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A Review of Artificial Intelligence-Based Approaches for Non-Invasive Liver Disease Diagnosis

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ABSTRACT

Liver disease is a significant clinical problem on a global scale and a leading cause of morbidity and mortality. Early and prompt diagnosis is essential to successful management, but the traditional diagnosis methods tend to require invasive procedures, or they are restricted by the limitations of varying observers. In recent years, the use of artificial intelligence (AI) and computer-aided diagnosis (CAD) systems has acquired significant popularity in the field of hepatology. Machine learning (ML) and deep learning (DL) technologies are actively used in medical imaging data, including ultrasound, CT, and MRI, to assist clinicians in identifying and classifying liver pathologies, i.e., fatty liver disease, cirrhosis, and hepatocellular carcinoma. The review is a synthesis of the recent developments in image processing, feature detection, and classification algorithms of liver disease diagnosis by AI. The most common ML algorithms include Support Vector Machines, random forests, decision trees, naive bayes, and K-nearest neighbors, in many cases using radiomic features derived using imaging data. Although deep learning models, especially convolutional neural networks and transfer learning implementations, are highly sensitive and highly perform in segmentation and classification tasks, traditional ML systems with radiomic features are frequently able to offer robust and efficient solutions to resource-bound environments. Even though these results are promising, there are still a number of challenges such as data heterogeneity, insufficient multi-center validation, and model interpretability. To reliably translate clinical findings into clinical practice and enhance patient outcomes, future research should focus on large-scale validation studies, multimodal data integration, and explainable AI frameworks.

Keywords: Artificial intelligence, Liver Disease Diagnosis, Machine Learning, Deep Learning, Medical Imaging, Computer-Aided Diagnosis, Radiomics, Image Processing

INTRODUCTION

Liver is an important organ and it plays a characteristic role in many physiological functions including metabolism, detoxification, immune regulation, energy storage, blood coagulation etc [1]. In spite of the multifunctionality, liver disease has emerged as one of the most significant global health issues considerably increasing the morbidity and mortality rates. About two million deaths are attributed to liver related disorders like cirrhosis, viral hepatitis and liver cancer annually. Liver disease is estimated to cause 4 per cent of the total deaths all over the world and one out of every twenty five deaths is associated with hepatic dysfunction [2].Although liver disease is one of the major causes of mortality, its actual burden is undervalued. In terms of population, India has a high percentage of the disease burden among the affected populations, with 18.3% of all deaths due to cirrhosis-related illnesses, and China leading with 11% [3].In Europe and America, where the disease is the primary risk, the use of alcohol is the leading factor of liver disease [4]. The total number of people around the globe living with chronic hepatitis B (HBV) is 400 million, and over 170 million people continue to live with persistent hepatitis C (HCV) [2]. An increase in incidence of liver disease with the rise of the Metabolic Dysfunction Associated Steatotic Liver Disease (MASLD) that was previously referred to as Non Alcoholic Fatty Liver Disease (NAFLD) has also been observed. The prevalence of MASLD is a stimulus of liver cirrhosis and hepatocellular carcinoma (HCC) development with a high incidence in the regions with high obesity rates such as India. Estimates of the number of overweight and obese adults are approximately 2 billion and 400 million adults have diabetes, both significant risk factors of MASLD and HCC. Also, in spite of high global burden of hepatitis caused by viruses, drug induced liver injury is now identified as a key cause of acute hepatitis. [3]. Not only is chronic liver disease a clinical issue, but also an economic burden and quality of life determinant. In terms of global and regional DALYs and years of life lost, cirrhosis is always in the top 20 causes of health related disabilities. The common and intricate liver diseases require correct and readily accessible diagnostic procedures to enhance the patient outcome and lower healthcare expenses.

The modern histopathological and imaging systems have transformed the diagnosis of liver diseases and their integration has helped in the improvement of patient care, characterisation of the disease and proper diagnosis. Liver biopsy, which has continued to be an anchor to the diagnosis, is ordered especially in cases where there is a failure in imaging to provide a clarifying outcome. Diagnostic accuracy has also been provided by immunohistochemistry of particular marker associated with liver tumors. However, because of the invasiveness of the biopsy, there has been a massive interest in other less invasive and more scalable methodologies [5].The need to develop less invasive and more scalable techniques has led to advances in imaging and computer analysis. Ultrasound (US) has always served as the front-line imaging technique because it is easy to access, affordable and noninvasive [6]. It remains an important method of diagnosing conditions, such as cirrhosis, fatty liver disease and hepatomegaly. Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) became well-established as a more sensitive technique due to structural analysis as US has low-resolution of smaller abnormalities [7]. The CT images are required in medical personnel when assessing focal liver lesions, staging and planning surgery of the HCC due to its high spatial resolution and ability to produce a detailed cross-sectional image [8]. The use of contrast on CT imaging of growths allows medical personnel to differentiate between benign and malignant growths that enhances diagnostic decisions. The MRIs offer superior soft-tissue contrast that helps the professionals detect different masses in the liver with high efficiency [9]. The level of expertise attained by the observer is very important in interpreting radiological images and hence results in variability of interpretations. Liver imaging has been rapidly evolving due to the ability of radiomics technology to extract quantitative characteristics of any medical image and provide accurate diagnosis of liver diseases such as fibrosis and steatosis. Upon analysis by ML algorithms these extracted features allow imaging to predict more efficiently, offering clinicians useful information about disease progression and responses to treatment. Studies indicate that the radiomic analysis has an accuracy of 95.98% in detecting the following elements found in the liver as far as classification of liver diseases is concerned; ballooning is essential in liver disease diagnosis [10].

The introduction of artificial intelligence (AI) into liver imaging is used to decrease the variability of the observers and increase diagnostic accuracy. The radiomics-extracted imaging characteristics allow AI-based Computer Aided Diagnosis to obtain superior liver pathology classification. ML and DL technologies used in CAD allow making the diagnosis of liver diseases more accurate by providing better workflow management and minimizing human error. Convolutional neural networks (CNNs) were used and have led to tremendous advancements in the segmentation of liver images in both MRI and CT imaging to identify fine abnormalities. Recent research using more intensive convolutional models has built upon these improvements, with the architecture, e.g. DenseNet 121 and ResNet 50, pushing the accuracy of classification even further higher, with DenseNet 121 being particularly impressive with its capability to propagate features and gradients across many layers efficiently [11]. Predictive DL models prove an effective HCC prognosis in patients with steatotic liver disease and provide precise outcomes with a high accuracy of over 81 percent [12]. Conventional ML methods can help these new advances by assessing liver functioning test data and picture pattern identification to predict hepatic issues in order to preventive health early and avoid future health issues. On its part, digital pathology has demonstrated greater diagnostic accuracy after being integrated with ML since the latter-ledclassifiers have comparable evaluation capabilities with pathologists when analysing histopathological slides [13]. The growing popularity of AI-based diagnostic tools suggests that radiomics with CAD technology will gain greater significance in the diagnosis and treatment of liver disorders. The analysis explores the usefulness of ML and DL models in the context of CAD tools in the diagnosis of liver disease by image processing methods. The article unveils the advantages of CAD applications in clinical practice that depend on the possibility to reduce variations in observers and enhance the accuracy of the diagnosis. Relevant literature studies were based on the IEEE Digital Library and PubMed as well as ScienceDirect based on the key words: liver diseases, medical imaging, and computer-aided diagnosis. Figure 1 shows the process of having selected the papers included in this review. Scopus, Google Scholar, and PubMed were used to gather 240 articles by selecting the keywords based on computer-aided diagnosis, machine learning, D, and liver disease. Articles on the use of CAD systems and ML and DL models in diagnosis and prediction of liver disease were evaluated. A total of 97 articles are incorporated in this research after passing the inclusion and exclusion criteria.

The perspectives that this review is expected to address are the following:

1. Detailed study of different image processing methods and features analysis used in the diagnosis of different liver diseases.
2. The state of art liver CAD systems developed on various radiological modalities such as CT, MRI, Ultrasound are described comparatively.
3. The use of CAD in diagnosis and detection of different liver diseases.
4. The thorough comparison of the various ML and DL models in the classification of multiple class liver diseases.

The paper makes novel contributions to the CAD of liver disease. It reviews the current research on the data diversity in CAD models, locating the gaps and ways to enhance the data reliability to increase the performance of diagnostic measures. It further discusses transparency of CAD systems in medical imaging, discussing the issues in clarifying model decisions and its consequences on clinical trust and acceptance.

