Original Research

Revista Brasileira de Física Médica (2026) 20:882

Deep Learning-Based Segmentation of Hepatic Structures: A Systematic Review of Model Architectures and Clinical Applications

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Abstract

Liver cancer is a major public health problem and remains among the most common neoplasms worldwide, with approximately 866,000 new cases reported in 2022, of which hepatocellular carcinoma accounts for the majority of diagnoses. Anatomical characterization of the liver and its lesions relies largely on computed tomography (CT) and magnetic resonance imaging (MRI), whose segmentation is still predominantly manual or semi-automatic. This process is time-consuming and may lead to variability between different observers or even for the same professional at different time points. This limitation has motivated the adoption of deep learning (DL)–based methods, particularly to improve the accuracy and reproducibility of hepatic segmentation. This review analyzed 16 studies selected based on predefined keywords and inclusion criteria, aiming to identify methodological trends, predominant network architectures, and reported clinical applications. A strong predominance of U-Net–based models and their variants was observed (9/16), alongside an increasing use of three-dimensional approaches (11/16) and a focus on vascular segmentation (6/16) or combined liver-and-vessel segmentation (6/16). Methodological strategies were equally divided between combined approaches (8/16) and single-step methods (8/16). Despite the high technical performance reported by several authors, studies showed substantial heterogeneity in acquisition protocols, evaluation metrics, and dataset sizes, which hampers direct comparisons and limits the translation of these results into clinical practice. It can be concluded that, although deep learning represents a significant advance in hepatic segmentation, methodological standardization and external model validation are still required for its consolidation in the clinical setting.

***Keywords**: Liver cancer; Hepatic segmentation; Deep learning; Artificial intelligence in healthcare.*

1. Introduction

The liver is one of the main organs of the human body and plays a crucial role in protecting the body from toxins and harmful substances. Among its primary and vital functions is the filtration of blood coming from the digestive tract; it acts as a support for all other organs of the body by regulating energy supply through glucose level control, metabolizing toxic substances, including alcohol, and neutralizing harmful compounds. In addition, it produces bile, which is essential for digestion, synthesizes various proteins important for immune defense and blood coagulation, and participates in the distribution of vitamins and minerals necessary for the proper functioning of the body (1).

Despite performing a complex, highly efficient set of functions essential to maintaining systemic homeostasis, the liver is also vulnerable to chronic injury. Structural and functional alterations of this organ can evolve into a wide spectrum of chronic liver diseases, many of which progress to cirrhosis and increase the risk of developing primary liver cancer (2).

Liver cancer is now a major global public health problem. According to the World Cancer Research Fund, liver cancer ranks as the sixth most common cancer worldwide, being the fifth most frequent among men and the ninth among women. In 2022, an estimated 866,000 new cases were diagnosed globally (3). Primary liver cancer can be categorized into three main pathological types: hepatocellular carcinoma (HCC), intrahepatic cholangiocarcinoma (ICC), and combined hepatocellular-cholangiocarcinoma (cHCC-CCA). Among these, HCC is the most prevalent form, accounting for approximately 75–85% of all primary liver cancers (4). Given its high incidence and the generally poor prognosis when diagnosed at advanced stages, early detection and accurate characterization of hepatic tumors are essential for improving patient outcomes.

The recommended approach for early detection of this disease is screening and monitoring of individuals at high risk for HCC. Screening can be performed using different medical imaging modalities, such as ultrasonography, computed tomography (CT), and magnetic resonance imaging (MRI). Postprocessing techniques applied to CT imaging can also be used to perform three-dimensional (3D) vascular reconstruction, quantify liver and tumor volumes, and assess metastases to other organs, such as the lungs and bones—methods widely adopted in clinical practice (4). However, despite these advances in image acquisition and postprocessing, detailed assessment of hepatic anatomy and lesions still relies heavily on manual or semi-automatic delineation performed by experts, which is time-consuming and subject to inter- and intra-observer variability. This scenario has driven the development of more automated, reproducible, and quantitative image analysis tools.

