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REVIEW ARTICLE

Advancements in Automatic Kidney Segmentation Using Deep Learning Frameworks and Volumetric Segmentation Techniques for CT Imaging: A Review

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Abstract

The efficiency of Three-Dimensional Convolutional Neural Networks (3-D-CNNs) in precisely delineating the complex architecture of the kidney has been well-established. Volumetric segmentation technologies, such as deformable registration, have shown promise in addressing the issue of variability in renal imaging. This variability can arise from differences across subjects as well as within the same subject. By offering an accurate template for image segmentation, these technologies have the potential to mitigate this obstacle effectively. The integration of deep learning frameworks and volumetric segmentation algorithms offers a robust and effective solution for the automated segmentation of kidneys. These methods can improve the accuracy of diagnosing kidney-related illnesses, specifically renal cysts, and offer the potential to better the monitoring of clinical development in individuals with such conditions.

1 Introduction

The application of deep learning frameworks and volumetric segmentation methodologies in the automated segmentation of kidneys in contemporary CT imaging techniques is significantly transforming the management of kidney diseases [1]. These developments are facilitating scientific professionals in accurately identifying renal pathology and delivering more precise therapies with little invasiveness. Sophisticated deep learning frameworks, such as U-net and Convolutional Neural Networks (CNN), are employed for the purpose of analyzing organ segmentation from clinical images [2]. These models possess expertise in analyzing pairs of images, where one image provides a detailed description of the organ's architecture, while the other image involves manual segmentation. After undergoing adequate training, the model demonstrates the capability to segment organs from the experimental data accurately. It has facilitated healthcare organizations in effectively understanding kidney injuries, managing therapy, and other disease progression [3]. Volumetric segmentation algorithms are employed for the purpose of partitioning the kidney from CT scans. Volumetric segmentation employs voxel-based methodologies to delineate structures by manipulating their densities and textures. This methodology allows for precise demarcation of the external barriers of the kidneys, hence providing a specific assessment of the kidneys' surface area and anatomical features [4]. List of classification used in this paper has shown in the following Table 1.

The main purpose of this study is to monitoring the course of illnesses, clinical trials and research, early disease identification, surgery, and treatment planning, as well as individualized medicine Improvements in Clinical Workflow Optimization, Telemedicine and Remote Consultation, Education and Training, and Enhanced Radiologist Efficiency. These applications collectively showcase and emphasize the extensive array of potential uses for automated kidney

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Table 1 List of classification used in this paper

S.No	Classification	Referred to
1	3D	Three dimensional
2	CNN	Convolution neural networks
3	CT	Computed tomography
4	RNN	Recurrent neural networks
5	MRI	Magnetic resonance imaging
6	ROI	Regions of interest
7	AKSRV	Advanced knowledge-based super-resolution and visualization
8	DLF	Deep learning frameworks
9	VST	Volumetric segmentation techniques
10	HM	Hybrid methods
11	ABS	Atlas-based segmentation
12	RBS	Region-based segmentation
13	THS	Threshold-BASED SEGMENTATION
14	RGS	Region growing segmentation
15	WTS	Watershed transformation segmentation
16	ACS	Active contours segmentation
17	DLS	Deep learning segmentation
18	VMS	Volumetric segmentation
19	AKSVS	Automatic kidney segmentation—volumetric segmentation

segmentation through the utilization of deep learning and volumetric segmentation techniques. These applications have the capability to enhance patient care, expand the scope of the healthcare system, and foster advancements in medical research. Efforts are currently underway to enhance the precision of automated kidney segmentation through the development of novel segmentation algorithms. The algorithms can identify subtle variations in the morphology of the kidney in both local and contrast-enhanced CT images [5]. These methods utilize mathematical models such as support vector machines and graph cuts to segment the organ in a single image accurately. The application of deep learning frameworks and volumetric segmentation algorithms has significantly transformed the process of automated kidney segmentation in contemporary CT imaging [6]. Precise segmentation of the kidneys enables enhanced prognostication and management of renal diseases. In addition, it also aids in reducing the level of radiation exposure experienced by the patient [7].

1.1 Importance of Kidney Segmentation in Medical Imaging

This study aims to conduct a comparative analysis and evaluation of current tactics, identifying their respective strengths and limitations in order to offer recommendations for future research. Automated kidney segmentation was performed utilizing deep learning frameworks, specifically the U-internet and V-internet architectures, in conjunction with volumetric segmentation methodologies, namely the location expanding algorithm and the extent set method [8]. However, there is a potential shortage of comprehensive and systematic assessment and analysis of these methodologies within the existing body of scholarly literature. Therefore, the purpose of this research article is to address this gap by providing a comprehensive review of the latest improvements in autonomous kidney segmentation [9]. The importance of automated kidney segmentation in CT imaging has shown in the following Table 2.

1.2 Challenges Faced in Manual Kidney Segmentation

The accuracy and reliability of computerized kidney segmentation have significantly improved because of advancements in deep learning and volumetric segmentation techniques. The automatic segmentation of kidneys in CT imaging has emerged as a subject of contemporary interest in the field of scientific image analysis [10]. Numerous clinical applications necessitate accurate segmentation of the kidneys from CT images, encompassing renal disease prediction, surgical planning, and radiation therapy. However, manual segmentation is a labor-intensive and prone-to-error process that necessitates the expertise of skilled clinicians [11]. Researchers have developed various automatic segmentation strategies to address this Endeavour, namely those based on deep learning frameworks and volumetric segmentation techniques. This comprehensive research provides a thorough examination of recent improvements in automatic kidney segmentation using advanced deep-learning

Table 2 Importance of automated kidney segmentation in CT imaging

Sector	Applications
Clinical analysis	It is a crucial aspect of diagnosing kidney-related illnesses, such as kidney cancer, renal cysts, and kidney stones. Accurate kidney segmentation plays a pivotal role in this process. Automated kidney segmentation provides reliable quantification of kidney size, morphology, and spatial orientation, thereby assisting medical practitioners in detecting anomalies and facilitating precise diagnostic evaluations
Treatment planning	The inclusion of automatic kidney segmentation is crucial in the process of treatment planning for diseases connected to the kidneys. For example, proper segmentation of the kidney and its tumors in cases of renal cancer enables physicians to strategize and perform minimally invasive surgical procedures, such as laparoscopic and robot-assisted surgeries. Moreover, the utilization of computerized kidney segmentation enables physicians to effectively strategize radiation therapy for kidney cancer and evaluate the efficacy of the treatment
Performance and time savings	Manual kidney segmentation is a time-consuming and arduous process that can require several hours to complete. The utilization of computerized kidney segmentation offers a more expedient and effective option, enabling clinicians to allocate their time towards other critical aspects of diagnosis and treatment
Consistency and accuracy	The process of guiding kidney segmentation is susceptible to inconsistencies and inaccuracies because of variations in data and subjective interpretations of scientific images. The utilization of computerized kidney segmentation demonstrates consistent and accurate outcomes, hence enhancing the dependability of analysis and treatment planning
Research and development	The study and enhancement of computerized kidney segmentation hold significant importance in the advancement and experimentation of novel medical imaging technologies and treatment modalities. The precise and reliable segmentation of kidneys provides a fundamental basis for the assessment of novel imaging modalities such as contrast-enhanced CT and MRI, as well as the development of innovative therapeutic approaches, including targeted medication delivery and gene therapy

frameworks and volumetric segmentation algorithms for CT imaging [12]. This analysis focuses on the utilization of deep modern frameworks and volumetric segmentation approaches for CT imaging, as demonstrated in Fig. 1.

Cutting-edge modern methodologies have demonstrated exceptional efficacy in the realm of scientific image analysis, encompassing crucial tasks such as segmentation, detection, and categorization. These approaches can autonomously acquire intricate functions and patterns from huge volumes of contemporary data, resulting in a high level of precision and resilience. The present study focuses on the utilization of contemporary CNN, RNN, and their respective adaptations for kidney segmentation. For instance, the application of a 3D CNN for kidney segmentation yielded favorable outcomes when applied to CT images [13]. Furthermore, RNNs have been employed for sequential segmentation in the context of dynamic assessment of the kidneys, leading to improved quality of CT images. Volumetric segmentation algorithms have been widely employed in the field of computerized kidney segmentation. These strategies aim to partition the kidney based on its three-dimensional shape and visual data. Despite the recent advancements in autonomous kidney segmentation, there remain several issues that need to be addressed. These challenges encompass the handling of noisy and occasionally suboptimal images, accommodating variations in kidney shape and size, and effectively integrating the segmentation results into medical workflows [14]. As a result, our assessment report critically examines current automated kidney segmentation approaches, explores their strengths and limitations, and proposes areas for further research.

1.3 Deep Learning Frameworks in Automating the Process

The aforementioned architectural development was undertaken by academics affiliated with the computer vision group at the University of Freiburg. U-internet is a community characterized by a fully convolutional nature, employing Encoder-Decoder architecture. The encoder is comprised

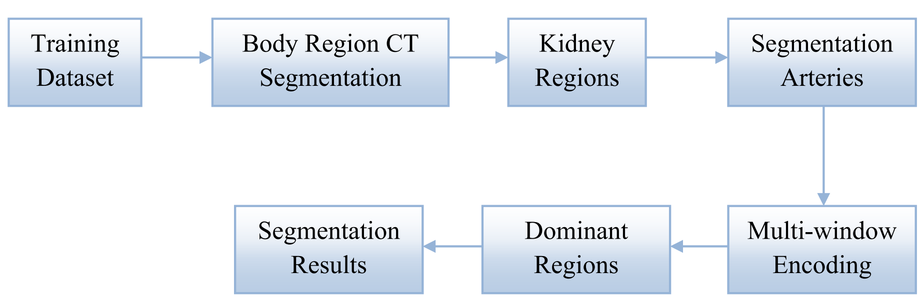


Fig. 1 Deep modern frameworks and volumetric segmentation approaches

of a sequence of convolutional layers that may be supplemented with max-pooling layers to facilitate feature extraction [15]. Figure 2 presents a discussion on the utilization of the region-expanding algorithm and the extent-set technique for kidney segmentation in CT images.

