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**REVIEW** **OPEN ACCESS**

# Artificial Intelligence Used for the Diagnosis, Treatment and Surveillance of Hepatocellular Carcinoma: A Systematic Review

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**Abstract**
**Introduction:** Hepatocellular Carcinoma (HCC) is the most common type of liver cancer, compromising about 75% of all liver cancers. The advancement in artificial intelligence (AI) has paved the way in the field of liver cancers to help clinicians with early diagnosis, treatment guidance and surveillance for HCC. The aim of this review was to summarize different AI-assisted methods that could be used in the diagnosis, treatment, and surveillance of HCC throughout the literature.
**Methods:** PubMed and MEDLINE OVID databases were searched for primary studies involving AI and HCC published from 2012 to February 2022. Data was obtained, including study characteristics and outcome measures: accuracy, area under curve (AUC), specificity, sensitivity, and errors. A narrative synthesis was used to summarize the findings.
**Results:** The systematic search produced 340 studies, of which 36 met the pre-determined eligibility criteria. The studies were published between 2012 to 2020. All the studies with their respective AI models/algorithms were described and summarized in the tables according to their role in the diagnosis, treatment, or surveillance of HCC. All the studies included used different AI algorithms, out of which, most were used for diagnostic purposes (44%), followed by treatment prediction (38%) and then surveillance of HCC (18%). Among studies, 38% reported their results as AUC, 33% of the studies reported accuracy, 19% reported sensitivity and specificity, 4% reported concordance indices (C-indices), 3% reported the mean errors and 2% reported AUROC values for respective AI models used. The accuracy of the diagnostic, treatment and surveillance tools range from 40% to 99%, 50% to 90% and 70% to 95% respectively.
**Conclusion:** Many AI models are available that show promising results for the different applications in diagnosis, treatment, and surveillance of HCC. However, the demand for the generalization of these results remains. Future research should focus on improving the results and accuracy of these algorithms used for HCC to reduce the risks in complicated procedures.

**Keywords:** hepatocellular carcinoma; artificial intelligence; diagnosis; treatment; surveillance

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**Introduction**

Liver cancer was the third most common cause of cancer death worldwide in 2020. Hepatocellular carcinoma (HCC) is the most common primary tumour of the liver, comprising 75-85% of liver cancer cases. HCC occurs when the cells of the liver, known as hepatocytes, begin to behave abnormally and become cancerous [1]. The most common risk factors for HCC are chronic infection with hepatitis B virus (HBV) or hepatitis C virus (HCV), a history of smoking, heavy alcohol intake, and obesity. Although HCC patients do not experience symptoms, most people have an underlying chronic liver disease, which causes cirrhosis of the liver leading to the development of HCC [2]. The liver is the largest and the most complex organ in the human body, which stresses the importance of caution with its treatment. Since HCC does not cause symptoms early in the disease, getting a prompt diagnosis is difficult [3]. Current methods of identifying liver cancer include imaging from CT or MRI scans or performing a biopsy. The best treatment options for liver cancer are either surgical resection or a liver transplant [4].

Artificial Intelligence (AI) is gaining traction in cancer management because of several recent advances. According to research, AI exhibited a better accuracy in identifying cancer from endoscopic images, when compared to experts. Some examples of AI applications in clinical settings include image interpretation using Whole Slide Images (WSI) [5], surgical interventions [6], drug discovery [6], surgical skills training and assessment [7], hospital-wide data analysis [8], and personalized treatment [9]. In gastric cancer, for instance, reviews focused on AI-assisted endoscopy, particularly used for identifying the disease in its earliest stages. AI-assisted methods are also greatly implemented in the early detection, treatment guidance, and prognosis prediction for liver cancer.

AI models and techniques have been proved to be particularly important for liver cancer treatment and prognosis. 3D visualization, virtual reality, and Whole Slide Images (WSI) are being used for the diagnosis of cancer and identifying proper recipient-donor matches in liver transplant surgeries. Additionally, Artificial neural networks (ANNs) models have been developed to improve the predictability of progression-free survival in HCC during clinical practice. This review article summarizes the key AI models capable of improving accuracy, sensitivity and precision or providing increased safety and ease in procedures currently used for liver cancer. No comprehensive review article exists that discusses these three aspects of liver cancer. As such this review will provide a comprehensive outline of the diagnosis, treatment, and surveillance of HCC as well as potential limitations and future directions of AI-assisted methods implemented.

