Intelligent Computational Frameworks for Early Detection and Diagnosis of Non-Alcoholic Fatty Liver Disease: A Comprehensive Survey

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***Abstract*—Non-alcoholic fatty liver disease (NAFLD) has become the most widespread chronic liver disorder worldwide, a trend driven largely by rising rates of obesity, metabolic syndrome and diabetes. Spotting the disease early and accurately is central to managing it in clinical practice, yet traditional tools such as liver biopsy and routine biochemical testing are invasive, costly and prone to variation between observers. This paper surveys data-driven strategies for NAFLD diagnosis that are built on machine learning (ML), deep learning (DL) and artificial intelligence (AI). It describes the clinical, laboratory and multimodal data on which these strategies depend, and it examines algorithms such as random forests, artificial neural networks, explainable AI and hybrid designs, noting what each does well and where it falls short. Newer graph-based learning approaches, which capture relationships between patients and trace disease progression, are discussed together with their drawbacks. Finally, the surveyed models are compared using standard evaluation measures, namely accuracy, sensitivity, specificity, F1-score and the area under the curve (AUC).**

***Index Terms*—Non-alcoholic fatty liver disease; laboratory data; random forest; explainable AI; graph-based learning; disease progression**

I. INTRODUCTION

Non-alcoholic fatty liver disease (NAFLD) is the most frequent cause of chronic liver illness across the globe. Liver biopsy is still regarded as the reference standard for grading the disease, but because NAFLD frequently produces no symptoms, many patients are only identified after the liver has already been harmed. A timely and reliable diagnostic approach is therefore needed to bring down the associated death rate. Biopsy, imaging and blood-based biochemical tests each come with their own shortcomings, and ML and AI have consequently emerged as strong alternatives that make use of large volumes of healthcare data.

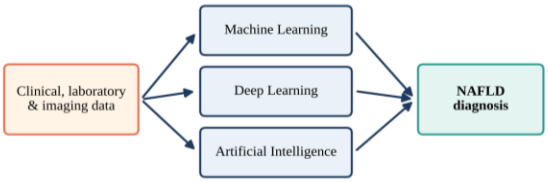


Figure 1. Families of techniques applied to NAFLD diagnosis.

Figure 1 outlines the families of techniques applied to NAFLD diagnosis. Such systems automate the identification of liver disease at different stages by combining varied data sources, including clinical records, laboratory findings and medical images, in order to uncover patterns that are not visible to the human eye. ML, DL and AI algorithms have delivered promising results when classifying patients and estimating their NAFLD risk, and they have reached high diagnostic accuracy. Together, these methods make earlier detection and personalised treatment planning feasible.

This article presents a structured survey of the techniques used to diagnose NAFLD in healthcare settings. It looks at classification-based diagnostic methods and weighs their strengths against their limitations, and it closes by outlining future work and stressing the need for richer healthcare data.

The main contributions are as follows:

- To describe the classification techniques that are applied to accurate NAFLD diagnosis in healthcare.
- To compare existing ML, DL and AI techniques with respect to diagnostic performance.

- To review the stages of the diagnostic workflow (pre-processing, feature selection and classification) as realised with ML, DL and AI.
- To identify future research directions for NAFLD diagnosis using medical data records.

The remainder of the paper is organised as follows. Section 2 reviews related work on disease diagnosis in healthcare. Section 3 explains the NAFLD diagnostic methods in detail. Section 4 reports the evaluation measures and the results obtained by the surveyed models. Section 5 discusses open challenges and future research directions, and Section 6 concludes the survey.

II. LITERATURE REVIEW

Detecting NAFLD early and correctly is essential for halting disease progression and improving patient outcomes, and a number of classification methods have been proposed for the purpose. One graph-based framework [1] builds a patient similarity network and applies a two-layer Graph Attention Network (GAT) to learn attention weights that express how strongly patients are related; the error rate of this approach, however, was left unexamined. Another model [2] estimated NAFLD risk with random survival forests (RSF). An explainable AI (XAI) framework named LivXAI-Net [3] was combined with Internet of Things (IoT) biosensors and tested in a real-time setting using historical data.

