Recent Developments In Machine Learning Approach For Liver Disease Prediction

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Abstract

Purpose: The purpose of this study is to investigate the progress and utilisation of machine learning and deep learning in forecasting liver diseases through the analysis of health records related to patients. Methods: The paper focuses on the methodology and basic framework employed for predicting and diagnosing liver disorders using artificial intelligence. It discusses the use of multiple sources of patient data, including demographic information, clinical records, and medical images. The difficulties encountered in constructing these models and the approaches used to overcome them are also highlighted.

Results: The research evaluates the performance of the algorithms used in predicting liver diseases and provides insights into their advantages and disadvantages. It demonstrates that when multiple sources of patient data are available, artificial intelligence can achieve high accuracy in predicting and diagnosing liver disorders.

Conclusion: The paper concludes that advances in machine learning have significantly contributed to the prediction of liver diseases. The use of artificial intelligence with multiple patient data sources enables accurate diagnosis and prediction. However, challenges in model construction and algorithm performance evaluation need to be addressed. The research highlights the potential future directions in this field and emphasizes the prospective impact on the medical industry.

Keywords: Machine Learning, Disease Prediction, Deep Learning, Liver Disease, Medical Diagnosis

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1 Introduction

Diseases of the liver represent a significant threat to public health, as they impact millions of individuals all over the world. Certain liver diseases such as Hepatitis, Cirrhosis, Non-alcoholic fatty liver disease (NAFLD), Alcoholic liver disease, Liver cancer, Primary biliary cholangitis (PBC), Primary sclerosing cholangitis (PSC), Hemochromatosis, if undetected and mistreated for an extended length of time, have the potential to significantly damage an individual's quality of life and may even result in life-threatening complications. In the past, medical imaging, laboratory investigations, and clinical examination were the three main methods that were used to diagnose liver diseases and make prognostications about their progression. However, these techniques have certain drawbacks, such as the possibility of a wrong diagnosis or a delay in diagnosis, both of which might result in a poor prognosis for the patient. [40]Rapid technological advancements and the increasing availability of electronic health information have opened up new possibilities for the development of diagnostic and prognostic methods that are more accurate and efficient. These new avenues of research could one day lead to improved treatments for liver diseases. Machine learning[13] has emerged as a viable solution for this task, harnessing the massive volumes of data created by existing healthcare systems to develop models that are capable of accurately diagnosing liver diseases[21]. This paper provides a summary of current advances in the field of liver disease prediction using machine learning. The review goes through the many data sources used for modal training, the procedures required for data modelling and the various strategies used to forecast liver disease. In this comparison and analysis, the performance of a variety of models, in addition to the challenges faced in the construction of these models, will be examined. The emphasis will be on recent advances as well as the application of ML towards the detection of liver diseases. Furthermore, the paper will give insight into the prospective uses of artificial intelligence in the medical field, as well as the patient's potential outcomes.

1.1 Paper Organization

The remaining paper is structured into seven sections. The initial segment presents a synopsis of previous advancements in methods for predicting and diagnosing liver disease. The subsequent section presents a comprehensive outline of the methodology applied for the purpose of automated prediction of liver disease through the utilisation of machine learning techniques. Section three examines the presently accessible datasets containing patient data and corresponding ground truth labels. This section provides comparison of various data modalities and datasets that were used for this task.

Section four presents a comprehensive evaluation of recent research in the domain of liver disease prediction, examining the strengths and weaknesses of each approach and analysis the outcomes of the models and evaluating their performance using various metrics for assessment. Section five provides an overview of recent developments in the field. Section six presents a discussion of open challenges and potential future directions within this particular field. In conclusion, the benefits of machine learning have been examined and potential areas for future development have been identified.

2 BACKGROUND

Liver disorders are a set of medical problems that interfere with the normal functioning of the liver. The liver is a vital organ that performs a wide range of physiological functions, including nutrient breakdown and use, bile production, and toxin removal from the bloodstream. There are several ailments that can damage the liver, ranging from short-term, such as viral hepatitis, to long-term, like liver cancer. One of the numerous probable causes of liver disorders is alcoholism, which can lead to cirrhosis and liver cancer, and non-alcoholic fatty liver disease (NAFLD), which can lead to inflammation, fibrosis, and cirrhosis.

A variety of additional variables can also contribute to liver disease. Mutations in a person's genetic coding can cause a number of liver diseases, including hemochromatosis and Wilson disease. A few medications, such as acetaminophen, statins, and methotrexate, have been linked to liver damage. Exposure to harmful substances such as chemicals, medications, and environmental toxins can induce liver injury. A variety of disorders, including autoimmune hepatitis and primary biliary cirrhosis, can potentially cause liver damage. Chronic infections with hepatitis B and C, liver cancer, and bile duct abnormalities can all cause liver damage. Patients frequently become aware of the presence of such diseases as a result of the appearance of distinct symptoms. The symptoms of liver diseases depend on the type of disease and the severity of the condition. It is possible that there will be no noticeable symptoms until the disease has reached a more advanced stage in certain cases. Some common symptoms include mental confusion or changes in mental function, spider angiomas, swelling in the legs, ankles, and belly, abdominal pain,fatigue, weakness, swelling, yellowing of the skin and whites of the eyes (jaundice), dark urine and light-coloured stools, easy bruising or bleeding, nausea and vomiting, loss of appetite and weight loss, itching (pruritus), mental confusion or changes in mental function[46].