**Methods**

We conducted a systematic literature search from February 20th, 2012, to February 20th, 2020, using the PubMed, and MEDLINE OVID databases. The terms “artificial intelligence”, “liver”, and “cancer”, including synonyms or equivalent terms, were used in certain combinations to obtain the relevant literature. The full search strategy can be found in Tables A1 and A2 in Supplemental Appendix A.

Article screening was conducted independently and in duplicate by two reviewers using the Covidence software [10]. Duplicates were excluded by reference manager software using Covidence. Databases were searched using the terms ‘liver or hepatopancreatobiliary or live* or hepatic or hepat*’, ‘liver* and (cancer* or tumo?r* or malignan* or carcinoma)’, ‘machine learning [MeSH] and ‘neural networks (computer)’. The manual inclusion criteria also included ‘primary study (cohort, case-control, case series, or RCT)’, ‘18+-year-old population’ and ‘population size of 5 patients. The manual exclusion criteria included ‘non-English language’, ‘review articles, thesis, conference abstracts, commentaries’, ‘no full-text availability’, and ‘publication older than 10 years.

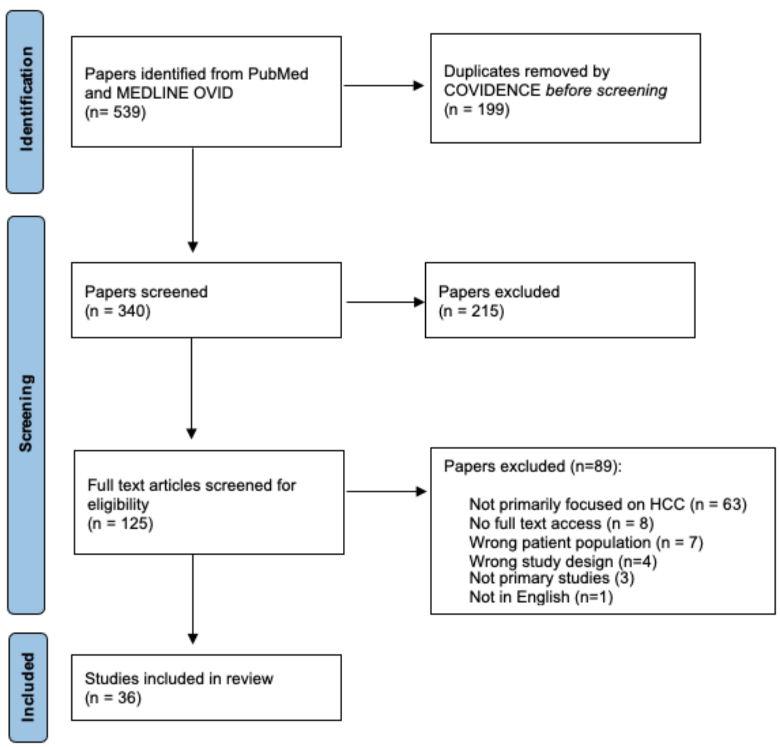


**Figure 1.** PRISMA diagram of research papers from identification to inclusion created using Covidence

The quality of each article was independently assessed by two reviewers. The studies were assessed according to Methodological Index for Non-Randomized Studies (MINORS) [11], consisting of 12 questions for both comparative and non-comparative studies. The studies evaluated for risk of bias. The quality of reporting was assessed according to the MINORS statement with 0 representing 'not reported', 1 representing 'reported but inadequate' and 2 representing 'reported and adequate'. Disagreement between the two reviewers in quality assessment was resolved by discussions concluding in consensus.

**Results**

The screening and inclusion process is outlined in Figure 1. The database searches yielded 341 studies, of which 215 were eliminated from the title and abstract screening. A total of 126 full-text papers were evaluated, and 36 met the eligibility requirements. These studies were then assessed using MINORS criteria [11] and were ranked out of 2 based on the information provided (Table A3 in Supplemental Appendix A). We found that all the studies reported a clear aim, the inclusion of consecutive patients, prospective collection of data and had endpoints appropriate to the aim of the study. However, only 5 studies reported unbiased assessment including double-blinded evaluation [13,24-26,32]. Similarly, only the studies using AI for surveillance of HCC reported an appropriate follow-up period with loss to follow less than 5% [41-45]. There was only one comparative study which included a control non-cancerous group [15].

