Automated Liver Tumor Segmentation and Detection for Enhanced Diagnosis

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Abstract—Liver tumor segmentation is critical for accurate diagnosis and treatment planning. This system employs deep learning models such as **ResNet-50** (main algorithm), **DeepLabv3+ with ResNet-101**, **VGG-16**, and **Fully Convolutional Networks (FCNs)** to segment liver and tumor regions from medical images. **ResNet-50** is chosen for its efficiency and strong feature extraction. **DeepLabv3+** captures multi-scale features, **VGG-16** offers a strong baseline, and **FCNs** provide dense pixel-level predictions. These models improve segmentation accuracy and reduce reliance on manual annotation. Evaluation is performed using metrics like Dice Score and IoU. The approach aims to support radiologists with precise, automated tumor localization. This enhances early detection and improves clinical outcomes.

****Index Terms—**ResNet-50, DeepLabv3+, FCN, VGG-16, Liver Tumor Segmentation, Medical Imaging.**

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I. Introduction

Liver tumor segmentation is essential for accurate diagnosis and treatment of liver cancer. Manual methods are time-consuming and prone to variability, highlighting the need for automated solutions. This project applies deep learning models for efficient and accurate liver and tumor segmentation. **ResNet-50**, chosen as the main algorithm, provides strong feature extraction and balanced performance. Additional models like **DeepLabv3+ with ResNet-101**, **VGG-16**, and **FCNs** are used to enhance segmentation accuracy. These networks capture spatial and contextual features, enabling precise boundary detection. The approach minimizes manual effort and supports better clinical decision-making.Literature Survey

II. System Analysis

Existing System:
Traditional liver tumor segmentation methods rely on manual annotations or basic image processing techniques, which are time-consuming, inconsistent, and prone to human error.

Proposed System: The proposed system leverages deep learning models such as **ResNet-50** (main algorithm), **DeepLabv3+ with ResNet-101**, **VGG-16**, and **FCNs** to perform accurate and automated liver and tumor segmentation from medical images.

Advantages:

- Improved segmentation accuracy through advanced deep learning techniques.
- Automated and consistent tumor boundary detection.
- Reduced reliance on manual annotation.
- Supports early diagnosis and enhances clinical decision-making.

TABLE I

Existing Work Overview

Authors	Title	Year	Summary
Jin Gyo Jeon et al	Deep 3D Attention CLSTM U-Net Based Automate Liver Segmentation an Volumetry fo Transplantation	2021	Whole liver: DS =0.899. Left lobe: DS =0.789. Right lobe DSC = 0.869. Caudat lobe: DSC = 0.955
Prabhu Kavi Balasubramaian	APESTNet with Mask R-CN for Liver Tumor Segmentatio and Classification	2023	Accuracy: 95.62%Precision: 98.32%Recall: 94.62%F1-Score: 94.53%
Song-Toan Tran	A Multiple Layer U-Net (Ur Net) for Liver and Live Tumor Segmentation in CT	2020	LiTS Dataset:Live Segmentation: DSC: 96.38% VOE: 3.62% Tumor Segmentation: DSC: 73.69% VOE: 26.31%

- Intuitive review-based insights

III. System Design

A.Input

- Medical imaging data (CT or MRI scans)
- Annotated segmentation datasets (e.g., liver and tumor masks)

B. Processing

- Preprocessing and normalization of input images
- Liver and tumor segmentation using ResNet-50 (main algorithm)
- Additional model comparisons using DeepLabv3+ with ResNet-101, VGG-16, and FCN
- Feature extraction and boundary detection for accurate segmentation

C.Output

- Segmented liver and tumor regions
- Visual overlays on original scans
- Performance metrics (e.g., Dice Score, IoU) in bar or pie chart format

IV .Modules Description

A. Data Preprocessing Module

Processes CT/MRI scan data by resizing, normalizing pixel values, and applying augmentation techniques to enhance model robustness.

B. Segmentation Module

B. Segmentation Module

Performs liver and tumor segmentation using ResNet-50 as the primary model, supported by DeepLabv3+ (ResNet-101), VGG-16, and FCNs for comparative analysis

C.Feature Extraction Module

Extracts spatial and structural features from medical images to precisely identify tumor boundaries and enhance segmentation accuracy.

D. Model Evaluation Module

Assess the performance of each model using metrics like Dice Similarity Coefficient and Intersection over Union (IoU) to determine segmentation quality.

E. Output and Visualization Module

Generates visual overlays of segmented regions on the original scans and displays evaluation metrics using bar and pie charts via Matplotlib and Seaborn for better clinical interpretation.

IV. SYSTEM ARCHITECTURE

The system architecture follows a multi-layered deep learning framework designed to optimize image preprocessing, model-based segmentation, and result visualization for liver tumor detection.

