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Research Article

Review on Liver Cirrhosis Detection using Machine Learning and Deep Learning Techniques

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ABSTRACT

Liver illnesses account for further than 2.8% of all fatalities in India each year. However, it can be challenging to spot liver disease in the early stages when the symptoms are minor. The majority of the time, symptoms of liver illness don't appear unless a critical phase has been reached, making it difficult to recognize and diagnose. Therefore, a thorough literature survey is conducted that aims in identifying liver diseases among patients by employing different techniques. The paper starts by discussing briefly about liver and various diseases related to it. Moreover, we have also analysed the impact of covid-19 on liver. After analysing the literature survey, it has been analysed that majority of researchers are working majorly with two classes of Machine Learning (ML) and Deep Learning (DL). However, due to some limitations in these models, authors started to shift their attention towards Nature Inspired Optimization Algorithms. We have reviewed some of the latest works in these three categories and at the end of each category a comparison table and inferences are given. Moreover, it has also been observed that by using optimization algorithms along with ML algorithms, the accuracy of liver disease detection models is enhanced significantly.

Keywords: Liver Disease detection, Learning methods, Deep Learning methods, Meta- heuristic approaches, Optimization Algorithms, Medical science, etc

INTRODUCTION

The liver is a very crucial organ for numerous bodily processes, including the breakdown of red blood cells. Liver is located just above the upper right position of abdomen which is the largest organ of body of human being (Singh et al.,2020). Any abnormality that is associated with the liver is referred to as liver disease. Inflammation or Hepatitis B or C, which originate from contagious or non-contagious reasons such biochemical or immunological hepatitis, are only a few of the issues associated with liver illness. The liver can also develop tumours, malignancies, cirrhosis, and metabolic problems, to name a few. In addition to this, with the rise of covid-19 pandemic in 2019, the susceptibility and vulnerability of getting infected with liver disease also increases (Nanyue et al.,2015; Karthik et al.,2011). Ever since, the virus has quickly spread over the globe, triggering the coronavirus illness 2019 (COVID-19), that is currently having a terrible impact on global healthcare (Williamson et al.2020; Ioannou et al.,2020). Despite the fact that the lungs are the primary organ affected by SARS-CoV-2 virus, damage can still be done to other organs like liver. As mentioned earlier, liver is a crucial part of the body; thus COVID-19 affected patients may also have to worry about it being exposed to virus particles. However, there is currently no solid proof indicating SARS-CoV-2 exposure to the liver cells occurs in severe instances. Furthermore, it is yet unknown how much liver diseases contribute to the complexity and fatality of COVID-19. With the rise in COVID-19, liver impairment is a growing issue as it was shown with related coronavirus SARS. According to past studies, the livers of approximately to 60% of any human individual showed impairment, and liver biopsy samples revealed viral nucleic acid and damages (Lee et al., 2003; Tsang et al., 2003). Since the majority of the participants in such experiments received large amounts of antibiotics, hepatotoxic antiviral medications, and steroids (Gori et al., 2020; Guan et al., 2020; Yang et al., 2020) the researchers of these studies speculated that this could have been the consequence of drug-induced liver injury. While there are various shortcomings in identifying the root causes of liver injury in severe disease stages, pre-existing liver situations were not enumerated in the majority of these experiments, and the communication of pre-existing liver failure with COVID-19 was not been explored. Nonetheless, there was a greater fatality rate in COVID-19 individuals who had high levels of alanine aminotransferase, decreased platelet count, and low albumin concentrations. While it still remains unclear whether such lab's related tests were showing the failure of liver brought on by the SARS-CoV-2 virus or they serve as a warning sign for hepatic illnesses that already exist in severe patients (Boettler et al., 2020). Furthermore, immune system overreactions can harm the liver and speed up the course of the liver injury disease in patients.

Increased cytokine concentrations in COVID-19 patients have been linked to respiratory diseases and even multiple organ failure (Abou-Arab et al., 2021), whereas a more severe cytokine storm may have an influence in the development of corona Virus among individuals (Moore et al., 2020). Therefore, the increased enzyme levels in liver and impact of covid-19 on these enzyme levels are associated with each other. Studies have revealed that the existing enzymes categorized under Interleukin (IL)-1 and 6, along with interferon (IFN)-induced protein 10. In addition to this while talking about the other tumour necrosis factor (TNF) the interferon-gamma (IFN-), protein named as macrophage inflammatory 1α and 1β, and vascular endothelial growth factor are cytokines which are raised in including patients COVID-19 (Huang et al., 2020). However, it has been seen that high IL-6 concentrations in general are linked to COVID-19 death and intensity. Because COVID-19 victims display a wide range of immunological responses and signs that are related to immune, individuals that are unable to inhibit SARS-CoV-2 proliferation seem to be more likely to demonstrate immune dysregulation linked to the pathogenesis. An enormous public health strain is being added by the ongoing global obesity pandemic, which has resulted in insulin resistivity, high sugar levels, and chronic liver disease (CLD). Studies provided the information that the leading causes due to which the CLD occur are chronic hepatitis B and C, and many other alcohol related diseases for liver. In addition to this non-alcoholic fatty liver disease (NAFLD) is also type of these diseases. Moreover, if not treated at the right time, CLD can also cause inflammation, fibrosis, and cirrhosis as well as hepatocellular carcinoma (HCC) diseases. Generally discussing, there are around 2 million deaths annually caused by cirrhosis, viral hepatitis and HCC (Sepanlou et al., 2020). Hepatocytes, that are found vastly in liver are a key protein source that is used in adaptive and innate immune responses. By inhibiting the systemically dissemination of microbial and food antigen which enter the body from the gut and by synthesizing solubility molecules necessary for efficient immune responses, the liver controls immunological homeostasis. As a result, liver damage can impair immune recognition by lowering the protein synthesis necessary for increasing immunity. In addition to this, pathogen-associated structural pattern is recognized in the liver.

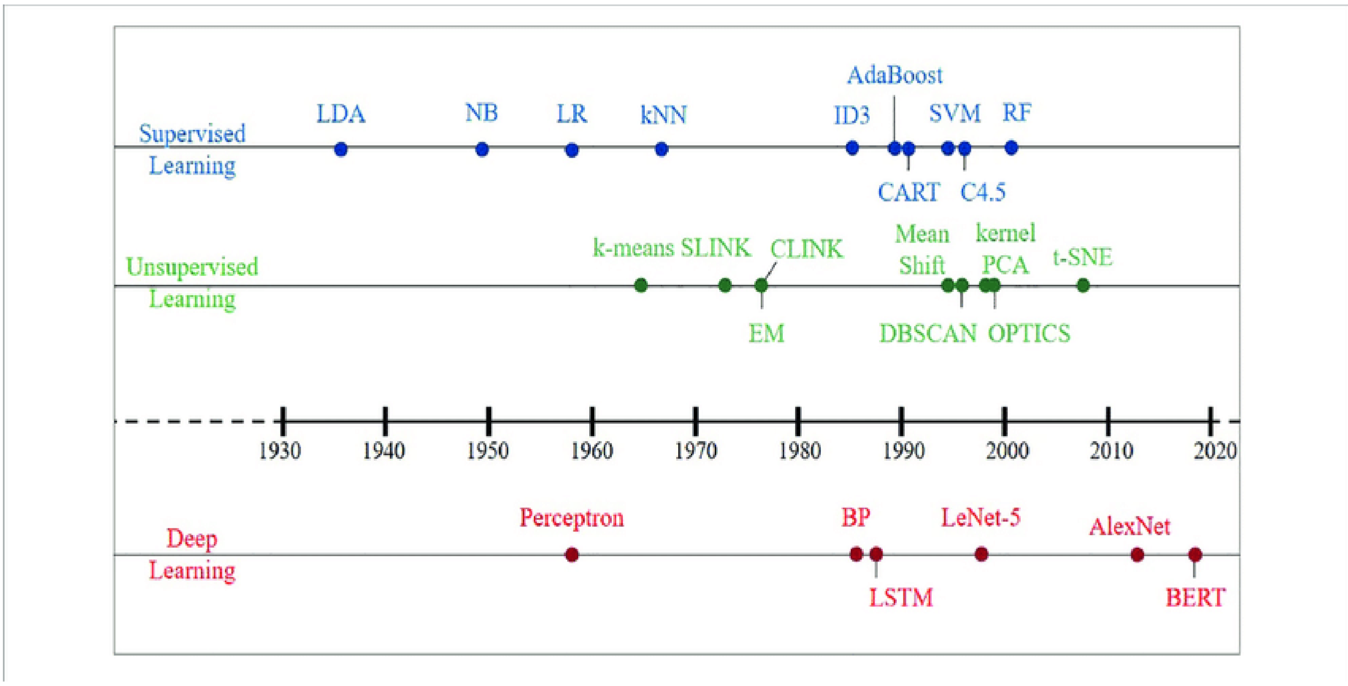

Fig 1. Evolution of Classical Algorithms

Immune dysregulation is characterized by both cirrhosis and CLD. The homeostatic function of the liver in the systemic immune response is compromised by CLD. Circulating immune cells become active and pro-inflammatory cytokines including TNF and IL-6 are found in higher concentrations in the serum as a result of the molecular patterns that are generated from injured liver cells, thereby causing inflammatory processes. Additionally, immunological dysfunction linked to the liver can make people more susceptible to diseases. In this light, it is not astonishing that death in COVID-19 and morbidity are mostly seen in individuals with CLD, mainly those with liver cirrhosis (Webb et al., 2020; Martinez et al., 2021). Because of the interactions of biochemical functions defined by immunological dysregulation, cirrhosis and SARS-CoV-2 infections seem to be a lethal combination. Liver transplantation is one of the influential measures for the patients suffering from decompensated cirrhosis that not only recovers important functions of liver but also reduces the likelihood of COVID-19 death among people. The severity of the disease, that can be deadly in the majority of instances as well, is associated with higher liver enzyme levels (Ling et al., 2017).

