

Artificial Intelligence in Hepatitis B: Advances in Diagnosis, Risk Stratification, Prognosis Prediction, and Clinical Decision

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ABSTRACT

Background: Hepatitis B virus (HBV) infection, which affects around 240 million people globally and causes significant morbidity and mortality through chronic hepatitis, liver cirrhosis, and hepatocellular carcinoma, is still a significant global public health concern. Optimal clinical therapy is still hampered by delayed diagnosis, poor risk stratification, uneven treatment response, and insufficient disease monitoring, even in the face of powerful antiviral medications and effective vaccinations.

Aim: This review critically evaluates the emerging role of artificial intelligence in hepatitis B management, emphasizing its applications in diagnosis, Liver Fibrosis Assessment, Risk Stratification, Prognosis Prediction, Clinical Decision Support, and Comparison with Conventional Management Strategies.

Results: Machine Learning, Deep Learning, Natural Language Processing, And Explainable AI Are Examples of Artificial Intelligence Technologies That Enhance Diagnostics, Non-Invasive Fibrosis Evaluation, Cirrhosis Prediction, Hepatocellular Cancer, And Antiviral Treatment Response. Artificial intelligence (AI) enables precision medicine and tailored patient management by combining Clinical, Laboratory, Imaging, And Electronic Health Record Data. Heterogeneous datasets, insufficient external validation, algorithmic bias, difficulties with interpretability, and ethical and legal restrictions continue to impede application.

Conclusion: AI can improve hepatitis B care by enhancing early diagnosis, fibrosis staging, risk prediction, and treatment decisions by combining clinical, lab, imaging, and follow-up data. Widespread clinical application necessitates improved validation, higher-quality data, model interpretability, and ethical standards. With careful development and integration, AI has the potential to be a reliable tool in HBV management.

Keywords: Hepatitis B; Artificial intelligence, Machine Learning, Deep Learning, Liver Fibrosis, And Hepatocellular Carcinoma; Risk Stratification; Prognosis Prediction; Clinical Decision Support; Precision Medicine.

1. INTRODUCTION

Hepatitis B is caused by the Hepatitis B virus (HBV), which is an encapsulated, partly double-stranded DNA virus from the Hepadnaviridae family, a potentially fatal liver illness. Hepatocytes are the main target of HBV infection, which can result in both acute and chronic liver damage ^[1,2]. The virus is most commonly transmitted from mother to child during childbirth, unprotected sexual contact, sharing contaminated needles, transfusion of unscreened blood and blood products, occupational exposure, and hazardous medical procedures ^[1,3]. HBV enters hepatocytes after infection and produces covalently closed circular DNA (cccDNA) in the nucleus, which enables the virus to continue multiply. Rather than direct viral cytotoxicity, liver injury is mostly caused by the host immunological response to infected hepatocytes, which leads in chronic inflammation and progressive hepatic damage ^[2,4]. Persistent HBV Infection Can Cause Chronic Hepatitis, Cirrhosis, Cirrhosis, Hepatic Failure, And Hepatocellular Cancer, which greatly increases liver-related morbidity and death globally even in the presence of effective vaccinations and antiviral therapies. ^[1,2].

Hepatitis B Virus: Structure, Transmission, and Replication in Human Liver Cells

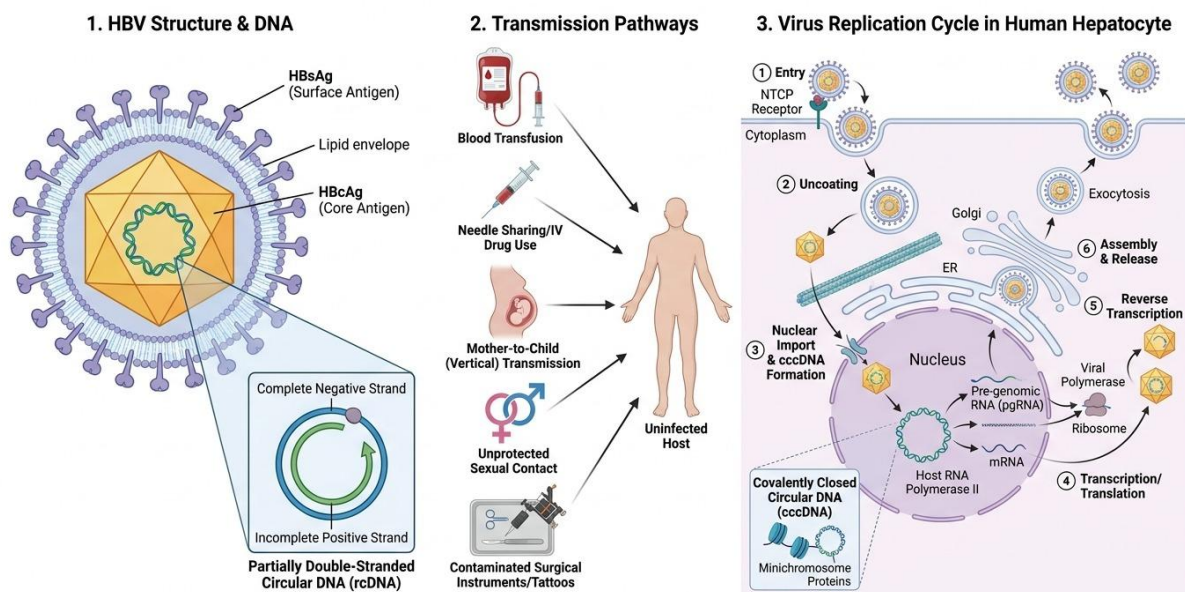


Figure 1: The Structure, Transmission Routes, And Replication Cycle of The Hepatitis B Virus (HBV) Are Shown Schematically.

