REVIEW

**Editorial Process:** Submission:05/07/2025 Acceptance:01/15/2026 Published:01/20/2026

# Advancing Diagnostic Accuracy in Liver Cancer: A Systematic Review of Artificial Intelligence Applications in Hepatocellular Carcinoma and Cholangiocarcinoma Detection Using Abdominal CT Imaging

**Schawanya Kaewpitoon Rattanapitoon[1,2], Patpitcha Arunsarn[2,3], Thirayu Meererksom[2], Chutharat Thanchonnang[1,2], Alisa Boonsuya[2], Sirichai Phinsiri[2], Parichart Nomsungnoen[2], Pattarasuda Pongseeda[2], Nattawut Keeratibharat[4], Jirapa Chansangrat[5], Phornpitcha Pechdee[6], Nathkapach Kaewpitoon Rattanapitoon[1,2]***

## Abstract

**Objective:** This study aimed to systematically evaluate the diagnostic performance of artificial intelligence (AI) in differentiating hepatocellular carcinoma (HCC) from cholangiocarcinoma (CCA) using abdominal CT and MRI, with an emphasis on its clinical implications for liver cancer management. **Methods:** Following the PRISMA guidelines, we conducted a comprehensive literature search across five major databases (PubMed, Web of Science, ScienceDirect, Scopus, and Google Scholar) from 2000 to May 6, 2025. Eligible studies included original research that applied AI for the diagnosis of HCC or CCA. Data were extracted on study design, population characteristics, imaging modality, AI methodology, diagnostic performance (sensitivity, specificity, accuracy, AUC), validation strategies, and risk of bias, which was assessed using QUADAS-2. **Results:** A total of 44 studies met the inclusion criteria. Most were retrospective, while only a few prospective designs provided real-time validation. CT and MRI were the dominant imaging modalities, with MRI showing superior sensitivity for small lesions, while CT was more effective for large tumors and vascular involvement. Convolutional neural networks (CNNs) were the most frequently used model architectures, although more advanced deep learning and hybrid radiomic–clinical models were also reported. Diagnostic performance was consistently strong: sensitivity and specificity ranged from 75% to 100%, overall accuracy from 73% to 96%, and AUC values from 0.74 to 0.99. Studies incorporating multi-modal imaging (CT+MRI) or radiomic–genomic features achieved the highest diagnostic performance, with accuracy and specificity exceeding 90–95%. Subgroup analyses revealed that tumor size, location, microvascular invasion, and patient demographics influenced AI model performance. Risk of bias was generally low-to-moderate, with limitations related to retrospective data and limited external validation. **Conclusion:** AI models, particularly CNN- and radiomics-based, show accuracy comparable to radiologists in distinguishing HCC from CCA. Multi-modal integration and feature fusion hold the greatest promise for improving workflows. Large-scale, multi-center validation is needed to confirm their utility and enable adoption in liver cancer care.

**Keywords:** Radiomics- deep learning- multi-modal imaging- clinical decision support- precision oncology

*Asian Pac J Cancer Prev,* **27 (1)**, 5-18

## Introduction

Diagnostic imaging is an essential tool for the non-invasive detection and characterization of diseases, particularly liver malignancies. The accurate differentiation of liver cancers, such as hepatocellular carcinoma (HCC) and cholangiocarcinoma (CCA), remains a significant challenge, often requiring the expertise of highly trained radiologists. However, interpretation variability exists, especially among less experienced or newly certified radiologists, which can lead to diagnostic delays and inconsistencies [1]. To address these challenges, artificial

*[1]Nathkapach Rattanatanpitoon, FMC Medical Center, Nakhonratchasima, Thailand. [2]Parasitic Disease Research Center, Suranaree University of Technology NakhonRatchasima, Thailand. [3]Faculty of Medicine, Vongchavalitkul University, NakhonRatchasima, Thailand. [4]School of Surgery, Institute of Medicine, Suranaree University of Technology, NakhonRatchasima, Thailand. [5]School of Radiology, Institute of Medicine, Suranaree University of Technology, NakhonRatchasima, Thailand. [6]Sirindhorn College of Public Health Suphanburi, Suphanburi, Thailand. *For Correspondence: nathkapach.ratt@gmail.com*

intelligence (AI) has emerged as a transformative force in medical imaging, offering the potential to enhance diagnostic accuracy and efficiency. By mimicking human cognitive functions, such as reasoning and decision-making, AI enables machines to autonomously process complex data with minimal human oversight [2]. The adoption of AI in healthcare is rapidly accelerating, with advances in computing power and large-scale data analytics driving improvements in diagnostic workflows and treatment planning [3]. AI applications are now being extended beyond hospitals to support community-level health services, including public health data collection and disease surveillance.

Globally, liver cancer is the sixth most commonly diagnosed cancer and the third leading cause of cancer-related mortality, accounting for approximately 905,000 new cases and 830,000 deaths annually [4]. HCC constitutes about 75–85% of primary liver cancers, while CCA represents 10–15% [5]. The burden is particularly pronounced in Southeast Asia, including Thailand, Laos, and Cambodia, where CCA prevalence is among the highest worldwide, largely driven by liver fluke infection and chronic biliary inflammation [6, 7]. These epidemiological disparities underscore the pressing need for precise, accessible diagnostic tools tailored to both global and regional contexts.

Liver cancer diagnosis, which requires specialized radiologic expertise, stands to greatly benefit from AI advancements. Deep learning models, in particular, have demonstrated superior performance in the classification, detection, and characterization of liver lesions in imaging studies [8]. Several reports have indicated that AI systems can achieve diagnostic accuracies comparable to, or even exceeding, those of experienced radiologists, especially in identifying HCC and CCA using computed tomography (CT) and magnetic resonance imaging (MRI) [9, 10]. AI has shown remarkable capabilities in analyzing complex imaging data, such as multiphasic CT [11], and has outperformed conventional imaging techniques in certain contexts, such as mass spectrometry-based automated liver cancer diagnosis [12]. Furthermore, AI models are increasingly being used in radiomic analysis to predict the aggressiveness and treatment response of liver tumors [13].

Nevertheless, important challenges remain. Data heterogeneity, algorithm generalizability, and integration into real-world workflows limit translation into daily practice. Moreover, previous reviews have often been descriptive, with limited pooled statistical analyses and without structured risk-of-bias assessments such as QUADAS-2. Few studies have addressed practical considerations such as interpretability, cost-effectiveness, and workflow implementation. These gaps highlight the need for more comprehensive evidence synthesis.

In light of these advancements and unmet needs, our research team undertook a systematic review to comprehensively evaluate the role of AI in the imaging-based diagnosis of hepatocellular carcinoma and cholangiocarcinoma. By incorporating pooled sensitivity, specificity, and AUC analyses, assessing study quality using QUADAS-2, and presenting visual comparative charts, this study aims to provide a robust overview of AI's diagnostic potential. Additionally, we examine the predictive factors incorporated in AI models for liver lesion classification and discuss their practical implications for clinical adoption. Ultimately, the goal of this review is to inform future AI development and enhance its clinical utility in diagnosing liver cancers, thereby contributing to improved disease prevention and control strategies [14-16].

## Materials and Methods

This systematic review adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [10]. A comprehensive literature search was conducted on May 6, 2025, across five major electronic databases PubMed, Web of Science, ScienceDirect, Scopus, and Google Scholar chosen for their broad coverage of biomedical and technical research. The search period was set from 2000 to 2025, reflecting the rise of AI applications in medical imaging during this timeframe.

*Search Strategy*

The search employed a combination of predefined keywords relevant to AI applications in liver cancer diagnosis, using Boolean operators to maximize comprehensiveness. The final search query included:

• ("*focal liver lesions*" OR "*FLLs*" OR "*hepatic focal lesions*" OR "*liver tumor*" OR "*hepatic tumor*")

• AND ("*artificial intelligence*" OR "*machine learning*" OR "*neural networks*" OR "*deep learning*" OR "*automated diagnosis*" OR "*computed tomography*" OR "*CT*" OR "*magnetic resonance imaging*" OR "*MRI*" OR "*computer-aided diagnosis*" OR "*automated CT*" OR "*automated MRI*")

Key terms such as "*Artificial Intelligence*," "*Cholangiocarcinoma*," "*Hepatocellular Carcinoma*," and "*Liver Cancer*" were incorporated to refine the search and ensure inclusion of the most relevant studies.

*Eligibility Criteria*

Studies were included if they met all of the following criteria:

• Publication period: Published between 2000 and 2025, with 2000 chosen to reflect the emergence and growth of AI applications in medical imaging.

• Study focus: Specifically investigated AI applications for the detection or diagnosis of hepatocellular carcinoma (HCC), cholangiocarcinoma (CCA), or liver cancer.

• Study type: Original research articles with full-text availability.

• Language: Written in English, acknowledging the potential for language bias.

