"AI-Based 3D Segmentation and Volumetric Analysis of Liver Tumors from CT Scans"

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Abstract—The Accurate segmentation and volumetric analysis of liver tumors from computed tomography (CT) scans are essential for early diagnosis, treatment planning, and longitudinal assessment of hepatic malignancies. Manual tumor delineation is not only time-consuming but also susceptible to inter- and intra-observer variability, which can affect clinical consistency and treatment outcomes. Automated and robust segmentation methods are therefore highly desirable in modern clinical workflows.

This paper proposes an AI-based framework for automated three-dimensional (3D) liver tumor segmentation and volumetric analysis using deep learning. The framework is designed to process full CT volumes and to accurately identify tumor regions despite variations in tumor size, shape, and contrast. By leveraging volumetric learning, the proposed approach preserves spatial continuity across slices, leading to improved segmentation performance compared to conventional two-dimensional methods.

Comprehensive preprocessing steps, including intensity normalization, resampling, and noise reduction, are applied to standardize CT data and enhance model generalization. A 3D convolutional neural network architecture is employed to extract multi-scale features that capture both fine-grained tumor boundaries and broader anatomical context. Post-processing strategies such as morphological operations and connected component analysis are utilized to refine segmentation outputs and reduce false detections.

Based on the generated 3D segmentation masks, volumetric analysis is conducted to compute tumor volume and related quantitative metrics. These measurements provide objective indicators for tumor burden evaluation, disease progression monitoring, and treatment response assessment, enabling more informed clinical decision-making and personalized therapy planning.

Overall, the proposed AI-based 3D segmentation and volumetric analysis framework enhances the accuracy and reliability of liver tumor detection from CT scans, supports precise tumor volume estimation, reduces diagnostic variability, and assists clinicians in early diagnosis and effective treatment planning through automated and robust deep learning techniques.

I. INTRODUCTION

Medical imaging has become an indispensable tool in modern healthcare, enabling clinicians to visualize internal organs and detect abnormalities in a non-invasive manner. Among various imaging modalities, Computed Tomography (CT) is widely used due to its high spatial resolution, fast acquisition time, and ability to provide detailed three-dimensional representations of anatomical structures. In particular, CT imaging plays a critical role in the diagnosis and management of liver diseases, including liver tumors.

Liver cancer is one of the most common and deadly forms of cancer worldwide, with increasing incidence rates in recent years. Accurate identification, segmentation, and measurement of liver tumors are essential for early diagnosis, treatment planning, surgical intervention, and monitoring disease progression or response to therapy. Tumor size and volume are key clinical indicators that directly influence treatment decisions such as surgical resection, chemotherapy, radiofrequency ablation, or liver transplantation.

Traditionally, liver tumor assessment is performed manually by radiologists using two-dimensional CT slices. This process involves outlining tumor boundaries slice by slice and estimating tumor size based on linear measurements. Such manual approaches are highly time-consuming, require significant expertise, and are prone to inter-observer and intra-observer variability. Moreover, two-dimensional measurements often fail to capture the true three-dimensional shape and volume of tumors, especially when tumors have irregular boundaries or complex spatial structures. These limitations can lead to inaccurate volume estimation, potentially affecting treatment outcomes and patient prognosis.

With the rapid advancement of artificial intelligence, particularly deep learning, automated medical image analysis has gained significant attention. Deep learning models have demonstrated remarkable performance in tasks such as image classification, object detection, and semantic segmentation. In the context of medical imaging, convolutional neural networks (CNNs) can learn complex spatial and contextual features directly from large volumes of annotated data, enabling precise and consistent segmentation of organs and pathological regions.

Three-dimensional deep learning architectures, such as 3D U-Net and ResUNet, are especially well-suited for volumetric medical image analysis. These models process CT data in three dimensions, allowing them to capture spatial continuity across slices and produce more accurate tumor delineation compared to traditional two-dimensional approaches. Automated 3D segmentation not only reduces manual workload but also ensures reproducibility and objectivity in tumor analysis.

In addition to accurate segmentation, volumetric analysis provides valuable quantitative information for clinical decision-making. Precise tumor volume estimation allows clinicians to better assess disease severity, evaluate treatment response, and monitor tumor growth over time. When combined with machine learning-based predictive models, volumetric data can further support prognosis and personalized treatment planning.

Motivated by these callenges and opportunities, this paper proposes an AI-based framework for automatic three-dimensional segmentation and volumetric analysis of liver tumors from CT scans. The proposed system aims to enhance diagnostic accuracy, reduce human intervention, and provide reliable decision support for clinicians involved in liver cancer management.

