# MRI-based Liver Tumor Image Segmentation using Deep Learning Techniques

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### Abstract

Segmentation of tumors from Magnetic Resonance Imaging (MRI) is very important for early diagnosis and treatment of the disease. In general, tumor segmentation is a challenging task due to different shapes and intensity levels of tumors, along with different liver tissues around the tumor. In this research, a hybrid network of U-net and Swin CNN has been proposed for automatic segmentation of liver tumors and quantification of tumor size using MRI images. The proposed system includes image pre-processing, hierarchical feature extraction, liver segmentation, tumor detection, and severity quantification into single pipeline. Feature extraction is done using convolutional neural network layers while long-distance contextual information is extracted using the Swin transformer blocks for enabling a better segmentation. Quantification is processed using the estimation of the liver area, tumor area, and ratio of tumor-to-liver area, and then visualization of the segmentation result. The proposed method achieves the highest accuracy of 96.5% on the MRI dataset.

**Keywords:** U-Net–Swin CNN, Liver Tumor Segmentation, Magnetic Resonance Imaging (MRI), Hierarchical Feature Extraction, Tumor Localization, Quantitative Liver Analysis.

## 1. Introduction

Liver diseases, like as hepatocellular carcinoma, metastatic tumors and cystic lesions represent a serious public health problem in the world and remain as one of the most common


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reasons for cancer-related death. Accurate identification and segmentation of lesions in both Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) images is vital for early diagnosis, treatment planning, surgical intervention, as well as disease monitoring. Nonetheless, radiologists carry out manual analysis of medical images, which is a time-consuming and labour-intensive task that heavily relies on clinical expertise and incurs inter-observer variability. Moreover, due to the complicated anatomy of liver, the differences in tumor sizes and shapes between cases, low-contrast delineating borders as well as varying quality of imaging modality used, accurately segmenting and detecting liver abnormalities is highly challenging. As a result, traditional image processing methods for automated liver and tumor analysis provide reliable and robust solutions

Artificial Intelligence (AI) and Deep Learning (DL) have revolutionized medical image analysis through improved automated and high accuracy diagnostic systems recently. By nature, Convolutional Neural Networks (CNNs) are very powerful in the local extraction of spatial features and learning target discriminative representations from medical images, while transformer-based architectures perform well at capturing long-range dependencies and global contextual information. All these methods make use of the hybrid deep learning models, which have been developed to create a more advanced version of the model that improves the segmentation performance and robustness in case of difficult medical imaging problems. These intelligent systems can help to reduce diagnostic load, increase consistency of interpretation, and assist with computer-aided diagnosis.

Thus, the power of several deep learning methods has been employed in liver segmentation and tumor detection but most of them only focus on increasing segmentation accuracy with a minimal support for the entire clinical analysis and visualization. To address these limitations, this work presents an intelligent Liver Segmentation and Tumor Analysis Dashboard built on the hybrid U-Net–Swin CNN architecture for automated MRI liver image analysis. The proposed framework combines liver segmentation and tumor detection, quantitative analysis, and clinical visualization into a single coherent system to provide an effective computer-aided diagnostic tool to aid radiologists during repetitive tasks and strengthen the quality of clinical decision-making processes. Main contributions of this work include A Hybrid Deep Learning Model Report Data Augmentation for effective Liver and Tumor Segmentation, An Automated framework based on L-MR & CT data to automatically assess tumor severity operation compared with manual assessment and the interactive dashboard design with visualization plots5-8 for expected results and Design Dashboards about Changing Detections times.

## 2. Related Works

Recent developments in deep learning have helped to achieve better segmentation of liver tumors using CNNs and Transformers, providing an effective way to learn the spatial features and context of liver images simultaneously. Convolution–transformer networks have been successful at achieving better segmentation performance for complicated liver shapes; multi-scale transformer-based U-Net networks have provided better feature extraction and boundary localization for liver tumors [1], [2]. Moreover, end-to-end transformer-based detection pipelines have helped in identifying the liver tumors by leveraging semantic information from medical images [3].

