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# A Survey on Liver Lesion Detection Using CT Images- Current Techniques and Future Perspectives

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**Abstract** Liver disease represents a significant global public health issue, with early detection playing a crucial role in the effective treatment and management of the condition. The utilization of Computed Tomography (CT) imaging has become increasingly important in liver detection, providing high-resolution images that facilitate precise diagnosis. Clinicians commonly seek information regarding the liver's shape for treatment planning in order to minimize harm to surrounding healthy tissues and hepatic vessels, underscoring the importance of developing a geometric model of the liver. Various methods for liver image segmentation have been developed over time. This article presents a thorough examination of Traditional segmentation techniques such as thresholding, region-based growing algorithm, Contour-based algorithm, as well as Machine Learning (ML) and Deep Learning (DL) methods for Segmentation utilizing CT images, shedding light on the different techniques, algorithms, and challenges associated with this domain. We explore diverse approaches to liver segmentation, assess the efficacy of different methods using established metrics, and conclude by outlining potential avenues for future research.

***Keywords:*** *Computer aided diagnosis (CAD) system, Computed tomography, Contour-Based Segmentation , Deep learning,, Liver segmentation, , Machine Learning, Region Based Segmentation.*

## 1. Introduction

The liver is one of the most vital organs in the human body, playing a crucial role in metabolism, detoxification, and protein synthesis. When normal cells start multiplying excessively, it leads to the formation of a mass known as a tumor. Liver tumors can be either non-cancerous (benign) or cancerous (malignant). Benign tumors do not spread to surrounding tissues or other parts of the body, while malignant tumors are cancerous and have the ability to grow and spread throughout the body. Various types of tumors can develop in the liver. These tumors can have different visual features, and these features may change when a contrast agent is introduced [1].

Liver cancer is the 6th most common type of cancer, but the 3rd leading cause of cancer-related deaths globally in 2020 [2]. Similar to other forms of cancer, early detection and prompt treatment are crucial for liver cancer. Screening for liver cancer typically involves the use of ultrasound and non-contrast computed tomography (CT) scans, while diagnosis often relies on multi-phase contrast-enhanced CT scans. According to the Liver Imaging Reporting and Data System (LI-RADS) [3] guidelines, contrast-enhanced CT or MRI scans can effectively identify liver lesions in most cases. Traditional manual delineation of the liver by radiologists is time-consuming and subject to inter- and intra-observer variability, necessitating the development of automated liver detection systems. Automated computer-aided diagnosis (CAD) systems offer a promising solution to address these limitations.

Detecting and classifying liver lesions in CT images is a challenging task. The liver is a large and complex organ, with significant variations in the morphology of both the liver itself and any lesions present. Factors such as location, size, shape, intensity, and texture can all contribute to the difficulty in accurately identifying and localizing lesions. The intricate network of blood vessels and ducts within the liver, as well as the surrounding organs, further complicates the process. Additionally, changes in liver texture due to conditions like fat accumulation and fibrosis can create ambiguity in lesion detection. Finally, there are many different types of malignant and benign liver lesions, and some of these can appear quite similar in CT scans, making them hard to distinguish.

Another challenge is the lack of suitable datasets. Specifically, there are no large-scale, high-quality datasets of liver CT scans that are publicly available to learn or extract comprehensive patterns. These datasets would need to cover various liver conditions and include labels for major tumor types, among other details. According to medical guidelines, radiologists require multi-phase contrast-enhanced liver CT images to determine tumor

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types, and in some cases, pathology reports are necessary. The ideal dataset would have comprehensive, voxel-level annotations of related organs, vessels, and liver lesions, as well as clinically-confirmed lesion types for all lesions, which are difficult to obtain. Most existing studies rely on their own in-house datasets with limited labels, such as only bounding box annotations of lesions and/or without labels for lesion types. Additionally, creating a high-quality liver lesion dataset involves sensitive, diagnosis-related privacy information and clinical practices, making it challenging to make such datasets publicly available.

## 2. Conventional Methods for Liver Segmentation

Early approaches to liver detection relied heavily on traditional image processing techniques. These methods typically involve a series of preprocessing steps such as noise reduction, contrast enhancement, and edge detection, followed by thresholding, region-based or contour-based segmentation.

