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Overview of Medical Image Segmentation Techniques through Artificial Intelligence and Computer Vision

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Abstract: Medical image segmentation is a crucial task in computer vision, playing a pivotal role in applications such as diagnostics, treatment planning, and medical research. The present study explores a wide range of methodologies employed in the field of medical research to achieve image segmentation. These techniques range from traditional approaches based on thresholding, edge detection, region-based and clustering, to modern artificial intelligence methods, particularly deep learning techniques. The strengths and limitations of each method are thoroughly examined. This paper focuses on analyzing various architectures used for medical image segmentation, specifically evaluating their performance. It aims to delve deeply into the different segmentation methods, offering a comparative perspective on their effectiveness. Furthermore, This document delves into the most recent technological progress in segmentation, emphasizing major breakthroughs capable of transforming the precision and productivity of analyzing medical images. Through an exhaustive compilation and detailed critique of the results obtained by employing a range of segmentation strategies, the study presents the outcomes of multiple approaches, accompanied by an in-depth analysis of the strengths and weaknesses inherent to the various techniques applied to medical image segmentation. This research enhances the comprehension of how these methods can be applied within the medical sector, especially in the area of computer vision.

Keywords: Segmentation, Computer vision, Medical image, Machine learning, Computed Tomography, Deep learning.

1. INTRODUCTION

The use of image analysis for disease diagnosis has been an established practice for many decades. Today, there are various modalities of medical imaging commonly used in medical practice, especially radiography, MRI, computed tomography (CT), ultrasound,and more. The choice of imaging modality depends on factors such as acquisition speed, image resolution, and patient comfort.

Once a medical image is acquired, a healthcare professional examines it carefully to detect possible diseases and their potential causes. The duration of this procedure varies, ranging from a few hours to multiple days, based on the case's complexity and requires the involvement of skilled clinicians and technicians. They assess the size of organs and determine if there are anomalies requiring treatment. All these tasks involve identifying regions of interest, even if segmentation is not always explicitly mentioned. This is why the importance of medical image segmentation is paramount across various medical applications, including the detection and quantification of abnormalities, the creation of surgical plans, tracking the advancement of diseases, and greatly aiding healthcare workers by pinpointing regions of interest within medical imagery. Medical image segmentation can be complex due to inherent challenges such as low contrast, noise, and artifacts in the images. Over the years, a variety of segmentation methods have been devised to tackle these challenges, with 'deep learning methodologies demonstrating exceptional efficacy. This review thoroughly examines the field of medical image segmentation, detailing their advantages, drawbacks, and usage across various imaging techniques. The selection of particular methods or algorithms in favor' of others is influenced by the kind of imaging and the specific issue at hand. The evolution of segmentation strategies in medical imaging has often been explored in literature reviews [1], [2]. Techniques for segmenting medical images may be divided into two main categories:traditional methods that apply machine learning and innovative strategies that make use of artificial intelligence.

Here is a representation of the predominant medical

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image segmentation techniques found in each category presented in Figure 1:

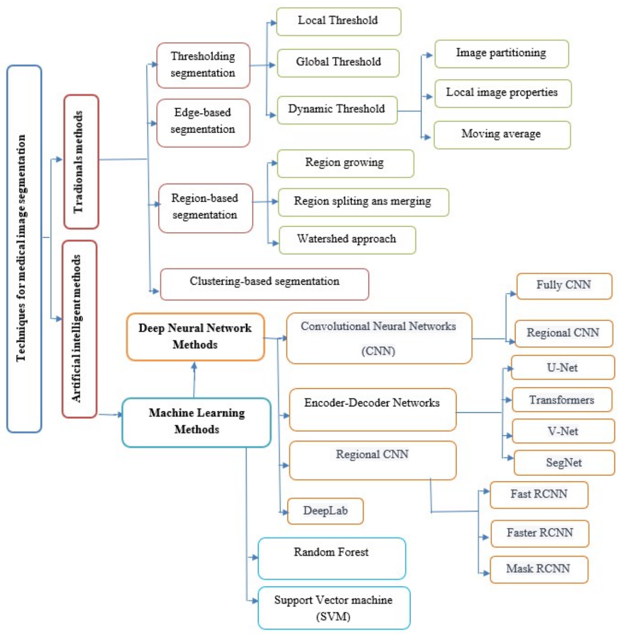

Figure 1. Techniques for Segmenting Medical Images.