On the contrary side, recognizing disease signs earlier can be helpful and increase the likelihood of identification. As was already established, liver enzyme levels are connected with diseases heterogeneity and the severity of liver damage, that are higher in individuals with COVID-19. Therefore, the condition of COVID-19 individuals can be enhanced by regulating their liver enzyme levels. The frequency of infected individuals has also significantly dropped as machine learning develops better methods to assess the severity of COVID-19 virus, motivating scientists in artificial intelligence (AI) and medical experts to utilize this area more broadly in the area of health. A typical AI system is responsible for learning features from raw data that is called as Machine Learning or ML. after this, efficient and important features are extracted from this raw data by using the pattern recognition algorithms and then these extracted features are used by ML algorithms in order to recognize relation between objects. The first machine learning algorithms stretch to the early 20th century, and many traditional techniques have been created during the last century. Traditionally, there are four subcategories of classical algorithms which are termed as different learning strategies reinforcement, supervised followed by deep and unsupervised learning. In Fig. 1, the development of these methods is depicted. Machine learning (ML) process and deep learning (DL) techniques were created to aid in the learning of machines. ML and DL algorithms can be used to tackle classification problems, and this technique has been applied in the healthcare sector to help with the early detection of a number of diseases. These computational methods do present some distinct difficulties, particularly during the feature-selection stage of estimate methods. As a result, many researchers are already developing such systems for quickly and accurately tracking patient liver enzyme concentrations.

In the coming up sections of this paper, we are going to review some renowned latest works in the field of liver disease detection. After careful consideration, we noticed that number of techniques are employed by various researchers in their works. However, majority of these work revolve under the category of Machine Learning (ML) along with Deep Learning (DL) and Optimization based models. In the regard, we divided the coming up sections of our review article in three categories of ML based Liver disease detection model, DL based Liver disease detection model and Optimization based Liver disease detection models. Along with this, we also provided a comparative table at the end of each section to have better understanding. Along with this, the problems associated with each category and the need for using advanced DL and Optimization based liver disease detection models is also discussed.

1. ML BASED LIVER DISEASE DETECTION MODELS

In order to detect liver diseases effectively and efficiently, researchers are working continuously with various ML algorithms to predict liver diseases at its initial stages. However, with the rise in Covid-19 cases, the likelihood of an individual to get affected with Chronic Liver diseases increases. In this section of paper, we are going to review and discuss some of the important ML based Liver disease detection models and their results. The general block diagram of ML is shown in Fig 2. We have analyzed and reviewed papers from famous publishing cites like IEEE, MDPI, Springer, Hindwai, Elsevier etc., by using keywords like “Liver disease detection”, “ML based Liver disease detection techniques”, “DL based Liver disease detection techniques” and so on.

To begin with, the authors in (Mashraqi et al., 2022), proposed DMLD (Detecting Model for Liver Damage) for recognizing and identifying the liver conditions in Covid-19 ICU patients. The researchers analyzed the performance of various ML algorithms like SVM, DT, NB, KNN and ANN in order to detect liver diseases. Through simulation results, it was observed that SVM and DT classifiers outperformed other three classifiers in terms of various performance dependency factors. Similarly, the authors in (Ayeldeen et al., 2015), again proposed a DT based liver disease detection model in which fibrosis enzyme level was monitored and tracked. The suggested model was able to attain an accuracy of 93.7% to prove its superiority. Again in (Minnoor et al., 2022), the authors proposed a software engineering based-liver disease detection model wherein they used LR, SMO, RF, NB, J48 and KNN ML algorithms to predict liver disease in patients. The suggested model was tested on Indian Liver Patient Dataset (ILPD) dataset upon which effective results were generated.

Currently available ML based liver diseases models are highly complex and more time-intensive. A lack of qualified experts exacerbates these issues. Several models make use of blood enzyme levels to identify liver illness in individuals. The researchers of (Soni, 2021) investigated the effectiveness of different supervised Ml techniques in the detection and treatment of liver illness while taking this into account. The outcomes showed that the Extra Trees classifier had the maximum accuracy (0.89) and F1 score (0.88). Similarly, the authors in (Sivasangari et al., 2020) also analysed the performance of four ML algorithms which included LR, RF, KNN and DT on liver patient data that comprises a total of 583 liver images. Results showcased that among all the given classifiers KNN produced best accuracy with 72.04%.

Again in (Abeysekera et al., 2022) analysed that it is very difficult to inspect liver diseases at very dawning stages because of its mild symptoms and sometimes symptoms are coming to light too late. As a result, liver-related diseases cause significant issues for those who live and it is now more crucial to understand their origins and begin the classification. As a result, an autonomous process that is more precise and trustworthy is needed for the premature identification of liver disease. In this regard, the authors of this paper analyzed the performance of three ML classifiers namely as; SVM, DT and RF to predict liver disease in patients with best accuracy and reliability results.The authors in (Abdar et al., 2017), reviewed various techniques/models particularly for detecting ALD and NAFLD. The authors summarized that samples can be collected from clinics randomly and then different techniques should be implemented on it for detecting liver diseases. By doing so, the patients can choose which pathway is more accurate, feasible, cost effective and efficient.When contrasted with previous studies on liver illness, the authors in (Sontakke et al., 2017) suggested a brand-new DT-based liver disease classification model that typically takes additional effective parameters into account and even had highly accurate forecasts. The researcher assessed Boosted C5.0 and CHAID's efficiency using a dataset out from UCI machine learning repository. By correlating the performance of algorithms, it is clearly showed that C5.0 algorithm had an accuracy of 93.75% via boosting technique. On the other hand, CHAID algorithm had an accuracy of 65.0%.

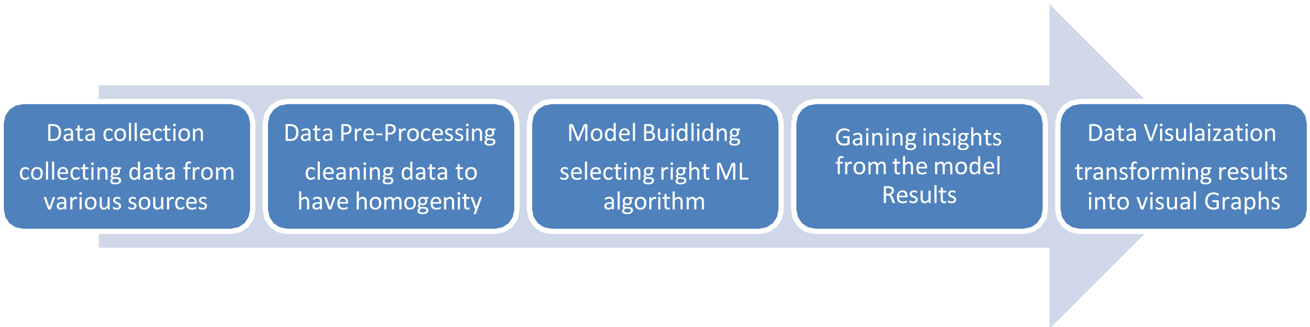

Fig 2. Process flow diagram of ML system.

Table 1: Comparison for various ML based Liver Disease Detection Models

References	**Work done**	**Outcomes Obtained**
Ruhul Amin et al., 2023	Proposed an ensemble learning model based on several ML techniques such as LR, RF,KNN, SVM and MLP.	Achieved an accuracy of 88.10% and precision of 85.33%.
Dritsas E, Trigka M., 2023	Proposed a voting mechanism with NB, SVM and LR approach for detection of liver disease.	Achieved an accuracy of 80.10% and a precision of 80.04%.
(Weng S, et al., 2023)	Developed a liver disease detection model using 8 different ML techniques.	Achieved highest accuracy of 89.77% for XGBoost approach.