Among the selected studies, we found that the mean age of patients across the studies was 56 years, with the study size ranging between 16 [12] and 7512 [13] subjects with HCC. Many of the studies (n=24, 67%) used either Computed Tomography (CT) or Magnetic Resonance Imaging (MRI) scans as the basis of their algorithm development [12-14,16,17,19-25,28-31,33-35,39,40,42-44]. A modest number of images (100 to 1000) were used for these studies, except for Kim et. al., 2020, which used 54900 MRI images from 549 patients for classifying HCC [14]. Among the studies, 42% of studies were conducted in the United States, 22% in Germany, 22% in England, 8% in Ireland, 3% in the Netherlands and 3% in Switzerland. While AI tools showed accurate results for HCC (Table 1, 2, 3), larger study sizes may be incorporated for better generalization of the results.

AI for Diagnosis of HCC

**Table 1**. Studies using different artificial intelligence techniques for the diagnosis of hepatocellular carcinoma

| Reference | AI Tool Used | Study Size | Techniques Studied | Results | Aim of the Study |
|---|---|---|---|---|---|
| Aatresh et. al., 2021 [15] | Liver net | 141 slides | Hematoxylin and Eosin (H and E) stained liver histopathology images | 90.93% accuracy | Automatic diagnosis of sub-types of HCC |
| Bousabarah et. al.,2021 [16] | DCNN | 175 patients with 231 lesions | MRI images | 75% accuracy with false positive of 2.80 per patient | Segment the liver and HCC automatically |
| Kim et. al., 2021 [17] | DL based algorithm | 1350 Multiphase CT scans from 1320 patients | CT scans | 84.4% sensitivity with 4.80 per CT scan false positives | Detection of primary hepatic malignancies |
| Kim et. al., 2020 [14] | Fully automated deep learning model using fine-tuned CNN | 54900 images from 549 patients | MRI images | AUC of 0.97<br>94% sensitivity and 99% specificity for test data | Detects and classifies HCCs in gadoxetic acid enhanced MRI |
| Le et. al., 2016 [12] | 3D Fast Marching Algorithm and SLFN | 25 tumors from 16 patients | MR images | Mean percentage volume error of 15.74% and mean volumetric overlap | Decreased time for liver tumor segmentation |

| Reference | AI Tool Used | Study Size | Techniques Studied | Results | Aim of the Study |
|---|---|---|---|---|---|
| | | | | error of 27.43% | |
| Liao et. al., 2020 [17] | Fully Automated Pipeline based on Machine learning | 1733 images | Histopathological Slides | 98.8% accuracy | Distinguish HCC from normal tissue and prognosis of HCC patients after surgical resection |
| Song et. al., 2021 [18] | DL model | 601 patients | DCE-MRI | AUC of 0.92 | Non-invasive approach to evaluate MVI before surgery |
| Thomaz et. al., 2018 [19] | Mahalanobis function | MDCT exams | MDCT exams | AUC of 0.84 | Classifying early HCC |
| Vivanti et. al., 2018 [20] | Baseline Scan tumor delineation | 222 tumors from 31 patients | Follow-up CT scan | Average overlap error of 17% and robustness of 100% | Accurate tumor tracking and failure detection in CT scans |
| Wang et. al., 2021 [12] | NoduleNet and HCCNet | 7512 patients | CT scans | Average AUROC of 0.88 | AI system achieved high performance in detection of HCC |
| Yamada et. al., 2019 [22] | TL using CNN and three phasic DCE-CT | 215 patients | CT scans | Average diagnostic performance was 43.5% | Reduced misregistration of multiphasic images and with DCE-CT, it had comparable results to abdominal radiologists |
| Yang et. al., 2021 [23] | Mask- R-CNN | 10130 images with 11,258 regions of interest (ROIs) | CT scans | AUC of 0.95 with Dice coefficient of 0.80 | Help radiologists to identify abnormal CT liver density |
| Yang et. al., 2021 [24] | DNN | 108 patients | CT images | Reproducibility features increased to 90% for tumor ring region | Increases reproducibility of CT images features in liver cancer |

| Reference | AI Tool Used | Study Size | Techniques Studied | Results | Aim of the Study |
|---|---|---|---|---|---|
| Yang et. al., 2019 [25] | MCF-3DCNN | 55 HCCs from 42 patients | DCE-MR | Average accuracy of 0.74 for differentiating pathologic grade of HCC and accuracy of 0.96 for discriminating HCC from others | Promising technology for evaluating HCC grade |
| Zhen et. al., 2020 [26] | ModelA-Model G | 31,608 images from 1210 patients | Just images | AUC of 0.95 | Accurate and time saving assisted diagnostic strategy |
| Zhou et. al, 2019 [27] | CNN | 100 patients | DWI | Accuracy of 80% | HCC grading |