The organization of this paper is outlined as follows: Section 2 presents an examination of the current literature, encompassing earlier related research efforts. Section 3 provides a summary of different conventional frameworks applied in the segmentation of medical images. Section 4 explores the recent frameworks utilizing artificial intelligence for segmenting medical images. Section 5 conducts a comparative analysis between various deep learning models and conventional frameworks. In conclusion, Section 6 wraps up the paper, highlighting potential avenues for future studies and applications within the realm of 'biomedical image segmentation.

2. Review of Literature

Various methodologies for medical image segmentation have been explored, with Lee. 2007 [3] introducing a statistical approach incorporating morphological operations and Gaussian mixture modeling, demonstrating efficacy in CT image segmentation. Similarly, Ashwani et al. [4] developed a technique based on thresholding and morphology for brain MRI segmentation, validated through CT Angiography. This approach achieved performance ratings of 95.4% for brain MRIs and 95.8% for CT-Angiography, assessed by completeness.

In a recent study, Bhosle et al. 2023[5] evaluated binary adaptive and Otsu thresholding techniques for lung segmentation in CT images, identifying adaptive thresholding as the superior method with a 78.69% accuracy rate. Binary inverse thresholding followed closely at 75.59%, while Otsu's method, despite its computational simplicity, only achieved 61.70% accuracy due to its lower efficacy in handling images with diverse pixel intensities. This research provides essential insights for selecting the optimal thresholding technique for image segmentation, balancing accuracy and the particular demands of varying image types.

Zhou et al. 2018 [6] explored the efficacy of an innovative segmentation method for identifying multiple organs in computed tomography (CT) images, leveraging a Convolutional Neural Network (CNN) architecture. Their evaluation focused on Mean Accuracy and the Jaccard Similarity Index (JSI), revealing that the method achieved a mean JSI of 79% with a 3D deep CNN and 67% using a 2D deep CNN across seventeen organ types. This indicates the technique's versatility and high performance in segmenting a variety of organs. Jia et al. 2017[7], introduced an approach based on Fully Convolutional Networks (FCN) for segmenting histopathology images using deep weak supervision. This method innovatively utilized superpixels rather than standard pixels, effectively enhancing the preservation of natural tissue boundaries. A key outcome of this approach was its superior performance in segmentation accuracy, as evidenced by an F1 score of 83.6%. This score notably exceeded that of other existing algorithms under weak supervision, marking a significant advancement in the field. Fully convolutional networks (FCN) [8], including models like U-Net [9], DeepMedic [10], and holistically nested networks [11], [12], have proven to be effective and accurate in a range of segmentation challenges, covering areas such as cardiac magnetic resonance (MR) [13], brain tumors [14], and abdominal CT scans [15], [16],.Inspired by DenseNet architecture [17].

Ummadi (2022) [18] reviewed U-Net and its derivatives (UNet++, R2UNet, Attention UNet, TransUNet), underscoring their pivotal role in facilitating non-invasive diagnoses through high-performance across diverse biomedical segmentation tasks. Inspired by the foundational work of GoogleNet [19], [20], Gu et al. [21] developed CE-Net, integrating the inception model into the domain of medical imaging segmentation. This integration augments feature extraction capabilities through the use of atrous convolution, allowing for an expanded capture of spatial details. Additionally, CE-Net utilizes 1×1 convolutions within its feature maps to incorporate the inception design, albeit this intricacy introduces hurdles in terms of model flexibility. Dosovitskiy et al. [22] introduced the Vision Transformer (ViT), marking a breakthrough in medical image analysis by providing an innovative alternative to conventional convolutional neural networks (CNNs). Originating from advancements in natural language processing, ViT has been successfully implemented in the segmentation of medical images, as evidenced by recent implementations such as TransUnet (2021) [23], Utnet (2021) [24], [25], and Swin-unet (2021) [26]. These applications highlight ViT's capability to manage complex interdependencies that exceed CNNs' scope. Combining ViT with CNN framework is emerging as an effective method for enhancing the precision and efficiency of segmentation in medical imaging. In the realm of medical image segmentation, the latest breakthroughs have been aimed at improving the precision of organ and lesion outlines. Chen et al. (2023) [27] developed TransAttUnet introduced TransAttUnet, marking a noteworthy progress in medical image segmentation technology. This attention based network boosts semantic segmentation by merging multi-level attention mechanisms and multi-scale connectivity within the U-Net structure.