The decoder comprises a series of up-sampling layers, potentially succeeded by convolution layers, to facilitate the reconstruction of the segmented image. The U-internet is comprised of bypass connections that facilitate the propagation of the feature map from the encoder to the decoder. Another deep learning framework that is utilized for kidney segmentation is the Horovod architecture [16]. The architectural design employed in this study utilizes a hybrid approach, incorporating both convolutional and recurrent neural networks. Convolutional layers are employed to extract information from input photos. Recurrent layers are utilized to analyze the temporal relationship between the input images and the output segmentation masks [17]. The resulting outcome of the Horovod model is a segmentation mask, which is then employed for computerized segmentation of the kidneys. In this discussion, we will examine the community of the mask R-CNN, which is a deep learning framework with a two-degree depth. Within this framework, the initial stage encompasses the utilization of a convolutional neural network for the purpose of generating region recommendations. The utilization of a sliding window methodology over the input images develops the area proposals [18]. The second degree involves a higher level of refinement, employing a series of convolutional and recurrent layers with attention mechanisms to accurately anticipate segmentation masks based on the proposed regions. The utilization of sophisticated learning frameworks has the potential to facilitate the automated segmentation of kidneys in medical imaging [19]. U-Internet, Horovod, and Mask R-CNN are among the prominent deep-learning architectures that can be employed for this purpose. All architectural designs employ specific methodologies for extracting and refining functions, hence aiding in achieving accurate segmentation outcomes. Layout of the paper has shown in the following Fig. 3.

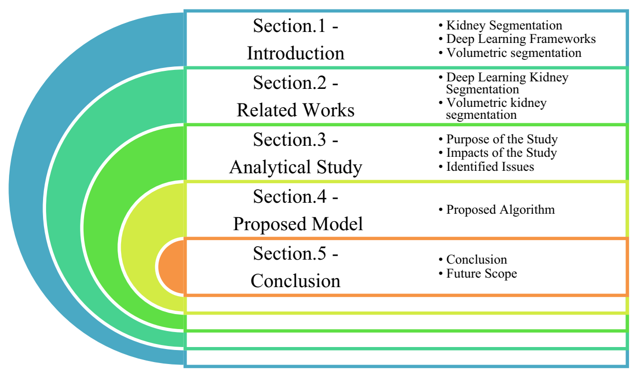
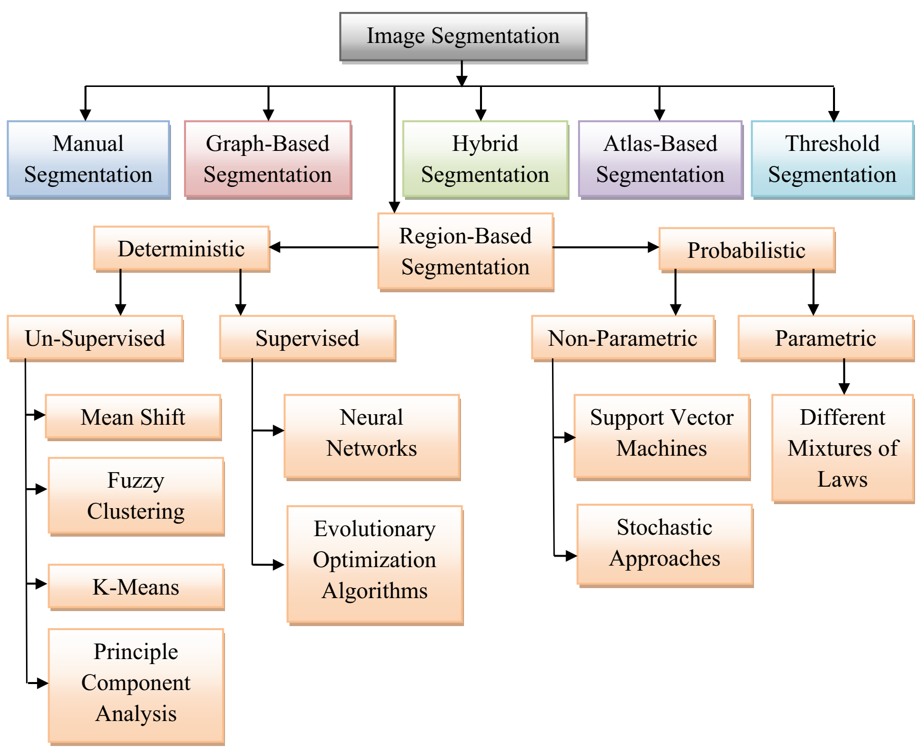


Fig. 3 Layout of the paper

Fig. 2 Tree chart of the existing algorithms



1.4 Volumetric Segmentation Techniques in Automating the Process

The application of volumetric segmentation techniques in automated kidney segmentation has the potential to transform scientific imaging significantly. Volumetric segmentation is an advanced imaging technique that can provide specific three-dimensional depictions of internal anatomical structures, such as organs, bones, and muscle tissue [20]. Through the use of cutting-edge advancements in computer vision, artificial intelligence, and medical imaging hardware and software, volumetric segmentation can autonomously identify the boundaries (or contours) of an organ's surface. This intervention has the potential to alleviate the strain burden on radiologists and improve the precision of CT and MRI scans [21]. Volumetric segmentation algorithms can be employed to accurately delineate the kidneys from various organs and tissues within the abdominal cavity in the context of automated kidney segmentation. The task is performed by the process of eliminating the obstacles that are present within the surrounding systems portrayed in the snapshot [22]. The segmentation system demonstrates the capability to delimit the boundaries of a fashionable organ by evaluating several characteristics, such as evaluation, density, and spatial relationships with neighboring organs and tissues. The automation of the segmentation system can be achieved through the utilization of advanced algorithms implemented in a novel device [23]. These algorithms can gather data from healthcare records in order to accurately identify the boundaries of an organ.

Automatic kidney segmentation using deep learning frameworks and volumetric segmentation algorithms serves a number of essential purposes in medical imaging and clinical practice, such as clinical support, patient care, accuracy and consistency, and simplifying the entire diagnosis and treatment procedure and incorporating automated segmentation into clinical operations can lead to better healthcare delivery. The use of deep learning-based automated segmentation techniques for kidney CT imaging has great promise for improving patient outcomes, improving diagnostic accuracy, advancing nephrology, radiology research and clinical practices.

The primary aim of our present research investigation is to undertake a thorough examination of the advancements made in the field of automated kidney segmentation. The primary objective of this assessment is to examine the application of advanced deep learning frameworks and volumetric segmentation algorithms that have been specifically designed for the analysis of CT imaging. The primary aim of this study is to enhance the existing body of knowledge in the relevant topic by examining contemporary approaches and offering helpful insights for future research endeavors.

2 Related Works

Automated segmentation of kidneys in CT imaging is of utmost importance in a wide range of scientific applications, encompassing the detection of renal illnesses, surgical strategizing, and radiation therapy, among others. The segmentation method, commonly performed by proficient medical professionals, poses several challenges attributed to its labor-intensive nature and vulnerability to errors [24]. Volumetric segmentation algorithms, such as the region growing algorithm and the level set method, aim to partition the kidneys based on their three-dimensional shape and appearance data. Figure 4 shows the kidney segmentation methods identified in literature review.

Furthermore, this methodology exhibits the potential to induce diversity among observers and relies on the information provided by the physician. Manual segmentation may be a challenging approach in certain circumstances, such as when dealing with extensive datasets or when real-time segmentation is required. Hence, several automatic segmentation solutions have been presented, particularly those that rely on deep learning frameworks and volumetric segmentation approaches [25]. Active kidney segmentation models have shown in the following Table 3

The utilization of deep learning techniques has the potential to yield significant improvements in accuracy and resilience. The regular acquisition of complicated functions and patterns from extensive datasets achieves it. CNNs, RNNs and their variants were utilized for kidney

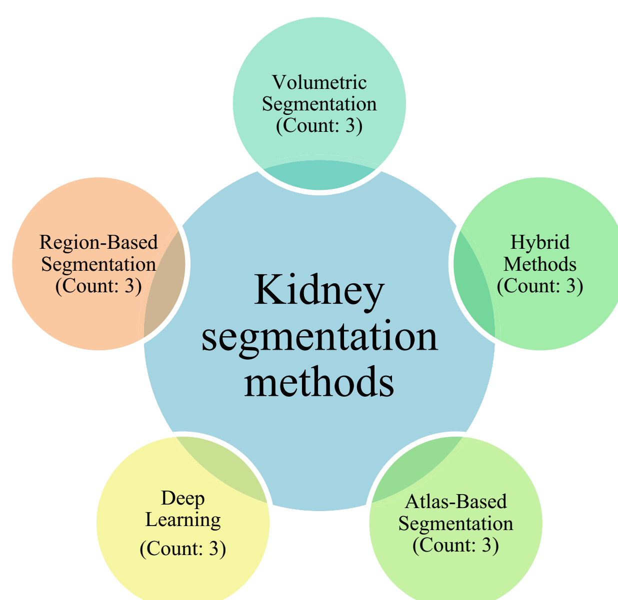


Fig. 4 Kidney segmentation methods identified in literature review

Table 3 Related active kidney segmentation models

Reference no	DLF	VST	HM	ABS	RBS
[27]	✓				
[28]	✓				
[28]	✓				
[29]		✓			
[30]		✓			
[31]		✓			
[32]			✓		
[33]			✓		
[34]			✓		
[35]				✓	
[36]				✓	
[37]				✓	
[38]					✓
[39]					✓
[40]					✓

DLF Deep Learning Frameworks, *VST* Volumetric Segmentation Techniques, *HM* Hybrid Methods, *ABS* Atlas-Based Segmentation, *RBS* Region-Based Segmentation

segmentation tasks [26]. The list of various kidney segmentation methods has shown in the following Table 4.