(Roja Boina, et al., 2023)	Analyzed the Decision Tree, Random Forest, Support Vector Machine (SVM), and linear models	Highest accuracy achieved for SVM with a value of 90.54%.
(Mashraqi et al., 2022) [19]	Proposed DMLD model wherein they analyzed the performance of like SVM, DT, NB, KNN and ANN for predicting liver diseases	Improved results were obtained for SVM ,DT over other classifiers and highest accuracy 85.7% of SVM.
(Minnoor et al., 2022) [21]	Evaluated performance of LR, KNN, Extra Trees, LightGBM and MLPNN	Extra Trees classifier provided the better accuracy rate of 89%.
(Kalaiselvi, et al. 2021) [28]	Explored the performance of KNN, DT and ANFIS	Results were improved and has high ANFIS accuracy 90.1%.
(Soni, 2021) [22]	Analyzed the performance of LR, RF, KNN and DT on liver patient data	KNN produced best accuracy with 72.04%
(Al Telaq, et al. 2021) [27]	analyzed the efficiency of 5 ML classifiers which included SVM, KNN, RF, ANN and different versions of EL on ILPD dataset	KNN, RF and SVM methods achieved accuracy of 88%
(Sivasangari et al., 2020) [23]	Analyzed the efficiency of SVM method, DT and RF to prophesy diseases of liver	Best accuracy 95.8% of SVM and reliability results
(Muruganantham, et al. 2020) [29]	Used SVM, DT and RF for predicting liver disease in patients.	Improved classification accuracy rate and has value 91%.
(Ridhi Deo, et al., 2019)	Implemented 5 different algorithm including boosting, tree algorithms, etc.	Gentle Boost tree approach shows highest accuracy of 79.03%.
(Abdar, et al., 2017) [25]	proposed novel DT based liver disease detection model that analyzed the performance parameter of Boosted C5.0 and CHAID on liver disease dataset	C5.0 algorithm had an accuracy of 93.75% via boosting technique

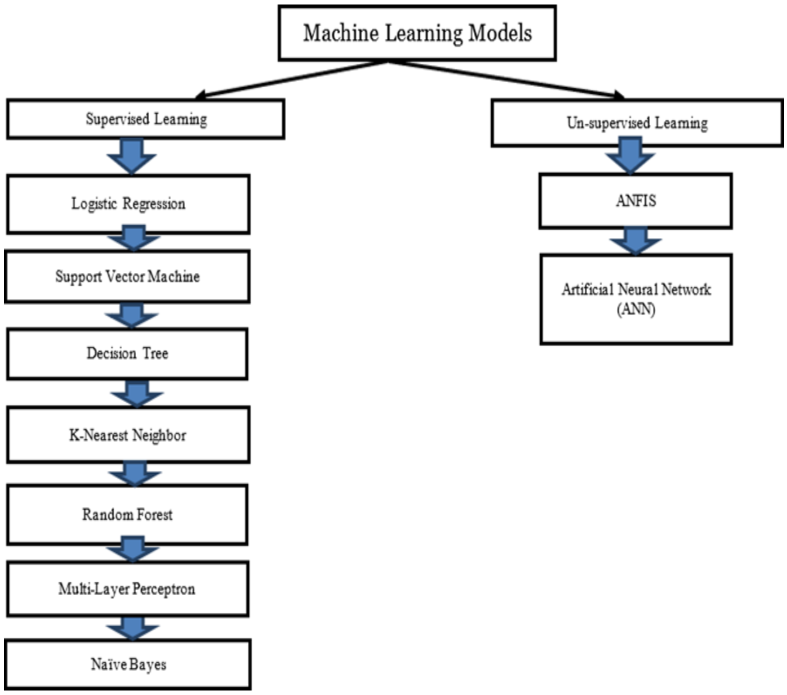

Fig 3. Taxonomy of ML algorithms used

Also, the authors' main goal in (AlTelaq et al., 2021) was to develop the diagnosis of liver disease by the process of doing examining 2 techniques of identification-patient parameters and genome expression. This paper examined the computational algorithms that can be used in previous methods. The researchers in (Rahman et al., 2019), also analysed the performance of 5 ML classifiers which included SVM, KNN, RF, ANN and different versions of EL on Indian Liver Patient Dataset (ILPD) dataset. Results revealed that EL of KNN, RF and SVM gained the great accuracy of 88%. Furthermore, in negative cases, EL of KNN with RF achieved highest TPR of 99% on negative cases. Also, it has been proved that PCA is one of the effective techniques that can be used for enhancing accuracy parameter of liver disease detection models. In order to build a decision support model which might assist the doctor in detecting liver illness from the database, the authors in (Singh et al., 2018) explored various data mining methods such KNN, DT, and ANFIS.

In (Chen et al., 2018), proposed and employed three ML algorithms like SVM, DT and RF for predicting liver disease in patients. They employed the binary classification technique for dividing the given database into two groups that signify whether the particular patient suffers from liver disease or not. The dataset includes information about patients' aspects like Total Bilirubin, Alanine, Aminotransferase, Bilirubin directly, Aspartate Aminotransferase, Age, Gender, Albumin, Total Proteins, Alkaline Phosphatase, Albumin and Globulin Ratio. The aforementioned methods were contrasted in terms of their accuracy as well as covering the range of various error estimations in order to choose the optimal strategy. To solve FLD forecasting concerns and improve accuracy outcomes, a multi-layer random forest (MLRF) framework that used RF ensemble approach was suggested in (Sellamuthu et al., 2022).The designed model comprised of three layers one was input, second was processing layer and third was output data layer, with every layers comprising of many RFs. The information recorded as from input data layer is examined layer by layer inside the processing layers till the finalized predicted results were created in the data layer at output. Outcomes showed the suggested model's correctness, which was supported by the outcomes of the experiments. In (Yao et al., 2020), the main goal of this study was to assign categorization approach for identifying between liver diseases and healthy persons. The system mainly was designed to characterize the existence of liver disease in patients, and the findings show that this was done utilizing methods of machine learning. Additionally, the researchers used the Logistic Regression Machine Learning technique to forecast liver disease among patients. The comparison table for above literature is given in Table 1. In addition to this, the taxonomy of ML models used in existing liver disease detection models is shown in Fig 3.

From the above literature it is observed that a number of authors are working towards increasing the accuracy of ML based liver detection systems. However, after carefully observing and studying these literatures, we concluded that the performance of ML algorithms was limited by various reasons and hence, there was a scope of improvement. One of the major limitations of ML algorithms is that such methods depend on handcrafted features provided by physicians or experts. Now, the question is what does this mean in content of hepatology. Automated solid tumor prognostication using imaging data is an illustration of AI in hepatology. Medical researchers create a list of quantifiable visual qualities manually, including the size, sphericity, symmetry, and severity of tumors on images. These characteristics are then passed to classification system, like SVM, RF, LR and so on that classify this information to detect disease in patients. As humans are prone to errors, therefore, it is not possible consider all important features that help in determining disease in patients hence, lowering the classification accuracy rate. The comparison of various techniques mentioned in this section are shown graphically in figure below

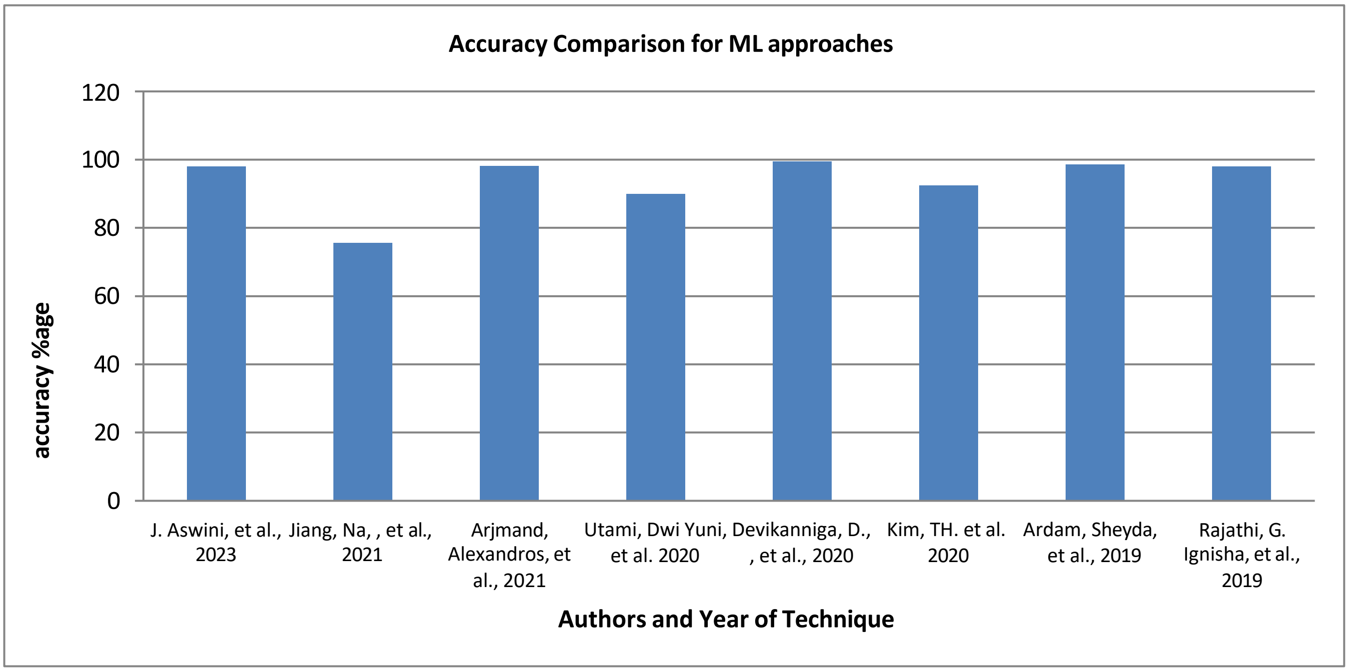

Fig. 4: Accuracy comparison of ML approaches

Moreover, the medical datasets are large in size and ML algorithms are not able to handle such large datasets and they undergo through Overfitting issues. Moreover, we also observed that majority of the researchers are using multiple ML algorithms in their work that enhance the complexity of model and hence processing time. Also, SVM, DT and LR are the three widely used ML algorithms for predicting liver disease detection, but they also have some inherited issues like binary classification. Keeping these things in mind, the researchers started to explore DL based liver disease detection models that are conceptually very much similar to ML algorithms yet have number of free parameters that make it more feasible and robust approach. Importantly, researchers do not compile lists of custom-made features while using a DL technique. Instead, the task of automatically discovering characteristics linked to an endpoint, in this case the clinical result, is given to a DL networks. n the next section, we are going to discuss some recently proposed DL based liver disease detection models.