• Methodological rigor: Studies were required to be methodologically sound and provide complete datasets, including sufficient data to assess AI diagnostic performance metrics (e.g., sensitivity, specificity, accuracy, and AUC).

*Studies were excluded if they met any of the following conditions*

• Publication period: Published outside the specified date range (2000–2025).

• Duplicates: Duplicate records identified across multiple databases.

• Study type: Reviews, case reports, conference abstracts or proceedings, letters, or editorials.

• Study focus: Investigations of cancers other than HCC or CCA, or studies including mixed cancer populations without separate analyses for HCC or CCA.

• Data availability: Studies lacking full-text access or providing incomplete, unclear, or insufficient data for extraction and evaluation of AI diagnostic performance.

*Study Selection*

The initial database search retrieved a total of 245 articles: 133 from PubMed, 65 from Scopus, 40 from ScienceDirect, and 7 from Google Scholar. After removing duplicates and applying the eligibility criteria, 236 articles remained. Title and abstract screening identified 183 potentially relevant studies, and subsequent full-text assessment resulted in 44 studies that met all inclusion criteria. The selection process is summarized in a PRISMA flow diagram (Figure 1).

*Data Extraction and Synthesis*

Data were independently extracted by three reviewers using a standardized form to ensure consistency and minimize bias. Extracted variables included:

• Author names and year of publication

• Study location and population characteristics

• Sample size and study design

• Imaging modalities employed (CT, MRI)

• AI methodologies applied (deep learning, machine learning, hybrid approaches)

• Diagnostic performance metrics (sensitivity, specificity, accuracy, AUC)

• Validation strategies (e.g., k-fold cross-validation, external datasets)

• Risk of bias assessment using the QUADAS-2 tool, evaluating patient selection, index test, reference standard, and flow and timing.

Extracted data were organized into structured tables to facilitate comparisons. AI techniques were evaluated for diagnostic capabilities in differentiating HCC and CCA [6, 8, 11].

*Quality Assessment*

The methodological quality of the included studies was evaluated using the QUADAS-2 tool, which assesses risk of bias across four domains: patient selection, index test, reference standard, and flow/timing. For this review, additional emphasis was placed on:

• Relevance and appropriateness of the AI model for liver cancer diagnosis.

• Adequacy of sample size to ensure statistical reliability.

• Clarity and transparency of the AI methodology, including data preprocessing, feature extraction, and training-validation strategies.

• Accuracy, completeness, and reporting transparency

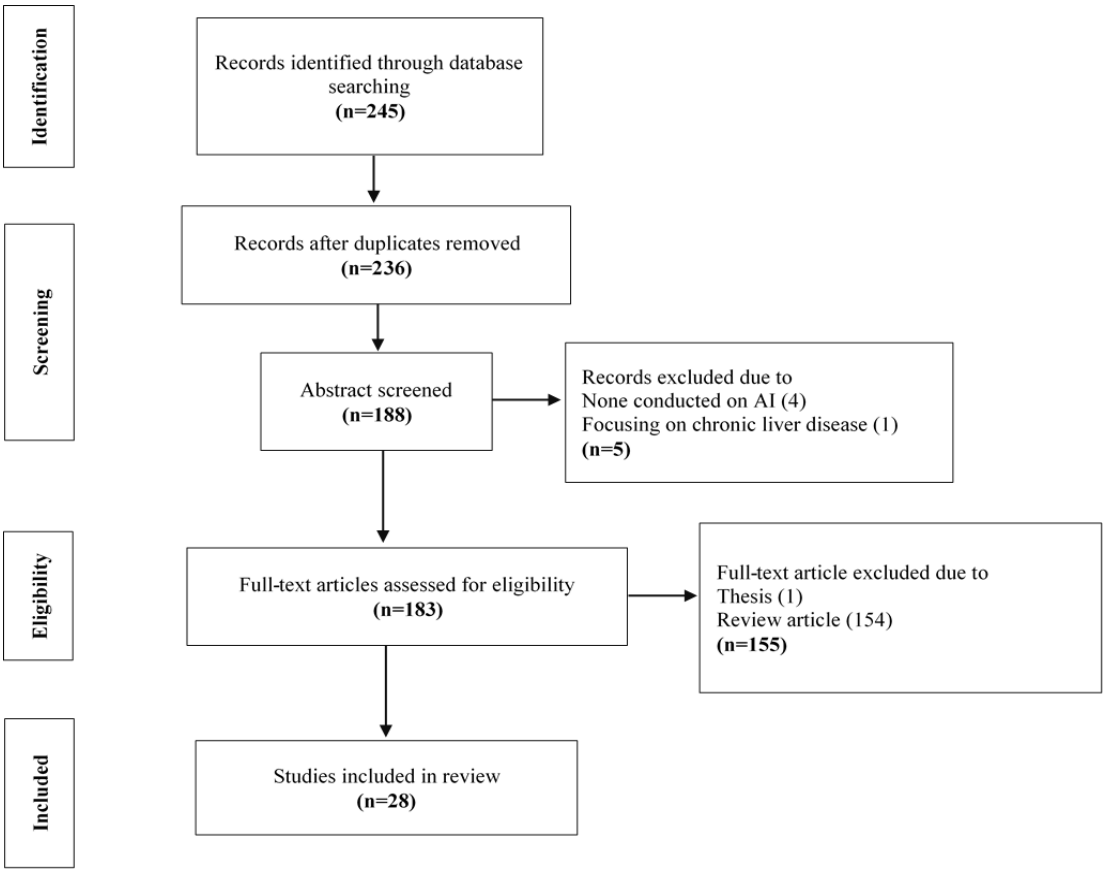


Figure 1. PRISMA Flow Diagram of the Study Selection Process

of diagnostic metrics.

Further considerations included the imaging modalities applied (CT and MRI) and the potential impact of language bias, as only English-language publications were included.

*Results Interpretation*

Extracted data were synthesized thematically and analyzed according to diagnostic performance, processing efficiency, specificity, and AI model architecture. Studies consistently demonstrated that AI models achieved diagnostic accuracy comparable to, and in some cases exceeding, that of experienced radiologists. Reported accuracy rates in differentiating HCC from CCA frequently approached or exceeded 90%, with sensitivities and specificities in the 80–95% range [8, 11]. Performance was further enhanced in studies integrating multimodal imaging or radiomic–genomic fusion approaches.

This rigorous methodology ensured a transparent and high-quality systematic review, providing critical insights into technological trends, clinical applicability, and the practical utility of AI-driven liver cancer diagnosis.

## Results

*Study Characteristics and Imaging Modalities*

A total of 44 studies were included in this systematic review, all focusing on the application of artificial intelligence (AI) in liver cancer, particularly differentiating hepatocellular carcinoma (HCC) from intrahepatic cholangiocarcinoma (ICC) or other liver malignancies (Table 1). The studies varied in design, sample size, and imaging modality but consistently evaluated AI-based approaches particularly deep learning and radiomics models for improving diagnostic accuracy.

*Retrospective vs. Prospective Designs*

Most studies adopted a retrospective design, leveraging pre-existing datasets to train and test AI models. Prospective studies were less common but provided opportunities for real-time patient data collection and external validation, enhancing clinical applicability.

*Imaging Modalities*

Contrast-enhanced CT and MRI were the most frequently utilized imaging modalities. CT provided detailed assessment of tumor vascularity, essential for differentiating HCC from ICC. MRI offered superior soft-tissue contrast, particularly when employing dynamic contrast-enhanced (DCE) and diffusion-weighted imaging (DWI) sequences. A limited number of studies explored hybrid modalities such as PET/CT, whereas ultrasound was rarely applied and demonstrated comparatively lower diagnostic yield.

*AI Models and Approaches*

• Model Architectures: Convolutional Neural Networks (CNNs) were predominant, capitalizing on automated feature extraction from raw imaging data. More advanced architectures, including Residual Networks (ResNets) and Fully Convolutional Networks (FCNs), were applied for improved segmentation and classification. In select studies, Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) models were incorporated for analyzing temporal imaging sequences.

• Input Modalities and Data Types: Most models were trained on CT or MRI datasets, with some integrating advanced MRI sequences. Studies combining radiomic features (e.g., texture, shape, and intensity metrics) with deep learning demonstrated superior performance. Multi-modal approaches integrating CT and MRI achieved the highest accuracy by leveraging complementary anatomical and functional information.

*Diagnostic Accuracy and Performance Metrics*

AI models reported sensitivity and specificity between 75–100%, with overall accuracy ranging from 73% to 96%. The area under the curve (AUC) consistently fell between 0.74 and 0.99, indicating strong diagnostic capability. Models integrating multi-modal imaging or radiomic–clinical features often outperformed single-modality approaches.

Figure 2 illustrates the reported AUC ranges across studies. The majority clustered between 0.75 and 0.90, with a subset achieving near-perfect performance (AUC >0.95).