Despite recent advancements in computerized kidney segmentation, there are still some challenges that need to be addressed. These challenges include.

- Effectively managing noisy and low-quality images,
- Accommodating variations in kidney shape and size, and
- Seamlessly integrating the segmentation results into clinical processes.

Computerized kidney segmentation is an efficacious technology that can optimize patient outcomes by enabling early diagnosis and treatment of kidney-related ailments. Additionally, it presents a time-saving and efficient chance to facilitate segmentation, thereby allowing clinicians to focus their attention on other critical aspects of patient care. Automatic kidney segmentation models have shown in the following Table 5.

Moreover, the process of automatic kidney segmentation holds significant importance in the advancement and evaluation of novel scientific imaging techniques and treatment modalities. An assessment of current techniques utilized for the automatic segmentation of kidneys in CT imaging has shown in the following Table 6.

The segmentation of kidneys in CT imaging using computerized methods holds significant importance in various medical applications, such as the diagnosis of renal diseases, surgical planning, and radiation therapy. Several automated segmentation strategies have been developed to tackle the challenges related to automatic kidney segmentation, specifically those that rely on deep learning frameworks and volumetric segmentation techniques. However, researchers still face several hurdles, including the management of noisy and low-resolution images, addressing variations in kidney shape and size, and effectively incorporating segmentation results into medical processes. Hence, doing a critical assessment of existing automated kidney segmentation methods can offer valuable insights into future research areas aimed at

Table 4 List of different kidney segmentation methods

Authors	Method	Description
Menze et al. (2015) [27] Milletari et al. (2016) [28] Milletari et al. (2016) [28]	Deep Learning Frameworks (DLF)	The CNN model is employed for the segmentation of the kidney from computed tomography (CT) images. The teaching process could be conducted using a large-scale dataset consisting of annotated images
Milletari et al. (2016) [29] Mukherjee et al. (2023) [30] Osher et al. (1988) [31]	Volumetric Segmentation Techniques (VST)	The complete three-dimensional computed tomography (CT) image is subjected to analysis in order to delineate and segment the kidney accurately. Utilizes algorithms in conjunction with place development, graph cuts, and stage setups
Pandey et al. (2023) [32] Pizer et al. (1987) [33] Rakhlin et al. (2018) [34]	Hybrid Methods (HM)	This study aims to enhance accuracy and robustness through the integration of deep learning and volumetric segmentation approaches
Roth et al. (2016) [35] Sato et al. (2020) [36] Sato et al. (2020) [37]	Atlas-Based Segmentation (ABS)	Utilizes a pre-segmented atlas image as a point of reference for the purpose of segmenting the kidney in the target photograph
Sato et al. (2020) [38] Sato et al. (2020) [39] Shan et al. (2023) [40]	Region-Based Segmentation (RBS)	Utilizes pre-established regions of interest (ROIs) for kidney segmentation

Table 5 Automatic kidney segmentation models

Reference No	THS	RGS	WTS	ACS	DLS	VMS
[41]	✓					
[42]		✓				
[43]			✓			
[44]				✓		
[45]					✓	
[46]						✓

THS Threshold-based segmentation, *RGS* Region growing segmentation, *WTS* Watershed transformation segmentation, *ACS*Active contours segmentation, *DLS* Deep learning segmentation, *VMS* Volumetric segmentation

overcoming these obstacles and enhancing the robustness and accuracy of automatic segmentation techniques.

2.1 Deep Learning for Kidney Segmentation

There has been a significant surge in the popularity of deep learning frameworks in the field of computer vision and image processing. The application of this particular generation has enabled the establishment of a robust and automated framework for the segmentation of organs. In this study, we have successfully explored the application of deep learning frameworks in the context of kidney segmentation. The U-net architecture has gained significant recognition in the field of machine learning for its effectiveness in kidney segmentation. Figure 5 shows the kidney segmentation methods identified in literature review.

Active deep learning-based segmentation have shown in the following Table 7.

Table 8 presents the recent segmentation algorithms that are based on deep learning techniques.

CNN is a deep neural network suitable for image evaluation tasks. Current advancements in methods based totally on convolutional neural networks for automatic kidney segmentation have yielded promising results. The performance of deep learning segmentation algorithms has shown in the following Fig. 6.

The strategies have been labeled primarily based on their underlying architecture and technique for kidney segmentation. The advantages of this classification mechanism encompass a clear evaluation of different architectures and their performance in kidney segmentation responsibilities. An extended deep learning segmentation algorithm has shown in the following Table 9.

The disadvantages consist of capacity oversimplification of the techniques and a need for cognizance of other elements which can impact their performance, inclusive of pre-processing techniques and information augmentation. Table.10 provides the performance of deep learning segmentation algorithms.

2.2 Volumetric Segmentation for Kidney Segmentation

In addition to the utilization of automated segmentation, the employment of volumetric segmentation can also be employed for the purpose of quantitatively evaluating clinical pictures. Through the methodical segmentation of organs, such as the kidney, it becomes feasible to estimate their size and shape accurately. Dice Similarity Coefficient has shown in the following Fig. 7. This study aims to give medical practitioners and radiologists crucial information that can enhance the analysis and outcomes of medical diagnoses and treatments. Volumetric segmentation approaches have the potential to greatly impact the field of automatic kidney segmentation and other clinical imaging techniques. By employing novel techniques to provide distinct three-dimensional depictions of internal organs, it has the potential to alleviate the workload of radiologists and enhance the precision of detecting various ailments, including kidney stones and other medical conditions. Extended volumetric segmentation for kidney segmentation models has shown in the following Table 11.

CNN-primarily based strategies for automated kidney segmentation have several strengths, along with excessive accuracy, robustness, and the ability to address complex image facts. However, they also have some areas for improvement, such as the want for massive annotated datasets for education and challenges in handling noisy and noisy and low-quality pictures. Those techniques can improve analysis and remedy-making plans in renal sickness and increase more correct and dependable segmentation strategies for other scientific imaging responsibilities. Table.12 shows the performance of volumetric segmentation for kidney segmentation.

3 Analytical Discussion

In recent times, there has been a notable enhancement in the effectiveness of automated kidney segmentation in CT imaging. The main component that contributes to

Table 6 Current techniques utilized for the automatic segmentation of kidneys in CT imaging

Author	Method	Description	Strength	Weakness
Shin et al. (2016) [41]	Threshold-based segmentation (THS)	The proposed methodology involves the implementation of a threshold value to discern kidney tissue from other tissues, taking into consideration the depth of the CT image	A straight forward and efficient methodology	The overall performance on snap pictures with low comparability is subpar
Wang et al. (2019) [42]	Region growing segmentation (RGS)	This methodology entails commencing with a seed factor and progressively refining the kidney localization by incorporating adjacent pixels that exhibit comparable characteristics	It can accurately describe the structures of the kidney	The individual has a heightened sensitivity to auditory disturbances and deviations in the morphology and dimensions of the renal organ
Wang et al. (2019) [43]	Watershed transformation segmentation (WTS)	This methodology involves partitioning the shot into distinct regions delineated by watershed lines, which demarcate parts of the photograph featuring exceptional residential properties	The ability to precisely segment renal structures	Individuals may exhibit sensitivity to variations in noise levels and differences in kidney morphology and size
Wu et al. (2019) [44]	Active contours segmentation (ACS)	The proposed methodology entails the iterative refinement of a shape that best aligns with the boundary of the kidney by minimizing an energy function	The ability to accurately partition renal systems	The process of initialization is delicate and prone to become trapped in local minima
Wu et al. (2019) [45]	Deep learning segmentation (DLS)	This methodology entails the training of a neural network using a vast dataset of categorized images, with the aim of discerning the distinctive features and characteristics that differentiate kidney tissue from other types of tissues	The proposed method demonstrates the ability to accurately segment renal systems even in the presence of noise and low-quality images	The training process necessitates the utilization of huge datasets that are organized into categories, and it may involve significant computer resources
Wu et al. (2019) [46]	Volumetric segmentation (VMS)	This technique entails the segmentation of the kidney in three-dimensional space by partitioning it into smaller voxels and subsequently identifying each voxel as either kidney or non-kidney tissue	This study aims to delineate the three-dimensional spatial arrangement of kidney structures accurately	Demands a substantial quantity of memory and computing resources

