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Advancing Hepatology with AI: A Systematic Review of Early Detection Models for Hepatitis-Associated Liver Cancer

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Abstract:-

- ***Background:***

Despite advancements in health technology, liver cancer remains one of the deadliest forms of cancer and chronic hepatitis B and C viral infections, referred to as HBV and HCV, are major risk factors for the development of HCC. Detecting liver cancer in its early stages is essential to improve cancer patients' results. However, there is a lack of appropriate instruments, such as imaging and biomarkers, which aid traditional cancer detection. The hope raised to counter such diagnosing impediments is the use of artificial intelligence, old-fashioned technologies incorporating development such as machine learning, deep learning and coordinated systems that can narrow the accuracy gap of a cancer diagnosis.

- ***Methods:***

This systematic review adhered to PRISMA statements and attempts to aggregate published articles on the use of artificial intelligence for diagnosis of primary liver cancer occurring in patients with hepatitis, published in 2020-2024. An extensive search using Booleans was performed in PubMed and Google. Of the 1940 studies found, 50 were appropriate for inclusion. Spine targets, Other AI models, Datasets, Performance metrics and Clinical relevance of the AI implementation were among the main details gathered. Both statistical and narrative approaches accompanied the synthesis of results.

- ***Results:***

The advancements and applications of AI in diagnosis using AI systems like convolutional neural networks (CNN) and the new hybrid systems are encouraging, with sensitivity and specificity rates consistently over 85% in many cases. Providing images, biomarkers, and other genomic data corroborated this, resulting in high ROC-AUC values. Nonetheless, dataset bias, insufficient real-world applicability, and the requirement for XAI all present significant challenges to using AI in practice.

- ***Conclusion:***

The use of AI holds great promise in optimizing the early diagnosis of hepatitis-associated HCC by overcoming the challenges posed by conventional methods of diagnosis. To this end, there should be a concentration on increasing the variation in datasets, carrying out extensive research clinical trials, and developing teams spanning different disciplines to allow for easy incorporation into clinical practice. These are promising prospects for enhancing the early detection and treatment of patients suffering from a disease in the Field of hepatology.

Keywords:- *Artificial Intelligence (AI), Hepatocellular Carcinoma (HCC), Multimodal Data Integration, Liver Cancer Diagnostics, AI Models in Hepatology, Biomarkers.*

I. INTRODUCTION

- *Background of Hepatitis-Associated Liver Cancer*

Chronic hepatitis, mainly due to the hepatitis B virus (HBV) and hepatitis C virus (HCV), is a significant risk factor for the development of hepatocellular carcinoma (HCC). HCC is associated with the majority (more than 80%) of cases of liver cancer worldwide (inertia in cancer mortality, Kobayashi et al., 2020). The progression from chronic hepatitis to HCC is a complex pathological progression composed of several steps, including inflammation, followed by fibrosis, and then dysplasia changes that are frequently associated with cirrhosis before any cancer is diagnosed. Early-stage screening is also paramount as it greatly benefits the patients; however, this is a difficult task because of the existing diagnostic modalities (Yang et al., 2023). Conventional techniques such as imaging (CT, MRI) and serologic examination, including tumour marker alpha-fetoprotein (AFP), often miss early HCC. Less invasive techniques, such as liver stiffness measurement (LSM) and the FIB-4 index, provide some information but are not accurate enough to justify such an early-stage diagnosis (You et al., 2020). Thus, there is a clear demand for more sophisticated approaches to predict HCC development in patients with hepatitis by combining clinical and biological data more effectively.

➢ *Importance of AI in Healthcare*

The advent of Artificial Intelligence (AI) has changed the healthcare landscape completely. This is because of its ability to process large volumes of data quickly and with impressive accuracy. In hepatology, AI-aided models based on machine learning and deep learning have been found to fill critical gaps in the early detection of offshore hijacking control (HCC). These algorithms are adept at finding complex imaging, genomic, and biochemical data that may be too complex for the human brain to interpret (Phan et al., 2020).

For example, computed tomography (CT) and magnetic resonance imaging (MRI) scans equipped with convolutional neural networks (CNNs) have been more sensitive and specific when distinguishing between early-stage HCC tumours and native tissue. Moreover, risk prediction models integrating risk factors such as plasma biomarkers and clinical variables help personalise the treatment management of such patients (Liu et al., 2021). Thus, a practical adoption model supports the integration of precision diagnoses in managing hepatitis-related HCC.

➢ *Rationale for the Review*

In recent years, engagement with AI-based diagnosis has risen. However, existing studies have not appropriately summarised the approaches used specifically for the early diagnosis of hepatocellular carcinoma associated with hepatitis B. There are differences across AI models, datasets, and clinical outcomes. Therefore, it is essential to bring together the results and address the general implications of these results. This systematic review intends to focus on the application of artificial intelligence, considering the challenge of distinguishing chronic hepatitis from hepatocellular carcinoma. The systematic review aims to answer the following research questions:

- **RQ 1.** To assess and compare the performance of different AI techniques in detecting early-stage HCC.
- **RQ 2.** To focus on the type of data incorporated in these modelling studies (imaging, biomarkers, clinical) and how they are combined.
- **RQ 3.** To consider the advantages, disadvantages, and biases of existing artificial intelligence systems.

To summarise, the continuity of disease from chronic hepatitis to hepatocellular carcinoma is fraught with difficulty in diagnosis that is often insurmountable by conventional means. AI is a valuable tool in overcoming this obstacle by synthesising vast data to improve prognosis. This review will assess the applicability of AI models and data strategies and evaluate relevant biases in improving precision diagnosis for hepatitis-associated HCC patients.

II. METHODOLOGY

This systematic review is prepared according to the PRISMA 2020 policies to promote transparency and ease in reproducing the review process. The review is centred on the utilisation of artificial intelligence (AI) to detect liver cancer, the most common form of cancer associated with hepatitis, at its earliest stages, in publications between 2020 and 2024. The methodology consisted of four steps: identification, screening, eligibility, and inclusion.

➢ *Step 1: Identification*

The identification phase was crucial for telling which studies could be included in a review. A systematic search was performed in many different databases, such as PubMed and Google Scholar. The search used Boolean operators to narrow the results, including the following string:

(("Artificial Intelligence" OR "Machine Learning") AND ("Hepatitis B Virus" OR "Hepatitis C Virus") AND ("Hepatocellular Carcinoma" OR "Liver Cancer") AND ("Early Detection" OR "Disease Progression") AND ("Medical Imaging" OR "Biomarkers") AND ("Sensitivity" OR "Specificity" OR "AUC"))

The search aimed to find studies on the use of AI in early detection or for monitoring liver cancer progression. This resulted in 1,940 papers, which were then organised to be analysed and screened.