3. Traditional methods

Traditional medical image segmentation methods encompass a variety of classical image processing and machine learning techniques, each with distinct advantages and limitations. These methods often require manual or semi-automatic intervention, relying on predefined rules, handcrafted features, and mathematical algorithms. Key traditional approaches include thresholding [28], which is simple and practical but can struggle with medical images containing diverse regions, leading to noise and over-segmentation issues. Advanced thresholding techniques like the OTSU method [29] aim to refine this process using local statistical information. Edge-based segmentation [30] accurately detects transitions in image properties but is sensitive to noise, whereas region-based techniques like region growing [31]and the watershed approach [32] group pixels based on similarity, offering diverse segmentation methods but potentially lacking in precision. Clustering-based segmentation groups similar pixels based on intensity or feature similarity. Popular algorithms like K-means or ISODATA [33], fuzzy c-means [34], and the expectation-maximization (EM) algorithm [35]vary in their approach to grouping data, with K-means focusing on mean intensities [36] and fuzzy c-means offering soft segmentations [37]. The EM algorithm assumes Gaussian mixture models to estimate mixture components and posterior probabilities. Each method showcases a unique array of advantages, making them suitable for specific image types and segmentation challenges. However, these approaches also come with inherent limitations, particularly when addressing the complexity of medical images that demand highly accurate segmentation. Often, enhancements are required to achieve greater precision and specificity across various medical imaging applications. The comparative tableI below offers an overview of these traditional methods, highlighting their strengths and limitations within the context of medical image segmentation.

TABLE I. Comparative Overview of Traditional Medical Image Segmentation Methods

Techniques	Advantages	Limitations
Thresholding	-Among the simplest and most effective methods.	-Ineffective for images with complex intensity distributions. -Struggles with images that have histograms close to unimodal.
Edge Detection	-Works well for images with clear edges.	-Not applicable to images with many edges. -Inadequate for images where edges are not well-defined.
Region Detection	-Ideal for images with distinct regions.	-Not applicable to images with many edges. -Ineffective for images where region borders are not clear.

4. Intelligence artificial methods

Amid swift progress in artificial intelligence, alongside machine learning and deep learning techniques, the approach to segmentation has undergone a transformative shift. Nevertheless, the advent of sophisticated neural networks, including Convolutional Neural Networks (CNN) and encoder-decoder architectures, has markedly enhanced segmentation efficacy. These advanced deep learning models are adept at extracting intricate features and identifying distinctive patterns within extensive datasets, resulting in segmentations that are both more precise and reliable. In the subsequent sections, an outline of traditional machine learning and contemporary deep learning approaches to medical image segmentation will be provided.

A. *Machine learning methods*

Machine learning techniques for segmentation are a crucial component of medical image analysis, facilitating the automated extraction and recognition of crucial structures and areas within medical images. The segmentation methods in medical imaging based on machine learning principles, focusing on Support Vector Machine (SVM) and Random Forest algorithms. SVM, a powerful learning system widely used in pattern recognition, computer vision, and bioinformatics, has demonstrated superior performance compared to traditional classifiers [38]. In medical imaging, SVMs utilize supervised learning to discern complex boundaries between structures, ensuring accurate segmentation of tissues or lesions. Meanwhile, Random Forest, another robust machine learning algorithm for medical imaging, relies on labeled training data, which can be challenging to obtain in medical domains. To address this challenge, semi-supervised learning methods like semi-supervised random forest [39], CoForest [40], and semi-supervised super-pixel method [41] have been introduced, integrating unlabeled data to enhance performance and optimize segmentation accuracy. These techniques represent significant advancements in automating medical image segmentation, enabling precise analysis and diagnosis.

B. Deep Neural Network Methods

Deep learning has achieved remarkable advancements in the field of image segmentation, outperforming traditional approaches. Subsequent parts will provide a detailed examination of diverse deep learning strategies for segmenting medical images. This includes Convolutional Neural Networks (CNNs) like R-CNN, encoder-decoder frameworks such as U-Net, V-Net, and SegNet, alongside DeepLab-based segmentation networks and Transformer models.

1) Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) have become widely recognized in the domains of computer vision and medical image analysis for their capacity to autonomously identify pertinent features within images, leading to remarkable performance in segmenting anatomical structures and abnormalities in medical images [42]. CNNs ((see Figure 2) consist of three main layers: the convolutional layer, which detects distinct features in images through mathematical operations; the pooling layer, which reduces spatial dimensions without changing depth, reducing computational requirements for subsequent layers; and the fully connected layer, where high-level reasoning and integration of feature responses occur, enabling accurate image analysis. These network architectures have proven effective in medical imaging tasks, revolutionizing the field and contributing significantly to precise image segmentation [42].