Hybrid CNN-Transformer models have been extensively researched for liver images because of their ability to combine local feature extraction along with global context modeling. Hybrid approach-based classification models have improved the detection of focal liver lesions while the fusion of features with Transformer model has improved accuracy in segmentation and maintained anatomical structure [4], [5], [6], [7]. Moreover, attention mechanisms with Swin Transformer and encoder-decoder model with multi-layered feature integration have proven effective for feature extraction in accurate segmentation and classification of liver tumors. The research community has also investigated transformer models to analyze medical images such as end-to-end lesion detection, 3D swin transformers, and unsupervised visual representation learning [3], [10], [11]. The above-mentioned approaches improve the performance of feature learning and contextual understanding while minimizing the use of engineered features. However, most existing approaches concentrate only on segmentation and classification tasks and have little support for clinical analysis. To mitigate the above problem, this developed a framework integrating liver segmentation, tumor localization, severity quantification, and interactive visualization into one unified U-Net-Swin CNN model for MRI liver tumor analysis.

## 3. Proposed Work

The intelligent AI-based liver segmentation and tumor analysis dashboard for automated diagnosis of abnormalities from MRI images is proposed in the framework shown in Figure 1. This dashboard integrates deep learning and medical image processing using interactive visualization techniques to automatically process MRI scans of medical images to detect liver boundaries, identify tumor regions, report clinical severity metrics without the need for manual intervention Furthermore, a hybrid UNET-Swin CNN architecture is used to provide convolutional feature extraction in addition to global attention with transformer based algorithms enabling precise segmentation of liver tumors also in extreme anatomical situations. It is a pipeline of multi-stage processing including pre-processing (i.e., normalization), liver segmentation, tumor detection, quantitative analysis and performance evaluation. Subsequent to extraction of results, visualization of the outputs is carried out through a stream-lit dashboard that enables clinicians to visualize overlays/metrics and download reports. With the incorporation of different AI models for diagnosis, real-time visualization and automated radiology reporting, provides timely diagnoses with minimum human intervention by providing accurate computer aided diagnosis to radiologists.

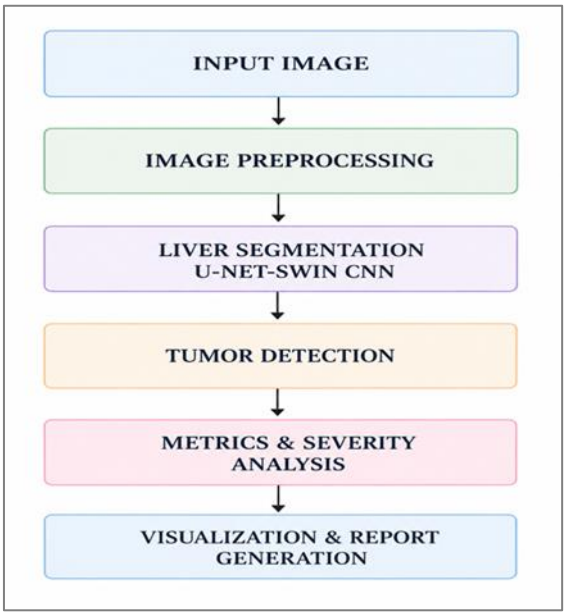


**Figure 1.** Workflow of the proposed liver tumor segmentation framework

### A. Medical Image Acquisition and Pre-processing

Initially, MRI liver scans are obtained from Swin-Unet Liver Tumor Segmentation dataset. All medical images are usually a bit noisy and variable in terms of intensity and resolution, thus pre-processing step performed before image input feeding to the model that helps it to perform better. Overall goal of the proposed framework is to apply 3 × 3 median filter to eliminate impulse noise along with edge information and liver boundary details maximally retained. The filtering operation can be formulated as

$$I_{\{filtered\}(x,y)} = Median\{I(i,j)\} \tag{1}$$

Where, $I(i,j)$ represents the neighboring pixels surrounding the pixel located at $x, y$. Subsequently, pixel intensity normalization and image resizing to a standard dimension of $128 \times 128$ pixels are performed to ensure consistency across the dataset and reduce computational complexity during model inference. Pre-processing stage helps in achieving robust feature extraction, improves segmentation performance, and reduces false detections in the process of liver and tumor segmentation.