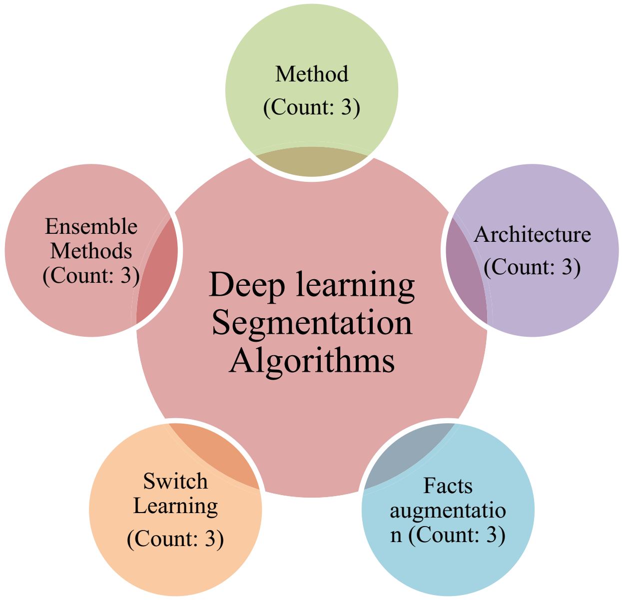


Fig. 5 Kidney segmentation methods identified in literature review

this improvement may be ascribed to the employment of deep learning frameworks and volumetric segmentation techniques. The application of deep learning frameworks, specifically CNNs, has enabled the accurate and efficient segmentation of kidneys from CT images. The efficacy of these sophisticated machine learning frameworks is contingent upon the utilization of comprehensive datasets that encompass annotated pixel values. This functionality allows the network to engage in a training procedure that facilitates precise differentiation of anatomical regions. Volumetric segmentation techniques, such as geodesic active contour processes and stage set approaches, are then utilized to accomplish the segmentation of the kidneys from the adjacent tissue. The use of automated techniques into segmentation methodology has shown notable progress when compared to traditional procedures, mostly due to its capacity to produce enhanced accuracy and expedited segmentation operations. Furthermore, these imaging technologies offer improved visibility of the renal system, equipping healthcare professionals with more efficient tools for the detection and treatment of specific renal disorders. Hence, it can be deduced that CT imaging has the potential to offer a more accurate comprehension of renal structures, thereby enhancing the ability to detect and treat kidney-related diseases.

Volumetric segmentation Technique (VST) and Atlas-based total segmentation (ABS) are techniques utilized in medical image processing to section and delineate structures or regions of interest inside medical pictures, like MRI or CT scans. These two are.

Atlas-Based Total Segmentation (ABS) ABS relies on a pre-existing atlas or template that contains labeled anatomical facts. This atlas serves as a reference guide, presenting facts about the predicted shapes and positions of facts within the pics. The ABS process entails registering the atlas to the affected person's photograph and using this alignment to switch the labeled records onto the patient's picture. It works correctly when the patient's anatomy is much like the atlas.

Volumetric Segmentation Technique (VST) VST, alternatively, includes a wider variety of strategies that directly examine the voxel intensities and spatial facts within the photo to delineate structures or regions. Those techniques also involve mathematical algorithms, machines learning

Table 7 Active deep learning-based segmentation

Reference no	Method	Architecture	Facts augmentation	Switch learning	Ensemble methods
[47]	✓				
[48]	✓				
[49]	✓				
[50]		✓			
[51]		✓			
[52]		✓			
[53]			✓		
[54]			✓		
[32]			✓		
[55]				✓	
[40]				✓	
[56]				✓	
[57]					✓
[58]					✓
[59]					✓

Table 8 Recent deep learning based segmentation algorithms

Authors	Field	Description	Strength	Weakness
Wu et al. (2019) [47] Yadav et al. (2020) [48] Neubauer et al. (2023) [49]	Method	The utilization of CNN methodologies in the context of computerized kidney segmentation within CT imaging	The attributes of great accuracy and resilience are of paramount importance	There is a demand for a substantial amount of systematically organized statistical data pertaining
Yadav et al. (2021) [50] Merdietio Boedi et al. (2023) [51] Yadav et al. (2020) [52]	Architecture	The utilization of advanced CNN designs, such as U-Net, ResNet, and DenseNet, is employed	Advancing accuracy and efficiency in educational settings entails augmenting the volume of educational data and enhancing generalization	the process of generating such data on a wide scale can significantly increase the computational complexity involved
Mukherjee et al. (2023) [53] Yadav et al. (2019) [54] Pandey et al. (2023) [32]	Facts augmentation	The utilization of data augmentation procedures, encompassing rotation, scaling, and flipping	This approach necessitates a reduced reliance on labeled records for educational purposes	this increased complexity may inadvertently introduce inaccuracies and distortions in the statistical information
Yadav et al. (2019) [55] Shan T et al. (2023) [40] Yadav et al. (2018) [56]	Switch Learning	The utilization of pre-trained convolutional neural network models using transfer learning techniques to boost performance	The implementation of this approach mitigates the influence of model variability	Performance might be limited by the degree of similarity between the source and target domains
Mourya et al. (2023) [57] Kushwaha et al. (2023) [58] Youssef et al. (2023) [59]	Ensemble methods	The utilization of ensemble approaches, such as version averaging and stacking, has been employed to enhance both the accuracy and robustness of predictive models	It enhances the capacity for generalization	It can result in increased computational complexity and resource demands

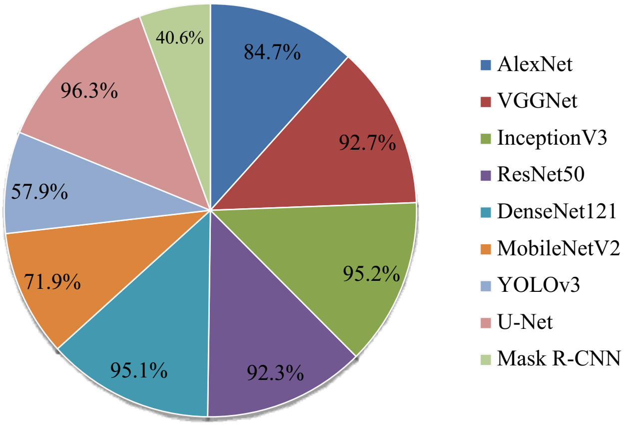


Fig. 6 Performance of deep learning segmentation algorithms

models, or different computational strategies to identify and section structures based totally on styles in the photograph information itself. VST methods do not always depend upon a pre-present atlas.

The connection among these techniques frequently involves the following:

Complementary Use VST strategies are often used to refine or correct the segmentation outcomes acquired from ABS strategies. For instance, ABS may also offer a preliminary segmentation, which may be high-quality-tuned. Use VST techniques to match the precise patient's anatomy or handle cases wherein the atlas-based approach will not be correct enough.

Hybrid techniques Researchers and practitioners frequently integrate each technique, creating hybrid techniques that leverage the strengths of both ABS and VST. It might involve the usage of ABS as an initialization step observed by VST techniques to enhance accuracy or

Table 9 Performance of deep learning segmentation algorithms

Reference no	Alex Net	VGG Net	Inception V3	Res Net50	Dense Net121	Mobile NetV2	YOLO v3	U-Net	Mask R-CNN
[60]	✓								
[61]		✓							
[62]			✓						
[63]				✓					
[64]					✓				
[65]						✓			
[66]							✓		
[67]								✓	
[68]									✓

Table 10 Performance of deep learning segmentation algorithms

Author	Model	Description	Parameters (in Millions)	Accuracy (in %)	Applications
Zhang et al. (2023) [60]	AlexNet	A deep CNN with eight layers for image class	60	84.7	Image analysis
Zhou et al. (2023) [61]	VGGNet	A deep CNN with sixteen or 19 layers for the photo category	138	92.7	Image analysis
Zhang et al. (2018) [62]	InceptionV3	A deep CNN with forty-eight layers for the image category	23	95.2	Image analysis
Shin et al. (2023) [63]	ResNet50	A deep CNN with 50 layers for image type	25.6	92.3	Image analysis
Zhang et al. (2018) [64]	DenseNet121	A deep CNN with 121 layers for photograph classification	8	95.1	Image analysis
Yamauchi et al. (2023) [65]	MobileNetV2	A deep CNN with a light-weight structure for image type	2	71.9	Image analysis
Zhang et al. (2018) [66]	YOLOv3	A deep CNN with actual-time item detection and localization	63	57.9 (mAP)	Object detection
Ahmad et al. (2023) [67]	U-Net	A deep CNN with U-fashioned architecture for image segmentation	31	96.3 (Dice)	Medical imaging
Zhang et al. (2018) [68]	Mask R-CNN	A deep CNN with example segmentation and object detection	66	40.6 (mAP)	Object detection

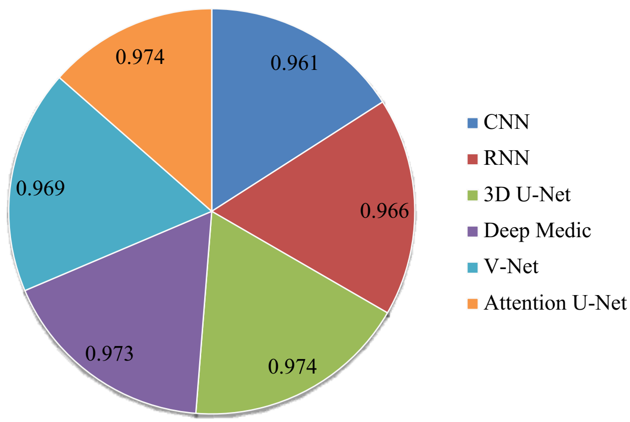


Fig. 7 Dice Similarity coefficient

incorporating ABS information into VST algorithms to manually the segmentation system.

