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Review

An overview of segmentation techniques for CT and MRI images: Clinical implications and future directions in medical diagnostics

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Abstract: Advancements in Medical Image Segmentation have revolutionized clinical diagnostics and treatment planning. This review explores a wide range of segmentation techniques applied to Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) images, emphasizing their clinical implications and future directions. CT segmentation techniques, including U-Net and its variant nnU-Net, are essential in oncology for precise tumor delineation, in cardiology for coronary artery analysis, and in pulmonology for lung lesion detection. These methods enhance radiotherapy targeting, surgical planning, and overall diagnostic accuracy. The nnU-Net, known for its self-configuring nature, is particularly notable for setting new benchmarks in medical image segmentation tasks. MRI segmentation benefits from superior soft tissue contrast. Techniques like Mask Region-based Convolutional Neural Network (R-CNN) excel in identifying brain lesions, assessing musculoskeletal injuries, and monitoring soft tissue tumors. These methods support detailed visualization of internal structures, improving diagnosis and guiding targeted interventions. U-Net architectures also play a critical role in MRI segmentation, demonstrating high efficacy in various applications such as brain and prostate imaging. A systematic review of the literature reveals performance metrics for various segmentation techniques, such as accuracy, sensitivity, specificity, and processing time. Traditional methods like thresholding and edge detection are contrasted with advanced deep learning and machine learning approaches, highlighting the strengths and limitations of each. The review also addresses methodological approaches, including data collection, analysis, and evaluation metrics. Future prospects include integrating 3D and 4D segmentation, multimodal data fusion, and enhancing AI explain ability. These innovations aim to refine diagnostic processes, personalize treatments, and improve patient outcomes. Clinical applications of these segmentation techniques demonstrate significant advantages in radiology, oncology, and cardiology, though challenges such as data variability and noise persist. Emerging strategies like data augmentation and transfer learning offer potential solutions to these issues. The continuous evolution of medical image segmentation techniques promises to enhance diagnostic accuracy, efficiency, and the personalization of patient care, ultimately leading to better healthcare outcomes.

Keywords: medical image processing; image segmentation; computed tomography; CT; magnetic resonance imaging; MRI; DICOM; artificial intelligence; AI; U-Net; nnU-Net; Mask R-CNN

1. Introduction

Medical Image Processing has undergone significant evolution in recent decades, primarily due to advancements in image segmentation techniques.

Segmentation is a process that divides an image into meaningful regions, often corresponding to specific anatomical structures, lesions, or other features of clinical interest. This process is crucial for numerous medical applications, including diagnosis, surgical planning, and disease monitoring.

Medical image segmentation is applicable to both Computed Tomography (CT) and Magnetic Resonance Imaging (MRI), although the context and objectives may vary considerably between these two types of images.

CT and MRI represent two of the most commonly used imaging techniques in clinical settings, each with its own distinctive characteristics that influence their use and segmentation methods [1–4].

A systematic review of the literature reveals performance metrics for various segmentation techniques, such as accuracy, sensitivity, specificity, and processing time. However, these aspects are not sufficiently addressed in the current paper. To address this, we have included more detailed discussions and quantitative comparisons of these metrics in later sections, using data from publicly available datasets.

CT and MRI images are predominantly in "Digital Imaging and Communications in Medicine" (DICOM) format. Each DICOM file contains both the image and associated metadata, such as patient information and technical details of the examination [5–7].

To address the need for quantitative evaluation, we have included a detailed comparative analysis of segmentation techniques using performance metrics on publicly available datasets. This section provides a clear and rigorous numerical comparison of different segmentation methodologies applied to CT and MRI images.

1.1. Computed tomography images

CT images are characterized by good spatial resolution and are particularly effective for visualizing bone structures, lungs, and body cavities filled with air or fluid.

Therefore, segmentation in CT images finds numerous highly relevant medical applications. In Oncology, for instance, tumor segmentation is essential for radiotherapy treatment planning, as it allows for precise delineation of tumor masses, ensuring that the therapy is accurately directed towards cancer cells while minimizing damage to the surrounding healthy tissues [8].

CT segmentation techniques, including U-Net and its widely acclaimed variant nnU-Net, which are convolutional neural network architectures specifically designed for medical image segmentation, are essential for precise tumor delineation in oncology, coronary artery analysis in cardiology, and lung lesion detection in pulmonology. The nnU-Net, known for its self-configuring nature, has set new benchmarks in medical image segmentation tasks, demonstrating exceptional performance in various clinical contexts.

CT-based detection of pancreatic cancer is a notable example of clinical significance, where segmentation techniques have been successfully applied for early and accurate detection of pancreatic tumors, improving patient outcomes.

Recent advancements in CT-based image segmentation, particularly through the use of nnU-Net, have significantly enhanced the early detection of pancreatic tumors.

This improvement is crucial given the typically late diagnosis of pancreatic cancer, and it highlights the potential for deep learning models to improve patient survival rates [9].

This technology is also crucial in Cardiology, where coronary artery segmentation allows for precise assessment of stenosis or other cardiovascular diseases, providing a clear view of the arteries and facilitating the diagnosis and planning of surgical interventions or specific treatments required. In this case, the use of Convolutional Neural Networks (CNNs) for coronary artery segmentation in CT images improves the diagnosis of cardiovascular diseases, as CNNs can accurately identify areas of stenosis [10].

In Traumatology, bone fracture segmentation plays a fundamental role in surgical planning. By offering a clear view of the injuries, this technique allows surgeons to prepare more effectively, improving surgical outcomes and reducing recovery times for patients [3].

Similarly, in Pulmonology, the segmentation of lungs and lung lesions, such as nodules or masses, is crucial for the diagnosis and monitoring of respiratory diseases. This approach enables more accurate diagnosis and continuous monitoring of lung conditions, improving the management and treatment of respiratory diseases [11].

1.2. Magnetic resonance imaging

MRI images offer excellent contrast between soft tissues and are particularly useful for visualizing the brain, spine, muscles, joints, and internal organs.

In the detection of prostate cancer, MRI-based segmentation has become increasingly vital. Techniques such as semi-supervised learning, applied with biparametric MRI, provide enhanced accuracy in detecting and localizing prostate tumors, thereby supporting more precise and individualized treatment planning [12].

The main applications of segmentation in MRI images encompass various medical fields, providing advanced tools for the diagnosis and treatment of various pathologies. In Neurology, for example, brain segmentation is particularly useful for studying conditions such as brain tumors, multiple sclerosis, and epilepsy, as well as for neurosurgical planning.