*Abbreviations: HCC- Hepatocellular Carcinoma; DCNN- Deep Convolutional Neural Network; DL- Deep Learning; MRI-Magnetic Resonance Imaging; CT- Computed Tomography; SLFN- Single Hidden Layer Feedforward Neural Network; MDCT- Multidetector CT; AUC- Area under curve; TL- Transfer Learning; CNN- Convolutional Neural Network; DCE-CT-Dynamic Contrast-Enhanced Computed Tomography; Mask-R-CNN- Mask Region-based Convolutional Neural Network; MCF-3DCNN- Multichannel Fusion three-dimensional Convolutional Neural Network; DCE-MR-Dynamic Contrast-Enhanced Magnetic Resonance Imaging; MVI- Microvascular Invasion; DNN- Deep Neural Network; DWI- Diffusion-Weighted Images*

As seen in Table 1, 16 studies (44%) were extracted that focused on different AI tools used for the diagnostic purposes of HCC or liver tumors. Many of the studies (n=12, 33%) used CT or MRI scans as the foundation of their technique and developed an AI algorithm to improve various characteristics of the images acquired [12-14,16,17,20-25]. Among the studies, the Fully Automated Pipeline based on Machine learning had the highest accuracy of 98.8% for differentiating HCC from normal tissue [18]). AI tools such as Convolutional Neural Network (CNN) [26], Multichannel Fusion three-dimensional Convolutional Neural Network (MCF-3DCNN) [25], NoduleNet and HCCNet [13], were used for grading, classification and detection of HCC also showed an accuracy range between 73% - 90% (Table 1).

AI for Treatment Response Prediction

**Table 2**. Studies using different artificial intelligence techniques for the treatment or prediction of responses to different treatments of hepatocellular carcinoma

| Reference | AI Tool Used | Study Size | Techniques Studied | Results | Aim of the Study |
|---|---|---|---|---|---|
| Abajian et. al., 2018 [28] | Logistic regression (LR) and Random Forest (RF) models | 36 patients | MR imaging | Accuracy of 78% with a specificity of 82.1% and sensitivity of 62.5% | Predicting trans arterial chemoembolization outcomes in HCC patients |
| Gu et. al., 2021 [29] | MS-Densenet | 455 patients | CT images | AUC of 0.80 | HCC histological grade |
| Liu et. al., 2021 [30] | CT radiomics | 185 patients | 1351 radiomic features extracted | Average AUC of 0.73 | Predictive value for MVI in solitary HCC ≤ 5cm |
| Liu et. al., 2021 | ResNet-18 | 309 | CT images | AUC of 0.84 | Estimating MVI |

| Reference | AI Tool Used | Study Size | Techniques Studied | Results | Aim of the Study |
|---|---|---|---|---|---|
| [31] | | patients | | | |
| Liu et. al. 2020 [32] | DL radiomics based CEUS model | 130 patients | Ultrasound examination (CEUS -B-mode) | AUC with CEUS was 0.93 and with B-mode was 0.81 | Accurate and personalized prediction of response of HCC to first TACE |
| Li et. al., 2022 [33] | DCNN | 1116 patients | Preoperative CECT and curative hepatectomy | AUC of 0.93 for DCNN | Preoperative prediction of MVI in HCC |
| Mao et. al., 2020 [34] | CECT based radiomics | 297 patients | Multiphasic dynamic CECT | 0.53 Accuracy, 0.65 sensitivity and 0.46 specificity | Preoperative prediction of pathological grades of HCC |
| Peng et. al., 2020 [35] | Residual CNN | 789 patients | CECT images | 84.3% accuracy | Predicting response of TACE therapy |
| Ren et. al., 2021 [36] | Ultrasonics | 193 patients | Ultrasound images | AUC of 0.80 on test set | Non-invasive preoperative prediction of pathological grading of HCC |
| Saillard et.al., 2020 [37] | SCHMADER and CHOWDER | 522 patients | WSI | C indices of 0.78 and 0.75 for SCHMOWDER and CHOWDER respectively | Prediction of survival after curative resection or ablation of HCC |
| Wang et. al., 2021 [13] | CNN | 97 subjects with 100 HCCS | Diffusion weight imaging (DWI) and apparent diffusion coefficient (ADC) | AUC of 0.79 with ADC | MVI prediction |
| Wei et. al., 2021 [38] | Registration Pipeline | 52 patients | 1035 clinical images | Average registration errors of 11.6° and 4.7 mm | Improve robustness and registration of intraoperative patient registration |
| Zhang et. al., 2021 [39] | Support vector machine recursive method and Naive Bayes Classifier | 88 patients with 90 HCCs | CT scans | Mean regeneration index was 142.99 with accuracy of 0.844 in test group | Predicting liver regeneration rate after liver hepatectomy after HCC |
| Zhang et. al., 2021 [40] | Fusion Model | 237 patients | MRI Images | AUC of 0.81, sensitivity of 69% and specificity of 79% on training set | MVI in HCC |

