IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⋇ Peer-reviewed & Refereed journal ⋇ Vol. 14, Issue 6, June 2025

DOI: 10.17148/IJARCCE.2025.14679

EARLY DETECTION OF LIVER DISEASE USING MACHINE LEARNING AND PREDICTIVE ANALYSIS

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Abstract: Liver diseases present significant diagnostic and management challenges due to their asymptomatic progression and the limitations of traditional diagnostic methods. Machine learning (ML) and deep learning (DL) techniques have emerged as transformative tools in liver disease diagnostics, enabling improved accuracy, efficiency, and automation in tasks such as disease classification, liver segmentation, and lesion detection. This review consolidates findings from recent studies, covering the use of logistic regression, support vector machines (SVMs), and convolutional neural networks (CNNs) in analysing clinical and imaging data. Advanced models such as DenseNet, YOLOv8, and DBN-DNN have demonstrated state-of-the-art performance in lesion detection, real-time diagnosis, and segmentation, achieving accuracy rates exceeding 95% in most cases. Despite their promise, challenges such as dataset limitations, variability in imaging protocols, and model interpretability remain significant barriers to clinical adoption. Future research should focus on enhancing generalizability across imaging modalities, incorporating explainable AI (XAI), and optimizing real-time deployment. This review highlights the potential of ML to revolutionize liver disease diagnostics, bridging existing gaps and paving the way for scalable, accurate, and efficient clinical solutions.

Keywords: Machine Learning, Liver Disease, Deep Learning, Segmentation, Classification, Real-Time Diagnostics, Multi-Modal Integration.

I. INTRODUCTION

Liver diseases constitute a major global health concern with conditions such as Non-Alcoholic Fatty Liver Disease (NAFLD), hepatitis, cirrhosis and Hepatocellular Carcinoma (HCC) affecting millions annually. These diseases often progress silently making early diagnosis critical to prevent severe complications and mortality. Traditional diagnostic techniques, including liver function tests, imaging modalities (e.g. ultrasound, Computed tomography (CT) and Magnetic Resource Imaging (MRI)) and biopsies are often invasive, subjective and reliant on expert interpretation. Consequently, there is a growing need for automated, accurate and non-invasive diagnostic tools.

Machine Learning (ML) and Deep Learning (DL) have emerged as transformative technologies in healthcare, offering solutions to the limitations of traditional diagnostic methods. ML algorithms, such as logistic regression, Support Vector Machines (SVMs) and decision trees, have demonstrated efficacy in analysing clinical data, while DL models particularly Convolutional Neural Networks (CNNs) excel in processing complex imaging data. Recent advancements have also explored hybrid approaches that combine traditional ML techniques with DL architectures to enhance performance in tasks like segmentation, classification and real-time detection.

The studies reviewed in this paper illustrate the broad spectrum of ML applications in liver disease diagnosis. For instance, DL models like DenseNet and Inception-ResNet-v2 have achieved remarkable accuracy in imaging-based diagnosis while hybrid frameworks like DBN-DNN have advanced liver segmentation. Moreover, real-time lesion detection using YOLOv8 and multi-modal integration of clinical and imaging data highlight the potential for comprehensive diagnostic systems. Despite these advancements, challenges such as dataset limitations, variability in imaging protocols, and the "black box" nature of DL models hinder widespread clinical adoption.

This review aims to synthesize insights from recent studies, categorizing their contributions into classification algorithms, segmentation techniques, and multi-modal approaches. Furthermore, it identifies challenges and proposes future directions to enhance the clinical applicability of ML in liver disease management. By bridging gaps in current methodologies, ML has the potential to revolutionize liver disease diagnostics and improve patient outcomes.

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II. BACKGROUND AND RELATED WORKS

2.1 Background

Liver diseases are a heterogeneous group of disorders, including NAFLD, viral hepatitis, cirrhosis, and HCC, which collectively account for significant morbidity and mortality worldwide. Traditional diagnostic methods often rely on invasive techniques such as liver biopsy, which carry risks of complications and sampling errors. Imaging modalities like ultrasound, CT and MRI are frequently employed but require skilled interpretation and are prone to inter-operator variability. The need for accurate, automated and non-invasive solutions has driven research into ML and DL technologies. ML techniques enable the analysis of structured data such as clinical and laboratory results while DL excels in processing unstructured data including medical images. Recent advancements in computational power, algorithmic efficiency and dataset availability have made ML and DL viable for clinical applications in liver disease diagnosis.

2.2 Related Works

Numerous studies have explored ML and DL methodologies for various aspects of liver disease diagnostics:

Classification of Liver Diseases: Logistic regression and decision trees have been applied to classify liver diseases using clinical data, achieving accuracies above 95%. SVM and K-Nearest Neighbors (KNN) have shown robust performance particularly when applied to datasets like the Indian Liver Patient Dataset (ILPD).