Challenges and improvements ABS methods can be restricted using the excellent of the atlas and its applicability to numerous anatomies. VST methods, even as versatile, may require vast computational assets and extensive training records. Researchers usually focus on refining each technique, aiming for extra correct and green segmentation techniques in clinical imaging.

ABS and VST are play good-sized roles in scientific image segmentation, and their relationship involves collaboration, integration, and improvements to improve the accuracy and reliability of segmenting anatomical systems in clinical Images.

3.1 Purpose of the Study

The primary goal of automated kidney segmentation is utilizing deep learning frameworks and volumetric segmentation algorithms within the domain of CT imaging. The aim of this method is to accurately delineate the boundaries of the kidney in a particular medical imaging investigation, specifically a CT scan. The segmentation method utilizes deep learning frameworks and volumetric segmentation strategies to construct a segmentation model that effectively detects and delineates the organs present in the image, facilitating later analysis for diagnostic purposes. This technology facilitates the automated identification and demarcation of the kidneys in clinical imaging tests, thereby obviating the need for manual delineation carried out by medical professionals. In addition, when integrated with diverse methodologies,

Table 11 Active kidney segmentation models

Reference No	CNN	RNN	3D U-Net	Deep Medic	V-Net	Attention U-Net
[69]	✓					
[70]		✓				
[71]			✓			
[72]				✓		
[6]					✓	
[73]						✓

Table 12 Performance of volumetric segmentation for kidney segmentation

Authors	Model	Dice similarity coefficient	Strength	Weakness
Nag et al. (2023) [69]	CNN	0.961	Powerful for gaining knowledge of complicated capabilities from the entered information	It can also require large amounts of annotated statistics for education
Zhang et al. (2018) [70]	RNN	0.966	Can study the temporal relationships between the entered information	It may be computationally high-priced and require extra schooling time
Xu et al. (2023) [71]	3D U-Net	0.974	Effective for volumetric segmentation	It may be afflicted by over fitting because of a wide variety of parameters
Zhou et al. (2023) [72]	DeepMedic	0.973	Effective for multi-scale segmentation	It can be computationally pricey
Cui et al. (2023) [6]	V-Net	0.969	Powerful for 3-D segmentation	May additionally be afflicted by sluggish convergence
Zhou et al. (2023) [73]	Attention U-Net	0.974	Effective for specializing in informative areas of the input facts	It can be computationally luxurious

such as radiographic assessment, this technology can be utilized to augment the precision and efficacy of diagnosing possible renal conditions. The application of segmentation can be a useful tool in facilitating the process of medical decision-making and treatment planning.

- Automated segmentation yields significantly higher levels of accuracy and precision when compared to other conventional methods.
- The real-time functionality of the segmentation system can effectively reduce the human effort and time needed for accurate segmentation of medical images.
- The utilization of this technology facilitates a more streamlined and effective exchange between the patient and the medical professional.
- The technology enables the automated evaluation of kidney conditions such as nephrolithiasis, polycystic kidney disease, hydronephrosis, and other anomalies in the upper urinary tract.
- It facilitates clinicians in making precise prognoses and developing more targeted treatment approaches.
- The utilization of CT imaging instead of invasive surgical methods aids the reduction of radiation exposure to the patient.

3.2 Impacts of the Study

The incorporation of deep learning frameworks in the domain of autonomous kidney segmentation has exerted a substantial influence on the discipline of medical image analysis. The primary reason for this skill is mostly attributed to its capacity to correctly and efficiently detect and differentiate specific components of the kidneys without requiring invasive procedures. The application of this specific methodology has the potential to enable the examination of medical images for the detection of abnormalities, hence improving the forecasting and treatment of kidney-related diseases. Moreover, this technological innovation has the potential to provide improved accuracy in assessing the size, composition, and extent of the kidneys, hence offering notable benefits for various medical therapies. Furthermore, the application of this specific generation has the capacity to yield enhanced outcomes for renal healthcare systems, along with elevated levels of patient care. The laptop-assisted clinical imaging technique, known as Automatic Kidney Segmentation utilizing Volumetric Segmentation, accurately quantifies the size and shape of the kidney. The software can accurately divide the kidneys into several parts, including the cortex, medulla, and pelvis, while also providing precise quantitative measurements. It has several effects, including:

- Diagnostic applications: The system can be utilized for the examination of renal ailments. The device can identify exceptional patterns and dimensions, potentially indicating irregularities within the internal architecture of the kidneys. This technology has the potential to aid in the timely identification of several medical conditions, such as kidney stones, polycystic kidney problems, and tumors.
- Precise Volumetric Measurement: It can provide precise volumetric measurements of the kidneys, enhancing our comprehension of this organ and undoubtedly resulting in more effective treatment approaches.
- The utilization of Advanced Knowledge-based Super-Resolution and Visualization Systems has the potential to enhance imaging resolution and readability, hence leading to enhanced accuracy and dependability in the analysis process.
- Enhanced monitoring and intervention: By providing more precise measurements, the Advanced Kinematic Sensing and Visualization System has the potential to optimize treatment planning, track the progression of ailments, and facilitate post-therapy follow-ups.

The AKSVS (Automatic Kidney Segmentation—Volumetric Segmentation) approach, universally recognized, holds significant value as a versatile tool applicable across various programmes, encompassing prognosis and treatment planning. The implementation of this technology has the potential to improve the quality and precision of volumetric measurements of the kidneys, hence facilitating more effective treatment and monitoring strategies.

3.3 Identified Issues

- Poor assessment of kidney and surrounding tissue: The kidneys are frequently surrounded via a large quantity of fat tissue, which can cause terrible assessment of the kidney and surrounding tissue, making it tough to segment the kidneys from the encompassing tissue accurately.
- Complicated anatomical capabilities: The kidneys regularly include complicated anatomical features, which include the renal sinus, renal columns, and perinephric fat, that may make it hard for some segmentation methods to seize these features appropriately.
- Low resolution of CT snapshots: Low-decision CT snapshots can make it difficult for some segmentation techniques to seize the best details of the kidney anatomy accurately.
- Restrained selection of schooling information: guide annotations of the kidney are time and useful resource-intensive, which could restrict the choice of training records available for version development.
- Over-segmentation or under-segmentation: this is the maximum common problem in automatic kidney segmentation. Over-segmentation refers to the mis-

classification of regions acting near the kidney, and below-segmentation results in the omission of small structures.

- Image artifacts: CT photos often contain various artifacts as a result of the limited subject of view or mistaken slicing. Those artifacts can motive problems for kidney segmentation algorithms.
- Historical past complexity: The kidney is regularly surrounded by different organs, including the bowels. Automated segmentation algorithms may also fail because of the complexity of the surrounding regions.
- Partial quantity impact: Computed Tomography (CT) photos consist of voxels of different sizes. It leads to a phenomenon called the partial volume impact, which can pose hard for automated segmentation.
- Poor contrast: Low tissue assessment could make it difficult to hit the limits of the kidney inside the picture.

4 Proposed Model

The academic approach to automatic order segmentation in CT imaging incorporates the utilization of deep learning algorithms and volumetric segmentation techniques to accurately and automatically separate the order from CT imaging scans. The present approach employs advanced deep convolutional neural networks (CNN) and volumetric segmentation techniques. Volumetric segmentation refers to the process of partitioning a three-dimensional data volume into distinct sections based on their unique properties. The process of segmentation entails the partitioning of the organism into its two distinct anatomical regions, namely the cortex and the medulla. The present analysis utilizes a profound literacy framework to examine the critical thinking assessment and discern the boundaries and attributes of the structure. This mechanism allows the frame to efficiently transmit the order to its sub cortical corridor with a high degree of accuracy. The utilization of volumetric segmentation techniques enhances the precision of the segmentation process by splitting intricate 3D data into a series of more manageable parts. Each region possesses specific features that provide more precise information about the structure of the object. The utilization of deep learning algorithms and volumetric segmentation techniques for CT image segmentation provides numerous benefits compared to conventional methods. These methods provide efficient, highly detailed, and precise segmentation processes with minimal driver involvement. The implementation of this approach has the potential to greatly enhance the precision and timeliness of order, judgment, and execution. The technique of deep studying for segmentation, specifically for computerized kidney segmentation for CT imaging, includes the following steps:

1. Pre-processing—This step consists of getting ready the statistics for segmentation by choosing a subset of the photographs, pre-processing the images (e.g. overlaying, clipping, normalization, and so on.), and labeling the information (i.e. developing schooling/checking out datasets). Let's consider the number of samples is take into the part of dataset.

$$N(p|o) = \left(\frac{N(p, o)}{N(o)} \right) \tag{1}$$

Pre-processing of deep learning algorithms for automatic kidney segmentation from CT imaging is the step within the image processing pipeline that is used before the kidney segmentation technique starts to evolve.

$$N(p|o) = \frac{1}{N(o)} * \frac{1}{N''} \exp\{p^o o + o^p p + O\} \tag{2}$$

$$N(p|o) = \frac{1}{N'} \exp\{p^o o + oP\} \tag{3}$$

The reason for this step is to prepare the CT imaging information for additional analysis. It includes putting off low-degree noise and heritage items, resizing the photos, and making comparison-improving ameliorations.

$$N(p|o) = \frac{1}{N''} \exp\left\{ \sum_{p=1}^{o_e} p_o * o_p + \sum_{p=1}^{o_f} o_p O_p \right\} \tag{4}$$

$$N(p|o) = \frac{1}{N''} \prod_{p=1}^{o_f} \exp\{p_o * o_p + o * p_o N_o\} \tag{5}$$

Further, in a few instances, statistics augmentation can be used to boost the availability of CT pictures for education and checking out functions. For deep learning, using those pre-processing steps allows for the enhancement of the final kidney segmentation accuracy. Ultimately, preprocessing is a vital step to ensure that the output from the deep learning segmentation algorithm is accurate and reliable.