### A. Thresholding Approach

Thresholding is one of the simplest methods where pixel intensity values are segmented based on a global or local threshold. However, due to the similar intensity values between the liver and its surrounding organs, thresholding alone often failed to provide accurate segmentation. Various studies propose different methods for automatic segmentation of liver lesions, such as H-minima transform filter combined with Otsu global thresholds for liver segmentation [4], fuzzy logic and Shannon's entropy function for tumor segmentation [5], multilevel thresholding with electromagnetism optimization (EMO) for liver tumor segmentation [6], and histogram thresholding for distinguishing liver tissues in CT images [7] have been proposed. Additionally, a method utilizing thresholding of the Cahn-Hilliard solution for liver lesion segmentation has been introduced, which separates healthy liver tissue from lesions based on image intensities [8].

### B. Region Based Segmentation

Region-based segmentation methods, such as thresholding and region growing, have been widely used for liver detection. These techniques rely on the intensity values of the pixels to differentiate the liver from surrounding tissues. Various approaches have been proposed to enhance liver image segmentation, such as contrast enhancement algorithms, intensity distribution analysis, and boundary incorporation to improve accuracy and achieve high Dice scores [9]. Additionally, size selection region growing algorithms have been developed to accurately extract liver regions from CT images, utilizing preprocessing steps like thresholding, region growing, and morphological operations [10]. Furthermore, the utilization of region growing techniques, combined with contrast stretching and morphological operations, has shown promising results in segmenting liver regions from other organs with high accuracy, validated through similarity index and achieving an overall accuracy of 91.3% [11]. Moreover, liver level set algorithms have been introduced to automatically segment disconnected liver regions, ensuring accurate segmentation results with a Dice similarity coefficient percentage of 87.5% [12].

### C. Conture Based Segmentation

Contour-based methods, including active contour models (snakes) and level sets, focus on delineating the liver boundaries. These approaches are more robust to intensity variations but can be sensitive to the initial placement of the contour and may converge to local minima, leading to suboptimal segmentations. A novel method utilizes a multi Gabor feature map to describe patch homogeneity nonlocally, leading to robust segmentation results with a mean overlap error of less than 23.86% [13]. Additionally, an active contour model with an embedded classifier, based on a Gaussian mixture model, has been developed to accurately extract liver tumors and vessels, showcasing flexibility and accuracy in complex background scenarios [14]. Furthermore, the use of a multidistribution level set method has shown significant improvements in segmenting liver tumors with low contrast and blurred boundaries, outperforming traditional level set methods [15].

**Table 1:** Performance Analysis of Conventional Liver Segmentation Approaches

| References | Methods | Data Set | Result | Remarks |
|---|---|---|---|---|
| Nazish, Khan et al. [4] | H-minima transform filter combined with Otsu global thresholds for liver segmentation | Private Data set from Rahman Medical Institute, Pakistan | Dice Score: 94%<br>Sensitivity: 93%, specificity: 87% | Variability in size, shape, position of liver and lesions. Presence of other organs with similar intensities. |
| Deepesh et al. [5] | multilevel thresholding with fuzzy logic and Shannon's entropy | Private Data Set | Accuracy: 93% | Execution time is too high when dealing with .jpg format image |
| Lamia et al. [6] | multilevel thresholding with | Private Data Set | Liver segmentation: Accuracy: 98.47% , | Difficult to find Optimal threshold identification for |