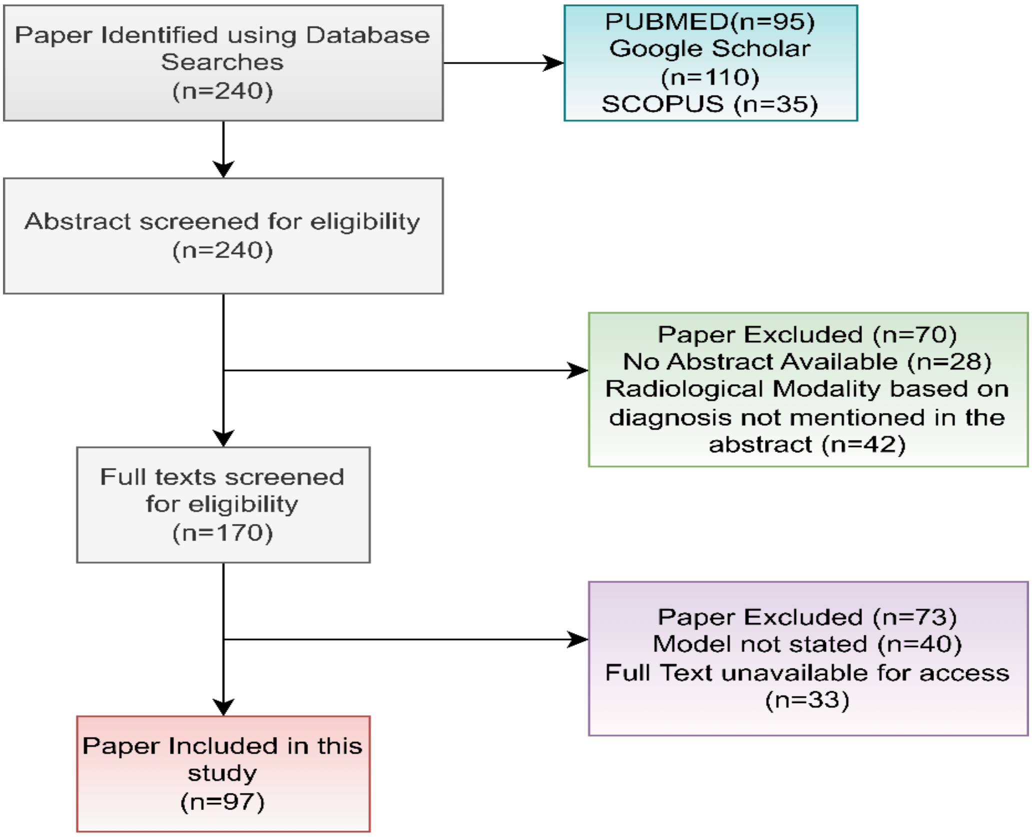


Figure 1. PRISMA flow diagram illustrating the study identification, screening, eligibility, and inclusion process for the review.

Fundamentals of Computer Aided Diagnosis

CADs have become essential areas of research within the past twenty years with a focus on improving the quality of diagnosis and facilitating the treatment process of radiologists and clinicians who work on the medical image analysis. The role of big data and AI, and in particular ML and DL algorithms in the field of healthcare is groundbreaking as it has made the field of healthcare more efficient, proactive, and personalized. CAD has become a fundamental discipline of medical imaging and diagnostic radiology. Although the first computerized medical image analysis had been started in the 1960s, the systematic research activities were the ones that gained momentum in the 1980s. This transition carried a shift in the CAD as a completely automated system towards a supportive tool that will increase the accuracy of the diagnosis made by the radiologist by giving unbiased data-driven information [14].At the end of the 1980s and at the beginning of the 1990s, AI-driven approaches, especially ML and DL methods, started to change the nature of CAD systems, turning them into a second opinion that will aid in the precision of the diagnostic decision made by the radiologist. These systems are usually implemented as a sequence of steps that include image processing, feature extraction and classification steps and tend to rely on artificial neural networks (ANN) to maximize detection and features [15]. The development of DL has continued to speed up in CAD and this has seen a big difference in the accuracy and efficiency of detection. As technologies keep progressing, AI CAD models are transforming radiological imaging, making way to more efficient and accurate diagnostic models. Figure 2 gives a visual overview of the pipeline used in various CAD programs and the standard procedures applied.

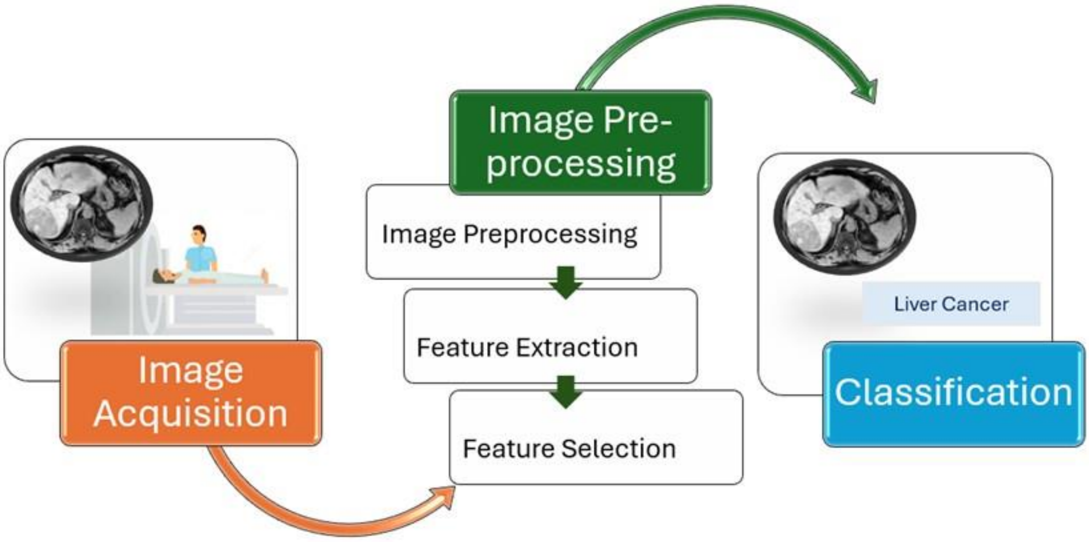


Figure 2: Pipeline architecture of a CAD system, detailing key stages from image acquisition to classification.

Image Acquisition

Medical imaging is a vital instrument in the early diagnosis of liver diseases and how to define their nature and track them to enable planning of their treatment. Both of the diagnostic methods have certain merits and the demerits that determine their reasonable use in the medical practice. The medical imaging techniques such as US, CT and MRI are the necessary ones in the diagnosis of liver diseases due to the varied benefits of sensitivity and specificity and clinical use. This segment explores various imaging procedures applied in the diagnosis of liver pathology and explains their advantages and limitations to the medical practice.

Ultrasound

The US examination of the liver is a critical part of disease diagnosis as it provides non-invasive and effective early detection facets as well as monitoring qualities. The recent advancements in imaging technology have enhanced the diagnosis of liver conditions by multiparametric ultrasound and elastography techniques that have enhanced the detection of simple steatosis and complex vascular diseases. The advancement of the new technology enables the doctor to thoroughly examine the liver anatomy and functions that result in improved clinical judgment. B-mode ultrasound preserves its original status of measuring liver size and measuring echogenicity whereas Doppler ultrasound identifies liver diseases by measuring blood flow [16]. Elastography not only allows the measurement of liver stiffness to quantify it, but also serves as an alternative measure to fibrosis in the monitoring of the progression of chronic liver disease [17,18]. Findings in research indicate that ultrasound is very sensitive in detecting the presence of abnormalities in the liver with particular attention to MASH [16,17]. Ultrasound has been more successful in diagnosis of diffuse liver parenchymal diseases when used with other imaging techniques such as FibroScan [18].

Nevertheless, there are a number of intrinsic ultrasound drawbacks that need to be taken into consideration. Bone and air-filled structures to a great extent block the passage of ultrasound waves, so that it is not possible to view areas that are covered by the ribs, bowel gas, or lungs. Furthermore, the differences in tissue composition within the abdomen cause inhomogeneity in the beam which scatters and bends the beam and consequently ruins the sharpness of the image in practice and diffraction-limited resolution is impractically achieved. Ultrasound also has poor sensitivity in mild steatosis instances and therefore it may require supplementary diagnostic studies to be conducted as a whole [19]. Moreover, its diagnostic reliability is highly subjective, and thus there is inconsistency in the outcomes unlike liver biopsy where the histological confirmation is essential and therefore the use of other diagnostic methods will be essential. The future of ultrasound in assessing liver disease is in the optimization of the ultrasound imaging modalities, the addition of artificial intelligence, and the strategic integration of ultrasound with other modalities to create a more precise and global diagnostic model.

Computed Tomography

CT imaging is a reliable method of detecting and assessing liver pathologies due to the fact that it provides key anatomical and functional data required in clinical decisions. These high-resolution imaging characteristics assist physicians with determining liver tumors at an exact localization and also characterize the tumor beside crucial volumetric measurements to assist in preoperative planning. The CT elucidates the feasibility of the surgery by measuring the total liver volume and tumor burden. The technology assists in producing the best patient outcomes due to the ability to accurately measure the remaining liver tissue that constitutes a considerable determinant of the surgical planning [17]. The CT perfusion imaging methods can be used to assess the parameters of blood flow in order to differentiate between benign and malignant liver lesions based on the measurements of blood flow and blood volume and mean transit time. Quantitative tests are beneficial in not only knowing about the flow of blood through the lesion but they also aid in the monitoring of therapeutic response [21].