Figure 3 summarizes the diagnostic performance across imaging modalities. MRI and CT demonstrated the highest mean AUC values, particularly when integrated with radiomic or clinical features. Hybrid approaches (multi-modal fusion) consistently outperformed single-modality models, whereas clinical-only datasets yielded lower performance (AUC ~0.70).

*Subgroup and Stratified Analyses*

Tumor characteristics (size, location, microvascular invasion) and patient demographics influenced diagnostic performance. MRI-based models showed higher sensitivity for small lesions, whereas CT-based models were more effective for large tumors or vascular involvement. Multi-modal integration consistently enhanced performance.

*Risk of Bias*

Most studies were rated as having low-to-moderate risk of bias using QUADAS-2, with limitations primarily due to retrospective designs and limited external validation. Independent validation cohorts were relatively few, affecting generalizability.

*Key Takeaways*

1. AI models, particularly CNN-based and radiomics–integrated approaches, achieved high diagnostic accuracy, frequently matching or exceeding experienced radiologists.

2. MRI-based models were more sensitive for small lesions, highlighting the importance of imaging modality selection.

3. Multi-modal integration of CT, MRI, and radiomic features enhanced overall diagnostic performance.

4. Widespread clinical adoption requires large-scale, multi-center validation with standardized imaging protocols.

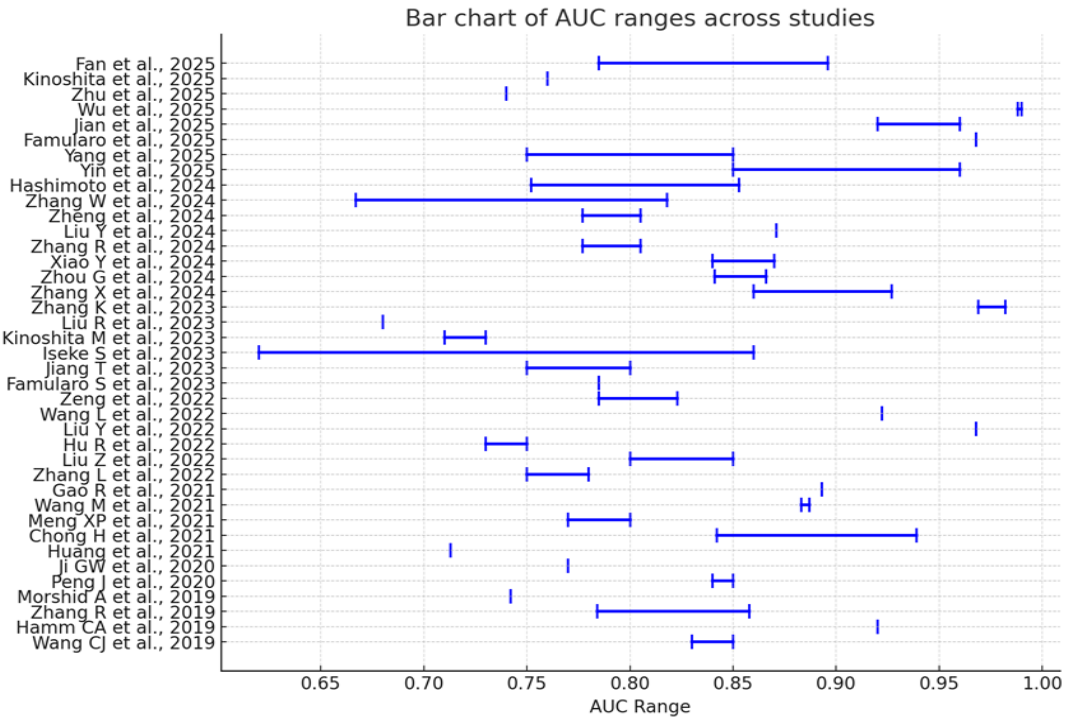


Figure 2. Distribution of Reported AUC Values Across Included Studies

## Discussion

This systematic review provides a comprehensive synthesis of artificial intelligence (AI) applications in liver cancer, particularly in differentiating hepatocellular carcinoma (HCC) from intrahepatic cholangiocarcinoma (ICC) and other liver malignancies. Across 44 included studies, AI models demonstrated strong diagnostic performance, with sensitivity and specificity generally ranging from 75–100%, overall accuracy between 73–96%, and area under the curve (AUC) values spanning 0.74 to 0.99. These findings highlight the rapid evolution of AI tools, which increasingly match or even surpass the performance of expert radiologists in complex diagnostic tasks [2, 5, 6, 12, 17].

*Imaging modalities and diagnostic implications*

CT and MRI emerged as the dominant imaging modalities applied in AI studies. CT provided robust assessment of tumor vascularity, which is essential

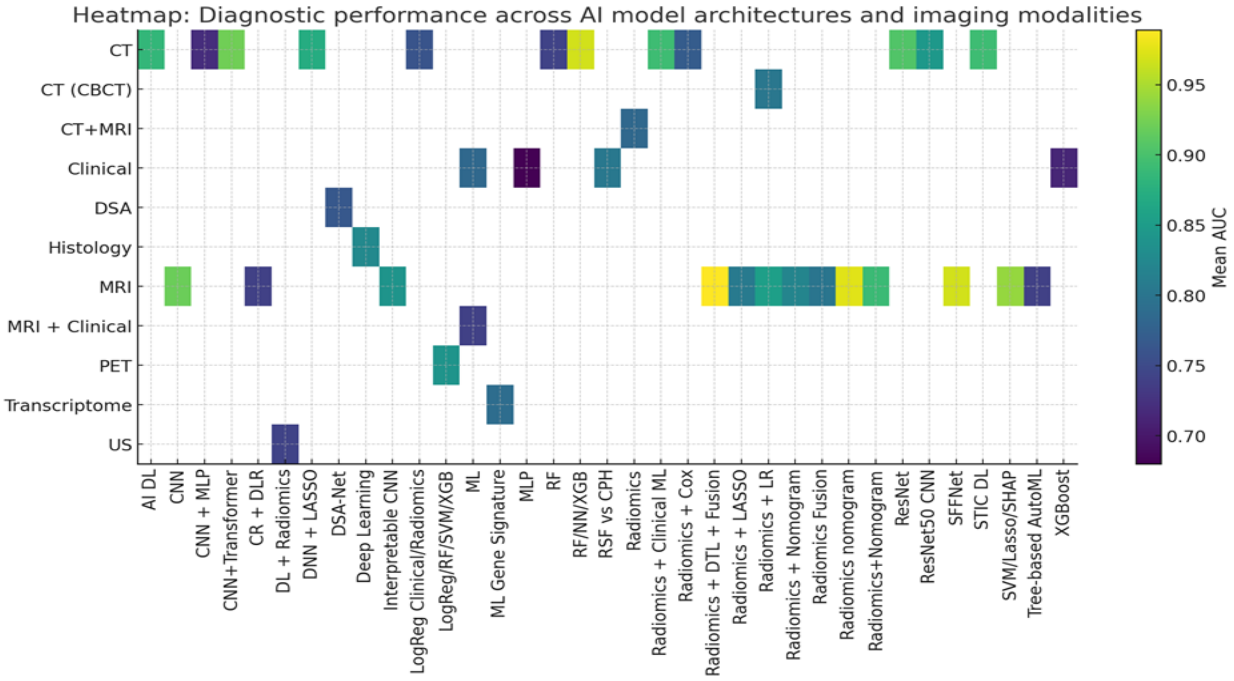


Figure 3. Heatmap Comparing Diagnostic Performance Across AI Model Architectures and Imaging Modalities