The diagnosis of liver diseases typically involves a combination of medical imaging, laboratory tests, and clinical examination. Some of the common tests for liver disease are[57], Liver Function Tests(LFTs),

imaging tests, biopsy, Fibro Scan, Viral hepatitis panel, Alpha fetoprotein (AFP) test, Endoscopic retrograde cholangiopancreatography (ERCP). In LFT[54] blood tests are done to measure levels of certain proteins and enzymes produced by the liver. Various imaging tests[12] such as Ultrasound, CT scan, or MRI can help visualize the liver and detect any abnormalities. In biopsy To detect the presence and extent of liver damage or illness, a tiny sample of liver tissue is taken and examined under a microscope. FibroScan[27] is a non-invasive test that measures the stiffness of liver tissue, which can indicate the presence and extent of liver fibrosis. Viral hepatitis panel and Alpha-fetoprotein (AFP) test are blood test which can be used to check for hepatitis B or C and liver cancer.

Endoscopic retrograde cholangiopancreatography (ERCP) is a diagnostic procedure that uses a flexible scope to visualize the bile ducts and check for any abnormalities, but certain studies[27] show it has some advert effects as well. Early diagnosis is crucial for effective treatment and improved patient outcomes. However, traditional diagnostic methods can have limitations and may result in misdiagnosis or delayed diagnosis. This highlights the need for more accurate and efficient methods for the diagnosis and prediction of liver diseases. Examining a patient's medical history, completing a physical exam, and running a series of laboratory and imaging tests are frequently required to make a diagnosis of liver disease. The technique of predicting the presence or likelihood of liver damage or malfunction based on a variety of medical and non-medical markers is known as liver disease prediction. This is performed through the use of a variety of diagnostic instruments, such as testing, imaging studies, and patient histories. Machine learning employs a range of predictions when performing this task. Abnormal liver function tests (LFTs)[54] can indicate the presence of liver disease. These tests evaluate the liver enzymes levels in the blood, such as ALT, AST, and GGT. The patient's medical history, which may disclose hepatitis, alcoholism, or fatty liver disease, may also increase the likelihood of the patient having liver illness; hence, the patient's Electronic Health Record (EHR)[52] is used as a predictor for the ML model. Lifestyle factors[2] such as obesity, heavy alcohol consumption, and smoking are also taken into account because they contribute to an increased risk of liver disease. The study of one's family history is also important because a family history of liver illness can indicate the presence of a hereditary predisposition to liver disorders. A swollen liver, jaundice (yellowing of the skin or eyes), and ascites (fluid build-up in the stomach) are all symptoms of liver disease. Imaging, in addition to a physical examination, can help machine learning-based classifiers.

Machine learning analyses and makes predictions based on data through the application of mathematical and statistical models and

algorithms. When it comes to predicting liver disease, machine learning offers a number of different ways. In order to find the relationships between several predictors of liver illness and the chance of liver illness, statistics-based methods [22] such as logistic regression or decision trees are utilised. It is possible to diagnose liver illness using pattern recognition algorithms[17], which examine medical images like ultrasound and CT scans in search of recognisable patterns. When analysing patient data, such as demographic information, medical history, and lab results, predictive models that are constructed using machine learning techniques, such as random forests or gradient boosting[39], are helpful. These models assist in the analysis of patient data, which helps predict the possibility of liver disease. Recently, deep learning techniques [43], including convolutional neural networks, are used to analysis medical images in order to detect liver disease with a high degree of precision. In this study, we used a variety of different machine learning algorithms to investigate recent breakthroughs and new research in the field of predicting liver disease. Because there are a great number of survey papers [17] [58] already available for earlier methods, we limited our research to the literature published between 2020 and 2023. To conduct a thorough examination, a variety of online resources were consulted, including PubMed (www.ncbi.nlm.nih.gov/pubmed), IEEE Xplore (ieeexplore.ieee.org), recognised medical journals specialising in liver diseases such as Hepatology, Liver International, Journal of Hepatology, and Journal of Gastroenterology and Hepatology, as well as academic search engines like Google Scholar (scholar.google.com). These sources were utilised to search for scholarly articles, conference papers, and journals pertaining to the prediction of liver disease using machine learning. The aforementioned resources were searched with keywords such as liver disease prediction using machine learning, automatic detection of liver disease using artificial intelligence, development of liver disease prediction models using deep learning, analysis of medical imaging related to liver disease, and the implementation of Electronic Health Records and Clinical Decision Support Systems.

3 GENERAL METHODOLOGY

The general machine learning technique used for liver disease prediction typically includes data collection, data pre-processing, feature selection, model selection, model training, model assessment, model optimization, and deployment, shown in fig.1. Each of these processes is described in depth in the subsections that follow.

