



A Comprehensive Survey of Deep Learning Applications for Liver Disease Diagnosis and Treatment

Swapna M^{1*} and Sujatha B²

¹Research Scholar, Department of Computer Science and Engineering, Osmania University, India

²Assistant Professor, Department of Computer Science and Engineering, Osmania University, India

Review Article

Volume 10 Issue 2

Received Date: October 02, 2026

Published Date: October 09, 2026

DOI: 10.23880/ijst-16000235

***Corresponding author:** Swapna M, Research Scholar, Department of Computer Science and Engineering, Osmania University, Hyderabad-500007, Telangana, India, Email: maragoniswapna761@gmail.com

Abstract

Liver illness represents a critical health issue worldwide, impacting countless individuals and leading to significant health complications and deaths. Timely and precise identification is essential for proper treatment and enhanced patient results. This research investigates the role of artificial intelligence (AI) in transforming the processes of diagnosing, forecasting, and treating liver disorders. We analyse the shortcomings of conventional diagnostic approaches, including blood analyses and imaging methods, and emphasize how AI technologies can address these obstacles by examining extensive collections of varied data to detect subtle trends. The document addresses the necessity for AI-driven assessment to improve early diagnosis, customize treatment strategies, and anticipate disease advancement. An in-depth review of existing literature is provided, outlining different AI and machine learning strategies used for categorizing fatty liver ultrasound images, diagnosing liver ailments, and delineating liver tumours from medical imaging. We pinpoint crucial research deficiencies, such as the requirement for enhanced accuracy and clarity in models. The driving force behind this study is to utilize AI to tackle the intricate issues associated with fatty liver, cirrhosis, and liver neoplasms. The challenge is framed as the necessity to use AI to boost diagnostic precision and productivity. The goals of the survey include developing robust AI systems for image classification, disease identification, and tumour delineation. The results indicate that ongoing investigation and partnership are crucial for effectively incorporating AI into medical practices, ultimately resulting in improved patient outcomes and more effective healthcare services.

Keywords: Liver Disease; Artificial Intelligence; Machine Learning; Deep Learning; Fatty Liver; Liver Cirrhosis; Liver Cancer; Hepatocellular Carcinoma

Abbreviations

AI: Artificial Intelligence; HCC: Hepatocellular Carcinoma; DALYs: Disability-adjusted Life Years; HBV: Hepatitis B Virus; HCV: Hepatitis C Virus; NAFLD: Non-alcoholic Fatty Liver Disease; NASH: Non-alcoholic Steatohepatitis;

AFLD: Alcoholic Fatty Liver Disease; HCC: Hepatocellular Carcinoma; ACM: Association for Computing Machinery; IEEE: Institute of Electrical and Electronics Engineers; PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses; ANN: Artificial Neural Network; LDA: Linear Discriminant Analysis; HD: Hausdorff Distance; DSC:

Dice Similarity Coefficient; VOE: Volume Overlap Error; RVD: Relative Volume Difference; FCN: Fully Convolutional Neural Network; GAN: Generative Adversarial Network; CT: Computed Tomography; WGD: Watershed Gaussian Based Deep Learning; GMM: Gaussian Mixture Model; DNN: Deep Neural Network; HEM: Hemangioma; HCC: Hepatocellular Carcinoma; MET: Metastatic Carcinoma; CNNs: Convolutional Neural Networks.

Introduction

Liver disorders include a variety of ailments that affect the liver's structure and functionality, resulting in considerable systemic implications. These ailments can range from mild, treatable issues to severe, potentially fatal conditions. Gaining insight into the complex nature of liver diseases is essential for enhancing detection, management, and preventative measures. The worldwide impact of liver disorders is significant and continues to grow. Liver-related illnesses are responsible for around two million deaths each year, making up nearly 4% of deaths globally, equating to one in every 25 fatalities [1]. A notable number of these deaths stem from complications associated with cirrhosis and hepatocellular carcinoma (HCC). Cirrhosis is the 11th most common cause of death worldwide and ranks 15th in terms of morbidity, contributing to 2.2% of worldwide fatalities and 1.5% of disability-adjusted life years (DALYs). In 2017, chronic liver disease (CLD) caused 1.32 million fatalities, with about two-thirds being men [2]. By 2019, the number of deaths linked to liver cirrhosis and other chronic liver issues had increased to around 1.47 million from 1.01 million in 1990 [3]. The rate of CLD cases has also risen sharply, with the incidence of liver cirrhosis and similar conditions increasing by over 60% from 1990 to 2019, resulting in more than 2.05 million cases. Despite this increase, age-standardized mortality rates have slightly decreased—from 24.43 to 18.00 per 100,000 individuals—indicating some advancements in clinical treatment and prevention [3].

As reported by the 2021 Global Burden of Disease Study, cirrhosis and other chronic liver conditions led to 1.425 million fatalities and 46.4 million DALYs. While the overall incidence is still on the rise, the minor drop in age-adjusted mortality and DALYs hints at steady improvements in handling the disease [4]. Traditionally, chronic viral hepatitis, particularly hepatitis B virus (HBV) and hepatitis C virus (HCV), has been the primary driver of CLD. In 2022, it was estimated that chronic HBV and HCV infections were responsible for approximately 1.3 million deaths, with around 3,500 people succumbing to these diseases daily. Globally, about 254 million individuals are affected by HBV, while approximately 50 million live with HCV [5]. Recently, non-alcoholic fatty liver disease (NAFLD) has emerged as a leading cause of liver issues, especially its advanced

form—non-alcoholic steatohepatitis (NASH). This increase corresponds with the rising global prevalence of obesity, type 2 diabetes, and metabolic syndrome. By 2019, NAFLD represented 59% of the existing CLD cases, whereas HBV and HCV accounted for 29% and 9%, respectively. Deaths related to NAFLD nearly increased by 77% from 1990 to 2019, even as the age-standardized mortality rate showed a slight decrease [6]. Liver cancer, often the final phase of chronic liver ailments, presents a growing public health issue. It is currently the sixth most prevalent cancer and the third leading cause of cancer-related deaths. The number of cases is expected to almost double from 870,000 in 2022 to 1.52 million by 2050. Significantly, around 60% of liver cancer cases arise from preventable risk factors, such as viral hepatitis, alcohol consumption, obesity, and NAFLD [7].