➢ *Step 2: Screening*

After that step, selected studies underwent a ray for relevance assessment. Out of the 1,940 papers, the titles and abstracts were inspected for inclusion by two researchers in each case. Studies that did not address the use of AI in hepatitis-related liver cancer or did not support an early detection objective were removed. Differences between the reviewers were resolved through conversations or involving a third party in the decision process. This step reduced the number of papers to 200.

➢ *Step 3: Eligibility Criteria*

To be by the purpose and goals of the review, the eligibility criteria were defined beforehand about the review screening (Brony et al., 2024). These criteria are presented in a summary form in Table 1:

Table 1 The Inclusion and Exclusion Criteria for the Initial Screening of Articles

Criteria	Inclusion	Exclusion
Timeframe	Studies published between 2020 and 2024	Studies published before 2020
Peer-Reviewed	Only peer-reviewed studies	Non-peer-reviewed articles, preprints, or grey literature
Focus Area	AI applications in early detection of hepatitis-associated liver cancer	Studies not addressing AI or liver cancer

Performance Metrics	Quantitative metrics such as sensitivity, specificity, or AUC	Studies lacking such metrics
Language	English or translatable into English	Non-translatable languages

- *Step 4: Inclusion*

The ultimate evaluation scrutinised the 50 chosen studies that satisfied the inclusion and exclusion criteria. Relevant information, such as the studies' aims, methodologies, datasets, metrics used, and clinical relevance, was extracted and synthesised to give a report. Below, Figure 1 is a flow chart showing the process of selecting studies according to the PRISMA guidelines.

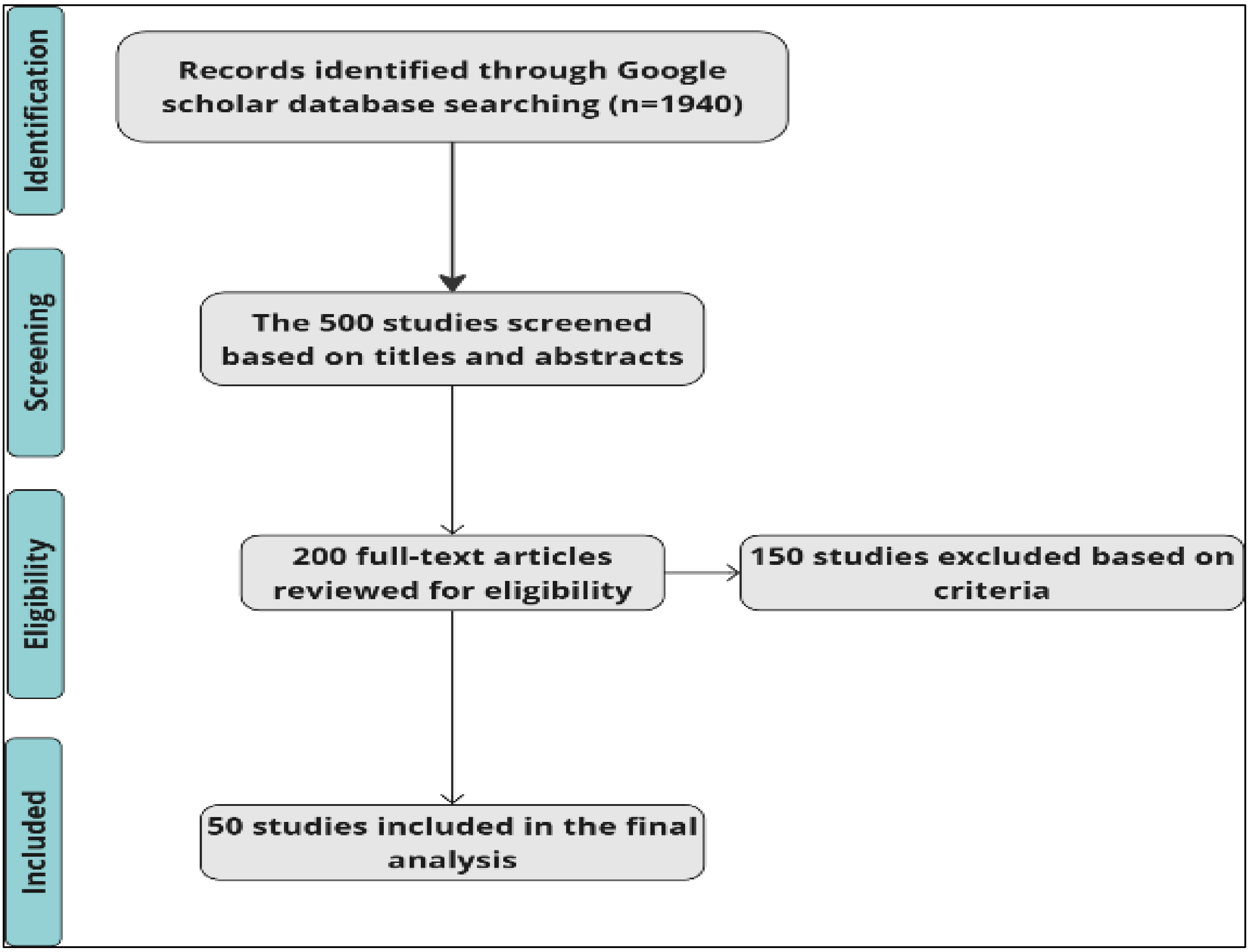

Fig 1 The Search Strategy for the Inclusion of Articles in our Analysis following PRISMA Guidelines.

- *Databases and Search Strategy*

For the literature review, PubMed and Google Scholar were used. These platforms were decided upon because they are all-encompassing databases related to research done in AI, medical imaging, and, more specifically, hepatology. The search strategy involved using Boolean operators to facilitate extensive study retrieval. Table 2 summarises the constructions and keywords used.

Table 2 The Summarised Search Strategy and Keywords for Databases

No.	Construct	Search Field/Limits
#1	"Artificial Intelligence" OR "Machine Learning"	TS=Topic
#2	"Hepatitis B Virus" OR "Hepatitis C Virus"	TS=Topic
#3	"Hepatocellular Carcinoma" OR "Liver Cancer"	TS=Topic
#4	"Early Detection" OR "Disease Progression"	TS=Topic
#5	"Medical Imaging" OR "Biomarkers"	TS=Topic
#6	"Sensitivity" OR "Specificity" OR "AUC"	TS=Topic
#7	2020–2024	PY=Year Published
#8	#1 AND #2 AND #3 AND #4 AND #5 AND #6	Language: English

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- *Search Methodology*

The research was executed in three predominant stages: (1) Searching for relevant articles and finishing their selection; (2) Using rigorous inclusion and exclusion criteria to analyse and filter out the selected research articles; and (3) Reviewing the remaining articles by content analysis based on primary data collected from the sources to assess the literature (Jiaqing et al., 2023).