*Abbreviations: AI- Artificial Intelligence; HCC; Hepatocellular Carcinoma; MVI- Microvascular Invasion; DL- Deep Learning; MRI- Magnetic Resonance Imaging; CT- Computed Tomography; CEUS- Contrast Enhanced Ultrasound; AUC- Area under curve; TACE-Transarterial Chemoembolization; DCNN- Deep convolutional neural network; CECT- Contrast*

*Enhanced Computed Tomography; MS-Densenet- Multiscale 2D dense connected convolutional neural network; WSI- Whole Slide Images; CNN- Convolutional Neural Network.*

Fourteen (39%) studies focused on different AI tools to aid in the prediction of responses to various treatments used for HCC (Table 2). Further analysis revealed that 5 (36%) studies were based on CT or MRI images [28,29,31,39,40]. However, studies using Ultrasonics [36] and DL radiomics based on Contrast-Enhanced Ultrasound (CEUS) [32] were based on Ultrasound images. Although all studies showed different AI models, 3 (21%) studies used CNN, Residual CNN and Deep Convolutional Network (DCNN) that were based on a common algorithm of CNN [13,33,35]. The fusion model, CNN and DCNN mainly helped to predict the post-operative microvascular invasion of HCC with an AUC of 0.81, 0.79 and 0.92, respectively [13,35,40]. On the other hand, the DL radiomics-based CEUS model and Residual CNN predicted the response to transarterial chemoembolization treatment for HCC with an AUC of 0.93 and accuracy of 84.3%, respectively [32,33]. The survival rate after curative resection or ablation was also predicted using SCHMOWDER and CHOWDER models with C indices of 0.78 and 0.75, respectively [37].

AI for Surveillance of HCC

**Table 3**. Studies using different artificial intelligence techniques for the treatment or prediction of responses to different treatments of hepatocellular carcinoma

| **Reference** | **AI Tool Used** | **Study Size** | **Techniques Studies** | **Results** | **Aim of the Study** |
|---|---|---|---|---|---|
| Bai et. al., 2021 [41] | 3D CEUS | 60 patients | Examination method | 91.1 % sensitivity | RFA - radiofrequency ablation, sensitivity to postoperative recurrence |
| Guo et. al., 201 [42] | LASSO Cox Regression Model | 133 patients | CT images | Average C index of 0.79 | Prediction of HCC recurrence after liver transplantation |
| Ji et. al., 2019 [43] | Three feature radiomics signature | 470 patients | CECT images | C index of 0.63 - 0.70 | Individual recurrence risk of HCC |
| Mai et. al., 2021 [44] | ANN | 903 patients | CT or MRI images | AUC of 0.73 | Postoperative monitoring without macroscopic vascular invasion |
| Saito et. al., 2021 [45] | SVM | 158 patients | H and E stain images | Accuracy of 89.9% | Prediction of recurrence of HCC |
| Yamashita et. al., 2021 [22] | HCC SurvNet | 128222 tiles from 36 WSI | H and E-stained digital whole slide images | Average concordance indices of 0.70 | Provide recurrence risk scores to help improve the prognosis for the patients undergoing surgical resection or HCC |

*AI- Artificial Intelligence; HCC; Hepatocellular Carcinoma; CEUS- Contrast Enhanced Ultrasound; LASSO- Least Absolute shrinkage and selection operator; ANN- Artificial Neural Network; MRI- Magnetic Resonance Imaging; CT- Computed Tomography; CECT- Contrast Enhanced Computed Tomography; SVM- Support Vector Machine*