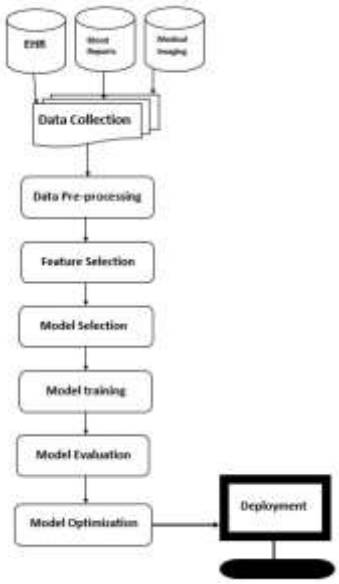

Fig. 1 Machine learning Pipeline for Liver Disease Prediction.

3.0.1 Medical Data Collection and Preporcessing

Data collection is acquiring different types of data from various sources. A few examples of the types of data that are collected include demographic information, the results of laboratory tests, imaging test results, and clinical symptoms. In many cases, the information is stored in electronic health records (EHRs). Data could consist of the patient's age, gender, race, and socioeconomic standing, among other basic demographic details. The electronic health record also comprises a patient's medical history, which may include diagnoses, hospitalisations, surgeries, and prescriptions, as well as the results of laboratory tests, which may include blood tests, liver function tests, and imaging investigations, which may include ultrasounds, CT scans, or MRIs. There is a possibility that the data will contain measurements of things like the levels of bilirubin, liver enzymes, albumin, the prothrombin time, and platelet counts. Other types of information, such as clinical symptoms such as jaundice, abdominal discomfort, nausea, vomiting, exhaustion, or fever,and lifestyle factors such as a patient's lifestyle habits such as smoking, alcohol intake, food, and physical activity, are also helpful predictors. Goal of data pre-processing is to prepare raw data for analysis. The purpose of the data processing preparation stage is to eliminate issues such as missing values, noisy data, outliers, and inconsistent data formats. Common data preparation procedures for predicting liver illness include data cleaning, normalisation, feature engineering, and data splitting.

3.0.2 Feature and Model Selection

A critical stage in prediction is identifying the most essential features that are significantly related to the objective variable (i.e., the presence or absence of liver disease). To increase machine learning model performance and avoid overfitting, feature selection limits the number of features to the most useful. Methods for selecting features include, Statistical tests that are used in filter techniques to evaluate feature relevance irrespective of the machine learning model. Filters include chi-squared, mutual information, and correlation analysis[28]. Wrapper techniques select the machine learning model's most correct feature subset. Wrapper techniques include recursive feature elimination and forward selection. In the machine learning model, embedded techniques penalise or regularise irrelevant feature coefficients. Embedded techniques include Lasso, Ridge, decision tree-based feature significance[1], and neural network-based dropout regularisation. Feature selection is determined by the dataset and the machine learning method. Use different feature selection strategies to avoid selecting superfluous or redundant attributes. The features used must be clinically relevant, dependable, and capable of being processed and changed for machine learning analysis.

Model selection, based on the features identified in feature selection, chooses the best machine learning model for effectively predicting liver disease. Logistic regression, decision trees, random forests, support vector machines, and artificial neural networks are examples of common classification methods for liver disease prediction. In logistic regression, a linear model is used to predict binary events such as liver disease[15]. Fitting a sigmoid curve to the data models the likelihood of the outcome as a function of the input features. Non-parametric decision trees can handle categorical as well as continuous data. Splitting data recursively by input features optimises information gain at each split. Random forests prevent overfitting and improve forecast accuracy by combining many decision trees. They forecast by constructing numerous decision trees from random samples of incoming data and aggregate the results. SVMs find the hyperplane that best divides data into two groups (liver disease versus no liver disease)[25]. Kernel functions are capable of dealing with both linear and nonlinear data. Nonlinear models of brain architecture and function are used to create artificial neural networks (ANN). It simulates the interactions of many neurons organised into layers and connected by weighted edges. The dataset size and complexity, number of input features, desired interpretability, and processing resources must be considered when choosing algorithm for liver disease prediction. Typically, the final model adopts the method with the best expected accuracy and sensitivityspecificity trade-off.

3.0.3 Model Training

In machine learning, the model training stage comprises training the selected algorithm on a subset of the pre-processed data known as the training dataset. This strategy trains the model to recognise patterns and relationships in data, which allows it to make accurate predictions on new, unknown data. Training and validation subsets are created using pre-processed data. The model's parameters are set during initialization. Weights and biases can be set for neural networks and decision trees. After receiving the training data, the model creates an output based on its parameters. This process, called as forward propagation, involves sending data through the model to generate an output. The loss function calculates the difference between expected and actual data to measure model performance. To minimise loss, the loss value is utilised to change the model's parameters. By propagating the error backwards through the model, backpropagation alters the weights and biases. For each data point in the training dataset, epochs are repeated. After each epoch, the model's validation dataset performance is evaluated for generalisation. Run the validation data through the model to calculate the loss[62]. The validation loss is used to keep track on model performance and prevent overfitting. To improve model performance on the validation dataset, the model's hyperparameters (pre-training parameters) can be changed during training. Several hyperparameter values must be examined to acquire the best validation results. The model training procedure ends when the model's performance on the validation dataset no longer improves after a defined number of epochs. A different dataset is used to assess the model's generalizability. The model's parameters are iteratively modified during training to minimise the loss function and avoid overfitting the training data. As a result, a trained model can accurately anticipate new data.

