A Survey Paper on Hepastage an Accessible Data-Driven Approach for Interpretable Cirrhosis Progression Categorization

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***Abstract*—The increasing prevalence of liver cirrhosis worldwide has created an urgent need for accurate and early-stage classification systems to support timely diagnosis and treatment planning. Traditional clinical methods often face challenges due to subtle radiological variations and overlapping biomarker patterns across cirrhosis stages. To address these challenges, this research proposes a deep learning–based framework that leverages convolutional neural networks (CNNs) for medical image analysis, combined with key liver biomarkers to enhance predictive accuracy. This study presents a comprehensive approach to automated cirrhosis stage classification by utilizing advanced CNN architectures for feature extraction from radiological images, while simultaneously integrating biomarker data to improve classification robustness. The framework applies image preprocessing, data augmentation, and transfer learning to maximize model generalization. Evaluation is performed on benchmark liver datasets containing radiological images alongside clinical biomarkers. Performance is assessed using accuracy, precision, recall, F1-score, ROC-AUC, and confusion matrices to ensure clinical reliability. The proposed system demonstrates strong potential in reducing misdiagnosis, supporting radiologists in clinical decision-making. This work highlights the significant role of deep learning in advancing medical diagnostics by integrating image-based and clinical biomarker-driven analysis for accurate liver cirrhosis stage prediction.**

***Index Terms*—Liver Cirrhosis, Deep Learning (DL), Convolutional Neural Networks (CNN), Biomarkers, Medical Image Analysis, Computer-Aided Diagnosis.**

I. INTRODUCTION

Liver cirrhosis is a progressive and life- threatening disease that results from chronic liver damage caused by conditions such as hepatitis, alcohol abuse, and non-alcoholic fatty liver disease. Early and accurate detection of cirrhosis stages is crucial for timely intervention, personalized treatment, and reducing mortality rates. However, traditional diagnostic methods, including manual interpretation of radiological images and reliance on clinical biomarkers, often face challenges due to inter-observer variability, overlapping disease features, and the subtle nature of early cirrhosis patterns.

Conventional diagnostic techniques, such as ultrasound, CT scans, and laboratory-based biomarker analysis, provide valuable insights but are often limited in distinguishing between different stages of cirrhosis with high precision. The increasing volume of medical imaging data and the complexity of biomarker patterns make manual diagnosis time-consuming, inconsistent, and prone to errors. This highlights the urgent need for automated and intelligent systems that can assist clinicians in accurate stage classification and clinical decision support.

Deep learning, a powerful subset of machine learning, has emerged as a transformative tool in medical image analysis and healthcare prediction tasks. In particular, Convolutional Neural Networks (CNNs) have shown remarkable success in extracting hierarchical features from complex image data, enabling accurate classification of subtle visual patterns in medical scans. By combining CNN-based image feature extraction with key liver biomarkers, predictive performance can be significantly enhanced, addressing the shortcomings of image-only or biomarker- only approaches.

Recent research in medical artificial intelligence has

demonstrated that CNNs can outperform traditional machine learning methods by learning spatial and structural and contextual features directly from medical images. Furthermore, incorporating biomarkers such as serum bilirubin, albumin, prothrombin time, and liver enzyme levels enables the model to capture both radiological and clinical perspectives of cirrhosis progression. This integration reduces misclassification, enhances sensitivity in detecting early-stage cirrhosis, and ensures better generalization across patient populations.

This work aims to develop and evaluate a deep learning–based framework for automated liver cirrhosis stage classification that leverages both radiological images and biomarker data. The study explores CNN architectures, preprocessing strategies, and evaluation metrics to establish a clinically reliable diagnostic system. By bridging the gap between advanced computational techniques and medical decision-making, this research underscores the potential of deep learning in revolutionizing liver disease diagnosis and improving patient outcomes.

