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Artificial Intelligence in Metabolic Dysfunction-Associated Steatotic Liver Disease (MASLD): Machine learning for Non-invasive diagnosis and risk stratification

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Abstract

Metabolic Dysfunction-Associated Steatotic Liver Disease (MASLD), formerly known as non-alcoholic fatty liver disease (NAFLD), represents a growing global health burden, contributing significantly to liver-related morbidity and mortality. Early detection and timely intervention are essential to prevent disease progression. Conventional diagnostic methods, which rely on specialized imaging and invasive liver biopsies, underscore the need for non-invasive, cost-effective alternatives. Artificial intelligence (AI)—particularly machine learning (ML) and deep learning (DL)—has emerged as a transformative tool in MASLD diagnostics, offering improved accuracy in risk prediction, imaging interpretation, and disease stratification. This review synthesizes recent advancements in AI-based MASLD diagnostics, highlighting key models, performance metrics, and clinical applications, while addressing ongoing challenges such as data standardization, interpretability, and clinical validation.

INTRODUCTION

Metabolic Dysfunction-Associated Steatotic Liver Disease (MASLD), formerly known as non-alcoholic fatty liver disease (NAFLD), is the most common chronic liver disorder worldwide, affecting approximately 30% of the general adult population and up to 70% of individuals with obesity or type 2 diabetes mellitus (T2DM)[1]. MASLD encompasses

a disease spectrum ranging from simple steatosis to metabolic steatohepatitis (MASH), fibrosis, and cirrhosis, and is associated with increasing morbidity and healthcare costs[2]. Early diagnosis and accurate risk stratification are critical to prevent disease progression; however, current diagnostic approaches—such as MRI-proton density fat fraction (MRI-PDFF) and liver biopsy—are costly, invasive, or inaccessible in many resource-limited settings. Therefore, the development of innovative, non-invasive strategies for disease detection, risk assessment, and management is urgently needed[3].

Artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), has emerged as a promising solution, offering non-invasive, scalable, and accurate tools for the diagnosis, staging, and prognostication of MASLD. AI algorithms can integrate clinical data (*e.g.*, electronic health records), biomarkers, and imaging modalities (*e.g.*, ultrasound, MRI) to outperform traditional risk scores such as the Fibrosis-4 (FIB-4) index[3]. This mini-review provides a concise yet comprehensive overview of current AI applications in MASLD diagnosis. It also discusses key challenges and limitations in translating AI into clinical practice, including issues related to data privacy, model interpretability, and the need for robust prospective validation. The aim is to inform clinicians, researchers, and policymakers on the practical implications of integrating AI technologies into MASLD management.

AI in MASLD Diagnosis: Machine Learning and Deep Learning Approaches

Several studies have investigated predictive scoring systems and risk factors for MASLD; however, their findings remain inconsistent and controversial[4,5]. ML offers a promising alternative for identifying optimal predictive models[6], as it enables the algorithms construction that learn from data without being explicitly programmed. Applications of ML in gastroenterology field are steadily expanding[7].

ML algorithms analyze anthropometric, demographic, and biochemical data to predict MASLD risk, and numerous studies have demonstrated their effectiveness through various modeling approaches. Yu *et al.*[3] developed an explainable random forest (RF) model incorporating 10 clinical features, including liver enzymes, BMI, and

metabolic markers. The model achieved excellent performance, with an area under the curve (AUC) of 0.928 in internal validation and 0.918 in external cohorts. Among six evaluated ML models, the RF algorithm demonstrated the highest discriminative ability, making it the preferred choice. The final model showed excellent calibration and discrimination, using only routinely collected clinical data.

Another ML approach using Support Vector Machines (SVM) was employed to assess liver fibrosis without relying on elastography or platelet counts, achieving AUCs of 0.886 for ≥ F2 fibrosis, 0.882 for ≥ F3, and 0.916 for cirrhosis detection[8]. Comparative studies by Ahn *et al*. and Spann *et al*.[6,7] have shown that ML models often outperform conventional risk scores (*e.g*., FIB-4, APRI) by integrating a broader range of clinical variables.

DL, a subset of AI, is particularly valuable for imaging analysis. Convolutional neural networks (CNNs), a prominent DL architecture, have enhanced the diagnostic accuracy of imaging based MASLD assessment. For instance, CNNs employing transfer learning applied to ultrasound images have achieved an AUC of 0.91 for detecting hepatic steatosis (defined as PDFF ≥ 5%)[9]. Additionally, CT and MRI have been utilized for DL-based analysis. Yasaka *et al*. (2018) demonstrated moderate accuracy in fibrosis staging using a CT-based DL model, although further refinement is needed before widespread clinical application[10].

Integration of AI with Non-Invasive Diagnostic Tools

AI models in MASLD utilize a wide range of data inputs, including clinical parameters (*e.g*., body mass index, diabetes status), laboratory results (*e.g*., liver enzymes, lipid profiles), imaging features (ultrasound, CT, MRI), and histology-confirmed outcomes. The integration of these multimodal data sources enhances predictive accuracy; however, variability in data acquisition remains a significant challenge (Table 1).

