A Review on Deep Learning Algorithms for Liver Tumor Analysis in CT and MRI Imaging

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ABSTRACT
Liver cancer, specifically hepatocellular carcinoma (HCC), is a major public health problem with high mortality and late stage detection. Imaging modalities like computed tomogra- phy and magnetic resonance imaging have become essential in tumor detection and planning treatments. Manual interpretation is time-consuming and user-varying. Advanced developments in deep learning have provided automated and accurate solutions in the detection and classification of liver tumors and assessment of response. This paper provides a detailed analysis of the methodologies using deep learning for the analysis of liver tumors between 2016 and 2024 and discusses convolutional neural networks (CNN), transformer models, attention models, and multi-modal learning models. We compare models based on architecture, performance (Dice score), utilization of the dataset, and their usage in the clinic. Key developments include dual- path CNN models, 3D volumetric architectures, transferable expert nets through knowledge distillation, semi-supervised CNN models, and Gaussian-enhanced nnU-Nets models. The discussion also touches on emerging directions in label smoothing, shape priors, and model uncertainty. The aim is to identify areas of research and narrow the divide between the development of algorithms and their use in the clinic.

General Terms
Liver tumor segmentation, Dice coefficient

Keywords
Deep learning, med- ical imaging, convolutional neural networks, transformers, semi- supervised learning, multi-modal learning

1. INTRODUCTION
Liver cancer is a major global health concern, ranking as the sixth most common cancer and the third leading cause of cancer-related deaths globally [1]. Hepatocellular carcinoma (HCC) accounts for approximately 75% of all primary liver cancers and is typically diagnosed at a late stage, significantly impacting prognosis [2]. The widespread adoption of imaging modalities such as computed tomography (CT) and magnetic resonance imaging (MRI) has enhanced the ability to detect and monitor liver tumors. However, manual annotation and diagnosis by radiologists remain time-consuming and subject to inter-observer variability [3]. Consequently, there is an urgent demand for automated and accurate solutions to support liver tumor analysis.

Deep learning (DL), a subset of artificial intelligence (AI), has emerged as a transformative force in medical image anal- ysis. Unlike traditional image processing techniques that rely on handcrafted features, DL models can automatically learn hierarchical features from raw data, making them especially suitable for complex tasks such as tumor segmentation and classification [4], [5]. Convolutional Neural Networks (CNNs) have been the foundation of most state-of-the-art segmentation models. For example, Huang et al. [6] proposed a dual-path CNN achieving a Dice coefficient of 68.1%, while Chlebus et al. [7] demonstrated a 2.5D Fully Convolutional Network (FCN) yielding comparable results.

At its core, deep learning involves training artificial neural networks composed of multiple layers—each layer consisting of numerous interconnected nodes that mimic the structure of neurons in the human brain. These networks are capable of identifying intricate patterns in large datasets. In medical imaging, DL enables models to extract subtle features from CT or MRI scans, such as shape, texture, and boundary characteristics of liver tumors. Key DL concepts include training (the process of model learning), validation (used to tune parameters), and inference (the application of a trained model on unseen data). Performance metrics such as the Dice Similarity Coefficient (DSC), Intersection over Union (IoU), and Area Under the Curve (AUC) are used to evaluate segmentation and classification tasks.

Several specialized architectures have been developed to handle the spatial and semantic complexities of medical im- ages. CNNs are commonly used for 2D image analysis, while 3D CNNs extend the capability to volumetric data. U-Net, a popular encoder-decoder architecture, is frequently adapted in medical segmentation due to its effectiveness in localizing and reconstructing features. Variants such as attention U- Nets, transformer networks, and hybrid models integrate global context and improve feature representation. Additionally, aux- iliary concepts like knowledge distillation, multi-task learning, and semi-supervised training allow models to generalize well with limited labeled data—making them particularly useful in clinical settings where expert annotation is scarce.