1.2 Hepatitis B Epidemiology and Disease Burden: International and Indian Views

Hepatitis B is still a serious global public health concern despite the availability of safe vaccinations and efficient antiviral treatments. The WHO Global Hepatitis Report 2024 estimates that 240 million individuals, or 2.9% of the world's population, are chronically infected with the hepatitis B virus (HBV). In 2024, there were 1.1 million HBV-related fatalities, mostly from cirrhosis and hepatocellular carcinoma, and over 900,000 new chronic infections ^[1,5]. Due to low diagnosis rates, insufficient treatment coverage, and ongoing mother-to-child transmission, progress toward the WHO 2030 hepatitis elimination targets is still insufficient. Antiviral medication was administered to fewer than 5% of eligible individuals ^[1,5]. About 29–35 million chronic HBV cases, or 10–15% of the world's total, are found in India, an intermediate-endemic nation ^[5,6]. The prevalence of HBV is

between 2% and 4%; tribal and high-risk populations have greater rates. HBV elimination in India is still hampered by delayed diagnosis, insufficient screening, and poor linkage to care, despite universal immunization and the National Viral Hepatitis Control Programme [2,6].

Global and Indian Burden of Chronic Hepatitis B in 2024: Key Challenges on the Road to Elimination

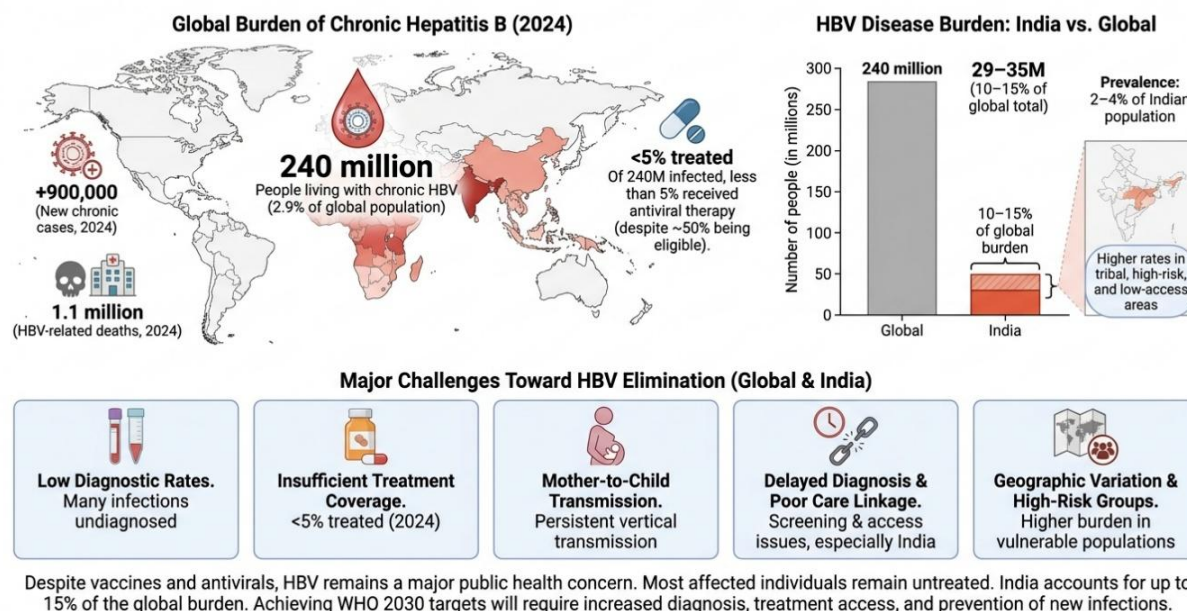


Figure 2: From Disease Burden to Elimination: A Global and Indian Perspective on Chronic Hepatitis B.
Source

1.3 Current Challenges in Hepatitis B Diagnosis and Management

Hepatitis B is still difficult to identify and treat despite breakthroughs in vaccine and antiviral medication. Many people may not show any symptoms for years and are only identified when they have advanced liver disease or its consequences [2,5]. Early detection is delayed when routine screening is not available, especially in situations with low resources. While serum biomarkers and transient elastography offer non-invasive fibrosis assessment, their diagnostic precision varies depending on the patient group [3,4]. Furthermore, despite its efficacy in predicting disease progression and antiviral therapy response, HBV genotype testing is prohibitively expensive and difficult to get in clinical settings. These limitations underscore the need for AI-assisted precision medicine, which can integrate multidimensional viral, host, and clinical data to enhance the prediction of cirrhosis, hepatocellular carcinoma, and therapeutic outcomes. [4,6].

1.4 Emergence of Artificial Intelligence in Hepatitis B Management

The need for sophisticated analytical techniques that can facilitate prompt and precise clinical decision-making has increased due to the growing complexity of managing Hepatitis B. Artificial Intelligence (AI), particularly Machine Learning And Deep Learning Algorithms, can analyse large and varied clinical datasets, including laboratory tests, medical imaging, electronic health records, and genomic data. [4,5]. AI is able to recognize intricate nonlinear relationships and produce customized forecasts with higher accuracy than traditional statistical models. According to recent research, AI-based models can improve Liver Fibrosis Assessment, predict Hepatocellular

Carcinoma (HCC) and disease progression, estimate treatment response, help clinicians manage patients individually, and improve early diagnosis of HBV infection ^[4,6]. Consequently, AI has emerged as a feasible supplement to conventional clinical treatment, with the potential to improve patient outcomes and optimize the utilization of medical resources ^[5,6].