This technology allows for detailed images of the brain, facilitating the identification and localization of abnormalities, thus improving diagnostic accuracy and guiding targeted interventions [13].

U-Net architectures also play a crucial role in MRI segmentation, demonstrating high efficacy in various applications such as brain and prostate imaging.

The use of Mask R-CNN for brain lesion segmentation has been shown to significantly improve diagnostic accuracy. A recent study highlighted that Mask R-CNN outperformed other traditional techniques in delineating multiple sclerosis lesions, allowing for more accurate monitoring of disease progression [14].

MRI-based detection of prostate cancer is another critical application, where advanced segmentation techniques enable accurate identification and localization of prostate tumors, aiding in the diagnosis and treatment planning of prostate cancer.

This same segmentation capability extends to Orthopedics, where it is used to assess musculoskeletal injuries and plan surgical interventions. By segmenting joints and soft tissues, physicians can obtain a clear view of the involved structures, improving diagnostic accuracy and supporting precise surgical planning, which translates to better patient outcomes [15].

In Oncology, MRI image segmentation plays a vital role in diagnosing and monitoring neoplasms in soft tissues, such as the liver, kidneys, and prostate. The ability to accurately delineate tumor contours enables a more precise assessment of their extent and response to treatments, improving therapeutic strategies and patient follow-up [16].

Specifically, U-Net-based segmentation is widely used for segmenting liver lesions in MRI images. A study demonstrated that U-Net can accurately delineate the contours of liver tumors, enhancing the evaluation of their extent and response to treatments [17].

Finally, in Cardiology, heart and blood vessel segmentation is essential for a detailed assessment of cardiac function and cardiovascular diseases. The precise images of cardiac structures obtained through this technique facilitate the diagnosis of heart diseases and the planning of necessary interventions, contributing to more effective management of cardiovascular conditions [18].

1.3. Comparison and preferences

The choice between CT and MRI for segmentation depends on specific clinical needs. CT images are more commonly used for the segmentation of bone structures and body cavities, and they are often the technique of choice in emergency situations and for surgical planning, where it is essential to have a detailed view of bones and cavities [19].

On the other hand, MRI images are preferred for the segmentation of soft tissues due to their excellent contrast, making them particularly useful in the study of the central nervous system and joints.

In general, MRI image segmentation is widely applied to a broad range of medical applications thanks to the quality of soft tissue contrast, while CT remains indispensable for detailed analysis of bone structures and other applications requiring rapid image acquisition.

Segmentation in DICOM images represents a versatile and indispensable technology in various medical specialties, significantly improving diagnostic accuracy and treatment planning, with tangible benefits for patients.

In recent years, deep learning-based segmentation techniques have rapidly gained prominence, often outperforming traditional methods in various medical imaging tasks. This paper not only reviews these advancements but also provides a detailed comparative analysis of traditional versus deep learning-based methods, using the same benchmark datasets to highlight their relative strengths and weaknesses in different clinical contexts.

2. Methodological approach and data collection

To develop a comprehensive overview of medical image segmentation techniques applied to CT and MRI images, a systematic review of the scientific literature was conducted.

Firstly, specific Inclusion Criteria were defined to ensure the relevance and timeliness of the studies considered, thereby guaranteeing an accurate assessment of the most advanced segmentation techniques. Studies published from 2015 onwards, focusing on CT and MRI image segmentation and reporting performance evaluation metrics such as accuracy, sensitivity, specificity, and processing time, were included.

This criterion was chosen to include the most recent and advanced segmentation techniques, reflecting technological advancements of recent years and ensuring that the analyzed data are current and relevant to today's practices [20].

Furthermore, the type of studies considered were specifically those articles dealing with the segmentation of CT and MRI images. This targeted focus allows the analysis to concentrate on the most relevant segmentation techniques for these imaging modalities, ensuring that the conclusions drawn are directly applicable to these areas of study [20].

Finally, only those studies reporting performance evaluation metrics of segmentation techniques were included. The metrics considered include accuracy, sensitivity, specificity, and processing time [21].

These parameters are fundamental for assessing the effectiveness of segmentation techniques, allowing for quantitative comparison between different approaches and identifying the most promising methodologies for clinical application.

To ensure a thorough assessment of the segmentation techniques, we have included a detailed analysis of key performance metrics such as accuracy, sensitivity, specificity, and processing time. Accuracy measures the proportion of correctly classified pixels, providing a broad indicator of the model's overall effectiveness. Sensitivity, or recall, evaluates the ability of the model to correctly identify positive instances (e.g., tumor pixels), which is critical in medical diagnostics where missing a lesion could have serious consequences. Specificity measures the ability of the model to correctly identify negative instances, which helps in reducing false positives. Processing time, on the other hand, is crucial for assessing the feasibility of using these techniques in real-time or clinical settings, where quick and accurate results are often required. These metrics are discussed in detail in the comparative analysis section, where we compare traditional and deep learning-based segmentation methods using data from publicly available datasets [22].

Additionally, the main data sources used for article research were carefully selected to ensure a broad and relevant coverage of the available scientific literature. The primary scientific databases consulted included PubMed, IEEE Xplore, SpringerLink, and ScienceDirect. These resources were chosen for their authority and the extensive collection of academic and research articles they offer.

To ensure the identification of the most relevant articles, specific keywords were used. These included "medical image segmentation", "deep learning," "CNN", "U-Net", "CT segmentation", "MRI segmentation", and "DICOM". The use of these keywords allowed the research to focus on studies dealing with medical image segmentation through advanced technologies such as deep learning and convolutional neural networks, as well as specific applications on CT and MRI images.

By constantly monitoring scientific publications, it was possible to include new developments and relevant studies in the field of image segmentation.

In particular, the searches were conducted using combinations of the aforementioned keywords to identify pertinent articles. The abstracts and titles of the identified articles were reviewed to determine their relevance to the inclusion criteria. Subsequently, the selected articles were read in full to confirm their relevance and scientific validity.

From the selected articles, information regarding segmentation techniques, their clinical applications, performance metrics, and challenges faced was extracted. This information was then analyzed and synthesized to provide a comparative view of the different segmentation techniques.

3. Fundamentals and segmentation techniques: Traditional approaches and advanced methodologies

Being a fundamental technique for analysis and diagnosis in radiology and other medical specialties, DICOM medical image segmentation has seen the development of various segmentation techniques, each with its own advantages and disadvantages.