AI algorithms that incorporate elastography data have shown improved performance in fibrosis detection by analyzing liver stiffness measurements[11]. Multimodal data integration—combining demographic, clinical, anthropometric, and biochemical

variables—enables more accurate population-level risk prediction[2]. AI plays a crucial role in fusing clinical, imaging, and laboratory data to enhance diagnostic precision and improve overall performance of non-invasive assessments[6].

Data Acquisition Heterogeneity

While advanced healthcare centers often benefit from automated extraction of data from electronic health records (EHRs) and picture archiving and communication systems (PACS)—including digital imaging and communications in medicine (DICOM) files and laboratory application programming interfaces (APIs)[2,11]—manual data entry is still required for non-digitized sources such as histopathology reports and calculated clinical scores (*e.g.*, APRI, FIB-4)[8,10]. The adoption of standardized data pipelines, such as Fast Healthcare Interoperability Resources (FHIR) for EHRs and AI-ready DICOM annotations, is essential for achieving scalability and real-world integration of AI applications[9].

AI for Risk Stratification and Disease Prediction

ML models have demonstrated the ability to predict MASLD progression using longitudinal data. For example, fibrosis prediction using Support Vector Machine (SVM) and Random Forest (RF) algorithms allows for patient stratification by fibrosis stage, facilitating personalized disease management[8].

Model training and validation are often enhanced through transfer learning techniques. Pretrained convolutional neural networks (CNNs), such as ResNet and VGG, are fine-tuned on liver-specific imaging datasets to improve diagnostic accuracy and reduce computational costs[9].

Integration of AI models into clinical workflows has followed several strategies. In rule-based systems, ML outputs—such as fibrosis probability scores—are mapped to established clinical fibrosis categories (F0–F4). Hybrid AI–clinical models combine algorithmic predictions with clinician input, such as incorporating a radiologist's elastography interpretation for platelet-independent fibrosis staging[8]. Furthermore,

AI-supported real-time decision tools are emerging. For instance, point-of-care ultrasound (POCUS) paired with AI can instantly grade hepatic steatosis[9], while automated laboratory data analysis can flag high-risk patients for further assessment[2].

Finally, AI systems increasingly incorporate metabolic risk factors—including insulin resistance, lipid profiles, and genetic markers—to provide a holistic assessment of MASLD risk and progression[12].

Clinical Implementation Feasibility

While AI tools for MASLD show diagnostic promise, real-world adoption depends on overcoming infrastructural and regulatory barriers. EHR-integrated models (*e.g.*, automated FIB-4 calculators) are most feasible, whereas imaging AI requires PACS interoperability and radiologist oversight. Prioritizing use cases with clear region of interest ROI (*e.g.*, fibrosis triage) and investing in clinician-AI collaboration frameworks will accelerate implementation. Prospective trials validating cost-effectiveness (*e.g.*, reduced biopsy rates) are critical for reimbursement and scaling.

Challenges and limitations

Despite advancements and AI promise in MASLD diagnosis, key challenges persist, as technically, data heterogeneity and computational demands limit scalability, while ethical concerns such as algorithmic bias and patient privacy require rigorous governance. Regulatory pathways remain nascent, with few AI tools achieving FDA clearance. Addressing these challenges necessitates collaborative efforts among developers, clinicians, and policymakers to ensure equitable, effective AI implementation. Variability in datasets limits model generalizability[6]. Challenges include ensuring model interpretability (via SHAP) and compliance with regulatory standards for real-world deployment[3]. For validation, most studies are retrospective, so prospective multicenter real-world trials are necessary[7].

Future Directions

The path to AI adoption in MASLD hinges on rigorous validation, regulatory compliance, and seamless clinical integration. Prospective trials to compare AI-driven diagnosis (*e.g.*, CNN-based US analysis) against liver biopsy in a multicenter cohort must be adopted as a benchmark for AI against gold standards. While regulatory bodies should prioritize transparent, generalizable models.

Global harmonization and collaborative efforts—align FDA (U.S.), EMA (EU), and PMDA (Japan) guidelines to streamline approvals as by IMDRF's AI Working Group, and integration into clinical guidelines—through consensus statements to endorse AI tools for specific use cases, as example, first-line steatosis screening in T2DM patients, or flag high-risk patients (*e.g.*, F2 fibrosis) for hepatology referral. Meanwhile, mobile AI solutions can bridge resource gaps, ensuring equitable access. A phased rollout **(Figure 1)** from pilot studies to global scaling will maximize impact while mitigating risks.

CONCLUSION

AI holds transformative potential in MASLD diagnosis, offering high accuracy, cost efficiency, and non-invasive alternatives to liver biopsy. ML and DL models excel in risk prediction, imaging analysis, and fibrosis staging, yet require further validation and standardization. Future research should prioritize explain-ability, multicenter collaboration, and integration into clinical workflows to optimize patient outcomes. Continued advancements in AI-driven hepatology will pave the way for more precise and personalized MASLD management.

Most studies adopted a hybrid approach, integrating laboratory, imaging, and (when available) histological data to optimize model performance. However, heterogeneity in data sources underscores the need for standardized multimodal datasets in future research.

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