The MDCT technology has a higher spatial resolution, and an improved temporal resolution compared to the standard CT scanners that increases its capabilities in detecting small hepatic abnormalities. The system is of great benefit in the treatment of hepatobiliary and pancreatic diseases by the way of planning before treatment and checking after the surgeries [17]. Also, the development of the image processing methods, including the use of anisotropic diffusion filters and morphological operations, has allowed the better identification of malignant tumors, which allows timely detection and intervention [22]. The CT imaging has a lot of advantages to medical diagnosis and there are certain performance limitations. Clinical CT imaging applications are hampered by the use of contrast agents and the limitation of radiation exposure and reduced sensitivity to small lesions.

The concept of CT imaging with contrast enhancement built into CAD models has served to assist the medical staff in identifying the benign and malign a lesion in the liver more efficiently. This development makes the new diagnostic framework automation possible [23]. CT is an important diagnostic tool in liver pathology identification despite the limitations it possesses because its combination with AI-based methods will increase its diagnostic capabilities to improve patient outcomes and clinical practice.

Magnetic Resonance Imaging

MRI is vital in the detection and characterization of liver pathologies since it assists in the separation of focal liver lesions such as HCC and other abnormalities of the liver. Its superior imaging technology, particularly when used with hepatobiliary-specific contrast agents, like gadoxetic acid, not only improves the accuracy of diagnosis but also provides information on liver diseases in detail. Multiparametric MRI combines several MRI techniques to enable the use of images of the tumor structure and blood flow, and cellular characteristics to influence the decision made by healthcare professionals before surgery in relation to HCC patients [24]. The outstanding quality of MRI in distinguishing between lesions in hepatoma is due to the fact that it is capable of distinguishing between atypical hemangiomas and metastatic deposits based on the characteristics of the signals presented as T1-weighted and T2-weighted images. Contrast-enhanced MRI makes patient management more effective because it indicates the patterns of vascularization which is crucial in the process of diagnosis [25]. Hepatobiliary-specific contrast agents that are administered results in the best lesion detectability as studies show that MRI has a high sensitivity and specificity level [26]. Diffusion-weighted imaging and magnetic resonance elastography as the types of innovative methods of MRI are combined to help professionals perform detailed examination of liver lesions based on blood supply and characteristics of tissues. AMRI is an abbreviated form of MRI which has demonstrated potential because it is a promising tool that is better in identifying focal lesions in the liver, as compared to ultrasound use in high-risk groups.

Although MRI is superior to other imaging techniques, it has limitations of cost, availability and motion artifacts, which restricts its prevalence in the clinical setting. The susceptibility to noise, the necessity to replace basic imaging methods with more complex ones to improve interpretability are still the fields of research. More so, MRI-guided interventions are generally more time-consuming than CT-guided procedures, whereas the former usually offer superior precision, which may be a limitation in emergency clinical practice [48]. The development of imaging technology and its availability is crucial to maximize the role of MRI in the diagnosis and treatment of liver disease.

Image Preprocessing

Preprocessing is the essential bridge between raw radiological imaging and model robustness. In CT imaging, strategies for mitigating beam-hardening artifacts and normalizing pixel intensities are standard for reducing inter-scanner variability [27]. In the case of MRI, the bias field correction and noise reduction are critical factors in retaining soft-tissue contrast [27]. Although histogram equalization (HE) and Contrast Limited Adaptive Histogram Equalization (CLAHE) are frequently used to improve contrast they may cause amplification of noise; modern architectures often combine the use of spatial filters with either wavelet transforms or Generative Adversial Networks -based systems to avoid this issue and retain fine anatomical detail [28]. In addition, standardized normalization, and specifically Z-score scaling, is essential to obtain reproducible fibrosis feature identifications across multi-center cohorts.

Feature Extraction

A paradigm shift is evident from manual, handcrafted radiomics toward automated feature extraction. Manual extraction, driven by radiologist-defined Regions of Interest (ROIs), utilizes statistical (first-order), textural (GLCM-based), and morphological (higher-order) descriptors to capture subtle tissue heterogeneity [29]. They are particularly applicable in clinical environments with small samples where DL model is vulnerable to overfitting [16]. On the other hand, automated extraction through CNNs allows hierarchical spatial features to be obtained without human involvement [30]. Although the sensitivity of DL architectures is stronger in the context of segmentation, the latter require large scale, annotated datasets to achieve stable performance [31]. Increasingly, research is taking a hybrid approach, using semantic features of radiomics (shape, location) in conjunction with deep-learned representations, to gain even greater accuracy in classification.

Feature Selection

The final phase of model interpretability and data redundancy minimization depends on feature selection. Radiomic datasets are high-dimensional, and dimensionality reduction methods, including Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA), are customary to simplify model inputs [32]. Sparse PCA has been especially successful in isolating clinically significant variables without compromising classification performance [33]. At the same time, LDA is often used to make the most of the separability between classes, which shows a positive effect on the precision of ML-based classifiers like Random Forests and SVMs. As more recent empirical studies confirm, intelligent feature selection, even in DL-dominated architectures, may still be a limitation that plays a critical role in improving diagnostic robustness when performing diagnosis in a variety of imaging modalities [34].

Feature Extraction

Feature extraction serves as the bridge between raw imaging data and predictive clinical modeling. In liver pathology, researchers distinguish between semantic features (interpretable radiological characteristics such as lesion shape, location, and vascularity) and agnostic features (quantitative measures of tissue heterogeneity) [35]. While semantic analysis remains primarily the domain of expert radiologists, agnostic feature extraction has become the foundation of computational liver diagnostics, enabling the quantification of structural and textural patterns that are often imperceptible to the human eye.

These agnostic features can be traditionally classified as statistical, transform-based, and structural analysis types [35]. Manual or automated extraction methodology is also another critical aspect in CAD design. Handcrafted radiomics Manual feature extraction Manual feature extraction is based on first-order (histogram-based) and higher-order (e.g., GLCM, GLRLM) statistical descriptors. These techniques have better interpretability and are especially useful with small and single-center datasets, where deep learning models are prone to overfitting [36].

Conversely, automated feature extraction leverages DL architectures to capture hierarchical, abstract representations of liver tissue without explicit manual feature engineering. This method is useful in reducing statistical bias that can be introduced by humans and has proven quite successful in applications like HCC detection and fibrosis staging [30]. The automated extraction, however, requires massive and heterogeneous datasets to guarantee the generalizability of the model. The existing evidence indicates that, although the DL-based automated extraction increasingly gains increased popularity due to its high diagnostic accuracy, handcrafted radiomic features continue to play a vital role in clinical practice because of their stability, fewer mathematical demands, and ability to support clinical decision-making. The flow of the radiomic analysis with the application of the two methods is depicted in Figure 3.

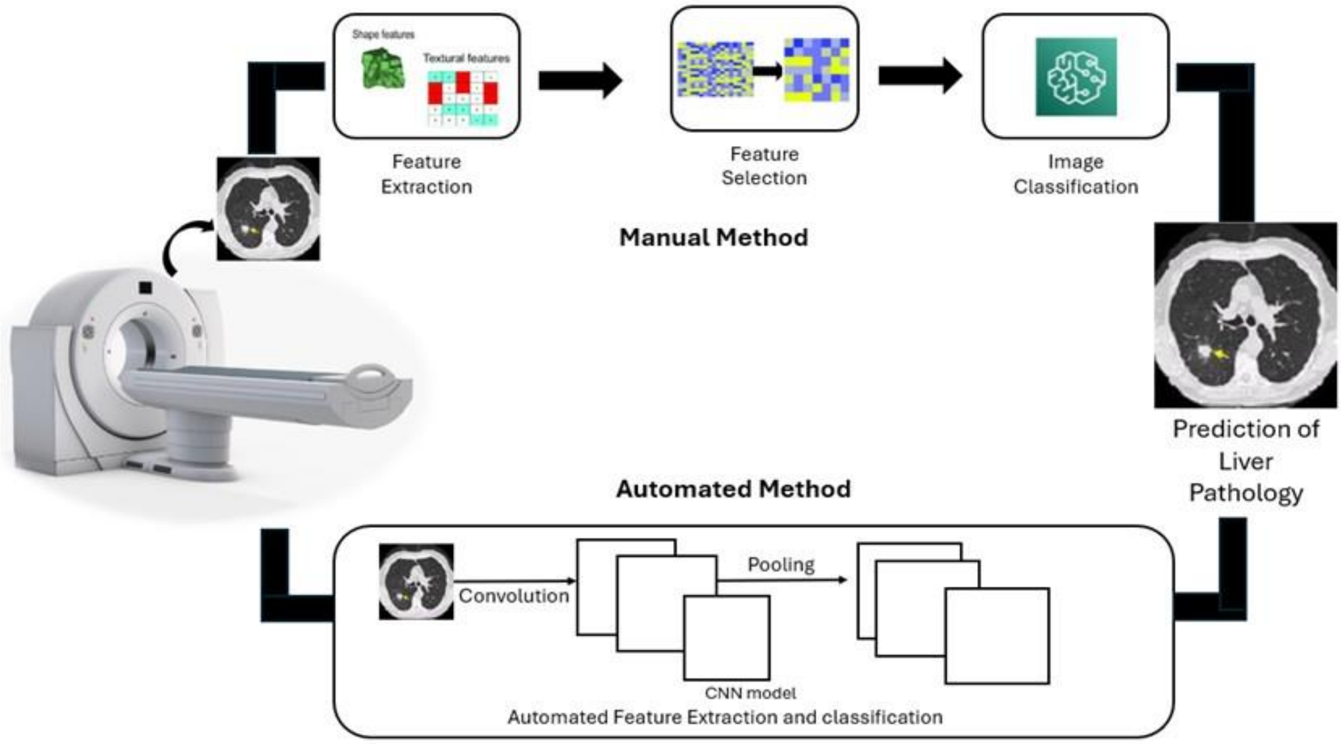


Figure 3: Workflow of radiomics analysis comparing manual and automated feature extraction approaches.