2. DL BASED LIVER DISEASE DETECTION

In order to overcome the limitations of ML algorithms, medical experts have started to use DL algorithms in their work. The generic block diagram of DL is shown in Fig 5. Some of the DL methods are discussed here; In [32], proposed a densely connected deep neural network (Dense DNN) for screening liver diseases in which they used 13 LFT indicators and subject's demographic information. Moreover, the authors tested the efficiency of their model on 76, 914 samples. Results revealed that proposed Dense DNN attained an AUC of 0.8919 while as, it was 0.8867 in standard DNN and 0.8790 and 0.7974 in standard RF and LR models respectively. Similarly, the authors in [33], proposed an automated technique in which liver lesions were segmented in CT images. The suggested model utilizes two deep CNNs wherein images are segmented using Retina Net, lesion segmentation was done by employing U-Net and finally segmentation refinement. Results revealed that Mathhews correlation coefficient of 83.62% was attained in proposed model on LITS database. Also, the value of sensitivity, specificity, dice coefficient, VOE and RVD was 83.86, 99.96, 82.99, 27.8 and 1.69 respectively. A comprehensive deep learning technique was created by the researchers of [34] for said segmentation and forecasting of liver cirrhosis depending on NAFLD. The proposed research includes a number of features, incorporating DNN and Spearman's rank order relationship. For prediction and classification, the 52 characteristics, including GLGCM features and GLCM texture characteristics, were used. Also, for classification and predicting features DNN was used. The numerous categorizations were carried out according to the various characteristics. Deep network is designed by use of various layers in order to estimate the correlation of the rank especiallyby employing Spearman's rank correlation. The whole simulation is done by using a dataset of MRI images.

Similarly, the researchers in [35], proposed stacked sparse auto-encoder that generally depends upon the deep learning architecture. The given stacked form sparse auto-encoder memorized the characteristics of input pixels of unlabeled images and then it distinguishes different images which had various focal diseases. Furthermore, by choosing the highest proportion of each class, softmax layer categorized the different focal liver disease. The authors compared their given technique with three different trending approaches i.e. Multi SVM, KNN and NB. After pre-processing the authors used level-set technique along with FCM clustering for segmenting the lower lesions. Moreover, they employed stacked sparse auto-encoder for extracting high level features from segmented images. The suggested methodologyachieved an overall classification accuracy of 97.2%. Also, in [36], developed a new DL based algorithm that enlisted 499 patents who had CLD and 122 healthy records. The authors used GoogLeNet-V3 and various fine-tuned modules. Results revealed that in data set test DL algorithm got accuracy of 99.4% (loss was nearly 0.7%) and AUROC was 0.998 for diagnosis. Furthermore, in validation test the authors obtained good validation result. For healthy controls result was 0.98292 and the error rate was 0.01708 and sensitivity for CLD was 0.99469 and error rate was 0.00531.

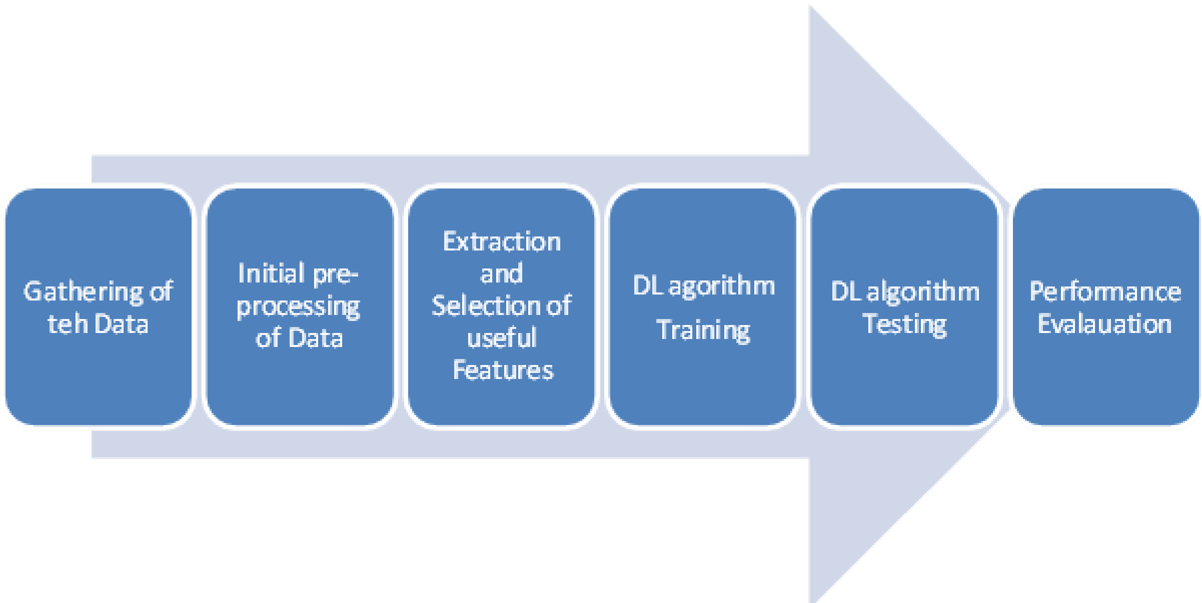

Fig 5. Block diagram of DL models

The researchers in [37], proposed Detection and Segmentation laboratory (DSL) modelin which Faster R-CNN and Deep Lab were used. The proposed DSL contains 2 steps, firstly, to decrease the domain of subsequent liver segmentation, Faster R-CNN was employed. The second step was to detect results that were input to Deep Lab for segmentation. Results revealed that DSL approach attained best performance in VOE, RVD, ASD and total score. Likewise, the researchers in [38], analysed the impact of low and high stiffness temporal stability on SWE pictures and CLD detection by studying clinical data and implementing deep learning (CNN) technique. The authors used wavelet transform and fuzzy c-means clustering approach for processing inverse RGB colormap-stiffness procedure for generating binary mask that demonstrate high and low stiffness temporal stability. The initial picture of SWE sequence was then given the mask, and resulting, masked SWE image was utilized to gauge its influence on CNN classification and standard clinical assessment. The efficacy of suggested approach was depicted in terms of ICC that was 0.92 and 0.76 in masked and non-masked images. For different CLD stage configurations, the masked SWE images had better classification accuracy rate whose range lies from 82.5% to 95.5%than the unmasked ones with 79.5% to 93.2% range.

In [39], in order to identify NAFLD in ultrasound, the authors proposed a neural network-based approach. To remove high-level details in liver B-mode ultrasound image sequences, the authors utilized Inception-ResNet-v2 DCNN that was previously trained on Image Net database. Apart from this, they compared hepatorenal index method and GLCM algorithm with proposed approach. Then, the authors applied SVM algorithm after the removal of features. The fatty liver had more than 5% of hepatocytes with steatosis on the basis of liver biopsy. To evaluate the steatosis level, the Lasso regression method was used. Results revealed that receiver operating characteristic curve gained by suggested technique was equal to 0.977 while as it was only 0.959 and 0.893 in hepatorenal index and GLCM. The hepatorenal index, the GLCMtechnique, and the steatosis level all had Spearman correlation coefficients of 0.78, 0.80, and 0.39, correspondingly, for regression. The authors in [40], To diagnose cirrhosis, the authors proposed a computer-aided cirrhosis diagnosis system specifically for Ultrasound images. Based on extracted liver capsule, they proposed a method to take out liver capsule on an ultrasound image. To remove the features of image patches cropped around liver capsules, fine-tuned deep CNN method was utilized. Eventually, the dataset is divided into normal and abnormal cases using a trained SVM classifier. Furthermore, results revealed that proposed algorithm had successfully removed the liver capsules and correctly categorized the ultrasound images. Also, the authors in [41], proposed a CNN for identification of liver disease. Moreover, CNN was distinguished with traditional ML methods on the basis of performance of CNN. These approaches involved NB, SVM, KNN and LR. Two datasets i.e. BUPA and ILPD were used. Simulations revealed that CNN was beneficial for classifying liver disease wherein, BUPA generated an accuracy rate 75.55% and ILPD generated 72.00%. The comparison table for above mentioned literatures is given in table 2. Additionally we have showed the graphical comparison of few latest deep learning based models accuracies with author details and years in figure 6. Finally, the taxonomy of DL models is shown in Fig 7.