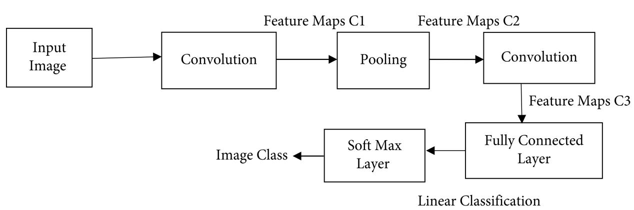

Figure 2. Convolutional neural network architecture.

As CNN models and architectures have continued to advance, medical image segmentation has achieved unprecedented levels of accuracy and efficiency. Notable deep neural network architectures for image segmentation, including U-Net, V-net, and DeepLab (illustrated in Figure 1), have played a pivotal role in this progress. These CNN-based segmentation techniques are in a constant state of evolution, continually enhancing segmentation outcomes and broadening the scope of clinical applications. Additionally, recent developments have introduced techniques like TransUNet, TransFuse, MedT, and TransAttUnet, which combine the power of Transformers and CNNs to further elevate the state of medical image segmentation. These hybrid methodologies have demonstrated potential in addressing intricate segmentation challenges within the domain of medical image analysis.

2) U-NET architecture

Ronneberger et al.[43] introduced the U-Net model at the MICCAI conference in 2015(see Figure 3), marking a significant advancement in leveraging deep learning for segmenting medical images. The U-Net model, a tailored Fully Convolutional Network (FCN) for the segmentation of biomedical images, features an encoder, a bottleneck module, and a decoder. Its design has been widely embraced due to its capability to meet the complex requirements of segmenting medical imagery. Figure 4 depicts the U-Net framework. Furthermore, a variety of fundamental U-Net models have been modified for the segmentation of medical images, seeing extensive application. These U-Net modifications and related deep learning frameworks strive to improve segmentation quality by increasing accuracy and computational efficiency, which is facilitated by adjustments in the network architecture and the incorporation of innovative modules. Subsequent iterations of U-Net, such as U-Net++, R2U-Net, Attention U-Net, and Trans U-Net, represent progressive enhancements to the original architecture, tailored to improve the accuracy and operational efficiency in medical image segmentation tasks. U-Net++ introduces nested connections to facilitate a more nuanced semantic interpretation and a smoother gradient propagation. R2U-Net merges residual with recurrent connections, enhancing the model's capability in handling temporal sequence data. Attention U-Net incorporates attention mechanisms to concentrate on particular areas of interest, and Trans U-Net amalgamates transformer network elements, boosting performance in complex segmentation tasks. These U-Net variations have shown remarkable efficacy, even when trained on limited datasets, proving their high precision in biomedical segmentation endeavors [43].

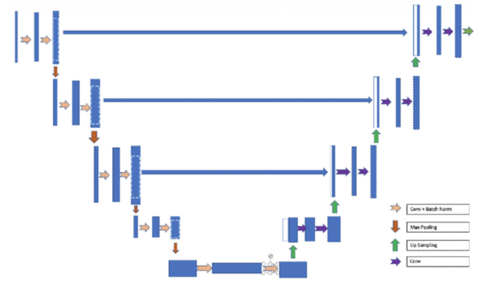

Figure 3. The structure of U-Net [43].

3) SegNet architecture

The SegNet architecture is called the CNN encoder decoder, which proved efficient in dealing with medical semantic image segmentation.[44] It symmetrically consists of five encoders and five decoders with convolution layers, batch normalization, a rectified linear unit layer, max-pooling layer, upsampling, and SoftMax classifier as in Figure 4. SegNet is an advanced medical image segmentation technique based on Convolutional Neural Networks (CNNs). Its fundamental principle revolves around the use of encoder-decoder architecture, where the image is encoded into low-level features and then decoded to produce segmentation. Unlike other architectures, SegNet employs an index mechanism during the decoding step. Indices of

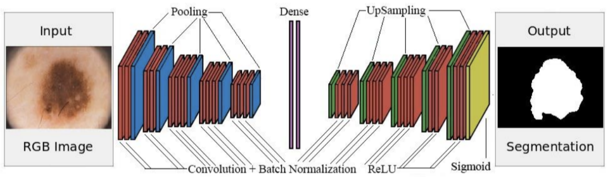

Figure 4. Polyp image segmentation with Segnet.