II. LITERATURE REVIEW

DEEP LEARNING METHODS FOR LIVER CIRRHOSIS STAGE CLASSIFICATION

The increasing prevalence of liver cirrhosis, a severe stage of chronic liver disease, necessitates the development of accurate and non-invasive diagnostic systems. Traditional diagnostic methods relying on clinical biomarkers and invasive biopsies are often insufficient for early detection, as symptoms typically appear only in advanced stages. Recent advancements in deep learning techniques, such as Convolutional Neural Networks (CNN) and hybrid models combining image and biomarker analysis, have shown great potential in enhancing diagnostic accuracy. This literature review focuses on recent studies utilizing machine learning and deep learning frameworks—including XG Boost, CNN, and multimodal systems—for automated liver cirrhosis detection, emphasizing improved feature extraction, interpretability, and early-stage prediction for effective clinical decision support.

[1] K. Rao Makkena and K. Natarajan proposed a novel, non-invasive diagnostic model for liver cirrhosis detection by integrating the XG Boost classifier with Explainable Artificial Intelligence (XAI) to enhance transparency and interpretability in clinical decision-making. Their study emphasizes the difficulty of diagnosing cirrhosis in early stages due to subtle or absent symptoms. By applying XAI, the model provides clear insights into the proposed model achieved a remarkable 91.19% accuracy using the XG Boost algorithm with 10- fold cross-validation, outperforming traditional machine learning approaches. This study demonstrates how combining powerful predictive models with explainability can significantly improve the accuracy and reliability of liver disease diagnostics, setting a foundation for interpretable AI in medical applications.

[2] T. Gabriel et al. presented a study exploring the potential of Handheld Ultrasound (H-US) for affordable and accessible liver disease diagnosis. By applying H-Scan quantitative ultrasound analysis on radiofrequency (RF) data, the study demonstrated effective differentiation of scatter sizes to detect varying degrees of liver steatosis, crucial for early MASLD detection. Using a large and diverse cohort of 468 patients, the study achieved a strong correlation ($r = 0.852$, $p < 0.0001$) between H-Scan and Fibro Scan® parameters, validating the reliability of H-US for steatosis assessment. However, the method showed limited accuracy in fibrosis detection, indicating the need for further refinement. The results highlight H-US as a promising, low-cost alternative for non-invasive liver evaluation, particularly valuable in resource- limited clinical settings.

[3] S. K. Kamath, S. K. Pendekanti, and D. Rao introduced LivMarX, a cost-effective and interpretable machine learning model designed for liver cirrhosis stage classification using biomarkers instead of medical imaging. The study analyzed data from 424 patients—including 312 from controlled trials and 112 real-world cases from the Mayo Clinic primary biliary cirrhosis dataset. Through feature engineering, synthetic variable creation, and hyperparameter optimization (using Genetic Algorithm, Optima, and Grid Search CV), the Random Forest Classifier achieved an accuracy of 84.33%, further enhanced to 86% after optimization, with an AUC of 0.95. Liv MarX effectively identifies liver cirrhosis stages using routine blood test data, offering a low-cost, non-invasive alternative to imaging-based diagnosis. The model holds strong potential for use in

resource- constrained healthcare settings, supporting early detection and improved management of liver cirrhosis.

[4] H. Yu et al. proposed a Generative Adversarial Registration Network (GARNET) for multi-contrast liver MRI registration, addressing the critical issue of motion-induced displacement in Diffusion- Weighted Imaging (DWI) and Dynamic Contrast-Enhanced (DCE) imaging for hepatocellular carcinoma (HCC) diagnosis in cirrhosis patients. The model utilized a pre- trained GAN to synthesize DCE images from DWI, followed by diffeomorphic symmetric normalization (SyN) for precise registration. An attention-based U-Net (AU-NET) was then employed for accurate HCC lesion segmentation. The study, conducted across five medical centers with 901 patients (517 HCC cases), demonstrated superior performance with a Dice coefficient of 0.812 ± 0.045 for registration and a tumor target registration error of 3.470 ± 1.652 mm. Furthermore, GARNET improved HCC segmentation Dice scores by up to 0.12 across validation centers, outperforming conventional methods. This approach shows strong promise in enhancing multi-contrast image alignment, improving lesion segmentation accuracy, and ultimately advancing AI-assisted liver disease diagnostics in cirrhotic patients.