1.5 Aim and Scope of the Review

This review thoroughly evaluates the role of artificial intelligence in hepatitis B management, focusing on risk stratification and clinical decision support. It critically compares AI-based techniques with traditional clinical approaches, highlighting clinical relevance, diagnostic and predictive accuracy, strengths and limitations, and the feasibility of integrating these technologies into routine hepatitis B care.

2. FUNDAMENTALS OF ARTIFICIAL INTELLIGENCE

2.1 Artificial Intelligence

Artificial intelligence (AI), a branch of computer science, enables robots to perform tasks that often require human intelligence, such as learning, reasoning, problem-solving, and decision-making. AI in healthcare combines algorithms with massive clinical datasets to find intricate patterns, produce forecasts, and assist in making evidence-based medical decisions. AI is a useful tool for illness diagnosis, prognosis, treatment planning, and individualized patient care across a variety of medical specialties, including hepatology, since it constantly improves its performance by learning from new data, in contrast to traditional statistical approaches ^[7,8].

2.2 Machine Learning

Machine Learning (ML) is a branch of artificial intelligence that enables computers to learn from data without requiring explicit programming. To create prediction models, machine learning algorithms find latent links in both organized and unstructured datasets. The three main Machine Learning techniques utilized in healthcare are Supervised, Unsupervised, And Reinforcement Learning. ML models are more accurate than traditional statistical models at Diagnosing Hepatitis B, Assessing Liver Fibrosis, Risk Stratification, And Predicting Treatment Results by Analysing Clinical, Laboratory, And Imaging Data ^[8].

2.2.1 Supervised Machine Learning Models

The most popular artificial intelligence technique in hepatitis B research is supervised machine learning (SML), which uses annotated clinical information to learn prediction connections. To anticipate predetermined clinical outcomes, algorithms are developed utilizing laboratory, virological, imaging, therapy, and demographic data ^[7,12]. Common techniques include support vector machines, logistic regression, artificial neural networks, decision trees, random forests, and extreme gradient boosting. These models accurately predict hepatocellular cancer, cirrhosis, liver fibrosis, antiviral treatment responsiveness, HBsAg Sero clearance, and prognosis^[12,13]. Before widespread clinical deployment, however, uniform datasets, external validation, and prospective multicentre investigations are still crucial ^[7,15].

2.2.2 Unsupervised Machine Learning Models

Without predetermined end variables, unsupervised machine learning (UML) examines unlabelled information to find hidden relationships, structures, and patterns. Principal component analysis (PCA), K-means clustering, hierarchical clustering, and self-organizing maps are among the frequently employed algorithms. In hepatitis B research, these techniques are applied to classify patients into distinct clinical subgroups, identify novel disease phenotypes, explore biomarker patterns, and discover previously unrecognized associations among virological, biochemical, and imaging variables. Such analyses support precision medicine by improving patient stratification and generating hypotheses for future predictive model development ^[12,15].

2.3 Deep Learning

Deep learning (DL) is an advanced area of machine learning that automatically extracts complex features from large datasets using multilayered artificial neural networks. Deep learning outperforms conventional machine learning algorithms in image, audio, and text processing and requires very little manual feature engineering. DL has proven to be highly accurate in the interpretation of radiographic images, digital pathology slides, and ultrasound tests in the field of hepatology. This has improved clinical prediction models and enabled automated identification of cirrhosis, hepatocellular carcinoma, and liver fibrosis ^[9].

2.4 Deep Learning Architectures

Multilayered artificial neural networks are used in deep learning (DL), a sophisticated area of machine learning, to automatically uncover intricate patterns from massive datasets ^[12]. Artificial neural networks, convolutional neural networks, recurrent neural networks, transformer-based models, and long short-term memory networks are examples of common structures. To detect Liver Fibrosis, Cirrhosis, And Hepatocellular Carcinoma in Hepatitis B, Deep Learning Analyses Ultrasound, Computed Tomography, Magnetic Resonance Imaging, And Histological Images ^[7,13]. Improved model interpretability, external validation, and high-quality datasets are necessary for clinical deployment ^[14,15].

2.5 Natural Language Interpretation

Computers can comprehend, interpret, and analyse human language from unstructured clinical writing thanks to artificial intelligence (AI) techniques called natural language processing (NLP). NLP transforms free-text input into structured clinical information by extracting relevant information from scientific literature, discharge summaries, pathology reports, and electronic health records. Through automated information retrieval and knowledge extraction, this capability supports prompt and accurate medical decision-making while improving disease surveillance, clinical recording, patient stratification, and research efficiency ^[10].

2.6 Ensemble and Hybrid AI Models

Ensemble and hybrid artificial intelligence models combine multiple algorithms or integrate diverse clinical data sources to improve predictive performance and model robustness. In order to improve classification accuracy while lowering bias and variance, ensemble learning techniques like Random Forest, Extreme Gradient Boosting (XGBoost), AdaBoost, and Gradient Boosting Machines combine predictions from several models^[7,12]. Hybrid models integrate machine learning algorithms with imaging, laboratory biomarkers, electronic health records, or

genomic information to provide comprehensive clinical assessment. These models help predict Fibrosis, Hepatocellular Carcinoma, Disease Progression, and therapy response in Hepatitis B patients. Their ability to capture complex multidimensional relationships makes them valuable tools for precision medicine and personalized clinical management, although further multicentre validation remains essential before widespread clinical implementation [7,15].