| References | Methods | Data Set | Result | Remarks |
|---|---|---|---|---|
| | electromagnetism optimization | | Sensitivity: 97.05%, Specificity: 99.88% Liver tumor segmentation: Accuracy: 96.86% , Sensitivity: 94.15% Specificity: 99.57% | image segmentation |
| Tugce et al. [7] | Watershed and histogram thresholding methods | Private Data set: collected from Radiology Department of Başkent University, Adana | Accuracy: 95.64% | Data set is too small only 22 images used for training |
| Jana et al. [8] | Thresholding based on Cahn-Hilliard phase separation. | Public Data set: 3Dircadb dataset LITS dataset | 3dircadb Dice: 0.61 ± 0.22 Sensitivity: 0.64 ± 0.18 Specificity: 0.99 ± 0.01 LIST Dice: 0.53 ± 0.27 Sensitivity: 0.70 ± 0.21 Specificity: 0.98 ± 0.02 | High noise in CT scans Low contrast between liver and lesions |
| Shima et al. [9] | adaptive 3D region growing algorithm with probabilistic atlas | Data set collected from Institutional Review Board (IRB) | Dice: 92.56% | Limited to liver segmentation only |
| Shaimaa et al.[10] | region growing and morphological operations. | Data collected from the liver imaging Atlas | Accuracy: 95% | Limited to liver segmentation only |
| Abdalla et al.[11] | Region Growing algorithm | Private data set | Accuracy: 91.3% | Some optimization techniques need to hybrid with proposed approach to improve result |
| Puteri et al. [12] | Liver level set algorithm enhancement of region growing | Private data set | Dice: 87.5% | Choosing the wrong first slice, would lead to wrong segmentation result |
| Chen et al. [13] | nonlocal active contours with multi Gabor feature map | Private Data set | Mean overlap error less than 23.86%. | The proposed method's performance heavily relies on the quality of the initial segmentation, which can impact the final results |
| Yanfeng et al. [14] | active contour model with embedded Gaussian classifer | Private data set | Proposed method well performed compare with Geodesic Active Contour, C-V (active contour without edges) | The paper mentions that the developed model is accurate, flexible, and suited for extracting objects surrounded by a complicated background. Still, it does not provide specific quantitative metrics or results to support these claims, making it challenging to assess the model's performance objectively. |
| Qianqian et | multidistribution | Public Data set: | Proposed model | Computational Complexity is |

| References | Methods | Data Set | Result | Remarks |
|---|---|---|---|---|
| al. [15] | level set method | 3Dircadb dataset | outperformed the CV model and LSACM model. | high |

**3. Machine learning (ML) based Liver Segmentation**

Machine learning techniques have introduced more sophisticated methods for liver detection by learning from annotated datasets. These approaches typically involve feature extraction, model training, and classification.

A methodology which involves the iterative application of a multi-class Bayesian classification system introduced [16]. Initially, models are developed to represent the Intensity of liver, tumor, and other relevant areas. Subsequently, the posterior probabilities for individual voxels are determined based on the multi-class distribution acquired earlier, in conjunction with a uniform prior distribution model. A 3D liver tumor segmentation which combines watershed transform and SVM classification is applied [17]. After undergoing various preprocessing steps, such as segmenting the liver parenchyma and enhancing liver contrast, the CT volume is divided into numerous catchment basins using watershed transform. Subsequently, a support vector machines (SVM) classifier is utilized to train on seed points selected by the user for tumor extraction from the liver parenchyma, with the feature vector for training and prediction being calculated based on each small region generated by watershed transform. Lastly, morphological operations are applied to the entire segmented binary volume in order to enhance the initial segmentation outcome of SVM classification. A methodology for automated segmentation of the liver in three dimensions is developed [18].The approach involves the application of a clustering technique based on k-means for the creation of a region of interest. This is succeeded by the utilization of a region growing algorithm for the initial segmentation, followed by the implementation of a localized contouring algorithm to achieve a more precise segmentation. An automated segmentation approach in which the initial delineation of tumors is achieved through the utilization of a Support Vector Machine (SVM) classifier [19]. This is then succeeded by the application of a Markov random field-based omnidirectional deformable surface model to further enhance the accuracy of the segmentation process. A novel approach for liver segmentation, which involves the delineation of initial liver boundaries through artificial bee colony clustering followed by morphological operations introduced [20]. Subsequently, a region growing technique is employed to achieve a more precise segmentation. An automated method for identifying liver lesions using an initial detection of the liver based on blood vessel information and histogram fitting with a variational Bayesian Gaussian mixture model presented [21].