- *Data Extraction and Analysis*

Data extraction targeted the purpose of studies, AI approaches employed, data used, metrics of performance, and clinical usefulness. In quantitative analysis, mean values like sensitivity and specificity and ROC – AUC metrics of different studies were compared because it was observed that multimodal AI models were more precise. Variations in AI methodologies due to dataset biases, absence of standardised data, explainable AI, and other challenges were discussed in qualitative analysis. The results were presented in sections addressing the promise of AI, the obstacles that exist today, and the aspects of future work in the research of hepatitis-related liver cancers, including the contraction of such cancers. Once the research is complete, a content analysis of the literature on the role of AI in Hepatitis-Associated Liver Cancer will be conducted as was done by Brony, Alivi, Syed, Dharejo, et al. (2024), which will aim to group the research studies based on the positive and negative impacts of various AI models.

III. FINDING AND RESULTS

➢ *Overview of AI Models*

Artificial intelligence (AI) approaches aimed at the early diagnosis of hepatocellular carcinoma (HCC) include both classical machine learning (ML) and recent advances in deep learning (DL). Techniques such as Random Forest, Support Vector Machine (SVM), and Gradient Boosting are standard ML models used to study structured clinical data.

These approaches are especially important for identifying and classifying biomarkers as Random Forest can rank the features while SVMs work best on small and clean data (Khan et al., 2022). Furthermore, a particular imaging technique known as stratification has also improved within deep learning, particularly in the case of convolution neural networks, due to their efficiency in extracting features from images in layers. For example, during the studies conducted by Guo et al. (2024), CNNs were found to have more than 90% sensitivity in identifying early HCC lesions using CT and MRI scans. More advanced architectures such as RNNs and transformers enhance their diagnosis, provide intelligent temporal prediction capabilities, and allow for multimodal integration of datasets, respectively (Dai et al., 2024). Nonetheless, ML techniques heavily depend on feature engineering and have minimal applications with unstructured data. In contrast, DL techniques suffer from overfitting and prefer large and annotated datasets, especially for classification in the earliest disease stage (Asif et al., 2024).

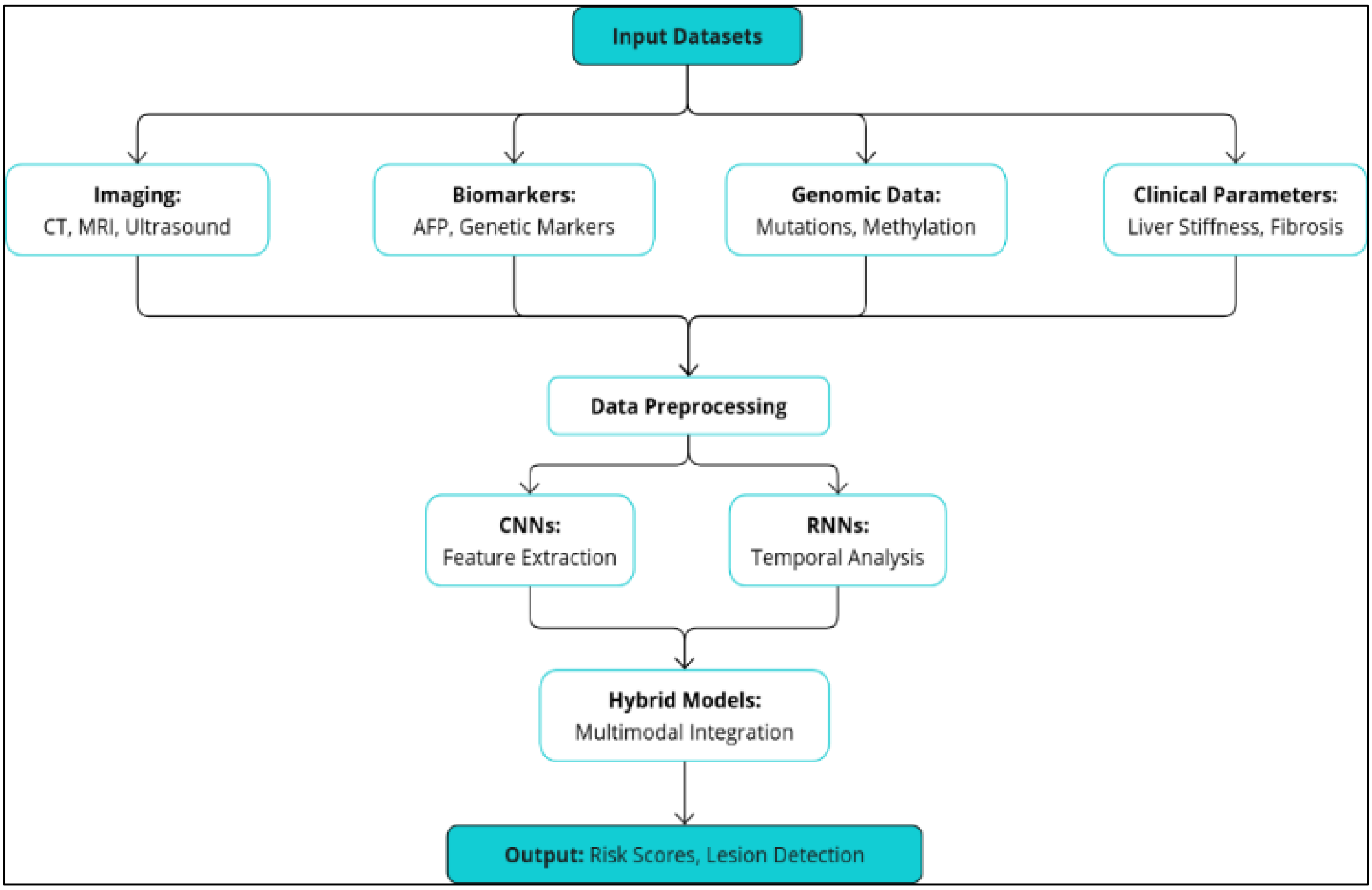

Fig 2 Schematic Representation of AI models Integrating Multimodal Datasets (Imaging, Biomarkers, Genomic Data, and Clinical Parameters) for Early Detection of Hepatocellular Carcinoma (HCC).

➢ *Datasets and Data Preprocessing*

Artificial intelligence's impact on detecting HCC tumours is possible due to the exploitation of appropriate data. Public sources such as The Cancer Genome Atlas LCC and the Liver Imaging Database Consortium provide imaging data and clinical annotations in standardised formatting, which helps train and compare models (Bal, 2024). Clinicalcept, the proprietary dataset, is used to train neural networks, but it employs real-life multimodal data even concerned with genetic profiling and assays, which are not available for outside validation (Mai et al., 2020). Thus, a proportionate dataset is challenging as most available cases are in the early stages and suffer from high dropout rates. This imbalance is tended to by using methods such as the Synthetic Minority Oversampling Technique (SMOTE) and augmenting data (Mansur et al., 2023). Changes made to images, such as normalising, reducing noise and cutting images into small parts, improve the performance of models, especially with imaging data (Kazi et al., 2024). Moreover, the outcomes from studies indicate that incorporating imaging modalities, biomarkers, and genomics produced improved accuracy of diagnosis, such as when CT imaging was combined with alpha-fetoprotein (Liu & Wen, 2024).