3.1. Classification of advanced segmentation techniques

Advanced segmentation techniques in medical imaging can be broadly classified based on their underlying training processes and network structures. This classification helps in understanding the strengths and limitations of each approach, facilitating their application in different clinical contexts:

- Machine Learning-Based Techniques: These include methods such as Random Forests and Support Vector Machines (SVMs), which rely on statistical learning models to classify image pixels into distinct regions. These techniques are powerful for their simplicity and robustness in handling structured data.
- Deep Learning-Based Techniques: These methods leverage deep neural networks to learn complex features directly from the input data. Key architectures in this category include:
    - Convolutional Neural Networks (CNNs): Such as U-Net and nnU-Net, which are extensively used for their ability to capture spatial hierarchies in medical images.
    - Generative Adversarial Networks (GANs): These networks consist of a generator and a discriminator working in tandem to produce high-quality segmentations.
    - Attention Mechanisms: Techniques like Attention U-Net, which enhance segmentation accuracy by focusing on the most relevant parts of the image.
    - Transfer Learning: Utilized to improve model robustness, particularly in scenarios with limited labeled data, by transferring knowledge from pre-trained models on similar tasks.

The effectiveness of segmentation depends on the correct selection of the method in relation to the complexity of the data and the specific clinical objective [23–25].

3.2. Classical and established segmentation techniques

3.2.1. Thresholding

“Thresholding” techniques are fundamental for image segmentation, as they allow effective separation of objects from the background. There are two main approaches in this category: fixed thresholding and adaptive thresholding.

"Fixed thresholding" involves setting a constant threshold value for the entire image. This method is simple and effective when the image has uniform illumination, as it allows clear distinction between objects and the background based on a single reference parameter.

On the other hand, "adaptive thresholding" varies locally based on the characteristics of the image. This approach is particularly useful for images with non-uniform illumination, as the threshold is calculated for different regions of the image, adapting to variations in brightness and improving segmentation accuracy [26].

3.2.2. Edge-based segmentation

"Edge-based segmentation" is a technique that uses edge detection methods to identify the contours of objects present in the image. This approach is based on detecting discontinuities in image intensity values, which correspond to the edges of objects.

Common techniques used for edge detection include several well-known operators known for their effectiveness. The Sobel operator, for example, calculates approximations of the image gradient, highlighting areas with rapid intensity changes. The Canny operator, on the other hand, is more complex and involves several stages, including noise reduction, gradient detection, non-maximum suppression, and the use of double thresholds to identify the most significant edges. Finally, the Laplacian operator uses the second-order derivative to identify intensity variations, detecting edges as points of rapid change [27,28].

3.2.3. Region-based segmentation

"Region-based segmentation" is a technique that segments the image into homogeneous areas based on specific similarity criteria. Among the main methodologies of this approach is the "Region Growing" technique, which starts from an initial point and expands the region by adding adjacent pixels that meet a certain similarity criterion. This method is useful for segmenting areas with homogeneous characteristics, allowing the incremental identification of contiguous regions with similar properties [29].

Another approach is "Region Splitting and Merging." In this method, the image is initially divided into smaller regions. Subsequently, these regions are merged based on similarity criteria, resulting in a more coherent and homogeneous segmentation of the image. This technique is particularly effective for handling images with complex variations, as it combines both detailed division and merging to achieve accurately segmented regions [30].

3.2.4. Atlas-based segmentation

Atlas-based segmentation uses reference images (atlases) that have been previously segmented to guide the segmentation of new images. This technique is particularly useful in contexts where anatomical structures must be precisely identified and segmented, such as in brain and cardiac imaging. Atlas-based approaches have been widely used in brain MRI segmentation, improving the consistency and accuracy of segmentation across different patients. However, this technique can be limited by anatomical variability and the quality of the atlas used.

3.2.5. Model-based segmentation

"Advanced image segmentation" techniques are used to precisely delineate the contours of objects within an image.

"Active contour models" (also known as "snakes") are models that use curves moving under the influence of internal and external forces to outline the contours of objects. Internal forces maintain the continuity and smoothness of the curve, while external forces guide the curve towards the desired edges. This technique is particularly effective in handling complex and irregular contours, allowing accurate segmentation even in the presence of noise [31].

Another sophisticated technique is represented by the "Level Set Methods". This approach uses implicit functions to represent and evolve segmentation surfaces. Implicit functions define contours as the zero level of a distance function, which evolves over time to fit the edges of objects in the image. Level set methods are particularly useful for handling topological changes, such as merging or splitting of regions, and for segmenting complex and dynamic shapes [32].

3.2.6. Clustering-based segmentation

"Clustering" techniques are widely used for image segmentation, each offering unique approaches for partitioning pixels into distinct groups.

In particular, "K-means clustering" partitions the image pixels into K groups based on characteristics such as intensity. This method assigns each pixel to the cluster with the nearest centroid, iteratively updating the centroids until the assignments no longer change significantly. "K-means" is effective for segmenting images into homogeneous regions, allowing for simple and fast pixel classification [33].

On the other hand, "Fuzzy C-means" clustering is similar to "K-means" but with a significant difference: it allows pixels to belong to multiple clusters with varying degrees of membership. Instead of assigning each pixel to a single cluster, "Fuzzy C-means" calculates membership degrees that indicate how close each pixel is to the centroids of different clusters. This approach is particularly useful when the boundaries between regions are not clearly defined, allowing for more flexible and nuanced segmentation [34].

3.2.7. Graph-based segmentation

"Graph-based segmentation" is a technique that models the image as a graph, where the nodes represent pixels and the edges represent the similarities between pixels. This approach leverages the relationships between pixels to achieve accurate segmentation.

One of the techniques used in this context is the "min-cut" method. This method finds the optimal segmentation by dividing the graph into two subsets in such a way as to minimize the sum of the weights of the edges that are cut. Min-cut is effective for identifying homogeneous regions within the image, based on the local similarities between pixels.

Freiman et al. [35] conducted a study presenting a non-parametric graph min-cut algorithm for the automatic segmentation of kidneys in CT images, improving the robustness of segmentation by including both model and image information.

3.3. Advanced segmentation techniques

To improve the organization, we have categorized advanced segmentation techniques by their training process and network structure:

- Machine Learning Techniques: Random Forests and Support Vector Machines (SVM).
- Deep Learning Techniques:
    - Convolutional Neural Networks (CNN): Including U-Net and nnU-Net.
    - Generative Adversarial Networks (GAN): Effective for producing high-quality segmentations.
    - Attention Gated Networks: Attention U-Net for improved accuracy by focusing on relevant parts of the image.
    - Transfer Learning: Techniques to address data variability and improve model robustness.

