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A Soft Computing Approaches to Predict Liver Prognosis and Classification: A Systematic Review

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Abstract:

The liver, with its two granular lobes on either side, is one of the biggest and most vital organs in the human body. Its location on the upper right side of the belly is enormous. The creation of bile, elimination of waste items from food, metabolic processes, cleansing of the blood through digestive regulation, and mineral and vitamin storage are all essential tasks performed by the liver. Glycogen storage, hormone production, etc., all rely on this vital organ. Any condition that affects the liver, whether it's in a chronic stage or not, requires prompt medical intervention. There is an increased chance of getting liver failure as this prognosis progresses. Fatty liver, fibrosis, cirrhosis, liver disease, metastasis, and so on are among the most prevalent liver illnesses. Both invasive and non-invasive methods can detect the slow onset of most hepatological disorders. Accurate estimates for the of Predict Liver Prognosis (PLP) are vital for setting clinical, research, and policy priorities. We aimed to review the incidence, prevalence, and mortality of PLP and its resulting complications. We reviewed the published literature on the incidence, prevalence, trends of various etiologies of PLP and its resulting complications. In addition, we provided updated data from the Centers for Disease Control and Global Burden of Disease Study on the morbidity and mortality of PLP. The goal of soft computing is to facilitate machine learning in all its forms—supervised, unsupervised, semi-supervised, and reinforced—by identifying patterns in massive data sets that can inform decisions. The research and computations of the results showed that these algorithms achieved respectable accuracy following feature selection.

Keywords: Machine Learning, Soft Computing, Ensemble Learning, Liver Prognosis

1. Introduction:

This review focuses on research that has used machine learning to simulate liver disease diagnosis and prognosis. The liver organ is irreplaceably very important for a human being to live due to its innumerable tasks handled (shown in **Figure 1**). The wellness of liver's workability - it fights infection and cleans the blood and also aids in digesting food for storing energy, ready for usage whenever it is necessary. The significance of the liver organ is the capability to repair the liver cells when gets damaged. The power to regenerate the liver cells when they are damaged and replace the old cell tissues with the new cell tissues is a miraculous work of the liver organ. The regeneration capacity of the liver organ is possible with a healthy volume of approximately 20-30% of liver for hepatic functioning, which insures the survival of the deceased, during regeneration process [1-2]. However, this threshold value varies from case to case. The liver might be suffering with various list of bizarre signs has been shown in

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Table 1.

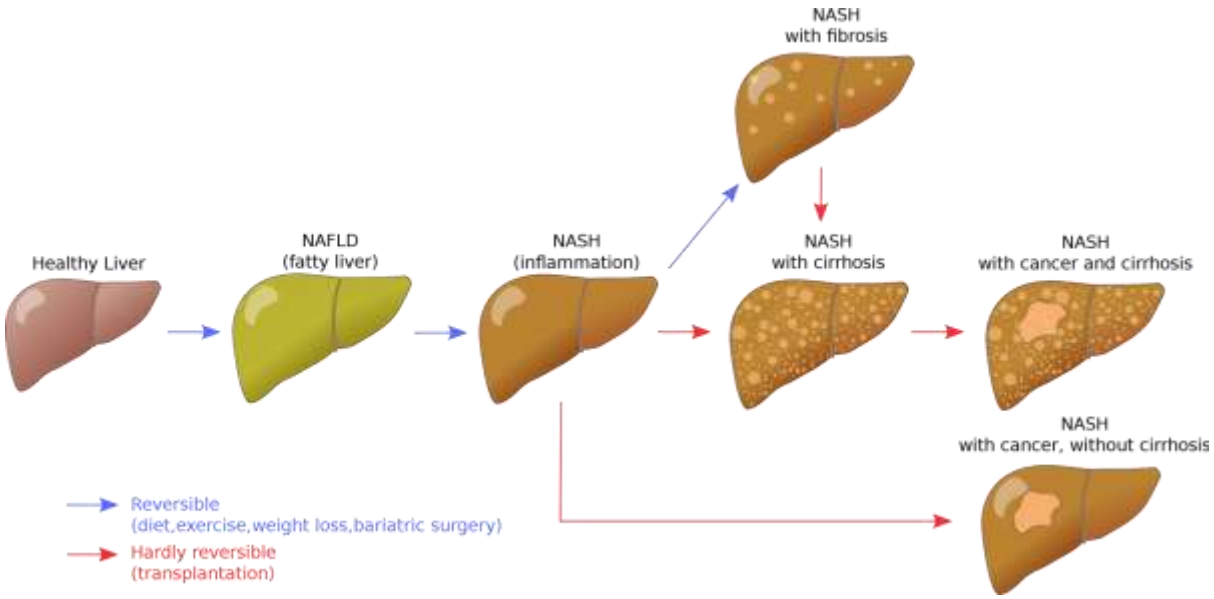

Figure 1: Liver states on various situations

The liver being an internal organ, it shows outward signs when affected. On prevalence of the same, the signs or symptoms of the liver damage prove its severity [3-4].