2.7 Explainable AI Models

Clinicians can better comprehend prediction mechanisms thanks to explainable artificial intelligence (XAI), which enhances the transparency and interpretability of AI models. Important clinical factors impacting predictions are found using methods like Shapley Additive Explanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME) [12,14]. XAI promotes safe clinical implementation, strengthens clinician trust, and supports evidence-based decisions in hepatitis B [12,15].

2.8 Systems for Clinical Decision Support

Clinical Decision Support Systems (CDSS) are AI-enabled technologies that help medical professionals by integrating clinical data, laboratory results, medical imaging, electronic health records, and evidence-based guidelines to provide suggestions relevant to each patient. AI-driven CDSS improves diagnostic accuracy, lowers clinical variability, and promotes individualized patient management and better healthcare outcomes in hepatitis B by supporting diagnosis, treatment selection, prognosis prediction, and disease monitoring [11].

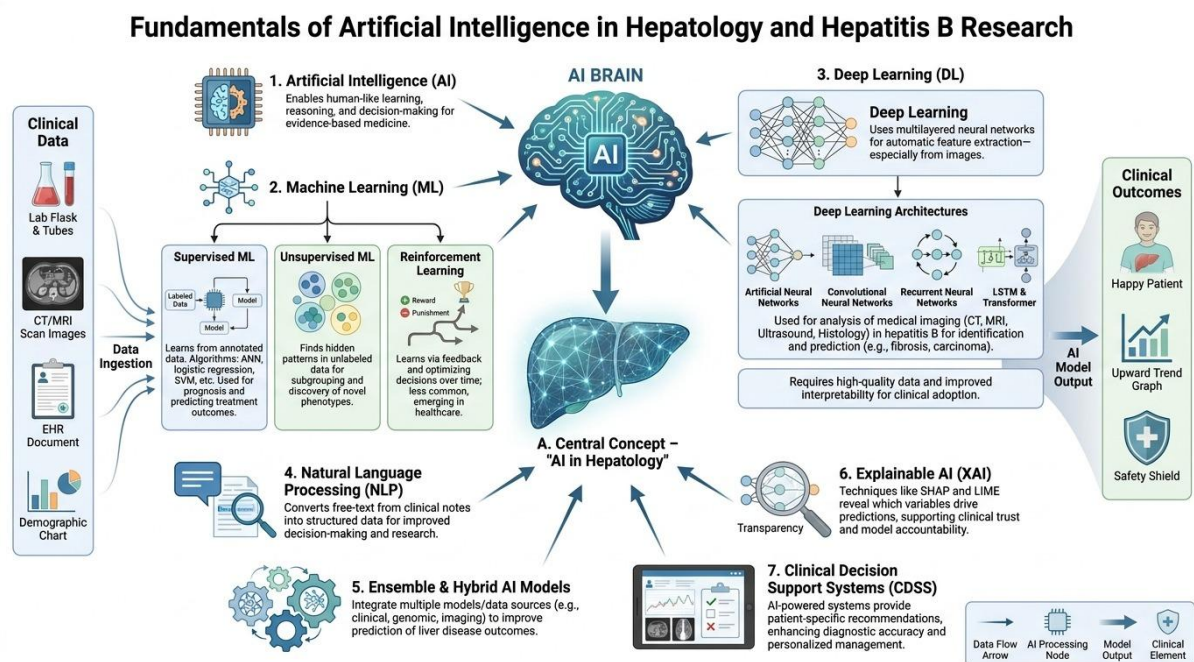


Figure 3: Artificial Intelligence in early diagnosis of Hepatitis B: Integration of laboratory predication models and AI- based imaging for improved disease detection.

3. AI APPLICATIONS IN HEPATITIS B

3.1 AI in Hepatitis B Early Diagnosis

3.1.1 Prediction models based in laboratories

Reducing HBV-related consequences and stopping the disease's development depend on early hepatitis B diagnosis. Artificial intelligence-based laboratory prediction models have emerged as valuable tools for the analysis of complex clinical parameters, including Alanine Aminotransferase (ALT), Aspartate Aminotransferase (AST), Hepatitis B Surface Antigen (Hbsag), Hepatitis B e Antigen (Hbeag), HBV DNA Levels, and Demographic Features. Machine Learning techniques like Random Forest, Support Vector Machine, Logistic Regression, And Gradient Boosting Models have been developed to improve HBV detection and predict clinical outcomes. These models can help detect infections early, especially in patients with unusual presentations or little clinical data, by finding hidden patterns in big datasets. By incorporating several factors at once, AI models show better prediction accuracy than traditional statistical methods [8,12].

3.1.2 Diagnosis based on Imaging

Artificial intelligence-based imaging has made it much easier to detect and characterize hepatitis B-related liver problems. In order to identify liver fibrosis, cirrhosis, and hepatocellular carcinoma, deep learning models—in particular, convolutional neural networks (CNNs)—analyze ultrasound, computed tomography (CT), and magnetic resonance imaging (MRI). By automatically extracting quantitative information, AI-assisted imaging lowers observer variability and enhances diagnostic consistency. By transforming medical images into high-dimensional quantitative data for disease categorization and prognosis, radiomics improves image analysis even further. In the management of hepatitis B, these AI-driven methods enhance traditional imaging by facilitating early diagnosis, better risk assessment, and prompt therapeutic intervention [13,16].