A. Key Layers:

In **Input Layer (Data Acquisition & Preprocessing):** The system collects CT/MRI scan data along with annotated liver and tumor masks. Preprocessing steps include resizing, normalization, and augmentation to enhance model performance.

Processing Layer (Model Training & Segmentation): Preprocessed images are fed into deep learning models for segmentation. **ResNet-50** serves as the primary model due to its strong balance between depth and efficiency. Other models like **DeepLabv3+ (ResNet-101)**, **VGG-16**, and **FCN** are used for benchmarking and performance comparison..

DecisionLayer(SegmentationEvaluation): Model outputs are evaluated using segmentation metrics such as **Dice Score** and **IoU** to assess accuracy and boundary precision. This layer helps in selecting the most reliable predictions for clinical use

Output Layer (Visualization & Interpretation): Segmentation results are overlaid on original scans and visualized using tools like **Matplotlib** and **Seaborn**. Evaluation metrics and model comparisons are presented through charts and graphs for easy interpretation by clinicians..

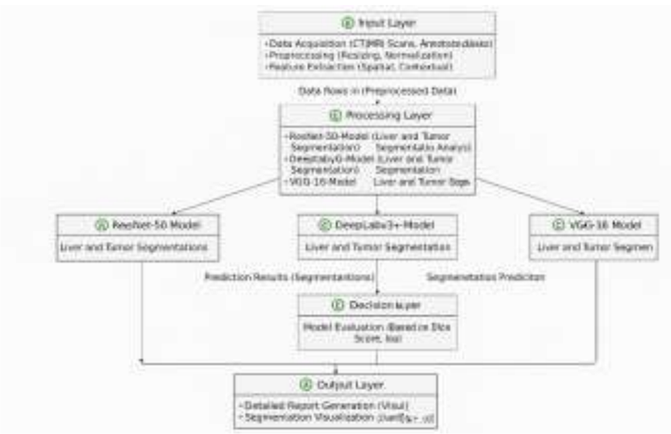

Fig.1.SystemArchitectureFlow

IV. MACHINE LEARNING MODELS USED

The liver tumor segmentation system employs state-of-the-art deep learning models to detect and segment liver and tumor regions from medical images with high precision. These models are chosen for their accuracy, robustness, and ability to generalize across varying imaging conditions.

A. ResNet-50 (Residual Network - 50 layers)

Purpose: Primary model for liver and tumor segmentation.

Function: Utilizes residual connections to enable deeper network training, effectively capturing both high- and low-level features critical for accurate segmentation.

Advantages: Strong performance with relatively low computational cost, effective in handling complex medical structures.

B.DeepLabv3+ with ResNet-101 Backbone)

Purpose: Benchmark model for comparison.

Function: Uses atrous spatial pyramid pooling and encoder-decoder structure to extract multi-scale context, enhancing boundary precision in tumor segmentation.

Advantages: High accuracy in segmenting complex regions with fine details.

C. VGG-16 (Visual Geometry Group - 16 layers)

Purpose: Alternative segmentation model.

Function: Applies sequential convolutional layers for feature extraction.

Advantages: Simple architecture and reliable baseline for medical image classification and segmentation tasks.

VI IMPLEMENTATION

Technologies Used:

- **Language:** Python

Libraries/Frameworks:

- PyTorch and TensorFlow – for building and training deep learning models
- OpenCV, SimpleITK – for medical image preprocessing and visualization
- NumPy, Pandas – for data handling
- Matplotlib, Seaborn – for plotting performance metrics

Sample Code Snippets:

Listing 1 resnet 50

```
# Load ResNet-50 model and modify for segmentation
resnet50 = models.resnet50(pretrained=True)
resnet50.fc = nn.Sequential(
```

Listing2 :Deep V3+ Resnet 101 Backbone

```
import torchvision.models.segmentation as segmentation

deeplab_model =
segmentation.deeplabv3_resnet101(pretrained=True)
deeplab_model.classifier[4] = nn.Conv2d(256, 2,
kernel_size=(1, 1))
```

```
from torchvision.models.segmentation import
fcn_resnet50
fcn_vgg = fcn_resnet50(pretrained=False, num_classes=2)
fcn_vgg.backbone = vgg16.features
```

VI Testing and Evaluation

Test Cases:

- Review: "Caused Liver tumor " → Severity: High
- Input: insert any MRI/CT image,
- Liver TUMOR → size of tumor shown

Performance Metrics:

