

Artificial Intelligence in the Early Detection and Elimination of Viral Hepatitis: Current Advances, Challenges, and Future Perspectives.

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Doi: <https://doi.org/10.5281/zenodo.22685862>

Received: 31 July 2026

Accepted: 22 August 2026

Abstract

Viral hepatitis remains a formidable global health threat, contributing to approximately 1.3 million deaths annually since 2022. Despite the World Health Organization's (WHO) 2030 elimination targets aiming for a 90% reduction in new infections and a 65% reduction in mortality, current diagnostic and treatment coverage remains critically low. This article explores the transformative role of Artificial Intelligence (AI), including machine learning (ML), deep learning (DL), and natural language processing (NLP), in revolutionizing the management of viral hepatitis. Current advances include the use of convolutional neural networks (CNNs) for non-invasive imaging, NLP for mining electronic health records (EHR) to identify high-risk individuals, and predictive analytics for disease progression and treatment adherence. Furthermore, the integration of computational models with traditional medicine, specifically the use of herbal compounds like *Shyonaka* (*Oroxylum indicum*) in managing chronic hepatitis B, presents a novel frontier in integrative hepatology. Despite these advances, significant challenges persist, including algorithmic bias, data privacy concerns, and regulatory hurdles in clinical translation. This review synthesizes current evidence to provide a roadmap for a multi-tiered, risk-stratified AI framework for the global elimination of viral hepatitis.

Keywords:

Artificial Intelligence, Viral Hepatitis, Early Detection, Machine Learning, Deep Learning, Disease Elimination, Integrative Hepatology.

Introduction

Viral hepatitis, primarily caused by hepatitis A (HAV), B (HBV), C (HCV), D (HDV), and E (HEV) viruses, constitutes the second deadliest communicable disease worldwide after COVID-19. According to the WHO Global Hepatitis Report 2024, an estimated 254 million people live with chronic HBV and 50 million with chronic HCV. Every day, approximately 3,500 people die from these infections, with HBV accounting for 83% of deaths. Chronic hepatitis is often labeled a "silent killer" because most patients remain asymptomatic until the development of advanced liver cirrhosis or hepatocellular carcinoma (HCC).

The current diagnostic landscape is hampered by a profound treatment gap: only 13% of HBV patients and 36% of HCV patients have been diagnosed globally. Standard diagnostic tools, such as liver biopsies, are invasive, prone to

sampling error, and lack scalability for mass screening. Furthermore, while antiviral therapies like tenofovir and pangenotypic sofosbuvir are effective, access in low- and middle-income countries (LMICs) is restricted by high costs and infrastructure deficits.

Artificial Intelligence (AI) provides a paradigm shift in addressing these limitations. By leveraging high-dimensional clinical, genomic, and imaging data, AI-driven models can identify undiagnosed carriers, stage fibrosis non-invasively, and predict complications with accuracy that often surpasses traditional clinical scoring systems. This article evaluates the current state of AI in hepatitis management, from early screening to the identification of novel therapeutic targets.

Current Advances in Early Detection

Machine Learning for Diagnostic Accuracy

Machine learning algorithms have demonstrated significant success in diagnosing viral hepatitis using simple blood test parameters. In a series of studies, the K-Nearest Neighbors (KNN) algorithm achieved an accuracy of 98.1% for predicting HCV status, while Support Vector Machines (SVM) and Random Forest (RF) have shown accuracy rates exceeding 90% for HBV and HCV classification. Advanced ensemble models like XGBoost and AdaBoost have further refined these predictions by identifying key biomarkers such as bilirubin and albumin as primary factors for mortality risk.

Non-Invasive Imaging and Radiomics

The integration of Deep Learning into medical imaging has enabled the automated staging of liver fibrosis and the detection of fatty liver disease without the need for biopsy. Convolutional Neural Networks (CNNs) are now employed to analyze ultrasound B-mode images, achieving an AUC of 0.98 for detecting metabolic dysfunction-associated steatotic liver disease (MASLD).

Furthermore, the U.S. FDA recently qualified the first AI tool, AIM-NASH, which uses cloud-based algorithms to analyze liver biopsy images for signs of inflammation and scarring in metabolic dysfunction-associated steatohepatitis (MASH) trials. Such tools standardize the assessment of liver tissue, reducing inter-observer variability among pathologists. In computed tomography (CT), DL models have achieved an AUC of 0.97 for advanced fibrosis and 0.95 for cirrhosis, identifying architectural changes that are often imperceptible to the human eye.

