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An Overview of Medical Image Segmentation Methods

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Abstract

Medical image segmentation plays a crucial role in the realm of medical imaging. The process involves the division of an image to obtain a comprehensive view and ensure precise diagnostics. There are various methods that are employed, ranging from traditional approaches to the more advanced deep learning techniques. Both play a significant role in enhancing healthcare. With the continuous advancement in technology, there is a growing need for accurate segmentation. While traditional methods such as thresholding and region growing are effective, they may require human intervention for complex cases. Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have significantly improved the process by learning intricate details and accurately segmenting the image. When these methods are combined, healthcare professionals can achieve high-quality, precise results. Furthermore, with the advancements in hardware and technology, real-time segmentation is now possible. Generally, the process of dividing medical images into segments is extremely important for the progress of healthcare with the help of artificial intelligence and the most recent advancements in the industry, such as explainable AI and multimodal learning. However, this meticulously detailed and in-depth review provides an all-encompassing and extensive analysis of the current methods utilized, their multitude of applications across various fields, and the promising emerging advancements that have the potential to pave the way for remarkable future improvements and innovations.

Keywords: Thresholding Based Technique, Region-Based Segmentation, Edge-Based Segmentation, Machine Learning-Based Methods

نظرة عامة على أساليب تجزئة الصور الطبية

الخلاصة:

تلعب عملية تقسيم الصور الطبية دورًا حاسمًا في مجال التصوير الطبي. تتضمن العملية تقسيم الصورة للحصول على رؤية شاملة وضمان التشخيص الدقيق. هناك طرق مختلفة يتم استخدامها، تتراوح من الأساليب التقليدية إلى تقنيات التعلم العميق الأكثر تقدمًا. يلعب كلاهما دورًا مهمًا في تحسين الرعاية الصحية. مع التقدم المستمر في التكنولوجيا، هناك حاجة متزايدة للتجزئة الدقيقة. في حين أن الطرق التقليدية مثل تحديد العتبة وتنمية المنطقة فعالة، إلا أنها قد تتطلب تدخلًا بشريًا للحالات المعقدة. لقد حسنت تقنيات التعلم العميق، وخاصة الشبكات العصبية التلافيفية (CNNs)، العملية بشكل كبير من خلال تعلم التفاصيل المعقدة وتقسيم الصورة بدقة. عندما يتم الجمع بين هذه الأساليب، يمكن لمهنيي الرعاية الصحية تحقيق نتائج عالية الجودة ودقيقة. علاوة على ذلك، ومع التقدم في الأجهزة والتكنولوجيا، أصبح التجزئة في الوقت الحقيقي ممكنًا الآن. بشكل عام، تعد عملية تقسيم الصور الطبية إلى أجزاء مهمة للغاية لتقدم الرعاية الصحية بمساعدة الذكاء الاصطناعي وأحدث التطورات في الصناعة، مثل الذكاء الاصطناعي القابل للتفسير والتعلم المتعدد الوسائط. ومع ذلك، توفر هذه المراجعة الدقيقة والمتعمقة تحليلاً شاملاً وموسعًا للطرق الحالية المستخدمة، وتطبيقاتها المتعددة في مختلف المجالات، والتطورات الناشئة الواعدة التي لديها القدرة على تمهيد الطريق لتحسينات وابتكارات مستقبلية ملحوظة..

1. Introduction to Medical Image Segmentation

Medical image segmentation plays a fundamental role in medical image analysis to accurately reveal specific clinical information by dividing the annotated area. Segmentation refers to partitioning an image of interest into multiple spatially coherent regions. [1][2][3] Medical image segmentation is an essential process because clinical doctors or radiologists can precisely diagnose the occurrence and development of the patient's disease; thus, they can plan the best individualized treatment for the patient. Currently, with the increasing number of aging-in-place facilities, the advent of home healthcare technologies, and even personal health devices, clinicians are faced with looking at a much larger number of diagnostic images than they used to. As a result, automated image analysis is expected to play an increasingly important role in clinical practice. [4][5][6][7][8]

Segmentation can be classified into three categories: structural, appearance, and functional based on geometric, temporal, and topical elements. This classification assists in tasks like tumor detection, organ mapping, and surgical planning by utilizing the specific spatial characteristics of diseases to diagnose and create treatment plans. Furthermore, unique structures of abnormal tissues and organs can be identified through segmentation [9][10][11][12]. The effectiveness of the analysis results will be improved according to the lesions. Typically, the signs of disease can be a regional color change and distribution irregularity. The textual color distribution of the medical image can reflect the basic components of those textures to execute the division operation. From a functional point of view, due to a pathological change in the tissue, the signal of the tissue may be simultaneously abnormal. Therefore, it will help in the segmentation of the group of tissues and ruptures to consider the existence of abnormal signals. The goal of segmentation is to divide the images into spatially meaningful regions that are perceptually distinctive [13][14][15]. It is a means of object interpretation that is typically connected to the actual object boundary, based on the similarity of characteristics such as color, depth, and texture. Automated medical image segmentation is a demanding research sector due to the variation in medical imaging, including inhomogeneity, high noise, sub-cellular features, and low image contrast. Pattern recognition and computer-aided diagnosis are characteristics of medical image segmentation, and the requirement for segmentation surgeries is increasing. To locate abnormalities, the process of medical image segmentation could be employed to enhance productivity [16][17][18][19].

Segmentation plays a crucial role in a multitude of medical domains such as radiology, pathology, and medical research. It aids in the identification and categorization of medical images, allowing for accurate diagnosis and treatment. The process of segmenting medical images involves extracting relevant anatomical structures or regions of interest, enabling healthcare professionals to observe and analyze specific areas with precision and clarity. By facilitating the localization and measurement of abnormalities, segmentation greatly enhances the accuracy of medical assessments, aiding in the detection of diseases and the development of efficient treatment strategies. Consequently, this indispensable technique is widely employed and continuously advancing across various medical specialties, paving the way for improved healthcare outcomes and patient well-being [20][10].

Medical image segmentation is an active area of research in the medical field. This section deals with an introductory and comprehensive overview of medical image segmentation. Usually, medical image segmentation is defined as the process of separating the different regions of interest, such as organs, tissues, lesions, and anatomical structures in an image. In order to simplify the analysis and interpretation of the obtained results and to extract the features, images are typically partitioned at various depths and levels. Furthermore, the significance of medical image analysis is particularly evident in medical diagnostics. The segmentation of a medical image provides the region of interest for each pixel element that can radically influence important administrative issues such as evaluation, diagnosis, and treatment [21][9].