Neural approaches are also well represented. An artificial neural network (ANN) [4] estimated NAFLD risk among adults in the United States, while a deep learning model [5] forecast the onset of hepatocellular carcinoma in NAFLD patients. The molecular problems underlying brain dysfunction caused by NAFLD were examined through the liver-intestine-brain axis, together with possible interventions [6]. A further ANN [7] relied on biochemical and genotypic parameters for diagnosis, and a broader review [8] highlighted the transformative potential of deep learning for improving diagnostic accuracy with clinical data. A temporal convolutional network [9] processed time-series thermography data to detect NAFLD.

Other work has concentrated on biomarkers and non-invasive sensing. Lipid-related insulin resistance (IR) indices [10] were used in patients with NAFLD and metabolic abnormalities (MA) to raise diagnostic efficiency. A stacked multimodal ML model [11] combined genetic and clinical data to identify NAFLD early and stratify prognosis, and an on-skin impedance sensor paired with attention-based deep learning [12] enabled non-invasive detection of early-stage fatty liver disease. A Double Graph Attention Network (DGAN) [13] was applied to predict NAFLD in patients with diabetes mellitus, whereas RF, LASSO and SVM-RFE [14] were used to select diagnostic biomarkers among regulatory factors, with ROC curves used for assessment. Tree-based models fed with electrocardiogram (ECG) features [15] detected liver disease with a high degree of interpretability.

Bioinformatics studies have related diagnostic biomarkers of NAFLD to the immune microenvironment [16], and weighted gene co-expression network analysis (WGCNA) [17] was used to study NAFLD-related genes in inflammation-linked pathways. Because the diagnosis of non-alcoholic steatohepatitis (NASH) is central to managing NAFLD patients, a machine learning model [18] was designed to distinguish NASH among them. Clinical characteristics were validated against patient data in light of society guidelines and their implications for practice [19], and a screening model [20] merged metabolic and non-metabolic indicators for diverse groups undergoing routine health examinations.

The progression of NAFLD through its various stages has been analysed with deep learning [21], where the expression patterns observed along the disease course determined the predictive power of candidate genes in an independent cohort. Age-related features of NAFLD patients were described in [22]. ML algorithms [23] pinpointed key risk factors with clinical applicability, and since early diagnosis lowers both morbidity and mortality, another ML model [24] merged risk factors for prediction. A time-series deep learning model trained on longitudinal health-check records [25] forecast NAFLD, and extreme gradient boosting (XGB) [26] was used alongside a reference prediction model. Mortality drivers in metabolic dysfunction-associated fatty liver disease (MAFLD) were identified with ML models [27], and an AI-based framework [28] forecast fatal outcomes in the same population. Finally, a deep learning system (DLS) [29] extracted diagnostic features from ultrasound to improve explainability and clinical usefulness, and an ML-based approach [30] predicted liver disease while ranking the clinical variables involved.

III. METHODOLOGY

NAFLD is a leading chronic liver condition that is reported to affect roughly a quarter of the world's population, with an estimated 3.6 million new cases appearing each year. It is closely tied to obesity and type 2 diabetes mellitus (T2DM) and is characterised by excess fat accumulating in the livers of people who drink little or no alcohol. The disease covers a range of abnormalities, from simple steatosis (NAFL) to the more severe NASH, fibrosis, cirrhosis and liver cancer, and it is linked to a higher rate of liver-related complications and death. Because of its strong association with metabolic disorders, NAFLD is now regarded as a global health concern. Diagnosing it early and accurately is therefore vital. Biopsy remains the gold standard, but it is invasive, expensive and carries a risk of complications. Progress in AI and ML has strengthened the diagnostic process: data-driven techniques exploit clinical and physiological data to support early detection, risk stratification and assessment of disease severity.

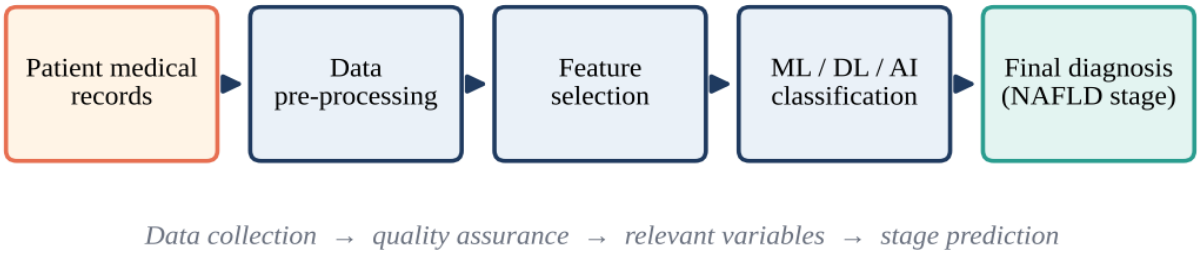


Figure 2. Architecture of the NAFLD diagnostic workflow.