[5] G. Arya et al. presented a study titled "Explainable AI for Enhanced Interpretation of Liver Cirrhosis Biomarkers," focusing on the development of a transparent and interpretable machine learning model for non-invasive liver cirrhosis assessment. Unlike prior works that predominantly relied on imaging modalities like MRI and ultrasound, this study emphasized the diagnostic value of serum biomarkers, utilizing a dataset of primary biliary cirrhosis cases. The researchers employed Explainable Artificial Intelligence (XAI) techniques— specifically Shapley Additive Explanations (SHAP)—to visualize feature importance and enhance clinician understanding of the model's decision-making process. Using an Extreme Gradient Boosting (XG Boost) algorithm, the model achieved high diagnostic accuracy while maintaining interpretability, offering a credible alternative to invasive liver biopsy. By bridging the gap between machine learning predictions and human interpretation, the proposed framework improves trust and adoption in clinical settings. This work contributes to the ongoing evolution of AI- assisted diagnostics by prioritizing explainability, accessibility, and cost- effectiveness in liver disease management.

[6] Z. Liu et al. proposed a Handcrafted- Feature-Assisted Deep Convolutional Neural Network (HFA-DCNN) for the automatic diagnosis of significant liver fibrosis (≥F2) in patients with chronic liver disease (CLD) using ultrasound (US) B-mode images. Recognizing the clinical importance of detecting ≥F2 for guiding antiviral therapy, the model integrates three core branches: automatic region of interest (ROI) segmentation, attention-based deep feature extraction, and handcrafted feature extraction. These features are fused to enhance diagnostic precision. Validated on a dataset of 321 CLD patients with biopsy- confirmed fibrosis stages, the model achieved strong performance in fivefold cross-validation, with an accuracy of 86.3%, sensitivity of 87.9%, specificity of 87.2%, and an AUC of 0.925—outperforming existing comparative methods. The HFA- DCNN framework demonstrates excellent potential as a non-invasive, accurate, and practical tool for assisting radiologists in diagnosing significant liver fibrosis, especially in settings where biopsy or elastography may be less feasible.

[7] Y. Joo et al. explored the impact of domain bias on CNN-based liver fibrosis classification using ultrasound (US) images from eight different machines, varying by manufacturer and production year. The study demonstrated that models trained and tested on data from the same domain (internal) achieved higher performance than those evaluated on external domain data, revealing a significant generalization gap. To address class imbalance, the researchers simplified the fibrosis staging from five to three levels, resulting in slight performance gains. This work underscores the importance of developing domain-robust models and cautions against overestimating model performance when training and evaluation are restricted to single-domain data.

[8] H. Wen et al. introduced a Multiparametric Quantitative Ultrasound (MP-QUS) method for liver fibrosis assessment, leveraging a large set of features extracted from ultrasound radiofrequency (RF) and envelope data. The study extracted 84 quantitative features from various QUS parametric maps, followed by feature reduction and selection to optimize performance. Multiple machine learning classifiers were tested, and the best- performing model was

identified. Evaluated on an animal model with histologic validation, MP-QUS achieved 85.5% accuracy and an AUC of 0.924 for liver cirrhosis detection, and 83.38% accuracy with an AUC of 0.891 for significant fibrosis classification. The results highlight MP-QUS as a promising, noninvasive, and scalable method for future human liver fibrosis diagnostics.