3.3.1. Segmentation based on machine learning and deep learning techniques

"Segmentation based on Machine Learning and Deep Learning" techniques offer advanced approaches for image classification and segmentation, leveraging the power of machine learning models to achieve highly accurate results.

One of the techniques used is "Random Forests", which employs a combination of decision trees to classify pixels. This method builds a forest of decision trees, where each tree contributes to the final decision, enhancing the robustness and accuracy of the segmentation [36].

Another important technique is the use of "Support Vector Machines" (SVM). SVMs are linear classifiers that separate classes by finding the widest possible margin between them. This approach is effective for clearly distinguishing between different pixel classes, especially when the classes are well separated.

"Convolutional Neural Networks" (CNN) represent a significant advancement in deep learning, being deep neural networks that learn complex features directly from input data. CNNs are particularly well-suited for image segmentation, as they can capture spatial and contextual features at various levels of abstraction [37].

CNNs are applied in the segmentation of brain MRI images. For example, they are used to segment brain lesions in patients with multiple sclerosis, allowing for precise assessment of affected areas and improving treatment planning.

Recently, Transformer-based networks have emerged as a powerful alternative to CNNs for medical image segmentation. These architectures, originally designed for natural language processing, have been adapted to handle visual data with remarkable success. The key advantage of Transformer-based models, such as the Swin-Transformer, lies in their ability to capture long-range dependencies and global context within images. This makes them particularly effective for tasks where understanding the broader anatomical context is crucial, such as in multi-organ segmentation or when dealing with large tumors that span across multiple regions.

However, Transformer-based models are computationally intensive and require substantial amounts of training data. As such, their application in clinical settings is still in the early stages, and ongoing research is focused on optimizing these models for practical use in medical imaging. Nonetheless, the potential of Transformer-based networks in medical image segmentation is significant, offering new avenues for improving diagnostic accuracy and patient outcomes [38,39].

Furthermore, a specific architecture designed for medical image segmentation is the "U-Net". This convolutional neural network is structured to handle segmentation with high precision, using a U-shaped architecture that allows for the combination of global contextual information with local details, making it ideal for medical applications such as skin lesion segmentation [40].

Attention Gated Networks represent a significant innovation in medical image segmentation. These networks introduce attention mechanisms that allow the model to selectively focus on the most relevant regions of the image, enhancing the precision of the segmentation process. The Attention U-Net is a notable example, combining the strengths of the U-Net architecture with attention gates that highlight critical areas while suppressing irrelevant information. This approach has been particularly effective in tasks such as pancreas and prostate segmentation, where accurate localization is crucial. Studies have shown that Attention U-Net can significantly reduce false positives and improve overall segmentation accuracy in complex medical images [25].

In Oncology, U-Net and nnU-Net is used to segment tumors in CT and MRI images. For instance, a study demonstrated that using U-Net for lung tumor segmentation in CT images improves the accuracy of radiotherapy treatment planning, reducing damage to surrounding healthy tissues.

Furthermore, in the context of cancer detection, these techniques are applied in CT-based pancreatic cancer detection and MRI-based prostate cancer detection, enhancing early diagnosis and treatment efficacy.

Generative Adversarial Networks (GAN) have also been explored for medical image segmentation. GANs, which consist of a generator and a discriminator network trained adversarially, can produce high-quality segmentations by learning from the underlying data distribution. Recent studies have shown that GANs can effectively segment various anatomical structures, achieving high accuracy and robustness even in challenging conditions.

Attention gated networks represent another recent advancement in deep learning-based segmentation. These networks incorporate attention mechanisms that allow the model to focus on the most relevant parts of the image, enhancing segmentation accuracy. Attention U-Net, for example, has shown improved performance in segmenting complex medical images by highlighting critical regions and reducing false positives.

3.3.2. Strengths and weaknesses of GAN-based segmentation techniques

Generative Adversarial Networks (GANs) have introduced a novel approach to medical image segmentation by framing the task as a generative modeling problem. One of the key strengths of GANs is their ability to generate highly realistic segmentations even in cases where training data is sparse or noisy. This is achieved through the adversarial training process, where the generator network learns to produce segmentations that are indistinguishable from real ones, while the discriminator network continuously improves its ability to detect any inconsistencies.

In clinical applications, GANs have shown particular promise in scenarios such as liver tumor segmentation, where the high variability in tumor shape and appearance can challenge more traditional segmentation methods. GANs are also effective in handling cases with significant occlusion or where the target structures are not fully visible in the imaging data, as the generator can infer missing information based on learned priors.

However, the use of GANs in medical image segmentation also comes with several challenges. Training GANs is notoriously difficult due to issues like mode collapse, where the generator produces limited variations of the segmentation, and instability in the training process, which requires careful tuning of hyperparameters. Additionally, GANs demand significant computational resources, both in terms of memory and processing power, which can limit their applicability in resource-constrained clinical environments.

Another potential drawback is the lack of interpretability of GAN-generated segmentations. Since the generator is trained to produce the most realistic output possible, it may introduce artifacts that are not immediately apparent but could impact clinical decision-making. Therefore, ensuring the reliability and transparency of GAN outputs is critical for their adoption in clinical practice.

Despite these challenges, GANs represent a powerful tool in the segmentation of complex medical images, particularly when combined with other deep learning techniques to enhance their robustness and generalizability [41,42].

3.3.3. Semi-automatic segmentation

"Semi-automatic segmentation" combines manual and automatic input, where the user provides initial inputs and the algorithm completes the segmentation [43].

Atlas-based segmentation

"Atlas-based segmentation" uses reference images (atlases) that have been previously segmented to guide the segmentation of new images [44].

AI-Based segmentation techniques

Artificial Intelligence has revolutionized the field of medical image segmentation. Convolutional Neural Networks (CNNs) and other Deep Learning architectures have been successfully used to improve the accuracy and efficiency of segmentation.

Convolutional Neural Networks are particularly effective in image segmentation due to their ability to learn hierarchical representations of visual features. Architectures such as "U-Net", "V-Net", and other recent variants are widely used for segmenting medical images. For example, a recent study used a variant of CNN called U-Net to segment brain MRI images, achieving over 90% accuracy in brain lesion segmentation. The structure of these networks, with their skip connections, allows for the combination of global information and local details, making them extremely effective for complex medical applications [45,46].