Manual Feature Extraction

Handcrafted radiomics remain highly relevant in liver pathology due to their established diagnostic utility in identifying structural and intensity-based tissue variations. They are typically grouped into three large categories: first-order (statistical), second-order (textural), and transform-based, each of which offers a different understanding of liver disease progression [35]. First-order features are the mean, variance, skewness and entropy properties of underlying pixel intensity distribution over a specified region of interest (ROI). Although they are computationally simple, these measures are useful in baseline differentiation of liver tissue states [29]. Second-order features are used to represent more intricate disease signatures by leveraging the spatial relationships between adjacent pixels, with the most widely used being Gray-Level Co-occurrence Matrices (GLCM). GLCM features, including contrast, homogeneity, and cluster shade, are important in the process of measuring subtle irregularities of the texture reflecting fibrosis and steatosis [29]. To perform more advanced diagnostics, more advanced features (e.g., NGTDM, GLRLM, GLSZM) are used to detect more complex spatial patters in liver tumors and tissue heterogeneity that cannot be revealed by lower-order statistical tools. These are complemented by transform-based features, which use the Wavelet transforms, Gabor filters, Local Binary Patterns (LBP) and the Histograms of Oriented Gradients (HOG) to analyze frequency distributions [29]. These transform-based methods are able to radically improve the definition of the tumor boundaries and the description of lesions margins by isolating certain spatial frequencies [37]. This combination of complementary feature sets (summarized in Figure 4) is critical to building strong classification models that demand high-fidelity descriptions of liver lesions.

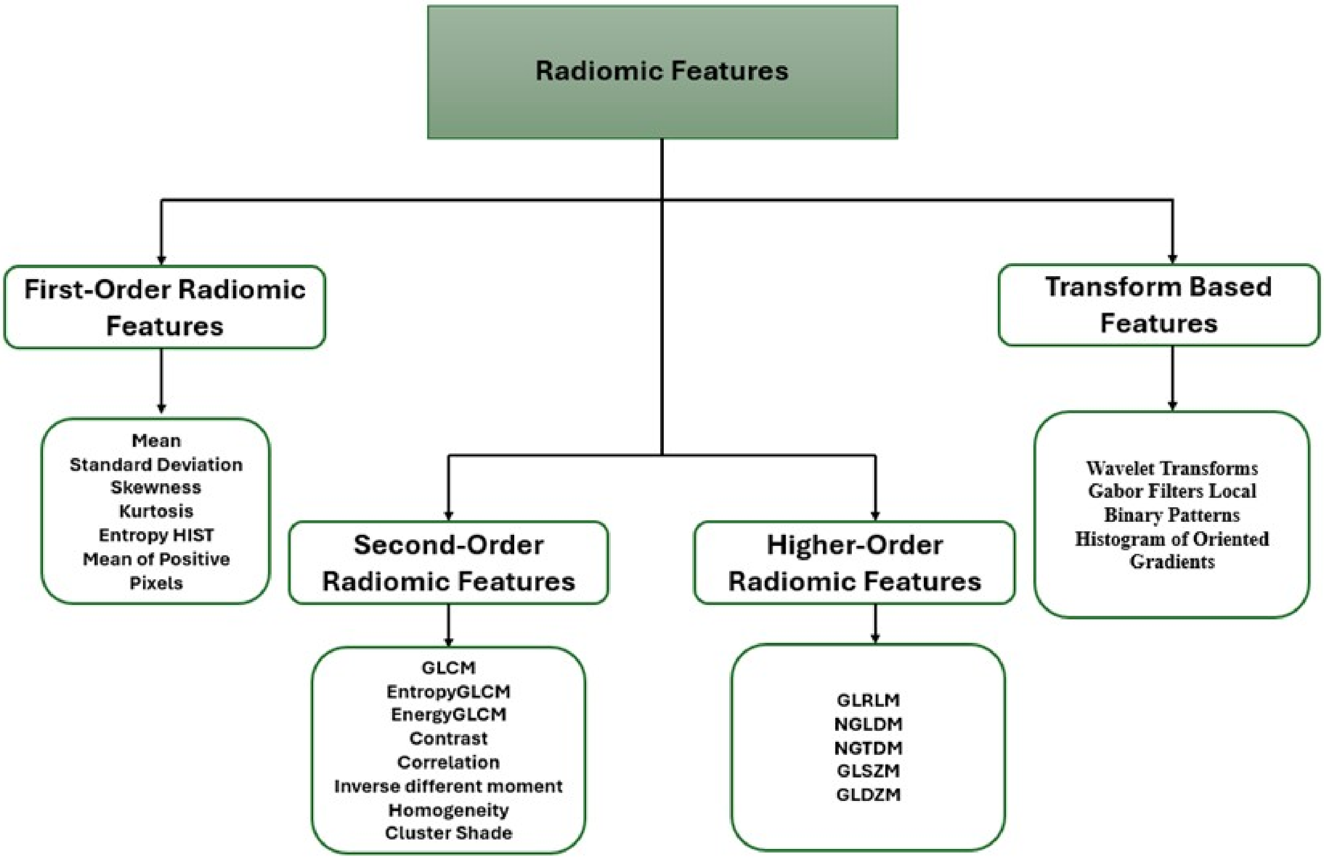


Figure 4: Categories of radiomic features commonly utilized for liver disease diagnosis.

Automated Feature Extraction

DL-based automated feature extraction has revolutionized liver CAD systems through its ability to hierarchically represent imaging data without manually engineered features. Compared to handcrafted radiomics, CNNs are able to learn hierarchy of spatial features, which has made remarkable progress in segmentation and classification of liver pathologies across CT, MRI, and ultrasound [30]. Recent research has turned to more advanced CNN models to enhance diagnostic sensitivity. Architectures like AlexNet, VGGNet, and ResNet have become the standards in liver pathology detection [38]. The superiority of DL models is supported by empirical evidence; e.g., Li et al. (2020) show that the sensitivity of HCC classification is 92.16 with Inception-V1 [39]. Moreover, comparative analyses, including Wang et al. (2018), have indicated that more complex models such as the ResNet always perform better than the simple models in the characterization of complex focal liver lesions [40]. In order to overcome a lack of data, transfer learning with pre-trained networks such as GoogLeNet and DenseNet--has become a typical procedure and has greatly improved the results in poor-data clinical cohorts [30]. Table 1 describes CNN layers. The implementation of CNN-based systems in clinical workflows is limited by three main challenges, even though they are very accurate:

1. Data Requirements and Overfitting: CNNs with high performance require large, labeled datasets. In medical imaging where this data is sparse, models are extremely vulnerable to overfitting. Data augmentation, dropout layers, and strong regularization strategies are compulsory to ensure model robustness [41].

2. Computational Demand: CNN training requires high-performance computing infrastructure, which is a limitation to practice in a standard hospital environment.
3. The Black-Box Limit: The black-box nature of deep learning decision-making has continued to be a barrier to clinical trust. Since CNNs are automatically trained on internal patterns, they lack transparency, which makes it difficult to match AI predictions to standard clinical reasoning [42].

As a result, explainable AI (XAI) and hybrid modeling are becoming more central to the future of liver CAD research to ensure that the balance between the accuracy of automated diagnostics and the responsibility of clinicians is achieved.

Table 1- Functions and descriptions of CNN layers [43]

CNN Layer	Description
Convolutional Layer	Fundamental Component It locates the set of features by scanning the image and performing convolutional filtering
Pooling Layer	Sub sampling layer usually placed after the convolutional layer. It receives the feature input from the convolutional layer and applied pooling operation which works on image size reduction while preserving the important characteristics of the image.
Activation Layer	demonstrates that the dependent variable as well as positive input have a linear relationship.
Fully Connected Layer	It is always fully connected and has its rol in classification. It recieves a vector from different feature maps which are computed by convolutional and pooling layer.