Due to the significant impact, death rates, and increasing prevalence of liver disorders—especially in areas with limited resources—prompt and precise diagnosis is essential for public health. Nevertheless, traditional diagnostic approaches like liver biopsies, imaging techniques, and blood tests face challenges such as being invasive, expensive, hard to access, and not very sensitive in the early stages of the disease. In addition, numerous liver conditions do not show symptoms until they have progressed significantly, resulting in late diagnoses and unfavourable medical results [8]. Liver diseases can be caused by various factors, including viral infections, alcohol abuse, obesity, metabolic disorders, genetic abnormalities, autoimmune diseases, drug-induced liver injury, and exposure to certain toxins [9]. Understanding the causes and risk factors associated with liver diseases is crucial for their prevention, early detection, and effective management. Here are some of the main causes and risk factors:

Viral Infections

Viral hepatitis is a significant cause of liver diseases. Hepatitis viruses, particularly hepatitis B virus (HBV) and hepatitis C virus (HCV), can cause acute or chronic liver inflammation. These viruses are primarily transmitted through contact with infected blood or bodily fluids, such as during unprotected sexual intercourse, sharing needles, or mother-to-child transmission during childbirth. Chronic hepatitis B or C infections can progress to liver cirrhosis, liver failure, or liver cancer.

Alcohol Abuse

Excessive and prolonged alcohol consumption can cause alcoholic liver disease. The liver is responsible for metabolizing alcohol, and excessive alcohol intake can lead to liver damage. Alcoholic liver disease encompasses a range of conditions, including fatty liver (accumulation of

fat in liver cells), alcoholic hepatitis (inflammation of the liver), and liver cirrhosis (scarring of liver tissue). The risk of developing alcoholic liver disease depends on the amount and duration of alcohol consumption.

Non-alcoholic Fatty Liver Disease (NAFLD)

Non-alcoholic fatty liver disease is characterized by the accumulation of fat in the liver cells of individuals who consume little or no alcohol. It is closely associated with obesity, insulin resistance, diabetes, dyslipidemia (abnormal lipid profile), and metabolic syndrome. The exact cause of NAFLD is not fully understood, but it is believed to be influenced by a combination of genetic, environmental, and lifestyle factors. NAFLD can progress to non-alcoholic steatohepatitis (NASH), a more severe form of liver inflammation that can lead to liver fibrosis, cirrhosis, and liver cancer.

Obesity and Metabolic Disorders

Obesity and metabolic disorders, such as diabetes and dyslipidemia, are significant risk factors for liver diseases. Excess body weight, particularly abdominal obesity, increases the likelihood of developing fatty liver disease. Obesity-related metabolic abnormalities, such as insulin resistance and elevated blood lipids, further contribute to liver inflammation and progression to more severe liver diseases.

Genetic Abnormalities: Certain genetic abnormalities can predispose individuals to liver diseases. Examples include hereditary hemochromatosis (excessive accumulation of iron in the liver), Wilson's disease (impaired copper metabolism), alpha-1 antitrypsin deficiency (a protein deficiency that affects liver function), and autoimmune hepatitis (immune system attacking liver cells). These genetic factors can increase the risk of developing liver diseases and may require specific management strategies.

Autoimmune Diseases: Autoimmune diseases occur when the immune system mistakenly attacks healthy cells and tissues. Autoimmune hepatitis is a condition in which the immune system targets liver cells, leading to inflammation and liver damage. Other autoimmune diseases, such as primary biliary cholangitis and primary sclerosing cholangitis, can also affect the liver and bile ducts, causing chronic inflammation and scarring.

Drug-Induced Liver Injury: Certain medications, herbal supplements, and recreational drugs can cause liver injury in some individuals. Drug-induced liver injury can result from direct toxicity to liver cells or an immune-mediated response. It is important to be cautious with medications

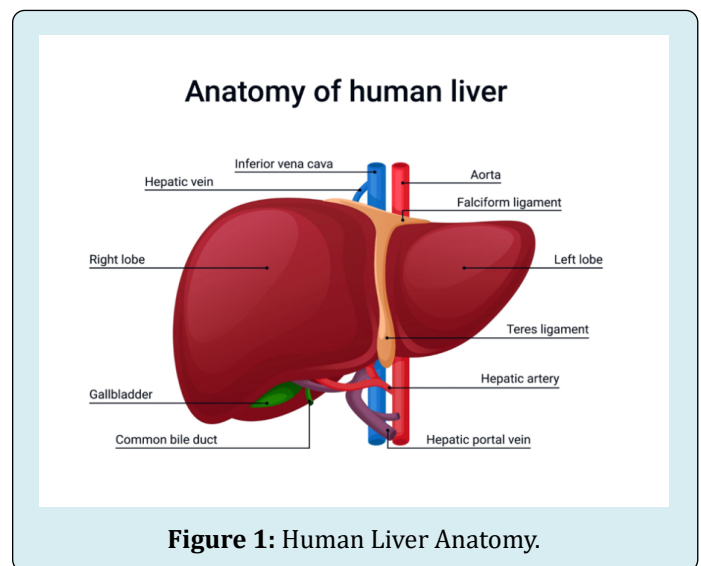
and seek medical advice to prevent drug-induced liver injury, particularly in individuals with pre-existing liver conditions or a history of drug sensitivity.

Environmental Toxins: Exposure to certain toxins and environmental pollutants can contribute to liver diseases. These include aflatoxins (toxins produced by molds on certain food products), industrial chemicals, pesticides, and heavy metals such as lead and arsenic. Occupational exposure to these toxins and contaminated drinking water sources can increase the risk of liver damage and the development of liver diseases.

Understanding these causes and risk factors can help in implementing preventive measures, early detection, and appropriate management strategies for liver diseases.

Liver anatomy

The liver is an essential organ located in the upper right side of the abdomen, beneath the diaphragm. It is the largest glandular organ in the human body and performs numerous vital functions. Understanding liver anatomy is crucial for comprehending its role and significance in maintaining overall health and well-being. Liver has a unique and intricate anatomical structure that enables it to carry out its functions efficiently. It is composed of several lobes, which are further divided into smaller lobules as shown in the (Figure 1).