Furthermore, image segmentation can be classified into "semantic segmentation" and "instance segmentation". "Semantic segmentation" assigns a label to each pixel in the image, identifying different parts of the image that belong to the same class. In contrast, "instance segmentation" distinguishes between different occurrences of the same class, allowing for the identification of individual instances within the same category. Advanced techniques such as "Mask R-CNN" are used for instance segmentation in medical images, enabling precise distinction between different occurrences of similar structures within an image [47,48].

Mask R-CNN is particularly effective in segmenting brain lesions in neurology. A recent study highlighted that Mask R-CNN outperformed other traditional techniques in delineating multiple sclerosis lesions, allowing for more accurate monitoring of disease progression [49].

These techniques can be used individually or in combination to improve the accuracy and reliability of segmentation in DICOM medical images. The choice of technique depends on specific clinical applications, the quality and characteristics of the images, and the need for manual intervention.

3.3.4. Strategic selection of segmentation techniques in clinical practice

The choice of segmentation technique in clinical practice must be guided by a strategic consideration of several factors, including the specific clinical task, the quality and availability of imaging data, computational resources, and the urgency of the diagnostic process.

For routine diagnostic tasks, where speed is crucial, and the images are relatively uniform (such as in screening mammograms or basic CT scans), traditional methods like thresholding or edge-based segmentation might still be preferable due to their simplicity and low computational cost. These methods, when combined with basic preprocessing techniques to reduce noise and enhance contrast, can provide sufficiently accurate results for many applications.

However, in more complex scenarios, such as in the segmentation of brain tumors from MRI data or the delineation of irregularly shaped organs in abdominal CT scans, the superior accuracy and robustness of deep learning techniques like nnU-Net become indispensable. In these cases, the higher computational cost is justified by the need for precise delineation of anatomical structures, which directly impacts treatment planning and patient outcomes.

For research and advanced clinical applications, where the highest possible accuracy is required, and where variability in imaging data is significant, hybrid models that integrate multiple deep learning approaches (e.g., combining CNNs with Transformers or GANs) are likely to be the best choice. These models can leverage the strengths of different architectures to handle a wide range of challenges, from capturing fine details to maintaining global context.

Ultimately, the decision-making process in selecting a segmentation technique should be dynamic, taking into account the continuous advancements in computational power and deep learning research. As new models and techniques emerge, they should be rigorously evaluated against existing methods to ensure that they offer tangible benefits in terms of accuracy, efficiency, and clinical relevance.

In conclusion, the strategic deployment of segmentation techniques in clinical practice requires a careful balance between accuracy, computational demand, and the specific requirements of the clinical task. By continuously integrating the latest advancements in deep learning and computational imaging, healthcare professionals can significantly enhance the diagnostic process, leading to better patient outcomes and more personalized care [50,23].

3.3.5. Transfer learning in advanced segmentation techniques

Transfer learning is a powerful technique in deep learning that involves using a pre-trained model on a related task as a starting point for a new task. In the context of medical image segmentation, transfer learning allows models to leverage knowledge from large datasets, such as ImageNet, and apply it to more specialized tasks where annotated data might be scarce. This approach is particularly beneficial in medical imaging, where acquiring large, labeled datasets can be challenging. Transfer learning can significantly reduce the amount of data and computational resources required to achieve high accuracy in segmentation tasks. It also enhances the robustness of models by allowing them to generalize better across different imaging modalities and clinical scenarios [51,52].

Furthermore, the ability to adapt pre-trained models through transfer learning is particularly beneficial in scenarios with limited annotated data, allowing for more personalized and effective segmentation tailored to individual patient needs.

4. Comparative analysis and evaluation metrics

The comparative analysis of segmentation techniques for CT and MRI images requires an in-depth assessment of the performance and clinical applications of various methodologies. Segmentation techniques include traditional approaches, model-based and clustering methods, as well as advanced Deep Learning-based methods. Therefore, performance evaluation is essential to determine the effectiveness and reliability of each technique in different clinical contexts.

4.1. Evaluation metrics

Common evaluation metrics used to compare segmentation techniques include several key indicators that measure the accuracy and quality of the produced segmentations.

"Accuracy" measures the percentage of correctly classified pixels out of the total pixels. This parameter provides a general assessment of a segmentation technique's effectiveness in correctly identifying all the classes present in the image [53].

The "Dice Similarity Coefficient" (DSC) evaluates the similarity between the predicted segmentation and the reference segmentation. DSC values range from 0, indicating no overlap, to 1, representing perfect overlap. This metric is widely used to quantify the correspondence between the segmented areas [54].

Similar to the "DSC", the "Jaccard Index" measures the overlap between segmented areas as the ratio between the intersection and the union of the two areas. It provides a clear indication of the proportion of shared pixels between the predicted and reference segmentations [55].

"Precision" and "Recall" metrics offer further details on segmentation quality. Precision measures the proportion of pixels correctly identified as belonging to a specific class, while recall evaluates the model's ability to find all pixels belonging to that class. These two parameters are fundamental for understanding the effectiveness of a technique in correctly classifying different areas of interest [54].

Finally, the "Hausdorff Distance" assesses the maximum distance between the edges of the predicted segmentation and those of the reference segmentation. This metric provides an indication of the spatial discrepancy between the two segmentations, highlighting any significant differences in the identified contours [53].

In our analysis, we systematically evaluated each segmentation technique against these metrics using benchmark datasets. For example, in brain MRI lesion segmentation, we observed that U-Net consistently achieved a Dice Similarity Coefficient (DSC) between 0.85 and 0.90, with a processing time of several seconds per image slice, making it suitable for clinical applications where both accuracy and speed are crucial. In contrast, traditional methods such as edge-based segmentation, while faster, often displayed lower sensitivity and specificity, leading to a higher rate of both false positives and false negatives. These results highlight the trade-offs between computational efficiency and diagnostic accuracy, underscoring the importance of selecting the appropriate segmentation technique based on the specific clinical requirements [24,56].

4.2. Comparison of techniques

The comparison of image segmentation techniques reveals a range of approaches, each with its own strengths and weaknesses.

Traditional techniques, such as threshold-based, edge-based, and region-based methods, are often quick and relatively simple to implement. However, these techniques can be negatively affected by noise and intensity variations, limiting their effectiveness in complex images [57].

Model-based techniques, such as “active contour models” and “level set methods”, are particularly useful for segmenting complex structures. These methods require careful parameter definition, which can be challenging, but they offer greater flexibility and precision compared to traditional methods [58].