➢ *Diagnostic Performance*

AI models have achieved, without exception, better performance parameters than existing diagnostic methods in early-stage HCC detection. The sensitivity and specificity rates for AI models range between 80% and higher, with some radiomic models based on CNN surpassing 90% (Guo et al., 2024). In addition, these models achieve much higher rates in the AUC of ROC curves than conventional methods, such as AFP testing, which has an average AUC of approximately 0.70 (Candita et al., 2023). In addition, interesting case studies illustrate AI's possibilities; for example, hybrid imaging and serum biomarker models performed better than radiologists achieving 92% diagnostic accuracy (Asif et al., 2024). All these aspects highlight the potential of AI technologies in enhancing the sensitivity and specificity of HCC diagnosis at an early stage.

- *Comparison of AI Models and Traditional Methods*

This table compares the performance of traditional diagnostic methods and AI models in early detection of hepatocellular carcinoma (HCC) based on studies included in the systematic review as Asif et al. (2024), Guo et al. (2024), Liu & Wen (2024), Candita et al. (2023), Mansur et al. (2023), Ronot et al. (2023).

Table 2 Comparison of AI Models and Traditional Methods

Metric	Traditional Methods (e.g., AFP, Imaging)	AI Models (e.g., CNNs, Hybrid Models)
Diagnostic Accuracy	70–80%	85–92%
Sensitivity	60–75%	85–90%
Specificity	70–85%	88–95%
ROC-AUC	~0.70	~0.85–0.93
Use of Multimodal Data	Limited	Extensive (e.g., integrating imaging, biomarkers, genomics)
Real-Time Analysis	Not possible	Possible with advanced AI systems
Observer Variability	High (depending on radiologist expertise)	Low (AI ensures consistent analysis)

➢ *Cost-Effectiveness and Implementation Challenges*

Also, traditional diagnostic methods and AI models' cost implications in early hepatocellular carcinoma (HCC) detection reveal distinct strengths and weaknesses. Traditional diagnostic methods involve CT or MRI scans and serologic tests such as alpha-fetoprotein [AFP], where highly technologised machines and domestic necessities are initially required. Occupying, though, seldom do the operational costs remain low, if at all, as they will be incurred whenever there is a need to interpret the output by experts such as radiologists and pathologists. Furthermore, given their low sensitivity and specificity, these techniques are seldom used once only, thus increasing costs. For example, the sensitivity of AFP testing, which stands at 60-75% range, usually calls for other tests to be carried out to validate the test. Such re-doing of tests, on top of the high patient cost sharing for the studies conducted, makes conventional diagnosis in such poor regions almost impossible. (Addissouky et al., 2024; Candita et al., 2023).

On the other hand, the cost structure of AI Models is different. AI is expensive to develop due to complex computational systems, purchasing vast data and training the model. Still, its operational costs are cheaper. After launching the AI systems, there are possibilities to perform tasks such as lesion detection or biomarkers assessment with them, and a much smaller dependency on human resources and costs can be achieved. The advantages of AI systems also include the trained model being scalable and being able to be used in various locations thanks to cloud services. This may further reduce the cost of diagnosing disease in the units over time. (Benhammou et al., 2022; Dai et al., 2024 Additionally, in the long term, costs incurred in treating advanced disease stages, such as expensive therapies or organ transplants, are minimised because AI facilitates effective early treatment of diseases. However, these positive aspects are countered by the high initial investment and technical know-how required to establish AI systems in low-resource environments. (Asif et al., 2024)

While AI systems hold many promises, their implementation has various challenges. For example, conventional diagnostic techniques depend on skilled personnel like radiologists and pathologists, which may not be practical in areas suffering from a shortage of these cadres. They are also highly observer-dependent, and there is a range of results based on the individual clinician's skills, often resulting in outcome variations (Candita et al., 2023). However, AI models embrace the standardisation of diagnostic accuracy. The models, however, need high-quality annotated datasets for training, which are lacking in impoverished regions. Additionally, AI models are also quite computationally demanding, so we are faced with hurdles as many healthcare facilities do not have the requisite capabilities (Dai et al., 2024). For AI tools to be practical, it is also necessary for healthcare professionals to undergo training on interpreting AI-driven results, which calls for funding of education and capacity-building initiatives (Asif et al., 2024).

The distinctive nature of these approaches is best illustrated using practical examples. As seen in the majority of cases in developing countries, traditional diagnostics has its drawbacks since it lacks advanced imaging technology and hence has to depend on serological tests such as AFP which are relatively low in performance (Candita et al., 2023). On the other hand, simple networks of AI solutions have been tried in some regions with great success. Such is the case of cloud AI solutions in Africa and South Asia where clinics even in rudimentary buildings are able to diagnose with the same accuracy as high-end centers thus demonstrating the coverage and affordability of AI (Benhammou et al., 2022; Dai et al., 2024). The combination of imaging, biomarkers, and genomic data always provides better sensitivity and specificity and is time and cost-effective as opposed to the conventional approach (Asif et al., 2024).

To put it plainly, addressing these issues requires a multi-pronged solution. For example, building customised cloud solutions and deploying lightweight AI models improve the chances of implementing advanced diagnostics in hyper and under-resourced settings. There are also ethical and regulatory concerns speech, such as the need for explainable AI (XAI), which are necessary to promote confidence and cooperation from health practitioners regarding data use. At the same time, integrating artificial intelligence in the education system of these practitioners would make sure that they can use the artificial intelligence. By balancing the best characteristics of traditional methods and AI, healthcare systems can provide proper access to all patients whatever their socioeconomic status.

➢ *Integration into Clinical Workflow*

Despite its promise, the implementation of AI in clinical practice is still met with several limitations. As it turns out, the majority of the studies are still in secondary validation phases, which makes their use in real-life applications almost impossible. There is a dire shortage of prospective trials which are essential in proving the clinical efficacy of the given technology (Liu et al., 2021). Besides that, there are also barriers to adoption like policy issues, absence of uniform strategy for assessment, and making it fit into the current systems of operation (Dana, 2024). These aspects, however, usually have a degree of optimism since many of the AI systems are aimed at automating even the most burdensome processes such as that of radiological segmentation which can shorten diagnostic time by as much as 40% (Dai et al., 2024). In enhancing clinician fidelity, the use of explainable artificial intelligence (XAI) approaches will be fundamental. The use of transparent models with interpretable outcomes will greatly help in fostering integration to enhance clinical interactions (Khan et al., 2022).

As a conclusion, it is evident that AI has progressed commendably in the development of new models and their ability to integrate multiple data in the diagnosis of early-stage HCC, but it needs to address wider aspects such as dataset biases, clinical validation and trust via explainability in order to be more practical. These will go a long way in ameliorating the discrepancies that exist between the research and the actual practice, which is critical in the early detection of diseases more so in patients with HCC.