Each lobule consists of hepatic cells called hepatocytes, arranged in a radial pattern around a central vein. These hepatocytes are the functional units of the liver and are responsible for its diverse metabolic activities. Liver receives a dual blood supply. Oxygen-rich blood enters the liver through the hepatic artery, while nutrient-rich blood from the digestive organs enters through the hepatic portal vein.

These blood vessels extensively branch throughout the liver, delivering nutrients, oxygen, and other substances for processing and metabolism by the hepatocytes. Liver is surrounded by a fibrous capsule called Glisson's capsule, which provides structural support. It is also associated with a network of bile ducts that collect and transport bile, a substance produced by the liver, to the gallbladder for storage and later release into the digestive system.

Importance of the Liver to the Body: The liver plays a vital role in maintaining overall bodily functions and is involved in numerous complex processes as shown in figure 2. Here are some key functions of the liver:

Metabolism: The liver metabolizes carbohydrates, proteins, and fats, playing a central role in energy production. It stores excess glucose in the form of glycogen and releases it when the body requires a quick energy boost. The liver also synthesizes important molecules, including cholesterol, lipoproteins, and blood-clotting factors.

Detoxification: One of the liver's primary functions is detoxification. It filters and removes toxins, drugs, metabolic waste products, and other harmful substances from the bloodstream. The hepatocytes in the liver break down these substances into less harmful forms and facilitate their elimination from the body.

Bile Production: The liver produces bile, a yellowish-green fluid that aids in the digestion and absorption of fats. Bile is stored and concentrated in the gallbladder and released into the small intestine when needed. Bile also helps eliminate waste products, including bilirubin (a by-product of red blood cell breakdown) and cholesterol.

Nutrient Storage: The liver serves as a storage site for various nutrients, vitamins, and minerals. It stores vitamins A, D, E, and K, as well as iron and copper. These stored nutrients are released into the bloodstream when the body requires them.

Immune Function: The liver plays a critical role in the immune system. It helps identify and remove pathogens, bacteria, and foreign particles from the bloodstream. Additionally, the liver is involved in producing immune factors and antibodies that contribute to the body's defence against infections.

Blood Clotting: The liver synthesizes several clotting factors, such as fibrinogen and prothrombin, which are essential for proper blood clotting. Dysfunction of the liver can impair clotting mechanisms and lead to bleeding disorders.

Drug Metabolism: The liver is responsible for metabolizing and breaking down medications, ensuring their effectiveness

and safety. It converts drugs into forms that can be easily eliminated from the body. The liver's importance to the body cannot be overstated. Its multifunctional roles are vital for maintaining overall health, metabolism, immune function, and detoxification processes. A healthy liver is essential for the proper functioning of various body systems and contributes significantly to overall well-being (Figure 2).

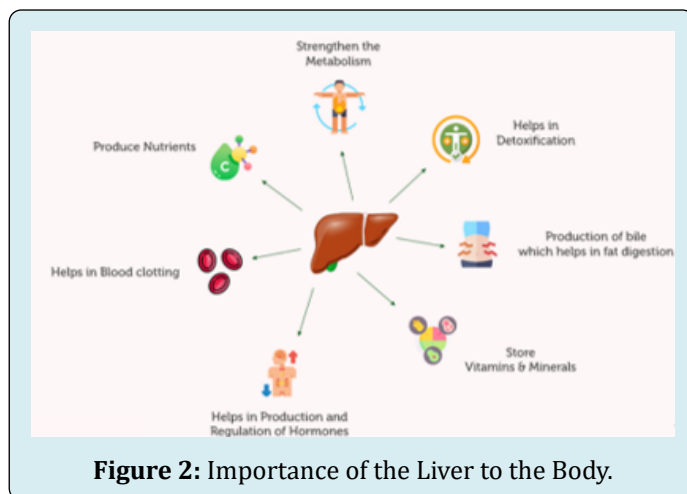


Figure 2: Importance of the Liver to the Body.

Most Common Liver Disease

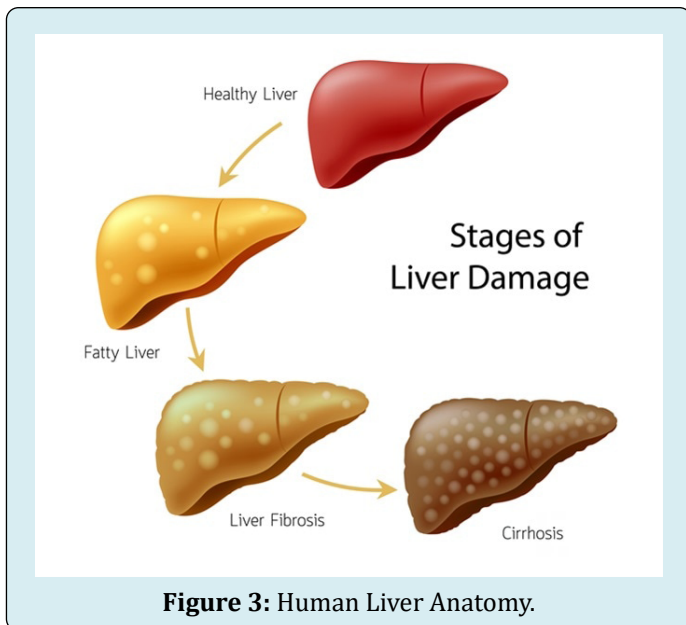
The most frequent liver diseases include fatty liver, liver cirrhosis, and liver cancer as shown in figure 3. Let's take a closer look at each of these conditions:

Fatty Liver Disease: Fatty liver disease is a prevalent liver condition characterized by the accumulation of excess fat in liver cells. There are two main types: alcoholic fatty liver disease (AFLD) and non-alcoholic fatty liver disease (NAFLD). AFLD is caused by excessive alcohol consumption, leading to fat deposition in the liver. NAFLD, on the other hand, is associated with metabolic factors such as obesity, insulin resistance, diabetes, and dyslipidaemia. NAFLD is now considered one of the most common liver diseases globally. If left untreated, fatty liver disease can progress to more severe conditions, such as non-alcoholic steatohepatitis (NASH), which involves inflammation and liver cell damage. NASH can further lead to liver fibrosis, cirrhosis, and an increased risk of liver cancer.