In this context, surgeons, radiologists, and oncologists employ various tools to assess the extent and stage of the disease, including the use of artificial intelligence (AI) techniques for segmentation (of organs or regions) (5), detection (of lesions) (6), and classification (7). With the growing availability of large medical imaging datasets and advances in computational processing, AI has become an essential tool in medical image analysis. In particular, deep learning (DL) (8,9) approaches, especially convolutional neural networks (CNNs) (7,10), have demonstrated remarkable performance in identifying complex anatomical patterns, surpassing traditional image processing methods in both accuracy and efficiency (11).

In hepatic imaging, these approaches have been applied to segment liver parenchyma, blood vessels, and lesions, as well as to detect and classify tumors. Such automated or semi-automated systems assist clinicians in improving diagnostic precision, treatment planning, and surgical decision-making, contributing to more personalized and reproducible clinical outcomes (12). Nevertheless, the diversity of imaging protocols, anatomical targets, and neural network architectures has created a heterogeneous methodological landscape, with considerable variation in performance metrics and clinical applicability.

Given the increasing relevance of these technologies and the need to organize the current body of evidence, the present review aims to provide a comprehensive overview and critical analysis of the main contributions and applications of neural network-based techniques for the segmentation of hepatic anatomical structures, including the liver, vessels, and lesions. The review also explores trends in imaging modalities, model architectures, and evaluation strategies, highlighting both the progress and the challenges in applying AI to hepatic medical imaging.

2. Materials and Methods

The literature search strategy is summarized in Table 1. The process followed a stepwise approach: initially, a search in PubMed using the keyword “Artificial Intelligence” retrieved 329414 results. Limiting the query to “Deep Learning” reduced the results to 65903, and further filtering by “Medical Imaging” yielded 27460 publications. Subsequent refinement focused on segmentation-related studies, resulting in 8200 articles, followed by filtering for algorithm-based research 7646 results, liver-related segmentation 405 results, and finally deep vessel segmentation, obtaining 51 studies.

For the evaluation of the selected studies, the four-reading method proposed by Gil (2008) (13) was adopted, providing a structured and progressive approach to literature. First, a recognition reading was conducted to determine the relevance of each article. This was followed by a selective reading to identify studies pertinent to the bibliographic review. Subsequently, an analytical reading was performed to extract central and comparable information, including objectives, methods, results, and conclusions. During the initial recognition reading, specific exclusion criteria were applied: (a) articles not written in English; (b) articles without free full-text availability; and (c) studies published more than ten years ago. Following this process, a final set of sixteen articles was selected for in-depth analysis, allowing for the systematic extraction and critical appraisal of information such as imaging modality, neural network type, region of interest, and methodological approach.

Table 1. Search strategy used in the PubMed database.

Base	Keywords	Results
PUBMED	#1 Artificial Intelligence	329414
	#2 Deep Learning	115719
	#3 Medical Imaging	3603058
	#4 Segmentation	534480
	#5 Algorithm	800319
	#6 Liver	1419352
	#7 Vessel	1136897
	#1 to #7	51

Source: The author (2026).

To facilitate comparative analysis, the selected studies were grouped according to how their deep learning models were integrated within the framework design. The identified categories were:

- Cascaded Models (CM): pipelines where two or more models are sequentially connected, meaning the output of one model serves as the input of the next, while maintaining the same network architecture.
- Hybrid Models (HM): combinations of distinct architectures, where each model performs a specific task within the overall system.
- Combined Approaches (CA): integration of deep learning methods with traditional computer vision algorithms for image analysis.
- Single-Step Approach (SA) or end-to-end learning: a single network trained to perform multiple tasks simultaneously within one unified model.