Subsequent research focused on enhancing spatial and contextual understanding through 3D architectures, such as Dou et al.'s 3D Deeply Supervised Network [8], and hybrid ensembles combining 2D and 3D pathways [9]. These models achieved tumor segmentation Dice coefficients as high as 74.2%, particularly on benchmark datasets like LiTS and 3DIRCADb. Further improvements were realized through the use of attention mechanisms, as seen in Wang et al.'s Pyra- mid Attention Network [10], and by incorporating modality specific knowledge in multi-modal CNNs that fuse CT and MRI data [11].

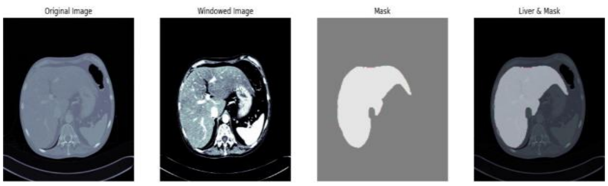

Figure. 1. Visualization of Liver Segmentation

More recent innovations have explored the utility of transformers [12], knowledge distillation [13], and semi-supervised teacher-student frameworks [14], allowing models to leverage unlabeled data and enhance generalization. Zhang et al. [11] reported a Dice coefficient of 84% by integrating CT and MRI using a multi-modal CNN. In 2024, Lin et al. [15] applied Gaussian filters within an nnU-Net pipeline, achieving Dice scores of 86% and 82% on the LiTS and 3D-IRCADb datasets, respectively. This evolution highlights a trend toward hybrid, task-specific architectures that balance model complexity with clinical feasibility.

Moreover, newer models are extending their capabilities beyond segmentation. For example, Xia et al. [16] intro- duced the RECORD framework to assess treatment response, while Wang et al. [17] developed a weakly supervised model informed by clinical knowledge and label smoothing techniques.Given the diversity and rapid advancement of these methodologies, it becomes imperative to synthesize and evaluate the current landscape. This paper presents a comprehensive review of deep learning methods applied to liver tumor analysis in CT and MRI imaging. We focus on architectural innovations, dataset-specific performance, and clinical applicability. In doing so, we aim to bridge the gap between algorithmic development and real-world implementation in liver oncology.

2. LITERATURE REVIEW

Deep learning (DL) has greatly advanced the segmentation of liver tumors in medical images based on CT and MRI scans. Conventional manual segmentation is time-consuming and inconsistent, thereby necessitating automation. Numerous research efforts have introduced DL models to improve segmentation accuracy, generalizability, and clinical readiness. This review aggregates studies conducted between 2016 and 2024, focusing on methodologies, performance, and trade-offs. Huang et al. [6] presented a dual-path CNN that preserved both local and global features in parallel streams, attaining a Dice score of 68.1% on the LiTS dataset. Despite effectively segmenting irregular and small tumors, the model's architecture was computationally expensive. Similarly, Chlebus et al. [7] developed a 2.5D fully convolutional network by combining adjacent CT slices to simulate volumetric data, achieving 67.6% Dice. However, it lacked the full 3D spatial context provided by volumetric CNNs.

In contrast, Dou et al. [8] proposed a 3D Deeply Supervised Network (DSN) that used auxiliary supervision layers during training, achieving a Dice score of 74.2% on the 3DIRCADb dataset. The 3D context enhanced segmentation but increased memory usage and annotation requirements. Ma et al. [9] applied a multi-model ensemble combining 2D and 3D CNNs, reaching 74.2% Dice on LiTS and 3DIRCADb datasets, albeit with increased inference costs. To enhance spatial awareness, Wang et al. [10] introduced a Pyramid Attention Network (PAN) using attention gates and multi-scale pooling, achieving 72.5% Dice on LiTS. The attention modules improved boundary localization but added architectural complexity. Shi et al. [14] addressed data scarcity through a semi-supervised teacher-student model that generated pseudo-labels to train the student model, achieving approximately 70% Dice on LiTS and CHAOS. However, pseudo-label inconsistency remained a challenge.