Accurate image segmentation has significant medical implications, such as estimating volume of pathological tissues, treatment planning with 3D visualization, and monitoring treatment outcomes. It is crucial for tasks like biomarker detection, defining anatomical objects for diagnosis, and adapting segmentation methods for different imaging modalities. Medical image segmentation supports computer-assisted work in radiology centers and attracts scientists due to its challenges. The complexity of research in computer vision and image segmentation has evolved from low-level to high-level approaches, emphasizing the importance of object extraction while controlling scene variability [22][23]. Wenjian Yao et al. in (2023) introduced a review, that explains the evolution of medical image segmentation models, whilst their transition from CNNs to Transformer-based architectures. It presents a theoretical characterization of representative models, their performance analysis on benchmark datasets, and major challenges in the area as well as future directions [24].

Yan Xu et al. Once these traditional segmentation methods include thresholding segmentation, edge-based methods, region-based methods, clustering and graph-based segmentation. It introduces new breakthrough in the field of medical image segmentation and it significant for diagnosis and treatment [25].

Xiangbin Liu et al. Reviewed the deep-learning based techniques for medical image segmentation in detail. Data-driven deep learning-based segmentation methods have attained commendable accuracy in diverse application domains over recent years; however, there exist certain issues that the researchers need to mitigate [26].

1.1. Applications in Medical Imaging

Medical image segmentation plays an important role in different kinds of medical imaging modalities. In radiology, it has been used for the accurate identification of anatomical structures for different parts of the human body. In oncology, it is used to segment tumors in images to help with diagnosis and therapy planning. Accurately segmenting brain tumors, for instance, can have a strong impact on clinical decision-making and on facilitating targeted therapy [27]. The location and extent of airway disease can be assessed based on CT images and support correct treatment strategies. In cardiology, segmentation can be used to measure particular clinically relevant metrics such as the left ventricular volume. In addition to the above traditional use cases, segmentation has also gained significant interest in this pandemic context for the development of personalized and home-based telemedicine systems that aim for early diagnosis and follow-up [21]. It has also been used in personalized predictive models based on medical images and deep learning for different diseases. In neuroimaging, where many distinctive anatomical regions exist, it is challenging to accurately segment because of low contrast in magnetic resonance images and inter-subject structural variability. Many of these aforementioned applications are greatly impacted by the data used, and how some characteristics of that data are known to affect the choice of model and loss [28].

In this section, we explore several real-life examples related to medical imaging and the associated challenges. Additionally, we provide a brief overview of the applications of medical imaging in areas such as oncology, radiology, and genetics. For example, in radiology, segmentation plays a crucial role in accurately identifying specific anatomical parts from X-ray, MRI, or CT images, such as the skull, lung, liver, and facial segments. Radiologists often spend a significant amount of time manually segmenting tumors and organs of interest in MRI images for cancer treatment planning. Biomedical and genetic research is used to precisely measure the internal structures of the body and compare organ segmentation across different individuals. The classification of various genetic diseases and their characteristics is becoming more intricate. Tumor cells in MRI images have low contrast, making it challenging for radiologists to detect and characterize them accurately. Brain tissue segmentation is employed to begin the process of categorizing different elements in images of the human brain, including the intracranial cavity, various human brain tissues, and the background visible in MRI images [17][29][30].

2. Traditional Segmentation approaches

Traditional segmentation methods can be categorized into three classes based on different segmentation techniques. These include (1) thresholding, (2) region-based, and (3) edge-based techniques. Thresholding is classified as the simplest technique and can be used for both grayscale and binary images. The most representative of this class of techniques is based on histogram analysis. It implements a technique that groups similar data and classifies them based on the range of pixel intensities, effectively separating objects from the background. Region-based is an extension of thresholding, which further refines the segmentation process. The first step is to group the neighboring pixels that share similar properties. This process allows multiple objects to be detected within a single image. Edge-based, on the other hand, determines the boundaries or edges of the object by finding any abrupt change in intensity value, which exposes the region of interest [20][31].

Each of the above methods has its advantages and drawbacks and should be carefully selected according to the specific requirements of the imaging technique. In general, the techniques mentioned are relatively fast in comparison to the newer methods, require less computational power, and are good for segmenting objects without overlapping boundaries. Improvements to these traditional methods in recent years are mostly due to enhanced image processing algorithms and advancements in computational resources. Some improvements in the existing algorithms have also been made in the form of fuzzy and rough set theory, while energy minimization has been employed to ensure more accurate and efficient segmentation of MR brain images. However, the above-mentioned algorithms still rely on initial user input that gives rise to a certain degree of uncertainty [32].

2.1. Thresholding Based Technique

Medical image segmentation can be achieved through various methods, one of which is thresholding. The method is fundamental in processing medical images because thresholding is used for converting grayscale images to binary ones. The conversion implements an attribute of intensity that is called the threshold value so that within the segmentation, only an object with an intensity value higher than the particular threshold value can be segmented. In terms of simplicity, thresholding methods are at the top of the list; thus, these are considered to be the most reliable simplified approach and have a short computational time. Although some disadvantages can be found, thresholding methods remain the most widely implemented approach since they can perform well, especially in an initial, straightforward segmentation task. The very basic principle of thresholding is relatively simple. The method employs at least one threshold value to convert a grayscale image into a binary image [33][34][35]. There are several thresholding methods that can be adopted as follows: global, one value of thresholding for the whole image data; adaptive, determining the threshold value in accordance with an image property; and automated. Each intensity value of the grayscale image is analyzed to be less than or greater than a particular threshold value that separates the object of interest from the background. An object of interest is a pixel retaining an intensity value higher than a given threshold, whereas the background is fully set as a pixel below the threshold. A limitation of this approach is its sensitivity to noise in medical images and consequently the changing of intensities using various illumination techniques. To solve the problem, accurate selection of the threshold data is crucial. Although in some cases, modifications in terms of thresholding technique are mandatory to realize accurate segmentation results [36][37][38].

2.2. Region-Based Segmentation

Region-based segmentation involves grouping neighboring pixels according to some predefined criteria. In principle, regions are seed nodes or the initial center and grow by incorporating the contiguous pixels with similar intensities or textures. The key advantage of region-based techniques is that the process typically does not involve an elimination step, thus segmentation errors that can result from boundary leakage are dramatically reduced. Visually, edge noise in the original image causes the boundaries of the regional object to be neither smooth nor regular. Several region-growing techniques have been proposed for use with ultrasound, CT, and MRI scans and have been shown to exhibit high performance [39][40].