Figure 2 shows the general architecture. Healthcare data are first collected and then pre-processed to ensure quality and consistency. A feature selection step keeps only the variables that are relevant in the input data, and ML, DL or AI models then classify the sample into the corresponding NAFLD stage.

3.1 Machine Learning-based NAFLD Diagnosis

Biopsy is the customary method for staging NAFLD, yet it carries risks such as bleeding, infection and sampling error. Given its cost and unsuitability for routine follow-up, reliable non-invasive diagnostic tools are strongly needed. Machine learning has become a powerful means of diagnosing NAFLD early and accurately by analysing complex healthcare data such as clinical records, laboratory results and imaging features, revealing hidden relationships that can support clinical decisions.

In the graph-based framework [1], each patient is a node in a similarity network. Edges are created with k-nearest neighbours (KNN) over clinical and biochemical features, and missing values are imputed so that plausible variability is preserved. Figure 3 depicts the structure of such a network.

As Figure 3 shows, the network consists of nodes joined by edges that link similar patients. A two-layer GAT assigns edge-specific attention weights to quantify the informative relationships between patients.

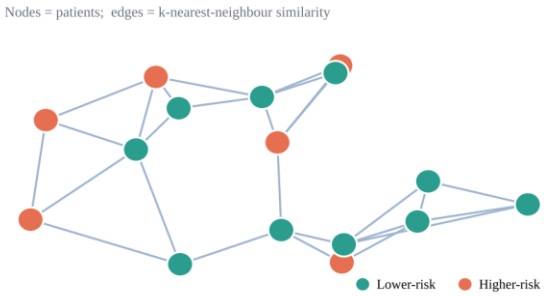


Figure 3. Structure of a patient similarity graph network.

The framework showed high accuracy and robustness in cross-validation and in adversarial-noise tests, and it covered lipidomic, glycomic, fatty acid and hormone panels. Its attention-based explanations highlight which patient similarities drive each prediction, so attention-driven graph learning supports non-invasive staging, early detection and personalised monitoring across varied clinical settings.

The prediction model in [2] applies random survival forests (RSF) to estimate NAFLD risk with little computation time. Data are divided into training and testing sets by a hold-out strategy, and predictors are chosen from all candidate variables with LASSO

regression on the training set. Both a Cox model and an RSF model are then built, and feature importance is derived through bootstrap resampling. Discrimination and calibration are evaluated with the integrated AUC (iAUC), time-dependent AUC (tAUC), integrated Brier score (iBS) and time-dependent prediction error (PE). The RSF model displayed excellent discrimination and calibration and divided subjects into high- and low-risk groups that differed significantly. Even so, ML-based approaches still struggle with data quality, dependence on features and integration into clinical routines, which hinders real-world deployment.

3.2 Deep Learning-based NAFLD Diagnosis

Deep learning learns complex patterns directly from clinical records and longitudinal data, extracting high-level features without manual effort and thereby enabling accurate, non-invasive and scalable diagnosis. The approach in [5] improved hepatocellular carcinoma risk prediction among NAFLD patients, using a national electronic health record (EHR) database to forecast the occurrence of cancer in a patient cohort.

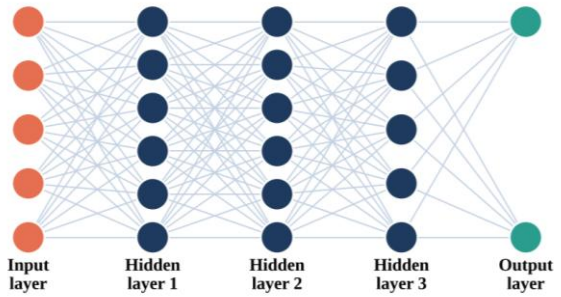


Figure 4. Structure of a deep learning classification network.