Liver Cirrhosis: Liver cirrhosis is the advanced stage of liver disease characterized by irreversible scarring and fibrosis of liver tissue. It can result from various underlying causes, including chronic viral hepatitis (especially hepatitis B and C), excessive alcohol consumption, NAFLD/NASH, autoimmune hepatitis, genetic disorders, and certain medications. As the liver tries to heal from ongoing inflammation and injury, scar tissue forms, disrupting the normal liver structure and function. In advanced cirrhosis, the liver becomes nodular

and may develop complications like portal hypertension (increased blood pressure in the portal vein), ascites (fluid accumulation in the abdomen), hepatic encephalopathy (brain dysfunction), and an increased risk of liver cancer.

Liver Cancer (Hepatocellular Carcinoma): Liver cancer, specifically hepatocellular carcinoma (HCC), is a primary malignancy that originates in the liver cells. It is the most common form of liver cancer and represents a significant global health burden. HCC often develops in individuals with underlying liver diseases such as chronic viral hepatitis, cirrhosis (regardless of its cause), NAFLD/NASH, and exposure to certain toxins like aflatoxins. The risk of liver cancer is higher in individuals with cirrhosis, as long-standing liver damage and inflammation can lead to genetic mutations and the development of cancerous cells (Figure 3).



Liver cancer is a highly aggressive cancer and often diagnosed at an advanced stage. Early detection and timely intervention are crucial for better treatment outcomes. It is important to note that these three liver diseases often have overlapping risk factors and can progress from one condition to another. For example, fatty liver disease can progress to NASH and subsequently to liver cirrhosis or liver cancer. The early identification, lifestyle modifications, appropriate medical management, and regular monitoring of these conditions are key to prevent or minimize their progression and associated complications.

Need for AI Based Liver Disease Analysis

Liver disease is a significant health concern worldwide, affecting millions of people and contributing to substantial

morbidity and mortality. Early and accurate detection of liver diseases is crucial for effective management and improved patient outcomes. In recent years, there has been a growing interest in utilizing Artificial Intelligence (AI) for liver disease analysis [2], offering new possibilities for enhanced diagnosis, prognosis, and treatment decisions. This essay explores the need for AI-based liver disease analysis and the potential benefits it can bring to the field of hepatology. Liver diseases encompass a wide range of conditions with diverse etiologies, symptoms, and outcomes. Detecting and diagnosing liver diseases can be challenging due to the complexity of liver function and the interplay of various factors. Traditional diagnostic methods, such as blood tests, imaging techniques (e.g., ultrasound, MRI), and liver biopsies, have limitations in terms of accuracy, invasiveness, and time-consuming analysis. This is where AI [3] can play a crucial role. AI algorithms have the ability to analyze large volumes of data, including patient medical records, laboratory results, imaging scans, and genetic information, to identify patterns and make predictions. By utilizing machine learning techniques, AI models can learn from these data sets and generate valuable insights to aid in liver disease diagnosis, risk stratification, and treatment planning [4].

One of the key advantages of AI-based liver disease analysis is its potential to improve early detection and diagnosis [5]. AI algorithms can process vast amounts of data, identifying subtle patterns and associations that may not be immediately apparent to human clinicians. This can help in detecting liver diseases at earlier stages when interventions and treatments are more effective. Additionally, AI-based analysis can enhance the accuracy of diagnosis, reducing the chances of misdiagnosis and unnecessary invasive procedures. Furthermore, AI can contribute to personalized medicine in liver disease management [6]. By analyzing patient-specific data, AI models can generate tailored treatment plans and prognostic predictions. This can assist healthcare providers in making more informed decisions regarding medication selection, dosages, and treatment strategies, ultimately leading to better patient outcomes and improved quality of life.

Another important aspect of AI-based liver disease analysis is its potential in predicting disease progression and assessing treatment response [7]. By continuously monitoring patient data and incorporating real-time information, AI models can provide dynamic predictions, enabling clinicians to intervene promptly and adjust treatment plans as needed. This proactive approach can help prevent disease exacerbation, reduce hospitalizations, and optimize resource utilization in healthcare systems. The integration of AI in liver disease analysis also holds promise for facilitating research and advancing scientific knowledge.

AI models can aid in identifying novel biomarkers, elucidating disease mechanisms, and uncovering hidden correlations within complex datasets. These findings can contribute to the development of innovative therapies, precision medicine approaches, and the overall understanding of liver diseases. However, it is important to acknowledge the challenges and considerations associated with AI-based liver disease analysis. Data privacy, security, and ethical concerns must be addressed to ensure the responsible use of patient data. Additionally, AI models should be validated, transparent, and continuously updated to ensure their reliability and accuracy.

The need for AI-based liver disease analysis stems from the complexity and impact of liver diseases on public health [8]. AI has the potential to revolutionize liver disease diagnosis, prognosis, and treatment by leveraging the power of data analysis and machine learning algorithms. By enhancing early detection, personalizing treatment plans, predicting disease progression, and advancing scientific knowledge, AI-based liver disease analysis can significantly improve patient outcomes, reduce healthcare costs, and contribute to the overall management of liver diseases. Continued research, collaboration between clinicians and data scientists, and the integration of AI in clinical practice will be essential to harness the full potential of AI in liver disease analysis.

Motivation

Liver diseases, including fatty liver, liver cirrhosis, and liver tumours, pose significant challenges to healthcare systems globally. Early and accurate detection of these diseases is critical for timely intervention and improved patient outcomes. With the rapid advancements in Artificial Intelligence (AI) and its potential to revolutionize healthcare, there is a compelling motivation to explore the application of AI models in liver disease analysis. This research aims to harness the power of AI to enhance the diagnosis, prognosis, and treatment decision-making processes for fatty liver, liver cirrhosis, and liver tumours.