Based on these methodological criteria, the sixteen eligible articles were carefully reviewed and analyzed. For each study, relevant technical information was extracted, including the Authors and publication year, the Imaging Modality (e.g., CT or MRI), the AI Type (e.g., CNN, U-Net), the Dimensionality (2D, 3D, or 4D), the Methodology category (CM, HM, CA and SA), the Region of Interest (ROI), and the Image Database used (marked as “clinical” for institution-specific datasets). This process allowed for a systematic comparison among the studies in terms of technological approaches and data availability. A summary of these characteristics is presented in Table 2, which provides an overview of the methodological diversity and range of neural network applications in hepatic image segmentation.

Table 2. Summary of selected studies on hepatic segmentation using deep learning

Study (Year)	Modality	AI Type	Dim.[1]	Meth.[2]	ROI[3]	Img. Base[4]
Ibragimov et al., 2017(14)	CT	CNN[5] + MRF[6]	N/S[13]	CA / HM	Vessel	Clinical
Roth et al., 2018 (15)	CT	3D FCN[7], U-Net	3D	CM / CA	Liver + Vessel	Clinical
Ahn et al., 2020(16)	CT	3D U-Net	3D	SA	Liver	Clinical
Zbinden et al., 2022 (17)	MRI	3D U-Net / nnU-Net	3D	SA	Liver + Vessel	Clinical
Zbinden et al., 2023 (18)	MRI	nnU-Net	3D	SA	Liver + Vessel	Clinical
Alirr & Rahni, 2023 (19)	CT	U-Net	2D/3D	SA	Vessel	3D-IRCADb + Clinical
Lee et al., 2024 (20)	CT	U-Net + DenseU-Net	2D/3D	CM / HM / CA	Lesion	Clinical
Chen et al., 2024 (21)	CT	XGBoost[8] + MRF, filters	3D	HM / CA	Vessel	3D-IRCADb
Gupta et al., 2024 (22)	CT	3D U-Net, nnU-Net, Attention U-Net	3D	CA	Liver	Clinical + Public (3D-IRCADb, CHAOS, Task 8 MID)
Tanahashi et al., 2024 (23)	CT	DLR[9]	3D	CA	Vessel + Lesion	Clinical
Li et al., 2024 (24)	CT	U-Net	3D	SA	Liver + Vessel	Clinical
Kock et al. 2024 (25)	CT	DNN[10]	3D	SA	Vessel	Clinical
Raab et al., 2025 (26)	MRI	nnU-Net, Swin UNETR[11]	3D	CA	Liver + Vessel + Lesion	Clinical
Cavicchioli et al., 2025 (27)	CT	D^2-RD-UNet[12]	3D/4D	CM / CA / HM	Vessel	AIMS-HPV-385 + 3D-IRCADb
Zheng et al., 2025 (28)	MRI	Topology CNN	N/S[13]	SA	Lesion	Clinical
Herold et al., 2025 (29)	MRI	3D U-Net	3D	SA	Vessel	Clinical

[1]Dim. = Dimensions.
[2]Meth = Methodology.
[3]ROI = Region of Interest.
[4]Img. Base = Images Base
[5]CNN – Convolutional Neural Network.
[6]MRF – Markov Random Field.
[7]FCN – Fully Convolutional Network.
[8]XGBoost – Extreme Gradient Boosting algorithm.
[9]DLR – Deep Learning Reconstruction.
[10]DNN – Deep Neural Network.
[11]Swin UNETR – Swin Transformer U-Net Encoder–Decoder using Transformers for representation learning.
[12]D^2-RD-UNet – Dual-Dense Residual Dilated U-Net.
[13]N/S - not specified.