The methods differ in terms of the criteria for adding new pixels to the growing region. Although all MRGS methods use some variation of the region growing strategy, two different points of view can be explicitly investigated. These methods, referred to as region splitting and region merging, are based on different primordial ingredients when attacking the problem of low-level or early vision. Region splitting supposes that the primary step is to consider a unique initial region derived from the whole image. Moreover, the segmentation method proceeds with splitting the existing region into two or more subregions. Notably, region properties help to select points that form subregions. The number of regions involved in the splitting process is generally determined by the number of disjointed regions in which the original region has been split. The region splitting view represents an agglomerative approach to image segmentation, since the original accidental and completely arbitrary region in the image is divided into homogeneous ones. Region merging, on the other hand, postulates the compelling concept of joining or merging individual pixels, with the idea that they are only added to the region if these pixels are sufficiently homogeneous. A splitting region merging approach has only rare or virtual applications since the concept of adding points is nothing else but region growing. As previously mentioned, the main difference between region splitting and region merging lies in how the processing is carried out. Region splitting uses a compatible region having suitable properties, whereas the region splitting method takes advantage of a unified region. In medical applications, either the region splitting or the region merging paradigm is used as an essential or dominant strategy. The traits of medical imaging, for instance, spatial ambiguity, the coexistence of multi-object shape, shape delineation difficulties, noise, contrast agents, and lesion overlap, as well as the appearance of an object surrounded by interior noise, prevent the direct use of older techniques. Region splitting is known sometimes for its lack of steering ability and potential under- or over-segmentation interior noise. In practical medical applications, certain MRGS approaches, particularly multi-atlas methods, are known to be quite effective. However, these methods also tend to require the selection of a number of regions or clustering regions used as seeds. Many of these approaches are not unsupervised methods. The regional techniques effectively segment objects on three medical imaging modalities: CT scans, histology sections, and in vivo retinal fundus images. It is worthy of note that this type of segmentation can also be used to segment homogeneous objects in UBM series [40][42][43].

2.3. Edge-based Segmentation

Edge-Based Segmentation: These techniques detect the intensity changes that mark the boundaries between tissues in images. The edge generally represents the exterior of the structure, intrinsically providing information on object position. Moreover, the edge is a one-dimensional information that is extracted by reducing the data from two-dimensional/three-dimensional to one-dimensional. In edge-based techniques, various methods exist to determine edges, such as gradient-based methods, gradient + operator based methods, the second derivative method, and the Laplacian of Gaussian operators. These features perform either selective enhancement of edges or decrease noise based on a filter implementation. The differentiation is suitable for detecting edges from complex textured medical images with delicate features. It also highlights edges irrespective of the objects being imaged [44].

However, these individual methods are sensitive to the noise in the entire image, which may cause the detection of false boundaries when applied to low-contrast medical images. Edge-based methods are preferred for anatomical structure delineation, contributing to the development of anatomical segmentation in medical images. To improve the robustness of edge-type segmentation, the general use of hybrid approaches that unite an edge concept with other techniques is gaining ground. In many medical segmentation-related works, the edge histogram is employed to elucidate the pixel spreading and form. Concepts of edge used on the basis of the vertices in such techniques were put forth. These are different from the gradient-based edge detectors that first locate differentials and then detect their change of sign. In the Bookstein operator, the edge is disclosed by morphing a ring around the chosen vertex. Moreover, the percentage of the ring that is significantly made up of the boundary is determined based on the intensity of the local feature statistics.

Many approaches to medical image registration have utilized edge-based techniques. An edge-based registration technique was developed to classify human vertebrae in magnetic resonance images, which included edge detection and closed boundary analysis. Today, gradient computation is considered to improve the steep contrast between the intensity of adjacent pixels. Gradients or after differentiation aligned to the desired directions are measurements of local edge strength, where edges are highly noticeable. Some landmark edge detection methods that use gradient computation only for the localization of the edges are the Gaussian first-order derivative, Laplacian of Gaussian, Canny edge detector, and Sobel edge detector.

Table 1 provides a comparison of Threshold-Based Segmentation, Region-Based Segmentation, and Edge-Based Segmentation methods used in medical image processing. The table highlights key aspects, including their approaches, performance, robustness, and limitations.

Table (1): Comparison between Threshold-Based Segmentation, Region-Based Segmentation, and Edge-Based Segmentation

Aspect	Threshold-Based	Region-Based	Edge-Based

	Segmentation	Segmentation	Segmentation
Key Approach	Segments based on pixel intensity values.	Groups pixels/regions based on similarity criteria (e.g., intensity, texture).	Detects boundaries based on intensity gradients or differences.
Examples	Global thresholding, Adaptive thresholding, Otsu's method.	Region growing, Region splitting and merging, Watershed.	Sobel, Canny, Laplacian operators.
Performance	Effective for high-contrast images.	Works well for images with homogenous regions.	Effective for well-defined boundaries.
Computational Complexity	Low; simple algorithms.	Moderate; depends on the size of the region and similarity checks.	Moderate to high; edge detection algorithms can be computationally expensive.
Robustness to Noise	Low; sensitive to noise and variations in intensity.	Moderate; may fail if noise disrupts region homogeneity.	Low; edge detection is highly sensitive to noise and artifacts.
Data Requirement	No training data required; relies on fixed intensity thresholds.	Requires a seed point or initial region as input.	No training data required; works directly on image gradients.
Adaptability	Poor; manual adjustment needed for different images.	Moderate; region criteria can be modified.	Moderate; edge criteria can be tuned.
Ease of Implementation	Very simple; requires basic image processing knowledge.	Requires more expertise to set region-growing criteria.	Moderate; edge algorithms are straightforward but require gradient tuning.
Applications	Skull stripping, simple organ segmentation.	Organ or tissue segmentation with consistent intensity ranges.	Boundary detection in anatomical structures (e.g., blood vessels, tumors).
Limitations	- Struggles with overlapping intensity values. - Fails in noisy or low-contrast images.	- Sensitive to initial seed selection. - Over-segmentation or under-segmentation is common.	- Poor performance with blurry edges or complex textures. - Requires post-processing to refine edges.
Advantages	- Easy to implement. - Fast and computationally efficient.	- Captures spatial coherence. - Can adapt to heterogeneous regions.	- Identifies sharp and well-defined edges. - Effective for high-contrast boundaries.