Fatty liver disease, liver cirrhosis, and liver tumours represent major health concerns with significant morbidity and mortality rates. These conditions require sophisticated diagnostic tools and treatment strategies due to their complex etiology, heterogeneity, and varying disease progression. The utilization of AI models in liver disease analysis holds tremendous promise in addressing these challenges. By employing AI algorithms, patterns, correlations, and predictive insights can be extracted from diverse datasets encompassing clinical, imaging, genetic, and other relevant information. This approach can facilitate early disease detection, aid in risk stratification, and provide valuable information for personalized treatment planning.

The application of AI models in liver disease analysis can contribute to significant advancements in healthcare. It has the potential to enhance the accuracy and efficiency of liver disease diagnosis, enabling timely intervention and potentially preventing disease progression. AI algorithms can also assist in predicting disease outcomes, such as the progression from fatty liver to liver cirrhosis or the risk of liver tumour development. These predictions can aid healthcare professionals in making informed decisions regarding treatment options, surveillance strategies, and patient management.

Furthermore, AI-based liver disease analysis can promote the development of precision medicine approaches. By leveraging machine learning techniques, AI models can integrate multiple data sources, identify relevant biomarkers, and generate personalized treatment plans tailored to individual patient characteristics. This approach has the potential to optimize therapeutic interventions, improve patient outcomes, and reduce healthcare costs associated with trial-and-error approaches.

Problem Formulation

Traditional diagnostic methods have limitations in terms of accuracy, invasiveness, and time-consuming analysis. Therefore, there is a pressing need to explore the potential of Artificial Intelligence (AI) models in liver disease analysis to improve early detection, risk stratification, and personalized treatment planning. The accurate diagnosis of fatty liver, liver cirrhosis, and liver tumours is crucial for effective disease management. However, the existing diagnostic methods may lack accuracy or require invasive procedures. The problem to be addressed is how AI models can be utilized to improve the accuracy and efficiency of diagnosing these liver diseases, leveraging diverse datasets and advanced machine learning algorithms.

This research aims to explore the potential of AI models in liver disease analysis, specifically focusing on fatty liver, liver cirrhosis, and liver tumours. The objective is to develop accurate diagnostic tools, prognostic models, and personalized treatment planning algorithms that can improve patient outcomes, optimize healthcare resources, and enhance the overall management of liver diseases. The research aims to contribute to the development of advanced algorithms and models that enhance the accurate classification of fatty liver ultrasound images, enable early detection and diagnosis of liver cirrhosis, and improve the segmentation of liver tumours from medical imaging data. The outcomes of this research will have significant implications for improved liver disease analysis, leading to more effective treatments, better patient outcomes, and more efficient healthcare decision-making.

Objectives of the Survey

The research aims to contribute to the development of advanced algorithms and models that enhance the accurate classification of fatty liver ultrasound images, enable early detection and diagnosis of liver cirrhosis, and improve the segmentation of liver tumours from medical imaging data. The outcomes of this research will have significant implications for improved liver disease analysis, leading to more effective treatments, better patient outcomes, and more efficient healthcare decision-making.

Objective 1: Categorizing Ultrasound Images of Fatty Liver

Fatty liver condition is a common ailment and frequently indicates the onset of more serious health issues, such as cirrhosis and liver cancer. Early identification is vital to thwart further complications. Conventional ultrasound evaluations often rely on the radiologist's interpretation, making them somewhat subjective. This study aims to create an artificial intelligence algorithm capable of autonomously and accurately categorizing ultrasound images related to fatty liver. Through extensive training on a comprehensive collection of ultrasound images, AI can learn to detect subtle patterns in texture and brightness that signify fat deposits, which might be overlooked by humans. This can lead to a more consistent, objective, and precise diagnostic instrument, improving accessibility and reliability for early diagnosis.

Objective 2: Detecting Liver Cirrhosis Early

Cirrhosis of the liver represents the later phase of liver disease, marked by permanent damage to liver tissue. Once this condition manifests, the chances of liver failure and cancer significantly rise. Early detection is essential for effective management, enabling treatments that can slow or prevent disease progression. The project aims to create a machine learning model to facilitate the early identification and diagnosis of liver cirrhosis. This model would utilize more than just imaging techniques; it would encompass various types of information, such as blood test outcomes, clinical signs, and patient background data. By evaluating these varied data sources, the model could forecast a patient's likelihood of developing cirrhosis well before it becomes obvious in clinical settings.

Objective 3: Isolating Liver Tumours from Medical Images

Accurately isolating liver tumours in medical imaging data, including CT and MRI scans, is an essential process for planning treatments, particularly for surgery, radiation

treatment, and liver transplant reviews. Manually tracing the outlines of tumours is labour-intensive and time-consuming, with accuracy levels that can differ widely. The aim in this case is to create a deep learning model that provides precise tumour isolation. This model would automatically and accurately mark the edges of tumours, furnishing healthcare providers with crucial details regarding tumour dimensions, shapes, and positions. This not only conserves significant time but also improves the accuracy of treatment strategies, resulting in enhanced surgical results and more effective treatments. AI's capability to execute this task accurately ensures comprehensive tumour treatment while reducing the risk of harming surrounding healthy liver tissue.

Literature Survey

This part provides an extensive review of existing research regarding the use of artificial intelligence in the study of liver conditions, concentrating on three main aspects: the categorization of fatty liver, the identification of liver diseases, and the segmentation of liver and tumours. Lei Zhang, et al. [10] developed the network structure to accommodate the features of B-mode ultrasound images, in order to categorize fatty liver ultrasound pictures, then use a CNN-based model to analyse the data. Haijiang Zhu, et al. [17] proposed a classification approach for fatty liver ultrasonic images. This method combines a convolutional neural network with differential image patches and is based on pixel-level information. It is able to make an automated diagnosis based on the ultrasonic pictures of a normal liver, a low-grade fatty liver, a moderate-grade fatty liver, and a severe fatty liver. The suggested solution not only addresses the issue of insufficient data but also makes the categorization process more precise.

V Sharma, et al. [18] presented several CAD frameworks, to differentiate between ultrasound pictures of a normal and fatty liver. The CAD systems created up to this point are not proven to be adequate for classifying the pictures. The measurement parameters for sensitivity and accuracy still need improvement. Despite the fact that this topic has been the subject of much study, it is one of major importance given the rising incidence of fatty liver across the world. CAD has emerged as one of the most significant study areas in both therapeutic imaging and diagnostic radiology. The article presents pattern recognition software, which examines worrisome characteristics on the picture and aids radiologists in problem-solving. Classifying liver ultrasound pictures has been the subject of burgeoning study in recent years. This study discusses existing difficulties and potential future approaches for improving the diagnostic precision as well as recent advances in ultrasound-based categorization of different liver disorders using computer-aided diagnosis systems.