3. Results and Discussion

The selected studies were analyzed comparatively according to their methodological design, focusing on how different deep learning (DL) strategies are structured to address the challenges of hepatic segmentation across modalities such as CT and MRI. In this context, two major trends emerge: combined or hybrid frameworks, which integrate multiple processing stages or complementary algorithms to improve robustness and anatomical consistency; and single-step, end-to-end approaches, which rely on a single, optimized network to perform segmentation directly from input images. This dichotomy enables the assessment of how model complexity, architectural modularity, and input preconditioning influence segmentation accuracy, topological preservation, and clinical translatability. The following subsections present a comparative synthesis of these approaches. For clearer comparison, studies involving multiple methodological categories were classified under Combined Approaches. Figure 1 summarizes the key information extracted from the 16 studies analyzed in this work.

3.1. Combined Approaches

Across the studies by Ibragimov B. et al. (14) , Roth et al. (2018) (15), Lee et al. (2024) (20), Chen et al (21). (2024), Gupta et al. (2024) (22), Tanahashi et al. (2024) (23), Raab et al. (2025) (26), and Cavicchioli et al. (2025) (27), a common methodological pattern emerges: all adopt combined or hybrid deep learning strategies designed to improve the segmentation of hepatic structures, vessels, and lesions, primarily in CT with varying acquisition phases and, in one case, multiphase MRI. Each work, however, tailors its approach to specific anatomical or data-driven challenges, such as low vascular contrast, branching complexity, class imbalance, or cross-phase harmonization.

Ibragimov B. et al. (14)addressed one of the most challenging segmentation targets: the automatic delineation of the portal vein (PV) for SBRT planning, where subtle contrast and complex topology undermine conventional pipelines. Their hybrid model integrates convolutional neural networks (CNNs) to learn appearance features, Markov Random Fields (MRFs) for spatial regularization and smoothing, and anatomically informed centerline analysis. This early fusion of learned representations with vascular priors set a template for subsequent frameworks that explicitly protect topology while refining voxel-wise predictions.