Table 3 The following Table Discusses Certain Comparisons among some of the Studies on AI as Applied to Hepatitis Induced Liver Cancer.

Author and Year	Study Design	Type of Data Used	Key Findings	Conclusion	Future Directions
Zhang et al. (2022)	Systematic review and meta-analysis	Imaging data (CT/MRI)	High diagnostic accuracy of AI for microvascular invasion prediction in HCC.	AI offers robust diagnostic capabilities for preoperative HCC evaluation.	Incorporate larger datasets and real-world validation.
Parikh et al. (2020)	Review article on biomarkers	Serum and genetic biomarkers	Summarised biomarkers for early HCC detection; no AI focus.	Biomarkers remain vital for early HCC detection; AI not discussed.	Focus on integrating biomarkers with AI for better early detection.
Decharatanachart et al. (2021)	Systematic review and meta-analysis	Imaging, biomarkers, and clinical data	AI improves diagnostic performance in chronic liver diseases.	AI holds promise for diagnosing and managing chronic liver diseases.	Expand AI applications to broader populations and liver conditions.
Wu et al. (2021)	A systematic review and external validation	Clinical records, imaging data	Reviewed prediction models; external validation showed mixed performance.	Effective models require rigorous validation for clinical utility.	Validate prediction models with real-world and diverse populations.

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Ioannou et al. (2020)	Cohort study with deep learning assessment	Clinical and imaging data (Hepatitis C)	Deep learning accurately predicts HCC in Hepatitis C cirrhosis patients.	Deep learning is a promising tool for HCC prediction in cirrhosis.	Refine and deploy deep learning models in clinical practice.
Tiyarattanachai et al. (2023)	Randomized controlled study	Ultrasound imaging data	Real-time AI improves lesion detection accuracy during ultrasound.	AI integration enhances ultrasound efficacy in detecting liver lesions.	Broaden AI use in different imaging modalities and settings.
Addissouky et al. (2024)	Review with recommendations	General discussion (no specific data)	Highlighted opportunities for responsible AI translation in HCC.	Recommendations can drive responsible AI use in HCC diagnosis and care.	Develop frameworks for responsible and equitable AI implementation.
Salehi et al. (2024)	Meta-analysis on AI diagnostic performance	Imaging data (CT/MRI, ultrasound)	High diagnostic accuracy of AI in detecting HCC across studies.	AI demonstrates high diagnostic potential for HCC across imaging methods.	Standardise AI protocols for global clinical adoption.
Wolf et al. (2021)	Systematic review and meta-analysis	Clinical records and imaging studies	HCC surveillance improves patient outcomes; no AI use is studied.	HCC surveillance is crucial for better outcomes; AI not involved.	Integrate AI into surveillance programs to improve outcomes.
Singal et al. (2022)	Meta-analysis on surveillance impact	Clinical surveillance records	Early detection and treatment via surveillance enhances survival in cirrhosis.	HCC surveillance leads to improved early detection and survival rates.	Enhance surveillance systems with AI to improve detection and treatment.
Ali et al. (2024)	Review article on AI in viral hepatitis management	General discussion (no specific data)	AI has significant potential in improving hepatitis management.	AI integration can revolutionise hepatitis management worldwide.	Integrate AI tools into routine hepatitis care globally.
Xu et al. (2024)	Development of machine learning-based predictive models	Clinical data from HBV cirrhosis patients	ML models improve personalised HCC risk prediction in HBV patients with low AFP.	Machine learning aids personalised risk assessment for HCC in HBV patients.	Refine and validate models for broader clinical use in HBV-related HCC.
Terlapu et al. (2022)	Probabilistic neural network approach for HCV diagnosis	Clinical and diagnostic data for HCV	Probabilistic neural networks offer accurate HCV diagnosis.	Neural networks are effective for HCV diagnosis in clinical settings.	Expand neural network approaches to other hepatitis strains.
Farrag et al. (2024)	Review on AI paradigms in endemic viral infections	Discussion on HCV management (no specific data)	AI can address challenges in managing endemic viral infections.	AI presents opportunities and challenges for endemic viral infection management.	Address ethical and technical challenges in AI application for viral diseases.
Larrain et al. (2024)	Review on AI/ML/DL for HCC diagnosis and management	General discussion on HCC imaging and clinical data	AI methods enhance HCC diagnosis and treatment pathways.	AI has transformative potential for HCC diagnosis and management.	Develop standardised protocols for AI in HCC management.

Siam et al. (2023)	Scoping review of multimodal deep learning in liver cancer	Multimodal imaging and clinical datasets	Multimodal deep learning has promising applications in liver cancer.	Multimodal AI approaches hold great promise in liver cancer research.	Investigate multimodal approaches in other liver diseases.
Wang et al. (2024)	Machine learning-based cohort study	Clinical data (HBV-related HCC)	Machine learning accurately predicts tumour recurrence post-therapy.	Machine learning models show strong potential in clinical HCC management.	Apply models to larger populations and diverse clinical settings.
Wong et al. (2022)	Novel machine learning risk score comparison	Clinical and viral hepatitis data	Machine learning models outperform traditional risk scores for HCC prediction.	AI-based models are superior for predicting HCC in chronic viral hepatitis.	Expand AI adoption in viral hepatitis-related HCC management.
Sato et al. (2021)	Review on AI in HCC management	Clinical imaging and laboratory data	AI enhances diagnostic and management capabilities for HCC.	AI is transforming HCC care with improved accuracy and efficiency.	Develop more robust AI systems for HCC management.
Patel et al. (2024)	Systematic review	Various datasets (review)	Comprehensive review of AI applications in HCC screening, diagnosis, and treatment.	AI is pivotal in advancing HCC healthcare practices.	Integrate AI into global HCC healthcare frameworks.
Parashar & Gautam (2024)	Book chapter discussing AI applications	Discussion-based (no specific data)	Highlights the importance of AI in liver disease characterisation.	AI supports accurate liver disease recognition and prediction.	Promote equitable access to AI in liver healthcare.
Kodinariya et al. (2020)	Artificial Neural Network Cohort study	Clinical and imaging data (HBV-related cirrhosis)	ANN models effectively diagnose cirrhosis in HBV-related HCC patients.	ANN models provide a reliable diagnostic tool for HBV-related HCC.	Validate ANN models with diverse datasets.
Kodinariya & Gondaliya (2024)	Review of machine learning applications	Liver disease-related datasets	Machine learning significantly improves liver disease prediction accuracy.	AI models are essential for predictive and preventive liver disease care.	Improve machine learning models for broader applicability.
Lu et al. (2023)	Decision tree model study	Clinical data (HCV eradication patients)	The decision tree algorithm accurately predicts HCC in post-HCV patients.	Decision trees are effective tools for HCC risk prediction.	Refine decision tree algorithms for better clinical utility.
Lazarus et al. (2023)	Review on prevention strategies	Various data sources for prevention review	HCC prevention strategies are critical in the post-HCV era.	Prevention strategies are vital for reducing HCC incidence post-HCV.	Implement prevention strategies with AI tools.
Lang et al. (2021)	Review on AI scenarios in liver cancer	Clinical and imaging data for liver cancer	AI facilitates precise diagnosis and treatment of liver cancer.	AI significantly improves the precision of liver cancer care.	Broaden AI applications in liver cancer diagnosis and care.
Kim & Ahn (2023)	Prediction model study	HBV-related clinical data	Prediction models improve prognosis for HBV-related HCC.	Prediction models hold promise for HBV-related HCC management.	Optimise prediction models for HBV-related HCC populations.