Ahmed Gaber, et al. [19] developed a Computer-Aided Diagnosis approach by using Machine Learning Algorithms and a voting-based classifier to identify liver tissues as being either fatty or normal, based on extracting ultrasound picture characteristics and a voting-based classifier. This is accomplished by employing Machine Learning Algorithms to learn from ultrasound images. The approach that the authors have created offers a number of significant advances, the most important of which are as follows: first, the categorization of liver pictures as either normal or fatty may be accomplished without the need for a segmentation step. Second, as compared to the work that they have presented, the dataset that was used in the earlier research was inadequate. The third contribution is a mixture of 26 different characteristics. The Gray-Level Co-Occurrence Matrix (GLCM) and First-Order Statistics (FOS) are the retrieved features. These features were determined by using the provided techniques. The voting classifier is the fourth part of the contribution, and it is utilized to establish the kind of liver tissue.

Fahad Muflih Alshagathrh, et al. [21] investigated the effectiveness of different AI approaches in diagnosing and quantifying non-alcoholic fatty liver disease using ultrasound (US) pictures. Methodology: In order to accomplish this goal, a comprehensive literature study was carried out. PubMed, the Association for Computing Machinery (ACM) Digital Library, the Institute of Electrical and Electronics Engineers (IEEE) Xplore, Scopus, and Google Scholar were the five scientific bibliographic databases that were searched. Only English-language papers, conferences, theses, and book chapters that were evaluated by other researchers were considered for inclusion. Synthesizing the data from the studies using narrative techniques in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines was carried out.

Golmei Shaheamlung, et al. [22] provided a comprehensive survey as well as a comparative analysis of all of the machine learning techniques that are currently being used in the medical field for the diagnosis and prediction of liver disease. These techniques have already been used for the prediction of liver disease by a number of authors, and the comparisons and analyses should be based on accuracy, sensitivity, precision, and specificity.

Krittika Dutta, et al. [23] employed a variety of data mining methods, such as Artificial Neural Network (ANN), Logistic Regression, K-Nearest Neighbour's, SVC, Gaussian NB, Decision Tree, Random Forest, LR-SGD Classifier, Passive-Aggressive, Ada Boost, and Voting Classifier, describe the process of diagnosing liver illness. Various evaluative metrics, both with and without the use of linear discriminant analysis (LDA), have been computed after each model has been tested both with and without it.

Taher M. Ghazal, et al. [24] utilized the method of machine learning, a suggested intelligent model to diagnose liver illness was developed. This model that has been suggested is more effective and comprehensive in terms of performance, with an accuracy of 0.884 and a miss-rate of 0.116 respectively. Vinayak Singh, et al. [25] implemented a number of machine learning techniques on selected features from the dataset in order to predict liver disease. These techniques included logistic regression, KNN, XG-Boost, SVM, Gaussian NB, Random forest, Decision tree, Gradient Boosting, CatBoost, AdaBoost, along with LightGBM.

Sang Hee Ahn, et al. [26] focused to a) study whether tailored, deep-learning-based auto-segmentation could overcome the constraints of manual contouring, and b) evaluate its performance to a standard, atlas-based auto-segmentation technique organ structures in liver cancer. Both of these objectives were centered on liver cancer. On-contrast computer tomography picture sets from seventy patients with liver cancer were used, and the four OARs (the heart, liver, kidneys, and stomach) served as reference structures and were manually defined by three highly skilled medical professionals. MIM Maestro 6.5 (MIM Software Inc., Cleveland, OH) and a deep convolution neural network (DCNN) were used to carry out the Atlas and deep learning auto-segmentations, respectively. The Hausdorff distance (HD) as well as the dice similarity coefficient (DSC), volume overlap error (VOE), and relative volume difference (RVD) were used in order to quantitatively analyse the four distinct approaches that were utilized in the instance of the reference set of the four OAR structures.

Hameedur Rahman, et al. [27] presented a hybrid ResUNet model, which combines the ResNet and UNet models in order to solve this gap as a more effective way for segmenting liver and tumours from CT image volumes. This method uses the UNet model. In this particular research, the two models that overlapped each other were used mostly for the purpose of segmenting the liver and evaluating regions of interest (ROI). In order to evaluate the liver using an abdominal CT image volume, segmentation of the liver must first be performed. The aforementioned model is constructed using CT volume slices taken from individuals who were diagnosed with liver tumours, and it was tested on the publicly available 3D dataset known as IRCADB01.

Omar Ibrahim Alirr, et al. [28] proposed the creation of an automated approach for the segmentation of liver tumours and lesions from CT data. The aforementioned approach used a fully convolutional neural network (FCN) with a region-based level set function as its foundation. The liver organ is first segmented from the CT image by the framework, and then the next step is to segment any malignancies that may be present inside the liver envelope. The fully convolutional

network is trained to estimate the coarse liver/tumour segmentation, while the localized region-based level seeks to improve the predicted segmentation in order to discover the proper final segmentation of the liver and tumour.

Javaria Amin, et al. [29] suggested a model that consisted of three components. These elements were the development of synthetic images, the localisation of the images, and the segmentation of the images. For the purpose of creating synthetic pictures, a generative adversarial network (GAN) that has been optimized is used. The enhanced localization model is used to localize the pictures that have been created. Within this model, deep features are retrieved from previously trained Resnet-50 models and then used as an input into a YOLOv3 detector. The minute hepatic tumour may be localized and classified with a mean average precision (mAp) of 0.99 thanks to the modified model that was suggested. The third step is called segmentation, and it utilizes a pre-trained version of Inceptionresnetv2 as the Base-Network of Deeplabv3, which then undergoes further training using fine-tuned parameters and annotated ground masks.