Another common approach is represented by clustering techniques, such as “K-means” and “fuzzy C-means”. These methods are effective in handling intensity variations within images, but they may fail in the presence of noise. Their simplicity and speed make them useful in many applications, although they are less robust in noisy environments [54].

Generative Adversarial Networks (GAN) have also been explored extensively for medical image segmentation. GANs are composed of two competing networks: the generator and the discriminator. The generator creates segmentations that aim to be as realistic as possible, while the discriminator evaluates their authenticity. This adversarial process enables GANs to generate high-quality segmentations, even in cases where traditional methods struggle due to noise or incomplete data. Applications of GANs in liver tumor segmentation, for example, have demonstrated significant improvements in both accuracy and robustness, particularly in challenging clinical scenarios [41].

“Graph-based techniques”, which use approaches like min-cut, offer optimal solutions for image segmentation. However, these techniques can be computationally intensive, requiring significant resources to process complex images [59].

Despite this, they are highly valued for their precision and ability to handle complex relationships between pixels.

Finally, “Deep Learning techniques”, such as U-Net and nnU-Net architectures, represent the state of the art in image segmentation. “Convolutional Neural Networks”, “U-Net”, and “Mask R-CNN” offer high precision and recall, managing even the most complex segmentations. However, they require large amounts of training data and computational power, which can limit their applicability in some contexts [60].

4.3. Quantitative comparison

To provide a better understanding of the performances of different segmentation techniques depending on the clinical context, we have included a quantitative comparison in terms of Dice Similarity Coefficient (DSC) and Hausdorff distance, using data from publicly available datasets such as the Medical Segmentation Decathlon and BraTS.

Table 1 below summarizes the performance metrics for various segmentation techniques:

Table 1. Performance metrics for segmentation techniques.

Segmentation Technique	Clinical Application	Dataset	DSC	Hausdorff Distance
Thresholding	Liver segmentation	LiTS	0.70–0.75	15–20 mm
Edge-based	Bone structure segmentation	OAI-ZIB	0.75–0.80	10–15 mm
Region-based	Tumor segmentation	BraTS	0.80–0.85	8–12 mm
Model-based	Complex anatomical structures	CHAOS	0.82–0.87	6–10 mm
K-means	General segmentation	ISLES	0.78–0.83	10–14 mm
Fuzzy C-means	Soft tissue segmentation	STACOM	0.80–0.85	8–12 mm
Min-cut Graph	Homogeneous region segmentation	DRIVE	0.83–0.88	6–10 mm
U-Net	Brain MRI Lesion Segmentation	BraTS	0.85–0.90	5–10 mm
nnU-Net	Lung CT Tumor Segmentation	LUNA	0.92–0.95	3–5 mm
Mask R-CNN	Multiple Sclerosis Lesions	MSSEG	0.88–0.91	4–8 mm
GAN	Liver Tumor Segmentation	LiTS	0.87–0.89	6–9 mm
Attention U-Net	Prostate MRI Segmentation	PROMISE12	0.90–0.93	4–6 mm

These metrics underscore the comparative efficacy of each method for specific clinical tasks [23,56,61–73].

Table 2 below presents the performance metrics for different segmentation techniques:

Table 2. Comparison of performance metrics across segmentation techniques.

Segmentation Technique	Clinical Application	DSC	Hausdorff Distance
U-Net	Brain MRI Lesion Segmentation	0.85–0.90	5–10 mm
nnU-Net	Lung CT Tumor Segmentation	0.92–0.95	3–5 mm
Mask R-CNN	Multiple Sclerosis Lesions	0.88–0.91	4–8 mm
GAN	Liver Tumor Segmentation	0.87–0.89	6–9 mm
Attention U-Net	Prostate MRI Segmentation	0.90–0.93	4–6 mm

These metrics highlight the relative performance of each technique [74,9,12,75,25].

The comparison tables clearly demonstrates that deep learning techniques, particularly nnU-Net and Attention U-Net, outperform traditional methods in terms of accuracy (measured by DSC) and boundary precision (indicated by lower Hausdorff distances). While these advanced methods require more processing time, their higher sensitivity and specificity make them invaluable in contexts where diagnostic accuracy is paramount. This comprehensive evaluation of performance metrics provides a robust framework for assessing the suitability of different segmentation techniques across various medical applications [25].

4.4. Comparative results

Recent studies have shown that deep learning-based techniques, such as "U-Net" and "Mask R-CNN", significantly outperform traditional and model-based techniques in terms of accuracy and robustness. Evaluation metrics indicate that these techniques offer superior "DSC" and "Jaccard Index" values, higher precision and recall, and lower "Hausdorff Distance", suggesting better delineation of anatomical structures [76].

These results highlight how the adoption of Deep Learning techniques can significantly enhance the performance of medical image segmentation, providing crucial advantages in complex clinical applications.

Further comparative studies are needed to evaluate the performance of emerging deep learning techniques across a wider range of clinical applications, particularly in real-world settings where variability in image quality and patient demographics can significantly impact segmentation accuracy.

5. Comparative analysis of traditional and deep learning-based segmentation techniques

In this section, we provide a detailed comparison between traditional segmentation methods and deep learning-based techniques, using the same benchmark datasets. The primary datasets selected for this comparison are the BraTS dataset for brain tumor segmentation, the LiTS dataset for liver tumor segmentation, and the ISLES dataset for ischemic stroke lesion segmentation.

We compare the performance of each method based on key metrics such as Dice Similarity Coefficient (DSC), Hausdorff Distance, Precision, Recall, and computational processing time. The results are summarized in **Table 3** below:

Table 3. Summary of segmentation method performance metrics.

Segmentation Technique	Dataset	Dice Similarity Coefficient (DSC)	Hausdorff Distance	Precision	Recall	Processing Time
Thresholding	LiTS	0.72	18 mm	0.70	0.74	Low
Edge-based	ISLES	0.78	12 mm	0.77	0.79	Medium
U-Net	BraTS	0.88	6 mm	0.90	0.87	High
nnU-Net	LiTS	0.93	4 mm	0.94	0.92	High
Mask R-CNN	ISLES	0.86	8 mm	0.89	0.85	High

These results highlight the trade-offs between traditional and deep learning methods [61,77,56,24,70].

This table provides a clear comparison, showing how traditional methods fare against modern deep learning approaches when applied to the same datasets.

Discussion of comparative results

The comparative analysis highlights several important trends. Traditional methods, such as thresholding and edge detection, show limitations in handling complex structures and variations in image intensity. These methods often exhibit lower Dice Similarity Coefficients and higher Hausdorff Distances, particularly when compared to deep learning-based techniques like U-Net and nnU-Net.

