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A Review - On Artificial Intelligence for Detecting and Preventing Non- Alcoholic Fatty Liver Disease

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Abstract:

Non-alcoholic fatty liver disease (NAFLD) is a growing global health problem. Liver biopsy is still considered the reference standard for diagnosis, but alternative non-invasive approaches are being proposed, including clinical scoring systems and conventional ultrasonography (US). Nevertheless, the utility of these non-invasive modalities, especially in the accurate characterization and quantitation of NAFLD, has been challenged. However, these limitations have recently made way for integrating artificial intelligence (AI) into Diagnosis Processes, successfully addressing some of the limitations. This study will analyze the performance and effectiveness of different AI techniques for the qualitative and quantitative evaluation of NAFLD, considering different algorithms' performance on ultrasound images. To that end, a systematic review was performed on this topic, narrowing its context to how artificial intelligence can improve the accuracy of non-invasive diagnostics. We conducted a systematic search of 5 major scientific bibliographic databases (PubMed, Association for Computing Machinery [ACM] Digital Library, IEEE Xplore, Scopus, and Google Scholar) to identify relevant studies. The results highlight the promise of AI to enhance the accuracy and consistency of NAFLD diagnosis. AI has proven to discover subtle features and measure hepatic fat content more sensitively and specifically than traditional goals using machine learning algorithms and deep learning models. Japan, and even making invasive procedures such as liver biopsy less necessary, thanks to the merging of artificial intelligence with classical diagnosis.

Keywords: Machine Learning, Deep Learning, Ultrasound Images.

Introduction

Different disease states can affect the liver's functions, and liver illnesses can range from a straightforward medication reaction to liver cancer. Liver issues may now be seen in all age groups in India as a result of a lack of physical activity, current unhealthy eating habits, smoking, alcohol usage, multiple sexual partners, and the use of injectable medicines. We regret to explain that they are all a part of Indian culture. The majority of diseases in India have several symptoms, and the majority of hospitalized patients have multiple ailments. Identifying each ailment and administering a separate course of treatment under these circumstances is quite challenging (Aneeshkumar & Venkateswaran, 2012). Non-alcoholic fatty liver disease (NAFLD), the most common chronic liver disease, is a pathology that is quickly escalating over the globe. Without drinking a lot of alcohol, it can be recognized when more than 5% of the hepatocytes develop steatosis (Popa et al., 2021). Women's livers weigh between 1200 and 1400 g while men's livers weigh between 1400 and 1800 g. The liver is an organ in the upper layer of the digestive system. It performs essential functions for nutrition storage, digestion, metabolism, toxin release, and immunization. Due to their severity, some liver disorders can be deadly. Non-alcoholic fatty liver disease, one of the most serious liver diseases, is characterized by an excess of lipids in the liver. The term "non-alcoholic steatohepatitis" is used when the liver cells are damaged and inflamed (Dritsas & Trigka, 2023). A frequent medical illness that causes severe misery and mortality is fatty liver disease (FLD). FLD eventually brings on hepatocellular carcinoma and non-cholestatic cirrhosis. Additionally, a rise in FLD has been linked to an increase in the incidence of metabolic diseases, obesity, and diabetes (Sahaja & Kameswara Rao, n.d.).