Figure 4 shows the structure of a deep learning classifier used for NAFLD diagnosis. The prediction task is treated as a classification problem that must cope with censoring and different lengths of follow-up. A backward masking scheme tackles the problem of delayed diagnosis in EHR analysis by quantifying how much longitudinal history actually affects the prediction. Time-varying covariates further lowered the error rate, and the model also dealt with covariate imbalance during data preparation. The same scheme could be reused to predict other disease risks from structured EHR data. Although deep learning reached high diagnostic accuracy, its dependence on data, limited interpretability, computational cost and difficult clinical integration remains unresolved.

3.3 Artificial Intelligence-based NAFLD Diagnosis

Liver disease is a heavy global burden, with stages that extend to cirrhosis and hepatic failure, and detecting it early is necessary to overcome the limits of conventional diagnostics. AI is used to detect, classify and predict the course of NAFLD by examining complex healthcare data. It brings together ML, DL and data analytics to provide automated, accurate and scalable diagnosis that lessens reliance on invasive procedures such as biopsy.

LivXAI-Net [3] is an explainable AI framework integrated with IoT and evaluated in a simulated real-time setting using a historical dataset. It acquires data continuously from wearable biosensors, such as sweat, platelet and prothrombin sensors, and is trained on the Mayo Clinic primary biliary cirrhosis (PBC) dataset. Random Forest (RF) and XGBoost (XGB) classifiers are used together with SHAP and Permutation Feature Importance (PFI) to make the results interpretable. Figure 5 shows a random forest, whose many decision trees jointly classify medical records.

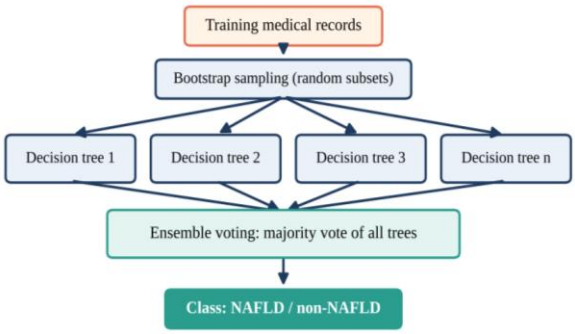


Figure 5. Random forest approach to NAFLD classification.

As Figure 5 indicates, each tree is trained on a bootstrap sample and chooses its best split from randomly selected inputs, and every tree is grown fully without pruning. Each tree casts a vote, and the majority vote determines the final classification. A mobile application called Hepatic Health Tracker delivers real-time risk predictions through a secure data pipeline, with SHAP identifying biomarkers such as albumin, cholesterol and triglycerides. LivXAI-Net cut latency and supported alert delivery through the mobile interface, combining interpretable ML with

live biosensor data for proactive liver disease management.

The ANN model in [4] added dietary retinol intake to predict NAFLD risk in American adults. Risk predictors were identified with logistic regression on the training set, the ANN then estimated risk, and ROC analysis on the training and validation sets confirmed its accuracy. The model showed that plant-derived dietary retinol has a significant effect on NAFLD and can help shape future health plans for the population.

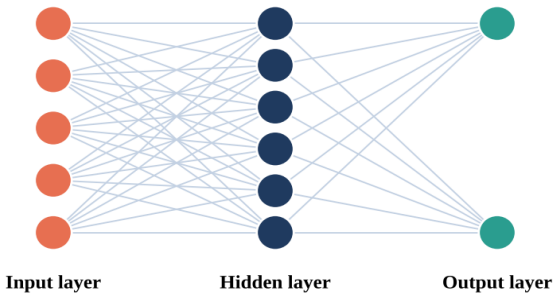


Figure 6. Structure of an artificial neural network.

Figure 6 presents the ANN, which has one input, one hidden and one output layer. Patient records enter at the input layer, are processed in the hidden layer, and the diagnosis is produced at the output layer. Although AI-based diagnosis is highly promising, issues of data quality, interpretability, generalisation and clinical integration must still be settled before it can be applied safely and effectively in practice.

IV. RESULTS AND DISCUSSION

This section compares five existing NAFLD diagnostic techniques: the graph-based framework [1], the RSF prediction model [2], the LivXAI-Net XAI framework with IoT [3], the ANN model [4] and the deep learning method [5]. The methods were evaluated on different datasets, listed in Table 1.