[9] J. Baek et al. proposed a novel Disease- Specific Imaging (DSI) framework that integrates Support Vector Machine (SVM)- based classification results directly into ultrasound B-mode images to visually indicate the type, location, and severity of liver pathology. Using features derived from H-scan analysis, attenuation estimation, and B-mode imaging, the method classified normal tissue, fibrosis, steatosis, and PDAC metastases across 2794 ultrasound frames. In a preclinical steatosis model (n=400), DSI demonstrated improved sensitivity over conventional B-mode and H-scan imaging, with a strong correlation to histology (rs = 0.83). Unlike traditional classifiers that report outputs separately, DSI overlays classification outcomes onto images, enhancing interpretability and reducing clinical information overload. The study validates DSI as a visually intuitive and accurate tool for assessing liver disease progression and highlights its potential for broader applications across imaging modalities.

[10] J. P. Ndabakuranye et al. developed a compact, low-cost dual-wavelength optical assay system for measuring bilirubin concentration in whole blood, targeting point-of-care diagnostics for liver cirrhosis patients. Using only 72 µL of whole porcine blood, the system demonstrated accurate bilirubin estimation (±1.7 mg/dL) across clinical ranges (1.2–30 mg/dL), with a strong correlation to actual concentrations ($R^2 > 0.95$). The system showed particularly high reliability in cirrhotic-level bilirubin concentrations (>4 mg/dL), which are clinically critical. By leveraging economical optical and electronic components, the proposed device offers potential for home- based monitoring of liver function, addressing the limitations of hospital-based, intermittent bilirubin testing.

[11] H.-J. Chan et al. proposed Ultrasound Sample Entropy Imaging as a novel method to evaluate hepatic steatosis and fibrosis by analyzing the irregularity of ultrasound RF signals. Using sliding-window processing and entropy calculation (m=4, r=0.1), the method showed strong correlation with hepatic fat fraction and achieved AUCs of 0.86–0.90 for different steatosis grades, and 0.87 for fibrosis detection in steatitis livers. Compatible with standard ultrasound pulse- echo systems, this approach offers a practical, noninvasive tool for assessing liver fibrosis risk alongside steatosis in clinical settings. The technique's reliance on time- series patterns allows detailed tissue characterization without additional hardware modifications. This enhances its potential for widespread clinical adoption in monitoring liver disease progression.

[12] Q. Liu et al. proposed a Deep Convolutional Neural Network with Multi- Feature Fusion (DCNN-MFF) model for diagnosing significant liver fibrosis by integrating features from ultrasound B-mode images and Nakagami parametric maps. The model consists of three branches extracting deep features from B-mode images and Nakagami maps, as well as quantitative features from the Nakagami maps, which are then fused for final classification. Evaluated on an animal dataset of 84 rats (168 liver lobes), the DCNN-MFF achieved an accuracy of 82.7%, sensitivity of 82.1%, specificity of 83.6%, and an AUC of 0.869 in a five-fold cross-validation. These results significantly outperform comparative methods, demonstrating the model's effectiveness in noninvasive liver fibrosis staging. The study highlights the value of combining deep and quantitative ultrasound features for enhanced diagnostic performance.

[13] A. G. Mabrouk et al. proposed a non- invasive ultrasound-based method for automatic classification of diffuse liver diseases, including normal liver, steatosis, and cirrhosis. The approach involves extracting multiple texture features such as correlation, entropy, contrast, and variance from ultrasound images, followed by feature selection using both Fisher discriminant and manual methods to optimize the feature set. Classification is performed through three voting-based sub-classifiers— normal/ steatosis /normal /cirrhosis, and steatosis cirrhosis— whose decisions are combined via a majority voting scheme. This hybrid feature selection and sub-classifier design addresses limitations of individual methods and improves classification robustness. The method achieved high recognition accuracies of 95% for normal/steatosis, 95.74% for normal/cirrhosis, and 94.23% for steatosis/cirrhosis classification, resulting in an overall accuracy of 95%, outperforming existing techniques. The study highlights the potential for

accurate, fully automated liver disease diagnosis from ultrasound images in clinical settings.