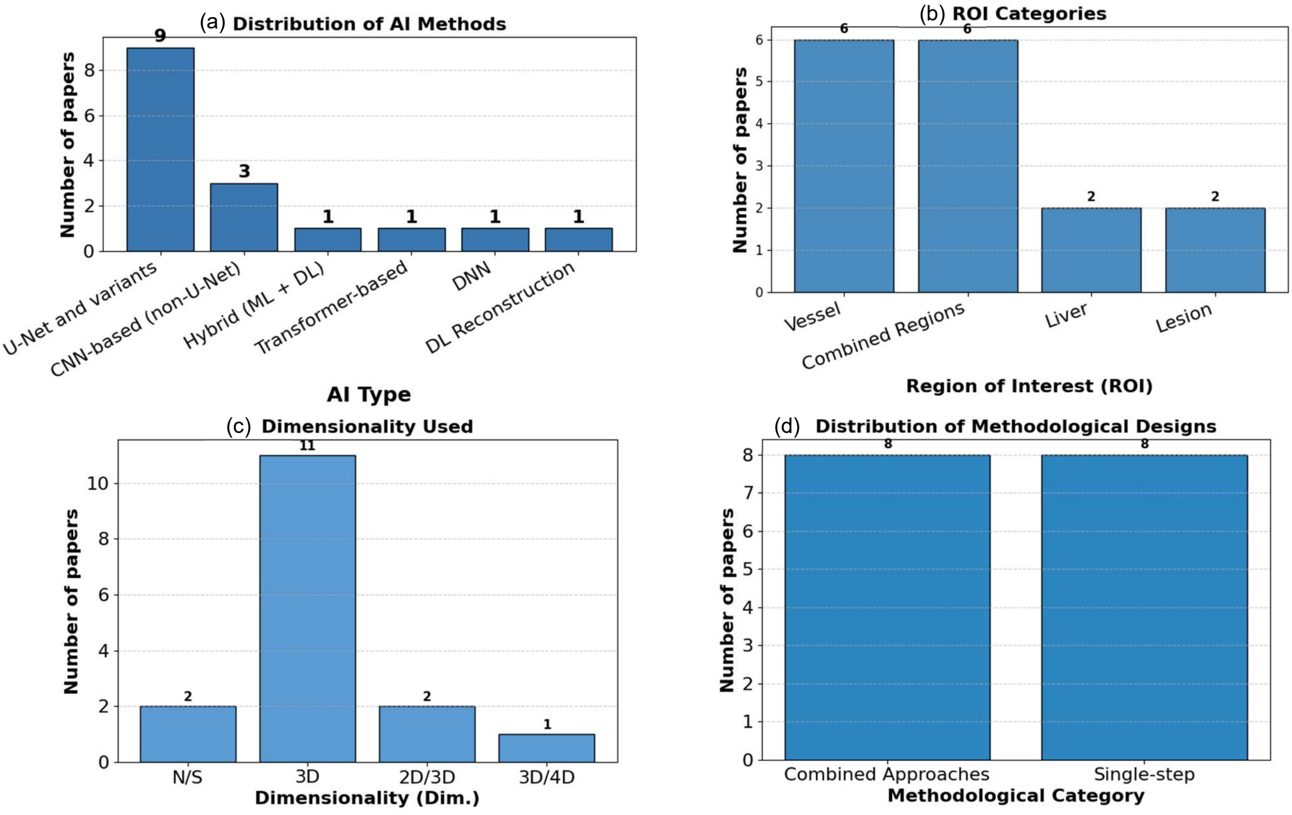

Figure 1. Quantitative summary of the 16 studies included in the review.(a) Distribution of AI methods: predominance of U-Net and variants (9/16), followed by non-U-Net CNNs (3/16) and other approaches (hybrid, transformer-based, DNN, and DL reconstruction; 1/16 each).(b) Segmented regions of interest (ROI): vessels and combined regions were the most frequent (6/16 each), followed by liver (2/16) and lesions (2/16). (c) Dimensionality: predominant use of 3D models (11/16), with occurrences of 2D/3D (2/16), 3D/4D (1/16), and not specified (2/16). (d) Methodological design: balance between combined approaches (CA/CM/HM; 8/16) and single-step (SA; 8/16). Numbers above the bars indicate the number of papers. Abbreviations: CNN = convolutional neural network; DNN = deep neural network; DLR = deep learning reconstruction; CA = combined approaches; CM = cascaded models; HM = hybrid models; SA = single-step; N/S = not specified.

Building on the same principle of hybridization, Roth et al. (2018) (15) implemented a coarse-to-fine 3D fully convolutional cascade that first restricts attention to candidate regions and then refines organ and vessel boundaries, improving Dice for small or intricate structures. In a complementary direction, Lee et al. (2024) (20) proposed a Hierarchical Fusion Strategy (HFS-Net) that divides the task by tumor size (using DenseU-Net for small lesions and U-Net for large ones) and fuses dynamic CT phases, achieving a global HCC Dice of 82.8%. By contrast, Chen et al. (2024) (21) emphasized data efficiency: a large 2D/3D filter ba, XGBoost classification, and MRF refinement accurately segmented liver vessels with limited annotation, illustrating how classical vesselness and texture cues can be combined with learning to reduce reliance on large labeled datasets.

Gupta et al. (2024) (22)explored attention-based architectures by comparing a 3D Attention U-Net with nnU-Net for liver and spleen contouring, reporting Dice up to 0.96 and showing that including spleen/vessel information during training helps sharpen organ interfaces and boundary definition. In a different but relevant angle, Tanahashi et al. (2024) (23) applied deep learning reconstruction (DLR) to Computed Tomography Hepatic Arteriography during Transcatheter Arterial Chemoembolization, demonstrating higher SNR/CNR and better visualization of small arterial feeders. Although not a segmentation model per se, DLR improves upstream image quality, thereby indirectly supporting downstream detection/segmentation and clinical confidence. Extending these advances to MRI, Raab et al. (2025) (26) compared nnU-Net and Swin UNETR in multiphase Gd-EOB datasets and found that CNN-based designs still outperform transformer variants for liver and vessel segmentation in practice, particularly when careful phase co-registration is enforced. Finally, Cavicchioli et al. (2025) introduced D²-RD-UNet, a dual-stage, dual-class network that merges dense and residual connections with a 4D input (CT plus vesselness filters) and a centerline-based connectivity correction.