Feature Selection

Although DL structures automatically extract features, they do not necessarily ensure optimal diagnostic efficiency. Redundant or irrelevant features in liver CAD modeling are also likely to cause noise, contributing to the potential overfitting issue due to the relatively small size of most public liver imaging datasets. Therefore, dimensionality reduction methods, including Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA), become necessary to enhance model predictability and interpretability.

PCA has been used as the criterion to identify the most useful texture descriptors in imaging modalities. Indicatively, research has effectively employed PCA to enhance the distinction of normal liver tissue, chronic active hepatitis, and cirrhosis [44]. However, the linearity of conventional PCA might not be able to identify non-linear relationships between features, making it necessary to adopt non-linear methods, such as mutual information measures or Sparse PCA, to ensure that only the most diagnostically meaningful features are selected [44].

On the other hand, the LDA is often favored in clinical classification where it explicitly maximizes the separation between classes which directly improves the predictive power of the chronic liver disease models [45]. LDA can be much more interpretable than PCA, as it tends to retain information that is specific to a class and reduce dimensionality. Recent literature emphasises synergistic potential of such techniques e.g. high classification accuracies (up to 98.31) have been reported when combing LDA with Random Forest models [45]. Moreover, the most recent studies indicate that a combination of PCA and LDA can create an optimal feature space that greatly enhances the performance of CNN-based architectures [46].

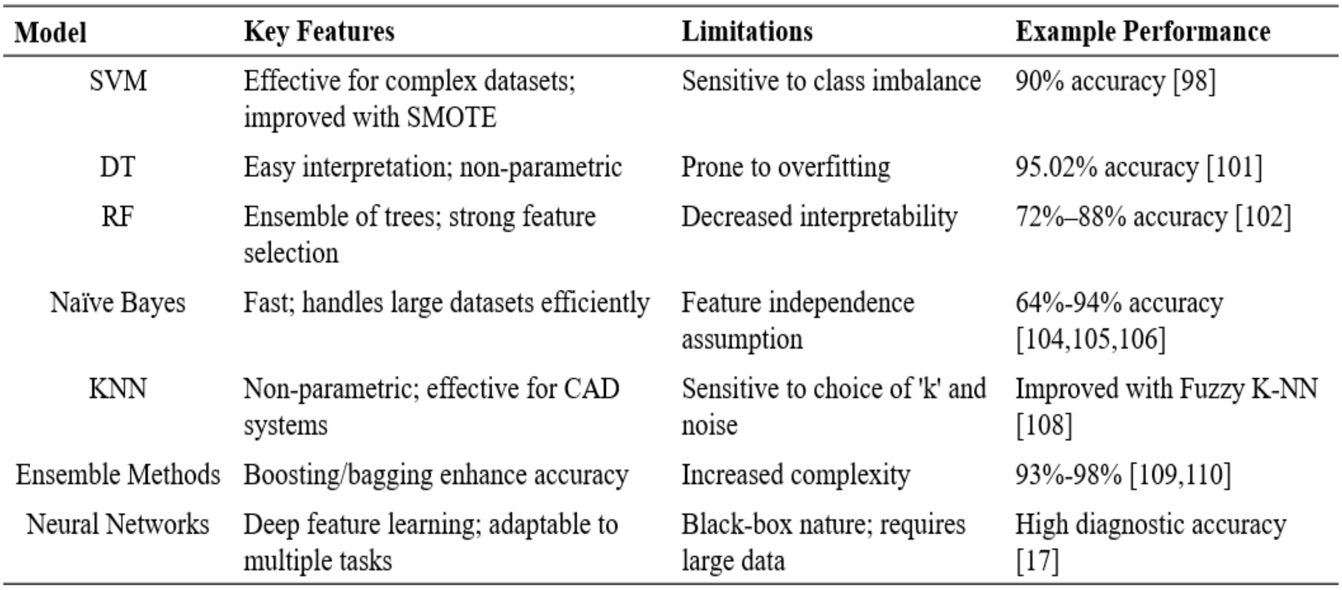
The successful implementation of these dimensionality reduction methods is not only a computational optimization but a clinical necessity. Through the elimination of irrelevant data, researchers develop more generalized and less affected by the black-box constraints of the high-dimensional DL architecture. This improves the accuracy of the diagnostic output and the ability of these models to be incorporated into a wider clinical decision support system.

Classification

The last phase of the CAD pipeline is training classifiers to project extracted features onto a particular clinical outcome. Many different ML models have been utilized in liver pathology, and their choice has often been determined by the amount of data, the dimensionality of features, and the need to have clinical interpretability. Support Vector Machines (SVM) continue to be a base algorithm in high-dimensional, multifaceted data, and studies have shown up to 90 percent accuracy on steatosis classification [47]. To mitigate the clinical issue of the imbalance in classes, SVMs are often used with the Synthetic Minority Over-sampling Technique (SMOTE) that has proven its efficacy in improving predictive stability [48]. Conversely, tree-based models provide a more transparent method of clinical decision-making. Decision Trees (DT) are valued due to zero-parameter constraints and have performed better than certain neural network architectures in a few CT-based hepatic lesion detect tasks [49]. Random Forest (RF) builds on this by leveraging frameworks of ensemble to provide robust classification; it is especially efficient in the assembly of heterogeneous demographic and laboratory data that has a consistent rate of accuracy ranging between 72% and 88% [50]. In situations that demand computational efficiency, Naive Bayes classifiers provide a quick, though sometimes constrained, answer. Its performance is very much dependent on data characteristics, frequently performing poorly when high feature correlation exists a familiar situation in medical imaging.

On the other hand, K-Nearest Neighbors (K-NN) is also a non-parametric alternative to SVMs that has proven superior in a few radiological data. This has been further refined into Advanced variants, like Variable-Neighbor Weighted Fuzzy K-NN, by adapting weight on the neighbors, but it is again sensitive to the original choice of distance measures [51]. Recent directions in the field of research prefer ensemble learning and neural architecture to achieve optimal diagnostic accuracy. Methods such as boosting (e.g., Extreme Gradient Boosting) and bagging have been found to reduce errors better in predicting liver diseases, combined models have reported an accuracy of up to 93% [52]. Moreover, Artificial Neural Networks (ANNs) such as CNNs that use spatial data and RNNs that use sequential data have established new standards in terms of detection accuracy. These neural models are very good at determining non-linear relationships, but their black-box quality is also a major challenge to clinical implementation. As a result, classification models are typically selected based on the trade-off between the predictive capabilities of the neural network at a high level and the transparency and robustness of more traditional ensemble and tree based methods as summarized in Table 2.

Table 2 Summary of classification models used for liver disease diagnosis.



Model	Key Features	Limitations	Example Performance
SVM	Effective for complex datasets; improved with SMOTE	Sensitive to class imbalance	90% accuracy [98]
DT	Easy interpretation; non-parametric	Prone to overfitting	95.02% accuracy [101]
RF	Ensemble of trees; strong feature selection	Decreased interpretability	72%–88% accuracy [102]
Naïve Bayes	Fast; handles large datasets efficiently	Feature independence assumption	64%-94% accuracy [104,105,106]
KNN	Non-parametric; effective for CAD systems	Sensitive to choice of 'k' and noise	Improved with Fuzzy K-NN [108]
Ensemble Methods	Boosting/bagging enhance accuracy	Increased complexity	93%-98% [109,110]
Neural Networks	Deep feature learning; adaptable to multiple tasks	Black-box nature; requires large data	High diagnostic accuracy [17]

Evaluation Parameters for liver pathologies diagnosis

The accuracy, recall, confusion matrix, precision, F1 score, and AUC are among the evaluation criteria used to assess performance of different ML and DL models. One of the easiest measures to understand is accuracy, which offers a broad indication of a model's overall performance by calculating percentage of correct predictions among all classifications. It reflects how frequently model's predictions correspond to actual results when considering both true positives and true negatives. However, accuracy alone may not adequately convey model performance, particularly when dealing with imbalanced datasets [53]. In such cases, precision becomes important, especially when false positives carry high costs. Precision is the percentage of correctly predicted positive cases out of all cases the model classified as positive. The metric holds special value when precise positive prediction accuracy matters because it focuses on reducing superfluous positive predictions from the model. Recall determines how well the model identifies positive cases through its assessment of which actual positive cases the model correctly predicted [54]. The detection of positive cases matters most when failing to identify them would result in serious outcomes because this measure shows how well the model detects relevant instances. The F1 score combines precision and recall through a harmonic mean to provide an equilibrium metric between the two metrics. F1 proves highly beneficial for situations with class imbalance because it prevents either precision or recall from being misrepresented [53].