3. Machine Learning-Based Methods

In these methods, rather than using predefined rules, the algorithm has to learn any information that is present in the input data and can also learn from the derived features using lower-level features. The information in the data can be visual, textual, or in the form of multimedia. The performance of the machine learning algorithms mainly depends on the knowledge representation of the information, the type of learner, and the search strategy used for learning from the input data. Neural networks provide systems with the power of the brain and are used for a large amount of data [45][46][47]. The learning system has to pass through four stages: input of sensory data to the learning system, passing the signal through the layers of the learning system, passing the output of the learning system for decision making, and feedback signal of decision making to the learning system. In traditional approaches, images are mainly processed using methods from mathematics and physics. However, one of the main issues with the traditional approach is that when we perform segmentation using traditional image processing algorithms on complex datasets, like medical images, which may include tumors, lymph nodes, or many types of biological areas, there is no defined set of rules for each of the areas in the images. In this case, machine learning can map the input image to the output image. In other words, it learns the segmentation rules implicitly [48][49][50]. Based on the amount of supervision required, these algorithms are classified into three types: Supervised learning, Unsupervised learning, Semisupervised learning [51].

3.1. Supervised Learning

In this subsection, we will provide an overview of supervised learning methods in medical image segmentation. According to whether the training process uses annotated samples, supervised methods can be classified as supervised learning algorithms or weakly supervised learning algorithms. A labeled dataset is essential during the training process of supervised learning methods. In the representational space, the main advantage of supervised learning algorithms over unsupervised learning techniques can be witnessed through the periodic adjustments, conciliation processes, and regularization of the cost function. These procedures seek to further decrease segmentation error, moving from local minima. From what has been mentioned above, it becomes apparent that the most important and sensitive module in the process of supervised image segmentation is the learning module. Given sufficient training data, the algorithm can accurately learn image features that can distinguish between distinct organs, tissues, and cells. Nonetheless, precise learning methods necessitate the use of ground-truth annotated images.

Supervised learning data can be represented as pairs of input-output samples. In this case, the input is represented by I, where n refers to the number of voxels. Each voxel has m-dimensional feature vectors that correspond to it; that is, where x and L represents the number of object classes. Supervised learning algorithms use ground-truth data from the given training images to estimate an optimal function. Suppose the function is defined as f(I, θ) and represents the mapping function from input features to class labels. The f(I, θ) uses parameterization to represent the function, including θ. The method finds the best possible parameters to minimize the output error. The learning method requires a training volume with a boundary-spaced region to understand and learn different information. Several supervised classifiers, such as support vector machines, decision trees, assignment methods, relevance vector machines, nearest-neighbor algorithms, and random forests, can perform the pixel-wise classification process in medical image segmentation [52][53][54].

3.2. Unsupervised Learning

Unsupervised learning includes methods used for training unlabeled data. It can identify patterns in input data based on the intrinsic structure of the data distribution. Since no labeled samples exist to guide the training process, unsupervised learning is useful when no prior information about the distribution and statistical properties of the data is available. Segmentation can be considered an unsupervised learning problem, as it often aims at defining the clusters of pixels or voxels in the image. Several clustering methods have been proposed and applied to medical image segmentation, such as k-means and hierarchical clustering [55][56].

Unsupervised learning carries several advantages, ranging from the ability to extend predictions to new data that have not been previously annotated to a negligible human effort for data annotation. Yet, challenges remain, which mainly stem from ambiguity in the results and the choice of an appropriate distance metric or a valid calibration of model hyperparameters, such as the number of clusters. It can be seen, therefore, how unsupervised learning tries to find a balance between exploring unknown behaviors in the data and explaining still unknown patterns that could lead to a better representation of the system under study. The possibility to explore hidden structures, if used as a feature, allows clinicians to hypothesize the characteristics and the clinical presentation of the subjects involved in the study. Case studies are now presented, encompassing unsupervised techniques to segment medical images for distinct applications [57][58].

Since clustering without feature engineering is becoming a basis of segmentation networks, the role of unsupervised learning will mature in the coming years. This holds for the rapidly evolving omics fields and neuroimaging where such large amounts of data are recorded and the discovery of patterns is consolidated.

3.3. Deep Learning

Deep learning, which is the most rapidly advancing technique in recent years, has greatly improved the performance of medical image segmentation methods. Convolutional neural networks are foundational models in processing and segmenting complex medical data. They are capable of learning the hierarchical features of the image in a data-driven manner, with a larger depth and many more parameters than traditional machine learning models. Deep learning has many advantages, such as its ability to perform feature learning automatically from raw input data, which significantly reduces the need for manual feature extraction. Moreover, the end-to-end approach used in deep learning also improves the efficiency of model development. Compared with traditional machine learning methods, deep learning has superior performance in image segmentation [59][60].

With the development of deep learning, many state-of-the-art network architectures in medical image segmentation have been proposed. The U-Net architecture, designed with skip connections and used for various medical image segmentation tasks, is one of the most well-known. Inverted-Net, SegNet, and V-Net are other architectures that have shown state-of-the-art performance when used in medical image segmentation tasks. In addition, with the challenge of insufficient labeled medical data, the integration of transfer learning with deep neural networks has helped improve learning performance. Similarly, adversarial training is also a data augmentation technique that has shown promising results. Despite their powerful advantages, there are still some challenges with deep learning-based medical image segmentation methods. It typically requires plenty of segmentation data with manual annotations to train the network. Moreover, deep learning with its "black-box" characteristics may not be suitable for some medical applications, where interpretability is very important. Because of this, generating methods and models, such as deep learning decision trees and attention maps, have been highlighted as promising future research topics [61].

3.3.1 U-Net

U-Net is a convolutional neural network (CNN) specially designed for biomedical image segmentation. It is composed of a contracting path (encoder) that captures context, and an expanding path (decoder) that enables precise localization. Skip connections between corresponding encoder and decoder layers keep spatial information intact and it is particularly suitable for small and convoluted structures like tumors or vessels.

3.3.2 Fully Convolutional Networks (FCN)

Instead of utilizing classical fully connected layers, FCNs substitute convolutional layers, allowing input images with a variable size. These types of neural networks employ an encoder-decoder structure similar to U-Net but usually do not include skip connections resulting in less performance for pixel-wise segmentation (detailed smal image segmentation tasks).

3.3.3 DeepLabV3+

DeepLabV3+ builds further on the details of FCNs and includes atrous (dilated) convolutions to extract multi-scale contextual information without the cost of a computational increase. The model also has an enhanced decoder module that adapts well to complex medical images with multiple textures and structures.