**Table 2:** Performance Analysis of Machine Learning based Liver Segmentation

| References | Method | Data set | Result | Remarks |
|---|---|---|---|---|
| Moti et al. [16] | multi-class Bayesian classification | MDCT data set 3Dircadb dataset | Liver and tumor volume estimation correlation: 0.98 and 0.99. Total score for the second database: 67.87% | It relies on user-defined voxel seeds for initialization, which may introduce variability based on seed selection |
| Xing et al. [17] | combines watershed transform and SVM | MICCAI 2008 data set | averaged overlap error: 31.14% | It does not address the potential user variability in selecting seed points for training the SVM classifier, which could introduce subjectivity and inconsistency in the segmentation results, |
| Goryawala et al. [18] | k-means based segmentation algorithm with region growing | 3Dircadb dataset | Volume accuracy: 97.22%, Dice Score: 0.92 | The algorithm's performance was evaluated using 34 liver CT scans, which may not fully represent the diversity of liver shapes and sizes in the general population |
| Vorontsov et al. [19] | deformable model and Texture based SVM | Private Data set | Dice score: 0.81 ± 0.06 | It is semi-automatic approach indicating that some level of user interaction or intervention may be required during the segmentation process, |
| Mostafa et | Clustering based | Private Data | Accuracy: 93.73% | The paper mentions the use of |

| | | | | |
|---|---|---|---|---|
| al. [20] | artificial bee colony optimization algorithm | set | | morphological operations to remove small objects in the segmented images, but it does not delve into the specific types of morphological operations employed or their impact on the segmentation results |
| Maklad et al. [21] | Bayesian Gaussian mixture Model | MICCAI 2008 data set | Total Score: 79.7% | The algorithm's performance was evaluated using 60 liver tumor CT scans, which may not fully represent the diversity of liver shapes and sizes in the general population |

**4. Deep learning (DL) based Liver Segmentation**

In recent years, deep learning has revolutionized the field of medical imaging, offering unprecedented accuracy and robustness in liver detection. Fully Convolutional Networks (FCNs) and their variants have become the state-of-the-art methods for this task. In a broader sense, FCN is a CNN with the FC layer replaced by deconvolutional (or transposed convolutional) layer to perform pixel wise classification.

In [22], two FCNs based on the VGG-16 model were devised specifically for the detection of liver and lesions. Conventional data augmentation methods such as scaling, transformation, and rotation were applied in this process. In [23], a Cascade Two FCN based UNet Model was employed for the segmentation of liver and lesions, with the refinement of output through the use of refined 3D Conditional Random Fields. The Pre-processing stage involved HU Windowing to eliminate irrelevant details, contrast enhancement via Histogram equalization, and the utilization of traditional data augmentation techniques. In [24], variously sized patches extracted from abdominal CT images were utilized as input for five Convolutional Neural Networks (CNNs), with pre-processing steps involving Gaussian smoothing filtering and Z-score normalization. In [25], the application of two deep convolutional neural networks (DCNN) incorporated long-range UNet and short-range ResNet skip connections, followed by the implementation of 3D connected component labeling on each DCNN output for result refinement. In [26], liver segmentation was conducted using Simple ResNet, followed by the development of a 2D-DenseUNet that integrated densely connected paths and UNet connections to combine inter-slice and intra-slice features. Pre-processing included HU Windowing and data augmentation through mirroring and scaling. In [27], a Cascade 3D FCN structure was employed, comprising multiple Attention Hybrid Connection Blocks (3-AHCBlocks) densely connected with long and short skip connections, as well as soft and hard self-attention modules, to achieve rapid and accurate semantic segmentation of medical images.

In [28], an enhanced version of FCN was created by introducing a variable pooling kernel to enhance liver region delineation, followed by the replacement of pooling and convolution layers in the second FCN with dilated convolution for improved global feature extraction of small tumors. Post-processing involved the use of Conditional Random Fields (CRFs) to further refine the results obtained from cascaded FCNs. In [29], two Cascade Unet Models were trained for liver and tumor segmentation, with the final outputs of each network being upsampled to their original dimensions using Bi-linear interpolation. Image enhancement was carried out through Contrast Limited Adaptive Histogram Equalization (CLAHE). In [30], a modified UNet architecture was proposed, incorporating a residual path with deconvolution and activation operations in the skip connection to prevent the duplication of low-resolution feature information. Additional convolution layers were added to the skip connection to extract high-level global features from small object inputs and high-level features from high-resolution edge information of large object inputs. In [31], the development of Cascade U-ResNets, inspired by U-Net and ResNet, for liver and lesion segmentation was discussed. The performance was evaluated using five different loss functions: Weighted Cross Entropy (WCE), Dice Loss (DL), Weighted Dice Loss (WDL), Teversky Loss (TL), and Weighted Teversky Loss (WTL).