**B. Dataset Description, Feature Extraction and Model Parameters**

The proposed liver tumor segmentation framework is based on labeled abdominal MRI Kaggle Swin-Unet Liver Tumor Segmentation dataset, which was adapted from the Liver Tumor Segmentation (LiTS) benchmark, it contains 3-D images with corresponding ground-truth liver and tumor masks [12]. The dataset includes healthy and diseased liver images which have variations that are high in diversity with regards to the size, shape, location, irregularity of the boundaries, and intensity of tissue. This makes the dataset suitable for evaluation using deep learning models in practical clinical scenarios. The details of the dataset characteristics and the deep learning model parameters are included in Table 1. All images are pre-processed before training a model: median filtering is used to reduce noise, histogram normalization reduce lighting variation during imaging of the same tissue samples with the use of different machines, and lastly resized to a fixed spatial resolution of 128 × 128 pixels. These pre-processing operations standardize the input images, improve image quality, reduce computational complexity and enhance consistency in feature extraction in preparation for training the model.

The proposed U-Net–Swin CNN effectively extracts hierarchical features automatically from medical images. The convolutional encoder extracts low-level visual features, such as intensity changes, edge information, texture distributions and organ margins; the Swin Transformer blocks multi-scale patches in a sliding window manner via self-attention to learn long-range contextual relations and interdependencies. The decoder incrementally integrates these multi-scale representations through skip connections to create accurate liver and tumor segmentation masks. The synthesis of local spatial representation and global contextual information provides the accurate localization of tumors with irregular shapes while reducing the segmentation errors.

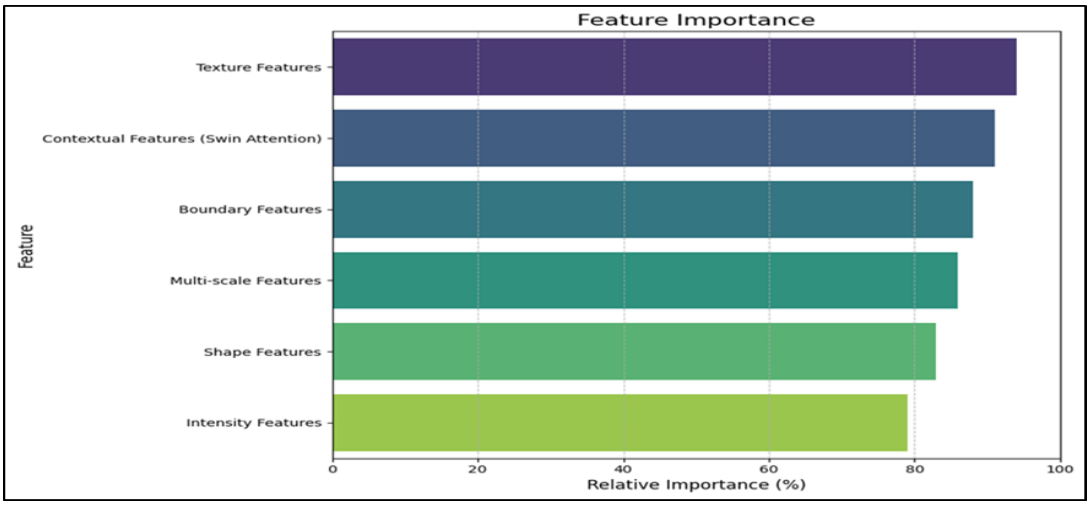


**Figure 2.** Feature contribution in the proposed U-Net–Swin CNN

Figure 2 shows the relative contribution of each learned feature category for the proposed deep learning framework. The boundary and texture features along with the context around them are used to distinguish tumor tissue from surrounding liver parenchyma, while the multi-scale representation can help in detecting segmented tumors near irregular lesion borders. Shape and intensity features give complementary anatomical information that promotes accurate liver localization and quantitative liver tumor assessment. Figure 2 clearly depicts the relative importance of the learned feature categories and not direct experimental measures of feature importance values.