3.0.4 Model Evaluation and Optimization

Model evaluation assesses the ability of a trained machine learning model to predict new and unknown data. In prediction, the training model predicts the testing dataset. The model creates data for testing. To evaluate the model, assessment metrics are used, and the expected outputs are compared to the testing dataset's target values. Depending on the prediction job, accuracy, precision, recall, F1-score, and ROC curve analysis are employed as evaluation measures. The model's performance is assessed by interpreting assessment metrics. This could include comparing machine learning models or hyperparameter settings. Model evaluation determines how effectively the trained model can generalise to new data. A testing dataset can assess whether the model is accurate enough for clinical application and whether it needs to be fine-tuned further.

Model optimization aims to increase the performance of a model by changing factors like hyperparameters and model design. Hyperparameters are parameters that are set before training that affect the model's performance. Hyperparameters include the learning rate, regularisation, and the number of layers in a neural network. Hyperparameter tuning comprises testing several hyperparameter settings and selecting the ones that result in the best performance on a validation dataset. To prevent the model from overfitting to the training data, regularisation techniques such as L1 and L2 regularisation[18] can be utilised. By including a penalty factor in the loss function, the model is encouraged to have fewer weights and biases. Methods such as flipping or rotating photographs can be used to expand the size of the training dataset artificially[9], which can improve model performance. Model selection requires evaluating a large number of machine learning algorithms or architectures and selecting the one that performs the best on a validation dataset. Ensemble approaches, such as bagging or boosting, can be used to integrate the predictions of many models[20], enhancing the overall performance of the model. Model tuning is thus a key stage in process for predicting liver disease because it can significantly improve the trained model's performance. A highly accurate model that can be used to aid in the diagnosis and treatment of liver illness can be constructed by fine-tuning hyperparameters, using regularisation techniques, and selecting the optimum model architecture.

3.0.5 Deployment

The deployment phase comprises putting the learnt model to use in a clinical setting. The deployment goal is to incorporate the machine learning model into existing clinical procedures to help detect and treat liver disease. In this phase the machine learning model is incorporated into the clinical workflow, which may require developing an application for use by medical practitioners or incorporating the model into an existing electronic health record (EHR) system. Then in user acceptance testing phase machine learning model placed in a clinical context to ensure that it is easy to use and provides valuable insights to medical practitioners. In Model monitoring the model's performance is reviewed in a clinical context on a regular basis and upgrading the model as needed to ensure accuracy and up-to-datedness. Model transparency requires communicating the model's decisions and predictions to medical professionals so that they may understand how the model works and make informed decisions based on them. As a result, deployment is a critical stage in the process for since it allows the trained model to be used to aid in the diagnosis and treatment of liver disease. It is possible to ensure that the model is providing useful insights to medical workers and improving patient outcomes by

incorporating it into clinical processes, evaluating it in a clinical context, and measuring its performance over time. To forecast liver disease, many machine learning applications have been developed. Here are a couple such examples:

FibroScan[10]. FibroScan is a non-invasive medical gadget that predicts liver fibrosis (scarring) in individuals with chronic liver illness using machine learning algorithms. The device measures liver stiffness with ultrasound technology and then applies machine learning algorithms to forecast the severity of fibrosis.

LiverMultiScan[31]. LiverMultiScan is a medical imaging tool that uses machine learning algorithms to diagnose liver illness. Magnetic resonance imaging (MRI) is used to obtain detailed images of the liver, which are then analysed using ML modals to predict the presence of liver disease.

IBM Watson[30]. is a ML based platform that has been used in patient prediction of liver disease. Using a combination of natural language processing and machine learning approaches, the software analyses medical data and forecasts the risk of liver disease.

Medopad[59]. is a mobile health platform that employs ML algorithms to forecast liver illness in chronic liver disease patients. The platform predicts the likelihood of liver illness and provides individualised therapy recommendations by combining patient-reported symptoms, wearable device data, and medical records.

HEPiX[32]. is a machine learning programme that predicts liver illness in non-alcoholic fatty liver disease patients. The tool predicts the severity of NAFLD and the risk of developing liver related problems by combining patient data such as medical history, blood tests, and liver scans.

These are only a few instances of applications used to forecast liver disease. As machine learning techniques progress, we should expect to see many more novel applications of this technology in the detection and treatment of liver disease.