Imaging-Based Diagnostics: DenseNet CNN achieved state-of-the-art accuracy (98.34%) for liver lesion detection in CT images, highlighting the potential of feature reuse and parameter efficiency. Inception-ResNet-v2 demonstrated the power of transfer learning for analysing ultrasound images, achieving 96.3% accuracy in liver steatosis classification.

Segmentation of Liver Regions: Traditional methods such as level-set and region growing have limitations in handling low-contrast boundaries and noise. The DBN-DNN hybrid framework addressed these challenges by integrating unsupervised pretraining with supervised fine-tuning, achieving Dice Similarity Coefficients (DSC) exceeding 94% on multiple datasets. Post-processing techniques, like active contour refinement, further improved segmentation accuracy.

Real-Time and Multi-Modal Approaches: YOLOv8 enabled real-time lesion detection in histopathological images, achieving a mean Average Precision (mAP) of 99.1%. Multi-modal approaches integrating clinical and imaging data, demonstrated enhanced diagnostic sensitivity and specificity.

III. LITERATURE SURVEY

- In this paper **Machine learning based liver disease diagnosis: A systematic review** [1] explores how machine learning (ML) algorithms can be used to improve the early detection of liver diseases**.** Liver disease is a major global health concern, and early diagnosis is essential to prevent severe complications. Traditional diagnostic techniques such as blood tests, imaging scans (CT, MRI, ultrasound), and biopsies are often time-consuming, expensive and operator dependent**.** The study evaluates several ML models, including SVM, Decision Trees, Naïve Bayes, KNN, and Artificial Neural Networks (ANN). The results show that ANN achieved the highest accuracy (97.8%)**,** outperforming traditional ML models. The paper highlights the potential of AI-driven classification models to assist in clinical diagnosis and reduce manual workload for doctors.

- In this paper **Prognosis of Liver Disease: Using Machine Learning Algorithms** [2] focuses on predicting liver disease progression using ML techniques. The paper analyses a dataset of 574 patients who underwent Liver Function Tests (LFTs) and applies various ML algorithms to predict whether a patient has liver disease. The study finds that Logistic Regression performed best with 95.8% accuracy, followed by Decision Trees and SVM. The main contribution of this research is demonstrating how machine learning models can improve prognosis by identifying patterns in biochemical markers (Bilirubin, Albumin, SGOT, SGPT) that indicate liver disease. The study suggests that ML can assist doctors in making more data-driven decisions and can be integrated into hospital management systems for automated diagnosis.

- In this paper **Diagnosis of Liver Disease Using Machine Learning Techniques** [3] investigates deep learning approaches for liver disease classification. Unlike traditional ML models that rely on handcrafted features, deep learning can automatically extract patterns from medical data, leading to improved accuracy. The study compares ANN, CNN, and Transfer Learning models for analysing ultrasound images and patient records**.** A Graphical User Interface (GUI) was developed to allow medical professionals to interact with the AI system in real-time. CNN-based models significantly outperformed traditional ML models, demonstrating the power of deep learning in medical diagnostics. The study concludes that deep learning models can be integrated into healthcare systems to provide fast, accurate, and non-invasive liver disease diagnosis**.**

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

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- In this paper **A DenseNet CNN-based liver lesion prediction and classification for future medical diagnosis** [4] presents a DenseNet-based CNN model for detecting liver lesions in medical images. The study highlights that HCC accounts for many liver cancer cases, and early detection is crucial for patient survival. Traditional diagnostic methods, such as manual interpretation of CT/MRI scans, are prone to human error. The proposed DenseNet CNN model automates liver lesion detection and classification, achieving 98.34% accuracy. The study compares the performance of CNN-based models with traditional feature extraction techniques and finds that deep learning models significantly outperform conventional methods. The findings suggest that AI-driven liver lesion detection can enhance diagnostic accuracy and reduce reliance on manual assessment.

- In this paper **Transfer learning with deep convolutional neural network for liver steatosis assessment in ultrasound images** [5] applies transfer learning techniques to assess liver steatosis (fat accumulation in the liver) using ultrasound images. The study highlights that NAFLD is increasing globally, and ultrasound-based diagnosis is subjective and operator-dependent. The authors use a pre-trained Inception-ResNet-v2 CNN model to automatically analyse liver ultrasound images. The results show that CNN-based feature extraction outperforms traditional texture analysis techniques such as the Hepatorenal Index (HI) and Gray-Level Co-Occurrence Matrix (GLCM). The model achieved an AUC (Area Under the ROC Curve) of 0.977, indicating high diagnostic accuracy. This paper demonstrates that transfer learning can be effectively used to improve liver disease diagnosis by leveraging pre-trained deep learning models.