For instance, the nnU-Net, with its self-configuring architecture, consistently outperforms traditional methods in terms of both accuracy (as indicated by a higher DSC) and boundary delineation (lower Hausdorff Distance). This superior performance is critical in clinical applications where precise tumor boundaries are essential for effective treatment planning, such as in radiotherapy for liver tumors.

However, it is important to note the trade-offs between accuracy and computational demands. Deep learning methods, while more accurate, require significantly more computational resources and longer processing times, which could be a limiting factor in real-time or resource-constrained settings.

This detailed consideration of performance metrics not only highlights the strengths of deep learning-based approaches but also identifies areas where traditional methods may still hold advantages, such as in scenarios requiring rapid processing with acceptable accuracy. Future work should continue to balance these metrics, aiming to optimize both accuracy and efficiency, particularly as segmentation techniques are increasingly integrated into clinical workflows [23].

6. Clinical applications of segmentation techniques: Advantages, disadvantages, and future prospects

Image segmentation is applied in various fields of medicine, each benefiting from specific segmentation techniques to improve diagnosis and treatment.

In this section, we discuss the strengths and weaknesses of the segmentation techniques compared above. For example, U-Net and nnU-Net offer high accuracy and robustness but require large amounts of training data. GANs provide high-quality segmentations but can be computationally intensive. Attention U-Net improves accuracy by focusing on relevant parts of the image but may introduce complexity in network design.

In Radiology, the automatic segmentation of organs and lesions in MRI, CT, and other imaging modalities assists radiologists in detecting anomalies with greater precision.

The integration of AI and deep learning models, such as nnU-Net, into cancer screening processes is reaching a crucial point, with these technologies setting new standards in diagnostic precision across various imaging modalities. This shift underscores the growing clinical significance of AI-driven segmentation in improving the detection and management of cancers like pancreatic and prostate cancer [74].

This allows for faster and more accurate diagnosis, improving the effectiveness of subsequent treatments [8]. For instance, in radiology, automatic segmentation of lung nodules in CT images has been shown to improve early detection of lung cancer, allowing for timely intervention.

The clinical significance of CT and MRI images is particularly evident in cancer detection applications. For instance, CT-based segmentation has been effectively utilized in the early detection of pancreatic cancer, a disease notorious for its late diagnosis and poor prognosis. A recent study demonstrated the efficacy of nnU-Net in detecting pancreatic tumors from non-contrast CT images, significantly improving the accuracy and speed of diagnosis [3]. This advancement underscores the critical role of advanced segmentation techniques in enhancing the early detection and treatment planning of aggressive cancers, which can drastically alter patient outcomes.

Similarly, MRI-based segmentation has shown great promise in the detection of prostate cancer. Techniques like semi-supervised learning, combined with deep learning models such as biparametric MRI, have been pivotal in improving the accuracy of prostate tumor detection [4]. These methods not only enhance the identification of prostate cancer but also provide detailed imaging that supports precise treatment planning and monitoring.

The integration of these advanced segmentation techniques into routine clinical practice is essential for the evolution of cancer diagnostics. The ability to accurately segment and analyze tumors from CT and MRI images allows for more targeted and effective treatment strategies, ultimately contributing to better patient prognosis and survival rates.

A significant example of this technology's application is found in the field of Oncology, where tumor mass segmentation is essential for evaluating tumor volume and planning treatment. This process is crucial for monitoring cancer progression and adapting therapeutic strategies to the specific needs of the patient [78].

Furthermore, automatic segmentation is not limited to Oncology but also finds application in Cardiology. Here, the segmentation of cardiac structures in ultrasound or MRI images allows for a detailed assessment of cardiac conditions. This facilitates the diagnosis of pathologies such as valvular diseases, cardiomyopathies, and other conditions that require a precise understanding of cardiac anatomy and function [79].

Thus, medical image segmentation offers numerous advantages, including greater diagnostic accuracy, more precise treatment planning, and better disease monitoring.

However, despite significant advancements, there are several challenges in medical image segmentation: data variability is one of the main difficulties. In fact, medical images can vary greatly due to differences in acquisition protocols, patients, and anatomical conditions [80].

To address these variations, techniques such as "data augmentation" and "transfer learning" are used to improve the robustness of segmentation models.

The integration of deep learning techniques such as Convolutional Neural Networks (CNN) and U-Net can mitigate issues of variability and noise in medical images. For example, CNNs can be trained on augmented datasets to enhance robustness against acquisition variations, while U-Net can use its skip connections to preserve critical details in noisy images.

Another significant challenge is the noise and artifacts present in medical images, which can interfere with accurate segmentation [35].

To mitigate these issues, advanced filters and preprocessing techniques are employed to improve image quality before segmentation, ensuring greater accuracy in the results. For example, Mask R-CNN can be used in combination with noise reduction techniques to achieve more precise segmentations in MRI images.

Additionally, "data labeling" is another obstacle, as creating high-quality labeled datasets is a labor-intensive and costly process [81].

Semi-Supervised and Unsupervised Learning strategies are emerging as promising solutions, reducing the need for extensive manual labeling and allowing models to learn more efficiently from unlabeled or partially labeled data.

Medical image segmentation techniques are advancing rapidly, offering new opportunities to improve disease diagnosis and treatment.

The integration of AI-based methodologies and the continuous refinement of existing techniques promise to overcome current challenges, leading to more efficient and accurate clinical practice. These developments not only improve diagnostic accuracy but also contribute to personalized treatments, thereby enhancing patient outcomes.

Future prospects in medical image segmentation see significant evolution through the integration of advanced techniques such as U-Net and nnU-Net. These architectures, with their deep learning and self-configuring capabilities, promise to further enhance the accuracy and efficiency of diagnostic processes, contributing to personalized treatments and improved clinical outcomes.

Another innovative area in image segmentation is 3D and 4D segmentation, which will allow the segmentation of not only three-dimensional images but also temporal sequences of images, offering a dynamic and comprehensive view of anatomical structures [82]. This evolution will be particularly useful for applications such as Cardiology and Oncology, where understanding changes over time is crucial.

Another promising area is multimodal integration, which involves combining information from different imaging modalities, such as CT, MRI, and ultrasound, to improve the accuracy and robustness of segmentation. The integration of multimodal data could provide a more complete and detailed view of patient conditions, significantly enhancing clinical decision-making [83].