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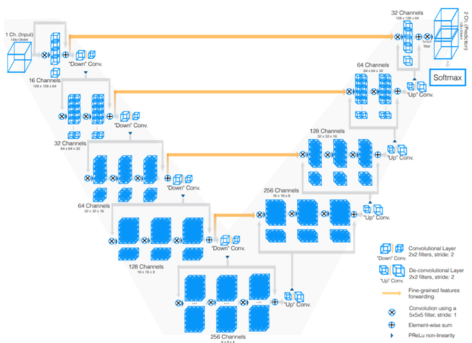

Figure 5. The structure of V-Net.

important pixels obtained during encoding are reused to produce accurate segmentation during decoding. This process enables SegNet to maintain crucial spatial information while reducing the number of parameters, making it efficient for complex medical image segmentation. Generally, the SegNet architecture is better than the various architectures, for example, U-Net [9] and FCN [45] because of its memory and less time.

SegNet stands out for its ability to retain important details through the use of max-pooling indices, thereby optimizing segmentation quality without the need for post-processing. This architecture reduces complexity and resource requirements, making the processing of high-resolution images more efficient. By producing smooth images directly, SegNet simplifies the segmentation workflow, offering an efficient and accurate solution for image segmentation, especially in the medical field.

4) VNet architecture

Milletari et al. [46] proposed a 3D deformation structure V-Net of the U-Net network structure. Its network structure is shown in Figure 5, V-Net is also an encoder-decoder architecture but specifically designed for 3D segmentation. Unlike U-Net, V-Net employs residual connections in both the encoder and decoder, allowing it to capture information at different spatial scales. V-Net is primarily used for 3D medical image segmentation, such as images from CT scans or MRIs. Due to its ability to handle 3D volumes, it is particularly suited for tasks where the 3D structure of the objects to be segmented is crucial.

5) R-CNN architecture.

The R-CNN technique [47] represents a groundbreaking application of deep learning in the field of object detection. Initially, this method involved creating a feasible number of potential object regions. For each of these regions, R-CNN utilized DNNs to extract features. Subsequently, enhancements were made to R-CNN, enabling the focus on Regions of Interest (RoIs) within feature maps through RoIPool. This advancement resulted in increased processing speed and improved precision. Several iterations of R-CNN have emerged in the research community, including Fast R-CNN, Faster R-CNN, and Mask R-CNN. Each iteration contributes unique enhancements and developments to the domain. TableII presented below outlines the progression of R-CNN technology, detailing the innovations and refinements each version offers. This comparison illuminates the distinct benefits and obstacles associated with each, showcasing the continuous advancement in the area of image segmentation.

6) DeepLab architecture.

DeepLab is a state-of-the-art semantic image segmentation model widely used in medical image segmentation tasks, DeepLab model employs pretrained CNN model ResNet-101/VGG-16 with atrous convolution to extract the features from an image[48]. Atrous convolutions offer key advantages, enabling precise feature resolution control and transforming image classifiers into dense feature extractors without extra parameters. Additionally, DeepLab utilizes conditional random fields (CRF) for detailed segmentation output. Despite these strengths, DeepLab requires meticulous hyperparameter tuning for optimal performance in medical image segmentation tasks. Various versions of DeepLab have been introduced in research, such as DeepLabv1 [49], DeepLabv2, DeepLabv3[50], and DeepLabv3+ [51]. Each version brings its own improvements and advancements in the field.The comparative table III below illustrates the evolution of the DeepLab architecture, highlighting the innovations and optimizations introduced by each version. It sheds light on the specific advantages and challenges, reflecting the ongoing progress in image segmentation.

7) Transformers

Recent developments in medical image segmentation research have been propelled by innovative neural network architectures. The seminal work by Vaswani et al., which introduced the Transformer by showcasing attention mechanisms, achieved outstanding outcomes across a range of language processing tasks [52]. Chen et al. demonstrated successful segmentation of medical images by integrating Transformers with U-Net, significantly enhancing both localization and contextual understanding [53]. Zhang and colleagues developed TransFuse, a concurrent framework that combines Transformers and CNNs, achieving top-tier results across various medical image segmentation contexts[54]. The integration of Gated Axial-Attention into MedT by Valanarasu et al. surpassed prior methods in

TABLE II. Comparative Overview of R-CNN Architectures: Fast R-CNN, Faster R-CNN, and Mask R-CNN.