3.3.4 Attention U-Net

Attention U-Net adds attention mechanisms to a standard U-Net, allowing the model to attend (focus) on relevant regions while ignoring (suppressing) that which is irrelevant. The method also really shines in tasks that require segmenting small targets or targets that vary in shape.

3.3.5 Vision Transformers (ViTs): Segmented Generations

Using self-attention mechanisms, ViTs are able to model long-range dependencies and are therefore effective for medical image segmentation tasks that require contextual awareness. ViTs differ from the conventional CNNs which are local receptive fields in the sense that they are capable of capturing more global features from input images. TransUNet is an example of a Transformer-based model that can combine CNN-based encoders with transformer-based decoders to leverage local and global representations.

In summary, the following figure 1 illustrates the machine learning-based segmentation pipeline steps.

In this manuscript, we compared in different aspects the medical image segmentation techniques available in the literature and discussed their pros and cons. Traditional (threshold based, region based, edge based) segmentation methods are simple, computationally efficient, and interpretable. Threshold-based approaches work well for high-contrast images but perform poorly in noise and need to be exact for the threshold selected. Region-based methods have good performance on homogeneous regions, are more robust to noise, but can be computationally expensive and sensitive to seed point selection.

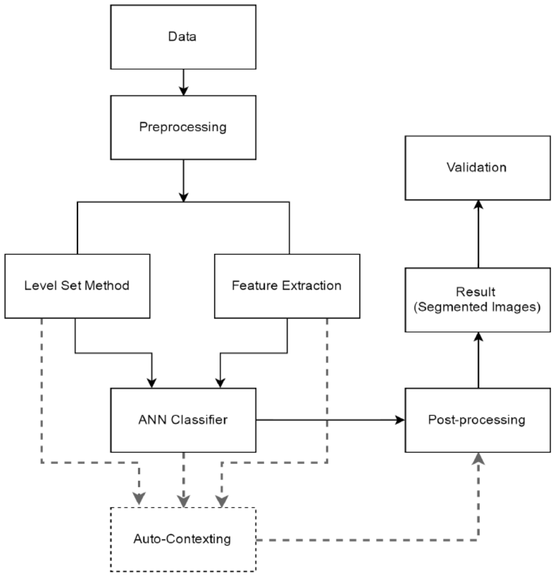

Figure (1): Block diagram of machine learning-based segmentation pipeline.

The Table2 below compares traditional-based, machine learning-based, and deep learning-based approaches in several key aspects:

Table (2): Comparison between traditional-based, machine learning-based, and deep learning-based approaches in several key aspects:

Aspect	Traditional-Based Methods	Machine Learning-Based Methods	Deep Learning-Based Methods
Key Approach	Uses image intensity, regions, or edges for segmentation.	Learns from handcrafted features to classify pixels or regions.	Learns features automatically from data using neural networks.
Examples	Thresholding, Region Growing, Watershed, Clustering.	Support Vector Machines (SVMs), Random Forests, Markov Random Fields (MRFs).	U-Net, Fully Convolutional Networks (FCNs), 3D U-Net, Vision Transformers.
Feature Extraction	Manual (intensity, gradients, texture, etc.).	Handcrafted features (intensity, shape, texture).	Automatic through deep neural network layers.
Performance	Moderate for simple structures and high-contrast images.	Improved accuracy with meaningful handcrafted features.	High accuracy, especially for complex and large datasets.
Computational Complexity	Low to moderate.	Moderate.	High (requires GPUs and

			large memory).
Data Requirement	Minimal; works well with limited or no training data.	Moderate; needs annotated data for training.	High; requires large, annotated datasets.
Robustness to Noise	Low; sensitive to noise and artifacts.	Moderate; depends on the features used.	High; can learn robust features with proper training.
Generalization	Poor; depends on manually set parameters	Moderate; generalizes with sufficient features and data.	High with proper training and augmentation.
Adaptability	Low; requires manual adjustments for new tasks.	Moderate; needs feature engineering for new tasks.	High; retraining can adapt to new tasks.
Ease of Implementation	Simple; no specialized expertise needed.	Moderate; requires expertise in feature design.	Complex; requires expertise in deep learning frameworks.
Applications	Basic tasks like skull stripping, organ segmentation in simple cases.	Segmentation of organs, vessels, or tumors with moderate complexity.	Tumor detection, organ segmentation, real-time segmentation, and multimodal tasks.
Limitations	- Fails for complex structures. - Sensitive to image artifacts and low contrast.	- Requires extensive feature engineering - Struggles with high-dimensional data.	- Requires large annotated datasets.- Computationally expensive.
Advantages	- Simple and interpretable. - Low computational cost.	- Balances complexity and interpretability. - Good for smaller datasets.	Automatically learns hierarchical features. - Best performance for complex segmentation tasks.

While edge-based techniques work well for images that have boundaries with strong edges, they are not robust to weak edges or retinal edges and typically need pre-processing for high performance.

Modern methods like machine learning based techniques and deep learning-based techniques achieve quite high segmentation accuracy and generalization capabilities. Although more accurate than traditional methods, machine learning-based methods need manual feature extraction and depend too much on the quality of labeled data. To address these limitations, deep learning–based methods learn complex patterns and features automatically and can be used to achieve high accuracy and scalability in PPI prediction. However, these algorithms are computationally expensive and need large annotated datasets to train on and provide limited interpretability.

This comparative analysis shall offer readers a straightforward insight into the trade-offs with regard to making segmentation methods choices across various medical imaging tasks.

4. Case Studies

This paper illustrates the continuum of range that exists between medical image segmentation methods, from thresholding to deep learning based techniques through three case studies. Depending on the imaging modality, data quality, and clinical requirements, each method has its advantages and disadvantages. It will further pave the way to more accurate, automated, and efficient solutions that would be a great help to the healthcare field.

4.1 Case Study I: Lung nodule Detection in CT-scans based upon Thresholding and Region Growing technique

Problem Statement: Lung cancer is a major cause of mortality globally, and timely identification of lung nodules can greatly enhance patient outcomes. Segmenting lung nodules from CT scans aids radiologists in pinpointing and monitoring these entities for additional assessment.

Methodology: A hybrid approach which employed a region growth and thresholding for segmenting lung nodules Discovery and iterative region growing were used to refine the results. First, to segment the lung area from the background, thresholding is applied and then lung nodules are detected and segmented using region growing methods. Thresholding is useful to filter out irrelevant tissue, and region growing is beneficial to refine the boundaries of the nodules.