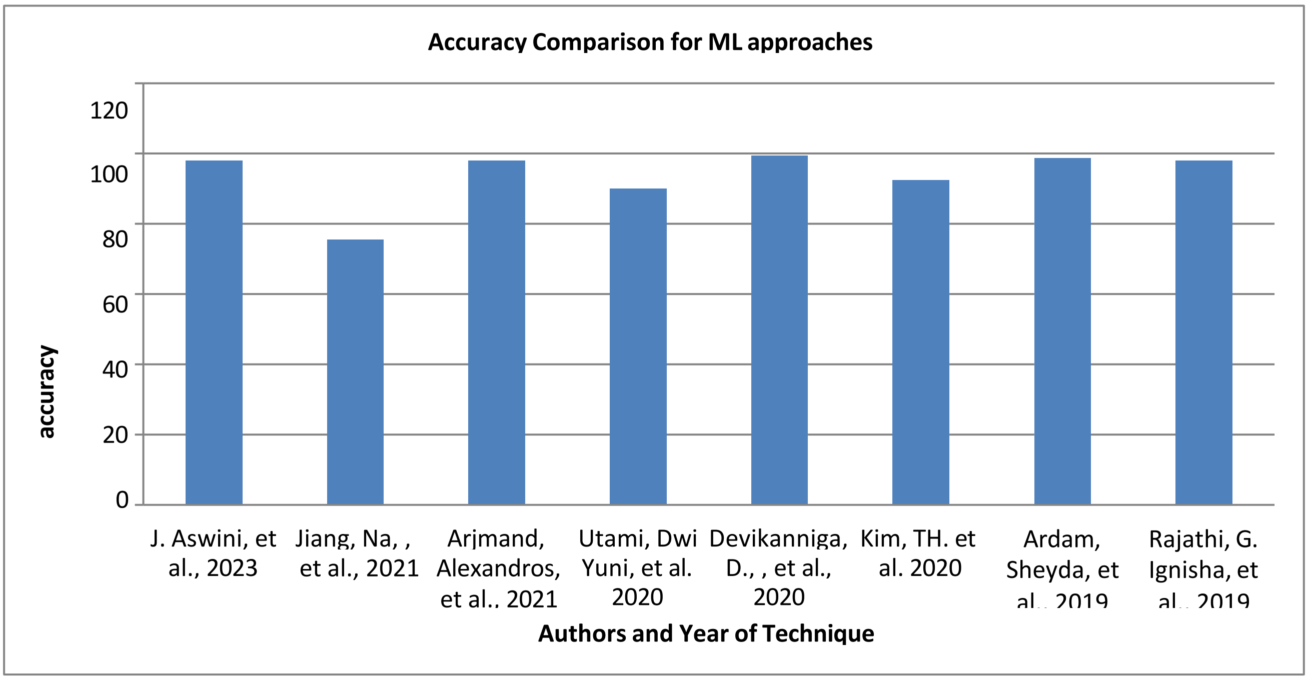

Fig. 6: Accuracy Comparison of DL approaches

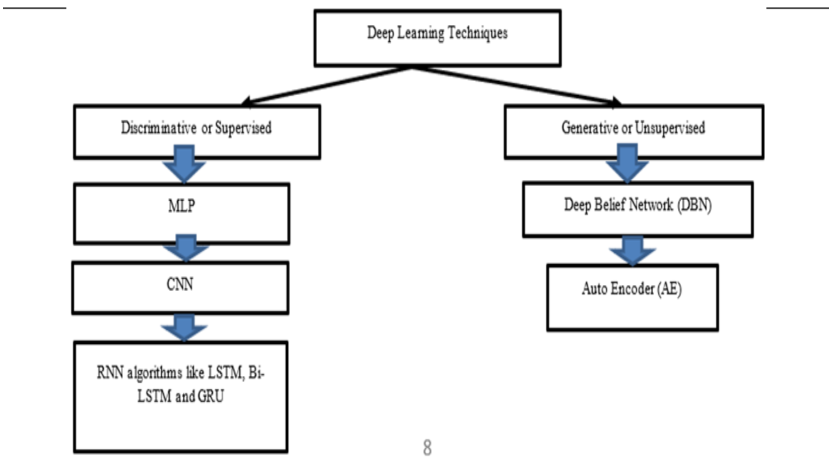

Fig 7. Taxonomy of DL algorithms

Table 2: Comparison table for DL based Liver Disease Detection Model

References	**Work done**	**Outcomes Obtained**
(J. Sujith, et al., 2023)	Developed a system to analyze DL approaches CNN, RNN and LR for liver disease detection.	Achieved a higher accuracy with RNN 66%.
Mutlu, E.N., et al. [41] 2022	Developed a Convolutional Neural Network (CNN) for the BUPA as well as ILPD records to identify liver illness.	Classification accuracy of 75.55% and 72.00% was generated on BUPA and ILPD datasets.
K. Prakash, et al. [34] 2022	Proposed DNN based for the categorization and prognosis of liver cirrhosis based on NAFLD	Improved classification accuracy rate considerably
José Denes, et al., 2021 [33]	Proposed two deep CNN based automated technique in which liver lesions were segmented in CT images	attained Mathhews correlation coefficient of 83.62%
[Yao et al., 32] 2020	Proposed Dense DNN model for screening liver diseases in which they used 13 LFT indicators and subject's demographic information.	attained an AUC of 89.19
[36] Kim, TH. et al. 2020	Developed a model based on GoogLeNet-V3 and various fine-tuned modules for differentiating the CLD on non-contrast abdominal CT images	accuracy of 99.4% on testing Dataset
[38] Ilias Gatos , et al., 2019	Proposed CNN based liver disease detection model by analyzing the impact of low and high stiffness temporal stability on SWE images and CLD detection by studying clinical data	For different CLD stage configurations, the masked SWE images had better classification accuracy (82.5% to 95.5%) than the unmasked ones (79.5% to 93.2%).
[37] 2018	Proposed DSL method which was based on Faster R-CNN and Deep Lab	results revealed that DSL approach attained best performance in VOE, RVD, ASD and total score
[39] 2018	Proposed a neural network-based approach for detecting NAFLD	ROC obtained was equal to 0.977
[40] 2017	Presented a technique exclusively for ultrasound images enabling computer-aided cirrhosis assessment. Moreover, to remove the features of image patches cropped around liver capsules, fine-tuned deep CNN method was utilized.	successfully removed the liver capsules

The above literatures are specifically associated with DL algorithms that are used for predicting liver diseases in humans. After examining the above given literatures carefully, it is observed that majority of experts were using CNN algorithm in their works. No doubt, DL methods extract features automatically and also handle large and complex datasets quite effectively, However, the problem with these models is that the accuracy rate is lower while as error rate is higher, which is not recommended while dealing with real time disease detection. Moreover, CNN need lot of training data which leads to gradient exploding problem and class imbalance. Also, the capability of convolution to retrieve visual patterns from various spatial places is constrained. Also, it must be noted that medical experts or doctors need to analyze huge information of patient's enzyme levels like platelets, bilirubin, alanine aminotransferase, creatinine etc., while detecting liver diseases. The essential to the hospital's ability to provide the appropriate medication is being able to swiftly identify which indicators, based on the patient's unique features, are vital to the origin of the patient's sickness. In this regard, nature inspired optimization algorithms may play a significant role. The next section of our manuscript is totally based on few optimization-based liver disease detection models for predicting liver disease.

3. OPTIMIZATION BASED LVER DISEASE DETECTION MODELS

To enhance the speed of current ML and DL based liver disease detection models, some of the researchers have used nature inspired meta-heuristic optimization algorithms. In this section, we are going to review and discuss the working of few recently proposed optimization based liver disease detection models. The authors in [42], enhanced the performance of Modified BP (backpropagation) model by using the Ant Colony Optimization (ACO) technique for processing the various index attributed items that corresponds to CLD. It was observed that proposed model had effective accuracy and precision values for detecting and identifying CLD in patients. These assertions were validated experimentally using 125 groups of 20-dimensional medical test indicator data objects from individuals with CLD to evaluate the suggested method. Furthermore, employing well-known ROC curves, test index feature components with high sensitivity to chronic liver disease were selectively chosen from a set of 13-dimensional index elements. To do so, the authors used PCA for condensing the 13-dimensional indexes into 5-dimensional comprehensive data objects. Results revealed that suggested model lowers the complexity along with this classification accuracy rate was also enhanced by 15.07%.

Furthermore, the authors in [43], tries to enhance the performance of SVM by tuning its hyperparameters. Despite with the most cutting-edge tools, medical professionals still struggle to detect liver disease in patients promptly and accurately. The usage of support vector machines is common in the medical field. It has demonstrated its effectiveness in creating accurate diagnostic criteria. The suggested model utilizes Crow Search Algorithm (CSA) for optimizing and tuning the parameters of SVM. The authors tested and validated the suggested CSA-SVM model on Indian liver disease database wherein the model demonstrated 99.49% accuracy results. In order to assist physicians and their patients in identifying the clinical signs, shorten the time it takes to diagnose the condition, and minimize fatalities, the authors in [44], offered a new approach of liver disease diagnosis. The suggested approach would use the Genetic Algorithm (GA) to optimize the principles from the BoostedC5.0 classification algorithm, thereby, speeding up and improving diagnosis process. Therefore, the authors employed GA to improve and reduce rules of another algorithm rather than utilizing an optimization technique to produce rules. Researchers demonstrated that, when compared to existing work in the field, their suggested approach offers greater performance and throughput with an accuracy of 93%.

Again in [45], an automated model was proposed in which fat deposition in steatotic liver biopsy specimens were assessed and analyzed. To accomplish this task, the authors used various image processing techniques, along with ML and Evolutionary algorithms. Results showed that their model attained 1.93% of mean classification error. In [46], the researchers proposed a hybrid model wherein AdaBoost model was used, whose performance was optimized by Firefly optimization algorithm for detecting liver diseases. The model was tested on dataset taken from University of California, Irvine containing 583 independent samples and 10 features of ML. Results demonstrated that accuracy of suggested hybrid model was 98.61% and 94.15% with 5 and all features respectively. The authors in [47] generally uses the immune system's capacity for memory and learning to address the challenge of diagnosing liver disease. To identify liver illness, the suggested system combines two artificial immune and genetic algorithm approaches. The performance of the suggested approach was validated on two benchmark datasets from the renowned UCI machine learning library. In comparison to previous diagnosis systems described in the literature, the acquired diagnosis accuracies were highly encouraging. These findings imply that this approach might be an effective automatic liver disease diagnosis tool.