Table 1. Summary of Studies Using Artificial Intelligence Models for Differentiating Hepatocellular Carcinoma (HCC) and Intrahepatic Cholangiocarcinoma (ICC)

| Authors | Country | Study design | Population | Training data | Techniques | Validation methods | Challenges | Reported outcome |
|---|---|---|---|---|---|---|---|---|
| Fan et al., 2025 [24] | China | Retrospective | HCC (n=84), MVI-confirmed by histopathology | 68Ga-FAPI PET radiomics (shape, first-, second-, higher-order features) | Logistic Regression / Random Forest / SVM / XGBoost | Nested test across SUVmax thresholds (30%, 40%, 50%, 60%) | Variation in SUVmax threshold for semi-automatic VOI delineation affecting model performance | AUC = 0.785–0.896; Accuracy = 87.5%; Sn = 100%; Sp = not reported |
| Kinoshita et al., 2025 [25] | Japan | Retrospective multicenter | HCC (n=533) | CT radiomics + clinical features | Logistic Regression, fused clinical-radiomics model | Training (n=426) / Test (n=107) | Non-standardized CT imaging protocols | AUC: Radiomics 0.76 vs Clinical 0.76; Fused model did not improve performance |
| Zhu et al., 2025 [26] | China | Retrospective multicenter | HCC (n=304) | Gd-EOB-DTPA MRI radiomics (intratumoral & peritumoral) | Conventional radiomics (CR) + Deep learning radiomics (DLR) | Training (n=216) / Testing (n=88) | Multi-center variability; single vs bi-regional feature extraction | Bi-regional CR-DLR model AUC = 0.740 (testing), Accuracy = 73.9%, Sn = 50%, Sp = 84.5% |
| Wu et al., 2025 [27] | China | Retrospective multicenter | HCC (n=138), DPHCC (n=122), ICC (n=121) | CE-MRI radiomics | Radiomics, Deep Transfer Learning (DTL), Fusion (vgg19) | Internal (n=244) / External (n=75) | Differentiating DPHCC from HCC & ICC | Fusion model macro-AUC = 0.988–0.990; Accuracy = 0.875–0.935; F1-score = 0.885–0.937 |
| Jian et al., 2025 [28] | China | Retrospective multicenter | Solitary HCC (n=319) | Clinical indicators, MRI, radiomics | SVM, Lasso regression, SHAP interpretation | Internal training/ validation + 2 external validation sets | Integration of heterogeneous multi-center data | Combined model AUC = 0.92–0.96; Improved predictive performance over individual models |
| Famularo et al., 2025 [29] | Italy | Retrospective multicenter | HCC (n=218) | 3-phase CT radiomics (tumoral, peritumoral, healthy liver) | Random Forest, Neural Network, XGBoost | Training (70%) / Test (30%) | Multi-center CT acquisition, high-dimensional data | RF model Accuracy = 96.8%; Sn = 95.2%, Sp = 97.6% |
| Yang et al., 2025 [30] | China | Retrospective multicenter | HCC (n=320) | DCE-MRI radiomics (intratumoral & peritumoral) | Radiomics, Clinical-radiomics fusion | Internal & external validation | Accurate segmentation and feature extraction from multiple MRI phases | Combined model AUC = 0.75–0.85; Associated with early recurrence & PFS |
| Yin et al., 2025 [31] | China | Retrospective | Unresectable HCC (n=172) | CT radiomics + clinical features | Deep learning (ResNet) based radiomics | Training/testing/ external validation | Multi-center heterogeneity, combination therapy response prediction | Treatment response AUC = 0.85–0.96; PFS prediction AUC = 0.762–0.874; C-index combination model = 0.75 |
| Mu et al., 2024 [32] | China | Retrospective | HCC ≤5 cm (n=331) | DCE-MRI | ResNet-based deep learning + clinical features | Random split train/ test | Early recurrence prediction; integration of clinical data | Early recurrence prediction; metrics not reported |
| Alshagathrh F et al., 2024 [33] | Saudi Arabia | Retrospective | Liver US images (NAFLD/NASH) | CNNs (InceptionV3, ResNet50, DenseNet121, EfficientNetB0) + Random Forest | Hybrid deep learning + ML | Cross-validation | Hepatocyte ballooning detection, dual dichotomy classification | Accuracy = 97.4%; AUC = 0.99; Sensitivity = 99% for 'Many' class |
| Hashimoto K et al., 2024 [34] | Japan | Retrospective | HCC nodules post c-TACE (n=103 in 71 pts) | CBCT lipiodol deposition | Radiomics + logistic regression | Train/test split 7:3 | Local tumor recurrence prediction | Clinical-radiomics WS model: AUC train = 0.853, test = 0.752 |
| Zhang W et al., 2024 [35] | China | Retrospective multicenter | HCC (n=576 lesions, 2 centers) | Ultrasound (B-mode, CEUS) | DL and radiomics, ROI enlargement, AFP integration | Cross-center internal/external validation | Cross-institutional robustness, modality comparison | DL AUC = 0.802–0.818 internal, 0.667–0.688 external; Radiomics AUC = 0.749–0.869 internal, 0.646–0.697 external |

Table 1. Continued

| Authors | Country | Study design | Population | Training data | Techniques | Validation methods | Challenges | Reported outcome |
|---|---|---|---|---|---|---|---|---|
| Zheng S et al., 2024 [36] | China | Retrospective | HCC cohorts (TCGA-LIHC, LIRI-JP) | Transcriptome + clinical | ML-based gene signature (HPRGS) | External validation cohorts | Prognosis prediction, treatment guidance | Prognostic 4-gene signature; validated OS prediction; treatment response guidance |
| Liu Y et al., 2024 [37] | China | Retrospective | HCC undergoing TACE (n=110) | CT-based radiomics | DNN + LASSO + clinical nomogram | Internal validation | Prediction of TACE response | DNN-nomogram: AUC = 0.871; Sens = 0.844; Spec = 0.873 |
| Zhang R et al., 2024 [38] | China | Retrospective | HCC (n=250: 175 train, 75 val) | DCE-MRI | Dynamic radiomics (SR, DR, DSR) + LASSO + logistic regression | External validation | MVI prediction | DSR signature best: AUC train = 0.805, external = 0.777 |
| Xiao Y et al., 2024 [39] | China | Retrospective + prospective | cHCC-CCA (n=143: 82 train, 36 val, 25 test) | MRI | Radiomics + logistic regression | Validation cohort + prospective test | MVI prediction, biological process exploration | Robust MRI-radiomics model for MVI prediction; prognostic and immune process insights |
| Zhou G et al., 2024 [40] | China | Retrospective | cHCC-CC (n=91) | DCE-MRI | Radiomics + LASSO | Training/validation cohorts | MVI prediction | Radiomics signature: AUC train = 0.866, validation = 0.841 |
| Zhang X et al., 2024 [41] | China | Retrospective | HCC undergoing first DEB-TACE (n=108) | CT + clinical | Radiomics + clinical-radiological + integrated ML | Train/validation split 8:2 | Predict objective response | Integrated model AUC train = 0.860, validation = 0.927; Sens/Spec = 0.875/0.833 |
| Zhang K et al., 2023 [42] | China | Retrospective multicenter | HCC (n=260: 140 train, 65 std external, 55 non-std external) | Gd-EOB-DTPA MRI | Radiomics nomogram + radiological predictors | External validation | Preoperative MVI prediction; patient stratification for PA-TACE | Nomogram AUC = 0.982 train, 0.969/0.981 external; identified patients benefiting from PA-TACE |
| Liu R et al., 2023 [43] | China | Retrospective | HCC post-hepatectomy (n=315) | Clinical + lab data | Machine learning (6 algorithms, MLP best) | 10-fold cross-validation | Recurrence risk prediction | MLP AUC = 0.680; SHAP identified top 5 predictive factors; web calculator constructed |
| Khan RA et al., 2023 [44] | China | Retrospective | Multi-class liver cancer | CT + pathology | Multi-modal deep neural network | Benchmark dataset | Small/imbalanced dataset; 3-class liver cancer classification | Accuracy = 96.06%; AUC = 0.832; integrated pathology + image data improved classification |
| Kinoshita M et al., 2023 [45] | Japan | Retrospective | Solitary HCC post-hepatectomy (n=543) | Arterial CECT | Deep learning (CNN + MLP) | Train/validation/ test split 8:1:1 | Early recurrence prediction (≤2 years) | AUC test = 0.71, validation = 0.73; high-risk group recurrence 73% vs low-risk 30% |
| Iseke S et al., 2023 [46] | USA | Retrospective | Early-stage HCC eligible for liver transplant (n=120) | Pretreatment MRI + clinical/lab | ML models (clinical, imaging, combined) | Six time-frame recurrence prediction; Kaplan-Meier | Recurrence prediction pre-treatment | AUCs: clinical 0.60–0.78, imaging 0.71–0.85, combined 0.62–0.86; MRI improved predictive performance |
| Jiang T et al., 2023 [47] | China | Retrospective | HCC post-resection (n=102) | Multiparametric MRI | Radiomics + LASSO + nomogram | Internal validation | Preoperative peritumoral MVI prediction | Nomogram achieved highest AUC; AFP identified as top clinical predictor |
| Famularo S et al., 2023 [48] | Italy | Retrospective registry + external validation | Recurrent HCC post-surgery (n=701) | Clinical registry | Machine learning predictive model | External validation: Italian + Japanese cohorts | Treatment allocation to maximize survival | AUC 78.5% at 5 years; patient-tailored algorithm identified optimal treatment (reoperative hepatectomy/ thermoablation, sorafenib, chemoembolization) |