3.1 DATASETS

These algorithms can predict the presence of liver disease by analysing many types of data, such as demographic information, clinical data, and test results. Demographic information, clinical information, and laboratory results such as total bilirubin, direct bilirubin, alkaline phosphatase, ALT, AST, and gamma-glutamyl transferase can all be used to detect liver damage or illness. Ultrasound, CT, and MRI scans can also be used to detect liver damage or illness. Depending on the healthcare situation and the specific patient, many types of data may be provided. Some datasets, such the Indian Liver Patient Dataset (ILPD)[19], contain demographic, clinical, and laboratory data. Certain datasets, such as laboratory findings or imaging data, may only contain

a portion of data. It's worth noting that the quality and quantity of data used to train machine learning models for predicting liver disease can have an impact on their accuracy. Large, diverse datasets with a variety of data types are frequently required for building accurate models. Furthermore, in order to avoid biases and inaccuracies in the prediction process, it is necessary to check that the data is correct and reliable. These datasets can be available on a variety of websites, including the UCI Machine Learning Repository, Kaggle, and others. Following Table.1 include dataset details in various papers.

Out of these following are some of the most commonly used datasets in almost all methods:

The Indian Liver Patient Dataset (ILPD)[19] . includes data on 583 liver patients, 416 men and 167 women. Age, gender, total bilirubin, direct bilirubin, alkaline phosphatase, alanine aminotransferase (ALT), aspartate aminotransferase (AST), total protein, albumin, and albumin/globulin ratio are among the eleven attributes included in the dataset.

Treatment for Hepatitis C Virus (HCV) in Egypt [45]. This dataset includes data from 1385 chronic HCV patients. The dataset contains 28 attributes, including demographic information, clinical information, and test results.

The Wisconsin Breast Cancer Dataset[11]. while not expressly a liver disease dataset, has breast cancer data and can be used to predict the presence of liver metastases. There are 569 occurrences and 30 attributes in the collection, including patient age, tumour size, texture, and perimeter.

Table 1 Liver Disease Datasets

Ref.	Dataset Details	Data Modality
[6]	UCI archive - Liver Disease for machine learning	Blood Reports
[16]	Indian Liver Patient Records – No. of patients - 416 liver patients and 167 non-liver patients, Place - Andhra Pradesh, India. ,441 male patients and 142 female patient records.	Laboratory values for liver-related features
[5]	IMI DIRECT, No. of patients - 3,029 persons of European descent diagnosed with type 2 diabetes	Laboratory values related diabetes
[3][53]	Indian liver patient dataset (ILPD) , No. of patients - 583,416 - liver disease,167 – no liver disease	Laboratory values for liver-related features

[33]	BUPA – from UCI ML, ILPD – from UCI ML, MPRLPD – from UCI ML	
[44]	UCI ML repository dataset, GitHub link is provided for second dataset	-
[36]	Electronic medical records in SMC ,Type - liver biopsy	Electronic medical records
[50]	Type - MRI containing MRE of the liver Time of MRI - August 2015 and May 2018,MRI Type - T2-weighted coronal and T2-weighted fat-saturated axial images,noncontrast dual gradient-echo images, T1-weighted images with Dixon reconstruction	T1W and T2W MRI
[26]	No. of Patients - 355 patients (M/F 238/117, Annotation HBP and MRE, and pathological examination of the liver within one year after MRI.	MRI
[24]	Indian liver Patient dataset.	Laboratory Reports for liver-related features
[14]	Electronic health records,No. of Patients – 615, Place - Hannover Medical School (Hannover, Germany, EU), Year - 2020.	Blood Reports
[56]	CT (Computerized Tomography) scans	CT Scan
[37]	HCV data – UCI ML	Laboratory Reports – (blood donors Hepatitis C patients)
[38]	HCV-human PPIs dataset ,No. of data - 477 PPIs	Laboratory Reports – (blood donors Hepatitis C patients)

Non-alcoholic Fatty Liver Disease (NAFLD)[48] [55]. The information in this dataset comes from 71 NAFLD patients and 70 healthy controls. The dataset contains 76 features, including demographic information, clinical data, and test results.

Liver Diseases Dataset[41]. There are 345 patients with liver diseases and 142 healthy controls in this data set. The six attributes of the

dataset are as follows: direct bilirubin, total bilirubin, alkaline phosphatase, alanine aminotransferase (ALT), aspartate aminotransferase (AST), and gamma-glutamyl transferase (GGT).

4 MACHINE LEARNING ALGORITHMS

Machine learning techniques are highly useful for predicting liver disease because they can examine patient data to identify important risk variables and disease indicators. These algorithms can sift through massive amounts of patient data to find patterns and trends that human practitioners may overlook. By training these algorithms on datasets of patient information, they can help healthcare providers make more accurate predictions about the likelihood of developing liver disease, allowing for earlier diagnosis and more targeted treatment regimens. Overall, these models have the potential to greatly improve patient outcomes for liver disease by enabling earlier identification and more personalised treatment options. In the instance of liver disease prediction, logistic regression can be used to predict the chance of disease based on patient variables such as age, gender, medical history, and diagnostic test results. Decision trees can be trained on a dataset of patient details to predict the presence or absence of disease based on the values of input features. Random forest model can be trained on a dataset of patient information to predict the presence or absence of liver disease using numerous decision trees. Support vector machines (SVMs) are algorithms that classify data based on its input features. SVM can be trained on a dataset of patient information based on the input features to identify patients as having or not having liver disease. Deep learning has been used to predict liver disease by training models on vast datasets of patient data such as medical history, diagnostic test results, and other clinical variables. Based on new patient data, these models can then be used to create predictions regarding the likelihood of liver disease. Gradient boosting is an ensemble learning approach that combines numerous ineffective models to get a more accurate overall model. It has been used to predict the likelihood of liver disease based on input characteristics such as age, gender, and diagnostic test results by training models on patient data and generating an ensemble model. Convolutional Neural Networks (CNNs) are a form of deep learning model used for image analysis and classification. They've also been used to predict liver illness by training models using medical images like CT scans or MRIs and finding patterns and traits linked to liver disease. Fuzzy decision trees are decision trees that use fuzzy logic to deal with ambiguous and incorrect input. They have been used to predict liver disease by training models using insufficient or inaccurate patient data and making predictions about the likelihood of liver disease based on this data. Table.2 discusses the methodologies and