Criteria	Fast R-CNN	Faster R-CNN	Mask R-CNN
Architecture	Utilizes the Region Proposal Network (RPN) and a CNN for feature extraction.	Utilizes RPN and a CNN, but with optimizations in region proposal method.	Builds on Faster R-CNN by adding a segmentation branch with RoI-Align for precise pixel-level instance segmentation.
Applications	Employed across a range of medical computer vision tasks, such as identifying tumors and segmenting organs within radiographic images.	Suited for cases where speed and precision are critical, such as computer-assisted surgery and real-time anomaly detection.	Instance segmentation and object detection for complex image analyses.
Speed	Relatively slow but offers strong performance in accurate segmentation of medical objects but The computation time is significantly increased.	Improved for increased speed compared to Fast R-CNN, suitable for real-time medical applications.The computation time is reduced.	Faster than R-CNN; additional computation for mask segmentation.Training time is significantly extended.
Accuracy	Provides high accuracy in detecting and segmenting complex medical objects.	Provides high accuracy in detecting and segmenting complex medical objects.	High accuracy for detection and instance segmentation, superior to previous models.

TABLE III. Comparative Table of DeepLab Versions.

‘**Version**	**Description**	**Advantages**	**Limitations**
DeepLabv1	Uses atrous convolution to extract features from an image and applies a Conditional Random Field (CRF) to refine object contours.	The use of atrous convolution is effective at capturing contexts at various scales, while Conditional Random Fields (CRF) enhance the accuracy of object contours.	Use of CRF increases computational complexity, making the algorithm slower.
DeepLabv2	Introduces Atrous Spatial Pyramid Pooling (ASPP) which applies atrous convolutions at different sampling rates and fuses them together.	ASPP enhances the segmentation of objects across different scales, proving robust for objects of varying sizes.	Challenges in capturing precise fine object contours.
DeepLabv3	Utilizes atrous separable convolution to better capture object boundaries.	Atrous separable convolution enables precise capture of object contours, leading to improved segmentation accuracy.	Despite improvements, challenges remain in refining object contours.
DeepLabv3+	Extends DeepLabv3 by adding a decoder module to refine segmentation results along object boundaries.	achieves refined delineation of object boundaries and enhances overall segmentation precision through its advanced atrous separable convolution technique.	Model complexity requires significant GPU memory for training on high-resolution images and batch sizes.

medical image segmentation, setting new benchmarks [25]. To augment semantic segmentation, Chen et al. developed TransAttUnet, employing guided attention to notably advance medical image segmentation efforts [56]. Lin and collaborators presented DS-TransUNet, which integrates the Swin Transformer with U-Net, signifying a notable advancement in the domain[55]. The realm of medical imaging has witnessed a paradigm shift with these advanced neural network architectures coming into play. Among these innovations, ViTransUNet emerges as a pioneering innovation that combines the strengths of Vision Transformers (ViT) with the traditional U-Net structure, improving the accuracy and efficiency of image segmentation tasks essential for a wide range of medical purposes. The architecture of ViTransUNet is illustrated in Figure 6.

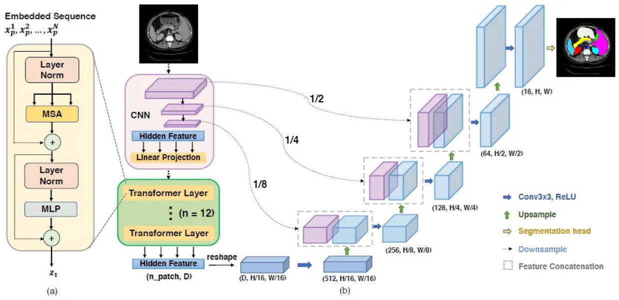

Figure 6. ViTransUNet architecture.

Incorporating transformers into segmentation frameworks like TransUnet and Swin-Unet has led to notable improvements in segmentation accuracy, especially in demanding tasks such as accurately delineating organs and lesions. This progress is not merely a technological leap; it represents a significant stride towards achieving more precise and minimally invasive diagnostics in healthcare.