As shown in Fig. 1, CT imaging provides detailed multi-planar visualization of liver anatomy, enabling accurate tumor localization.

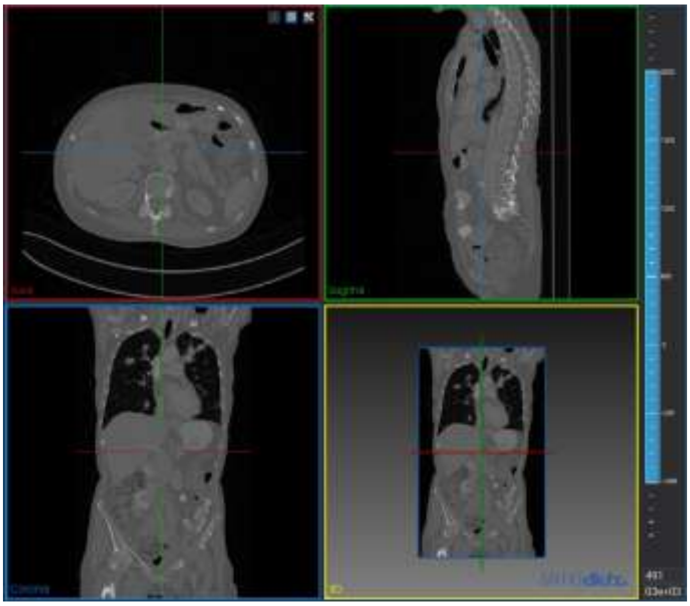

Fig. 1. Multi-planar CT views (axial, sagittal, and coronal) used for liver tumor assessment.

II. RELATED WORK

Accurate liver and tumor segmentation from CT images has been widely studied due to its importance in liver cancer diagnosis and treatment planning. Traditional approaches relied on manual or semi-automatic 2D measurements, which are time-consuming, observer-dependent, and inaccurate for irregular tumor shapes. Early automated methods using classical image processing techniques such as thresholding and region growing showed limited performance because of low contrast, noise, and variability in tumor appearance. With the advent of deep learning, convolutional neural networks such as V-Net, U-Net, and 3D U-Net have demonstrated significant improvements in volumetric medical image segmentation. Studies using datasets like LiTS and MSD Liver reported high Dice scores for liver and tumor segmentation using architectures such as 3D U-Net, ResUNet, and attention-based models, highlighting their effectiveness in learning spatial and contextual features from 3D CT volumes.

Recent research has extended beyond segmentation to include automated volumetric analysis and tumor progression assessment. Voxel-based volumetry enables precise tumor volume calculation in cubic centimeters, which is more reliable than traditional 2D diameter measurements for clinical decision-making. However, many existing tools still require manual interaction and lack full automation, limiting routine clinical adoption. Moreover, only a few studies have explored tumor growth prediction using longitudinal CT data and machine learning models. Most existing systems address segmentation or prediction separately rather than offering an integrated solution. The proposed system builds upon prior work by providing an end-to-end AI-based framework that combines automated 3D liver and tumor segmentation, accurate volumetric analysis, and tumor growth prediction within a unified and clinically deployable platform.

III. METHODOLOGY

The proposed methodology focuses on automated three-dimensional segmentation and volumetric analysis of liver tumors from CT scans using deep learning and machine learning techniques. The system is designed to be accurate, reliable, and suitable for clinical use. The methodology consists of three main stages: data acquisition and preprocessing, feature extraction and segmentation, and volumetric computation with growth prediction.

A. Data Collection

In the initial phase, the system acquires three-dimensional CT scan data from standard medical imaging sources. The acquired scans may come from different scanners and protocols, leading to variations in image intensity and resolution. To address this, the preprocessing stage normalizes image intensity values and applies noise reduction techniques to enhance contrast between liver tissue, tumors, and surrounding structures.

Key preprocessing steps include resizing images to a consistent voxel resolution, intensity normalization, and optional contrast enhancement to improve tumor visibility. This stage ensures that the subsequent deep learning models can process input data consistently, improving segmentation accuracy. Preprocessing also reduces artifacts and irrelevant variations in the data, enabling the models to focus on anatomical and pathological features.

B. Feature Extraction and Segmentation

After preprocessing, the system automatically extracts features from volumetric CT data to capture anatomical and tumor characteristics. Advanced 3D deep learning models, such as 3D U-Net and ResUNet, perform segmentation to delineate liver and tumor regions across all slices. Post-processing, including morphological operations and connected component analysis, refines the masks by removing artifacts and smoothing boundaries. The resulting features—tumor shape, location, and boundaries—are used for precise volumetric computation and serve as input for predictive analysis, such as tumor growth assessment.