Table 1. Continued

| Authors | Country | Study design | Population | Training data | Techniques | Validation methods | Challenges | Reported outcome |
|---|---|---|---|---|---|---|---|---|
| Zeng et al., 2022 [49] | China | Retrospective multicenter | HCC (n=4,758) after curative resection | 15 clinical/pathological features (age, gender, labs, tumor characteristics, invasion, cirrhosis) | Random Survival Forests (RSF) vs Cox Proportional Hazard (CPH) | Internal validation + external validation cohort | Need to handle high-dimensional survival data, non-linearity not well captured by CPH | RSF C-index = 0.725–0.762; Time-dependent AUC (2y) = 0.785–0.823; Outperformed ERASL, Korean, AJCC, BCLC, Chinese staging systems; Stratified risk groups ($p<0.0001$) |
| Wang L et al., 2022 [50] | China | Retrospective | HCC (n=138) | CT-based radiomics | Deep learning: MVI-Mind (CNN + transformer) | Test set | End-to-end prediction of MVI | Segmentation mIoU 0.9006; prediction AUC 0.9223; prediction time ~1 min per patient |
| Liu Y et al., 2022 [51] | China | Retrospective | Mass-forming ICC and HCC | MRI, small datasets | Deep learning: SFFNet + Semi-SP preprocessing | Internal | Small dataset; feature extraction and fusion | Accuracy 92.26%, AUC 0.9680; sensitivity 86.21%, specificity 94.70% for MF-ICC/HCC classification |
| Hu R et al., 2022 [52] | Taiwan | Retrospective | HCC vs ICC | Multiphasic MRI | Automated ML: Tree-Based Optimization Tool + genetic programming | Manual vs automated optimization | LR-M subset classification; workflow automation | Accuracy 73–75%; sensitivity 65–75%, specificity 71–79%; performance similar to radiologists |
| Liu Z et al., 2022 [53] | China | Retrospective multicohort | HCC post-resection or liver transplant (n=1118) | Histological slides, nuclear architecture | Deep learning: U-net + MobileNetV2_HCC_class | Independent validation on LT set and TCGA set | Prognostic prediction for recurrence-free survival | HR 3.44 LT set, HR 2.55 TCGA set; maintained higher discriminatory power than known prognostic factors |
| Zhang L et al., 2022 [54] | China | Retrospective | Intermediate-stage HCC post-TACE (n=605) | DSA videos | Deep learning: DSA-Net (U-net + ResNet) | Internal + external validation | Real-time TACE response prediction | Dice 0.73–0.75; accuracy 75.1–78.2%; significant difference in PFS between responders/non-responders ($p=0.002$) |
| Gao R et al., 2021 [55] | China | Retrospective | 723 patients with HCC, ICC, metastatic liver cancer | Multi-phase CECT + clinical data | Deep learning STIC model (CNN + gated RNN) | Internal & external | Multimodal data integration; limited external validation | Accuracy HCC vs ICC: 86.2%; AUC 0.893; Overall malignant tumor classification accuracy: 72.6%; External test accuracy: 82.9%; Assisted doctors improved accuracy +8.3%, sensitivity +26.9% for ICC |
| Wang M et al., 2021 [56] | China | Retrospective | 7512 patients with HCC | CT images | Deep learning AI system | Internal (385) & external (556) | Heterogeneity of CT data; explainability | Internal AUROC 0.887; External AUROC 0.883; Accuracy ~81%; Sensitivity 78–89%; Comparable to radiologists; Saliency heatmap accuracy 92.1% |
| Meng XP et al., 2021 [57] | China | Retrospective | 402 patients with solitary HCC | CT and MRI | Radiomics RS, R, RR models | Internal validation | Modality comparison; tumor size influence | MRI-based models slightly higher AUC than CT; MRI RS added value for 2–5 cm tumors; Overall performance comparable |

Table 1. Continued

| Authors | Country | Study design | Population | Training data | Techniques | Validation methods | Challenges | Reported outcome |
|---|---|---|---|---|---|---|---|---|
| Oestmann PM et al., 2021 [58] | Switzerland | Retrospective | 118 patients, 150 lesions (HCC and non-HCC) | Multiphasic MRI | 3D CNN | Cross-validation (150 runs) | Atypical imaging features; small sample | CNN can classify typical and atypical HCC lesions; proof-of-concept |
| Chong H et al., 2021 [59] | China | Retrospective | 323 HCC patients without macrovascular invasion | Gd-EOB-DTPA MRI | Peritumoral dilation radiomics + nomogram | 5-fold cross-validation | Integration of radiomics and clinical features | Training AUC 0.939; Validation AUC 0.842; NRI improvement 35.9–66.1% |
| Huang et al., 2021 [60] | China | Retrospective multicenter | HCC (n=7,919) after surgical resection | Clinical + pathological features from EHSH & MHH | XGBoost (best model vs others) | Internal validation + external validation (Kaplan-Meier stratification) | Time-dependent variation in recurrence risk; heterogeneity across centers | XGBoost c-index = 0.713 (internal); Stratified external cohort into distinct risk groups ($p<0.05$); Tumor factors drive 0–1y relapse, HBV/ smoking drive 3–5y relapse; Risk heat map enabled personalized follow-up |
| Naeem S et al., 2020 [61] | Pakistan | Retrospective | Benign & malignant liver lesions | Fused MR + CT images (1200) | Hybrid-feature extraction; MLP, SVM, RF, J48 | 10-fold cross-validation | Multimodal fusion; feature selection | MLP accuracy 99% on fused dataset |
| Ji GW et al., 2020 [62] | China | Retrospective | 295 early-stage HCC patients | Contrast-enhanced CT | Radiomics + Cox regression models | External validation (118 patients) | Prediction of recurrence; multi-institutional data | C-index ≥0.77; Lower prediction error; Better net benefit than non-radiomics models |
| Peng J et al., 2020 [63] | China | Retrospective | 789 patients (3 centers) with intermediate-stage HCC | CT images | ResNet50 residual CNN | Internal + 2 independent validation cohorts | Prediction of TACE response; heterogeneous cohorts | Training accuracy 84.3%; Validation 85.1% & 82.8%; High AUC for CR, PR, SD, PD |
| Morshid A et al., 2019 [64] | USA | Retrospective | 105 HCC patients | CT quantitative features + clinical data | Random Forest | Internal | Small sample; feature selection | Accuracy 74.2% (features + BCLC) vs 62.9% (BCLC alone) |
| Zhang R et al., 2019 [65] | China | Retrospective | 267 HCC patients | Multimodal MRI | Bi-regional radiomics + nomogram | Internal validation | MVI prediction; tumor heterogeneity | Fusion radiomics AUC 0.784–0.820; Nomogram AUC 0.858; Outperformed clinical model |
| Hamm CA et al., 2019 [66] | USA | Retrospective | 494 hepatic lesions | Multiphasic MRI | CNN-based deep learning | Internal test (60 lesions) | Limited lesion types; small test set | Accuracy 92%; Sn 92%; Sp 98%; HCC Sn 90% vs radiologists 60–70% |
| Wang CJ et al., 2019 [67] | USA | Retrospective | Same 494 lesions as above | Multiphasic MRI | Interpretable CNN; feature maps & relevance scoring | Internal test (60 lesions) | Explainability; misclassification | PPV 76.5%; Sn 82.9%; Misclassified lesions 12%; Feature maps consistent with predictions |

in differentiating HCC from ICC [2, 5]. By contrast, MRI—especially dynamic contrast-enhanced (DCE) and diffusion-weighted imaging (DWI) sequences-proved more sensitive for small lesions and intratumoral heterogeneity [8, 9, 18]. These modality-specific strengths translated into differential diagnostic advantages: MRI-based models were superior in early tumor detection, whereas CT-based models were more effective for evaluating vascular invasion and larger lesions. Hybrid modalities, including PET/CT, and ultrasound-based AI approaches were less common but demonstrated potential when combined with radiomics or machine learning techniques [2, 12]. This suggests that multimodal fusion strategies may represent the most effective approach for maximizing diagnostic accuracy. Importantly, imaging access differs by region. In Southeast Asia, where ICC prevalence is disproportionately high due to liver fluke infection, CT is more widely available than MRI [14–16, 19]. Thus, tailoring AI models to available imaging infrastructure may improve diagnostic equity in resource-limited regions.

*AI model architectures and feature integration*

Methodologically, convolutional neural networks (CNNs) were predominant, with newer studies employing residual networks (ResNets), fully convolutional networks (FCNs), and deep transfer learning architectures [7, 13]. These advances improved tumor segmentation and classification, even in atypical imaging presentations [5, 12]. Radiomics capturing quantitative features such as texture, shape, and intensity was widely integrated with clinical data to form fused models [12, 20]. Evidence consistently showed that combined radiomics-clinical models outperformed single-domain approaches. For example, multi-center studies employing clinical, radiomic, and genomic signatures reported significantly enhanced performance in predicting recurrence and microvascular invasion (MVI). Multi-omics frameworks further expanded predictive capability: transcriptomic signatures [21] and hepatitis B virus (HBV)-specific risk biomarkers [22] have been successfully integrated into AI pipelines, demonstrating how computational models can inform both diagnosis and therapeutic stratification. These findings underscore that AI's clinical utility extends beyond image interpretation toward precision hepatology and personalized treatment decision-making [12, 17].