- Accuracy
- Recall
- AUC-ROC Score
- F1-Score
- Recall
- Dice score

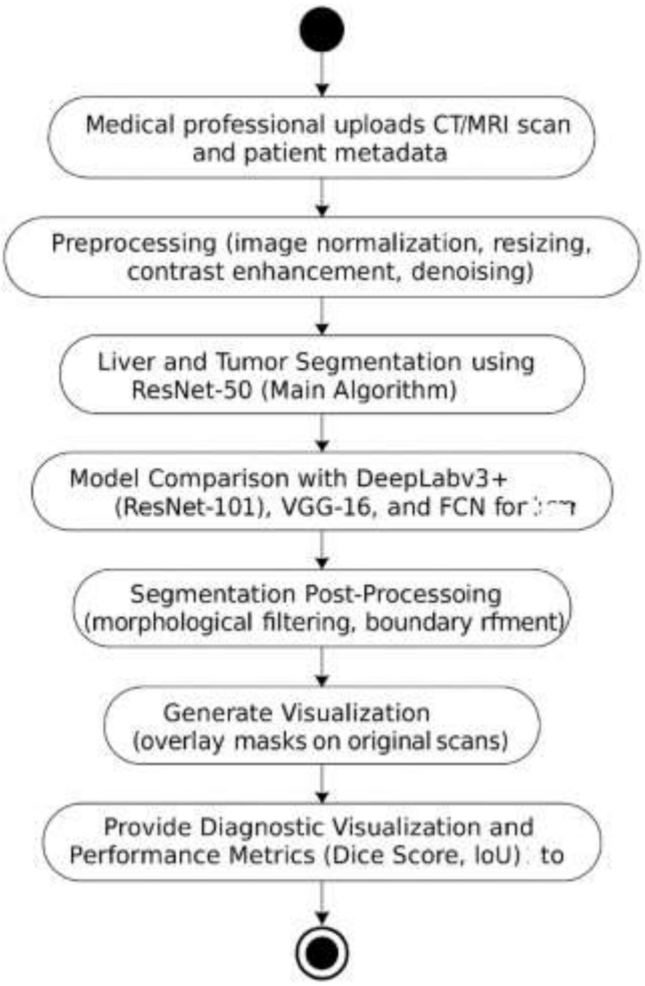

Fig. 2. Process Flow Chart

VII Dataset Overview

The dataset used for liver and liver tumor segmentation and detection consists of high-resolution 3D medical imaging data such as CT and MRI scans. These images are annotated with expert-labeled masks identifying liver and tumor regions, enabling supervised learning. The dataset serves as the foundation for training deep learning models like **ResNet-50 (main algorithm)**, **DeepLabv3+ with ResNet-101**, **VGG-16**, and **Fully Convolutional Networks (FCN)**.

Key Attributes:

Scan Information: Patient ID, modality (CT), number of slices, pixel spacing, and resolution.
Annotations: Ground truth segmentation masks for liver and tumor regions.
Alternative Architectures: Model performance using DeepLabv3+ (ResNet-101), FCN, and VGG-16 for comparison.
Segmentation Output: Tumor boundaries, volume, and overlap with liver regions.
Risk Estimation: Tumor size, location, and spread prediction using segmentation analysis.*Dataset Classes:*

A. Dataset Classes:

Scan Information: Scan Modality (CT), Patient ID, Slice Count, Pixel Resolution, Scan Orientation
Liver Segmentation: Ground Truth Liver Mask, Predicted Liver Mask,DiceScore, IoU
Tumor Segmentation: Ground Truth Tumor Mask, Predicted Tumor Mask, Tumor Volume, Count, Region Label
Risk & Severity: Tumor Size Category, Spread Estimate, Tumor Overlap Ratio, Segmentation Confidence Score
Comparison Models: DeepLabv3+ (ResNet-101), FCN, VGG-16 – evaluated on accuracy, recall, Dice score
Dataset Source:
• LiTS (Liver Tumor Segmentation Challenge Dataset) – 131 CT scans with annotated masks