- In this paper **Accurate diagnosis of liver diseases through the application of deep convolutional neural network on biopsy images** [6] investigates the use of deep learning models to analyse liver biopsy images. Biopsy remains the gold standard for diagnosing liver fibrosis, cirrhosis, and other abnormalities, but manual interpretation is time-consuming and subjective. The paper evaluates object detection models such as YOLO (You Only Look Once), Faster R-CNN, SSD (Single Shot MultiBox Detector), and segmentation models such as Mask R-CNN and U-Net. The findings reveal that YOLOv8 achieved the highest lesion detection accuracy (99.8%), while U-Net achieved 97.3% Dice Similarity Coefficient (DSC) in segmentation tasks. The study concludes that AI-based biopsy analysis can improve accuracy and reduce the workload of pathologists, making liver disease diagnosis faster and more reliable.

- In this paper **A Critical Study of Selected Classification algorithms for liver disease diagnosis** [7] compares multiple ML classification algorithms for liver disease detection using two datasets: Andhra Pradesh Liver Dataset and the BUPA Liver Disorders Dataset. The study evaluates Naïve Bayes, C4.5 Decision Tree, ANN, SVM, and KNN to determine the most effective classification technique. The results indicate that ANN (98%) and SVM (96.4%) outperformed all other models, while Naïve Bayes had the lowest accuracy (80.2%). The research highlights the importance of feature selection, data preprocessing, and model optimization for improving ML-based liver disease diagnosis. The findings emphasize that AI models can enhance disease detection accuracy, assisting doctors in early diagnosis and prognosis.

- In this paper **Machine Learning in liver disease diagnosis: Current progress and future opportunities** [8] provides a comprehensive review of AI applications in liver disease diagnosis, classification, and segmentation from 2015 to 2020. It explores various ML and DL models, including SVM, Random Forest, ANN, CNN, and Generative Adversarial Networks (GANs). The study finds that deep learning-based models outperform traditional ML algorithms in accuracy and robustness. The review also identifies key challenges in AI-based liver disease diagnosis, such as small dataset availability, lack of explainability in deep learning models, and variability in medical imaging quality. The authors suggest that future research should focus on Explainable AI (XAI), multi-modal learning, and real-time AI deployment in hospitals.

- In this paper **An intelligent model for liver disease diagnosis** [9] introduces an AI-based hybrid model combining Classification and Regression Tree (CART) and Case-Based Reasoning (CBR) for automated liver disease diagnosis. The model was tested on 510 medical records from Taiwan and achieved 92.94% classification accuracy using CART and 90.00% accuracy using CBR. The study emphasizes that hybrid AI models can improve diagnostic reliability by combining rule-based decision-making with case-based learning. The proposed system can be integrated into hospital databases for real-time liver disease classification.

- In this paper **Deep Belief Network Modeling for Automatic Liver Segmentation** [10] presents a Deep Belief Network (DBN) combined with a Deep Neural Network (DNN) for automated liver segmentation from CT scan images. Traditional segmentation methods, such as Graph Cuts and Atlas-based approaches, often fail in cases with low contrast and shape variations. The proposed DBN-DNN model achieved 94.80% Dice Similarity Coefficient (DSC), outperforming traditional segmentation techniques. The model also integrates a 3D Active Contour (Chen-Vese) method for refining liver boundaries. The research concludes that deep learning-based segmentation can enhance accuracy and automate liver region detection in medical imaging.

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REFERENCE NUMBER	METHOD	DATASET	ACCURACY	MERITS	DEMERITS
R.A. Khan et al [1]	Logistic regression	Indian Liver Patient Dataset (ILPD)	95.8%	Simple, interpretable, and efficient for structured clinical data.	Limited scalability to complex or non-linear datasets.
Vyshali J Gogi & Dr. Vijayalakshmi M.N [2]	Support Vector Machines (SVM)	Indian Liver Patient Dataset	97.47%	Handles non-linear data effectively and provides robust performance with small datasets.	Computationally intensive for large datasets.
Joel Jacob et al [3]	K-Nearest Neighbors (KNN)	Liver Function Test Dataset	97.73%	Non-parametric, simple implementation, and effective with structured data.	Sensitive to noisy data and requires optimal value of K for best results.
Nanda Prakash et al [4]	DenseNet CNN	CT Scan Dataset	98.34%	Efficient feature reuse, reduced overfitting, and excellent for CT imaging tasks.	Computationally expensive and requires large training datasets.
Michał Byra, et al [5]	YOLOv8 for Lesion Detection	Histopathological Image Dataset	99.1% (mAP)	Real-time detection, high precision, and suitable for clinical workflows.	Requires significant computational resources for training and deployment.
Soumyajit Podder, et al [6]	Inception-ResNet-v2	Ultrasound Image Dataset	96.3%	Transfer learning reduces data dependency; suitable for ultrasound-based steatosis classification.	May not generalize well across modalities without further fine-tuning.
Bendi Venkata Ramana et al [7]	DBN-DNN for Segmentation	MICCAI-Sliver07 & 3Dircadb01	94.8% (DSC)	Effective for liver segmentation in CT images, robust against noise.	Training is time-consuming and computationally expensive.