*Diagnostic accuracy and subgroup performance*

The pooled diagnostic performance across studies was encouraging, with most models achieving AUCs between 0.75 and 0.90, and several exceeding 0.95. MRI-based models offered superior sensitivity for small lesions [9,18], whereas CT-based approaches proved advantageous for evaluating macrovascular invasion and resectability [2, 5]. Multi-modal fusion consistently outperformed single-modality approaches [12, 18]. Subgroup analyses revealed that tumor characteristics (size, location, vascular involvement) and patient demographics influenced AI model performance. For instance, younger patient cohorts and smaller tumor subsets were more accurately assessed with MRI-based approaches, while CT was more reliable for large and vascularly complex lesions. Such stratified analyses indicate that modality selection should be tailored not only to tumor biology but also to patient demographics.

*Sources of bias and methodological limitations*

Despite promising findings, several methodological limitations warrant attention. The majority of studies were retrospective, relying on pre-existing datasets [1, 5]. Prospective and multicenter validation studies remain scarce, which limits generalizability. Imaging heterogeneity arising from differences in acquisition protocols, scanner hardware, and contrast administration posed additional barriers to reproducibility. These concerns highlight the need for harmonization of radiomic features and standardized imaging protocols [20]. High-dimensional data and relatively small sample sizes also raise risks of overfitting, while class imbalance in datasets may distort model performance [4, 13]. Another critical challenge is explainability: many deep learning models function as "black boxes," making clinical adoption more difficult in high-stakes decision-making contexts [4, 13].

*Clinical implications and public health perspectives*

AI tools have the potential to substantially impact hepatology practice. Integration into clinical workflows could reduce inter-observer variability, enhance diagnostic efficiency, and provide decision support [10, 12, 18]. Comparative analyses suggest that AI systems often complement rather than replace radiologists, improving detection and classification when used in tandem [2, 5, 10]. Beyond diagnosis, AI has shown value in predicting recurrence, treatment response, and MVI, with implications for surgical planning, transplant eligibility, and allocation of therapies such as TACE and immunotherapy [9, 23]. These prognostic utilities are particularly important in high-burden regions, where liver cancer outcomes remain poor and resources are constrained [14–16, 19]. Cost-effectiveness analyses and implementation studies will be critical in bridging the gap between technical performance and real-world utility [4].

*Future directions*

To advance clinical adoption, future research should prioritize large-scale, prospective, multicenter studies with external validation [1, 20]. Standardization of imaging acquisition and radiomic feature extraction is urgently needed to ensure reproducibility across institutions [20]. Multi-omics integration linking imaging, clinical, and genomic features represents a frontier for precision hepatology [21, 22]. Development of explainable AI systems will be essential to enhance clinician trust and regulatory approval [4],130. Moreover, AI should be designed for seamless integration into existing radiology and oncology workflows, with attention to user interface, interpretability, and clinical decision support. Finally, consideration of public health perspectives particularly in high-burden regions such as Asia—will be vital to ensuring that AI technologies address global disparities in liver cancer care [14–16, 19].

In conclusion, AI has demonstrated substantial promise

in differentiating HCC from ICC, with performance metrics frequently rivaling expert radiologists. While challenges remain in terms of reproducibility, standardization, and clinical translation, ongoing advancements in multi-modal integration, multi-omics approaches, and explainable AI systems point toward a future where AI can play a central role in precision hepatology and global liver cancer control.

## Author Contribution Statement

All authors contributed equally in this study.

## Acknowledgements

This study was supported by Suranaree University of Technology (SUT), the SUT Research and Development Fund, Thailand Science Research and Innovation (TSRI), and National Science, Research, and Innovation Fund (NSRF) (NRIIS number 160366). We would also like to express our sincere gratitude to the Parasitic Diseases Research Center (PDRC) at SUT.

*Declarations*
*Funding*
Thailand Science Research and Innovation (TSRI), and National Science, Research, and Innovation Fund (NSRF) (NRIIS number 160366)

*Ethics approval*
Ethical clearance for this study was obtained from the ethics committee of Suranaree University of Technology, under the auspices of protocol number EC63-41.

*Conflict of interest*
No conflict of interest.

*Abbreviations*
ACA – Adenocarcinoma
MRI – Magnetic resonance imaging
AI – Artificial intelligence
MS – mass spectrometry
ANN – Artificial neural network
MVI – Microvascular invasion
AUC – Receiver operating curve or area under the curve
NN – Neural network
AW – Advanced workstation
OARs – Organ-at-risk
AutoML – Automated machine learning model
PESI – Probe Electrospray Ionization
CBCT- cone-beam computed tomography
PET – Positron Emission Tomography
CCA – Cholangiocarcinoma
ResNet – Residual Net
CGP – Comprehensive genomic profile
RF – Random Forest
cHCC-CCA – Combine hepatocellular carcinoma cholangiocarcinoma
SBRT – Stereotactic body radiation therapy
CNN – Convolutional neural networks
SCC – Squamous cell carcinoma
CT – Computer tomography
Semi-SP – Semi-segmented preprocessing
CUP – Cancer of unknown primary
SFFNet – strided feature fusion residual network
1D-CNN – 1D convolutional neural network
Sp – Specsitivity
1D-Inception – 1D Inception convolutional neural network
Sn – Sensitivity
3D VR – Three-dimensional volume rendering
SPECT – Single Photon Emission Computed
18F-FDG PET/CT – 18F-fluorodeoxyglucose positron emission tomography/computed tomography
SVM – Support vector machine
HB – Hepatobiliary
TARE – Transarterial radioembolization
HBV – Hepatitis B virus
TCGA – The Cancer Genome Atlas project
HCC – Hepatocellular carcinoma
TPOT – Tree-Based Pipeline Optimization Tool
MIP – Maximum intensity projection
ICCA – Intrahepatic cholangiocarcinoma
UDC – Undifferentiated carcinoma
ICGC – International Cancer Genome Consortium
VAE – Variational autoencoder
KNN – K-nearest neighbor
VCAR – Volume computer assisted reading
MF-ICC – Mass-forming intrahepatic cholangiocarcinoma WSI – Whole-slide image
ML – Machine learning
$^{90}$Y – Yttrium 9

## References

1. Liberati A, Altman DG, Tetzlaff J, Mulrow C, Gøtzsche PC, Ioannidis JP, et al. The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate healthcare interventions: explanation and elaboration. BMJ. 2009 Jul 21;339:b2700. doi:10.1136/bmj.b2700.
2. Zhou LQ, Wang JY, Yu SY, Wu GG, Wei Q, Deng YB, et al. Artificial intelligence in medical imaging of the liver. World J Gastroenterol. 2019 Feb 14;25(6):672-682. doi:10.3748/wjg.v25.i6.672.
3. Esteva A, Robicquet A, Ramsundar B, Kuleshov V, DePristo M, Chou K, et al. A guide to deep learning in healthcare. Nat Med. 2019 Jan;25(1):24-29. doi:10.1038/s41591-018-0316-z.
4. Chen JH, Asch SM. Machine learning and prediction in medicine - beyond the peak of inflated expectations. N Engl J Med. 2017;376(26):2507-2509. doi:10.1056/NEJMp1702071
5. Ahn JC, Qureshi TA, Singal AG, Li D, Yang JD. Deep learning in hepatocellular carcinoma: Current status and future perspectives. World J Hepatol. 2021 Dec 27;13(12):2039-2051. doi:10.4254/wjh.v13.i12.2039.
6. Miranda J, Horvat N, Fonseca GM, Araujo-Filho JAB, Fernandes MC, Charbel C, et al. Current status and future perspectives of radiomics in hepatocellular carcinoma. World J Gastroenterol. 2023 Jan 7;29(1):43-60. doi:10.3748/wjg.v29.i1.43.
7. LeCun Y, Bengio Y, Hinton G. Deep learning. Nature. 2015 May 28;521(7553):436-44. doi:10.1038/nature14539.