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Ahn et al. (2021)	Review of AI in liver diseases	Various data sources (AI applications)	AI applications streamline diagnosis and treatment in liver diseases.	AI is a valuable asset in liver disease diagnosis and treatment.	Expand AI applications in liver disease management.
Benhammou et al. (2022)	Technology development study	Early detection technology datasets	DETECT technologies offer promise for early HCC detection.	Early detection technologies enhance HCC prognosis.	Refine DETECT technologies for early-stage HCC.

IV. DISCUSSION

➢ *Machine Learning in HCC Diagnosis*

Thus, machine learning (ML) is an important aspect when it comes to the diagnosis of HCC, with special focus on identifying patients who are likely to suffer from the disease while they have chronic hepatitis. ML techniques make it possible to use large amounts of data ranging from the medical history of patients or clinical biomarkers and images into a predictive analysis. These models harness a variety of learning methods like supervised learning or unsupervised learning as well as ensemble approaches to aide diagnosis and detect signs of HCC at the earliest possible stage. Predictive models based on supervised learning techniques such as that of decision trees and support vector machines (SVMs) have been reported to have successfully predicted the risk of disease progression of HCC using structured data with known outcomes. A class of learning methods called regression-based learning methods, encompass random forest model and gradient boosting machine (GBM) techniques and help in refining model outputs by combining predictions from different models, which increases accuracy and combats overfitting. Such techniques are of great importance when it comes to complex cleft system tissues that have many interacting clinical and laboratory characteristics.

Numerous research works have demonstrated the use of ML approaches in the diagnosis of HCC. Asif et al. (2024), for instance, examined the use of ML techniques like decision trees and neural networks in diagnosing HCC caused by viruses and non-viruses by using imaging and corresponding biomarkers. Likewise, the study conducted by Khan, Luo, and Wu (2022) offered systematic review of machine learning techniques employed in livers diseases' diagnosis emphasising chronic hepatitis to HCC. This review has shown how feature engineering can be employed to elevate the performance of models in classifying patients on several risk zones. Also, Mai et al. (2020) incorporated artificial neural networks (ANNs) in diagnosing liver cirrhosis in HBV patients, achieving higher accuracy in diagnosing the early stages of the disease. These results point to the fact that the use of ML techniques can fill the diagnostic voids that are inherent in the conventional methods.

The most significant advantage of ML systems in diagnosing HCC is the ability to analyse and correlate various types of data in order to fully grasp the complexity of the disease as it advances. Since these devices respond to these technological enhancements, ML models have been known to outperform the conventional diagnostic techniques quality and accuracy wise. However, there are some aspects that can be improved. One such aspect is the problem of overfitting the model, which is particularly pertinent to the fact that there are not too many intuitive and diverse datasets. In the majority of the cases, machine learning models are trained using localised datasets which limits their application to a specific ethnic or regional group of patients. It is essential to solve these problems by utilising more extensive, systematic, and representative datasets along with their external validation and proofing.

In addition, A key strategy in improving AI specificity and sensitivity, especially in the diagnosis of difficult disease conditions, has been the use of multiple types of data. Shiwlani and others (2024) surveyed how cardiovascular diseases (CVDs) are diagnosed using deep learning techniques on images based on multimodal data including medical history, images, and biomarkers. It has given imaging-centered analysis of CVDs, which is a strong reason for the use of these methods in hepatology. in this case, multimodal visions may incorporate picture techniques and blood tests as well as radiation and genetic data to help identify HCC at its intrusively most asymptomatic stage. This is also consistent with the current practice in the field of hepatology whereby such disorders call for the development of second-generation multimodal AIs for diagnostics and treatment.

➢ *AI in Imaging Diagnostics.*

The imaging examination has remained the most reliable method and primary step in the diagnosis of HCC, as computed tomography (CT) scan, magnetic resonance imaging (MRI) and Ultrasound proved very efficient in the assessment of liver structures. There is no doubt that artificial intelligence (AI) has turned around the application of these imaging tools by automating the detection of lesions, segmenting images and analysing radionics. With these technologies, the accuracy of HCC diagnosis has improved even more, were making away features of the imaging for low volumetric lesions that are cases of early cancer has become a challenge for many clinicians.

The adoption of artificial intelligence has made imaging diagnostics in modern oncology more rapid and productive, the same way it is used in breast cancer screening for mammography. Shiwlani et al. (2024) undertook a systematic review of studies that utilised deep learning to classify mammograms and radiology reports for the assessment of the BI-RADS categories. The review further demonstrated that such systems can effectively manage lesion detection and achieve high accuracy levels for impossibly consistent predictions within a radiologist's working day. In the same way, these imaging-related improvements would also be applicable in the field of hepatology, especially in the area of taking care of the sensitivity and specificity for the detection of liver lesions in patients with early hepatocellular carcinoma (HCC) using computed tomography (CT) and magnetic

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resonance imaging (MRI). The positive outcome from mammography is an important lesson to borrow while designing any computable imaging devices meant for radiology in the field of liver medicine, aside from its other applications in enhancing diagnostic accuracy and minimising inter-observer differences.

Advanced AI systems for the development of imaging diagnostics have shown great potential in recent works. For example, Guo and others (2024) used a three-phase computed tomography scan to construct a deep-learning radionics model, and the model achieved high accuracy in diagnosing early HCC in patients with liver cirrhosis. The model was also able to assess the malignant nature of nodules that would have otherwise been missed in routine evaluations. Likewise, Candita et al. (2023) in a recent review of the literature addressed modern imaging techniques for HCC and how AI has been incorporated into imaging so that it improves diagnosis and analysis. One of the main studies, also by Ronot et al. (2023), evaluated the impact of AI technology on the predictive imaging biomarkers for HCC prognosis, showing clear benefits in clinical risk stratification and guiding therapy.