In comparative terms, these studies converge on three methodological axes: (i) staged pipelines (cascades, hierarchical fusion) to address class imbalance and multi-scale structure; (ii) topology-aware regularization (MRF, centerlines) to preserve vascular continuity and limit breakages; and (iii) input enhancement (phase selection/fusion, DLR, vesselness filters) to increase separability between target classes. Taken together, these elements yield models that are increasingly anatomically faithful and operationally robust, better positioned for clinical generalization (external/cross-scanner validation) and for reducing manual workload.

3.2. Single-Step Approach

The studies by Ahn et al. (2020) (16), Zbinden et al. (2022) (17), Zbinden et al. (2023) (18), Alirr & Rahni (2023) (19), Li et al. (2024) (24), Kock et al. 2024 (25), Zheng et al. (2025) (28), and Herold et al. (2025) (29) exemplify the single-step (end-to-end) strategy, where a single network, which are the most often a U-Net/nnU-Net variant in 2D/3D, is trained to perform the target task without explicit multi-stage detection, hierarchical fusion, or dedicated topological postprocessing.

In portal-venous phase CT, Ahn et al. (2020) (16) focused on liver and spleen segmentation and volumetry with a direct single-pass pipeline, reflecting a setting in which intrinsic contrast and organ-scale geometry are already favorable. Similarly, Li et al. (2024) (24) and Kock et al. 2024 (25) leveraged nnU-Net (and variants) for liver, vessels, and segments. When acquisition phases are curated and pre-processing is standardized, these end-to-end models achieve strong geometric accuracy with meaningful time savings compared to manual delineation, supporting clinical applicability.

Within MRI T1-VIBE Dixon without contrast, Zbinden et al. (2022, 2023) (17,18) demonstrated that choosing a single optimal channel can outperform multimodal combinations, and that a well-configured single-step network can handle liver, portal vein, and hepatic veins, as well as derived endpoints such as Liver Segmental Volume Ratio (LSVR). This underscores a practical insight: the right phase/channel can replace part of the pipeline complexity otherwise provided by combined approaches.

From a clinical-outcome perspective, Zheng et al. (2025) (28) coupled single-step segmentation with topological descriptors to enable non-invasive prediction of microvascular invasion (MVI) in HCC, with solid internal and external validation. In a related direction, Herold et al. (2025) (29) used Gadoxetic acid–enhanced Magnetic Resonance Imaging (EOB-MRI) to compute vessel-to-volume ratios (Total Vessel Volume Ratio (TVVR), Hepatic Vein Volume Ratio (HVVR), Portal Vein Volume Ratio (PVVR)), showing associations with disease severity markers. These studies move beyond geometric scores to demonstrate clinical utility through prognostic or disease-stratification relevance, shortening the path from segmentation to decision-making.

Overall, when the imaging modality/phase provides sufficient contrast (CT portal venous; MRI Dixon in-phase; EOB-MRI with reliable phase registration) and the target is macro-anatomical (liver, segments, spleen), single-step networks tend to be simpler, reproducible, and efficient, while remaining competitive in accuracy. Moreover, their direct coupling to derived biomarkers (topology for Microvascular Invasion (MVI); vessel-to-volume ratios) highlights downstream clinical value, bridging the gap between segmentation and prognosis and planning.