The confusion matrix enables deep target comparison between actual values and model predictions in classification model analysis. Actual classes in confusion matrix occupy rows and the predicted classes occupy columns. The confusion matrix shows how many times a model correctly identifies its predictions while also showing the count of incorrect predictions known as false positives and negatives and true positives and negatives. Multiple performance metrics including accuracy, recall, precision and F1 score can be calculated from the initial values obtained from the model evaluation process [53]. The performance measurement known as area under the receiver operating characteristic curve (AUC-ROC) determines the likelihood of correctly placing positive examples higher than negative examples when randomly selected. ROC curve graphically illustrates how the true-positive rate (sensitivity) changes with the false-positive rate (specificity) at different threshold settings [54]. A higher AUC indicates a better discriminative ability of the model in distinguishing between positive and negative classes, thereby summarizing the model's overall classification performance [54]. These assessment factors are summarized in Table 3, which also describes the applicability and usefulness of each statistic in evaluating model performance.

Table 3 Performance metrics for evaluating machine learning and deep learning models in liver disease diagnosis [115]

S.No	Metric	Definition
1.	Accuracy	Accuracy is the proportion of correct predictions out of the total predictions made. $Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$ Where: TP = True Positives TN=True Negatives FP=False Positives FN=False Negative
2.	Precision	Out of all expected positive cases, precision quantifies the percentage of accurately predicted positive situations. $Precision = \frac{TP}{TP+FP}$
3.	Recall	Out of all actual positive cases, recall quantifies percentage of accurately predicted positive cases. $Recall = \frac{TP}{TP+FN}$
4.	F1-Score	The F1 score has been determined as the precision and recall harmonic means. It offers a harmony between recall and precision. $F1Score = 2 \times \frac{Precision \times Recall}{Precision+Recall}$

5.	Area Under Curve	The likelihood that a randomly selected positive instance will be ranked higher than a randomly selected negative instance is represented by the AUC. Plotting the genuine positive rate (sensitivity) against the false positive rate (specificity) at different threshold values is what the ROC curve is.

Recent Advances in Machine Learning and Deep Learning for Liver Disease Diagnosis:

As per the review of literature, CAD plays a vital role in supporting the subjective interpretation of radiological images for liver disease diagnosis. In recent years, the application of image processing algorithms in the medical field particularly in liver disease detection has become a critical area of focus. ML models such as SVM, RF, Naïve Bayes and KNN have demonstrated significant potential in classifying liver-related conditions. For instance, SVM achieved an accuracy of up to 96.27% in identifying liver cirrhosis from multimodal imaging datasets, and RF reached up to 99.6% accuracy in HCC detection using CT images [55]. Similarly, ensemble models combining radiomic features and clinical data reported AUCs as high as 0.9975 with XGBoost for HCC classification. DL models, especially CNNs, have revolutionized the diagnostic process by enabling automatic feature extraction and high-precision image analysis [56]. Furthermore, transfer learning using architectures such as ResNet50, MobileNetV2, and DenseNet201 has demonstrated classification accuracies up to 93.75% for hepatic steatosis stages in NAFLD patients using ultrasound images [57]. The detailed comparative performance of ML and DL models across different studies is summarized in Tables 4 and 5.

Table 4: Performance of various machine learning models for liver disease classification across different imaging modalities.

Reference No./Year of Publication	Images utilised	Pathology	Feature Extracted	Classifier Used	Performance
[58]/2025	CT Images	Microvascular Invasion (MVI) in HCC	First and second order radiomics features (672 variables), PCA reduced to 58 dimensions	RF, MLP (NeuralNet), XGB	RF: Acc = 96.8% (Sens: 95.2%, Spec: 97.6%) XGB: Acc = 68.7% (Sens: 38.1%, Spec: 83.7%) NeuralNet: Acc = 50% (Sens: 52.3%, Spec: 48.8%)
[55]/2025	CT Images, Ultrasound Images, MRI Images (Online Available Dataset)	Liver Cirrhosis	GLCM	ANN, SVM	Accuracy: ANN: 0.9478 SVM: 0.9627
[59]/2025	CT, MRI	HCC	Radiomic features, vectorized tabular data	XGBoost	Accuracy: 0.89±0.05, AUC: 0.93±0.03
[60]/ 2025	MRI Images	HCC, Regenerative Nodules (RNs), Dysplastic Nodules (DNs)	2264 Radiomic Features, Semantic Features	Machine Learning (Five-fold Cross-validation)	Combined Model: AUC = 0.896, Radiomics-based Model: AUC = 0.859, Semantic Feature-based Model: AUC = 0.883
[61]/2025	MRI	Rectal Metachronous	MR Radiomics	Generalized Linear	GLRM: AUC = 0.765 (Training), AUC = 0.767

		Liver Metastasis		Regression Model (GLRM), RF	(Validation) RF: AUC = 0.919 (Training), AUC = 0.901 (Validation)
[62]/2025	CT Images	Fatty Liver (Mild, Moderate, Severe)	2D and 3D Radiomics Features	RF, Bagging DT	RF (2D Radiomics Model): AUC = 0.973 Bagging DT (2D Radiomics Model): Sensitivity = 0.873, Specificity = 0.939, Accuracy = 0.864, Precision = 0.880, F1 Score = 0.876
[63]/2025	CT images	Severe coronary artery stenosis in T2DM patients with NAFLD	Shape, first-order statistics, texture, wavelet features (radiomics), and clinical features (e.g., diabetes duration, GLS, LDL-C)	SVM (for clinical model), XGBoost (for radiomics and combined models)	Clinical model AUC: 0.747 (SVM); Radiomics model AUC: 0.838 (XGBoost); Combined model AUC: 0.883 (XGBoost); highest F1 score, accuracy, and precision in validation
[64]/2024	MRI Images	Liver Fibrosis	107 Radiomic Features	Gradient Boosted Tree Model	AUC: 0.997–0.998 (training), 0.617–0.830 (test), Highest AUC: 0.830 (95% CI 0.520–0.830) for grade 2 fibrosis classification
[65]/2024	MRI Images	Proliferative HCC	Original and Delta Radiolics Features	Machine Learning Algorithms, Logistic Regression	AUC: 0.838 (Training), 0.801 (Validation)
[66]/2024	CT images	HCC	Histogram, Run-length, Co-occurance, wavelet transform	RF, Boost, DT, SVM	Accuracy- (DT: 96.5% RF: 99.6% Boost: 99.7% SVM: 98.0%)
[67]/2024	CT images	HCC	GLCM, GLDM, First Order Statistics, (GLSZM), GLRLM, and NGTDM	SVM, Logistic regression, RF, Adaboost, Xgboost, and naive Bayes algorithms	AUC- Xgboot-0.9975 SVM-0.9825 RF- 0.9861 Logistic Regression-0.9727
[68]/2023	Ultrasound Images	NAFLD	Ultrasound image-based features from	SVM	Sensitivity: 72.2%, Specificity: 94.6%,

			10 liver regions per subject		Accuracy: 83.4%, PPV: 93.1%, NPV: 77.3%
[69]/2023	CT and MRI Images	HCC	GLCM, GLRLM, GLDM, First-order statistics, GLSZM and NGTDM	RF, XGBoost, and SVM	AUC MRI-(XGBoost-0.917, RF-0.979, SVM-0.961) Accuracy MRI-(XGBoost-88%, RF-88%, SVM-94%) AUC CT-(XGBoost-0.822, RF-0.860, XGBoost-0.938) Accuracy MRI-(XGBoost-84%, RF-48%, SVM-96%)
[70]/ 2023	MRI Images	HCC	833 radiomic features	RF	AUC: 0.70 ± 0.09
[71]/ 2022	Ultrasound Images	Fibrosis, Steatosis, Normal	Computer-extracted texture features	Logistic Regression, RF	Logistic Regression (2-class): AUC = 0.928; RF (multi-class): AUC = 0.917
[72]/2022	Ultrasound Images	Fatty liver disease	FOS ,GLCM	Voting Based Classifier	F1-score 95.64% Precision-94.28% Sensitivity-97.05% Accuracy-95.71% Specificity-94.44%
[73]/2022	CT images	Portal Hypertension in Cirrhosis Patients	FOS and 4 wavelet features	Logistic Regression	Accuracy-65.8% Sensitivity-89.9% Specificity-33.3%
[74]/2021	Ultrasound	Primary liver cancer vs. metastatic liver cancer	First-order, two-dimensional shapeGLCM, GLRLM, gray-level size-zone matrix, NGTDM, GLDM	KNN, Logistic Regression (LR), MLP, RF, SVM	LR: Accuracy 0.843 ± 0.078, AUC 0.816 ± 0.088, Sensitivity 0.768 ± 0.232, Specificity 0.880 ± 0.117
[75]/2019	Ultrasound images	HCC and liver abscess	GLCM and GRLCM	(i) sequential forward selection (SFS), (ii) sequential backward selection (SBS), and (iii) F-score)	Accuracy- (SFS- 89.25%) (SBS-88.87%) F-Score- 88.87%

Table 5: Performance of various deep learning models for liver disease classification based on imaging datasets.