Results: The average sensitivity of detection of lung nodule using the proposed segmentation approach was found to be 92%. Moreover, the method supplied 89% accurate nodules segmentation, which was enough for further analysis by the radiologists. Using this hybrid approach, the detection is not only real-time but also takes less than 10 seconds to process each scan.

Pros: The method produced good results on datasets that contained well-defined lung nodules;

Cons: The approach was poor on small and/or irregularly shaped nodules, sometimes leading to false negatives. Also, we found that artifacts such as motion blur or metal implants affected the segmentation accuracy [62][63][64], figure 2 shows Lung nodule segmentation before and after processing

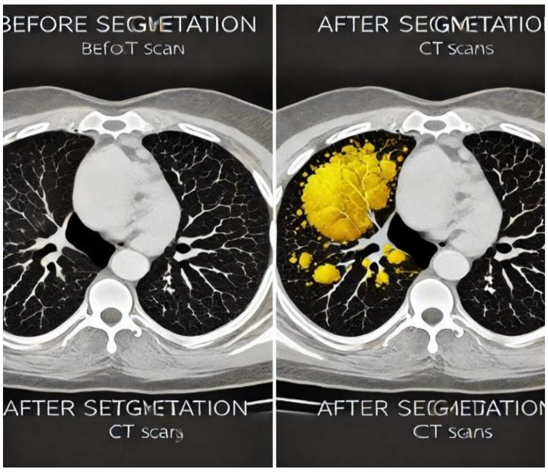

Figure (2): Lung nodule segmentation before and after processing.

4.2 Case Study II: Deep learning based Brain Tumor Segmentation:

Problem Statement: Brain tumor detection and segmentation is of utmost importance for diagnosis, treatment planning and post surgical evaluations. The precise segmentation can assist with delineating the tumor boundary, identifying the type of tumor, and tracking the tumor advancement over time.

Method: Recently, deep learning methods, especially convolutional neural networks (CNN), have achieved promising results for brain tumor segmentation using MRI scans. One prominent method is by leveraging a 3D U-Net architecture that employs both patch-level and whole-image features for tumor detection. Annotated datasets like BRATS (Brain Tumor Segmentation) dataset containing diverse MRI images with tumor annotations are used to train the U-Net.

Results: The 3D U-Net was able to achieve state-of-the-art performance for glioma segmentation, with an average Dice similarity coefficient (DSC) of 0.85, demonstrating a strong overlap between the predicted and ground-truth tumor regions. It was also able to differentiate tumor types, such as glioblastoma multiforme (GBM) from lower-grade gliomas, refining the ability to personalize treatment.

Challenges: The inconsistency between MRI scans (e.g., noise, resolution, and artifacts) made it difficult to achieve consistent outcomes. Also, training and deploying the model were limited by the dataset size as well as the high computational resources needed [65][66][67], figure 3 shows the brain tumor segmentation before and after processing.

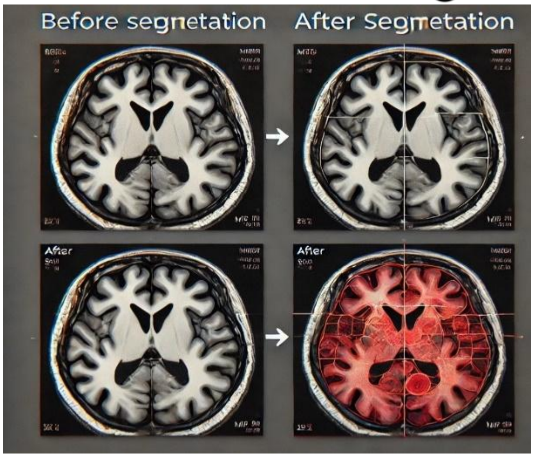

Figure (3): The brain tumor segmentation before and after processing

4.3 Case Study III: Graph Cuts for Retinal Vessel Segmentation

Problem Statement: Retinal vessel segmentation is critical for the diagnosis of diabetic retinopathy, glaucoma, and other vascular diseases. Accurate segmentation of the vessels is important to detect pathological changes in the retina.

Methodology: Because graph cut-based segmentation methods enable to formulate the problem as an energy minimization problem, the methods have been applied for retinal vessel segmentation. This Graph-convolutional neural network for image segmentation based is heremade in: to use each pixel in an image as a node and connect them via edges weighted by some similarity based on learned features to determine whether the node belongs to the image vessel. Then, a min-cut algorithm is used to separate the vessels from the background.

Results: Graph cut based methods performances are high with an average DSC of 0.88 in the DRIVE (Digital Retinal Images for Vessel Extraction) dataset. Our proposed method achieved the best segmentation results, especially on narrow and small vessels, which are generally ignored by traditional techniques.

Challenges: Introduction of a method for segmentation of retina images with a background-less green channel-based brain image acquired using a stereo-vision-eye-based retinal IMU in those multiple images. A direct implementation of graph cuts is quite expensive computationally, however, which need be optimized for use in clinic [68][69][70], figure 4 shows retinal vessel segmentation before and after processing.

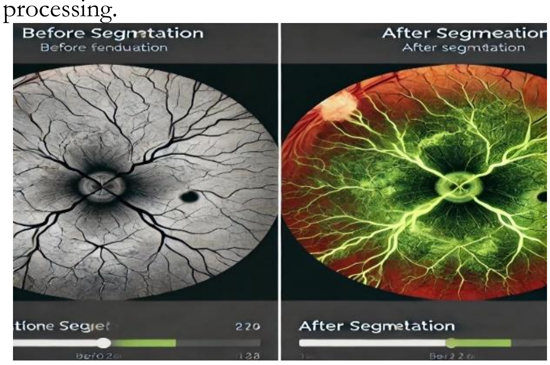

Figure (4): Retinal vessel segmentation before and after processing

5. Evaluation Metrics

Several new algorithms are constantly being developed for quantitative medical image segmentation, but no definitive standard for accuracy exists. It is crucial to quantify segmentation results for reliable clinical use. Common evaluation metrics include outlier tolerance percentage, regional error rate, segmentation similarity, localization distance, grayscale distance, and classification accuracy [71][72]. Evaluation metrics for medical image segmentation are essential to quantify the performance of segmentation algorithms. Several metrics evaluate medical image segmentation based on the accuracy of predictions compared to ground truth segmentations. Metrics can be broadly divided into overlap-based metrics, metrics focused on capturing the boundaries of the segmentation mask, and clinical validation protocols to ensure downstream usability.

5.1 Overlap-Based Metrics (Region Similarity)

5.1.1 Dice Similarity Coefficient (DSC)

The Dice coefficient represents the ratio of twice the intersection area of the manually segmented reference and the automatic segmentation image, over the sum of the manually segmented reference and the automatic segmentation image [73][74].