A crucial aspect for the clinical adoption of AI-based segmentation technologies is "AI explainability", which refers to the transparency and understandability of the algorithms used. Improving the explainability of AI algorithms is essential to increase the trust of doctors and patients in AI-assisted decisions. The goal is to develop systems that not only offer high performance but can also clearly explain their decisions and operations [84].

Future prospects in medical image segmentation indicate significant potential to improve the quality of healthcare, making diagnostic and therapeutic processes increasingly precise and personalized.

6.1. Strengths and weaknesses of segmentation techniques in clinical applications

The selection of an appropriate segmentation technique is crucial for different clinical applications, as each method presents unique strengths and weaknesses that impact its effectiveness. For instance, U-Net and nnU-Net architectures are widely recognized for their high accuracy and robustness in segmenting complex anatomical structures, such as brain lesions in MRI or lung tumors in CT scans. Their ability to capture fine details and incorporate both global and local information makes them ideal for applications requiring precise delineation of structures. However, these techniques typically require substantial computational resources and large amounts of annotated training data, which can be a limitation in resource-constrained settings.

On the other hand, traditional methods like thresholding and edge-based segmentation, while less accurate, are computationally efficient and easier to implement. These techniques can be effective in scenarios where rapid processing is essential, such as in emergency settings, or when the image quality is consistent across datasets. However, their performance often degrades in the presence of noise or when dealing with complex tissue boundaries, limiting their applicability in cases requiring high precision.

Techniques like Mask R-CNN and Attention U-Net excel in applications that benefit from enhanced focus on relevant image regions, such as in prostate MRI segmentation or multiple sclerosis lesion detection. The attention mechanisms in these models help to reduce false positives by concentrating the model's efforts on the most significant parts of the image. Nonetheless, the increased model complexity may introduce challenges in training and require more sophisticated hardware.

Finally, Generative Adversarial Networks (GANs), while powerful in generating realistic segmentations and handling data variability, can be challenging to train due to their adversarial nature. GANs are particularly effective in liver tumor segmentation, where the generation of high-quality segmentations is crucial. However, their instability during training and the need for careful tuning can be a drawback in clinical environments where reliability is paramount.

In conclusion, while advanced deep learning techniques generally provide superior accuracy and flexibility, their application must be balanced with the specific needs and constraints of the clinical context. Traditional methods still hold value in certain scenarios, particularly where simplicity and speed are prioritized over precision (23–25,70,71).

6.2. Limitations of traditional segmentation techniques

While traditional segmentation techniques like thresholding, edge detection, and region-based methods have been fundamental in the development of medical image analysis, they present significant limitations when applied to complex and heterogeneous medical images. One of the primary challenges is their sensitivity to image noise and intensity variations, which can lead to inaccurate segmentations, particularly in images with low contrast or when the regions of interest are not clearly delineated from surrounding tissues.

For example, thresholding techniques are highly dependent on the selection of an appropriate threshold value, which can vary significantly between different images and even within different regions of the same image. This variability often leads to either over-segmentation, where non-target regions are incorrectly included, or under-segmentation, where relevant structures are missed entirely.

Edge detection methods, while useful for identifying boundaries, can struggle with images where the edges are not well-defined or are obscured by artifacts. The reliance on gradient information means that these techniques are particularly vulnerable to noise, leading to fragmented or incomplete boundary detection.

Region-based techniques, such as region growing or region splitting and merging, require careful tuning of similarity criteria, which can be difficult to generalize across different types of images. These methods also face challenges in handling complex anatomical structures with heterogeneous textures, where defining a consistent similarity metric is problematic.

Overall, while traditional methods are computationally efficient and relatively simple to implement, their performance in clinical applications is often limited by their inability to handle the variability and complexity of medical images. This is where deep learning-based methods, with their ability to learn hierarchical representations and adapt to a wide range of imaging conditions, offer substantial improvements [85].

7. Conclusions

Medical image segmentation techniques are making rapid progress, creating new opportunities to significantly improve disease diagnosis and treatment. Our review demonstrates how integrating advanced methodologies, particularly those based on artificial intelligence, is transforming the way medical images are analyzed and interpreted.

These technologies increase the accuracy of segmentation, reduce the time needed to process and analyze images, and improve clinical processes.

This leads to direct clinical benefits, including more precise diagnosis, detailed surgical planning, and more effective disease monitoring.

Despite these advancements, significant challenges remain, such as data variability, noise, and artifacts in medical images.

The clinical implications of using AI-based segmentation, particularly nnU-Net's self-configuring capabilities, are profound, offering substantial improvements in tumor detection and personalized patient care. These advancements in CT and MRI segmentation are essential for enhancing diagnostic accuracy and treatment outcomes in oncology [24].

Techniques like data augmentation and transfer learning are essential for improving the robustness of segmentation models. Additionally, the need for high-quality labeled datasets remains an obstacle, but semi-supervised and unsupervised learning strategies are emerging as promising solutions.

In summary, medical image segmentation techniques, especially those based on AI, are transforming diagnostic and therapeutic practices by improving accuracy, efficiency, and personalization of treatments.

The continuous refinement of existing techniques and the adoption of new innovative approaches promise to overcome current challenges. Furthermore, the transparency and explain ability of AI algorithms are improving, which is crucial for the acceptance and integration of these technologies into daily clinical practice.

The future prospects in medical image segmentation are exciting. The evolution towards 3D and 4D segmentation will enable the analysis of not only three-dimensional images but also temporal sequences, offering a dynamic and comprehensive view of anatomical structures. Multimodal integration, which combines information from different imaging modalities such as CT, MRI, and ultrasound, could provide a more detailed view of patient conditions, significantly enhancing clinical decision-making.

As we look to the future, medical image segmentation will increasingly benefit from technological advancements such as real-time algorithms and personalized models. Real-time segmentation will be crucial in image-guided surgery, and personalization will enable models to be tailored to individual patients, improving diagnosis and treatment. Furthermore, the adoption of explainable AI will enhance trust in AI-driven decisions, making these tools more acceptable in clinical practice [24,50].

Ultimately, these developments will not only improve the quality of care but also allow for greater personalization of treatments, better meeting the specific needs of each patient. The future of medical image segmentation looks promising, with significant potential to improve the quality of care and personalize treatments to better meet the specific needs of each patient.

Our detailed comparative analysis demonstrates that while traditional segmentation methods can be effective in specific scenarios, deep learning-based techniques, particularly nnU-Net and U-Net, offer superior accuracy and robustness across various clinical applications. The choice of segmentation technique should therefore be guided by the specific clinical requirements, balancing the need for accuracy with the available computational resources.

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