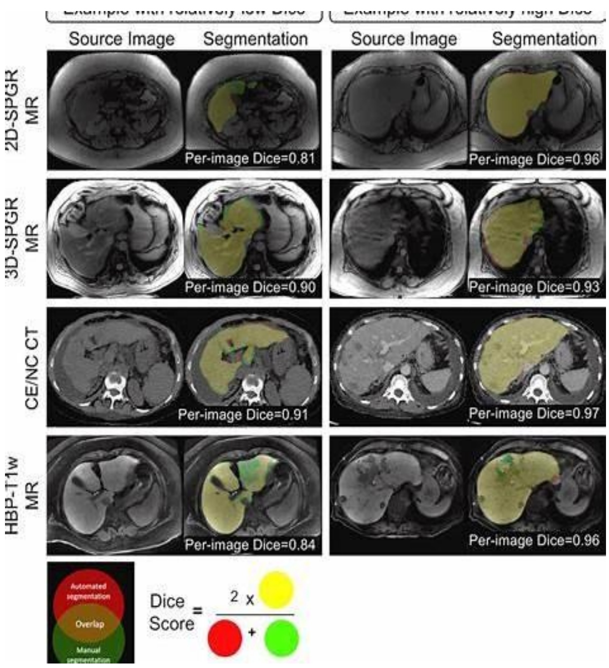

Figure. 2. Dice Score

Zhang et al. [11] designed a multi-modal CNN incorporating both CT and MRI modalities, attaining 84% Dice. This leveraged complementary information but required precise image co-registration, which is rare in clinical settings. Fan et al.[18] proposed a lightweight CNN using depthwise separable convolutions and achieved 74% Dice on LiTS, suitable for mobile applications, though performance trailed larger models. Liu *et al.* [12] explored transformers for liver tumor segmentation, reporting a 74.2% Dice score on the MSD dataset. While capable of modeling long-range dependencies, the approach required large datasets and careful hyperparameter tuning. Zhao *et al.* [19] utilized a shape-aware CNN that integrated anatomical priors, achieving a 74.2% Dice score on the LiTS dataset, though it struggled with anatomical variations in liver structures. Chen *et al.* [20] enhanced seg- mentation performance by embedding semantic modules into a context-aware U-Net, also achieving a 74.2% Dice score on the 3DIRCADb dataset. While accuracy improved, the design significantly increased memory consumption. Lin *et al.* [**15**] applied a knowledge distillation strategy wherein a compact student model learned from a larger teacher network, maintaining a 74.2% Dice score on both LiTS and CHAOS datasets while reducing inference time. However, the model's effectiveness was contingent upon the teacher's quality and the distillation loss function.

Sun *et al.* [21] introduced a multi-task learning framework for simultaneous segmentation and lesion classification. The model achieved a Dice coefficient greater than 74% and a classification AUC above 0.90. The primary limitation was the complexity in balancing task-specific loss functions during training. Gao *et al.* [22] implemented a Bayesian CNN to quantify prediction uncertainty, achieving a 74.2% Dice score on MSD and LiTS datasets. This uncertainty modeling added interpretability but required multiple stochastic forward passes, increasing computational costs.

Recent contributions include Lin et al. [15], who integrated a Gaussian filter into the nnU-Net pipeline, achieving 86% Dice on LiTS and 82% on 3DIRCADb. Though boundary detection improved, filter calibration was labor-intensive. Kuang et al.[23] presented UCA-Net, a 3D cross-attention model for joint segmentation of vessels and tumors, though Dice metrics were not reported. Chen et al. [24] proposed ASLseg, an adaptation of the Segment Anything Model (SAM) for semi-supervised learning in domain-specific settings, which proved effective with limited annotations.