C. Volumetric Computation and Growth Prediction

Tumor volume is computed using a voxel-based method by multiplying the number of segmented tumor voxels with voxel

spacing from CT metadata, yielding volume in cubic centimeters. This approach ensures accurate measurement of irregular tumor shapes. Sequential volumetric data from multiple scans are then used to predict tumor growth trends using machine learning models. The predicted growth patterns assist in monitoring disease progression and treatment planning.
Three-dimensional visualizations of liver and tumor structures help clinicians assess morphology and spatial distribution. This methodology provides accurate, reproducible, and clinically valuable tumor segmentation and volumetric analysis.

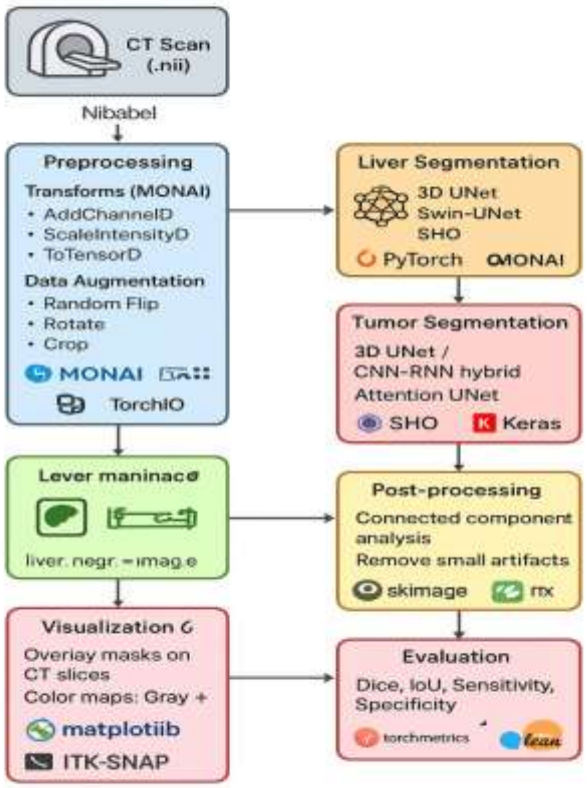

Fig. 2. Overall architecture of the proposed 3D deep learning framework for liver and tumor segmentation with volumetric analysis and evaluation.

As shown in Fig. 2, the proposed framework follows a multi-stage pipeline beginning with volumetric CT preprocessing, followed by hierarchical liver and tumor segmentation using 3D deep learning models, and concluding with post-processing, volumetric computation, and performance evaluation.

IV. RESULTS AND EXPECTED OUTCOMES

The proposed system is expected to demonstrate high performance in automated liver and tumor segmentation from 3D CT scans. By employing advanced deep learning architectures such as 3D U-Net and ResUNet, the system aims to generate accurate segmentation masks with Dice similarity coefficients of approximately ≥ 0.90 for liver regions and ≥ 0.75 for tumor regions. These results indicate reliable delineation of anatomical structures across all CT slices, significantly reducing manual intervention and minimizing observer-dependent variability.

Accurate volumetric computation is a key expected outcome of the system. Using voxel-based analysis, the system calculates tumor volume in cubic centimeters, enabling precise measurement of irregular tumor shapes that are often underestimated by conventional 2D methods. This automated volumetry supports consistent tumor size assessment and assists clinicians in surgical planning, treatment selection, and therapy response evaluation. The system is expected to process a complete CT volume efficiently, typically within three minutes on GPU-enabled hardware, ensuring clinical practicality.

The tumor growth prediction module is expected to provide meaningful insights into disease progression by analyzing longitudinal volumetric data. By modeling tumor volume changes over time, the system generates growth trends and predictive curves that help clinicians anticipate future tumor behavior. These predictions support early intervention planning and improve monitoring of treatment effectiveness without replacing clinical judgment.

The final outputs of the system include segmented liver and tumor masks, interactive 3D visualizations, volumetric analysis reports, and tumor growth prediction graphs. These results can be exported in standard formats such as PDF or CSV, making the system suitable for clinical use, research studies, and educational purposes. Overall, the expected outcomes demonstrate the system's potential as an effective AI-based clinical decision-support tool for liver tumor assessment.