2. Feature extraction—This step entails extracting relevant capabilities from the photographs for use within the deep learning technique. These features may additionally encompass edges, textures, shapes, and greater. Feature extraction is an important step within the computerized Kidney Segmentation process for CT imaging.

$$N(e_p = 1|o) = \frac{N(e_p = 1|o)}{N(e_p = 0|o) + N(e_p = 1|o)} \tag{6}$$

It performs an important role in extracting the relevant data from the inputs for further processing. It involves using function selection techniques to identify capabilities that may be used to differentiate between the background and the kidney.

$$N(p_o = 1|o) = \frac{\exp\{p_o + p^o O_{p,o}\}}{\exp\{o, p\} + \exp\{p_o + p^o O_{p,o}\}} \tag{7}$$

$$N(p_o = 1|o) = \psi(p_o + o^p O) \tag{8}$$

Generally, the features can also consist of spatial and geometric facts, depth records, textures, and morphological functions. By applying characteristic choice techniques, applicable functions are recognized, and more accurate kidney segmentation may be carried out.

3. Training—This step includes training a deep learning version on the extracted features, and education labels are a good way to learn how to phase the photographs.

$$\frac{\partial o}{\partial p} = \lim_{p \to 0} \frac{p(p+o) - p(o)}{o} \tag{9}$$

The training of a deep studying algorithm for automatic Kidney Segmentation for CT Imaging includes initially amassing a big dataset of CT slices, encompassing both healthful and diseased kidneys.

$$\frac{\partial o}{\partial p} = \lim_{o \to 0} \frac{\left(\frac{1}{p+o}\right) - \frac{1}{p}}{o} \tag{10}$$

$$\frac{\partial o}{\partial p} = \lim_{o \to 0} \frac{\left(\frac{1}{p+o} * \frac{p}{p}\right) - \left(\frac{1}{p} * \frac{p+o}{p+o}\right)}{o} \tag{11}$$

$$\frac{\partial o}{\partial p} = \lim_{p \to 0} \frac{\left(\frac{p-p-o}{(p+o)p}\right)}{o} \tag{12}$$

This dataset is then split into education, validation and trying out units. The training set is used to optimize the version parameters of the deep getting-to-know algorithm with the use of an optimization set of rules, including stochastic gradient descent or L-BFGS.

$$\frac{\partial o}{\partial p} = \lim_{p \to 0} \frac{\left(\frac{-p}{(p+o)*p}\right)}{o} \tag{13}$$

$$\frac{\partial p}{\partial o} = \lim_{p \to 0} \frac{\left(\frac{-1}{(p+o)*p}\right)}{o} \tag{14}$$

$$o = \frac{-1}{p^2} \tag{15}$$

The validation set is used to make sure that over-fitting does not arise by tracking the overall performance of the algorithm at each new release. The checking out, though not important, may be used to measure the performance of the version before its miles are launched into the actual world. Figure 8 shows the flow diagram of the proposed model.

4. Inference—This step involves running the educated deep studying model at trying out images to perform the segmentation.

$$N = \lim_{p \to 0} \left(\frac{o(p+o) - o(p)}{o}\right) \tag{16}$$

$$N = \lim_{p \to 0} \left(\frac{\left(\frac{1}{o+p-1}\right) - \left(\frac{1}{o-1}\right)}{p}\right) \tag{17}$$

The interface stage of a deep getting-to-know algorithm for computerized Kidney Segmentation for CT Imaging

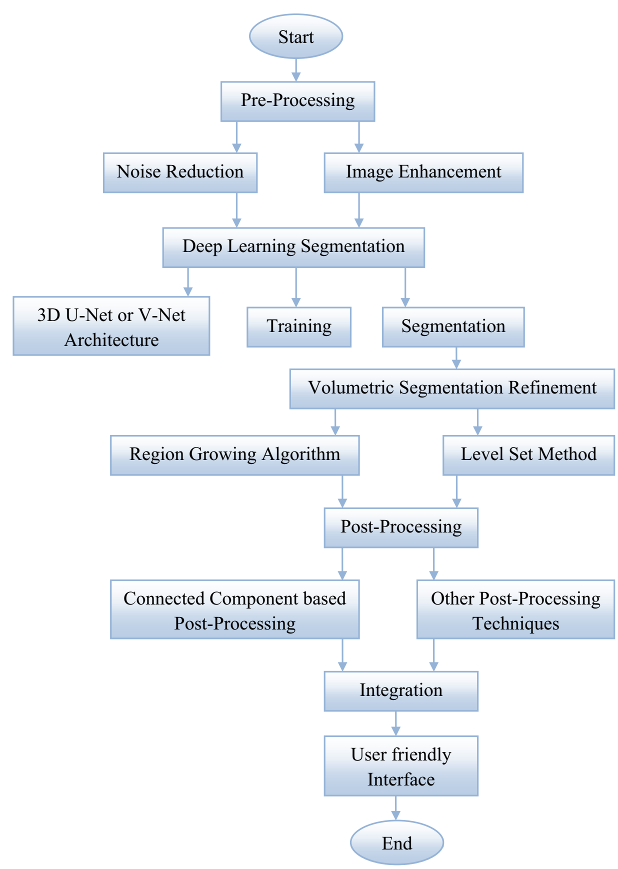


Fig. 8 Proposed flow diagram

includes the use of a CNN to analyze the snapshots comprised of a CT imaging scan.

$$N = \lim_{p\to 0}\left(\frac{\left(\frac{1}{o+p-1}\right)\left(\frac{o-1}{o-1}\right)-\left(\frac{1}{o-1}\right)\left(\frac{o+p-1}{o+p-1}\right)}{o}\right) \tag{18}$$

$$N = \lim_{p\to 0}\left(\frac{(o-1)-(o+p-1)}{p(o-1)(p+o-1)}\right) \tag{19}$$

The CNN takes inside the set of pics, which is processed pixel-by means of pixel to analyze the character intensities and systems of the pictures.

$$N = \lim_{p\to 0}\left(\frac{(-p)}{p(o-1)*(o+p-1)}\right) \tag{20}$$

It is followed by way of the initialization of a specific operation in the CNN, consisting of a convolution layer, pooling layer, activation layer, and so others for the detection and segmentation of the kidneys.

$$N = \lim_{p\to 0}\left(\frac{(-1)}{(o-1)*(o+p-1)}\right) \tag{21}$$

$$N = \left(\frac{(-1)}{(o-p)^2}\right) \tag{22}$$

The CNN then appears for one-of-a-kind characteristics, such as shapes and outlines, to define the boundary of the kidneys. Once the process has been completed, the result is a segmented image of the kidneys, which could then be used for further evaluation.

5. Post-processing—This step consists of cleansing up the segmented photographs, consisting of removing any artifacts delivered through the version and filling any holes that were no longer crammed at some point of the segmentation technique. The post-processing stage of the deep mastering algorithm for automated Kidney Segmentation for CT Imaging is a vital step in optimizing the general overall performance of the model.

$$p''(o) = \lim_{o\to 0}\frac{o(p+o)-o(p)}{p} \tag{23}$$

$$p''(o) = \lim_{p\to 0}\frac{o^{p+o}-o^p}{p} = \lim_{p\to 0}\frac{o^p o^o - o^p}{p} \tag{24}$$

$$p''(o) = \lim_{o\to 0}\frac{o^p(o^p-1)}{p} = o^p \lim_{p\to 0}\frac{p^o-1}{o} \tag{25}$$

It commonly consists of numerous steps, which include optimization of the version parameters, elimination of redundant segments, filling of gaps, smoothing of segmented surfaces, and removal of small errors.

$$p''(o) = o^p \lim_{p\to 0}\frac{o^p-1}{p} \tag{26}$$

$$p = o^p - 1 => o^p = o+1 => p = \log_o(o+1) \tag{27}$$

$$As, o \to 0 => \log_o(p+1) \to 0 => p+1 \to 1 => p \to 0 \tag{28}$$

The optimization of parameters involves careful tuning of the numerous hyper parameters of the model consisting of studying charge, batch size, number of convolutional layers, and range of neurons in step with layer to maximize the accuracy of the segmentation.

$$p''(o) = o^p \lim_{p\to 0}\frac{p^o-1}{o} = p^o \lim_{o\to 0}\frac{o+1-1}{\log_o(p+1)} \tag{29}$$

$$p''(o) = p^o \log_o o \tag{30}$$

As soon as the model is optimized, redundant segments are eliminated to make sure that only the actual kidneys are segmented. Gaps are stuffed to make sure that there are no missing or scattered segments.

$$\ln(o) = \ln(p^o) \tag{31}$$

$$\ln(o) = p * \ln(o) \tag{32}$$

Smoothing is then carried out on the segmented surfaces to make sure that the limits are clean. Small mistakes are eliminated, and the final segmentation accuracy is classified

$$\frac{1}{o} * \frac{\partial o}{\partial p} = \ln(o) \tag{33}$$

$$\frac{\partial o}{\partial p} = o * \ln(p) \tag{34}$$

$$\frac{\partial o}{\partial p} = p^o * \ln(o) \tag{35}$$

Volumetric segmentation is an algorithm used for automatic kidney segmentation for CT imaging. Its miles a PC-primarily based algorithm that is used to process CT scanning facts and phase the kidneys from other tissue. The set of rules works by way of isolating the kidneys from the heritage noise within the test information. It then creates a three-dimensional extent which contains the kidneys and other anatomical structures. This extent is then analyzed to perceive the kidneys and different kidney-related systems. Numerous segmentation strategies are used, including thresholding, location growing, and morphological operations, to become aware of and separate the kidneys from other anatomical structures inside the quantity. As soon as the kidneys have been identified, additional image-processing strategies are used to refine the segmentation further. These techniques encompass texture evaluation, boundary detection, and intensity variant strategies. The ultimate purpose of volumetric segmentation is to allow for correct and reproducible urinary tract segmentation for the motive of unique picture-guided interventions.