Reference No. /Year of Publish	Images utilised	Pathology	Deep Learning Model	Performance
[76]/2025	MRI Images	Focal Liver Diseases	DL Model	Dice coefficient: 0.62; Detection rate: DL+ Radiologist (0.894) vs. Radiologist alone (0.825); Sensitivity: DL (0.883) vs. Radiologist (0.806); Sensitivity for lesions <20mm: 0.848 vs. Radiologists: 0.788; Detection for lesions ≥20mm: DL (0.867) vs. Radiologists (0.881), P = 0.671
[77]/2025	CT Images	HCC	3-D Convolutional Block Attention Module (CBAM)	Internal validation AUC: 0.807 (95% CI 0.772-0.841), Radiologist AUC: 0.851 (95% CI 0.820-0.882), At-risk patient AUC: 0.769, Indeterminate scans AUC: 0.815, Small lesions <2 cm AUC: 0.773, External testing AUC: 0.789 (95% CI 0.750-0.827)
[78]/2025	CT Images	HCC	Spatio-Temporal 3D Convolution Network	Internal validation: AUC 0.919 (observation level), 0.901 (patient level); External testing: AUC 0.901; Compared to radiological interpretation (AUC 0.839 & 0.822); Negative predictive values: 0.966 (observation) & 0.951 (patient level); Observation-level AUCs for at-risk patients, 2–5 cm lesions, and singular portovenous phase: 0.899, 0.872, and 0.912, respectively.
[79]/2025	CT Images	Liver Tumors	U-Net, Detectron2	U-Net: Mask IoU = 0.903 (effective in simpler cases); Detectron2: Mask IoU = 0.974 (better in complex cases with segmented liver regions)
[80]/2025	MRI Images	MVI in HCC	CNN, TopoCNN, TopoCNN+Clinic	For tumours ≤ 3.0 cm: TopoCNN: 0.879 (internal), 0.763 (external) TopoCNN+Clinic: 0.929 (internal), 0.758 (external) TopoCNN: 0.890 (internal), 0.871 (external) TopoCNN+Clinic: 0.895 (internal), 0.879 (external)

[81]/2025	CT Images	Fatty Liver	2D & 3D DL models, 2D & 3D radiomics models	Best AUC: 0.973 (2D radiomics model with random forest) Best Sensitivity: 0.873 Best Specificity: 0.939 Best Accuracy: 0.864 Best Precision: 0.880 Best F1 Score: 0.876 (2D radiomics model with Bagging decision tree)
[82]/2025	MRI Images	HCC	Swin Transformer	AUC: 0.77-0.79 (Radiomics), AUC: 0.79 (Pathomics), C index: 0.69 (Training), 0.60 (Internal), 0.67 (External), Time-dependent AUCs for 3-year PFS: 0.83, 0.81, 0.78
[83]/2025	CT Images	Focal Liver Lesions	GAN for data augmentation	- Localization: Mean Average Precision = 0.81 - Multiclass Classification Accuracy: 0.97 (95% CI: 0.95-0.99) - Accuracy for FLLs ≤ 3 cm: 0.83 (95% CI: 0.68-0.98) - Accuracy for FLLs > 3 cm: 0.87 (95% CI: 0.77-0.97) - Classification Accuracy for FLLs ≤ 3 cm: 0.95 (95% CI: 0.92-0.98) - Classification Accuracy for FLLs > 3 cm: 0.97 (95% CI: 0.94-1.00)
[66]/2025	Ultrasound Images	Hepatic Steatosis (HS) in NAFLD patients	InceptionV3, MobileNetV2, ResNet50, DenseNet201, NASNetMobile	- 89.15%-93.75% (S0-S1 vs. S2-S3) with augmentation - 79.69%-91.21% (S0 vs. S1 vs. S2 vs. S3) with augmentation - 80.45%-82.73% (S0-S1 vs. S2-S3) without augmentation - 59.54%-63.64% (S0 vs. S1 vs. S2 vs. S3) without augmentation - HRI measurement by radiologists: 82% (S ≥ S1), 91.56% (S ≥ S2), 96.19% (S = S3)
[84]/2024	CT and MRI Images	HCC – MVI prediction	Multimodal DL using DenseNet121 + ELM; Transfer Learning applied	AUC = 0.844 (MDL model); AUC = 0.871 (MDL + clinical features); Outperformed single-modality models (AUC = 0.706–0.776 CT, 0.706–0.717 MRI)
[85]/2024	MRI Images	HCC	DL Model	Improved image quality and detection rates (91.4%-93.4%) compared to PI-DWI and CS-DWI; especially effective in hepatic dome lesions (94.8%-97.4%)

[86]/2024	CT Images	HCC, intrahepatic cholangiocarcinoma (ICC), metastatic tumors (MET), focal nodular hyperplasia (FNH), hemangioma (HEM), cysts (CYST)	Liver Lesion Network (LiLNet)	Benign vs Malignant: ACC = 94.7%, AUC = 97.2% HCC, ICC, MET: ACC = 88.7%, AUC = 95.6% FNH, HEM, CYST: ACC = 88.6%, AUC = 95.9%
[87]/2023	CT and MRI Images	MVI in HCC	ResNet18 (DLCT_ALL, DLMRI_ALL, DLCT + MRI), SVM (CALL)	DLCT + MRI: AUC 0.819 (vs. DLCT_ALL 0.742); DLMRI_ALL: AUC 0.794 (vs. RMRI 0.766); CALL model significant for prognosis ($P < 0.001$)
[88]/2023	MRI Images	Early-stage HCC recurrence	VGG16 + XGBoost	AUC-ROC: 0.71–0.85; 5/6 models significant for RFS ($p < 0.05$)
[89]/ 2022	MRI Images	Focal liver lesions	EfficientNetB0	AUC: 0.84 (±0.1), Sensitivity: 0.78 (±0.14), Specificity: 0.86 (±0.08), NPV: 0.89 (±0.08), PPV: 0.71 (±0.17)
[90]/2022	CT Images	MVI,HCC	Pretrained CNNs via transfer learning; SVM classifier	MVI Prediction: AUC 0.909, Accuracy 96.47%, Sensitivity 90.91%, Specificity 97.30%, PPV 83.33%, NPV 98.63%
[91]/2022	CT Images	Colorectal Liver Metastasis (CRLM), Ablation Zone	Hybrid-WNet (also compared: 3D-UNet, Residual 3D-UNet, Dense 3D-UNet)	DSC (3D-IRCADb): 0.73 (0.41–0.88), Global DSC (LiTS): 0.810, Surface distance: 1.75 mm, Sensitivity for lesions ≥ 15 mm: 98%, Likert score ≥ 4 for CRLM: 100%, ablation zones: 84%
[92]/2021	CT Images	Small HCC (sHCC ≤ 2 cm) in cirrhotic liver	PM-DL (Pattern Matching + Deep Learning using CNN)	Sensitivity: 89.74%, PPV: 85.00%, DICE coefficient: 0.77 ± 0.16.
[93]/2021	CT Images	Microvascular Invasion (MVI) in HCC	3D-CNN, XGBoost	Training AUROC: 3D-CNN – 0.980; RRC (XGBoost) – 0.952 Validation AUROC: 3D-CNN – 0.906; RRC – 0.887
[94]/2020	CT and MRI Images	Clinically Significant Portal Hypertension (CSPH)	Deep CNN	AUC: 0.998 (Train), 0.912 (Validation), 0.933 (Test)

Critical Comparison between Machine Learning and Deep Learning models.

Although the literature reviewed in this work is rapidly growing, with a significant number of studies appearing in Tables 4 and 5, a critical review indicates that the popular discourse of the superiority of deep learning (DL) in the diagnosis of liver diseases is not always backed up by empirical evidence. Rather, model performance highly depends on the size of datasets, imaging modality, strategy feature engineering, and rigor of validation-something that is not adequately recognized. Although, unlike other image-based models, DL models, specifically CNN-based models, prove to be highly beneficial in lesion localization, lesion segmentation, and detection of tiny or hidden abnormalities, they are not universally more beneficial than other image-based models in terms of diagnostic goals. Radiomics-driven machine learning (ML) pipelines are also able to match or surpass end-to-end DL pipelines in several CT-based and MRI-based studies, especially in classification, including HCC detection, fibrosis staging, and MVI prediction. Interestingly, RF and XGBoost models are repeated to show AUC scores above 0.95, sometimes nearly 0.99, whilst numerous DL models level off at similar or worse performance after being trained on small or single centre datasets. The observation contradicts the belief on which the superior performance of a diagnostic can be ensured solely on architectural complexity.

The enduring effectiveness of ML models highlights the ongoing usefulness of handcrafted radiomic features, particularly in clinical environments, where dataset sizes are limited by their nature. ML techniques based on radiomics have the advantages of: lower data requirements, greater training stability, and enhanced inter-cohort reproducibility.

By contrast, DL models often use aggressive data augmentation or transfer learning in order to cover inadequate training samples, which brings up issues of model overfitting and domain shift. In several real-life liver imaging cases, therefore, ML models provide a more realistic performance-to-feasibility trade-off.