Diabetes mellitus has recently risen to the top of the list of chronic diseases to which people are most vulnerable. Aspects of contemporary lives, such as bad eating habits and a lack of exercise, are making people more susceptible to this disease. Ineffective blood glucose management results in a variety of problems. One such problem is non-alcoholic fatty liver disease (NAFLD). Diabetes patients who consume little to no alcohol see this impact. Fat builds up in the liver cells of NAFLD patients, and there is a danger of liver injury and inflammation. It also makes albumin and clotting factors, cleanses the blood, breaks down food and medicine, and stores glucose, fat, vitamins, and bile. Additional functions of the liver include tasks. Consequently, recognizing liver illnesses is crucial to reducing their negative effects (Reddy et al., 2018). Blood tests, CT scans, MRIs, and ultrasounds can all be used to identify liver conditions. A comprehensive analysis resulted in a projected worldwide incidence of chronic HBV infection of 4.1%, or 316 million infected people, in 2019. Between 1990 and 2019, the incidence decreased by 31.3% across all age categories, with children under the age of 5 experiencing a more dramatic fall of 76.8%. The World Health Assembly launched the WHO Global Health Sector Strategy on Viral Hepatitis (WHOGHSS) in 2016 to eliminate viral hepatitis as a risk to public health. The WHO-GHSS proposed effect targets of 95% fewer new cases and 65% fewer deaths from HBV by 2030 in comparison to the baseline year of 2015. When compared, 2015 served as the baseline year. The single-stranded RNA virus known as the hepatitis C virus (HCV) is the cause of hepatitis C infection (Harabor et al., 2023). In addition, B-ultrasound scans, a quick and affordable substitute for conventional ultrasound, are commonly used to both prevent and detect fatty liver disease in people. Doctors frequently use liver ultrasound imaging to assess the different degrees of fatty liver (Zhang et al., n.d.). Patients with metabolic syndrome who were diagnosed with NAFLD early were able to successfully intervene in several ways to slow the disease's progression, including making significant lifestyle changes, strictly controlling risk factors, and using certain drugs. However, patients with late discovery will suffer costly and catastrophic repercussions. Liver biopsy is now the gold standard for diagnosing and staging NAFLD, but since it is so invasive, it cannot be utilized in population-based studies. According to a recent meta-analysis, ultrasonography had a greater area under the summary receiving operating characteristics (ROC) curve (.93) than liver histology for identifying moderate to severe NAFLD. The American Association for the Study of Liver Diseases (AASLD) 2012 guideline discourages screening for liver disease due to the lack of apparent long-term benefits and cost-effectiveness of

NAFLD in high-risk groups (obesity or diabetes) (Phisalprapa et al., 2017).

1.1 MAJOR CAUSES OF LIVER DISEASE

When the liver isn't functioning properly, we might have serious issues with our health. There are several factors and medical illnesses that might recklessly harm the liver.

- The most frequent factor in liver impairment is excessive alcohol consumption. When a person consumes alcohol, the liver switches its attention away from its other duties and focuses primarily on transforming alcohol into a less harmful form.
- Body fat levels rise as a result of obesity, which tends to collect around the liver and result in fatty liver disease.
- If you have diabetes, your risk of having liver disease is doubled.
- Smoking irritates the liver (Bantu et al., n.d.).
- Parasites and viruses can infect the liver, causing inflammation and impaired liver function. The viruses that cause liver damage can be spread by direct contact with an infected person, contaminated food or drink, blood or semen, or tainted objects.
- Autoimmune illnesses, in which your immune system attacks certain bodily organs, may affect your liver (Mayo Clinic, n.d.).

1.2 TYPES OF LIVER DISEASES

- **Fatty Liver**: Through the process of limiting, large triglyceride fat vacuoles build up in the liver cells, causing the reversible disease known as fatty liver. Both heavy drinkers and those who have never used alcohol may experience it(Banu Priya et al., 2018).
- **Hepatitis:** Hepatitis A, B, and C viruses are frequently responsible for liver illness. Hepatitis can also result from other non-infectious factors such as excessive alcohol or drug usage, allergies, obesity, or allergic responses. Figure 1 shows the types of liver disease.