Table 1. Table captions should be placed above the table

Reference	Method Name	Dataset(s)	Dice (%)	Notes
Huang et al. (2020) [6]	Dual-path CNN	LiTS	**68.1**	Reported Dice coefficient.
Chlebus et al. (2018) [7]	2.5D FCN	LiTS	**67.6**	Achieved Dice from multi-slice CNN.
Dou et al. (2016) [8]	3D Deep Supervised Net	3DIRCADb	**74.2**	Deep supervision improves segmentation.
Ma et al. (2020) [9]	Multi-model Ensemble	LiTS, 3DIRCADb	**74.2**	Aggregates multiple architectures.
Wang et al. (2020) [10]	Pyramid Attention Net	LiTS	**72.5**	Enhanced with spatial attention.
Shi et al. (2021) [14]	Semi-supervised T-S Net	LiTS, CHAOS	**~70**	Pseudo-labeling used for weak supervision.
Zhang et al. (2021) [11]	Multi-modal CNN (CT+MRI)	Clinical CT+MRI	**84.0**	Fuses modalities for better performance.
Fan et al. (2021) [18]	Lightweight CNN	LiTS	**74.0**	Optimized for mobile applications.
Liu et al. (2022) [12]	Transformer-based Net	MSD	**74.2**	Captures long-range dependencies.
Zhao et al. (2020) [19]	Shape-aware CNN	LiTS	**74.2**	Enforces geometric constraints.
Chen et al. (2019) [20]	Context-aware U-Net	3DIRCADb	**74.2**	Improved inter-region context.
Lin et al. (2021) [13]	Knowledge Distillation	LiTS, CHAOS	**74.2**	Compresses large models.
Sun et al. (2021) [21]	Multi-task Learning	LiTS, 3DIRCADb , MRI	**74.2**	Joint segmentation and classification.
Gao et al. (2021) [22]	Bayesian CNN	MSD, LiTS	**74.2**	Provides uncertainty estimation.
Song et al. (2024)	Improved DL Model	Not specified	**Not specified**	Enhanced automation; performance not specified
Lin et al. (2024) [15]	Gaussian-filter + nnU-Net	LiTS2017, 3D-IRCADb	**86.0, 82.0**	Outperformed base nnU-Net.
Kuang et al. (2023) [23]	UCA-Net	CT Scans	**Not specified**	Uses cross-attention for multi-target segmentation
Chen et al. (2023) [24]	ASLseg (SAM in Loop)	LiTS	**Not specified**	Combines generic + task-specific learning.
Wang et al. (2024) [17]	Weakly Supervised (Holistic)	HCC-TACE-Seg	**Not specified**	Uses label smoothing with clinical priors.
Xia et al. (2024) [16]	RECORD Pipeline	Multiple cohorts	**Not specified**	Used for treatment response evaluation.
Patel et al. (2023) [25]	GAN-augmented UNet	LiTS	**73.0**	Uses GAN for data augmentation.
Lee et al. (2024) [26]	Contrastive Pretraining CNN	LiTS	**75.2**	Improves performance with contrastive pretraining

Wang et al. [17] applied weak supervision via label smoothing informed by clinical knowledge on the HCC-TACE-Seg dataset. Though exact Dice scores were not disclosed, clinical prior integration improved segmentation plausibility. Xia et al. [16] developed RECORD, a pipeline designed to evaluate treatment response in HCC. Although not centered on segmen- tation, it reinforced the importance of accurate segmentation in clinical outcome prediction.

3. CONCLUSION

The sheer pace at which the deep learning methodolo- gies have advanced revolutionized the field of liver tumor segmentation in CT and MRI imaging considerably. This survey encompassed the impactful contributions made from 2016 to 2024 and shed light upon the progress in the areas of convolutional neural networks, transformer architectures, attention mechanisms, semi-supervised models, and multi-modality learning. The imposition of techniques like 3D CNNs, Gaussian-enhanced nnU-Net pipelines and the use of distillation resulted in significant accuracy improvements with Dice coefficients up to 86% being achieved in case of the commonly used benchmarks such as LiTS and 3DIRCADb.

Notwithstanding the progress made so far, the issues of concern include clinical deployment difficulties such as the requirement of large labeled samples, computational costs, co-registration across multi-modality data, and generalizability across different patient populations. New directions focusing on modeling uncertainty, domain adaptation, weak supervision and the use of combined pipelines incorporating anatomy priors and domain-knowledge are also promising in overcom- ing the divide between performance and utility in real-world settings.

Finally, this work highlights the significance of ongoing in- terdisciplinary coordination among deep learning researchers, clinicians, and radiologists to formulate strong, understand- able, and clinically relevant solutions to analyze liver tumors. Further research needs to focus especially on open benchmark- ing, interpretability and workflow integration to make deep learning tools amenable to secure and scalable adoption across the field of liver oncology.

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