- Calculates the spatial overlap between the predicted segmentation and the ground truth
- Ranges between 0 (smallest overlap) and 1 (best match).
- Mostly implemented in medical image segmentation (e.g. brain tumor segmentation on MRI scans) and DSC formula is given as follow:

$$\mathbf{DSC=2|A\cap B|\ /\ |A|+|B|}$$

5.1.2 Jaccard Index (Intersection over Union, IoU)

The J-index calculates the overlapping ratio over twice the area of the reference image minus the area of the automatic segmentation. Both the DICE coefficient and the J-index range from 0 to 1, where 0 indicates no overlap and 1 indicates a perfect match. They are directly linked to the quality of segmentation. Some researchers prefer to analyze the inverse Dice, so that the higher the result, the better the matching of the areas in the input images. The DICE coefficient, the J-index, sensitivity, and specificity reflect different contents of binary objects and different metrics. Manual and partial thresholding evaluation cannot provide a comprehensive judgment of image segmentation results [75][76][77].

- Tanimoto coefficient also goes under this name and gives a stricter measure than DSC.
- IoU is less than DSC for identical segmentation mask, since it is punish oversegmentation.
- Applied in tasks such as lung nodule segmentation in CT images and **IoU** formula is given as follow:

$$\mathbf{IoU=|A\cap B|\ /\ |A\cup B|}$$

The DICE coefficient is commonly used to evaluate glossary or partial segmentation. While sensitivity and specificity values are calculated to assess, they do not fully capture the segmentation result and data reliability. To thoroughly evaluate the segmentation result of a medical image in various scenarios, a comprehensive analysis and comparison of basic evaluation methods, single evaluation methods, and data reliability is essential [78][79][80].

5.2 Boundary Focused Metrics

Overlap-based metrics are agnostic to the exact match of a segmented region's boundary to the actual object's edge. Boundary metrics are a more direct measure of segmentation because they only take into account contours.

5.2.1 Hausdorff Distance (HD)

Computes the maximal distance of the border between predicted (et) and our reference (gt) segmentations.

- Sensitive to outliers and erratic segmentations (i.e., when the segmentation contains false positives that are far away from actual boundary).
- Lower HD, indicates better segmentation performance.
- In common use in tumor segmentation, where precise boundaries are particularly important for surgical planning .

5.2.2 Average Hausdorff Distance (AHD)

- A variant of HD that is less sensitive, by averaging the distances instead of taking the worst-case value.
- When the HD metric may be impacted by a couple of extreme outliers.

5.2.3 Average surface distance (ASD)

- Average error of the predicted segmentation boundary with respect to the ground truth boundary
- HD more sensitive to small boundary changes.
- Commonly used for cardiac segmentation to evaluate the boundaries of the heart chambers.

5.2.4 BF Score — Boundary F1 Score

- Calculate PR balance at object boundary
- Helpful in vascular segmentation where edge precision is important (e.g., retinal vessel segmentation)

5.3 Clinical Validation Protocols for Segmentation Models

Besides thorough algorithmic evaluation, there is need for rigorous clinical validation of medical segmentation models before they enter real-world usage. To guarantee an application in the real world, segmentation models are clinically validated by testing in multi-center datasets, assessment of interobserver variability, prospective clinical trials, and regulatory approvals. Models should be tested on heterogenous datasets to assess generalisation in multiple imaging modalities and patient populations. Reliability of AI-Based Mammogram Breast Segmentation System. Real world use cases are confirmed in clinical trials that test AI performance in real life, assessing time savings, accuracy gains and implications for impact on patient outcomes. Moreover, regulatory approvals (FDA, CE certifications) are essential to validate compliance with medical devices standards and ethical implementations in clinical environments.

A suggestion to generalize sensitivity, accuracy, precision, F-measure, and the Matthews correlation coefficient has been put forward. Since these parameters alone can be misleading, using a combination may enhance judgment reliability. The proposed evaluation metrics are suitable for determining the presence of pathological tissue or physiological function. It is crucial to ensure these metrics are compatible with the standard. There is a need to address limitations in the future and test the practicality of the proposed evaluation metrics. Additionally, evaluating and differentiating disease grade levels and subregions remains open for future research [81][82][83]. Table 3 provides an overview of metrics and validation techniques.

Table 3: provides an overview of metrics and validation techniques.

Category	Metric/Method	Description	Use Case
Overlap-Based Metrics	DSC (Dice Similarity Coefficient)	Measures overlap between prediction and ground truth	Brain tumor segmentation
	Jaccard Index (IoU)	Stricter overlap measure than DSC	Lung nodule segmentation
Boundary-Focused Metrics	Hausdorff Distance (HD)	Measures worst-case boundary error	Surgical tumor margin assessment
	Average Surface Distance (ASD)	Measures average deviation from ground truth boundary	Cardiac segmentation
	Boundary F1 Score (BF Score)	Assesses boundary precision	Retinal vessel segmentation
Clinical Validation	Multi-Center Dataset Testing	Trains models on diverse datasets	Generalization check
	Interobserver Variability	Compares AI with multiple radiologists	Consistency validation
	Prospective Clinical Trials	Evaluates real-world deployment	AI impact assessment
	Regulatory Approval	Follows FDA, CE, and ISO standards	Ensures compliance

6. Challenges and Future Directions

Medical image segmentation has many existing challenges, of which rapid growth is recorded in recent years. Several challenges are already identified and prominently noted, such as flexibility to different imaging modalities, deep and varying anatomical structures, manual handling of data due to complexity, performance assessment, cross-comparison, practical and clinical significance, statistical significance, and validation possibility. Complex techniques like shape modeling and prior anatomical knowledge are often used to meet these challenges. Furthermore, manual reviewing of large volumes of medical image data is time-consuming and causes fatigue and loss of accuracy; hence, medical experts need automated tools to do the job more rapidly and accurately. Consequently, designing such a system is difficult due to the enormous diversity of medical imaging data. They are complex, expensive, and time-consuming to obtain, and may exhibit numerous artifacts due to equipment limitations, patient motion, or poor coordination. Improving the accuracy and efficiency of medical image analysis and the diagnostic process has led to the development of medical image segmentation techniques to analyze or review medical images. Gradually, the application of cutting-edge computational technologies in medical image processing is emerging as a potential healthcare provider.