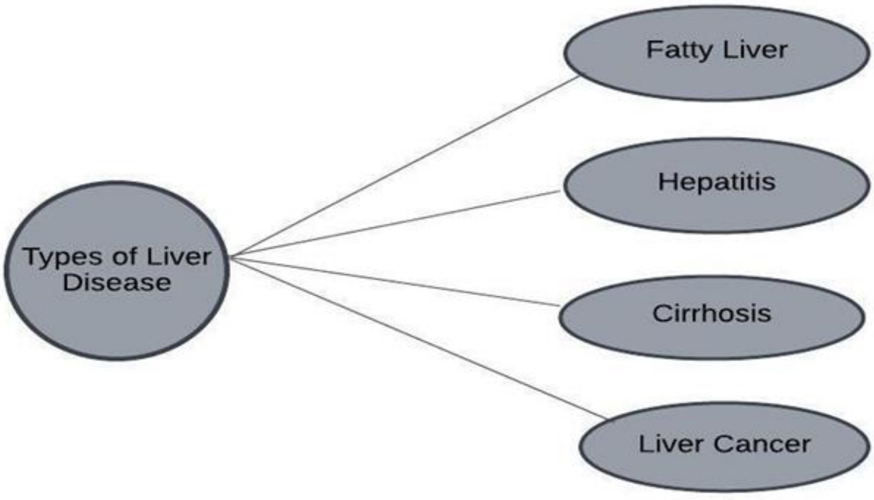

Figure 1Types of liver disease

- **Cirrhosis:** Long-lasting liver injury from any source can result in persistent scarring, often known as cirrhosis. The liver then loses its ability to perform effectively.
- **Liver Cancer**: The most common kind of liver cancer, hepatocellular carcinoma, often arises when cirrhosis is present (WebMD, n.d.).

1.3 DETECTION OF FATTY LIVER DISEASE USING TECHNOLOGICAL INTERVENTIONS

The use of common laboratory tests in the medical field, such as albumin, total bilirubin, indirect bilirubin, alanine aminotransferase (ALT), aspartate aminotransferase (AST), alpha-fetoprotein (AFP), postprandial glucose test (PC%), international normalized ratio (INR), amount of HCV_RNA, white blood cells (WBC) count, hemoglobin (Hb), platelet count (Hashem et al., 2018). Both artificial intelligence-based and pre-defined non-AI medical procedures can be used to identify fatty liver. Numerous studies have shown that learning is necessary for intellect to grow. Among the many different machine learning techniques are supervised, unsupervised, semi-supervised, reinforcement, evolutionary learning, and deep learning. These techniques are used to group the data gathering (Fatima & Pasha, 2017). The fast development of artificial intelligence technology and the diagnostic assessment of the stage of liver fibrosis have both benefited substantially from deep learning. Using this method to diagnose NAFLD will increase the sensitivity of imaging. In addition, we assessed the efficacy of several image-processing techniques to find any elements useful for NAFLD diagnosis. In addition, we intended to look at how deep learning might be used to analyze US images. Table 1 displays the various AI detection methods (Cao et al., 2019).

Iteratively calculating weak classifiers is the goal of the gradient boosting-based integrated learning approach known as XGBoost, which aims to enhance classification performance. Additionally, the XGBoost network structure enables it to process high-level sparse data more quickly, which cuts down on the model's training and prediction timeframes. XGBoost has been widely used in industries like risk analysis, recommender systems, and other things. The logistic regression model develops a multiple regression relationship between a dependent variable and several independent factors to predict the chance of an event (Liu et al., 2021). Due to its incredibly high accuracy rates, several studies and tests have shown that the SVM classifier is the most accurate algorithm currently in use. However, the Naive Bayes classifier exhibits higher appropriateness in that regard because it completes the forecasting process in the smallest amount of time (Durai et al., n.d.). Table 1 various AI detection methods

Fatty Liver detection	**Machine Learning Techniques**	**Deep Learning Techniques**
CT scan	Simple Linear Regression	Convolutional Neural Networks
MRI	Multilinear Regression	Recurrent Neural Networks

X-Ray	Logistics Regression	Generative Adversarial Networks
	Decision Tree	Radial Basis Function Networks
	SVM	Multilayer Perceptrons