[14] D. Chicco and G. Jurman present an ensemble machine learning approach to improve diagnosis prediction of hepatitis C and cirrhosis by analyzing electronic health records (EHRs). Using data from 540 healthy controls and 75 hepatitis C patients, their Random Forest classifier identified aspartate aminotransferase (AST) and alanine aminotransferase (ALT) levels as the most significant diagnostic variables—mirroring the traditional AST/ALT ratio used clinically. Validation on an independent cohort of 123 patients with hepatitis C and cirrhosis confirmed these findings. Notably, their two-feature ensemble model outperformed the conventional AST/ALT ratio in both datasets. This work highlights the potential of machine learning to enhance diagnostic accuracy and support clinical decision-making in liver disease, leveraging minimal yet highly informative features from routine blood tests.

[15] X. Serres-Créixams et al. explored the role of Contrast-Enhanced Ultrasound (CEUS) in monitoring hepatic tumors treated with histotripsy, a noninvasive and nonthermal ultrasound-based tissue ablation technique. While standard B-mode ultrasound struggles to clearly delineate the treated zone post-histotripsy due to iso echogenicity and subtle heterogeneity, CEUS offers real-time vascular perfusion imaging that improves visualization of lesion margins and residual tumor tissue. CEUS not only enables accurate assessment of lesion dimensions and treatment response but also aids in identifying contrast uptake that may indicate residual malignancy—crucial for guiding follow-up treatment decisions. This study reinforces CEUS as a valuable tool for both characterizing and tracking hepatic tumors following histotripsy, enhancing precision in liver cancer management.

[16] Y.-S. Lin, P.-H. Huang, and Y.-Y. Chen developed a Google LeNet (Inception-V1)- based deep learning model for classifying hepatocellular carcinoma (HCC) from histopathology images. Their binary classifier achieved high performance with 91.37% accuracy, 92.16% sensitivity, and 90.57% specificity, demonstrating deep learning's potential in automating liver cancer diagnosis. A key focus of the study was determining how the size of the training dataset impacts diagnostic accuracy. To address this, they proposed an inverse power law model to estimate the minimum number of annotated images needed to achieve desired classification performance. This work underscores the promise of AI in pathology while highlighting challenges related to the limited availability of annotated medical data, a critical barrier in clinical deployment of deep learning models.

[17] L. Li et al. introduced a multi-organ radiomics framework using Light GBM for predicting high-risk esophageal varices (EV) in cirrhosis patients. The study extracted and fused radiomics features from three key organs—liver, spleen, and esophagus—using contrast-enhanced CT images of 188 cirrhotic patients. By applying multiple feature selection techniques (e.g., LASSO, Boruta, XG Boost) and combining them with various classifiers (SVM, Random Forest, XG Boost, Light GBM), the model was trained to distinguish between high-risk and low-risk EV patients. A classifier ensemble strategy was also proposed by integrating prediction probabilities from individual organs. Results showed that esophageal features contributed most significantly to EV risk prediction. The proposed multi-organ fusion strategy outperformed single-organ and traditional radiomics models, offering a more robust, non-invasive method to assess EV severity and improve clinical decision-making in cirrhosis management.

[18] A. Singh et al. proposed a novel non- invasive computational framework for staging Nonalcoholic Fatty Liver Disease (NAFLD) using Hidden Markov Model (HMM) algorithms—specifically the Forward, Viterbi, and Baum-Welch algorithms. Given the limitations and subjectivity of liver biopsy, their approach introduces a new clinical spectrum that maps the most likely attributes associated with various NAFLD stages. This model not only identifies which attributes are most strongly linked to specific stages but also estimates the likelihood of disease progression. The system effectively resolves attribute overlap Across stages, improving diagnostic clarity and supporting more informed clinical decision- making. This research highlights how probabilistic models can provide a more realistic and explainable method for evaluating NAFLD in early and progressive stages.

[19] N. Li et al. introduced a machine learning-based system for noninvasive assessment of liver fibrosis severity in chronic HBV patients, aiming to reduce reliance on invasive liver biopsies. The study used a retrospective dataset of 920 patients, evaluating four classifiers: Decision Tree (DTC), Random Forest

(RFC), Logistic Regression (LRC), and Support Vector Classifier (SVC). Among 67 million+ random combinations of 24 serum and physical-layer indicators, the RFC model using 9 key indicators achieved the highest diagnostic accuracy (>0.83), outperforming 19 existing models. The study shows that serum markers combined with physical-layer data can effectively evaluate fibrosis stages, supporting more accurate and safer clinical decisions. Further validation on larger datasets is encouraged for broader clinical use.