5 Conclusion

The utilization of deep learning frameworks and volumetric segmentation in the process of automatic kidney segmentation has been found to be a highly effective and precise approach in the field of medical image segmentation. The integration of deep learning frameworks and volumetric segmentation techniques enables the attainment of enhanced accuracy, speed, and precision in the segmentation of medical pictures. Furthermore, the incorporation of many approaches has exhibited the capacity to produce accurate segmentation results in various medical imaging scenarios. The discipline of medical imaging is expected to witness widespread utilization of deep learning frameworks and volumetric segmentation procedures when additional enhancements are made. The use of this technology holds the potential to improve the effectiveness and precision of automated sickness identification and treatment. Deep learning frameworks have the potential to significantly improve the accuracy and efficiency of kidney segmentation in the future. On the other hand, the application of volumetric segmentation allows for enhanced analysis and offers a more comprehensive understanding of the size and shape of the kidneys. Through the utilization of this data, healthcare practitioners can strengthen their capacity to assess a patient's condition and get a more thorough understanding of renal performance. Moreover, the incorporation of technological advancements, such as 3D printing, allows for the creation of physical models that accurately depict segmented kidneys. This facilitates improved visualization and understanding of the intricate structure of the renal system. It is anticipated that forthcoming advancements will lead to the development of more sophisticated methodologies for automated kidney segmentation. Additionally, automated systems capable of swiftly segmenting and analyzing many images for convenient comparison are expected to emerge.

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Data Availability Source data and their information is mention in the manuscript.

Declarations

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References

1. Abdelrahman A, Viriri S (2023) FPN-SE-ResNet model for accurate diagnosis of kidney tumors using CT images. Appl Sci 13(17):9802
2. Adams R, Bischof L (1994) Seeded region growing. IEEE Trans Pattern Anal Mach Intell 16(6):641–647
3. Chen SH, Wu YL, Pan CY, Lian LY, Su QC (2023) Renal ultrasound image segmentation method based on channel attention and GL-UNet11. J Radiat Res Appl Sci 16(3):100631
4. Çiçek Ö, Abdulkadir A, Lienkamp SS, Brox T, Ronneberger O (2016) 3D U-Net: Learning dense volumetric segmentation from sparse annotation. In: Ourselin S, Joskowicz L, Sabuncu MR, Unal G, Wells W (eds) International conference on medical image computing and computer-assisted intervention. Springer, Cham, pp 424–432
5. Çiçek Ö, Abdulkadir A, Lienkamp SS, Brox T, Ronneberger O (2016) October). 3D U-Net: learning dense volumetric segmentation from sparse annotation. International conference on medical image computing and computer-assisted intervention. Springer, Cham, pp 424–432
6. Cui H, Ma Y, Yang M, Lu Y, Zhang M, Fu L, Song S (2023) Automatic Segmentation of Kidney Volume using Multi-Module Hybrid based U-shape in Polycystic Kidney Disease. IEEE Access. 11:58113–58124
7. Delgado A, Quinteros C, Villalba Meneses F, Tirado-Espín A, Cadena-Morejón C, Cruz-Varela J, Almeida-Galárraga D (2023) Tumor Kidney Segmentation from CT Images Using Residual U-Net Architecture. In: Maldonado-Mahauad J, Herrera-Tapia J, Zambrano-Martínez JL, Berrezueta S (eds) Conference on Information and Communication Technologies of Ecuador. Springer, Cham
8. Dong X, Lei Y, Zhang G, Wang T, Chen Y, Liu Z, Tian J, Wang Q (2019) 3D convolutional neural network for efficient and robust segmentation of kidney from CT volumes. Comput Biol Med 1(104):63–71. https://doi.org/10.1016/j.compbiomed.2018.10.012. (**Epub 2018 Oct 18 PMID: 30390405**)
9. Dong X, Lei Y, Chen L (2019) Kidney segmentation from CT images using 3D fully convolutional neural networks. Comput Methods Programs Biomed 170:1–9

10. Dong X, Lei Y, Li Q (2019) Automatic segmentation of kidneys from CT images using a 3D convolutional neural network (CNN) with threshold-based segmentation. Med Sci Monit 25:2113–2122
11. Dong Y et al (2019) 3D deep learning for multi-modal imaging-guided renal tumor segmentation. IEEE Trans Med Imag 38.10:2281–2291
12. Gonzalez RC, Woods RE, Eddins SL (2004) Digital image processing using MATLAB. Pearson Education India.
13. Han J, Shi Y, Li J, Li Y, Tao T, Wang Y (2018) A modified 3D U-Net for liver segmentation with an improved loss function. In: International Conference on Medical Image Computing and Computer-Assisted Intervention. Springer, Cham, pp. 143–151
14. Hansen S, Gautam S, Salahuddin SA, Kampffmeyer M, Jenssen R (2023) ADNet++: A few-shot learning framework for multi-class medical image volume segmentation with uncertainty-guided feature refinement. Medical Image Analysis. pp. 102870
15. Haralick RM, Sternberg SR, Zhuang X (1987) Image analysis using mathematical morphology. IEEE Trans Pattern Anal Mach Intell 4:532–550
16. Hatsutani T, Ichinose A, Nakamura K, Kitamura Y (2023) Segmentation of Kidney Tumors on Non-Contrast CT Images Using Protuberance Detection Network. In: International Conference on Medical Image Computing and Computer-Assisted Intervention. Springer, Cham, pp. 13–22
17. He W, Zhang C, Dai J, Liu L, Wang T, Liu X, Liang X (2023) A statistical deformation model-based data augmentation method for volumetric medical image segmentation. Med Image Anal 91:102984
18. Huang X, Zhang H, Wang Y, Zeng Y, Yu D (2020) Automatic kidney segmentation based on U-Net for CT images. J Med Syst 44(5):95
19. Huang X et al (2020) Automatic kidney segmentation in CT images using the deep convolutional neural network. Med Phys 474:1441–1451
20. Hwang EJ, Park SJ, Jin KN, Lee JH (2019) Automatic segmentation of kidneys using deep learning for total kidney volume quantification in living kidney donors: a retrospective, multicenter study. Sci Rep 9(1):1–9
21. Ji Y, Hwang G, Lee SJ, Lee K, Yoon H (2023) A deep learning model for automated kidney calculi detection on non-contrast computed tomography scans in dogs. Front Vet Sci. https://doi.org/10.3389/fvets.2023.1236579
22. Liang J, Hu P, Zhang J, Yang X, Wang H, Su Z (2020) Deep learning for automatic kidney segmentation in CT imaging: a review. Comput Biol Med 125:103967. https://doi.org/10.1016/j.compbiomed.2020.103967. (**Epub 2020 Aug 11 PMID: 32823284**)
23. Litjens G, Kooi T, Bejnordi BE, Setio AA, Ciompi F, Ghafoorian M, Sanchez CI (2017) A survey on deep learning in medical image analysis. Med Image Anal 42:60–88
24. Liu J, Yildirim O, Akin O, Tian Y (2023) AI-driven robust kidney and renal mass segmentation and classification on 3D CT images. Bioengineering 10(1):116
25. Mahmud S, Abbas TO, Mushtak A, Prithula J, Chowdhury ME (2023) Kidney cancer diagnosis and surgery selection by machine learning from CT scans combined with clinical metadata. Cancers 15(12):3189
26. Manjula M, Kumar N, Vekariya V, Giri S, Pandey AK, Gupta S, Bhatt R (2023) Nanoparticle analysis based on optical ion beam in nuclear imaging by deep learning architectures. Opt Quant Electron 55(10):863
27. Menze BH, Jakab A, Bauer S, Kalpathy-Cramer J, Farahani K, Kirby J, Arbel T (2015) The multimodal brain tumor image segmentation benchmark (BRATS). IEEE Trans Med Imag 34(10):1993–2024
28. Milletari F, Navab N. Ahmadi SA (2016) V-Net: Fully convolutional neural networks for volumetric medical image segmentation. In: 2016 Fourth International Conference on 3D Vision (3DV). IEEE. pp. 565–571
29. Milletari F, Navab N, Ahmadi SA (2016) V-net: Fully convolutional neural networks for volumetric medical image segmentation. In: 2016 fourth international conference on 3D vision (3DV). IEEE. pp. 565–571
30. Mukherjee P, Lee S, Elton DC, Nakada SY, Pickhardt PJ, Summers RM (2023) Fully automated longitudinal assessment of renal stone burden on serial CT imaging using deep learning. J Endourol 37(8):948–955
31. Osher S, Sethian JA (1988) Fronts propagating with curvature-dependent speed: algorithms based on Hamilton-Jacobi formulations. J Comput Phys 79(1):12–49
32. Pandey M, Gupta A (2023) Tumorous kidney segmentation in abdominal CT images using active contour and 3D-UNet. Irish J Med Sci 192(3):1401–1409
33. Pizer SM, Amburn EP, Austin JD, Cromartie R, Geselowitz A, Greer T, Zimmerman JB (1987) Adaptive histogram equalization and its variations. Comput Vision, Gr Image Process 39(3):355–368
34. Rakhlin A, Shvets AA, Iglovikov VI, Kalinin AA (2018) Deep convolutional neural networks for breast cancer histology image analysis. In: International Conference on Medical Image Computing and Computer-Assisted Intervention. Springer, Cham, pp. 657–665
35. Roth HR, Lu L, Farag A, Shin HC, Liu J, Turkbey EB, Summers RM (2016) Deeporgan: Multi-level deep convolutional networks for automated pancreas segmentation. In: International conference on medical image computing and computer-assisted intervention. Springer, Cham, pp. 556–564
36. Sato Y, Nishio M, Kawai N, Tominaga J, Nishizawa N, Okada T, Ogawa K (2020) Kidney segmentation in dynamic contrast-enhanced CT images using recurrent neural networks. Comput Biol Med 123:103867. https://doi.org/10.1016/j.compbiomed.2020.103867. (**Epub 2020 Jun 2 PMID: 32540513**)
37. Sato S, Nakamura Y, Shimizu Y, Furukawa R, Otake Y (2020) Sequential segmentation of kidneys in dynamic contrast-enhanced CT images using recurrent neural networks. Int J Comput Assist Radiol Surg 15(8):1303–1310
38. Sato Y, Nakamura Y, Shimizu A, Tsukamoto Y, Takahashi H (2020) Sequential segmentation of kidneys in dynamic contrast-enhanced CT images using recurrent neural networks. Int J Comput Assist Radiol Surg 15(7):1239–1249
39. Sato Y et al (2020) Dynamic contrast-enhanced CT image analysis using 3D fully convolutional networks: simultaneous liver and kidney segmentation for living donor liver transplantation. Phys Med Biol 652:025003
40. Shan T, Ying Y, Song G (2023) Automatic Kidney segmentation method based on an enhanced generative adversarial network. Diagnostics 13(7):1358
41. Shin HC, Roth HR, Gao M, Lu L, Xu Z, Nogues I, Summers RM (2016) Deep convolutional neural networks for computer-aided detection: CNN architectures, dataset characteristics and transfer learning. IEEE Trans Med Imag 35(5):1285–1298
42. Wang G, Li W, Aertsen M, Deprest J, Ourselin S, Vercauteren T (2019) Automatic Fetal brain segmentation by deep learning segmentation propagation with anatomical guidance. IEEE Trans Med Imaging 38(11):2482–2493
43. Wang S, Shi J, Qiu S, Zhang R, Wu J, Wang C (2019) A review of segmentation methods of lung, lesion and kidney in CT images. Artif Intell Rev 51(1):107–131