**Table 1.** Dataset characteristics and training parameters

| Parameter | Value |
|---|---|
| Dataset Source | Swin-Unet Liver Tumor Segmentation (LiTS-based) |
| Imaging Modality | MRI |
| Image Format | PNG |
| Image Resolution | 128 × 128 pixels |
| Color Channels | RGB |
| Segmentation Classes | Background, Liver, Tumor |
| Network Architecture | U-Net–Swin CNN |
| Learning Rate | 0.001 |
| Batch Size | 16 |

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### C. Liver Segmentation using U-Net–Swin CNN Hybrid Model

The liver segmentation module isolates MRI images to find a liver region. The propose approach based on hybrid U-Net-Swin CNN architecture incorporates segmentation blocks of convolutional neural networks along with Swin Transformer blocks to optimize the overall performance. The encoder obtains hierarchical image representations and the proposed Swin Transformer employs shifted-window self-attention to collect global contextual information, allowing accurate segmentation of complex liver structures as well as irregular boundaries.

The decoder continues the process of creating the segmentation mask of the liver using up sampling and skip connection operations, maintaining anatomically fine details and boundaries. Feature fusion at multiple levels improve the results of segmentation by integrating spatial features from lower levels and semantic information from higher levels. Self-attention operation is formulated as

$$Attention(Q,K,V) = Softmax\left(\frac{QK^{T}}{\sqrt{d_k}}\right)V \tag{2}$$

where, $Q$, $K$, and $V$ represent the query, key, and value matrices, respectively, and $d_k$ denotes the dimensionality of the key vectors.

The obtained liver mask is the region of interest for the subsequent tumor detection stage, reducing background noise and improving the accuracy of quantitative tumor analysis.

### D. Tumor Detection and Localization

Following liver segmentation, the proposed framework identifies tumor regions by analyzing only the segmented liver area, thus eliminating interference from surrounding anatomical structures. The convolutional neural network learns to characterize discriminatory tumor features from the segmented MRI image. A light-weighted convolutional neural network is used to extract tumor characteristic features from the segmented MRI image. The neural network learns tumor features by extracting hierarchical spatial features using convolution and pooling processes and then the feature aggregation and classification is performed. The overall model structure for tumor identification is summarized in Table 2.

Tumor feature representations are used to produce a binary tumor mask, which marks potentially suspicious regions inside the liver. On the basis of the identified tumor regions, the tumor measurement values such as tumor area, tumor number, tumor to liver area ratio, and maximum tumor diameter are computed. Such values provide clinical meaningful information that helps to assess the level of tumor growth. The restriction of analysis to the segmented region of the liver results in better localization and increased accuracy of further analysis and visualization.

**Table 2.** Tumor detection network configuration

| Layer | Configuration | Output |
|---|---|---|
| Input | Segmented MRI liver image (128 × 128 × 3) | 128 × 128 × 3 |
| Convolution Block | Conv2D + ReLU + Max Pooling | Feature Maps |
| Feature Learning | Multi-layer CNN Feature Extraction | High-level Features |
| Classification Layer | Global Average Pooling + Dense | Tumor Representation |
| Output Layer | Sigmoid Activation | Tumor / Non-Tumor |

### E. Quantitative Analysis and Evaluation Metrics

The quantitative analysis module evaluates the efficiency of the segmentation algorithm using defined medical image-based parameters for segmentation and tumor localization. Metrics such as the dice similarity coefficient, Intersection over Union (IoU), accuracy, precision, recall, and F1-score are calculated by the system to assess the prediction results. Additionally, the system calculates clinical parameters such as the tumor-to-liver ratio, the severity of the condition, and the risk category (low, moderate, or high). The obtained values are useful for doctors for assessing the progression of the condition and developing treatment strategies. The knowledge in both technology and medicine is required for keeping the system interpretable and relevant.

Evaluation of the Quantitative Analysis module, the performance of segmentation and detection is estimated using predefined parameters of medical imaging. The performance is assessed in terms of quality of prediction using the parameters such as Dice coefficient, IoU, accuracy, precision, recall, and F1 score. In addition to performance parameters, the system computes the clinical parameters such as the ratio of the area of the tumor to that of the liver, severity level, and risk classification into low, moderate, or high. These numerical results assist doctors to analyze the progress of the disease and come up with treatment strategies.

### F. Interactive Visualization and AI Dashboard

The proposed framework includes the use of a Streamlit-based AI dashboard to provide an intuitive interface for automatic MRI liver tumor analysis. The dashboard contains the navigation panel with such modules as Comprehensive Analysis, Tumor Focus, Batch Processing, Model Analytics, Train Model, and About, which will allow easy access to various diagnosis tools. In particular, there is a special interface to upload the image of interest in PNG, JPG, and JPEG format using drag-and-drop or file browser. In order to aid visual interpretation of results, there are samples of images of malignant, benign, and normal liver cases that can be used by doctors for comparison with the produced segmentation results. There is also a model information panel that gives information about some important details of the framework, such as U-Net–Swin CNN architecture, input image size (128 × 128), liver and tumor segmentation output, and diagnostic possibilities.