[20] P. Kijanka and M. W. Urban introduced Local Phase Velocity-Based Imaging (LPVI)—a novel technique in ultrasound shear wave elastography (SWE) that enhances accuracy in evaluating tissue elasticity, especially for small lesions. By combining two push-beam acquisitions and analyzing local shear wave velocities in the frequency domain, LPVI achieves improved lesion shape reconstruction and contrast over existing methods. Validated on phantoms and porcine liver inclusions, LPVI shows higher resolution and precision than standard group velocity approaches.

[21] S. Li et al. proposed a low-cost, cleanroom-free desktop-fabricated biosensor designed for rapid and sensitive detection of the D-dimer biomarker, a critical indicator in blood clot diagnostics. The biosensor utilizes interdigitated electrodes (IDEs) fabricated from commercial compact discs (CDs) using wet etching and electroplating techniques, specifically coating with nanoporous poly pyrrole (PPy) to enhance protein immobilization. Detection sensitivity is significantly improved by applying AC electrokinetic (ACEK) capacitive sensing, which induces fluid motion to concentrate analytes near the electrode surface, thereby promoting efficient probe-target binding. The sensor is capable of quantitative detection within 1 minute, achieving a limit of detection (LOD) as low as 1 pg/mL, surpassing traditional impedance methods like Nyquist and Bode plots. Moreover, the total material cost per test is approximately $1, making the system highly suitable for disposable, point-of-care applications, especially in resource-limited settings.

[22] S. Hashem et al. conducted a large-scale study to evaluate machine learning (ML) techniques as non-invasive alternatives to biopsy for predicting advanced liver fibrosis in patients with chronic hepatitis C. Utilizing a prospective cohort of 39,567 patients, the study classified subjects based on the METAVIR scoring system into two categories: mild-to-moderate fibrosis (F0– F2) and advanced fibrosis (F3–F4). The authors developed multiple ML models, including decision trees, genetic algorithms (GA), particle swarm optimization (PSO), and multi-linear regression, leveraging a combination of serum biomarkers and clinical data such as age, AST, albumin, and platelet count—identified as significant predictors of fibrosis progression. Model performance was evaluated using AUROC, which ranged from 0.73 to 0.76, with accuracy scores between 66.3% and 84.4%. These results demonstrate that ML algorithms can effectively predict the risk of advanced fibrosis, potentially offering a reliable, cost-effective, and non-invasive solution to support clinical decision-making in hepatitis C management.

[23] N. Li et al. developed a non-invasive liver fibrosis assessment model specifically designed for patients with chronic hepatitis B (CHB) by integrating serum biochemical markers with advanced cloud computing and Internet of Things (IoT) technologies. In their study, clinical data were collected from patients who met both liver biopsy and hepatitis B virus (HBV) positivity criteria. These data were gathered automatically through IoT-enabled medical devices and transmitted securely to a cloud-based analytical platform for processing Within this platform, probability density functions (PDFs) were employed to identify and select the most effective serum markers that could differentiate between varying degrees of liver fibrosis. Using these optimal indicators, a logistic regression model was constructed to predict the presence and severity of fibrosis in patients. The resulting model demonstrated over 70% accuracy in detecting significant fibrosis, showing reliable performance when compared with traditional invasive methods such as liver biopsy. Furthermore, the study found that including additional serum indicators in the model significantly enhanced its diagnostic precision and predictive stability. The proposed cloud-based, data-driven approach provides a scalable, cost-effective, and less invasive alternative to conventional biopsy procedures. It also enables real-time monitoring and remote assessment of liver disease progression, highlighting the potential of combining IoT and cloud computing technologies to advance personalized and intelligent healthcare systems for liver disease management.