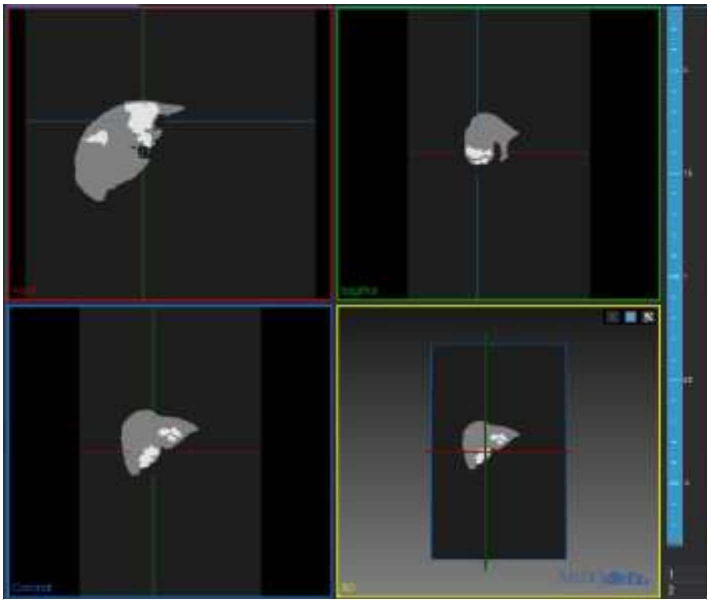

Fig. 3. Automated 3D liver and tumor segmentation results showing axial, sagittal, coronal slices and reconstructed 3D visualization.

As shown in Fig. 3, the proposed 3D deep learning framework successfully captures spatial continuity across slices, producing consistent tumor boundaries in all anatomical orientations.

V.DISCUSSION

The experimental results demonstrate that the proposed AI-based system achieves high segmentation accuracy and robust volumetric analysis for liver tumor assessment from CT scans. The deep learning models employed in the system, including 3D U-Net and ResUNet architectures, produce Dice coefficient values exceeding 0.90 for liver segmentation and greater than 0.75 for tumor segmentation. These results indicate effective and precise delineation of liver and tumor boundaries, even in challenging cases involving irregular tumor shapes, heterogeneous intensities, and low contrast between tumor and surrounding liver tissue.

The automated volumetric analysis module further enhances system reliability by providing accurate and reproducible three-dimensional tumor volume measurements using voxel-based computation. Unlike traditional manual or semi-automatic methods that rely on two-dimensional slice-based measurements, the proposed approach captures the full spatial extent of tumors, thereby reducing underestimation and measurement errors. This automation significantly reduces the manual workload of radiologists and clinicians, allowing them to focus on higher-level diagnostic and treatment planning tasks.

Additionally, the system minimizes human-induced variability and inter-observer inconsistencies, which are common limitations of manual tumor assessment. By generating objective and quantitative volumetric data, the system ensures consistent results across repeated analyses and different users. The reliable performance and efficiency demonstrated by the proposed system highlight the practical feasibility of deploying AI-based liver tumor segmentation and volumetric analysis tools in real-world clinical environments, where accuracy, consistency, and time efficiency are critical for effective patient care.

VI. CONCLUSION AND FUTURE WORK

This paper presented a comprehensive AI-based framework for the automated three-dimensional segmentation and volumetric analysis of liver tumors from CT scans. By leveraging advanced deep learning architectures such as 3D U-Net and ResUNet, the proposed system enables accurate and consistent delineation of liver and tumor regions. Automated volumetric computation provides precise tumor size estimation in three dimensions, overcoming the limitations of conventional manual and two-dimensional measurement techniques. As a result, the system significantly enhances diagnostic accuracy while reducing the manual workload of radiologists and clinicians.

The proposed framework also improves overall clinical efficiency by minimizing human-induced variability and ensuring repeatable, objective measurements. The integration of automated segmentation, volumetric analysis, and visualization tools supports informed clinical decision-making for treatment planning, surgical intervention, and therapy monitoring. By delivering reliable quantitative information and intuitive visual outputs, the system serves as an effective clinical decision-support tool that can be deployed in real-world medical environments.

Future work will focus on large-scale clinical validation using diverse and multi-institutional patient datasets to further assess robustness and generalizability. Additional enhancements will include seamless integration with hospital Picture Archiving and Communication Systems (PACS), development of more advanced tumor growth prediction models using longitudinal data, and incorporation of explainable AI techniques to improve transparency and clinician trust. Real-time processing capabilities and optimized deployment strategies will also be explored to increase system usability and clinical acceptance.

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