3.2 AI FOR EVALUATION OF LIVER FIBROSIS

3.2.1 Elastography Ultrasound

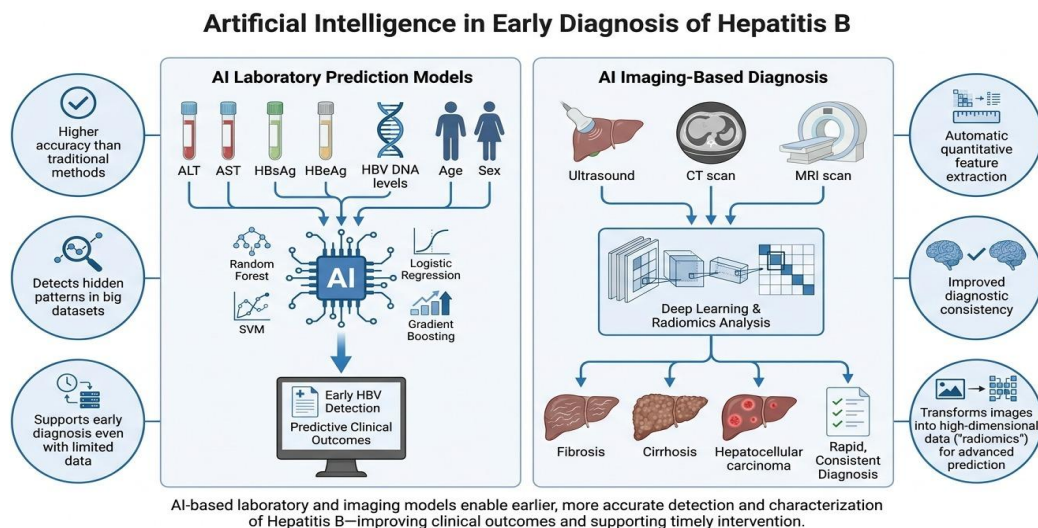


Figure 4: Artificial Intelligence in hepatitis B: Laboratory and Imaging-Based Approaches for Early Diagnosis

Because liver fibrosis stage affects prognosis, treatment eligibility, and disease severity, assessment of hepatic fibrosis is an essential part of managing chronic hepatitis B. The automated interpretation of liver stiffness

measures and the classification of fibrosis have been improved using AI-based methods combined with ultrasound elastography. When compared to individual measurements, machine learning methods can increase the accuracy of fibrosis prediction by combining elastography characteristics with clinical and laboratory factors. These models offer a non-invasive substitute that could lessen reliance on liver biopsies ^[15].

3.2.2 Models Based on CT

By extracting quantitative imaging features, AI models based on computed tomography (CT) have shown promise in assessing cirrhosis and liver fibrosis associated with HBV. CT images can be analysed by deep learning algorithms to find minute structural alterations linked to the advancement of fibrosis. When paired with clinical biomarkers and laboratory results, these methods facilitate automated evaluation of liver morphology and enhance the prediction of advanced fibrosis ^[17].

3.2.3 Models Based on MRI

Artificial intelligence models based on magnetic resonance imaging (MRI) offer a thorough assessment of liver tissue properties and have demonstrated potential in the stage of fibrosis. To distinguish between distinct stages of fibrosis, deep learning and radiomics algorithms analyse MRI-derived characteristics, such as texture patterns and tissue alterations. When compared to traditional visual interpretation, AI-assisted MRI analysis improves repeatability and may aid in the early detection of liver disease risk ^[18].

3.2.4 Deep Learning and Radiomics

Advanced AI techniques that transform medical images into quantitative information for automated disease evaluation include radiomics and deep learning. Models based on radiomics in hepatitis B Examine CT, MRI, and ultrasound pictures to find imaging biomarkers linked to cirrhosis, hepatocellular carcinoma risk, and the degree of fibrosis. Without the need for human feature selection, convolutional neural networks and other deep learning architectures can automatically extract intricate image patterns. These models show excellent diagnostic performance and could be used in conjunction with traditional fibrosis assessment techniques such serum-based scoring systems, transient elastography, and liver biopsy. However, prior to normal clinical use, consistent imaging techniques and external validation are necessary ^[15,18].