Furthermore, the authors in [48] again proposed a hybrid SVM and Artificial Bee colony (ABC) technique for predicting liver disease in patients in timely manner. The authors have used ABC and SVM specifically for feature selection and classification purposes respectively. The purpose of this research would be to ascertain how the removal of irrelevant and out-of-date collection attributes affects the efficiency of categorization through using SVM classifier. The suggested technique was utilized to identify diabetes, liver disorders, and hepatitis. Furthermore, Hepatitis, fewliver relatedissues, and a dataset of diabetes that is taken from the UCI web portal were employed for the diagnosis of these illnesses, and the suggested approach achieved classification accuracy rates of 94.92%, 74.81%, and 79.29%, respectively. The 10-fold cross-validation approach was used to determine the classification accuracy for these databases. The outcomes demonstrate that the technique's efficiency was quite impressive when compared to other findings obtained and appears to be very effective enough to handle teh pattern recognition systems.

Similarly, the authors in [49], tried to detect and classify the CLD, by using Hybrid WOA along with Simulated Annealing (WOA-SA) in which only critical features were selected. They utilized a total of seven feature sets wherein 73 features were 3D texture features. Furthermore, they used an ensemble learning classifier in which they integrated SVM, KNN and RF. Clinical CT imaging databases, that comprise normal liver, fatty liver, metastasis, cirrhosis, and malignant samples, were subjected to experiments. The ensemble classifier's accuracy in classifying the liver is nearly 98%, with a 95% confidence interval (CI) of (0.7789, 1.0000) and a 1.9% failure rate. When the suggested method's efficiency was contrasted to that of two other methods, the overall averages for sensitivity and specificity were 96% and 93%, correspondingly, with 95% confidence intervals of 0.7513 and 1.0000 and 0.7126 and 1.0000. Identification of CLD using an ensemble classifier exemplifies the usefulness of the suggested approach, and a comparative study reveals its supremacy. Similarly, the authors in [50], proposed yet another liver disease detection model in which they segmented the restorative data of patient by using a cross breed counterfeit neural model. These records were arranged in such a way that it depicts the plausibility of disease presence. The highlighted data factor selection in this suggested method was done using M-PSO, and the disease order was calculated using M-ANN. When compared to current order computations, the crossover approach that was demonstrated enhances precision. The focus of this work was feature extraction using the PSO technique.

One of the world's most frequently diagnosed, liver disease, can be avoided with early detection and modern medical care. With the help of improvements in machine learning and intelligence approaches, diseases may now be accurately diagnosed and predicted, improving patient care and lowering treatment costs. A swarm intelligence technique called the Whale Optimization Algorithm was developed in response to the social behaviour of whales. K-Nearest Neighbour, used for pattern classification, is considered one of the most efficient classification methods. Keeping these facts in mind, the authors in [51], proposed an effective liver disease detection model wherein thy hybridized KNN and WOA techniques. The authors used two databases in their proposed work namely as; BUPA and ILPD for testing model’s efficacy. Results revealed that proposed model was able to generate an accuracy of 81.24% on BUPA database and 91.28% on ILPD database respectively. These results prove the supremacy and efficacy of proposed WOA-KNN approach.

One of the major hurdles that researchers faced while detecting liver diseases is that, even when disease is spread, it can be challenging to detect liver disease. Therefore, the authors in [52], analysed the performance of three classifiers i.e. NB, NB with GA and bagging in order to decide which classifiers shows better results. To test the efficacy of these classifiers, the authors took data from UCI ML repository. The efficacy of the suggested system was tested and evaluated in terms of confusion matrix and ROC curve respectively on given dataset. Simulating outcomes determined that NB with GA and Bagging classifiers have higher accuracy results than the Standard NB technique. The accuracy value achieved by researchers in NV model was only 66.66% while as, the accuracy value achieved in NB with GA and Bagging models were 72.02%. These results show that accuracy value is improved by around 5.36% in proposed NB with GA and Bagging models. The comparison table for these liver disease detection techniques is given in table 3. Also in figure 8 we have shown the graphical representation of different algorithm from this category to show comparison among the techniques.

Table 3: Comparison table for Optimization based Liver Disease Detection Models

References	**Work done**	**Outcomes Obtained**
(J. Aswini, et al., 2023)	Proposed a POA modified MRCNN model	An accuracy of 98%.
Jiang, Na, , et al [42] 2021	enhanced the performance of Modified BP (backpropagation) model by using the Ant Colony Optimization (ACO) technique	classification accuracy rate was enhanced by 15.07%.
Devikanniga, D., , et al. [43] 2020	Optimized the performance of SVM by using CSA optimization algorithm on ILPD for predicting liver diseases	Obtained an accuracy of 99.49%
M. Hassoon, , et al [44] 2017	Used GA to optimize the principles from the BoostedC5.0 classification algorithm	Attained accuracy of 93%.
Arjmand, Alexandros, et al. [45] 2021	used various image processing techniques, along with ML and Evolutionary algorithms for assessing fat deposition in steatotic liver biopsy specimens	Obtained 1.93% of mean classification error
Ardam, Sheyda, et al. [46] 2019	Proposed AdaBoost based model whose performance was optimized by Firefly optimization algorithm	accuracy of suggested hybrid model was 98.61% and 94.15% with 5 and all features respectively
Liang, Chunlin , et al. [47] 2013	combined two artificial immune and genetic algorithm approaches for detecting liver diseases	effective automatic liver disease diagnosis tool
Mustafa Serter Uzer, et al. [48] 2013	proposed a hybrid SVM and Artificial Bee colony (ABC) technique for predicting liver disease in patients in timely manner	Obtained accuracy rates of 94.92%, 74.81%, and 79.29% for Hepatitis, liver problems, and diabetes
Rajathi, G. Ignisha, et al. [49] 2019	Proposed WOA-SA in which only critical features were selected. Furthermore, they used an ensemble learning classifier in which they integrated SVM, KNN and RF	Results revealed ensemble classifier's accuracy in classifying the liver is nearly 98%
L.Anand, et al. [50] 2013	Proposed a liver disease detection model in which they used M-PSO and M_ANN for feature selection and classification respectively.	Proposed model had better precision results.
Hajihashemi, Vahid, et al. [51] 2019	Proposed an effective liver disease detection model wherein thy hybridized KNN and WOA techniques.	proposed model was able to generate an accuracy of 81.24% on BUPA database and 91.28% on ILPD database respectively.
Utami, Dwi Yuni, et al. [52] 2020	Analyzed the performance of three classifiers i.e. NB, NB with GA and bagging in order to decide which classifiers shows better results.	Accuracy rate was improved by 5.36 in proposed NB with GA classifier.