A very evident interaction of modalities-model interaction is also delivered in the synthesis but is mostly neglected in individual studies. CT-based datasets are always the strongest with the two approaches- ML and DL, especially with HCC-related tasks. MRI-based DL models are only better at multiparametric and prognostic but more variable across external validation cohorts. dl models based on ultrasound, although promising, are highly sensitive to the variability in acquisition as well as operator dependence, and as such are not robust. These results imply that the choice of models must be made in a modality-conscious manner as opposed to the one-size-fits-all DL paradigm.

Hybrid ML-dl models often improve standalone models, and the reported AUC improvements are between 3-8% , which indicates that the feature fusion strategies are more effective than depth-only network improvement. This underscores a changes in method of models to data driven optimization. The existing evidence lacks universal dominance in the application of deep learning models over machine learning methods in the diagnosis of liver diseases. Rather, performance optimization can be achieved through modality-sensitive model selection, feature engineering based on radiomics and hybrid solutions that combine clinical and imaging information.

Limitations and Challenges of CAD Systems for Liver Pathology Detection

Although there are great advances, CAD liver pathology detection systems have a range of issues that are critical in preventing their use in clinical settings. One significant shortcoming is that not all training data sets are diverse due to the lack of diverse populations in the development of many CAD systems resulting in biases and differences in model performance over other patient demographics, disease prevalence, and imaging modalities. To mitigate this, it is necessary to implement multi-center datasets collection to enhance the robustness and external validity of AI models. Moreover, the complexity of deep learning models poses interpretability issues, where it is necessary to understand how a model has made a decision in order to obtain clinician trust; a variety of Explainable AI methods such as Grad-CAM, SHAP, and LIME provide some answers, but typically do not achieve complete transparency, resulting in hesitation to adopt them because they do not align with conventional clinical reasoning. The regulatory acceptance of AI-based CAD systems is also a demanding process that requires robust evidence of clinical safety and efficiency, and ethical concerns including patient privacy, data security, and informed consent should be addressed with caution, especially in a case of multi-institutional data sharing to conduct model training. Lastly, the implementation of CAD systems into the current Picture Archiving and Communication Systems (PACS) and hospital processes is practically challenging, with current systems potentially not fitting AI-powered systems, and active work of CAD developers, medical practitioners, and regulatory agencies is required to harmonize the standards of a seamless integration of AI-based tools.

Future Perspectives

The application of modern CAD methods in screening liver pathology is changing the face of medical imaging by boosting the quality and speed of diagnosis. Multimodal imaging integrates CT, MRI and lab findings making it possible to approach the diagnostic process in a holistic manner. The inclusion of multiple data sources makes CAD models capable of obtaining a more detailed insight of the conditions of the patient and enhances the accuracy of the diagnosis and clinical decision-making process. Recent models such as contextual convolutional neural network (COCOn) apply contextual information to more effectively segment liver pathology, surpassing conventional single-modality models with complementary imaging data. Applications of AI are currently being spread across different imaging modalities, such as CT and MRI, and enable the identification of focal lesions and chronic liver disease. The introduction of AI into clinical practice has proven to be able to expand the diagnostic abilities of radiologists, resulting in better patient outcomes. Federated learning is especially effective in responding to data sharing challenges when sensitive patient data are involved. The methodology facilitates the cooperation of various medical facilities and ensures patient privacy to create powerful AI models that can be implemented on a large scale. XAI is one of the most important aspects that are more significant in this scenario. To become open in a way that clinicians will trust them and regulators will approve them, AI models will require XAI that will accelerate their implementation in medical settings. The comparison between ML and DL models reveals that the patterns of performance of the two models are significant in the detection of liver disease despite all studies lacking confidence intervals (CIs) or p-values to determine the reliability of performance. Statistical validation tests such as t-tests and ANOVA should be applied in the research to understand whether the performance of the DL models is significant at a significant p value of 0.05 or the difference in the performance is due to the variation in the data sets. Federated learning and self-supervised methods also enhance CAD applications by resolving issues of data scarcity and privacy issues. Self-supervised learning allows models to utilize extensive volumes of unlabeled medical imaging data, avoiding the reliance on costly labeled datasets. Federated learning enables institutions to collaborate but at the same time keep patient data confidential, which makes AI models more generalizable across diverse populations. Such methods are not only effective in enhancing the efficiency of CAD models, but also in large-scale implementation in clinical environments. AI-based personalized medicine is transforming liver disease treatment by forecasting disease progression and responses to treatment. Machine learning models process data unique to patients (e.g., genetic profiles, medical history) to personalize interventions, with a maximum accuracy of 80% in identifying liver disease, greatly outperforming other diagnostic methods [95]. Predictive models can be implemented to ensure high-risk patients can be identified early, and prompt actions can be taken to improve their prognosis and lower healthcare expenses. The development of DL architecture, such as Vision Transformers (ViTs), CNN-RNN hybrid frameworks, and attention-based AI, have further optimized medical imaging analysis, allowing them to extract more features [96]. These architectures are highly effective in modeling long-range dependencies, as well as capturing contextual information, and are thus appropriate in the challenging imaging problems in liver pathology detection. CNNs and RNNs hybrid models enhance the sequential imaging data analysis, thereby enhancing an understanding of the disease progression [97]. In spite of these developments, there are still challenges. The need of a large and diverse dataset is to guarantee model generalizability in the context of various patient groups and imaging modalities. To make AI-driven CAD models useful in the detection of liver pathology in real-world scenarios, future investigations must center on multi-center clinical trials, standard evaluation benchmarks, and better techniques of AI interpretability.

CONCLUSION

Incorporation of CAD systems has transformed liver disease diagnosis through enhanced accuracy of diagnosis, minimized bias in observers and facilitated early intervention. The review identified AI-driven CAD models in three significant facets of image preprocessing and feature extraction and classification processes. Studies on ML and DL models have discovered their capability to enhance the diagnosis of non-invasive liver diseases using CNN-based architectures that yielded high scores in the segmentation and classification tasks. There are several critical challenges that continue to exist in the wake of these developments. The generalizability of CAD models is compromised by the lack of variety in the dataset and the absence of multi-centre verification. Also, black-box characteristics of deep learning models create an important obstacle to clinical acceptance because clinicians need interpretable and transparent decisions. The regulatory restrictions and complexity of adapting AI-driven CAD to hospital workflows are also a hindrance to real-life implementation. Research directions should involve future studies to make models more robust and clinically applicable with the use of federated learning, multimodal data fusion, and self-supervised learning techniques. A radiological imaging combination with clinical and molecular biomarkers has the potential to create more specific, explicable, and patient-centric diagnostic models. Radiologists, AI researchers, and policymakers are required to collaborate in order to close the gap between AI research and clinical practice. Data standardization, interpretability, and real-world validation will be essential in pushing CAD systems to routine clinical application. As the field of AI-based CAD advances and becomes more refined, it has the potential to revolutionize the process of managing liver disease and achieve better patient outcomes and precision medicine in hepatology.

List of abbreviations

Abbreviation	**Full Form**
HCC	Hepatocellular Carcinoma
ML	Machine Learning
DL	Deep Learning
CAD	Computer-Aided Diagnosis
CNN	Convolutional Neural Networks
AUC	Area Under Curve
AI	Artificial Intelligence
MASLD	Metabolic Dysfunction Associated Steatotic Liver Disease
NAFLD	Non Alcoholic Fatty Liver Disease
US	Ultrasound
CT	Computed Tomography
MRI	Magnetic Resonance Imaging
MDCT	Multi Detector Computed Tomography
AMRI	Abbreviated Magnetic Resonance Imaging
PCA	Principal Component Analysis
HE	Histogram Equalization
CLAHE	Contrast Limited Adaptive Histogram Equalization
GLCM	Gray-Level Co-occurrence Matrices
NGTDM	Neighborhood Gray-Tone Difference Matrix
GLRLM	Gray-Level Run-Length Matrix
GLSZM	Gray-Level Size Zone Matrix
GLDM	Gray-Level Distance Zone Matrix
LBP	Local Binary Patterns
HOG	Histogram of Oriented Gradients
LDA	Linear Discriminant Analysis
KNN	K-Nearest Neighbor
SVM	Support Vector Machine
DT	Decision Trees
MLP	Multilayer Perceptrons
RF	Random Forest
RNN	Recurrent Neural Networks
ANNs	Artificial Neural Networks
TP	True Positives
TN	True Negatives
FP	False Positives
FN	False Negative
ROC	Receiver Operating Characteristic
ELM	Extreme Learning Machine
PPV	Positive Predictive Value
NPV	Negative Predictive Value
XAI	Explainable Artificial Intelligence

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No datasets were generated or analysed during the current study.

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The authors declare no conflicts of interest related to this work.

Declarations

Ethics Approval and Consent to participate

Not applicable.

Consent for publication

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Competing interest

The authors declare no competing interests

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