It assessed the severity of fat using a multinomial logistic model and extracted several components from the image, such as the slope of the frequency downshift and GLCM characteristics like autocorrelation and signal-to-noise ratio. The estimation of liver fat has recently been done using a cubic support vector machine classifier with scattering parameters and features based on curvelets. Computer-aided diagnosis techniques in the literature categorize data using handcrafted qualities (Reddy et al., n.d.). Contrary to conventional machine learning techniques that build classifiers based on human-designed characteristics, convolutional neural networks, the most popular method for creating deep neural networks for image analysis, perform end-to-end learning to automatically extract features by learning multiple convolutional filters and training classifiers at the same time. CNNs are composed of convolutional layers, pooling layers, and fully connected layers. These layers share few parameters and have sporadic communication. Except for the final few fully connected layers, CNNs stack several convolutional blocks made up of convolutional layers and pooling layers alternatively for feature learning from low to high levels. CNNs have been utilized to partition the liver region of CT images and estimate the stage label to stage fibrosis. CNNs are employed to automatically evaluate the ballooning, inflammation, steatosis, and fibrosis histological features in histology images (Wong et al., 2021).

2. LITERATURE REVIEW

This essay will concentrate on using machine learning (ML) techniques to predict early illness. In the content of this study work, several machine learning models and ensemble techniques were studied and compared in terms of accuracy, precision, recall, f-measure, and area under the curve (AUC) to anticipate the incidence of liver disease. The experimental results showed that the voting classifier beat the other models with accuracy, recall, and F-measure of 80.1%, a precision of 80.4%, and an AUC of 88.4% after SMOTE with 10-fold cross-validation (Dritsas & Trigka, 2023). It focuses on the appropriate dataset with the appropriate properties. For the prediction task, ensemble algorithms were applied, and finally, the method with the best performance was identified. In addition to ensemble approaches like bagging, random forest, and Ada-boost, individual classifications like Naive Bayes (NB) and C4.5 decision trees were also considered. The NB tree algorithm, which combines C4.5 and Naive Bayes, was put in comparison to these machine learning techniques. The assessment metrics of accuracy, recognition rate, negative predictive value (NPV), false negative rate (FNR), and false positive rate (FPR) were calculated for each technique under consideration. The algorithms are then contrasted using these criteria to determine which algorithm is the best. Individual Naive Bayes and C4.5 classifiers performed worse than the other techniques examined (Reddy et al., 2022). The model assesses computer-aided hepatic abnormality detection and evaluates diffusely localized liver illness. The main focus of this survey is on three image-capturing modalities: ultrasound, computed tomography (CT), and magnetic resonance imaging. We provide a comprehensive analysis and discuss the advantages and disadvantages of each preliminary stage concerning the preliminary processing, attribute analysis, and classification methodologies to carry out clinical diagnostic tasks. We look at and compare well-liked segmentation, deblurring, and denoising methods utilized in the initial processing. The most popular models for denoising are nonlinear ones. On the other hand, deep neural networks are frequently employed for deblurring and automatically segmenting regions of interest. Texture qualities are part of the most often-used approach to attribute analysis. Three approaches largely employ the support vector machine (Khan et al., 2022). The research proposes a method to classify livers using textured analysis of ultrasonography images. The method uses two-level wavelet packet transform analysis to extract statistical characteristics from the best regions of interest. Hierarchical differentiation is used to separate heterogeneous, fatty, and normal livers. The Support Vector Machine classifier outperforms the k nearest neighbor classifier in terms of accuracy and sensitivity. This computer-aided diagnosis system can be used in clinical settings to assist radiologists and specialists in interpreting liver disorders, achieving a high level of accuracy (Alshagathrh & Househ, 2022). It suggested a disease prediction (LDP) method that could be applied by researchers, students, and medical experts to anticipate liver disease. There are five techniques used: SVM, Naive Bayes, K-Nearest Neighbours (K-NN), Linear Discrimination Analysis (LDA), and Classification and Regression Trees (CART). The accuracy is evaluated using R and Python, and the best classification system for predicting liver disease is chosen. While K-NN received the best accuracy from the data with 91.7%, the autoencoder network achieved 92.1% accuracy, which is beyond the acceptable level of accuracy and may be taken into consideration for the forecasting of liver illness (Bhupathi et al., n.d.). The study presents a machine learning voting system for diagnosing and detecting NAFLD, combining genetic systems, neural networks, random forest, and logistic regression. The system uses KNN to add missing values and PPFS to select 11 features. The top five factors for NAFLD are alanine aminotransferase, body mass index, triglycerides, GT, and LDL. Ten fundamental machine learning algorithms were employed, with the genetic algorithm, neural network, random forest, and logistic regression being the most accurate. The system was tested against 10 other techniques and performed the best (Cao & Zhang, 2022).