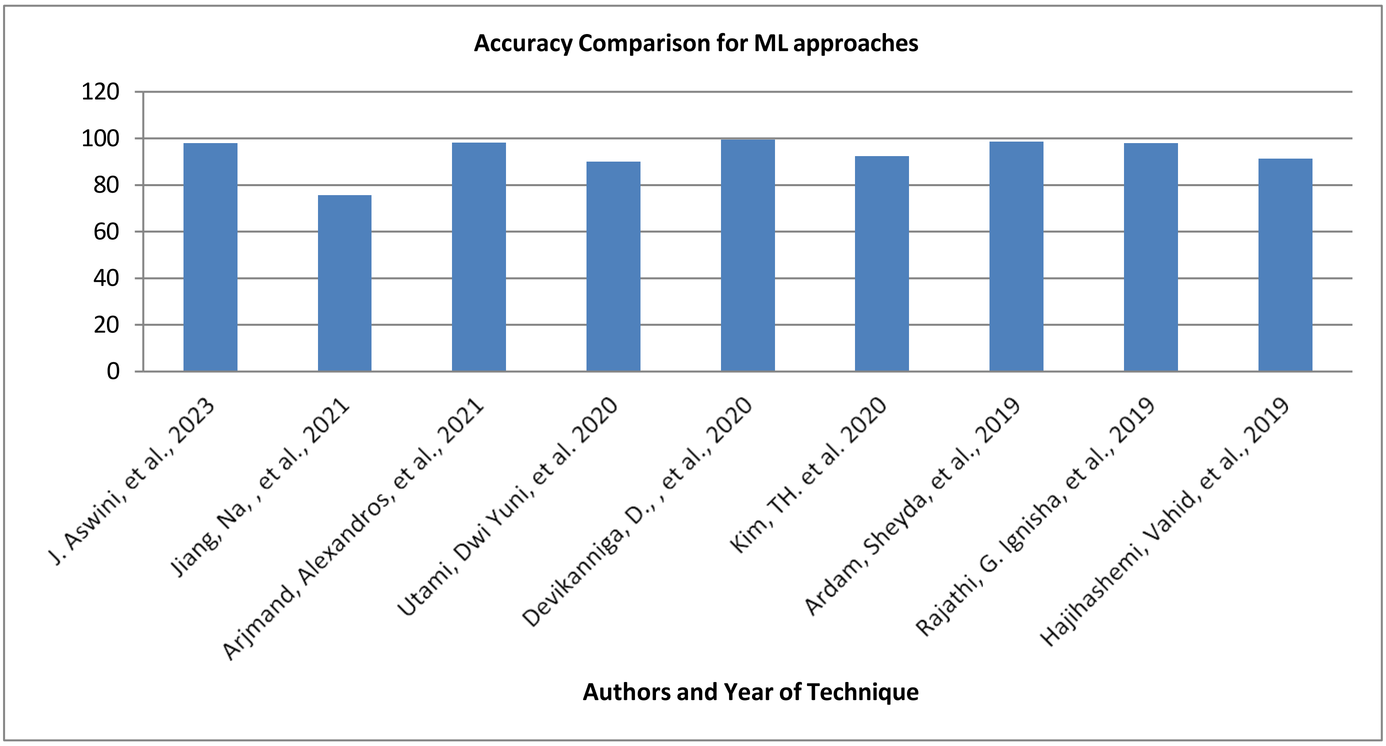

Fig 8. Accuracy Comparison of Optimization based approaches

After analysing the above literatures, it can be seen that number of authors are using optimization-based liver disease detection models in their work with the objective of enhancing the detection accuracy. A significant number of positive results has been seen in literatures. However, there are some limitations in exiting works that hinder efficacy of entire disease detection system. For an example, the optimization algorithms used by researchers either have slow convergence rate or they get trapped in local minima while searching for global solutions. This increases the complexity and processing time in existing optimization-based liver disease detection models. Another challenge faced by researchers is that there exits n number of optimization algorithms, so it becomes difficult for scholars to decide which algorithm will give best results. Therefore, it can be concluded that no doubt optimization algorithms enhance the detection accuracy rate but choosing an appropriate optimization algorithm is still a challenge that needs attention.

CONCLUSION

In this review paper, some of the recently proposed liver disease detection models have been reviewed and discussed. During the literature analysis, it has been observed that majority of the researchers are employing ML algorithms like SVM, DT and LR in their work for predicting liver diseases. However, as these ML models were not able to handle large datasets efficiently therefore, authors shifter their attention towards more advanced techniques like DL. One of the widely used DL algorithm was CNN. No doubt that efficacy was enhanced considerably by DL algorithms however, they need lot of training data which enhances complexities. As experts need to analyze huge amounts of data, therefore researchers needed a method that can pinpoint important features quickly that aid in enhancing model performance. Therefore, the role of optimization algorithms comes into play. It has been observed that by employing optimization algorithms along with ML or DL algorithms, the classification accuracy rate for predicting liver disease enhances significantly while the complexity is reduced. This signifies that by using effective optimization algorithm along with ML approaches, the performance of liver disease detection model is improved.

References

[1] Singh, J., Bagga, S., & Kaur, R. (2020). 'Software-based prediction of liver disease with feature selection and classification techniques'. *Procedia Computer Science*, *167*, 1970-1980.

[2] Nanyue, W., Youhua, Y., Dawei, H., Bin, X., Jia, L., Tongda, L., ... & Jia, W. (2015). 'Pulse diagnosis signals analysis of fatty liver disease and cirrhosis patients by using machine learning'. *The Scientific World Journal*, *2015*.

[3] Karthik, S., Priyadarishini, A., Anuradha, J., & Tripathy, B. K. (2011).'Classification and rule extraction using

rough set for diagnosis of liver disease and its types'. *Advances in Applied Science Research*, *2*(3), 334-345.

[4] Williamson, E. J., Walker, A. J., Bhaskaran, K., Bacon, S., Bates, C., Morton, C. E., ... & Goldacre, B. (2020). 'Factors associated with COVID-19-related death using OpenSAFELY'. *Nature*, *584*(7821), 430-436.

[5] Ioannou, G. N., Locke, E., Green, P., Berry, K., O'Hare, A. M., Shah, J. A., ... & Fan, V. S. (2020). 'Risk factors for hospitalization, mechanical ventilation, or death among 10 131 US veterans with SARS-CoV-2 infection'. *JAMA network open*, 3(9), e2022310-e2022310.

[6] Lee, N., Hui, D., Wu, A., Chan, P., Cameron, P., Joynt, G. M., ... & Sung, J. J. (2003). 'A major outbreak of severe acute respiratory syndrome in Hong Kong'. *New England Journal of Medicine*, 348(20), 1986-1994.

[7] Tsang, K. W., Ho, P. L., Ooi, G. C., Yee, W. K., Wang, T., Chan-Yeung, M., ... & Lai, K. N. (2003). ;A cluster of cases of severe acute respiratory syndrome in Hong Kong'. *New England Journal of Medicine*, *348*(20), 1977-1985.

[8] Gori, A., Dondossola, D., Antonelli, B., Mangioni, D., Alagna, L., Reggiani, P., ... & Rossi, G. (2020). 'Coronavirus disease 2019 and transplantation: a view from the inside'. *American Journal of Transplantation*, *20*(7), 1939.

[9] Guan, W. J., Ni, Z. Y., Hu, Y., Liang, W. H., Ou, C. Q., He, J. X., ... & Zhong, N. S. (2020). 'Clinical characteristics of coronavirus disease 2019 in China'. *New England journal of medicine*, 382(18), 1708-1720.

[10] Yang, X., Yu, Y., Xu, J., Shu, H., Liu, H., Wu, Y., ... & Shang, Y. (2020). 'Clinical course and outcomes of critically ill patients with SARS-CoV-2 pneumonia in Wuhan, China: a single-centered, retrospective, observational study'. *The lancet respiratory medicine*, *8*(5), 475-481.

[11] Boettler, T., Newsome, P. N., Mondelli, M. U., Maticic, M., Cordero, E., Cornberg, M., & Berg, T. (2020). 'Care of patients with liver disease during the COVID-19 pandemic: EASL-ESCMID position paper'. *JHEP reports*, *2*(3), 100113.

[12] Abou-Arab, O., Bennis, Y., Gauthier, P., Boudot, C., Bourdenet, G., Gubler, B., ... & Mahjoub, Y. (2021). 'Association between inflammation, angiopoietins, and disease severity in critically ill COVID-19 patients: a prospective study'. *British Journal of Anaesthesia*, *126*(3), e127-e130.

[13] Moore, J. B., & June, C. H. (2020). 'Cytokine release syndrome in severe COVID-19'. *Science*, *368*(6490), 473-474.

[14] Huang, C., Wang, Y., Li, X., Ren, L., Zhao, J., Hu, Y., ... & Cao, B. (2020). 'Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China'. *The lancet*, *395*(10223), 497-506.

[15] Sepanlou, S. G., Safiri, S., Bisignano, C., Ikuta, K. S., Merat, S., Saberifiroozi, M., ... & Padubidri, J. R. (2020). 'The global, regional, and national burden of cirrhosis by cause in 195 countries and territories, 1990–2017: a systematic analysis for the Global Burden of Disease Study 2017'. *The Lancet gastroenterology & hepatology*, *5*(3), 245-266.

[16] Webb, G. J., Marjot, T., Cook, J. A., Aloman, C., Armstrong, M. J., Brenner, E. J., ... & Moon, A. M. (2020). 'Outcomes following SARS-CoV-2 infection in liver transplant recipients: an international registry study'. *The lancet Gastroenterology & hepatology*, *5*(11), 1008-1016.

[17] Martinez, M. A., & Franco, S. (2021). 'Impact of COVID-19 in liver disease progression'. *Hepatology Communications*, 5(7), 1138-1150.

[18] Ling, Q., Dai, H., Zhuang, R., Shen, T., Wang, W., Xu, X., & Zheng, S. (2017). 'Predicting short-term survival after liver transplantation on eight score systems: a national report from China Liver Transplant Registry'. *Scientific reports*, 7(1), 42253.

[19] Mashraqi, A., Halawani, H., Alelyani, T., Mashraqi, M., Makkawi, M., Alasmari, S., ... & Alshehri, A. (2022). 'Prediction model of adverse effects on liver functions of COVID-19 ICU patients'. *Journal of Healthcare Engineering*, 2022.

[20] Ayeldeen, H., Shaker, O., Ayeldeen, G., & Anwar, K. M. (2015, November). 'Prediction of liver fibrosis stages by machine learning model: A decision tree approach'. In *2015 Third World Conference on Complex Systems (WCCS)* (pp. 1-6). IEEE.

[21] Minnoor, M., & Baths, V. (2022, June). 'Liver Disease Diagnosis Using Machine Learning'. In *2022 IEEE World Conference on Applied Intelligence and Computing (AIC)* (pp. 41-47). IEEE.

[22] Soni, A. (2021, October). 'Performance Analysis of Classification Algorithms on Liver Disease Detection'. In *2021 IEEE Mysore Sub Section International Conference (MysuruCon)* (pp. 1-5). IEEE.

[23] Sivasangari, A., Reddy, B. J. K., Kiran, A., & Ajitha, P. (2020, October). 'Diagnosis of liver disease using machine learning models'. In *2020 Fourth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud)(I-SMAC)* (pp. 627-630). IEEE.

[24] Abeysekera, K. W., Macpherson, I., Glyn-Owen, K., McPherson, S., Parker, R., Harris, R., ... & Dillon, J. F. (2022). 'Community pathways for the early detection and risk stratification of chronic liver disease: a narrative systematic review'. *The Lancet Gastroenterology & Hepatology*.