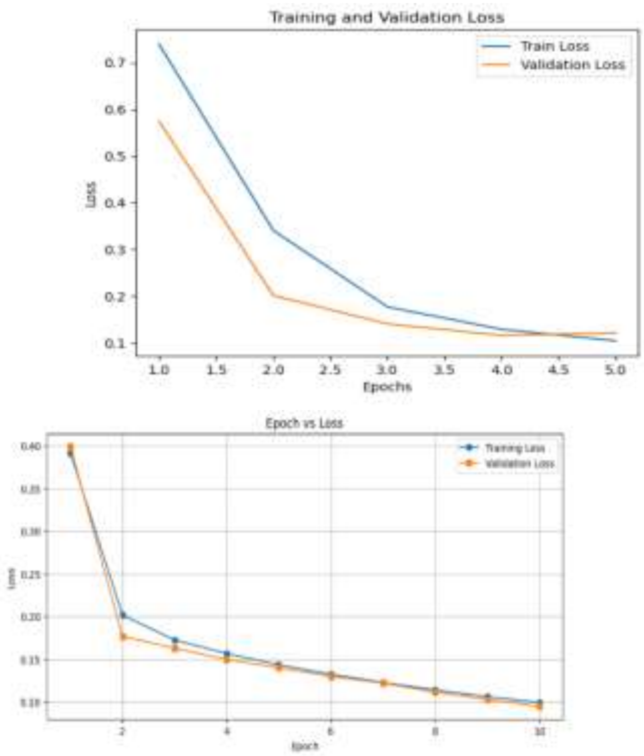

Fig. 3. Loss vs Epoc Graph for Resnet 50 and Deep v3+ resnet 101

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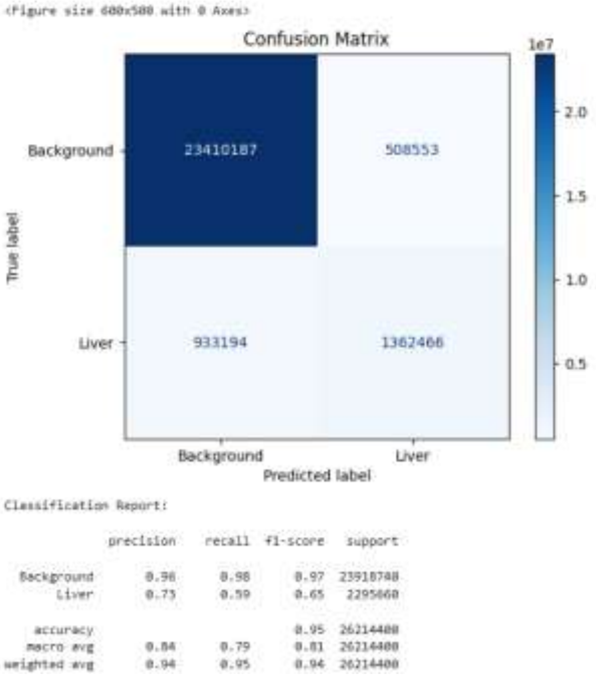

Fig. 4. Confusion Mtrix for Resnet -50

V. Conclusion and Future Scope

Future Scope: The liver tumor segmentation system will be enhanced by integrating with hospital PACS systems for seamless scan processing. A mobile-friendly interface will enable clinicians to upload CT/MRI scans and receive segmented outputs in real-time. Advanced explainable AI modules will provide visual justifications for each segmented region, improving clinical trust. The system will incorporate pharmacogenomic and pathological data to support treatment planning. Few-shot learning techniques will address limited data scenarios, especially for rare tumor types. Support for multi-modal imaging (e.g., combining CT and MRI) will improve segmentation accuracy. Cloud deployment will enable scalable access for remote healthcare centers. Continuous training on LiTS and 3D-IRCADb-01 datasets will ensure robustness. A clinical dashboard will provide real-time performance metrics like Dice Score and IoU. Overall, the system aims to enhance precision, accessibility, and clinical decision-making in liver cancer care.

The liver and tumor segmentation system will integrate with clinical imaging platforms for real-time diagnostic support. A mobile and web-based dashboard will allow radiologists to upload scans and view segmented regions with risk indicators. Future enhancements include few-shot learning for rare tumor types and small datasets. Pharmacogenomic data will be explored to personalize treatment planning. Explainable AI will be implemented to visualize model decisions, increasing trust in clinical use. Integration of multi-modal inputs like MRI and CT will improve accuracy. 3D segmentation refinement and automation will further assist surgical planning and monitoring.

Conclusion: The liver tumor segmentation and detection system leverages deep learning and computer vision to enhance diagnostic accuracy and treatment planning. By analyzing 3D medical imaging data (CT/MRI), it accurately segments liver and tumor regions using advanced architectures like ResNet-50 (primary model), DeepLabv3+, ResNet-101, VGG-16, and FCN. The system achieves robust performance across datasets such as LiTS and 3D-IRCADb-01, ensuring consistency and reliability. Key accomplishments include high Dice and IoU scores, efficient boundary detection, and comparative analysis across multiple models. Visual overlays and metric-based evaluations assist clinicians in understanding tumor extent and shape. Challenges remain in handling variations in tumor size, shape, and scan quality, as well as ensuring real-world generalizability. However, the system demonstrates strong potential in supporting early detection, improving surgical planning, and serving as a reliable clinical decision-support tool. With future enhancements like multi-modal input integration and explainable AI, it is poised to significantly advance personalized liver cancer care.

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