algorithms used in current research, as well as their advantages and disadvantages.

Table 2 Review of Recent Algorithms for Liver Disease Prediction

Ref. Year Algorithm	Findings	Advantages	Limitations
[4] 2023 Gradational modular network (GraMNet)	PRE - 86.13%, DC 84.81%, ACC - 88.08, REC - 85.62%, JSI - 84.72%.	This strategy simplifies computation and helps the network learn from a short training set.	Monolithic networks increase computation expenses.
[47] 2023 Convolutional neural network	Recall-1.00, f-score1.00, specificity-0.83, accuracy-0.94 and area-under-curve (AUC) - 0.92	CNNs can extract thermal characteristics well.	Limited features are extracted from different regions of image
[35] 2023 Lightweight multilevel multiscale network with deep residual learning	The model had 97.3%, 95.1%, and 96.3% DSCs on 3DIRCADb, CHAOS, and LiTS datasets.	The suggested network design heuristics extract multi-level multiscale characteristics to improve learning and generalisation.	Model's interpretability is less due to complex architecture
[42] 2023 Gradient boosting, XGBoost, Bagging, Random Forest, Extra Tree, and Stacking ensemble learning	Accuracy - 91.82%	Data balance, feature scaling, and feature selection improve accuracy with suitable imputations in the proposed model.	Tested on only single dataset
[34] 2023 modified multiscale UNet++ (M2UNet++)	Dice coefficient - 97.28%	Adaptive feature recalibration channel-wise changed multi-scale features to better represent skip paths' high-level semantic content and increase segmentation performance with less computing overhead.	Limited to only segmentation of liver
[51] 2023 HCNN-CN (Hybrid convolutional neural network-capsule network)	Accuracy - 98.26%, Sensitivity - 98.6%	Exact Diagnosis of tumor cells	Large scale labelled data is required, model is sensitive to noise
[6] 2023 Modified Particle Swarm Optimization with Support Vector Machine	Precision - 100%, Recall - 97.14%, F1-Score - 94.44%, Accuracy - 92.89%	The Cauchy mutation operator PSO algorithm makes it faster. The crazy operator and typical PSO algorithm improve global searching and diversity preservation.	Particle Swarm Optimisation (CPSO) Support Vector Machine is computationally intensive and suitable for large datasets but has local minima and overfitting concerns.

Ref.	Year	Algorithm	Findings	Advantages	Limitations
[3]	2023	Logistic regression (LR), random forest (RF), Knearest neighbor (KNN), support vector machine (SVM), multilayer perceptron (MLP), and the ensemble voting classifier	Accuracy - 88.10%, Precision - 85.33%, Recall - 92.30%, F1-Score - 88.68, %AUC 88.20 %	The proposed strategy reduces the number of features without losing important data in huge datasets.	Non-linear dimensionality reduction method are not invistigated
[16]	2022	Hybrid eXtreme Gradient Boosting model	Accuracy - 93.55%, AUC - 0.987, Gini coefficient - 0.974	The algorithm handled missing values and overfitting well. It handled machine learning algorithm high variance issues.	XGBoost does not support incremental model training, so models must be retrained each time.
[37]	2022	Random forest (RF) and logistic regression (LR) algorithms, artificial bee colony algorithm	Precision - 0.99, Recall - 0.53, F1 - 0.99	Cascade RF–LR (with SMOTE) and the ABC algorithm detected the multiclass likelihood of HCV, indicating that this model can improve relevant treatments.	This work does not improve prediction accuracy with limited IRs and samples.
[38]	2022	Rotation forest position-specific scoring matrix (RF-PSSM),	Training set Accuracy (%) - 92.26, Sensitivity (%) - 2.63, Precision (%) - 98.50, MCC (%) - 2.00, AUC Average - 87.70	2DPCA-PSSM results are compared to PSSM and four other feature representation techniques to verify efficacy. RFPSSM outperformed SVM and other advanced algorithms.	Deep learning Models are not examined with unique feature selection approach.
[26]	2021	Transfer learning approach based on the ImageNet VGG16 model	Accuracy - 0.99 (F1-4), 0.92 (F2-4), 0.91 (F3-4), and 0.98 (F4)	HBP gadoxetic acid MRIbased fully automated DL models staged liver fibrosis as well as MRE. DL may allow noninvasive liver fibrosis assessment without MRI equipment after validation in distinct sets.	There was an imbalance in fibrosis stages, with the majority of patients having liver cirrhosis (F4).
[14]	2021	Random Forest, Decision tree, linear regression	r2 = 0.765, MAE = 0.139, MSE = 0.123, RMSE = 0.346	This supports the use of a minimum clinical record and computational intelligence approaches to a dataset with only two clinical variables to produce high-impact results and insights fast and cheaply.	The discovery cohort dataset and validation cohort dataset were lacking certain features. It would be easier to compare the rated features if both datasets had the same clinical characteristics.