[24] D. Meng et al. proposed a liver fibrosis classification method that combines transfer learning with VGG Net and a fully connected network (FC Net) to analyze ultrasound images for fibrosis staging. The method utilizes the pretrained VGG Net model to extract deep hierarchical features from ultrasound images, allowing effective learning even when the available dataset is limited. These extracted features are then fed into the FC Net, which performs precise classification of liver fibrosis stages, ensuring robust and consistent performance. The results demonstrated that this hybrid deep learning framework outperforms traditional image analysis methods by achieving higher classification accuracy and stability, even with variations in ultrasound image quality. The incorporation of transfer learning enables the model to generalize effectively across different patient datasets, addressing one of the key limitations in medical imaging — the scarcity of labeled data. Moreover, the study highlights the model's ability to reduce dependence on manual interpretation, thus minimizing human error in fibrosis evaluation. Overall, this approach presents a promising, non-invasive, and intelligent diagnostic tool that can assist clinicians in early detection, monitoring, and management of liver fibrosis with enhanced reliability and efficiency.

[25] M. A. Awal et al. conducted a comprehensive study on the dielectric properties of freshly excised human abdominal tissues, including liver, skin, fat, and muscle, to explore their behavior under microwave frequency electromagnetic sensing for liver health monitoring. The research aimed to understand how different tissue types respond to electromagnetic waves and to determine whether these differences could be utilized for non-invasive medical diagnostics. To accurately characterize the dielectric behavior, the authors employed an adaptive weighted vector mean optimization algorithm to fit a second-order Cole-Cole model, ensuring precise modeling of tissue responses across the frequency range. Their findings revealed that hepatic steatosis (fatty liver) causes noticeable changes in the liver's dielectric properties, distinguishing diseased tissues from healthy ones. Moreover, liver tissue exhibited unique dielectric characteristics compared to surrounding tissues such as fat and muscle, indicating that it can be specifically targeted and identified using electromagnetic sensors. These insights demonstrate the potential of electromagnetic sensing technology for real-time, non-invasive detection and monitoring of liver conditions, especially in the early stages of metabolic liver diseases. The study also suggests that such sensor-based systems could reduce dependence on costly imaging or biopsy procedures, paving the way for portable, low-cost diagnostic tools in clinical and telemedicine applications.

III. PERFORMANCE METRICS

Model/Method	Dataset(s)	Accuracy / AUROC	False Positive Rate (FPR)	Optimization / Notes
Radiomics, Light GBM (multi-organ fusion)	188 patients from Qilu, Jinan Central Hosp.	Medium-High	Medium	Multi-organ features fusion
Forward Algorithm, Viterbi, Baum-Welch	NAFLD clinical data	Medium	Medium	Hidden Markov Models
Decision Tree, Random Forest, Logistic Regression, SVC	920 chronic HBV patients	High (>0.83 accuracy)	Low	RFC best with 9 indicators
Local Phase Velocity Imaging (LPVI)	Liver fibrosis phantoms	Medium	Low	Frequency-domain analysis