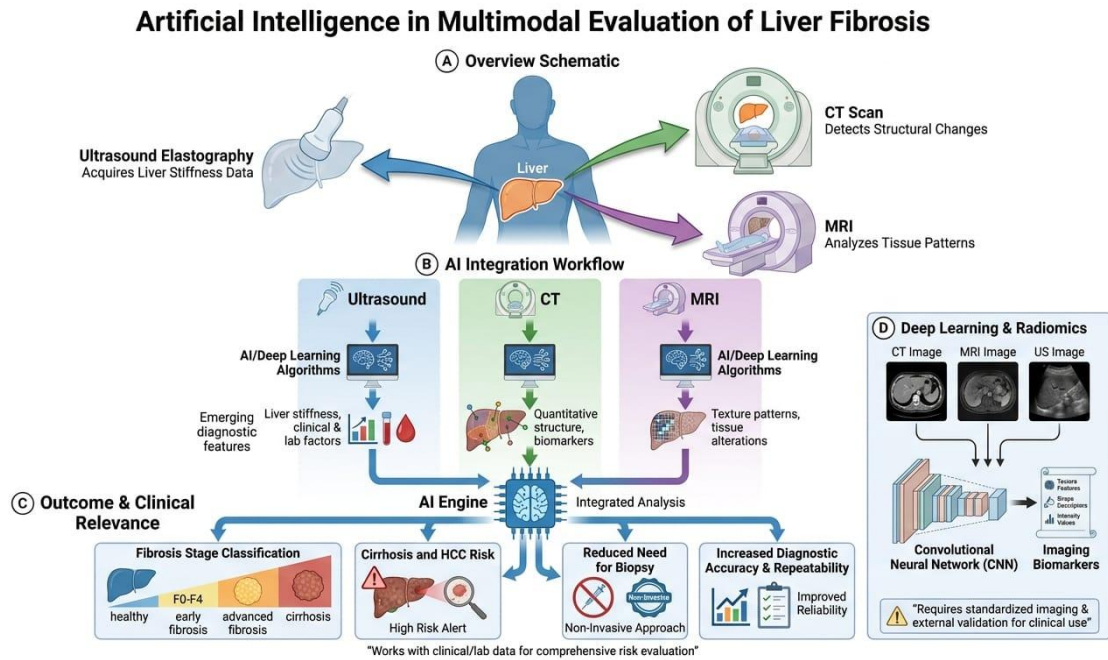


Figure 5: Artificial Intelligence-Based Multimodal Assessment of Liver Fibrosis in Chronic Hepatitis B.

3.3 Risk Stratification using AI

3.3.1 Predicating Disease Progression

Risk stratification is essential for identifying patients with chronic hepatitis B who are at high risk of developing severe liver disease and require continuous monitoring. To forecast the course of an illness, artificial intelligence models examine a variety of clinical factors, such as age, viral load, liver enzymes, serological markers, and imaging results. Machine learning algorithms are able to identify intricate relationships between these variables and offer personalized risk assessments. AI-based models show better prediction accuracy for identifying individuals at risk of cirrhosis, fibrosis development, and liver-related consequences when compared to traditional risk ratings ^[19].

3.3.2 Predicating Cirrhosis

AI-based prediction models have shown promising results in detecting and predicting the development of cirrhosis in individuals with chronic hepatitis B. Machine learning methods such as random forest, support vector machines, and gradient boosting models use laboratory data, clinical characteristics, and imaging markers to classify patients according to their risk of cirrhosis. These techniques allow for timely intervention and improved disease surveillance by identifying high-risk people prior to conventional examinations ^[20].

3.3.3 Identifying High Risk

Hepatocellular carcinoma and hepatic decompensation are two major outcomes that can be prevented by identifying patients with high-risk hepatitis B. AI algorithms can analyse longitudinal clinical data and large-scale electronic health records to identify patterns associated with adverse outcomes. By combining demographic, virological, biochemical, and imaging data, AI-based systems provide targeted follow-up strategies and

customized risk prediction. These techniques could improve clinical judgment and optimize the allocation of medical resources [12,19].

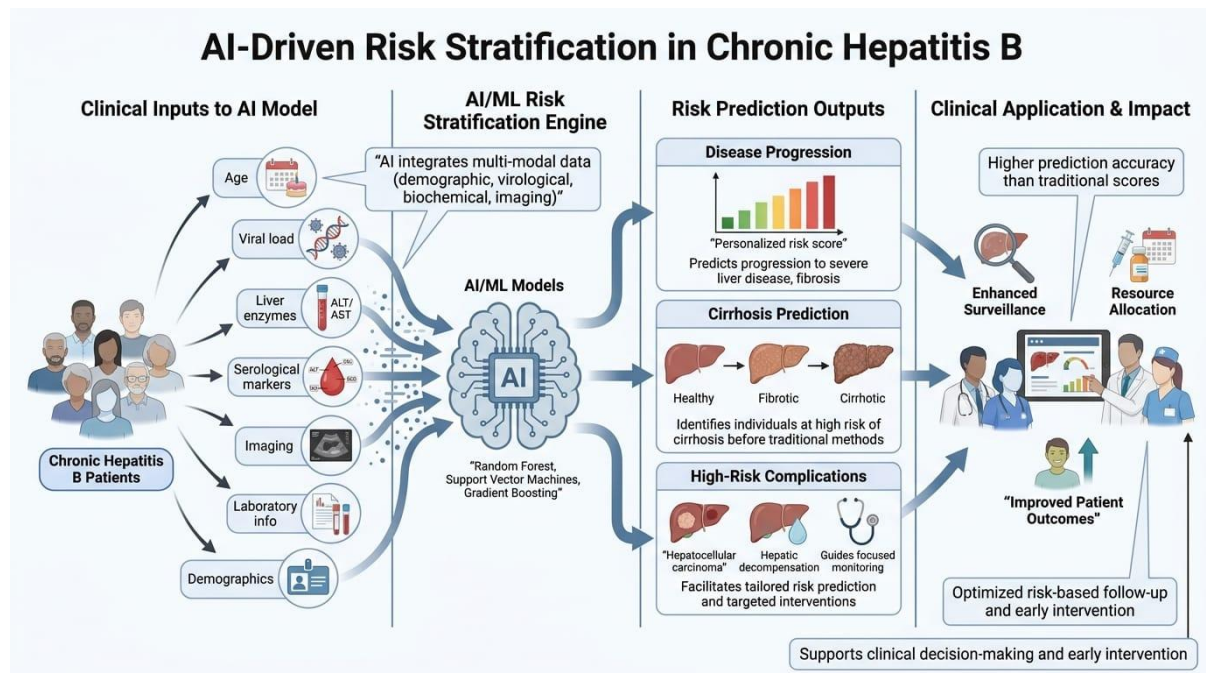


Figure 6: AI-Driven Risk Stratification Framework for Patients with Chronic Hepatitis B.