Natural Language Processing (NLP) and EHR Mining

NLP has proven essential in identifying undiagnosed patients within large healthcare systems. By searching unstructured clinical notes and pathology reports, rule-based NLP algorithms have identified thousands of patients with evidence of hepatic steatosis who lacked formal diagnostic codes. In a Veterans Affairs study, machine learning identified over 500,000 veterans with undiagnosed MASH by analyzing age, obesity, and abnormal liver function tests. NLP also uncovers social determinants of health and risk factors, such as substance misuse or prior incarceration that are often inconsistently documented in structured EHR fields.

AI in Disease Management and Elimination

1. Predicting Progression to HCC

A critical component of hepatitis elimination is the early detection of hepatocellular carcinoma (HCC), which has a low 5-year survival rate of 18%. AI-assisted surveillance strategies integrate demographics, viral load, and metabolic factors to generate personalized risk scores. Models such as HCC-SurvNet analyze digital histopathology images to estimate recurrence risk post-resection, outperforming traditional Tumor-Node-Metastasis (TNM) classification. Recurrent Neural Networks (RNNs) have also demonstrated a superior ability to predict HCC development in patients with HCV-related cirrhosis by capturing long-term longitudinal data.

2. Treatment Adherence and Drug Discovery

AI-powered platforms like AiCure use facial recognition on smartphones to provide synchronized confirmation of medication ingestion, offering timely reminders to patients and reducing the risk of viral resistance. In drug discovery, AI accelerates the identification of antiviral medicines and vaccines through high-throughput screening. Techniques like AlphaFold predict protein folding with high precision, which is vital for targeting hepatitis-specific viral proteins.

3. Integrative Hepatology: Herbal Bioactive's

A novel area of research involves the use of AI and network pharmacology to validate the efficacy of herbal compounds in liver disease. *Shyonaka (Oroxylum indicum)*, a plant used in Ayurvedic medicine, contains flavonoids such as baicalein, baicalin, and chrysin that have shown compelling anti-HBV activity.

Baicalein inhibits HBV trafficking via the CDC88A-AKT-mTOR pathway and induces autophagy in infected hepatocytes.

Chrysin has been shown to reduce HBsAg secretion by up to 45% with a binding affinity superior to lamivudine.

AI frameworks like AIM-PBC and predictive analytics are being developed to identify patient subgroups who may benefit from these phytochemical interventions as adjuncts to standard antiviral therapy.

Discussion: Challenges and Barriers

Algorithmic Bias and Inequality

A primary concern in AI implementation is the digital divide. Most AI models are trained on datasets from high-income countries, which may not generalize to diverse populations in Africa or Asia where HBV burden is highest. For instance, a model developed on 3T MRI equipment may be unsuitable for LMICs where scanners operate at $\leq 1.5T$. Ensuring fairness and equity requires diverse training sets and bias audits to prevent underdiagnosis in underserved communities.

The "Black Box" Problem

Deep learning systems often function as "black boxes," providing accurate predictions without explainable reasoning. This opacity hinders clinical trust. The emergence of Explainable AI (XAI), using methods like SHAP (Shapley Additive Explanations), aims to provide transparency by highlighting the specific clinical features (e.g., platelet count, age) that drive a model's decision.

Regulatory and Structural Barriers.

Moving AI from academic prototypes to clinical practice the Valley of Death is hindered by the need for redesigned workflows, doctor training, and data standardization. Regulatory frameworks for Software as a Medical Device (SaMD) are still evolving to handle algorithms that continuously learn and change over time.

Future Perspectives

The future of viral hepatitis elimination lies in a multi-tiered AI infrastructure.

1. Primary Care: AI should assist grassroots workers in risk stratification and patient education.
2. Municipal Level: "Trusted data spaces" must be established to host AI systems while ensuring patient privacy and data security.
3. Global Level: An international platform should aggregate compatible AI models to enhance generalizability across populations.

Research must transition toward multimodal data fusion, integrating clinical notes, advanced imaging, and molecular comics to provide a truly holistic view of patient health.

Conclusion

AI represents a breakthrough opportunity in the global fight to eliminate viral hepatitis. By improving early detection rates through non-invasive imaging and EHR mining, optimizing treatment adherence, and facilitating the discovery of new therapeutic agents including the scientific validation of herbal bioactives AI can bridge the massive treatment gaps identified by the WHO. However, its success depends on overcoming ethical minefields related to bias and privacy and ensuring that these powerful tools are accessible in the resource-constrained environments that bear the highest burden of disease. If implemented through an equitable, explainable, and multi-tiered framework, AI can catalyze the 2030 goal of a hepatitis-free world.

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