AI models have been integrated into non-invasive diagnostic instruments to improve their performance. Research on AI-assisted detection of liver fibrosis and non-alcoholic fatty liver disease (NAFLD) was conducted on MEDLINE, Scopus, the Web of Sciences, and Google Scholar. The model assessed diagnostic efficacy using a summary receiver operating characteristic curve and area under the curve. The study included 19 papers on AI-assisted ultrasound imaging, elastography, CT, MRI, and clinical parameters. The combined predictive value (PPV, NPV, DOR, sensitivity, specificity) is used to diagnose liver fibrosis. Functional validations are necessary before clinical application (Decharatanachart et al., 2021). It focuses on offering a fully automated, three-deep learning neural network hepatic steatosis prediction model. Hepatic steatosis may therefore be properly and automatically identified. Transfer learning is used to first semantically partition the liver and kidney (L-K) on parasagittal ultrasound pictures, and then the L-K region is cropped from the original ultrasound image. The second neural network additionally applies semantic segmentation by removing the L-K area from the original US image and confirming the presence of a ring that is typically present encircling the kidney. These clipped L-K sections are then sent into the final neural network, Steatosis Net, which determines the severity of the fatty liver disease. The results of the experiments demonstrate that the proposed model may predict fatty liver disease (Rhyou & Yoo, 2021). This paper examines the results of several machine learning methods, such as logistic regression, random forest, XGBoost, support vector machine (SVM), AdaBoost, K- NN, and decision tree, to predict and diagnose chronic liver disease. Several measurement measures, including specificity, area under the curve (AUC), recall, accuracy, and precision, are used to evaluate the classification algorithms. The random forest algorithm scored better than the other algorithms at predicting liver illness, with an accuracy of 83.70 percent. Furthermore, the random forest approach showed superior accuracy, F1, recall, and AUC measures. Therefore, it is believed that random forest is the best algorithm for predicting early liver illness (Ghosh et al., 2021).

A machine learning-based classification algorithm was developed to identify non-alcoholic fatty liver disease (NAFLD) from normal liver tissue. A digital image analysis was performed on ultrasonic liver images, using ImageJ and MAZDA tools. Different classification techniques were examined, and the gradient boost algorithm successfully distinguished NAFLD from normal. The texture-based ML model outperformed intensity-based indices-based models in predicting accuracy, demonstrating the effectiveness of this approach in identifying NAFLD in children (Das et al., 2021). It focuses on using artificial intelligence to predict liver disease. Some of the many layers of steps that go into forecasting liver illness include pre-processing, feature extraction, and classification. In this work, samples taken from the Kaggle database of Indian hepatic patient records are gathered to test a hybrid classification system for predicting liver disease. The proposed model's accuracy rate is 77.75%. The proposed approach is employed, and the results are assessed in terms of recall, precision, and accuracy. To verify the efficacy of deep learning in the diagnosis of non-alcoholic fatty liver condition (NAFLD), compare three image-processing techniques (Shaheamlung & Kaur, 2021). A study has developed convolutional neural networks (CNNs) to identify fatty liver conditions in photos using pixel and diagnosis labels. The models were trained on a dataset of 629 images, including normal and liver steatosis images. Two pre-trained models, Inception-v3 and VGG-16, were evaluated using the ImageNet dataset. The models were trained on 234 normal liver images and 262 liver steatosis images, and evaluated on 70 liver steatosis images and 63 normal liver images. The algorithms produced over 90% of test results (Constantinescu et al., 2020). Using B-mode ultrasound (US) pictures, it developed a neural network-based algorithm to identify and classify fatty liver. to develop B-mode US scans from a waiting list of patients into four- class, two-class, and three-class diagnostic models for prediction. The images were regarded as acceptable if they were confirmed by a minimum of two gastroenterologists. We assessed the pre-trained convolutional neural network models ResNet-50 v2, MobileNet v2, Xception, and Inception v2 for the visual geometry group (VGG) 19. We produced more than 100 images for each severity group using 20% of the data set for validation (Chou et al., 2021). This study investigated four alternative machine learning (ML) strategies for classifying the Indian Lover Patients dataset, including logistic regression, decision trees, random forests, and additional trees. Remove meaningless attributes from the collection using person correlation. A boosting technique is also applied to enhance the prediction precision of those methods. The comparison analysis's accuracy, recall, ROC, and F-1 score are evaluated (Rabbi et al., 2020). This article surveys and compares machine-learning methods used in healthcare to identify and predict liver disease. Techniques include supervised, unsupervised, and semi-supervised reinforcement learning, SVM, KNN, K-mean clustering, neural networks, and decision trees. Each method has its accuracy, precision, and sensitivity. Decision trees, J48, and ANN are found to offer more accuracy in identifying and proposing liver illness, according to the review and study (Shaheamlung et al., n.d.).