3.4 Prognosis Prediction with AI

3.4.1 Hepatocellular Carcinoma Prediction

Hepatocellular carcinoma (HCC) is one of the most serious side effects of chronic Hepatitis B, and early detection and effective surveillance depend on a precise evaluation of HCC risk. By incorporating demographic variables, viral markers, laboratory measurements, clinical history, and imaging characteristics, artificial intelligence models have shown promise in predicting the development of HCC. Deep neural networks, random forests, and gradient boosting are examples of machine learning techniques that can recognize intricate patterns linked to malignant transformation. By extracting quantitative imaging data from CT, MRI, and ultrasound scans, deep learning-based radiomics models improve HCC prediction even more. When compared to traditional surveillance methods, these AI techniques may enhance risk assessment and early detection [21].

3.4.2 Mortality Prediction

AI-based prognostic models have also been developed to predict mortality and liver-related outcomes in individuals with chronic Hepatitis B. Machine learning algorithms can assess an individual's mortality risk by analysing longitudinal clinical data, such as liver function tests, virus activity, comorbidities, and imaging results. For patients at higher risk of hepatic failure, sequelae from cirrhosis, and death, these models offer dynamic risk prediction and may facilitate early clinical intervention [8].

3.4.3 Antiviral Treatment Response Prediction

Antiviral medication response prediction is essential for optimal hepatitis B management and improving long-term outcomes. AI models can evaluate baseline clinical data, HBV DNA levels, HBsAg concentrations, biochemical indicators, and patient-specific characteristics to forecast response to nucleotide analogue therapy or functional cure results. In order to identify patients who are more likely to achieve viral suppression or HBsAg decrease, machine learning algorithms have shown promise. These predictive algorithms could assist doctors in developing customized treatment plans and selecting the optimal course of action ^[21,22].

3.5 AI in Clinical Decision Support

3.5.1 Treatment Selection

Artificial intelligence-based clinical decision support systems (CDSS) can assist doctors in selecting personalized treatment regimens for patients with Chronic Hepatitis B. Machine learning algorithms integrate Liver Function Markers, Comorbidities, Treatment History, HBV DNA levels, HBeAg status, and clinical characteristics to predict treatment outcomes. By identifying patients who are most likely to benefit from specific therapeutic approaches, these algorithms may increase personalized care, optimize treatment decisions, and promote the selection of antiviral medications ^[23, 24].

3.5.2 Monitoring Disease Progression

AI-enabled monitoring systems can continuously analyse longitudinal patient data, including lab results, imaging findings, and electronic health records, to spot changes in disease activity. Patients at higher risk of Cirrhosis, Hepatocellular Carcinoma, Fibrosis progression, or therapy failure may be identified by predictive algorithms. AI-based CDSS can facilitate prompt therapeutic interventions and enhance long-term disease surveillance in the management of chronic Hepatitis B by offering early alarms and risk assessments ^[24,25].

3.5.3 Personalized Medicine

The purpose of Personalized Medicine is to design hepatitis B treatment based on each patient's unique characteristics. By combining multidimensional data, such as viral indicators, clinical factors, and therapy responses, AI models enable precision medicine. These methods can assist patient-specific treatment choices, direct follow-up tactics, and forecast antiviral response. Personalized care powered by AI has the potential to enhance results while lowering needless interventions and healthcare costs ^[12,24].

4. COMPARISON OF CONVENTIONAL APPROACHES AND ARTIFICIAL INTELLIGENCE

Table 4: COMPARISON OF CONVENTIONAL APPROACHES AND ARTIFICIAL INTELLIGENCE

S.NO	Aspect	AI based approach	Present standard treatment
1	Diagnosis	AI evaluates clinical, imaging, and laboratory data to increase diagnostic precision and promote hepatitis B early diagnosis ^[9,12] .	Clinical assessment, serological markers (HBsAg, HBeAg), HBV DNA quantification, liver

			function tests, and imaging studies are used to make the diagnosis ^[26,27] .
2	Disease Prediction	AI uses multidimensional clinical data to forecast the likelihood of hepatocellular carcinoma (HCC), cirrhosis, liver fibrosis, and disease progression ^[11,12] .	Clinical scores, laboratory measurements, imaging results, and routine patient follow-up are used to evaluate the course of the disease ^[28,30] .
3	Treatment Selection	By combining patient-specific clinical, laboratory, and virological data, AI suggests individualized therapy plans ^[11,23] .	Physician judgment and evidence-based international clinical practice recommendations are used when choosing a course of treatment ^[26, 31] .
4	Monitoring	AI makes it possible to continuously monitor patients through digital health technology, electronic health records, and prediction algorithms ^[9,11] .	Laboratory tests, imaging evaluations, and planned clinical follow-up are necessary for disease monitoring ^[27,28] .
5	Accuracy	When trained and externally validated on high-quality datasets, AI models achieve great diagnostic and prediction accuracy ^[9,12] .	The quality of investigations, physician expertise, and adherence to clinical guidelines all affect diagnostic accuracy ^[26,30] .
6	Cost	Software development, computing infrastructure, and deployment of AI require large upfront investments ^[9, 23] .	Although conventional therapy is generally accessible, it increases long-term healthcare expenditures by requiring frequent hospital stays, laboratory testing, and imaging ^[39, 41] .
7	Limitations	Before being routinely used in therapeutic settings, AI needs big standardized datasets, external validation, and methods to lessen algorithmic bias ^[34, 36] .	Conventional management is time-consuming, reliant on the availability of healthcare resources, and susceptible to