There are many benefits to incorporating AI technology into imaging processes. Diagnostic accuracy is improved by detecting specific image characteristics in the studied object, which radiologists at this stage may find difficult to locate, especially in the earlier stages of HCC. Moreover, AI also addresses the challenge of inter-observer variability – diagnostic outcomes are the same irrespective of the reader's level of expertise. Furthermore, analysis of imaging studies using AI takes place within the examination therefore improving performance and enabling quick actions after the ordinary examination. In view of these developments, however, certain obstacles to the acceptance of AI in imaging diagnosis still exist. The majority of AI approaches are trained using retrospective data. Hence, their use in realistic conditions is limited. To bring these models into routine clinical evidence-based practice, prospective studies and clinical trials are required. Lastly, AI models are still not completely interpretable with the necessity of building explainable AI (XAI) reliability upon clinicians.

➢ *Biomarker-Based AI Models*

Biomarkers mark an important step in the evolution of screening for HCC in which alpha-fetoprotein is the most frequently employed marker. However, AFP alone is not sensitive or specific enough for a diagnosis of early-stage HCC. Models of artificial intelligence have become indispensable in helping combine biomarker information with clinical history and imaging studies to enhance accuracy of diagnosis and risk stratification in patients. Original studies have shown the relevance of AI-based biomarker modelling strategies. For instance, Zhang et al.2023 conceived a diagnostic model based on machine learning, which used biomarker and immunoassay data, enabling HCC from non-malignant cases to be named with high sensitivity and specificity. In the same fashion, Mansur et al. (2022) delved into the applications of Ai in the search for new biomarkers of HCC, emphasising the merging of Ai and molecular diagnostics. Gil-Rojas et al. Sporty uses ML techniques to predict the risk of HCC based on A range of AFP levels, thus proving the ability of these models to lower the rate of early HCC development and enhance positive treatment results. Nevertheless, AI models leveraging biomarkers suffer from some disadvantages and threats. First, the main obstacle is the lack of extensive and well-populated age- and sex-specific, stage-specific biomarkers that might capture the entire spectrum of the disease. Also, due to differences in populations, the variation in expression of a given biomarker hinders the wider applicability of the models. These issues will necessitate the development of standard datasets as well as widening the scope of biomarker studies through cooperation.

➢ *Bibliometric Trends and Hotspots*

The use of artificial intelligence in diagnosing hepatocellular carcinoma (HCC) has greatly increased with a central emphasis on targeted treatment and predictive medicine. It is possible to bibliometric analyse the trend which shows a greater degree of integration of different fields of expertise such as hepatology, radiology, and computer medicine in early HCC where most if not all the patients are asymptomatic.

Dai et al. (2024) performed a bibliometric analysis to find the research trends on the application of artificial intelligence in HCC detection. They indicated trends in the application of real-time diagnostics and analytics emphasising the role of artificial intelligence in the enhancement of medicines aimed at personalised treatment. In the same way, Lee et al. (2023) used the bibliometric technique based on machine learning to analyse three decades of HCC scientific literature, showing the changes over time in the use of artificial intelligence for liver cancer treatment and prevention. The increasing importance attached to artificial intelligence for providing enhanced diagnostic pathways and enhanced patient care is illustrated in these studies. The key focus of the inventions includes increased use of real-time diagnostic devices, emergence of novel AI approaches such as federated learning alongside explainable artificial intelligence (XAI), and application of multimodal data to increase prediction precision. Such developments indicate the increasing appreciation of the role of AI in revolutionising HCC diagnosis and enhancing the chances of early detection of the disease.

V. CHALLENGES AND LIMITATIONS

Utilizing artificial intelligence (AI) for the early identification of liver cancer consequent to hepatitis infection is promising. Yet, it causes several issues and drawbacks as well. Such problems range from technical, ethical, and implementation challenges that need to be solved to make sure that the AI systems are functional, fair, and easily adapted in the clinical setting.

➢ *Data Standardization*

The most important problem faced while creating and implementing AI models is that there are no common datasets across the various studies. Human resource development processes depend on professional and technological data systems, which are situationally overwhelming and highly annotated, due to the need for specific Ay systems. For example, owner-related databases are full of many types of data including images, clinical test data, and genomic data, but often such data cannot be accessed by outside researchers so it cannot help in validating the model nor can it be used for comparison across the studies (Mai et al. 2020; Mansur et al. 2023).

In addition to this issue, AI systems cannot be benchmarked with any degree of competence because there are no uniform metrics used across AI models. Parameters like sensitivity and specificity or measurement of the area under the curve of the receiver operating characteristics (ROC) have been reported in an arbitrary manner in various publications, thereby making it difficult to rank various model performances. Standards for how to prepare data used in the analyses e.g., normalisation or augmentation even further add to this variability and hinder replicability (Asif et al., 2024).

- *Ethical Concerns*

The prevalence of bias within Al systems is an ethical problem which cannot be overlooked particularly when the training algorithms are applied on unbalanced or non-diverse datasets to represent all possible patient populations. For example, models which rely on the input of data about specific areas or ethnicity perform poorly in populations that have not been represented in the studied data augmenting the existing limitations in healthcare services (Liu et al., 2021). This is especially true in the case of hepatitis related liver cancer in which genetic and environmental causes differ from one population to another.

In addition, many AI algorithms work as a black box, which is a design issue with respect to transparency and interpretability. This is the reason why there is a problem as far as doctors and patients who will use the diagnosis based on the system. Why should clinicians wish to use such a system that is inconsiderate enough to explain how judgments are made? The absence of explainability assists in the little or no acceptance of the AI services and even creates risks legally and ethically because people have reasons for providing such medical decisions (Khan et al., 2022).

- *Clinical Implementation*

Even though research has made a reasonable stride forward, it is transforming the findings of AI into everyday clinical routines that pose a significant challenge. Many of the AI systems are often tested and validated in research conditions and do not have real-world applications. The field is mainly characterised by retrospective studies, while there have been relatively few prospective multicenter studies to evaluate the performance of AI in actual clinical settings (Dana, 2024). Moreover, embedding AI into current clinical practices would entail major infrastructural costs which include computing technologies as well as cost of linking up to electronic health records (EHR) systems; and this may be unrealistic especially in resource-poor environments.

Apart from economic constraints, the setting up of AI systems within clinical practice requires extensive orientation of the health workforce. For instance, many of the doctors do not know how to use AI tools hence can't read and work on model results. There are also regulatory hurdles that inhibit the aggression of these technologies such as lack of uniform standardisation of the processes for the approval of AI-based medical devices (Liu & Wen, 2024).

VI. FUTURE DIRECTIONS

In order to address these issues and harness the full power of artificial intelligence in the management of hepatitis-related liver cancer, particular proactive measures will be required. These strategies include developing better artificial intelligence (AI) systems, building synergies, running adequate trials, and working on the integration of AI into clinical systems. These technologies extend beyond the field, which demonstrates how accurately artificial intelligence is used in predicting various fetal health abnormalities. Ahmad al (2024) provides a review of machine learning editing techniques for brain and heart defects in fetuses, thus illustrating how sophisticated algorithms can enhance timely and correct results in diagnosis among patients. Such bears witness to the disruptive technology that is AI, but more so its versatility across applications in health. Primary among those is an understanding of why different aspects of AI should and can be used together. Emulating paradigms like this one in hepatology is sure to result in much-needed innovations in early diagnosis, and prognosis of hepatitis-related HCC owing to the capacity of such technologies to assess large amounts of data and provide individual-level risk stratification.