## 4. Results and Discussion

The performance of the proposed U-Net-Swin CNN architecture was analyzed through the usage of MRI images of livers with the purpose to estimate its segmentation ability in various clinical cases. For such estimation, typical criteria like Accuracy, Precision, Recall, Specificity, F1-Score, and AUC were employed to measure the diagnostics capabilities of the model. The comparative results for all three model's discussion are given in Table 3. The proposed model demonstrated superiority in contextual learning significantly improves segmentation accuracy and diagnostic reliability.

**Table 3.** Diagnostic performance of proposed models on the validation dataset

| **Model** | **Accuracy (%)** | **Precision (%)** | **Recall/ Sensitivity (%)** | **Specificity (%)** | **F1-Score (%)** | **AUC** |
|---|---|---|---|---|---|---|
| CNN | 89.4 | 88.7 | 87.9 | 90.2 | 88.3 | 0.91 |
| U-Net | 92.8 | 91.6 | 92.1 | 93.4 | 91.8 | 0.94 |
| Proposed Hybrid Model | 96.5 | 95.8 | 96.2 | 97.1 | 96.0 | 0.98 |

Reliable segmentation should produce both high accuracy in predictions and high agreement with expert annotations. Hence, a statistical comparison was conducted using Kappa Score, F1-Score and significance testing as shown in Table 4. The proposed framework achieved the highest agreement with manual annotations, demonstrating consistent segmentation performance and improved robustness. The statistical significance further validates that the observed performance improvement is not due to random variation and hence, the applicability of the proposed framework for automated liver tumor analysis is supported.

**Table 4.** Statistical evaluation of segmentation performance

| Method | Accuracy (%) | Kappa Score | F1 Score | P-Value |
|---|---|---|---|---|
| Expert Manual Analysis | 90.6 | 0.82 | 0.90 | – |
| CNN | 89.4 | 0.79 | 0.88 | <0.05 |
| U-Net | 92.8 | 0.85 | 0.92 | <0.01 |
| Proposed Hybrid | 96.5 | 0.93 | 0.96 | <0.001 |

Interpretation of the visualized results is significant for confirming the accuracy of the process of segmentation. The following figure 3 shows the entire MRI liver tumor analysis process that has been generated using the developed approach, which includes the MRI image, the segmentation liver mask, the detected tumor area, overlay visualization, the representation of features, and the severity assessment. The developed segmentation masks effectively preserve the borders of the liver while being able to identify tumor areas.