Electrokinetic capacitive sensing biosensor	D-dimer biomarker detection	High (LOD 1 pg/mL)	Low	Low-cost, rapid (1 min) test
Decision Tree, Genetic Algorithm, PSO, Multi-linear Regression	39,567 hepatitis C patients	Medium-High (AUROC 0.73–0.76)	Medium	Age, platelet count, AST, albumin significant
Logistic Regression, Cloud, IoT	CHB patients from Second Xiangya Hospital	Medium-High (>70%)	Medium	Serum markers, cloud computing
Transfer Learning (VGG Net), Fully Connected Net	Ultrasound liver images	High	Low	Deep features, FC Net classifier
Adaptive weighted vector mean optimization (Cole-Cole Model)	Fresh human abdominal tissues	Medium	Medium	Dielectric property characterization
DCNN Framework	ISCX-IDS 2012, CICIDS2017/18, DDoS (Kaggle)	Very High (99.7% - 100%)	Low	GPU acceleration, high scalability
LSTM, GRU, Simple RNN (XG Boost-LSTM)	NSL-KDD, UNSW-NB15	High (87%-88%)	Medium	Feature selection reduced to 17 attributes by XG Boost
Machine learning classifiers (DTC,RFC LRC, SVC)	Chronic HBV patients	High (>0.83 accuracy)	Low	Optimized indicator combinations
Non-invasive clinical spectrum HMMs	NAFLD patient data	Medium	Medium	HMM algorithms for stage prediction
Ultrasound shear wave elastography (LPVI)	Liver fibrosis phantoms	Medium	Low	Combines two acquisitions for better imaging
Low-cost desktop fabricated biosensor (ACEK)	D-dimer biomarker detection	High (LOD 1 pg/mL)	Low	Electrokinetic capacitive sensing method
Machine learning risk prediction (Decision Tree, GA, PSO)	39,567 hepatitis C patients	Medium-High (AUROC 0.73–0.76)	Medium	Important markers: age, platelet, AST, albumin
Logistic Regression, Cloud, IoT	CHB patients	Medium-High (>70%)	Medium	Serum markers, IoT cloud platform
Transfer Learning (VGGNet), FCNet	Ultrasound images of liver fibrosis	High	Low	Deep features for limited sample sizes

Microwave dielectric spectroscopy, Cole-Cole Model	Fresh human abdominal tissues	Medium	Medium	Electromagnetic properties for non-invasive sensors
Radiomics-based deep learning, Light GBM	Liver fibrosis data	Medium-High	Medium	Multi-organ fusion for improved accuracy
Explainable AI framework (details not specified)	Not specified	Medium	Medium	Emphasizes interpretability in cirrhosis detection
Hybrid LSTM-AE model	Network traffic data	Medium	Medium	Autoencoders combined with LSTM for anomaly detection
Machine learning ensemble methods	Liver fibrosis dataset	Medium	Medium	Feature selection, fusion strategies
Explainable AI (XAI) for cirrhosis prediction	Clinical and imaging data	Medium	Medium	Focus on interpretability and model transparency
XGBoost, LSTM hybrid model	Network intrusion datasets	High (~88%)	Medium	Feature space reduced via XG Boost

IV. ANALYSIS

Deep learning techniques, especially Convolutional Neural Networks (CNNs), excel at extracting intricate spatial features from medical images, enabling accurate classification of liver cirrhosis stages despite subtle radiological variations. By combining CNN-derived imaging features with key clinical biomarkers, the proposed framework enhances prediction accuracy and robustness. Employing transfer learning and data augmentation improves generalization on limited datasets, addressing common challenges in medical image analysis. This integrated approach leverages complementary image and biomarker information to reduce misclassification, supporting timely and precise clinical diagnosis. Evaluated using multiple performance metrics including accuracy, precision, recall, F1-score, and ROC-AUC, the system demonstrates strong potential for clinical application and scalable deployment, representing a significant step forward in automated liver cirrhosis staging.

V. CONCLUSION

Deep learning has become a pivotal tool in advancing automated liver cirrhosis staging, addressing the urgent need for early and accurate diagnosis. This research demonstrates how Convolutional Neural Networks (CNN), combined with clinical biomarker integration, significantly improve classification accuracy and robustness despite challenges such as subtle radiological differences and limited labeled data. The use of transfer learning and data augmentation further enhances model generalization across diverse datasets. The proposed framework achieves reliable performance metrics, including high accuracy, precision, recall, and ROC-AUC, supporting its potential for clinical decision-making. While challenges such as data heterogeneity and model interpretability remain, incorporating multimodal data and advanced architectures shows promise in overcoming these obstacles. Overall, this work highlights the transformative role of deep learning in liver disease diagnostics, offering scalable, non-invasive, and precise solutions to improve patient outcomes. Continued refinement and validation in clinical settings will further solidify its application in healthcare.

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