4. Conclusion

To support accurate and rapid diagnosis, hepatic image segmentation using deep learning represents a significant advantage in clinical practice. Among the approaches identified in the literature, U-Net variants stand out for their flexibility, stability, and strong generalization capability across different imaging modalities. Combined and hybrid models show advantages when dealing with vascular topology and multiphase data, whereas single-step approaches remain efficient and are preferred for faster processing and greater clinical translation.

Future studies should emphasize external validation and the integration of multimodal imaging, such as CT–MRI fusion, to enhance model robustness and generalizability. Ultimately, the integration of deep learning–based segmentation into clinical workflows has the potential to improve early detection, treatment planning, and personalized management of liver diseases, reinforcing the role of AI as an essential ally in hepatic imaging and precision medicine.

Acknowledgements

The authors would like to express their gratitude to the Faculty of Medicine of Botucatu for their institutional and technical support throughout this study.

References

1. Khan N, Ahmed I, Kiran M, Adnan A. Overview of technical elements of liver segmentation. International Journal of Advanced Computer Science and Applications. 2016;7(12).
2. Forner A, Reig M, Bruix J. Hepatocellular carcinoma. The Lancet [Internet]. 2018;391(10127):1301–14. Available from: https://www.sciencedirect.com/science/article/pii/S0140673618300102
3. World Cancer Research Fund. Liver cancer. 2025 [cited 2025 Oct 15]. World Cancer Research Fund. Available from: https://www.wcrf.org/preventing-cancer/cancer-types/liver-cancer/
4. Zhou J, Sun H, Wang Z, Cong W, Zeng M, Zhou W, et al. Guidelines for the diagnosis and treatment of primary liver cancer (2022 edition). Liver Cancer. 2023;12(5):405–44.
5. Hu P, Wu F, Peng J, Liang P, Kong D. Automatic 3D liver segmentation based on deep learning and globally optimized surface evolution. Phys Med Biol. 2016;61(24):8676.
6. Pham DD, Dovletov G, Pauli J. Liver segmentation in CT with MRI data: zero-shot domain adaptation by contour extraction and shape priors. In: 2020 IEEE 17th international symposium on biomedical imaging (ISBI). IEEE; 2020. p. 1538–42.
7. Fabijańska A, Vacavant A, Lebre MA, Pavan ALM, de Pina DR, Abergel A, et al. U-CatcHCC: An accurate HCC detector in hepatic DCE-MRI sequences based on an U-Net framework. In: International Conference on Computer Vision and Graphics. Springer; 2018. p. 319–28.