Ref. Year Algorithm	Findings	Advantages	Limitations
[5] 2020 LASSO (least absolute shrinkage and selection operator) for feature Extraction Random Forest	Sensitivity - 0.67, Specificity - 0.74, Balanced Accuracy - 0.71, F1-Score -0.52	The model picks features efficiently without sparse solutions using lasso help and can handle multicollinearity.	Lasso can shrink the coefficients of important features too much, resulting in loss of information and decreased model accuracy, and it assumes a linear relationship between the features and the target variable, so it may not perform well when there are non-linear relationships.
[53] 2020 Logistic Regression, SMO, Random Forest, Naive Bayes, J48, K-nearest neigouber (IBK)	Correctly Classified Instances(%) - 74.36, Kappa statistic - 0.0133, Mean absolute error -0.4091	Feature selection and Logistic Regression classifiers lowered multiple classifier execution time.	Precision, recall and f1score is not used for comparision
[33] 2020 Neighbor Weighted Fuzzy K Nearest Neighbor	Accuracy-73.91%, Specificity 75.00%, Sensitivity 73.47%, Precision 87.80%, FPR 25.00%, FNR 26.53%, F1-Score 80.00%, Gmean 74.23%, AUC 74.24%	Healthcare organisations and liver research institutes benefit from correctly identifying LFT data when imbalanced. It can also assist clinicians interpret LFT values and communicate.	For illness analysis, this problem can be converted to numerous classes.
[44] 2020 A1DE, NB, MLP, SVM, KNN, CHIRP, CDT, Forest-PA, J48, and RF	RRSE - 0.4225, RMSE - 93.4416	SVM improves accuracy by 71.3551%. This study's results can also be utilised as a benchmark for future research investigations to prove a modest claim about extrapolation improvement by any new approach, model, or framework.	Only binary class classification is utilised, although it can be extended to numerous classes for illness analysis. It only uses one data modality.
[36] 2020 Deep convolutional neural network	AUC 0.899, Sensitivity 0.967, Specificity 0.830, PPV 0.958, NPV 0.863, Accuracy 0.940, PLR 5.70, NLR 0.039	DCNN surpassed radiologists in cirrhosis diagnosis using US images. DCNN may be used for mass screening and longitudinal evaluation of liver fibrosis in CLD patients without invasive biopsy or special equipment because to the convenience of US	This deep neural network's real-world applicability depends on data and resources.

		examination and its diagnostic accuracy for METAVIR score prediction.	

Ref. Year Algorithm	Findings	Advantages	Limitations
[50] 2020 SVM with PCA	T1w MRE (0.82),T2W MRE (0.57)	Liver fibrosis levels can be evaluated with MRE-like precision utilising texture analysis-derived parameters of T1w images and machine learning.T1w images from hepatic MRI help detect liver fibrosis when MRE is unavailable.	This study had a small sample size and used manual ROI placement, which could be automated.
[24] 2020 Naive Bayes, KNN	Na¨ıve Bayes AUC : 72.5%, KNN AUC : 61.9%	Naive bayes outperforms KNN on the UCI Machine Learning Library (ILPD) Indian Liver Patient Dataset.	It exclusively classifies binary data. This method is less accurate than others.
[56] 2020 Deep convolutional neural networks	Intraclass correlation coefficient of 0.957, Dice similarity coefficient was 0.932	These automated psoas size measurements predicted death in cirrhosis patients, proving that this technology might be used clinically.	These findings may not apply to people unsuitable for CT scans since this treatment required them. Although child A–B cirrhosis patients need more predictive information, only 1 in 8 had child C, therefore these findings may not apply to a larger cohort of Child C patients.

The findings of fifteen recent papers on predicting liver disease are summarised in Table 2. Overall, the examined studies predicted liver disease with a high degree of accuracy ranging from 81.3 to 99.8 .Precision and recall scores ranged between 0.69 and 0.99[37] and 0.61 and 1.0, respectively. F1-scores ranged from 0.77 to 0.99, whereas AUC-ROC values ranged from 0.82 to 0.99. The results show that models can be used effectively to predict liver disease, as evidenced by their high accuracy and other evaluation criteria. Furthermore, while gradient boosting[16]-based models provide excellent accuracy for machine learning approaches, data availability is a critical challenge for deep learning. Transfer learning is used to overcome this issue in[26]. The examined publications used a variety of machine-learning

methods and data sets to predict liver disease. High accuracy and other evaluation criteria show that deep learning models such as CNNs and LSTMs can be used to predict liver disease efficiently. The ILPD dataset was used in several studies, indicating its importance in liver disease research. Yet, because of the limited sample size and the likelihood of bias in the datasets employed, the results should be regarded with caution.