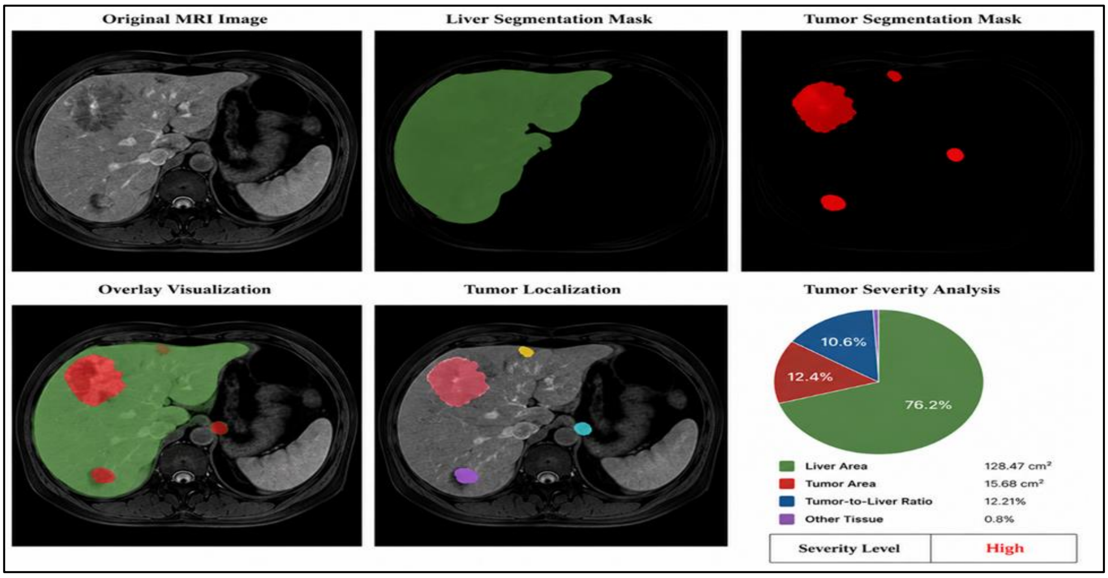


**Figure 3.** Visualization of MRI liver tumor segmentation and analysis

The quantitative estimation of the segmented regions of the liver gives extra information compared to the subjective evaluation process. This framework is used to estimate liver composition based on the area of the segmented liver, tumor area, and the healthy area. Figure 4 shows quantitative analysis of liver composition in which the distribution of liver tissue and tumor regions based on the results of segmentation is clearly indicated.

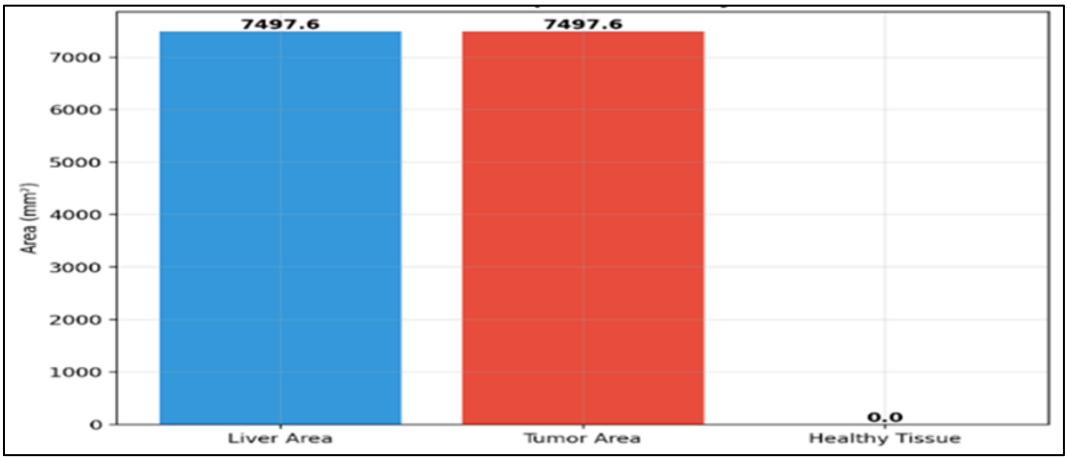


**Figure 4.** Quantitative analysis of liver and tumor areas

The experiment results show the efficiency of using the proposed U-Net-Swin CNN model successfully integrates liver segmentation, tumor localization, and quantization of the tissue. It is important to highlight the combination of the advantages of the convolutional feature extraction and the Transformer's contextual learning makes the liver segmentation more effective. Thus, the visualization and the evaluation severity help to interpret the obtained results. This means that the proposed model can be used in the computer-aided diagnosis of liver tumors using MRI.

## 5. Conclusion and Future Work

In this research, the proposed U-Net–Swin CNN framework for automatic liver tumor segmentation and quantitative evaluation based on MRI images. This automated framework comprises image pre-processing, hierarchical deep feature extraction, liver segmentation and tumor localization with quantitative evaluation in a unified workflow oriented towards computer aided diagnosis. The framework accurately delineates liver and tumor regions through hierarchical, multi-dimensional learning that amalgamates abbreviated information from CNNs through local image feature extraction with global context embedding learned from Swin Transformer attention weights. Quantitative liver composition analysis and visualization further improve segmentation results, thus providing clinically meaningful information for disease assessment and treatment planning. Proposed framework proved that the combination of deep learning-based segmentation and quantitative analysis can provide a reliable MRI liver tumor evaluation. The future research will aim to validate the framework on larger and more diverse MRI datasets, extend the method to three-dimensional liver segmentation, explore multimodal medical imaging, and implement a clinically scalable system for real-time diagnosis and individualized treatment assistance.

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