8. Kim J, Min JH, Kim SK, Shin SY, Lee MW. Detection of hepatocellular carcinoma in contrast-enhanced magnetic resonance imaging using deep learning classifier: A multi-center retrospective study. Sci Rep. 2020 Jun 11;10(1):9458. doi: 10.1038/s41598-020-65875-4.
9. Wang KD, Guan MJ, Bao ZY, Shi ZJ, Tong HH, Xiao ZQ, et al. Radiomics analysis based on dynamic contrast-enhanced MRI for predicting early recurrence after hepatectomy in hepatocellular carcinoma patients. Sci Rep. 2025 Jul 1;15(1):22240. doi: 10.1038/s41598-025-02291-6.
10. Kim HE, Kim HH, Han BK, Kim KH, Han K, Nam H, et al. Changes in cancer detection and false-positive recall in mammography using artificial intelligence: a retrospective, multireader study. Lancet Digit Health. 2020 Mar;2(3):e138-e148. doi: 10.1016/S2589-7500(20)30003-0.
11. Sreng S, Maneerat N, Hamamoto K, Win KY. Deep learning for optic disc segmentation and glaucoma diagnosis on retinal images. Applied Sciences. 2020; 10(14):4916. doi. org/10.3390/app10144916
12. Fahmy D, Alksas A, Elnakib A, Mahmoud A, Kandil H, Khalil A, et al. The Role of Radiomics and AI Technologies in the Segmentation, Detection, and Management of Hepatocellular Carcinoma. Cancers. 2022; 14(24):6123. doi.org/10.3390/cancers14246123
13. Zhou SK, Greenspan H, Davatzikos C, Duncan JS, van Ginneken B, Madabhushi A, et al. A review of deep learning in medical imaging: Imaging traits, technology trends, case studies with progress highlights, and future promises. Proc IEEE Inst Electr Electron Eng. 2021 May;109(5):820-838. doi: 10.1109/JPROC.2021.3054390.
14. Sung H, Ferlay J, Siegel RL, Laversanne M, Soerjomataram I, Jemal A, Bray F. Global Cancer Statistics 2020: GLOBOCAN Estimates of Incidence and Mortality Worldwide for 36 Cancers in 185 Countries. CA Cancer J Clin. 2021 May;71(3):209-249. doi: 10.3322/caac.21660.
15. Li Q, Ding C, Cao M, Yang F, Yan X, He S, et al. Global epidemiology of liver cancer 2022: An emphasis on geographic disparities. Chin Med J (Engl). 2024 Oct 5;137(19):2334-2342. doi: 10.1097/CM9.0000000000003264.
16. Oh JH, Jun DW. The latest global burden of liver cancer: A past and present threat. Clin Mol Hepatol. 2023 Apr;29(2):355-357. doi: 10.3350/cmh.2023.0070. Epub 2023 Mar 9. PMID: 36891606; PMCID: PMC10121295.
17. Bakrania A, Joshi N, Zhao X, Zheng G, Bhat M. Artificial intelligence in liver cancers: Decoding the impact of machine learning models in clinical diagnosis of primary liver cancers and liver cancer metastases. Pharmacol Res. 2023 Mar;189:106706. doi: 10.1016/j.phrs.2023.106706.
18. Hill CE, Biasiolli L, Robson MD, Grau V, Pavlides M. Emerging artificial intelligence applications in liver magnetic resonance imaging. World J Gastroenterol. 2021 Oct 28;27(40):6825-6843. doi: 10.3748/wjg.v27.i40.6825.
19. Akinyemiju T, Abera S, Ahmed M, Alam N, Alemayohu MA, Allen C, et al. The burden of primary liver cancer and underlying etiologies from 1990 to 2015 at the global, regional, and national level: Results from the global burden of disease study 2015. JAMA Oncol. 2017;3(12):1683–1691. doi:10.1001/jamaoncol.2017.3055
20. Chamseddine I, Kim Y, De B, El Naqa I, Duda DG, Wolfgang J, et al. Predictive Modeling of Survival and Toxicity in Patients With Hepatocellular Carcinoma After Radiotherapy. JCO Clin Cancer Inform. 2022 Feb;6:e2100169. doi: 10.1200/CCI.21.00169.
21. Shin H, Hur MH, Song BG, Park SY, Kim GA, Choi G, et al. AI model using CT-based imaging biomarkers to predict hepatocellular carcinoma in patients with chronic hepatitis B. J Hepatol. 2025 Jun;82(6):1080-1088. doi: 10.1016/j.jhep.2024.12.029.
22. Wang Q, Cheng L, Yan H, Yuan J. Multi-Omics Integration: Predicting progression and optimizing clinical treatment of hepatocellular carcinoma through malignant-cell-related genes. Int J Mol Sci. 2025 Jun 26;26(13):6135. doi: 10.3390/ijms26136135.
23. Haga A, Takahashi W, Aoki S, Nawa K, Yamashita H, Abe O, Nakagawa K, et al. Standardization of imaging features for radiomics analysis. J Med Invest. 2019;66(1.2):35-37. doi: 10.2152/jmi.66.35.
24. Fan R, Long X, Chen X, Wang Y, Chen D, Zhou R. The Value of machine learning-based radiomics model characterized by PET imaging with 68Ga-FAPI in assessing microvascular invasion of hepatocellular carcinoma. Acad Radiol. 2025 Apr;32(4):2233-2246. doi: 10.1016/j.acra.2024.11.034.
25. Kinoshita S, Nakaura T, Yoshizumi T, et al. Real-world efficacy of radiomics versus clinical predictors for microvascular invasion in patients with hepatocellular carcinoma: Large cohort study. Hepatol Res. 2025 Apr;55(4):567-576. doi: 10.1111/hepr.14149.
26. Zhu Z, Wu K, Lu J, et al. Gd-EOB-DTPA-enhanced MRI radiomics and deep learning models to predict microvascular invasion in hepatocellular carcinoma: a multicenter study. BMC Med Imaging. 2025 Mar 31;25(1):105. doi: 10.1186/s12880-025-01646-9.
27. Wu Q, Zhang T, Xu F, et al. MRI-based deep learning radiomics to differentiate dual-phenotype hepatocellular carcinoma from HCC and intrahepatic cholangiocarcinoma: a multicenter study. Insights Imaging. 2025;16(1):27. doi:10.1186/s13244-025-01904-y
28. Jian W, Zhan L, Zhaowang L, et al. Predicting microvascular invasion in solitary hepatocellular carcinoma: a multi-center study integrating clinical, MRI assessments, and radiomics indicators. Front Oncol. 2025 Feb 19;15:1511260. doi: 10.3389/fonc.2025.1511260.
29. Famularo S, Penzo C, Maino C, et al. Preoperative detection of hepatocellular carcinoma's microvascular invasion on CT-scan by machine learning and radiomics: A preliminary analysis. Eur J Surg Oncol. 2025 Jan;51(1):108274. doi: 10.1016/j.ejso.2024.108274.
30. Yang J, Dong X, Jin S, et al. Radiomics model of dynamic contrast-enhanced MRI for evaluating vessels encapsulating tumor clusters and microvascular invasion in hepatocellular carcinoma. Acad Radiol. 2025 Jan;32(1):146-156. doi: 10.1016/j.acra.2024.07.007.
31. Yin L, Liu R, Li W, Li S, Hou X. Deep learning-based CT radiomics predicts prognosis of unresectable hepatocellular carcinoma treated with TACE-HAIC combined with PD-1 inhibitors and tyrosine kinase inhibitors. BMC Gastroenterol. 2025 Jan 21;25(1):24. doi: 10.1186/s12876-024-03555-7.
32. Mu T, Zheng X, Song D, et al. Deep learning based on multiparametric MRI predicts early recurrence in hepatocellular carcinoma patients with solitary tumors ≤5 cm. Eur J Radiol Open. 2024 Nov 15;13:100610. doi: 10.1016/j.ejro.2024.100610.
33. Alshagathrh F, Alzubaidi M, Gecík S, et al. Hybrid Deep Learning and Machine Learning for Detecting Hepatocyte Ballooning in Liver Ultrasound Images. Diagnostics (Basel). 2024 Nov 24;14(23):2646. doi: 10.3390/diagnostics14232646.
34. Hashimoto K, Haraguchi T, Nawata S, et al. Creation of a prediction model of local tumor recurrence after a successful conventional transcatheter arterial chemoembolization Using cone-beam computed tomography based-radiomics. Cardiovasc Intervent Radiol. 2024 Nov;47(11):1495-1505. doi: 10.1007/s00270-024-03854-2.
35. Zhang W, Guo Q, Zhu Y, et al. Cross-institutional evaluation