5. Comparative Study

In this study, we evaluate the effectiveness of advanced deep learning models compared to conventional methods for lung field segmentation from chest X-rays, utilizing the JSRT (Japanese Society of Radiological Technology Database) and MC (Montgomery) dataset[56]. The findings, presented in Table IV and represented as percentages, spotlight the remarkable performance of the TransAttUnet model, which achieves an exceptionally high DICE score of 98.88%. This surpasses previous models, both traditional and AI-based, with a notable 2.71% improvement in DICE score over benchmark models like U-Net (96.17%). This enhancement highlights the benefits of the TransAttUnet's attention-guided encoder-decoder mechanism and multi-scale skip connections. These features allow the model to capture global context and distinct characteristics that distinguish the lung field from adjacent anatomical structures. Furthermore,TransAttUnet consistently surpasses recent approahes such as Attention U-Net (97.59‘%), FCN (95.1%), and ResUNet++ (97.92%), showcasing its exceptional effectiveness in enhancing detailed segmentation quality. Additionally, it also outperforms traditional methods like Thresholding and Edge Detection, thereby setting a new benchmark in the field.

The superiority of deep learning over traditional techniques is attributed to its flexibility and ability to adapt to the specifics of medical images. Conventional methods, limited by unchangeable parameters, struggle to handle the complex variability of medical data. In contrast, deep learning adjusts its models for precise segmentation, efficiently leveraging the diversity of features and anomalies present.

This juxtaposition not only validates the advancements brought about by deep learning in the analysis of medical images but also emphasizes the pivotal role of attention mechanisms in enhancing model sensitivity to relevant features for segmentation. The comparison reveals that while traditional techniques and early neural network models provided a foundational approach for segmentation, the integration of attention mechanisms and advanced neural architectures such as TransAttUnet offers a significant enhancement in segmentation precision. This becomes particularly clear in complex endeavors such as segmenting lung fields from chest X-rays, where accurately outlining the lung edges is vital for correct diagnosis and treatment formulation.

6. Conclusions and Future Work

In our summary and outlook for future research, we draw distinctions between traditional image segmentation methods like thresholding and edge detection. These techniques, while straightforward and requiring minimal training data, face challenges in handling complex images marked by variations in intensity and noise. Conversely, artificial intelligence (AI)-based methods, particularly those employing Convolutional Neural Networks (CNNs) and attention-based networks, exhibit high accuracy. These approaches utilize large datasets to automatically identify relevant features in medical images, proving more adept at handling variations and noise. However, their implementation is complex, requiring significant computational resources and extensive training data, while also being sensitive to data quality and hyperparameter configurations.

Recent advancements, exemplified by models like TransAttUnet, underscore the potential of AI-based approaches in managing complex segmentation tasks and adapting to various medical imaging modalities. The choice between traditional and AI-based methods will depend on the specific needs of the segmentation task, available resources, and the desired performance level.

Future research should prioritize refining data preprocessing methods for medical image segmentation, crucial for addressing noisy data and enhancing the quality and accuracy of image analysis. Additionally, investigating the integration of various CNN architectures with other AI strategies is recommended to develop hybrid models that amalgamate the strengths of different methodologies for more precise and efficient image segmentation.

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TABLE IV. Evaluation of Segmentation Techniques Against Cutting-Edge Benchmarks on the JSRT and Montgomery (MC) Datasets.

Methodology	**Dataset**	**Dice**	**Accuracy**	**Recall**	**Precision**
U-Net[9]	JSRT	96.17	98.21	94.94	97.50
FCNN [57]	JSRT& MC	95.1	97.7	95.1	98.0
Encoder-Decoder Structure [58]	JSRT	96.0	-	95.1	-
Improved Segnet [59]	JSRT	-	98.7	-	-
Edge Detection & Morphology [60]	JSRT	-	82.9	-	-
Thresholding [4]	JSRT	-	89.63	88.75	78.76
Fuzzy C-Means (FCM) [4]	JSRT	-	93.34	85.14	92.02
ResUNet [61]	JSRT	97.12	98.64	96.61	97.70
Attention U-Net [62]	JSRT	97.59	98.81	98.82	96.41
UNet++ [63]	JSRT	97.84	98.93	99.28	96.47
ResUNet++ [61]	JSRT	97.92	98.68	98.48	98.48
Swin-Unet [64]	JSRT	97.67	98.71	95.42	98.36
TransUNet [65]	JSRT& MC	-	98.36	-	-
UCTransNet [66]	JSRT	98.32	99.37	-	-
TransAttUnet [67]	JSRT	**98.88**	**98.41**	**98.88**	**99.04**

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