The information was gathered and divided into four categories for NAFLD: normal, mild, moderate, and significant NAFLD groups. Two-dimensional hepatic imaging was examined using the signal envelope, grayscale signal, and deep-learning index produced by three image- processing techniques. The values for the three methods varied from 0 to 65,535, 0 to 255, and 0 to 4, respectively. The suggested program examined the data from the 4 groups, produced receiver operation characteristic curves, and assessed area under the curve (AUC) values to find the best image-processing technique (Cao et al., 2019). It will be advantageous to create a model that enables medical professionals to predict if a patient is most likely to have liver disease at an early stage. Liver infections are quite prevalent in India as a result of a desk-bound lifestyle, rising alcohol use, and smoking. Effective treatment requires an early identification of liver disease. The suggested work compares additional techniques for better accuracy (Bhoite & Idris, 2019). The study explores the liver's anisotropic texture, which can be identified using various techniques such as grey level difference histogram, pair correlation function, probabilistic local directionality statistics, and unpredictability of texture. Three alternative data sets are produced using five classifiers: Bayesian, multilayer perceptron, probabilistic neural network, learning vector quantization, and support vector machine. Comparative evaluations of specificity, sensitivity, discrimination score, and accuracy were conducted, showing that PNN and SVM improve anisotropy characteristics (Neogi et al., 2018). Implementing machine learning to diagnose multiparametric ultrasonic data to detect substantial liver fibrosis. There were 144 chronic hepatitis B patients in this prospective trial. Using conventional radionics, original radiofrequency (ORF), and contrast-enhanced micro- flow (CEMF) characteristics, ultrasonics—high-throughput quantitative data from ultrasound imaging of liver fibrosis—were produced. Pairwise correlation and hierarchical clustering were employed to examine three different feature categories. The diagnostic tests for fibrosis, activity, and steatosis stage were used to choose the features, with the histopathological findings serving as the standard. By measuring the area under the receiver-operator characteristic curve (AUC), machine learning methods were used to assess the fibrosis staging performance of ultrasonic models using combinations of the chosen characteristics (Li et al., 2018). Developed a method based on neural networks for diagnosing non-alcoholic fatty liver disease with ultrasound. to perform high-level feature extraction on liver B-mode ultrasound image sequences using the pre-trained Inception-ResNet-v2 deep convolutional neural network. Each liver's level of steatosis was assessed using wedge biopsies. The proposed technique was compared to the grey-level co-occurrence matrix methodology and the hepatorenal index method. After feature extraction, we applied the support vector machine approach to classify images showing fatty liver (Byra et al., 2018).