			inter-observer variability [40,43].
8	Data Processing	AI supports evidence-based decision-making by quickly analysing vast amounts of structured and unstructured healthcare data [35, 36].	Conventional methods assess a small set of predetermined clinical characteristics, such as imaging and laboratory results [38, 42].
9	Risk Prediction	Precision medicine is made possible by AI's ability to anticipate HCC, disease progression, and treatment-related consequences on an individual basis [35, 37].	Physician evaluation for population-based risk estimation and established clinical grading systems are the foundation of conventional risk prediction [39, 43].
10	Pros	• By analysing complicated clinical, laboratory, and imaging data, AI can lower diagnostic mistakes and assist evidence-based clinical decision-making [44,45]. • Through digital health apps, automated reminders, and remote patient monitoring, AI may increase medication adherence [33,34].	• Conventional management is practical in the majority of healthcare settings because it is less reliant on sophisticated computing technologies or sizable AI training datasets [26,27]. • International guidelines and clinical trials have demonstrated the long-term safety and efficacy of traditional antiviral treatments [28,31]. • In hospitals and healthcare facilities around the world,

		By combining patient-specific demographic, clinical, virological, and imaging data, AI facilitates individualized treatment recommendations [32,34].	conventional hepatitis B treatment is widely accessible and often used [26,28].
11	Cons	- Large, high-quality datasets and thorough external validation are necessary for AI to produce accurate and dependable predictions across a variety of demographics. For external validation are required [32, 33] - Widespread adoption may be hampered by high implementation, infrastructure, software development, and maintenance expenses, especially in environments with restricted resources [33,34].	- Due to their heavy reliance on physician assessment and repeated clinical evaluations, diagnosis, treatment selection, and patient monitoring may take longer [27,31]. - Due to variations in experience, how investigations are interpreted, and how clinical standards are followed, healthcare providers may make different clinical decisions [26,31].

5. CHALLENGES AND FUTURE DIRECTIONS

5.1 AI's Present Limitations

Despite significant advancements, a number of barriers stand in the way of artificial intelligence's widespread application in clinical settings for Hepatitis B Therapy. The absence of standardized, representative, and high-quality datasets needed to create trustworthy AI models is a significant drawback. Numerous studies use retrospective data from a single center, limiting the model's generalizability to diverse groups [9,35]. Variations in laboratory measurements, imbalanced data, and missing clinical information can all lower prediction effectiveness. Furthermore, real-world adoption is hampered by a lack of prospective clinical investigations and a lack of external validation [36]. Additionally, a lot of deep learning models operate as "black boxes," which

diminishes clinician trust and interpretability. Moreover, computing resources, digital health integration, and insufficient healthcare infrastructure continue to be major obstacles, especially in low- and middle-income nations [37].

5.2 Regulatory and Ethical Issues

The use of artificial intelligence in the treatment of hepatitis B presents significant moral, legal, and regulatory issues. Patient privacy and data security are crucial since AI models depend on massive amounts of clinical, imaging, genomic, and electronic health record data [38]. Prediction accuracy and fairness across various populations may be compromised by algorithmic bias brought on by non-representative datasets. To increase dependability and clinician trust, transparent reporting, explainable AI, and ongoing model monitoring are essential [39]. Furthermore, there is ambiguity about long-term performance, accountability, and validation due to changing regulatory frameworks. Strong regulations and standardized governance are necessary for the ethical, responsible, and safe application of AI^[40].

5.3 Clinical Practice Integration

Robust digital infrastructure, compatibility between electronic health record systems, and smooth integration into current clinical processes are necessary for the successful integration of artificial intelligence into hepatitis B management. By making prompt, evidence-based suggestions, AI technologies should serve as decision-support systems that enhance rather than replace clinical competence. To increase AI literacy and enable proper interpretation of model results, healthcare personnel must receive enough training. Additionally, to guarantee safe installation and ongoing model evaluation, interdisciplinary cooperation between physicians, data scientists, engineers, and legislators is required. Before AI systems may be regularly implemented in clinical practice, cost-effectiveness assessments, prospective multicentre validation studies, and standardized reporting guidelines are also necessary. By resolving these implementation issues, healthcare delivery will be improved, clinician confidence will rise, and the clinical advantages of AI for patients with chronic hepatitis B will be maximized [11,42].

5.4 Prospects for Further Research

Future studies should concentrate on creating artificial intelligence models that are reliable, transparent, and broadly applicable using huge multicentre datasets that reflect a variety of patient demographics. Precision medicine in hepatitis B treatment may benefit from the integration of multimodal data, such as clinical records, laboratory measures, imaging, genomes, and wearable device information. By facilitating cooperative model training across institutions while protecting patient privacy, federated learning presents a potential strategy. Explainable AI methods should also be improved in order to boost physician confidence and make regulatory approval easier. To assess the efficacy, safety, and cost-effectiveness of AI-assisted therapies, prospective clinical trials and real-world implementation studies are necessary. Establishing common AI frameworks and expediting the integration of novel technologies into mainstream hepatitis B care will require international cooperation between researchers, physicians, and regulatory bodies [32,33].

6. CONCLUSION

Artificial Intelligence is starting to play a significant role in the treatment of hepatitis B. By analysing clinical, laboratory, imaging, and follow-up data, AI can improve early diagnosis, assess liver fibrosis, predict disease progression, identify patients at high risk, and support treatment decisions. These capabilities may help clinicians provide more accurate and individualized care than conventional methods alone. However, widespread use of AI in hepatitis B still requires high-quality data, external validation, better interpretability, ethical safeguards, and strong clinical integration. Multicentre investigations, explainable models, and practical application should be the main areas of future research. AI has the potential to improve patient outcomes and strengthen hepatitis B treatment with further research.

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