The full-text analysis revealed 6 studies (17%) that focused on the surveillance of post-operative recurrence of HCC (Table 3). While 3 studies (50%) were based on CT scans [42-44], 2 (33%) studies [21,44] focused on Hematoxylin and Eosin-stained imaging for surveillance. 3D CEUS [41] had the highest accuracy of 96.2 percent in predicting radiofrequency ablation post-operative recurrence of HCC, while SVM (Support Vector Machine) had the second-highest accuracy of 89.9 percent [45]. Post-operative monitoring without macrovascular invasion was also predicted by the Artificial Neural Network (ANN), with an AUC of 0.733 [43].


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**Discussion**

This systematic review summarizes the different AI models and algorithms which can be used for the diagnosis, treatment, and surveillance of HCC. The 36 studies included in this article provide insight into the accuracy and the aim of different algorithms used. Among the extracted studies, 16 (44%) studies were focused on the AI algorithms such as CNN, DCNN and Fully automated pipelines based on machine learning that helped in the diagnosis by grading, classification and detection of HCC based on CT or MRI imaging. Similarly, 14 (39%) studies focused on predicting the response to different treatments for the HCC including transarterial chemoembolization (TACE) therapy, tumour ablation and microvascular invasion (MVI) of HCC using Residual CNN and DL radiomics-based CEUS. The rest of the studies aimed to provide insight into the AI tools such as HCC SurvNet, ANN, and 3D-CEUS for the surveillance of post-operative recurrence of HCC. Larger study sizes account for greater generalizability, while a higher accuracy represents confidence in AI model techniques. Both characteristics were found to be important when analysing extracted studies; 5 studies were selected that best aligned with these parameters.

A recent systematic review examined the use of AI in the diagnosis and treatment of HCC [46]. In comparison to our review, Pérez & Grande (2020) detailed the capabilities of AI in current diagnosis and treatment procedures [46]. Their study discussed the incorporation of abdominal ultrasounds, MRI, PET, histology, and CT scans with IV contrast for the diagnosis mechanisms of HCC. The treatment techniques included radiomics, surgical resection, arterial chemoembolization, and radiofrequency ablation. However, unlike this study, which offers insights on all the AI tools available for the diagnosis, surveillance, and therapy of HCC, their analysis was restricted to the application of the listed AI techniques. Common findings included the use of CT and MRI scans for the development of CNN, DL and ML algorithms with AUC range of 67% - 97% for the interpretation and analysis of resulting images. These algorithms are currently being used in the medical field because they are cost-effective and time efficient compared to traditional medical practices. Although AI techniques reviewed in this study show great capabilities for the diagnosis and prognosis of HCC, there is a need for improvement before integrating them into the medical field.

Among diagnostic studies, Liao et. al., 2020 [18] achieved the highest accuracy of 98.8% by developing a fully automated pipeline based on machine learning. Their findings suggest that ML models built upon image features can be used to assist clinicians in HCC diagnosis by distinguishing it from the normal tissue and predicting prognosis after surgical resection. However, the study analysed only 1733 images based on histopathological slides, which debates the generalizability of the results. A similar contrast between the study size and accuracy results has been found in another study involved in the surveillance of HCC. Mai et. al., 2021 [43] developed an ANN model to predict post-hepatectomy early recurrence (PHER) of HCC in people treated with liver resection, using a study size of 903 patients. They conducted a multivariable analysis to identify characteristics associated with PHER and used the criteria for their ANN model development. Their AI had greater discriminatory abilities than pre-existing recurrence models. This development can have a large impact on the efficiency of healthcare by improving PHER surveillance. However, this study achieved an AUC of 0.73. Due to the non-generalizability of the results from both studies, these AI technologies need to be improved along with larger study sizes to allow for their scope in the medical field. In contrast, Li et. al., 2022 [32] had both characteristics of large study size and high AUC. The study developed a DCNN model to predict perioperative MVI in HCC and used a CECT to assess clinical outcomes. With a study size of 1116 patients, the DCNN model acquired an AUC of 0.93 alone, while a radiology and DCNN combined model had an AUC of 0.94 in the training cohort. This combination approach proposes potential avenues of medical treatment concerning MVI detection of HCC before liver surgery. This AI technology provides a future scope of expansion in the medical field.