However, medical image segmentation is a significant step and key enabling technology in many computerized diagnostic procedures and medical disciplines. It plays a significant role in delivering accurate and efficient outcomes, and with automated computerized and quantitative analyses, it allows the objectivity and reproducibility of clinical measurements of anatomy and physiology. With such measures, a virtual patient may arise, including quantification and statistical analysis of normally and abnormally located anatomy and physiology, representing important knowledge in large-scale medical databases. Consequently, this knowledge is available to be used as informative tools for data mining and network collaboration, without reexamination of patients.

There are numerous challenges in medical image segmentation, and many of these challenges has gained increased attention with the rapid growth in imaging technologies and computational techniques. Challenges such as respect to active learning need to be considered here, and additional challenge of this problem can be listed as adapting to different imaging modality behaviors, the jagged and heterogeneous character of the data for example in the case of the anatomy, and the manual cost because the enormous intricate cooks of the medical imaging data. Moreover, questions regarding performance assessment, cross-comparison, statistical validation, as well as, practical and clinical relevance are still paramount issues.

6.1 Addressing Data Scarcity

Data scarcity is one of the most pressing challenges, which results from needing large amounts of high-quality, annotated datasets of images in areas where it is expensive, by medical experts who can annotate them, and where patient privacy hampers our ability to collect enough data. Novel techniques are solving this problem with data augmentation approaches that create synthetic diversity of the existing data. Transfer learning is also a promising method, wherein existing models previously trained on related tasks are fine-tuned on a limited number of medical datasets, offering a substantial reduction in the requirement for large-scale labeled data. Furthermore, generative adversarial networks (GANs) approaches help in illustrating the promise of synthetic data generation, where realistic and diverse datasets can be synthesized for training to overcome challenges faced in data scarcity.

6.2 Improving Noise Sensitivity

Medical images are often noisy due to artifacts introduced during imaging, including patient movement, equipment constraints, or sub-optimal circumstances. Recently, many improved models address the lap of noise robustness by noise-aware training mechanisms and robust loss functions. For instance, models are now explicitly trained to identify and treat noise in the input (gathered) data. Furthermore, denoising algorithms, commonly based on deep learning methods, have been incorporated within segmentation pipelines to improve the quality of input data and thus enhance segmentation accuracy and reliability.

6.3 Future Directions

Here are few avenues of exploration and breakthroughs to consider that could help to push the field forward:

1. **Collaborative training with federated learning**

Meanwhile, federated learning in the presence of multiple institutions enables the collaboration of model training for segmentation without directly distributing raw data, which avoids privacy concerns and provides access to heterogeneous data across institutions. This technique could ultimately improve model generalizability and do so while preserving patient privacy.

2. **Fusion of Multimodal Imaging Data**

Combining data from multiple imaging modalities (CT, MRI, PET, etc.) provides a more comprehensive view of anatomical and pathological properties. In latent spaces of multiple modalities, the strengths of one modality can compensate for the weaknesses of another. Exploratory methods can learn simultaneously different modalities that can express complementary information, which makes complementary information can obtain better segmentation precision.

3. **Building on Generative AI Models**

They are developing into new pathways to generate realistic high-fidelity medical images and segmentation through generative models, including GANs and diffusion models. These models can help in data generation, augmentation, and even directly perform segmentation tasks.

4. **Recent Clinical Applications of Real-Time Segmentation**

Advances in computational hardware and optimization techniques are allowing for real-time segmentation systems. These systems might enable clinically useful time-sensitive applications that currently require intraoperative imaging to visualize targets without mobilizing the sensors while needing quick segmentation of the distance between targets.

5. **Adaptability, explainability and interpretability**

As machine learning systems grow in sophistication, there is an increasing demand for explainable AI (or XAI) techniques. XAI can be incorporated in segmentation pipelines to understand model prediction on the input image which helps medical practitioners to trust the predictions made by the model.

7. Discussion and Conclusion

In this comprehensive review article, we present a detailed and thorough summary of the various methods that have been devised for medical image segmentation. The field of image segmentation offers a range of techniques, which can broadly be classified into two categories: mathematical models or algorithms based on learning methods. Learning methods, in turn, can be further categorized as either supervised or unsupervised learning. Additionally, segmentation methods can also be influenced by the nature of the imaging type, especially in the case of medical imaging. Moreover, in this article, we aim to address the segmentation problem from different perspectives and scales. We explore global segmentation techniques, which focus on capturing the overall structure of the image. On the other hand, we delve into structural segmentation methods that aim to identify and segment specific structures within the image. Furthermore, this article delves into regional segmentation techniques that aim to isolate and segment specific regions of interest within the image. Lastly, we explore local segmentation methods, which aim to segment smaller, localized areas within the image. By thoroughly examining and presenting these various methods, this article provides a comprehensive overview of the current techniques and approaches in the field of medical image segmentation. We hope that this summary will contribute to further advancements in this vital area of medical image analysis.

The use of medical image segmentation methods is crucial due to the increasing need for non-invasive, non-radiative techniques. These methods provide a meaningful representation of human anatomy and physiology, aiding in accurate diagnosis, treatment planning, therapy guidance, and non-invasive or minimally invasive surgery. Despite challenges like noise, intra-slice variation, and missing slices, intelligent machine learning and computational algorithms address these issues. The goal is to develop a method that can effectively handle diversity and achieve efficacy, efficiency, accuracy, and robustness for use in clinical practice. In healthcare, medical image segmentation is critical for boosting diagnostic accuracy and tailor treatment strategies. This paper gives a detailed description of several segmentation methods: classical, those based on machine learning, and also those on deep learning. Traditional approaches have interpretability and computational simplicity, but usually fail with intricate medical images and noise. Data-driven techniques based on machine-learning for accuracy at the cost of feature engineering. Conversely, initial, deep-learning based methods learned to automatically identify complex features and patterns, however they were costly and also required substantial annotated datasets (or labels) to help train the learning machine.

These advances notwithstanding, many challenges remain open. This includes developing segmentation models that are robust to noise, adaptive to multimodal data, and interpretable for clinical use. Additionally, improving upon existing deep learning approaches by mitigating their high computational demands and overcoming the scarcity of labeled datasets will be vital to future advancements.

Future work includes investigating hybrid approaches that leverage the benefits of both traditional and modern methods, improving model generalizability across diverse imaging modalities, and decreasing dependence on having a large corpus of annotated data via unsupervised and semi-supervised techniques. Furthermore, should focus on light weight models for real time applications and ethical deployments in clinical settings.

In highly competitive fields such as medical image segmentation a larger number of training datasets can lead to lower performance and quality of the results.

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