Table 1. Datasets used by the surveyed methods

Method	Dataset	Nature of data
Graph-based framework [1]	ILBS dataset and a public dataset	Clinical and biochemical panels
RSF prediction model [2]	Chinese Liver Disease Association data	Health-checkup cohort
LivXAI-Net [3]	Mayo Clinic PBC dataset	Biosensor and clinical data
ANN model [4]	NHANES (National Health and Nutrition Examination Survey)	Population survey and dietary data
Deep learning method [5]	Cerner Health Facts® database	National EHR records

The performance measures considered are accuracy (A), precision (P), recall (R), F1-score (F), specificity (S), sensitivity (Se), area under the curve (AUC), Matthew's correlation coefficient (MCC), explainability (Exp) and the Youden index. Accuracy, precision, recall, specificity and error rate are derived from the counts of true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN), as defined in Table 2.

Table 2. Performance metrics and their formulas

Metric	Formula / meaning
Accuracy	(TP + TN) / (TP + TN + FP + FN) × 100
Precision	TP / (TP + FP) × 100
Recall / Sensitivity	TP / (TP + FN) × 100
Specificity	TN / (TN + FP) × 100
F1-score	2 × (Precision × Recall) / (Precision + Recall)
MCC	(TP×TN − FP×FN) / √[(TP+FP) (TP+FN) (TN+FP)(TN+FN)]
Youden index	Sensitivity + Specificity − 1

Accuracy is the share of correctly classified patient records among all records. Precision is the proportion of true positives among all predicted positives, while recall (equivalently, sensitivity) is the proportion of actual positives that are correctly identified. Specificity is the proportion of actual negatives that are correctly recognised.

The F1-score balances precision against recall, and AUC is the area under the receiver operating characteristic (ROC) curve, which summarises how

well a classifier separates the classes. The Youden index measures the effectiveness of a medical classifier, and MCC takes all four outcome counts (TP, TN, FP, FN) into account to give a balanced single score.

Table 3. Performance parameters reported by each surveyed method

Method	A	P	R	F	S	Se	AUC	MCC	Exp	Youden
Graph-based framework [1]	✓			✓	✓	✓	✓			
RSF prediction model [2]	✓				✓	✓	✓			
LivXAI-Net [3]	✓	✓	✓	✓	✓	✓	✓	✓	✓	
ANN model [4]	✓				✓	✓	✓			✓
Deep learning method [5]	✓						✓			

Table 3 together with Figures 7 to 9 present the reported AUC, sensitivity, specificity and accuracy of the five methods. The graph-based framework [1] reported an accuracy of 75.2%, sensitivity of 75.8%, specificity of 74.6%, F1-score of 75.2% and AUC of 76.8%.

The RSF model [2] reached an AUC of 85.6%, with sensitivity between 83.7% and 87.4% and specificity between 73% and 78%. LivXAI-Net [3] achieved accuracy, precision, recall and F1-score of 89%, an MCC between 0.698 and 0.782, specificity between 0.93 and 0.99, and an AUC between 92% and 96%.

The ANN model [4] obtained an accuracy of 80.7%, sensitivity of 80.7%, specificity of 78.5%, Youden index of 58.9% and AUC of 87.4%. Finally, the deep learning method [5] recorded an AUC of 90.6% and an accuracy of 95.2%.

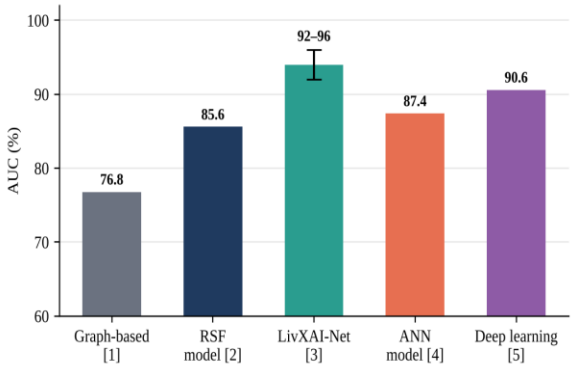


Figure 7. Comparison of AUC. The LivXAI-Net bar shows the midpoint of its reported 92–96% range.