Despite AI's great capabilities discussed in this article, the question of its performance quality when compared with physicians still remains. To investigate this, Niikura et al. [47] performed a primary study to test expert diagnosis against AI-assisted diagnosis of gastric cancer. In the study, expert endoscopists and AI were both assigned upper gastrointestinal endoscopic images and asked to identify gastric cancer within 500 subjects, 100 of which had cancer. The CNN AI was able to detect cancer in 49 of the 49 subjects (100%), while the experts were able to detect cancer in 48 of the 51 subjects (94.12%). In addition, the AI per-image rate of cancer diagnosis was 13.3% higher than the expert group. The study results suggest that AI has a greater advantage in diagnosing gastric cancer than experts; however, the study only evaluated two experts, impacting the generalizability of the data. Although the proposed question is still unanswered, the study offers an opportunity to further test the capabilities of AI compared to physicians.

This review had several strengths, including an evidence-based systematic search through two databases and multiple screeners, which reduced the potential of single reviewer bias. Additionally, the broad eligibility criteria allowed for a variety of studies to be reviewed and included, thus the study is generalizable. However, there were limitations to this study. Firstly, the review was limited to English, introducing language bias. Furthermore, this study only focused on HCC in adult populations and excluded articles detailing other liver tumours and metastases commonly related to liver cancers. As such, results may not be generalizable to other liver conditions and may not be suitable for the diagnosis, management, or surveillance of other diseases. In conjugation with the review, we believe that future studies may choose to focus on the AI classification of other liver lesions. Additional areas of interest may be the detection of HCC in a paediatric population, research on the prognosis and treatment of HCC using AI techniques in cirrhotic vs non-cirrhotic patients, as well as the differentiation of primary and metastatic liver lesions.

In recent years, the development in computational methods has offered promising possibilities for accurate diagnosis and prognosis of hepatocellular carcinoma. AI technologies such as WSI, machine learning and deep learning have shown application in clinical cancer research. Studies reviewed in this article highlight the numerous achievements AI technologies have made in cancer research. These studies can translate into an effective tool as they continue to evaluate the AI software for accuracy and precision and suggest improvements.

## Conclusions

While most of the algorithms showed accuracy ranging between 70% and 98%, AI has the potential to improve the diagnosis and prognosis of HCC by enhancing the grading, detection, and treatment prediction for microvascular invasion. Future studies may choose to include larger study sizes for HCC trials to generalize their results. Further research is required to improve the accuracy of AI used for HCC to mirror its risk in complicated procedures. Moreover, the predictions generated by AI may require further evaluation and interpretation from professional physicians due to ethical and safety issues. Although AI technologies will not completely replace physicians in clinical practice, equipping physicians with AI can achieve higher efficiency. While the AI investigated in this review is not superior to current guidelines for HCC diagnosis, treatment and surveillance, the emerging use of AI in several health sectors is inevitable.

## List of Abbreviations Used

AI: artificial intelligence
HCC: hepatocellular carcinoma
DCNN: deep convolutional neural network
DL: deep learning
MRI: magnetic resonance imaging
CT: computed tomography
SLFN: single hidden layer feedforward neural network
MDCT: multidetector CT
AUC: area under curve
TL: transfer learning
CNN: convolutional neural network
DCE-CT: dynamic contrast-enhanced computed tomography
Mask-R-CNN: mask region-based convolutional neural network
MCF-3DCNN: multichannel fusion three-dimensional convolutional neural network
DCE-MR: dynamic contrast-enhanced magnetic resonance imaging
MVI: microvascular invasion
DNN: deep neural network
DWI: diffusion-weighted images
CEUS: contrast enhanced ultrasound
TACE: transarterial chemoembolization
CECT: contrast enhanced computed tomography
MS-Densenet: multiscale 2D dense connected convolutional neural network
WSI: whole slide images
LASSO: least absolute shrinkage and selection operator
ANN: artificial neural network
CECT: contrast enhanced computed tomography
SVM: support vector machine

## Conflicts of Interest

The authors declare that they have no conflict of interests

## Ethics Approval and/or Participant Consent

This literature review did not require ethics approval and/or participant consent as it is a literature review.

## Authors' Contributions

D: made contributions to the design of the study, collected and analysed data, drafted the manuscript, and gave final approval of the version to be published.
ZA: contributed to study design and planning, assisted with the collection and analysis of data, and gave final approval of the version to be published.

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