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REFERENCE NUMBER	METHOD	DATASET	ACCURACY	MERITS	DEMERITS
Neha Tanwar and Khandakar Faridar Rahman [8]	Multi-Modal CNN	Ultrasound & Lab Reports	Sensitivity: 100%, Specificity: 88.2%	Integrates imaging and clinical features, improving diagnostic sensitivity.	Limited generalizability to datasets with different acquisition protocols.
Rong-HoLin [9]	Decision Trees	Biopsy Data	96.27%	Easy to interpret and implement; suitable for small datasets.	Prone to overfitting with complex datasets; limited scalability.
Mubashir ahmad et al [10]	Hybrid DBN-DNN with Active Contour	MICCAI-Sliver07 and 3Dircadb01	94.8% (MICCAI), 91.83% (3Dircadb	Integrates unsupervised and supervised learning, achieving high segmentation accuracy.	Active contour post-processing adds additional computational overhead.

IV. CHALLENGES AND LIMITATIONS

4.1 Dataset Limitations

- **Small Sample Sizes**: Study emphasized the limited size and variability of datasets, which hinder model generalizability.
- **Imaging Protocol Variability**: Differences in acquisition settings across datasets impact model performance.

4.2 Model Interpretability

The lack of explainability in DL models restricts their clinical adoption. Future systems must incorporate explainable AI (XAI) to build clinician trust.

4.3 Computational Demands

Advanced DL models require significant computational resources, limiting their deployment in low-resource settings. For instance, the DBN-DNN model requires 48 hours of training.

V. CONCLUSION AND FUTURE WORK

5.1 Conclusion

The reviewed studies underscore the transformative potential of ML and DL in liver disease diagnostics. Classification models, such as logistic regression and support vector machines, have shown high efficacy in analysing clinical data, achieving accuracies exceeding 95%. Deep learning architectures like DenseNet and Inception-ResNet-v2 have revolutionized imaging-based diagnostics, with state-of-the-art results in tasks such as lesion detection and steatosis grading. Real-time applications using YOLOv8 and hybrid frameworks like DBN-DNN have further extended ML's utility to real-time lesion detection and precise segmentation, respectively.

Despite these advancements, significant challenges remain. The reliance on small, heterogeneous datasets limits generalizability, while the "black-box" nature of DL models restricts interpretability and clinical adoption. Additionally, computational demands present barriers to deploying advanced models in resource-constrained settings.

5.2 Future Work

To address these challenges and further enhance ML applications in liver disease diagnostics, the following directions are proposed:

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1. **Expanding Dataset Diversity**: Collaborative efforts across institutions to create large, standardized, and diverse datasets. Inclusion of multi-centre data to address variability in imaging protocols and patient demographics.
2. **Integrating Multi-Modal Data**: Development of models that seamlessly combine clinical, biochemical, genetic, and imaging data to improve diagnostic accuracy. Exploration of multi-omics data, including genomics and proteomics, for a comprehensive understanding of liver diseases.
3. **Enhancing Model Interpretability**: Incorporating explainable AI (XAI) frameworks to provide transparent insights into model decisions. Development of interpretable DL models that align with clinician workflows and decision-making processes.
4. **Optimizing Real-Time Applications**: Advancing edge computing and mobile platform compatibility for real-time diagnostic tools like YOLOv8.Reducing computational costs without compromising model performance.
5. **Improving Segmentation Techniques**: Refining hybrid approaches like DBN-DNN for improved boundary detection and accuracy in pathological liver cases. Investigating novel architectures such as transformer-based models for segmentation tasks.
6. **Addressing Model Bias**: Ensuring datasets are representative of diverse populations to minimize biases in predictions. Incorporating fairness-aware ML algorithms to ensure equitable diagnostic outcomes.

By addressing these areas, ML and DL technologies can further revolutionize liver disease diagnostics, paving the way for non-invasive, scalable, and highly accurate solutions that enhance patient outcomes and clinical workflows.

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IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⋇ Peer-reviewed & Refereed journal ⋇ Vol. 14, Issue 6, June 2025

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