of deep learning and radiomics models in predicting microvascular invasion in hepatocellular carcinoma: validity, robustness, and ultrasound modality efficacy comparison. Cancer Imaging. 2024 Oct 22;24(1):142. doi: 10.1186/s40644-024-00790-9.
36. Zheng S, Su Z, He Y, et al. Novel prognostic signature for hepatocellular carcinoma using a comprehensive machine learning framework to predict prognosis and guide treatment. Front Immunol. 2024 Sep 24;15:1454977. doi: 10.3389/fimmu.2024.1454977.
37. Liu Y, Liu Z, Li X, et al. Non-invasive assessment of response to transcatheter arterial chemoembolization for hepatocellular carcinoma with the deep neural networks-based radiomics nomogram. Acta Radiol. 2024 Jun;65(6):535-545. doi: 10.1177/02841851241229185.
38. Zhang R, Wang Y, Li Z, et al. Dynamic radiomics based on contrast-enhanced MRI for predicting microvascular invasion in hepatocellular carcinoma. BMC Med Imaging. 2024 Apr 8;24(1):80. doi: 10.1186/s12880-024-01258-9.
39. Xiao Y, Wu F, Hou K, et al. MR radiomics to predict microvascular invasion status and biological process in combined hepatocellular carcinoma-cholangiocarcinoma. Insights Imaging. 2024;15(1):172. doi:10.1186/s13244-024-01741-5.
40. Zhou G, Zhou Y, Xu X, et al. MRI-based radiomics signature: a potential imaging biomarker for prediction of microvascular invasion in combined hepatocellular-cholangiocarcinoma. Abdom Radiol (NY). 2024 Jan;49(1):49-59. doi: 10.1007/s00261-023-04049-y.
41. Zhang X, He Z, Zhang Y, Kong J. Prediction of initial objective response to drug-eluting beads transcatheter arterial chemoembolization for hepatocellular carcinoma using CT radiomics-based machine learning model. Front Pharmacol. 2024 Jan 25;15:1315732. doi: 10.3389/fphar.2024.1315732.
42. Zhang K, Zhang L, Li WC, et al. Radiomics nomogram for the prediction of microvascular invasion of HCC and patients' benefit from postoperative adjuvant TACE: a multi-center study. Eur Radiol. 2023 Dec;33(12):8936-8947. doi: 10.1007/s00330-023-09824-5.
43. Liu R, Wu S, Yu HY, et al. Prediction model for hepatocellular carcinoma recurrence after hepatectomy: Machine learning-based development and interpretation study. Heliyon. 2023 Nov 19;9(11):e22458. doi: 10.1016/j.heliyon.2023.e22458.
44. Khan RA, Fu M, Burbridge B, Luo Y, Wu FX. A multi-modal deep neural network for multi-class liver cancer diagnosis. Neural Netw. 2023 Aug;165:553-561. doi: 10.1016/j.neunet.2023.06.013.
45. Kinoshita M, Ueda D, Matsumoto T, et al. Deep learning model based on contrast-enhanced computed tomography imaging to predict postoperative early recurrence after the curative resection of a solitary hepatocellular carcinoma. Cancers (Basel). 2023;15(7):2140. doi:10.3390/cancers15072140
46. Iseke S, Zeevi T, Kucukkaya AS, et al. Machine learning models for prediction of posttreatment recurrence in early-stage hepatocellular Ccarcinoma using pretreatment clinical and MRI features: A proof-of-concept study. AJR Am J Roentgenol. 2023 Feb;220(2):245-255. doi: 10.2214/AJR.22.28077.
47. Jiang T, He S, Yang H, et al. Multiparametric MRI-based radiomics for the prediction of microvascular invasion in hepatocellular carcinoma. Acta Radiol. 2023 Feb;64(2):456-466. doi: 10.1177/02841851221080830.
48. Famularo S, Donadon M, Cipriani F, et al. Machine learning predictive model to guide treatment allocation for recurrent hepatocellular carcinoma after surgery. JAMA Surg. 2023 Feb 1;158(2):192-202. doi: 10.1001/jamasurg.2022.6697.
49. Zeng J, Zeng J, Lin K, et al. Development of a machine learning model to predict early recurrence for hepatocellular carcinoma after curative resection. Hepatobiliary Surg Nutr. 2022;11(2):176-187. doi:10.21037/hbsn-20-466.
50. Wang L, Wu M, Li R, et al. MVI-Mind: A Novel Deep-Learning Strategy Using Computed Tomography (CT)-Based Radiomics for End-to-End High Efficiency Prediction of Microvascular Invasion in Hepatocellular Carcinoma. Cancers (Basel). 2022 Jun 15;14(12):2956. doi: 10.3390/cancers14122956.
51. Liu Y, Wang B, Mo X, et al. A Deep learning workflow for mass-forming intrahepatic cholangiocarcinoma and hepatocellular carcinoma classification based on MRI. Curr Oncol. 2022;30(1):529-544. Published 2022 Dec 30. doi:10.3390/curroncol30010042.
52. Hu R, Li H, Horng H, et al. Automated machine learning for differentiation of hepatocellular carcinoma from intrahepatic cholangiocarcinoma on multiphasic MRI. Sci Rep. 2022;12(1):7924. doi: 10.1038/s41598-022-11997-w.
53. Liu Z, Liu Y, Zhang W, Hong Y, Meng J, Wang J, Zheng S, Xu X. Deep learning for prediction of hepatocellular carcinoma recurrence after resection or liver transplantation: a discovery and validation study. Hepatol Int. 2022 Jun;16(3):577-589. doi: 10.1007/s12072-022-10321-y.
54. Zhang L, Jiang Y, Jin Z, et al. Real-time automatic prediction of treatment response to transcatheter arterial chemoembolization in patients with hepatocellular carcinoma using deep learning based on digital subtraction angiography videos. Cancer Imaging. 2022 May 12;22(1):23. doi: 10.1186/s40644-022-00457-3.
55. Gao R, Zhao S, Aishanjiang K, et al. Deep learning for differential diagnosis of malignant hepatic tumors based on multi-phase contrast-enhanced CT and clinical data. J Hematol Oncol. 2021 Sep 26;14(1):154. doi: 10.1186/s13045-021-01167-2.
56. Wang M, Fu F, Zheng B, Bai Y, Wu Q, Wu J, et al. Development of an AI system for accurately diagnose hepatocellular carcinoma from computed tomography imaging data. Br J Cancer. 2021 Oct;125(8):1111-1121. doi: 10.1038/s41416-021-01511-w.
57. Meng XP, Wang YC, Zhou JY, et al. Comparison of MRI and CT for the prediction of microvascular invasion in solitary hepatocellular carcinoma based on a non-radiomics and radiomics method: Which imaging modality is better? J Magn Reson Imaging. 2021 Aug;54(2):526-536. doi: 10.1002/jmri.27575.
58. Oestmann PM, Wang CJ, Savic LJ, et al. Deep learning-assisted differentiation of pathologically proven atypical and typical hepatocellular carcinoma (HCC) versus non-HCC on contrast-enhanced MRI of the liver. Eur Radiol. 2021 Jul;31(7):4981-4990. doi: 10.1007/s00330-020-07559-1.
59. Chong H, Gong Y, Pan X, et al. Peritumoral dilation radiomics of gadoxetate disodium-enhanced MRI excellently predicts early recurrence of hepatocellular carcinoma without macrovascular invasion after hepatectomy. J Hepatocell Carcinoma. 2021 Jun 9;8:545-563. doi: 10.2147/JHC.S309570.
60. Huang Y, Chen H, Zeng Y, et al. Development and validation of a machine learning prognostic model for hepatocellular carcinoma recurrence after surgical resection. Front Oncol. 2021 Feb 1;10:593741. doi: 10.3389/fonc.2020.593741.
61. Naeem S, Ali A, Qadri S, Khan Mashwani W, Tairan N, Shah H, et al. Machine-learning based hybrid-feature analysis for liver cancer classification using fused (MR and CT) images. Appl Sci. 2020; 10(9):3134. https://doi.org/10.3390/app10093134
62. Ji GW, Zhu FP, Xu Q, et al. Radiomic features at contrast-

enhanced CT predict recurrence in early stage hepatocellular carcinoma: A multi-institutional study. Radiology. 2020 Mar;294(3):568-579. doi: 10.1148/radiol.2020191470.
63. Peng J, Kang S, Ning Z, et al. Residual convolutional neural network for predicting response of transarterial chemoembolization in hepatocellular carcinoma from CT imaging. Eur Radiol. 2020 Jan;30(1):413-424. doi: 10.1007/s00330-019-06318-1.
64. Morshid A, Elsayes KM, Khalaf AM, et al. A machine learning model to predict hepatocellular carcinoma response to transcatheter arterial chemoembolization. Radiol Artif Intell. 2019 Sep;1(5):e180021. doi: 10.1148/ryai.2019180021.
65. Zhang R, Xu L, Wen X, et al. A nomogram based on bi-regional radiomics features from multimodal magnetic resonance imaging for preoperative prediction of microvascular invasion in hepatocellular carcinoma. Quant Imaging Med Surg. 2019 Sep;9(9):1503-1515. doi: 10.21037/qims.2019.09.07.
66. Hamm CA, Wang CJ, Savic LJ, Ferrante M, Schobert I, Schlachter T, et al. Deep learning for liver tumor diagnosis part I: development of a convolutional neural network classifier for multi-phasic MRI. Eur Radiol. 2019 Jul;29(7):3338-3347. doi: 10.1007/s00330-019-06205-9.
67. Wang CJ, Hamm CA, Savic LJ, Ferrante M, Schobert I, Schlachter T, et al. Deep learning for liver tumor diagnosis part II: convolutional neural network interpretation using radiologic imaging features. Eur Radiol. 2019 Jul;29(7):3348-3357. doi: 10.1007/s00330-019-06214-8.