8. Kashala Kabe G, Song Y, Liu Z. FireNet-MLstm for classifying liver lesions by using deep features in CT images. Multimed Tools Appl. 2022 Jan 1;81(2):1607–23.
9. Zheng R, Wang Q, Lv S, Li C, Wang C, Chen W, et al. Automatic liver tumor segmentation on dynamic contrast enhanced MRI using 4D information: deep learning model based on 3D convolution and convolutional LSTM. IEEE Trans Med Imaging. 2022;41(10):2965–76.
10. Ahmad M, Qadri SF, Qadri S, Saeed IA, Zareen SS, Iqbal Z, et al. A lightweight convolutional neural network model for liver segmentation in medical diagnosis. Comput Intell Neurosci. 2022;2022(1):7954333.
11. Liu X, Song L, Liu S, Zhang Y. A review of deep-learning-based medical image segmentation methods. Sustainability (Switzerland). 2021 Feb 1;13(3):1–29.
12. Hennedige T, Venkatesh SK. Imaging of hepatocellular carcinoma: diagnosis, staging and treatment monitoring. Cancer Imaging. 2013;12(3):530.
13. Gil AC. Como elaborar projetos de pesquisa. Vol. 4. Atlas São Paulo; 2002.
14. Ibragimov B, Toesca D, Chang D, Koong A, Xing L. Combining deep learning with anatomical analysis for segmentation of the portal vein for liver SBRT planning. Phys Med Biol. 2017;62(23):8943.
15. Roth HR, Oda H, Zhou X, Shimizu N, Yang Y, Hayashi Y, et al. An application of cascaded 3D fully convolutional networks for medical image segmentation. Computerized Medical Imaging and Graphics. 2018; 66:90–9.
16. Ahn Y, Yoon JS, Lee SS, Suk HI, Son JH, Sung YS, et al. Deep learning algorithm for automated segmentation and volume measurement of the liver and spleen using portal venous phase computed tomography images. Korean J Radiol. 2020;21(8):987.
17. Zbinden L, Catucci D, Suter Y, Berzigotti A, Ebner L, Christe A, et al. Convolutional neural network for automated segmentation of the liver and its vessels on non-contrast T1 vibe Dixon acquisitions. Sci Rep. 2022;12(1):22059.
18. Zbinden L, Catucci D, Suter Y, Hulbert L, Berzigotti A, Brönnimann M, et al. Automated liver segmental volume ratio quantification on non-contrast T1–Vibe Dixon liver MRI using deep learning. Eur J Radiol. 2023; 167:111047.
19. Alirr OI, Rahni AAA. Hepatic vessels segmentation using deep learning and preprocessing enhancement. J Appl Clin Med Phys. 2023;24(5): e13966.
20. Lee IC, Tsai YP, Lin YC, Chen TC, Yen CH, Chiu NC, et al. A hierarchical fusion strategy of deep learning networks for detection and segmentation of hepatocellular carcinoma from computed tomography images. Cancer Imaging. 2024;24(1):43.
21. Chen W, Zhao L, Bian R, Li Q, Zhao X, Zhang M. Compensation of small data with large filters for accurate liver vessel segmentation from contrast-enhanced CT images. BMC Med Imaging. 2024;24(1):129.
22. Gupta AC, Cazoulat G, Al Taie M, Yedururi S, Rigaud B, Castelo A, et al. Fully automated deep learning-based auto-contouring of liver segments and spleen on contrast-enhanced CT images. Sci Rep. 2024;14(1):4678.
23. Tanahashi Y, Kubota K, Nomura T, Ikeda T, Kutsuna M, Funayama S, et al. Improved vascular depiction and image quality through deep learning reconstruction of CT hepatic arteriography during transcatheter arterial chemoembolization. Jpn J Radiol. 2024;42(11):1243–54.
24. Li S, Li X, Zhou F, Zhang Y, Bie Z, Cheng L, et al. Automated segmentation of liver and hepatic vessels on portal venous phase computed tomography images using a deep learning algorithm. J Appl Clin Med Phys. 2024;25(8): e14397.
25. Kock F, Thielke F, Abolmaali N, Meine H, Schenk A. Suitability of DNN-based vessel segmentation for SIRT planning. Int J Comput Assist Radiol Surg. 2024;19(2):233–40.
26. Raab F, Strotzer Q, Stroszczynski C, Fellner C, Einspieler I, Haimerl M, et al. Automatic segmentation of liver structures in multiphase MRI using variants of nnU-Net and Swin UNETR. Sci Rep. 2025;15(1):25740.
27. Cavicchioli M, Moglia A, Garret G, Puglia M, Vacavant A, Pugliese G, et al. D2-RD-UNet: A dual-stage dual-class framework with connectivity correction for hepatic vessels segmentation. Comput Biol Med. 2025; 195:110530.
28. Zheng T, Zhu Y, Jiang H, Yang C, Ye Y, Bashir MR, et al. MRI-Based Topology Deep Learning Model for Noninvasive Prediction of Microvascular Invasion and Assisting Prognostic Stratification in HCC. Liver International. 2025;45(3): e16205.
29. Herold A, Sobotka D, Beer L, Bastati N, Poetter-Lang S, Weber M, et al. MRI-derived quantification of hepatic vessel-to-volume ratios in chronic liver disease using a deep learning approach. Eur Radiol Exp. 2025;9(1):75.

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