**Table 3:** Performance Analysis of Deep Learning based Liver Segmentation

| References | Method | Data Set | Result | Remarks |
|---|---|---|---|---|
| Ben-Cohen et al. [22] | Two FCN with Tradition Data Augmentation | Private Data set: Sheba medical center<br>Public Data set: | Liver segmentation:<br>Dice: 0.89<br>Sensitivity: 0.86<br>Precision: 0.95<br>Lesion detection: | Segmentation output of the liver may not include some boundary pixels that are darker and less similar to the liver parenchyma |

| References | Method | Data Set | Result | Remarks |
|---|---|---|---|---|
| | | SLIVER07 | True Positive rate: 0.86<br>False Positive rate: 0.6 | |
| Christ et al. [23] | Cascade Two FCN based UNet Model is utilized for Liver and lesion segmentation + Post processing-Output are refined using refined 3D Conditional Random Fields | Public Data set:<br>3Dircadb dataset | Dice: 94% | In Native UNet, contextual information of the low-level encoder feature is insufficient, leading to poor performance for pixel-wise recognition when concatenating with the corresponding high-level decoder feature |
| Wen Li et al. [24] | 5 CNN with Patch extraction from CT image | Private Data set collected from Zhujiang Hospital affiliated with Southern Medical University | Patch size 17 x 17<br>Dice: 80.06%<br>Precision: 82.67%<br>Recall: 84.34% | Poor Performance in case of segmenting tumor in with heterogeneous intensity and unclear boundary |
| Han et al. [25] | Two DCNN with a 3D connected component labelling as Post processing | Public Data set:<br>LIST 2017 | Dice: 67% | Training of each model took about 4 days using a single NVIDIA Titan X GPU with 3584 cores and 12 GB memory. |
| X. Li et al. [26] | ResNet and 2d-DenseUNet | Public Data set:<br>3Dircadb dataset<br>LIST 2017 | 3D IRCADb-01<br>Liver segmentation: 92.9%<br>Tumor segmentation: 82.4%<br>LiTS<br>Liver segmentation: 96.5%<br>Tumor segmentation: 82.4% | To improve small tumor detection, perceptual generative adversarial networks (GANs) can be used |
| H. Jiang et al. [27] | 3D FCN with attention modules | Public Data set:<br>3Dircadb dataset<br>LIST 2017 | 3D IRCADb-01<br>Liver segmentation: 95.9%<br>Tumor segmentation: 73.4%<br>LiTS<br>Liver segmentation: 94.5%<br>Tumor segmentation: 62% | To enhance tumor segmentation result post processing can be applied |
| Yuwei Pang et al. [28] | TWO FCN with Dilated Convolution | Public Data set:<br>3Dircadb dataset<br>LIST 2017 | DICE coefficient for 3D IRCADb-01 dataset: Tumor segmentation: 85.71% and LiST dataset: Tumor segmentation: 82.43% | While the proposed modifications show improved performance in segmenting small tumors, the paper does not discuss the potential impact on the segmentation of larger or more complex tumors, |
| Albishri et al. [29] | Cascade two Unet with Bi-linear | Public Data set: | LiTS data set- Dice Value | While the model achieved high Dice scores of 0.894 for liver segmentation and |

| References | Method | Data Set | Result | Remarks |
|---|---|---|---|---|
| | interpolation | LIST 2017 | Liver segmentation: 89.4%<br>Tumor segmentation: 59.5% | 0.595 for tumor detection, the evaluation was based on these metrics alone. Including additional metrics such as sensitivity, specificity, or false positive rate could provide a more comprehensive assessment of the model's performance. |
| H. Seo et al. [30] | Cascade two Unet with deconvoluation | Public Data set: 3Dircadb dataset<br>LIST 2017 | 3D IRCADb-01<br>Liver segmentation: 96.1%<br>Tumor segmentation: 68.14%<br>LiTLiver segmentation: 98.51%<br>Tumor segmentation: 89.72% | The paper highlights that the conventional U-Net's duplication of low-resolution information through skip connections can cause smoothing of object boundary information, particularly problematic for objects with fuzzy boundaries. This limitation can impact the network's ability to precisely delineate object boundaries in CT images. |
| X. Xi et al. [31] | Cascade U-ResNets (inspired by U-Net and ResNet) | Public Data set:<br>LIST 2017 | Liver segmentation: 94.9%<br>Tumor segmentation: 75.2% | The paper focuses on investigating the performance of different loss functions for liver and lesion segmentation but does not compare the computational efficiency or training time of these methods, which could be crucial for practical implementation. |