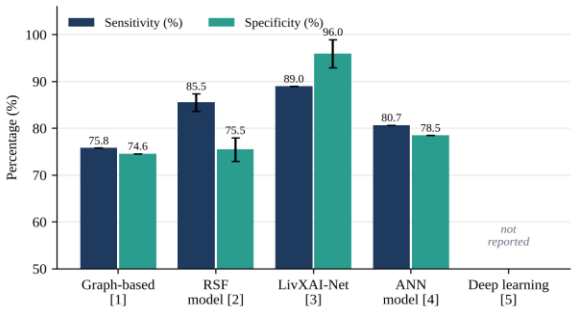


Figure 8. Sensitivity and specificity. Error bars show reported ranges; the mid-range is plotted for [2], and LivXAI-Net sensitivity equals its reported recall of 89%.

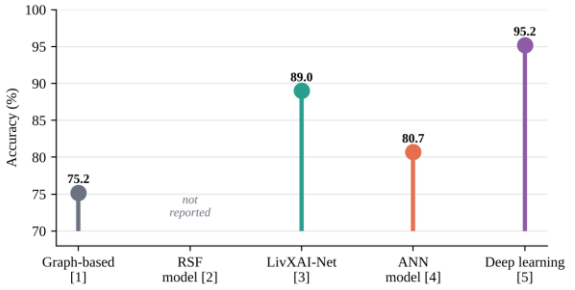


Figure 9. Reported accuracy of the surveyed methods (not reported for [2]).

Table 4. Comparison of the three diagnostic paradigms

Paradigm	Strengths	Open limitations
Machine learning	Reveals hidden patterns in clinical, laboratory and imaging data; supports early, non-invasive decisions.	Data quality, dependence on hand-chosen features, and clinical integration.

Deep learning	Learns high-level features automatically; scalable and accurate on longitudinal records.	Heavy data requirements, limited interpretability, computational cost, clinical integration.
Artificial intelligence	Combines ML, DL and analytics; supports explainable, real-time and wearable-based monitoring.	Data quality, interpretability, generalisation and safe clinical deployment.

Overall, the results indicate that deep learning and AI-based methods delivered stronger diagnostic outcomes than the other techniques: the deep learning method [5] reported the highest accuracy (95.2%), and LivXAI-Net [3] reported the highest AUC range together with a broad set of balanced measures. These figures should nevertheless be read with care, because the methods were trained and tested on different datasets and prediction tasks, and not every study reported the same metrics, so the comparison is indicative rather than strictly like-for-like.

V. CHALLENGES AND FUTURE DIRECTIONS

The surveyed work shows that data-driven models can make NAFLD diagnosis faster, cheaper and less invasive, but several obstacles still stand between published results and everyday clinical use.

The most important ones, together with promising ways forward, are summarised below.

- Data quality and availability. Models depend on large, well-labelled and representative datasets. Future studies should draw on multi-centre cohorts that cover different populations, devices and clinical protocols, with careful handling of missing values and class imbalance.
- Interpretability. Clinicians are reluctant to rely on opaque predictions. Explainable AI tools such as SHAP and attention-based explanations should be built into models from the start so that every prediction can be justified.
- Generalisation and validation. Most studies are validated on a single dataset. External validation on independent cohorts, together with prospective clinical trials, is needed to demonstrate real-world reliability.
- Multimodal and graph-based learning. Combining clinical, laboratory, genetic, imaging and wearable-sensor data, and modelling relationships between patients with graph networks, is a promising route to better staging and progression modelling.
- Clinical integration. Computational cost, privacy, security and workflow fit must be addressed so that tools such as mobile risk trackers and real-time IoT monitoring can be deployed safely in hospitals and primary care.

VI. CONCLUSION

NAFLD is a major global health concern because it is so prevalent and can advance to fibrosis, cirrhosis and liver cancer. Early and accurate diagnosis is essential to prevent complications and improve patient outcomes. This survey shows that conventional diagnostic methods are costly and variable, whereas AI, DL and ML offer more effective and non-invasive alternatives by analysing multimodal clinical, laboratory and imaging information. Deep learning and AI models have shown particularly strong performance, and graph-based models such as Graph Attention Networks uncover relationships between healthcare factors that improve both prediction and interpretability.

Looking ahead, larger and more varied multi-centre datasets, explainable and deep learning-driven diagnostic tools, and closer integration with clinical workflows should further raise the quality of NAFLD diagnosis.

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