44. Wu Y, Zhang L, Zhang H, Xia F, Wang L, Xie Y, Yan F, Chen W, Zhu W, Liu J (2019) Automatic kidney segmentation in CT images using region growing and deep prior shape constraint techniques. Med Phys 46(2):796–807. https://doi.org/10.1002/mp.13382. (**Epub 2019 Jan 7 PMID: 30586236**)
45. Wu L et al (2019) A fully automated method for kidney segmentation in CT images based on region growing and morphology operation. J X-ray Sci Technol 27.6:1011–1021
46. Wu W, Chen Y, Zheng Y, Huang J (2019) Automatic kidney segmentation from abdominal CT images using the region growing algorithm. Int J Comput Assist Radiol Surg 14(11):1977–1985
47. Wu X, Li H, He Y, Li W (2019) Automatic kidney segmentation in CT images based on region growing and morphological filtering. Med Phys 46(4):1612–1622
48. Yadav SP, Yadav S (2020) Image fusion using hybrid methods in multimodality medical images. Med Biol Eng Compu 58:669–687
49. Neubauer J, Wilhelm K, Gratzke C, Bamberg F, Reisert M, Kellner E (2023) Effect of surface-partial-volume correction and adaptive threshold on segmentation of uroliths in computed tomography. PLoS ONE 18(6):e0286016
50. Yadav SP (2021) Emotion recognition model based on facial expressions. Multimed Tools Appl 80(17):26357–26379
51. Merdietio Boedi R, Shepherd S, Oscandar F, Mânica S, Franco A (2023) 3D segmentation of dental crown for volumetric age estimation with CBCT imaging. Int J Legal Med 137(1):123–130
52. Yadav SP, Yadav S (2020) Fusion of medical images in wavelet domain: a hybrid implementation. CMES-Comput Model Eng Sci. https://doi.org/10.32604/cmes.2020.08459
53. Mukherjee S, Korfiatis P, Khasawneh H, Rajamohan N, Patra A, Suman G, Goenka AH (2023) Bounding box-based 3D AI model for user-guided volumetric segmentation of pancreatic ductal adenocarcinoma on standard-of-care CTs. Pancreatology 23(5):522–529
54. Yadav SP, Yadav S (2019) Fusion of medical images using a wavelet methodology: a survey. IEIE Trans Smart Process Comput 8(4):265–271
55. Yadav SP, Yadav S (2019) Mathematical implementation of fusion of medical images in continuous wavelet domain. J Adv Res Dynam Control Syst 10(10):45–54
56. Yadav SP, Yadav S (2018) Fusion of medical images in wavelet domain: a discrete mathematical model. Ingeniería Solidaria 14(25):1–11
57. Mourya GK, Gogoi M, Talbar SN, Dutande PV, Baid U (2023) Cascaded dilated deep residual network for volumetric liver segmentation from CT image. Research Anthology on Improving Medical Imaging Techniques for Analysis and Intervention. IGI Global, Pennsylvania, pp 1153–1165
58. Kushwaha A, Mourad RF, Heist K, Tariq H, Chan HP, Ross BD, Hadjiiski LM (2023) Improved repeatability of mouse tibia volume segmentation in murine myelofibrosis model using deep learning. Tomography 9(2):589–602
59. Youssef B, Alksas A, Shalaby A, Mahmoud A, Van Bogaert E, AlGhamdi NS, El-Baz A (2023) Integrated deep learning and stochastic models for accurate segmentation of lung nodules from computed tomography images: a novel framework. IEEE Access 11:99807–99821
60. Zhang J, Jiang H, Shi T (2023) ASE-Net: a tumor segmentation method based on image pseudo enhancement and adaptive-scale attention supervision module. Comput Biol Med 152:106363
61. Zhou T, Li L, Bredell G, Li J, Unkelbach J, Konukoglu E (2023) Volumetric memory network for interactive medical image segmentation. Med Image Anal 83:102599
62. Zhang Y, Zhang H, Chen X, Wei W, Huang S, Shi Y, Zhou X (2018) A level set method based on improved fractional-order regularization for kidney segmentation in CT images. Biomed Eng Online 17(1):49. https://doi.org/10.1186/s12938-018-0483-3. PMID:29606118;PMCID:PMC5875728
63. Shin H, Kim H, Kim S, Jun Y, Eo T, Hwang D (2023) SDC-UDA: Volumetric Unsupervised Domain Adaptation Framework for Slice-Direction Continuous Cross-Modality Medical Image Segmentation. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 7412–7421
64. Zhang F et al (2018) A level set method for automatic kidney segmentation using CT images. Comput Methods Prog Biomed 165:91–99
65. Yamauchi Y, Yatagawa T, Ohtake Y, Suzuki H (2023) Bin-scanning: segmentation of X-ray CT volume of binned parts using Morse skeleton graph of distance transform. Comput Vis Med 9(2):319–333
66. Zhang K, Liu J, Wang L, Guo Y (2018) An efficient and effective kidney segmentation approach based on the level set method with intensity normalization. Computational and mathematical methods in medicine.
67. Ahmad I, Xia Y, Cui H, Islam ZU (2023) AATSN: anatomy aware tumor segmentation network for PET-CT volumes and images using a lightweight fusion-attention mechanism. Comput Biol Med 157:106748
68. Zhang Q, Sun J, Zhou X, Li Y, Gu L (2018) Level set method with shape and appearance priors for automatic segmentation of kidneys from CT images. Biomed Eng Online 17(1):1–21
69. Nag MK, Liu J, Liu L, Shin SY, Lee S, Lee JM, Summers RM (2023) Body location embedded 3D U-Net (BLE-U-Net) for ovarian cancer ascites segmentation on CT scans. In: 18th International Symposium on Medical Information Processing and Analysis 12567: 108–114. SPIE.
70. Zhang Y, Han X, Xie Z, Yang X, Lian Z (2018) Automatic kidney segmentation in CT images based on multi-atlas fusion and level set method. Biomed Eng Online 17(1):53
71. Xu H, Abdallah N, Marion JM, Chauvet P, Tauber C, Carlier T, Hatt M (2023) Radiomics prognostic analysis of PET/CT images in a multicenter head and neck cancer cohort: investigating ComBat strategies, sub-volume characterization, and automatic segmentation. Eur J Nucl Med Mol Imag 50(6):1720–1734
72. Zhou Z, Xiong Z, Cheng R, Luo Q, Li Y, Xie Q, Li Z (2023) Volumetric visceral fat machine learning phenotype on CT for differential diagnosis of inflammatory bowel disease. Eur Radiol 33(3):1862–1872
73. Zhou X, Ye Q, Yang X, Chen J, Ma H, Xia J, Yang G (2023) AI-based medical e-diagnosis for fast and automatic ventricular volume measurement in patients with normal pressure hydrocephalus. Neural Comput Appl 35(22):16011–16020