## 5. Publicly Available Data Set

Publicly available datasets currently consist of the cancer imaging archive of the Frederick National Laboratory for Cancer Research [33], the 3Dircadb dataset from the Research Institute against Digestive Cancer [34] ,the MIDAS liver tumor dataset from the National Library of Medicines Imaging Methods Assessment and Reporting (IMAR) project [34] and the Sliver’07 dataset from The Medical Image Computing and Computer Assisted Intervention Society MICCAI liver segmentation challenge [35]. Manual outlining of liver (Sliver’07, 3Dircadb), liver tumor contours (MIDAS, 3Dircadb), and liver blood vessel contours (3Dircadb) by radiological experts was conducted on a slice-by-slice basis to establish the ground truth. Segmentation of the 3Dircadb and Sliver’07 datasets was performed by a single radiologist, whereas the MIDAS dataset underwent segmentation by five different radiologists.

## 6. Challenges and Future Directions

Despite significant advancements, several challenges remain in liver detection using CT images:

1. **Variability in Liver Appearance**: The liver's appearance can vary widely due to differences in patient anatomy, pathology, and imaging conditions.
2. **Proximity to Other Organs**: The liver is located near other organs with similar intensity values, making it difficult to distinguish boundaries.
3. Limited Annotated Data: High-quality annotated datasets are essential for training robust models, but such data is often scarce.
4. **Noise and Artifact**: CT images often contain noise and artifacts, complicating accurate segmentation.

Future research should focus on addressing these challenges through:

1. **Data Augmentation and Synthesis**: Generating synthetic data to augment training datasets and improve model robustness.
2. **Multi-Modal Approaches**: Combining information from multiple imaging modalities (e.g., MRI, PET) to enhance liver detection accuracy.
3. **Transfer Learning**: Leveraging pre-trained models on related tasks to improve performance with limited data.
4. **Interactive Segmentation**: Developing user-friendly tools that allow clinicians to interactively refine segmentations for improved accuracy

## 7. Conclusions

This paper discusses the various approaches used for Traditional, ML and DL based liver and tumor segmentation. Numerous inferences can be drawn from previous research. Initially, techniques that solely depend on pixel intensity appear inadequate for segmenting lesions other than metastases. Subsequently, segmenting liver lesions within a liver envelope seems to enhance accuracy, especially for automated segmentation approaches. Lastly, the incorporation of machine learning methods appears to significantly improve tumor detection and segmentation precision.

Relying solely on intensity for segmentation is not effective for tumors and vasculature. While some primary tumors and many metastases exhibit distinct intensity ranges compared to healthy liver tissue, these ranges can vary depending on imaging systems and patient anatomy. Moreover, accurate identification of many primary tumors relies on their texture characteristics. This trend is evident in the literature, where approaches integrating texture features and machine learning techniques demonstrate the most precise segmentation across various types of lesions. The utilization of machine learning can markedly enhance the precision of liver tumor segmentation, as the most effective methods employ machine learning techniques. Conversely, conducting segmentation within a liver envelope yields superior outcomes for lesion segmentation and classification within the liver. Previous studies have indicated that segmenting liver lesions solely within the liver results in higher accuracy, particularly with automated methods.

In comparison to recent automated techniques, semi-automatic methods do not present significant advantages. The most favourable outcomes for liver tumor segmentation are typically achieved through automated approaches. Additionally, automatic segmentation offers two notable benefits over semi-automatic methods. Firstly, it does not necessitate user interaction and is generally quicker than alternative segmentation methods. Furthermore, it ensures reproducibility by eliminating the need for constant user input.

In recent era, DL based fully automated liver and tumor segmentation is widely used. Main problem with this techniques computationally expensive and required huge amout of annoted data set.

Despite the numerous liver segmentation methodologies proposed, there remains room for enhancement, particularly in pathological livers characterized by irregular shape and intensity patterns posing challenges for automated segmentation. Moreover, methods for segmenting tumors and vasculature are relatively underdeveloped and underexplored due to the insufficient availability of suitable datasets

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