To better understand how dietary components interact to control the aspects of diets that influence health and illness, this strategy integrates nutrients and foods into a model. Western diets, which are typically high in soda, frozen junk food, juice, red meat, processed meats, whole-fat dairy foods, fatty snack foods, take-out food, cakes, and biscuits, and low in cereals, whole grains, vegetables, fruit, additional virgin olive oil (EVOO), and fish, are typical of patients with non-alcoholic fatty liver disease. Customized dietary advice for the prevention and treatment of NAFLD can be provided by using artificial intelligence (AI) algorithms to create a personalized diet for each patient 1. (Berná & Romero-Gomez, 2020). The most recent scientific ESPEN recommendation serves as the foundation for the Clinical Nutrition in Liver Disorder Practical Recommendation. It has been simplified and converted into flow charts for convenience of use in clinical practice. The recommendation is meant for all healthcare providers, such as doctors, dietitians, nutritionists, and nurses, who provide treatment to patients with chronic liver disease. When considering A total of 103 declarations and recommendations are presented along with brief explanations for the nutritional and metabolic management of patients with (i) acute liver failure, (ii) alcoholic steatohepatitis, (iii) non-alcoholic fatty liver disease, (iv) cirrhosis of the liver, and (v) liver surgery or transplantation. General recommendations on nutritional status diagnostics in liver patients and liver issues connected with therapeutic nutrition come before the disease-specific guidelines (Bischoff et al., 2020). The summary discusses the "multiple multiple hits" theory, which suggests that NASH develops through multiple hits. The summary highlights the growing interest in Traditional Herbal Medicine (THM) as a potential treatment for NAFLD and discusses the advantages and drawbacks of modernizing THM and its widespread acceptance as a treatment for NAFLD (Yan et al., 2020). NAFLD claims that metabolic diseases including type 2 diabetes, dyslipidemia, and obesity are all intimately linked to the condition. A significant risk factor for NAFLD is insulin resistance. Diets rich in marine n-3 polyunsaturated fatty acids (PUFAs) have been related to a decreased risk of cardiovascular disease and can lower plasma triacylglycerol. It gathered information on marine n-3 PUFAs as a NAFLD therapeutic option. Studies on the effects of marine n-3 PUFAs in human subjects with NAFLD and the effects of marine n-3 PUFAs on hepatic fat metabolism are available. Table 2 displays the comparison of various techniques (de Castro & Calder, 2018).

2.1 Comparison Table

Table 2 Literature comparison table

S. No	**Name of the Author**	**Name of Journal**	**Objectives**	**Methodolog y**
1	Dritsas et al. 2023	MPDI	Early disease prediction utilizing machine learning (ML) methods	Ml model

2	Reddy et al. 2022	EAI	Ensemble algorithms were applied for the prediction	Decision Tree, bagging, random forest
3	Khan et al., 2022	Elsevier	Evaluate diffusely localized liver disease and examine computer- aided hepatic abnormality diagnosis.	Support vector machine
4	Alshagathrh et al. 2022	MDPI	Detect and measure non-alcoholic fatty liver disease	Support vector machine, K-nearest neighbor
5	Bhupathi et al., 2022	Conferen ce paper	Find the effectiveness of machine learning in predicting liver disease	SVM,KNN
6	Cao et al. 2022	Research Square	Prediction and Detection of Non-alcoholic Fatty Liver Disease	KNN
7	Decharatanac hart et al., 2021	BMC Gastroen terology	In order to enhance the performance of non-invasive diagnostic instruments	Random Forest
8	Rhyou et al.,	MDPI	the prediction of hepatic steatosis.	KNN

9	Ghosh et al., 2021	Tech Science Press	to predict and diagnose chronic liver disease	Logistic regression,ra ndon forest ,XGBoost,SV M,KNN
10	Das et al., 2021	Elsevier	to diagnose pediatric non-alcoholic fatty liver disease	ML classification techniques
11	Golmei shaheamlung, 2021	Info tech in industry	create A hybrid classification model for liver disease prediction	Hybrid classification model
12	Constantines cu et al., 2021	Medical ultrasono graphy	automatic assessment of liver steatosis in ultrasound images	CNN
13	Chou et al., 2021	Chin Med Assoc	to evaluate fatty liver and categorize the severity.	VGG,ResNet -50,Xception
14	Rabbi et al., 2020)	IEEE	Prediction of liver disorders using Machine Learning	LR, DS, RF AND ET
15	Golmei Shaheamlung ,2020	IEEE	overview and comparative analysis of all machine learning approaches	SVM,KNN,N N,DT