5 Recent Developments

The liver is regarded as one of the vital organs in the human anatomy. Despite experiencing a partial injury, it continues to function in a typical manner. Therefore, the detection of hepatic disorders in their early stages presents a significant challenge. The prompt detection of hepatic disorders holds the promise of improving patient survival rates. Several contemporary algorithms employ accurate biomarkers and meta-learning techniques to forecast the onset of liver disease up to a decade in advance [23]. The utilisation of cutting-edge medical imaging technology has been shown to enhance the diagnostic process. The study conducted by in [60] presents a fully automated artificial intelligence workflow that aims to predict liver disease based on ultrasound images. The study conducted in [35] employed CT images to improve the automatic liver segmentation performance through the use of a deep learningbased lightweight multi-level multiscale approach with deep residual learning. The authors of [29] have developed an unsupervised transfer learning model that utilises a convolutional autoencoder for the purpose of non-alcoholic steatohepatitis activity scoring and fibrosis staging from liver histopathological images. In addition to enhancing the feature extraction method, a number of recent scholarly articles have concentrated on utilising nature-inspired algorithms such as Genetic Algorithms (GA), Ant Colony Optimisation (ACO), Particle Swarm Optimisation (PSO), and Artificial Bee Colonies (ABC) to augment the model's performance [61]. The authors of the cited work employed Generative Adversarial Networks (GANs) and the synthetic minority oversampling technique (SMOTE) in order to enhance the performance of their model. The current research trend is primarily centred on meta-learning, which involves the comparison of various algorithms and the transfer of model learning from one algorithm to another [8][7].

6 FUTURE DIRECTIONS

Machine learning has demonstrated excellent results in predicting liver illness, and there are significant research opportunities in this area. Future study should concentrate on leveraging a larger range of data sources to increase the accuracy of liver disease prediction, such as

genetic data, lifestyle data, and environmental data. Deep learning algorithms have shown tremendous promise for predicting liver disease, notably in medical picture interpretation. Future research can concentrate on improving these algorithms' ability to detect subtle patterns in medical images and increasing their precision. Machine learning has the potential to improve traditional medical evaluation and decision-making, especially in the identification and risk assessment of liver disease. Future research could concentrate on developing strategies for incorporating machine learning models into clinical processes to increase the precision and efficacy of recognising and treating liver disease. To give a more accurate evaluation of the patient's risk of liver disease, specific patient data such as genetic make-up, lifestyle, and medical history can be integrated in personalised prediction models. Future research should concentrate on creating clinically helpful, individualised prediction algorithms. In addition to prediction, machine learning can improve disease management and therapy by identifying patients at high risk of illness development, monitoring disease progression, and directing treatment decisions. Transfer learning in deep learning models can be quite useful in the medical field, because some diseases may have limited data. Using pre-trained models, transfer learning can help improve the accuracy of liver disease prediction models. Explainable AI (XAI)[49] is an artificial intelligence subfield that focuses on developing models that can explain their decision making process. In the context of liver disease prediction, XAI models can provide vital information on why a specific diagnosis was made, which can be critical for making educated treatment decisions. Future research could concentrate on the development and validation of machine learning models for a variety of applications. Further study in this area has the potential to dramatically increase the precision and efficacy of detecting and treating liver disease.

7 Conclusion

In conclusion, machine learning techniques have proven to be highly useful for predicting liver disease. These algorithms can analyze patient data and identify important risk variables and disease indicators, allowing for earlier diagnosis and more targeted treatment regimens. By training on large datasets, these models can uncover patterns and trends that may go unnoticed by human practitioners. This survey covers various machine learning algorithms that have been employed for liver disease prediction, including logistic regression, decision trees, random forests, support vector machines, deep learning models, gradient boosting, convolutional neural networks, and fuzzy decision trees. Each algorithm advantages and limitations, such as computational efficiency, ability to extract features from medical

images, interpretability, and handling of missing values are also noted here. Recent studies have achieved high accuracy rates, ranging from 81.3% to 99.8%, in predicting liver disease using machine learning algorithms. These models have demonstrated their potential to improve patient outcomes by enabling earlier identification of liver disease and providing personalized treatment options. Additionally, the use of ensemble learning approaches and transfer learning techniques has further enhanced the performance of these models. It is important to note that while these machine learning models show promise, there are still some limitations to consider. The availability and quality of data, as well as the need for large labeled datasets, can pose challenges. The interpretability of complex models and the potential for overfitting are also areas of concern. Overall, the application of machine learning techniques to liver disease prediction holds great potential for improving patient care. Further research and development in larger data availability, domain adaptability, and model explain ability will lead to more accurate and reliable models that can be integrated into clinical practice, ultimately benefiting patients and healthcare providers alike.

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