- *Improving AI Models*

The implementation of proper APIs will ultimately depend on the availability of the relevant and diverse datasets needed for the development of effective and fair AI systems. In the future, emphasis must be made on engaging the minorities present in the population so that the developed AI models can be applied to all tribes, nations, and even the stage of the disease (Mansur et al., 2023). The incorporation of multimodal data that consists of images, biomarkers, and genomic data, will help to improve the accuracy of the models and also their application in a clinical setting.

In addition, Explainable Artificial Intelligence (XAI) approaches have to be implemented to promote trust and usability. XAI provides clinicians with understandable explanations of how predictions were made by the AI systems which in turn enhances the acceptance of the technology among healthcare practitioners thereby aiding management(Khan et al., 2022).

- *Clinical Trials and Collaboration and Integration into Practice*

To prove the effectiveness and safety of the AI treatment options, large-scale, multicentric, real-world-simulated clinical trials are indispensable. These trials must consider various patient populations and reflect the actual clinical settings during which the AI aims to assess the performance of early-stage HCC. In this aspect, Regulatory bodies have to provide a clear pathway and financial resources for conducting these types of clinical trials which in turn will enable quick assessment and deployment of AI based solutions (Dana, 2024).

To accelerate the adoption of AI in diagnostics interdisciplinary work is of great importance. Involving hepatologists, radiologists and AI engineers is useful to solve the problems that are particular to the domains, like finding the proper biomarkers and the best imaging techniques. Also, it can be beneficial for researchers to combine their efforts with regulations and society focused on industry development to innovate in AI technologies (Liu et al., 2021).

The AI tools should prioritise ease of use and clinical relevance. The introduction of user-friendly designs and other automated features would ease the clinician's burden and improve workflow. For instance, Radiology AI tools that automate the detection and classification of nodules assist in reducing the diagnosis time and enhancing productivity (Dai et al., 2024). In turn, this will be reinforced by training focused on healthcare practitioners and the introduction of curricula dependent on AI in medicine.

Practical Strategies for Clinical Integration of AI in Resource-Constrained Settings While integrating any novel technology such as artificial intelligence (AI) into clinical workflows is often burdensome as in the case of low-resource settings where there are challenges such as lack of infrastructures, readiness of the workforce, and limited data availability. Strategic approaches to these challenges exist and thus, there is a potential for effective execution of AI in practical healthcare settings.

- *Use of Cloud Infrastructure*

The necessity of a computational infrastructure is one of the primary impediments associated with the practical realisation of AI strategies which is often lacking in healthcare systems with limited resources. In this sense, cutting-edge cloud-based platforms help to resolve this problem by eliminating the need to install high-power hardware on-site and providing access to the advanced technological tools remotely. In this way, hospitals and clinics with little infrastructure can be able to use artificial intelligence systems for diagnosis without the need of having sophisticated equipment to be brought in the facilities (Benhammou et al., 2022). For example, intensive healthcare focus has cloud-based AI Simply Sapien, recommended for use in tuberculosis screening with a high degree of accuracy in remote regions of Africa.

- *Design of Portable AI Applications*

Additionally, along with the cloud infrastructure, adopting lightweight AI applications explicitly built for low-power devices will mitigate the technical limitations. These can be installed on a typical laptop, tablet, or even a smartphone, all of which can be utilised by healthcare workers at the periphery. For example, clear evolution has been shown in the application of such AI-enabled systems in portable ultrasound machines in the correct evaluation of focal liver lesions occurring in low-resource areas (Candita et al., 2023).

- *Improvement of Data Accessibility*

The successful training and validation of AI models require all-purpose and well-curated datasets. In order to overcome the problem of unavailability of such representative datasets, data-sharing agreements are to be encouraged instead. These agreements would in turn provide for the establishment of imaging, biomarkers and clinical datasets from various ethnic groups in a single place. Public domain resources or the ones created specifically for liver images and genomics would make qualitative databases and hence AI systems more robust and generalisable (Dai et al., 2024).

- *Training of the Workforce and Building Capacity.*

The use of AI devices introduced into routine practice would also mean that the practitioners have to appreciate the technology and its benefits to the extent of trusting it, which is a huge gap. Programs designed for this specific group of people to help them with AI understanding, decision-making, and drawbacks can solve this issue. Such courses can also be part of programs in medical schools or offered as further education. An example of such strategies includes the AI-based segmentation of MRI images where such systems accept clinicians readily after training (Asif et al., 2024).

- *Explainable AI (XAI) to Build Stakeholder Confidence.*

Clinicians are often predisposed to scepticism toward artificial intelligence (AI) systems, hence the requirement for the designs to be interpretable and comprehensible to the users. Explainable artificial intelligence (XAI) systems aim at providing the users of AI systems with context relevant reasoning to allow for the systemic assimilation of the output of the AI system by the user. Such context is necessary to facilitate the 'buying in' of the usefulness of the justification and the output itself, especially in AI clinical tools. As a case in point, XAI systems have been utilised for augmenting the quality of radiological judgments by indicating which specific features influenced the diagnosis (Dai et al., 2024).

VII. CONCLUSION

This article provides insightful evidence on how artificial intelligence (AI) has the power to positively influence the early diagnosis of liver cancer associated with hepatitis, also referred to as hepatocellular carcinoma (HCC). AI models, especially deep learning algorithms such as convolutional neural networks (CNNs) that combine diverse datasets like images, biomarkers and clinical data, have been found to perform better in sensitivity, specificity and overall accuracy than conventional ones. Moreover, due to the interaction of different predictive sources so much so that stand alone diagnostics are no longer capable of measuring such performance.

With all these developments, however, there are still problems. The absence of deep and broad datasets, the issues of fairness and prejudice against AI and its limitations through clinical practice to the extent that it has not been adopted in practice, are all barriers to the extensive application of AI, and its acceptance into the workflow, particularly in the workplace. In addition, XAI must be incorporated in such systems, in a way that will make automated decision processes accessible to the clinicians in such a way that they will be confident in using AI. The high costs associated with the establishment of the necessary working conditions as well as the legal restrictions also pose challenges, especially in developing countries. Another area of focus in the future should be on solving these problems with the use of well-planned and organized multi-site research strategies. It will also be important to create clinically appropriate AI systems A collaboration between hepatologists, radiologists, and AI specialists will be relevant in this regard. Over and above these challenges, however, there is great potential for the use of AI in enhancing early diagnosis of HCC, which will undoubtedly improve disease management and change the face of hepatology.

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