[25] Abdar, M., Zomorodi-Moghadam, M., Das, R., & Ting, I. H. (2017). 'Performance analysis of classification algorithms on early detection of liver disease'. *Expert Systems with Applications*, 67, 239-251.

[26] Sontakke, S., Lohokare, J., & Dani, R. (2017, February). 'Diagnosis of liver diseases using machine learning'. *International Conference on Emerging Trends & Innovation in ICT (ICEI)* (pp. 129-133). IEEE.

[27] Al Telaq, B. H., &Hewahi, N. (2021, October). 'Prediction of Liver Disease using Machine Learning Models with PCA'. *International Conference on Data Analytics for Business and Industry (ICDABI)* (pp. 250- 254). IEEE.

[28] Kalaiselvi R., K. Meena and V. Vanitha, (2021), 'Liver Disease Prediction Using Machine Learning Algorithms'. *In 2021 International Conference on Advancements in Electrical, Electronics, Communication, Computing and Automation*, pp. 1-6.

[29] Muruganantham B., A.Murugan, Kriti Taparia, S.Ganesh Kumar, Mukul Kumar, (2020), "Liver Disease Prediction Using Classification Algorithms", *International Journal of Advanced Science and Technology*, 29(08), 311 - 319.

[30] Chen, M., & Zhao, X. (2018, December). 'Fatty liver disease prediction based on multi-layer random forest model'. In *Proceedings of the 2018 2nd International Conference on Computer Science and Artificial Intelligence* (pp. 364-368).

[31] Sellamuthu, K., Sylviya, P., Pugazharasi, K., & Rajalakshmi, S. (2022, April). 'Liver Disease Prediction using Logistic Regression'. In *2022 8th International Conference on Smart Structures and Systems (ICSSS)* (pp. 01-06). IEEE.

[32] Yao, Z., Li, J., Guan, Z., Ye, Y., & Chen, Y. (2020). 'Liver disease screening based on densely connected deep neural networks'. *Neural Networks*, 123, 299-304.

[33] Araújo, J. D. L., da Cruz, L. B., Ferreira, J. L., da Silva Neto, O. P., Silva, A. C., de Paiva, A. C., &Gattass, M. (2021). 'An automatic method for segmentation of liver lesions in computed tomography images using deep neural networks'. *Expert Systems with Applications*, 180, 115064.

[34] Prakash, K., & Saradha, S. (2022, April). 'A Deep Learning Approach for Classification and Prediction of Cirrhosis Liver: Non Alcoholic Fatty Liver Disease (NAFLD)'. In *2022 6th International Conference on Trends in Electronics and Informatics (ICOEI)* (pp. 1277-1284). IEEE.

[35] Hassan, T. M., Elmogy, M., & Sallam, E. S. (2017). 'Diagnosis of focal liver diseases based on deep learning technique for ultrasound images'. *Arabian Journal for Science and Engineering*, 42, 3127-3140.

[36] Kim, T. H., Noh, S. H., Jeong, C. W., Lee, C., Kim, J. E., Kim, S., & Yoon, K. H. (2021). 'Discrimination of Chronic Liver Disease in Non-contrast CT Images using CNN-Deep Learning'. In *Intelligent Systems and Applications: Proceedings of the 2020 Intelligent Systems Conference (IntelliSys) Volume 3* (pp. 717-722). Springer International Publishing.

[37] Tang, W., Zou, D., Yang, S., & Shi, J. (2018). 'DSL: Automatic liver segmentation with faster R-CNN and DeepLab'. In *Artificial Neural Networks and Machine Learning–ICANN 2018: 27th International Conference on Artificial Neural Networks, Rhodes, Greece, October 4-7, 2018, Proceedings,* Part II 27 (pp. 137-147). Springer International Publishing.

[38] Gatos, Ilias, et al. 'Temporal stability assessment in shear wave elasticity images validated by deep learning neural network for chronic liver disease fibrosis stage assessment'. *Medical physics* 46.5 (2019): 2298- 2309.

[39] Byra, M., Styczynski, G., Szmigielski, C., & Kalinowski, P. (2018). Micha» owski º, Paluszkiewicz R, Ziarkiewicz-Wróblewska B, Zieniewicz K, Sobieraj P, Nowicki A. 'Transfer learning with deep convolutional neural network for liver steatosis assessment in ultrasound images'. *Int J Comput Assist Radiol Surg*, 13, 1895-1903.

[40] Liu, X., Song, J. L., Wang, S. H., Zhao, J. W., & Chen, Y. Q. (2017). 'Learning to diagnose cirrhosis with liver capsule guided ultrasound image classification'. *Sensors*, 17(1), 149.

[41] Zidoum, H., Al-Sawafi, S., Al-Ansari, A., & Al-Lawati, B. (2022, April). 'Unsupervised Learning Approach to Drive Therapeutic Precision in a Complex Disease'. In *2022 2nd International Conference on Computing and Machine Intelligence (ICMI)* (pp. 1-7). IEEE.

[42] Jiang, N., Zhao, Z., & Xu, P. (2021). 'Predictive analysis and evaluation model of chronic liver disease based on BP neural network with improved ant colony algorithm'. *Journal of Healthcare Engineering*, 2021, 1-7.

[43] Devikanniga, D., Ramu, A., & Haldorai, A. (2020). 'Efficient diagnosis of liver disease using support vector machine optimized with crows search algorithm'. *EAI Endorsed Transactions on Energy Web*, 7(29), e10-

e10.
[44] Hassoon, M., Kouhi, M. S., Zomorodi-Moghadam, M., & Abdar, M. (2017, September). 'Rule optimization of boosted c5. 0 classification using genetic algorithm for liver disease prediction'. In *2017 international conference on computer and applications (icca)* (pp. 299-305). IEEE.
[45] Arjmand, A., Christou, V., Tsoulos, I. G., Tsipouras, M. G., Tzallas, A. T., Gogos, C., ... &Giannakeas, N. (2021). 'An evolutionary algorithm-based optimization method for the classification and quantification of steatosis prevalence in liver biopsy images'. *Array*, 11, 100078.
[46] Ardam, S., &SoleimanianGharehchopogh, F. (2019). 'Diagnosing liver disease using firefly algorithm based on Adaboost'. *Journal of Health Administration*, 22(1), 61-77.
[47] Jiang, Q., Ma, J., Ma, Z., & Li, G. (2013). 'A privacy enhanced authentication scheme for telecare medical information systems'. *Journal of medical systems*, 37, 1-8.
[48] Uzer, M. S., Yilmaz, N., & Inan, O. (2013). 'Feature selection method based on artificial bee colony algorithm and support vector machines for medical datasets classification'. *The Scientific World Journal*, 2013.
[49] Rajathi, G. I., & Jiji, G. W. (2019). 'Chronic liver disease classification using hybrid whale optimization with simulated annealing and ensemble classifier'. *Symmetry*, 11(1), 33.
[50] Selvaraj, G. (2013). 'Improved feature selection based on particle swarm optimization for liver disease diagnosis'. In *Swarm, Evolutionary, and Memetic Computing: 4th International Conference, SEMCCO 2013, Chennai, India, December 19-21, 2013, Proceedings, Part II* (pp. 214-225).Springer International Publishing.
[51] Hajihashemi, V., Hassani, Z., Dehmajnoonie, I., & Borna, K. (2019). 'Hybrid Algorithms of Whale optimization algorithm and k-nearest neighbor to Predict the liver disease'. *EAI Endorsed Transactions on Context-aware Systems and Applications*, 6(16).
[52] Utami, D. Y., Nurlelah, E., & Hikmah, N. (2020). 'Attribute Selection in Naive Bayes Algorithm Using Genetic Algorithms and Bagging for Prediction of Liver Disease'. *Journal of Informatics And Telecommunication Engineering*, 4(1), 76-85.
[53] Ruhul Amin, et. al., "Prediction of chronic liver disease patients using integrated projection based statistical feature extraction with machine learning algorithms", *Informatics in Medicine Unlocked*, Vol. 36, 2023.
[54] Dritsas E, Trigka M., "Supervised Machine Learning Models for Liver Disease Risk Prediction", *Computers 2023*, Vol. 12, no 1, 2023.
[55] Weng S, Hu D, Chen J, Yang Y, Peng D. Prediction of Fatty Liver Disease in a Chinese Population Using Machine-Learning Algorithms. *Diagnostics. 2023*; 13(6):1168
[56] Boina, R. ., Ganage, D. ., Chincholkar, Y. D. ., Wagh, S. ., Umakant Shah, D. ., Chinthamu, N. ., & Shrivastava, A. . (2023). Enhancing Intelligence Diagnostic Accuracy Based on Machine Learning Disease Classification. *International Journal of Intelligent Systems and Applications in Engineering*, 11(6s), 765.
[57] Ridhi Deo and Suranjan Panigrahi. 2019. Prediction of Hepatic Steatosis (Fatty Liver) using Machine Learning. *In Proceedings of the 2019 3rd International Conference on Computational Biology and Bioinformatics (ICCBB '19)*. Association for Computing Machinery, New York, NY, USA, 8–12.
[58] J. Sujith et al., "Computative Analysis of Various Techniques for Classification of Liver Disease", *Journal of Physics, Conf. Ser.*, vol. 2466, 2023.
[59] J. Aswini, B. Yamini, K. Venkata Ramana, "An Efficient Liver Disease Prediction Using Mask-Regional Convolutional Neural Network and Pelican Optimization Algorithm", *IETE Journal of Research*, 2023.