Sidra Gul, et al. [30] provided a summary of the several available deep learning algorithms for segmenting the liver and identifying liver tumours, as well as the assessment metrics for these systems, such as accuracy, volume overlap error, dice coefficient, and mean square distance. This study also includes a comprehensive analysis of the many distinct designs for three-dimensional volumetric imaging that have been developed particularly for the purpose of semantic segmentation. There is also a comparison of the methodologies that were presented in past competitions for the segmentation of the liver and tumours, together with their corresponding die scores that were acquired from the relevant site sources.

Shyam Lal, et al. [31] developed NucleiSegNet is a powerful deep learning network architecture for the purpose of segmenting nuclei in H & E-stained pictures of liver cancer histology. The architecture that the authors have presented is comprised of three different blocks: a block for resilient residuals, a block for bottlenecks, and an attention decoder block. For the purpose of the effective extraction of high-level semantic mappings, a brand-new block called the robust residual block has been suggested. The suggested architecture's overall performance is improved as a result of the attention decoder block's implementation of a novel attention mechanism, which allows for more effective object localisation and results in fewer false positives. When used to perform the job of nuclei segmentation, the suggested deep-learning architecture produced results that were superior to those produced by state-of-the-art nuclei segmentation approaches.

Amita Das, et al. [32] developed a novel approach known as watershed Gaussian based deep learning (WGDL) as an efficient means of delineating cancerous lesions in computed tomography (CT) images of the liver. In this particular piece of work, a total of 225 pictures were used in order to construct the model that was presented. First, the liver was divided using a marker-controlled watershed segmentation technique, and then the Gaussian mixture model (GMM) algorithm was used to divide the cancer-affected lesion. Following the process of tumour segmentation, many different textural characteristics were collected from the area that had been segmented. These segmented characteristics were then input into a deep neural network (DNN) classifier in order to perform automated classification of the three different kinds of liver cancer, which are referred to as hemangioma (HEM), hepatocellular carcinoma (HCC), and metastatic carcinoma (MET).

Sultan Almotairi, et al. [33] presented a deep learning-based approach for semantic pixel-wise categorization of road sceneries has been taken and modified to suit liver CT segmentation and classification. This was done. A hierarchical correspondence of encode-decode layers makes up the architecture of the deep convolutional encoder-decoder, which goes by the moniker SegNet. R.V. Manjunath, et al. [34] presented an automated technique that is based on semantic segmentation convolutional neural networks (CNNs) to segment liver from CT scans and lesions from segmented liver section. This method was developed to segment liver from CT scans. The authors concentrated primarily on developing deep learning algorithms for segmenting the liver and its tumor from abdominal CT scan pictures, with the end goal of reducing the amount of time and effort required for the identification of liver illnesses. The design of a modified ResUNet serves as the foundation for this algorithm's implementation.

Lu Meng, et al. [35] focused on the human liver and liver tumour segmentation method based on convolutional neural network (CNN), and particularly created a three-dimensional dual path multiscale convolutional neural network (TDP-CNN). In order to strike a healthy balance between the performance of the segmentation and the demand for computing resources, the network was designed with a dual route. At the conclusion of the pathways, the feature maps from both of the paths were combined. The authors used conditional random fields, also known as CRF, in order to refine the segmentation results by getting rid of the incorrect segmentation points that were included in the segmentation results and so improving the accuracy. Xi Fang, et al. [36] designed a liver segmentation system based on deep learning and utilize the segmented surfaces to aid picture fusion with guided needle insertion techniques for the detection and treatment of liver cancers. In order to

extract context information, the segmentation technique that was created combines multi-scale input and multi-scale output characteristics in a single network. A diagnostic picture and an interventional CT are registered using the findings of automated segmentation. The registration aids in guiding the interventional procedure and aids in visualizing the target.

Conclusion

The extensive examination regarding the use of artificial intelligence in the analysis of liver ailments highlights its vast potential to revolutionize contemporary hepatology. The increasing global rates of liver diseases, coupled with high mortality figures, pose a significant challenge to public health. While conventional diagnostic techniques are important, they frequently lack in areas such as affordability, accessibility, and the capacity to identify diseases at their earliest and most treatable stages. Artificial intelligence presents a compelling solution by delivering a non-invasive, objective, and highly precise approach to interpreting complex clinical and imaging information. This investigation has indicated that research driven by AI is actively tackling essential diagnostic and therapeutic issues. From the creation of advanced deep learning models aimed at classifying fatty liver in ultrasound images to sophisticated machine learning systems for early detection of cirrhosis and accurate segmentation of tumours in CT and MRI scans, AI is proving to be a significant resource. These advancements not only improve the accuracy of diagnoses but also have the potential to optimize clinical processes and enable more tailored treatment strategies. Nevertheless, the journey toward broad clinical integration is fraught with challenges. A vital research deficiency persists in enhancing the comprehensibility of AI systems. The opaque nature of many algorithms can hinder clinicians, who require insight into the rationale behind diagnoses to foster trust and effectively incorporate these technologies. Future studies should focus on developing AI systems that are both transparent and understandable. By promoting closer partnerships between data specialists and healthcare providers, we can ensure that AI advancements are validated in clinical settings and uphold ethical standards. In the end, the ongoing development of artificial intelligence in the analysis of liver diseases is essential for achieving earlier interventions, better patient results, and a more streamlined and efficient healthcare framework.

References

1. Devarbhavi H, Asrani SK, Arab JP, Nartey YA, Pose E, et al. (2023) Global Burden of Liver Disease. *J Hepatol* 79(2): 516-537.
2. Lippincott Journals (2022) Global Epidemiology of

Cirrhosis. Lippincott.