16	W. Cao et al., 2020	Ultrasou nd in medical	the diagnosis of non- alcoholic fatty liver disease (NAFLD).	Picture-processing algorithms
17	Bhoite et al., 2019	CATR	predict, whether a patient is likely to have the liver problem	LR, SVM, RF,adaboost, bagging
18	Neogi et al., 2019	Springer	for identification of liver steatosis from ultrasound images	MLP,PNN,L QV
19	Li et al., 2019	Springer	to detect severe liver fibrosis	SVM, RF, AdaBoost,
20	Byra et al., 2018	Springer	ultrasound evaluation of non-alcoholic fatty liver disorder.	CNN
21	Berná et al. 2020	Elsevier	The role of nutrition in non-alcoholic fatty liver disease	
22	Bischoff et al., 2020	Elsevier	Clinical nutrition in liver disease	ESPEN guideline
23	Yan et al., 2020	Elsevier	The role and mechanisms of widely researched traditional herbs in treating NAFLD	THM(Traditi onal herbal medicine)
24	Castro et al. 2018	Elsevier	compile the most recent data on marine n-3 PUFAs as a 48-treatment strategy in NAFLD	n-3 PUFAs

3. Challenges of non-alcoholic fatty liver disease

The buildup of fat in the liver is a prevalent feature of non-alcoholic fatty liver disease (NAFLD), which is not brought on by excessive alcohol intake. It includes a variety of liver conditions, including non-alcoholic steatohepatitis (NASH), which can lead to cirrhosis and liver failure, as well as basic fatty liver (steatosis). NAFLD presents several difficulties, some of which are highlighted here.

1. **Natural without symptoms:** Early on, NAFLD frequently exhibits no symptoms, making diagnosis difficult. Before the problem evolves to more severe phases or consequences appear, people might not be aware of it (Chalasani et al., 2018).

2. **Lifestyle and Risk Factors:** Obesity, insulin resistance, and metabolic syndrome are directly related to NAFLD. NAFLD management frequently necessitates dietary and lifestyle changes, including weight loss, which can be difficult for patients (Eslam, Sanyal, & George, 2016).

3. **Limited Options for Treatment**: There are currently no particular pharmaceutical remedies for NAFLD or NASH that have been authorized. Since lifestyle modifications are the main focus of management, it can sometimes be challenging to successfully address the illness (Friedman et al., 2018).

4. **Conditional progression**: NAFLD can develop into more severe types including cirrhosis, hepatocellular carcinoma (HCC), and NASH. It is still difficult to determine whether people are at a higher risk of advancement (Targher et al., 2016).

5. **Diagnose and Screening:** NAFLD staging and accurate diagnosis sometimes necessitate invasive treatments like liver biopsies. It is a continuous struggle to develop non-invasive diagnosis and risk assessment techniques (Hofmann, 2016).

6. **Patient Education and Awareness**: NAFLD patients frequently aren't aware of their illness. Early intervention is dependent on increasing understanding of NAFLD among patients and healthcare professionals (Williams et al., 2011).

7. **Health Resource Demand:** There is a significant strain on healthcare resources, such as specialized clinics, liver transplant programs, and research efforts, as a result of the rising incidence of NAFLD and its propensity to advance to severe liver disease (Vernon, Baranova, & Younossi, 2011).

4. Conclusion and Future Work

Efforts to identify and categorize fatty liver disease and its associated clinical phases with more accuracy than humans have grown over time. Extracting features from processed photos and using these characteristics to accomplish the assignment has taken up the majority of the work.

More work has to be put into developing models that address problems and conducting randomized clinical trials on larger numbers of patients in order to advance possible future research. The discoveries will support the advancement of comprehensible AI in the future. To establish the most accurate phases of the images, taking into consideration the structural changes between the images, more work must be put into processing images and extracting characteristics. The comparison of computing complexity/power and classification accuracy should also be taken into account when contrasting DL and ML approaches. This will result in a better choice for detecting and quantifying NAFLD using US images.

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