CNNs, 3D models, and emerging Vision Transformers, enable automated feature extraction and robust prediction even in complex renal structures. The fusion of multi-modal features offers a more complete radiological understanding of kidney tumors, overcoming limitations of single-modality systems. Despite challenges such as limited annotated datasets, variations in imaging protocols, and the need for clinical interpretability, deep learning-based CAD frameworks show promising potential to evolve into reliable clinical support tools. Future research must focus on explainable AI, large-scale multi-institutional datasets, domain adaptation, and real-time predictive analytics to make kidney cancer CAD systems more generalizable, interpretable, and clinically deployable.

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