3. BioMed Central (2023) Trends in Chronic Liver Disease Mortality, 1990–2019. *BMC Public Health* 22.
4. PubMed Central (2023) Global Burden of Disease Study 2021 Results. PMC.
5. WHO (2025) Hepatitis B and C Factsheet. World Health Organization.
6. PubMed Central (2023) Epidemiology of NAFLD and NASH: Global Impact PMC.
7. The Guardian (2023) Liver Cancer Set to Double by 2050. The Guardian.
8. The Sun (2022) Why Early Diagnosis of Liver Disease Matters. The Sun Health.
9. Stanislav L, Magnan C, Asghar A, Stolz A, Tayek JA, et al. (2022) Differentiating between liver diseases by applying multiclass machine learning approaches to transcriptomics of liver tissue or blood-based samples. *JHEP Reports* 4(10): 100560.
10. Yifang L, Wang X, Zhang J, Zhang S, Jiao J (2022) Applications of artificial intelligence (AI) in researches on non-alcoholic fatty liver disease (NAFLD): A systematic review. *Reviews in Endocrine and Metabolic Disorders* 23(3): 387-400.
11. Amit D, Connell M, Khetarpal S (2021) Digital image analysis of ultrasound images using machine learning to diagnose pediatric nonalcoholic fatty liver disease. *Clinical Imaging* 77: 62-68.
12. Helena C, Baiges-Gaya G, Hernández-Aguilera S, Rodríguez-Tomás E, Fernández-Arroyo S, et al. (2021) Coupling machine learning and lipidomics as a tool to investigate metabolic dysfunction-associated fatty liver disease. A general overview. *Biomolecules* 11(3): 473.
13. David N, Chapiro J, Paradis V, Seraphin TP, Kather JN (2022) Artificial intelligence in liver diseases: Improving diagnostics, prognostics and response prediction. *JHEP Reports* 4(4): 100443.
14. Genoveva B, Romero-Gomez M (2020) The role of nutrition in non-alcoholic fatty liver disease: pathophysiology and management. *Liver International* 1: 102-108.
15. Kathryn AS, Penrice DD, Simonetto DA (2022) Artificial Intelligence in the Assessment and Management of Nutrition and Metabolism in Liver Disease. *Current Hepatology Reports* 21(4): 120-130.

16. Yoshihisa T, Dungubat E, Kusano H, Fukusato T (2023) Artificial intelligence and deep learning: New tools for histopathological diagnosis of nonalcoholic fatty liver disease/nonalcoholic steatohepatitis. *Computational and Structural Biotechnology Journal* 21: 2495-2501.
17. Lei Z, Zhu H, Yang T (2019) Deep Neural Networks for fatty liver ultrasound images classification. 2019 Chinese Control and Decision Conference (CCDC), pp: 4641-4646.
18. Haijiang Z, Liu Y, Gao X, Zhang L (2022) Combined CNN and Pixel Feature Image for Fatty Liver Ultrasound Image Classification. *Computational and Mathematical Methods in Medicine* 13: 9385734.
19. Sharma V, Juglan KC (2020) Ultrasound-based classification of fatty liver disease: A review. In *Journal of Physics: Conference Series*, IOP Publishing 1531(1): 012033.
20. Ahmed G, Youness HA, Hamdy A, Abdelaal HM, Hassan AM (2022) Automatic classification of fatty liver disease based on supervised learning and genetic algorithm. *Applied Sciences* 12(1): 521.
21. Muflih AF, Househ MS (2022) Artificial Intelligence for Detecting and Quantifying Fatty Liver in Ultrasound Images: A Systematic Review. *Bioengineering (Basel)* 9(12): 748.
22. Golmei S, Kaur H, Kaur M (2020) A Survey on machine learning techniques for the diagnosis of liver disease. 2020 International Conference on Intelligent Engineering and Management (ICIEM), pp: 337-341.
23. Krittika D, Chandra S, Gourisaria MK (2022) Early-Stage detection of liver disease through machine learning algorithms. *Advances in Data and Information Sciences*, Springer, Singapore, pp: 155-166.
24. Taher MG, Rehman AU, Saleem M, Ahmad M, Ahmad S, et al. (2022) Intelligent Model to Predict Early Liver Disease using Machine Learning Technique. 2022 International Conference on Business Analytics for Technology and Security (ICBATS), pp: 1-5.
25. Vinayak S, Gourisaria MK, Das H (2021) Performance analysis of machine learning algorithms for prediction of liver disease. 2021 IEEE 4th International Conference on Computing, Power and Communication Technologies (GUCON), pp: 1-7.
26. Hee AS, Yeo AU, Kim KH, Kim C, Goh Y, et al. (2019) Comparative clinical evaluation of atlas and deep-learning-based auto-segmentation of organ structures in liver cancer. *Radiation Oncology* 14(1): 213.
27. Rehman A, Butt MA, Zaman M (2022) Liver lesion segmentation using deep learning models. *Acadlore Transactions on AI and Machine Learning* 1(1): 61-67.
28. Ibrahim AO (2020) Deep learning and level set approach for liver and tumor segmentation from CT scans. *Journal of Applied Clinical Medical Physics* 21(10): 200-209.
29. Javaria A, Anjum MA, Sharif M, Kadry S, Nadeem A, et al. (2022) Liver tumor localization based on YOLOv3 and 3D-semantic segmentation using deep neural networks. *Diagnostics* 12(4): 823.
30. Sidra G, Khan MS, Bibi A, Khandakar A, Ayari HA, et al. (2022) Deep learning techniques for liver and liver tumor segmentation: A review. *Computers in Biology and Medicine* 147: 105620.
31. Shyam L, Das D, Alabhya K, Kanfade A, Kumar A, et al. (2021) NucleiSegNet: Robust deep learning architecture for the nuclei segmentation of liver cancer histopathology images. *Computers in Biology and Medicine* 128: 104075.
32. Amita D, Acharya UR, Panda SS, Sabut S (2019) Deep learning-based liver cancer detection using watershed transform and Gaussian mixture model techniques. *Cognitive Systems Research* 54: 165-175.
33. Sultan A, Kareem G, Aouf M, Almutairi B, Salem AM (2020) Liver tumor segmentation in CT scans using modified SegNet. *Sensors* 20(5): 1516.
34. Manjunath RV, Kwadiki K (2022) Automatic liver and tumour segmentation from CT images using Deep learning algorithm. *Results in Control and Optimization* 6: 100087.
35. Lu M, Tian Y, Bu S (2020) Liver tumor segmentation based on 3D convolutional neural network with dual scale. *Journal of applied clinical medical physics* 21(1): 144-157.
36. Xi F, Xu S, Wood BJ, Yan P (2020) Deep learning-based liver segmentation for fusion-guided intervention. *International journal of computer assisted radiology and surgery* 15(6): 963-972.