Table 1 show the list of bizarre signs that the liver might be suffering

S.No	Symptom	Cause	Effect
1.	Bruise and bleed easily	Stop Producing Proteins	bleed very easily
2.	Itchy skin	bile duct	feel itchy all over their skin
3.	Turning yellow- Skin and Eyes	Jaundice	white of eyes and even skin to turn yellow
4.	Blemishes and hyper-pigmentation on face	melanin	This pigmentation causes blemishes on the face or the entire body
5.	Red palms	Palmar Erythema	the palms which turns reddish with burning and itching
6.	Swelling in the legs, feet and ankles	fluid balance	fluid accumulates in unwanted places, such as the ankles, feet, legs, or abdomen
7.	Abdominal pain and swelling	abdominal pain	the lower right side of the rib cage
8.	Nausea or vomiting	Weakness	Nausea and vomiting

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9.	Abnormal Blood Vessels	higher levels of Oestrogen	They are small capillaries seen under the skin in translucent nature
10.	Changes in urine & stool color	internal bleeding	The color of urine appears to be brown
11.	Bad breath	foetor hepaticus	the whiffy breath which indicates many health problems, like sinusitis or gum disease
12.	Feeling tired and chronic fatigue	fatigue or vertigo	feel strength-less, weak and extremely tired
13.	Genital disorders	erectile dysfunction	the defective men develop enlarged breasts, small testes or shrinking testicles
14.	Loss of appetite and Weight Loss	swelling of the belly and legs hide	defective human body results in highly noticeable weight loss
15.	Lack of concentration – Confusion	Unable To Segregate Ammonia	Lack of Concentration, Drastic Struggle

In the initial phase of most liver diseases, the liver may experience inflammation. It has the potential to become sensitive and swollen. Inflammation is an indication of the body's immune response to combat an infection or facilitate the healing process of a wound. However, if inflammation persists, it can cause long-term damage to the liver. Inflammation in most other areas of the body typically results in increased temperature and discomfort. However, an inflamed liver often causes minimal discomfort, and individuals with inflammation generally do not perceive it. If recognized and treated correctly at this point, this liver condition may result in the resolution of inflammation.

In rare instances, there is scarcely any indication that something is amiss. The University of Iowa Hospitals and Clinics cautions that as many as 50% of individuals with liver disease may experience no discernible symptoms. However, in instances where only moderate symptoms are observed, the predominant consequences are generally nonspecific and encompass exhaustion, extreme tiredness, lack of motivation, and occasional itching.

When the person with the flaw goes past the early signs, the damage to the liver and the side effects get worse. "People may have the blood vessels leading to their livers burst," says the American Liver Foundation. "Toxins could build up in their brains and make it hard for them to think clearly, and they could feel sick and have diarrhea." It says on the foundation, "As liver failure gets worse, the symptoms get worse." "The patient might get lost and confused, and they'll be very sleepy." There is a chance of going into a coma and dying. It may be necessary to have a liver donation at this point in order to cure the condition, so it is very important to look for signs of liver damage as soon as possible.

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Research on Liver disease has evolved during the past few decades [5-6]. Scientists used early screening to discover liver diseases before they develop symptoms. They also established early liver therapy outcome prediction methods. The medical research community has access to vast amounts of liver disease data because to modern technology. Predicting disease outcomes is one of doctors' most exciting and difficult tasks. ML approaches are common among medical researchers. These methods can find patterns and links in complex datasets and forecast disease outcomes.

Taking into consideration the significance of personalized medicine and the developing trend of applying soft computing techniques, the purpose of this article is to provide a review of research that make use of these methods in relation to the prediction and prognosis of liver disease. During the course of these researches, prognostic and predictive characteristics are taken into consideration. These characteristics may be independent of a particular treatment or they may be combined in order to guide therapy for patients suffering from diseases [5]. Additionally, we analyze the various sorts of soft computing methods that are now being utilized, the various forms of data that they integrate, the overall performance of each proposed scheme, and we also discuss the benefits and drawbacks of each of these schemes.

A common theme in all suggested studies is the incorporation of hybrid datasets, combining clinical and genetic information. But one thing that we found in a few of these works is that they don't test or validate their models with outside parties to see how well they forecast. Recurrence, survival, and vulnerability to liver disease could all be better predicted with the use of soft computing technologies. Following the implementation of soft computing approaches, the accuracy of disease prediction outcomes has been enhanced by 15% to 20% in recent years, according to [5].

Research gap

The results of literature researches, which are based on various methodologies that potentially allow for the early diagnosis of infectious liver disease, show that the disease's impact on the liver determines the prognosis. The classification of liver diseases [7] is highly decisive and mainly deserves pressing attention with accurate diagnosis appropriately. To enunciate this classification, most importantly aiding as the second opinion to derive at a conclusion without human intervention, is a major desire for every radiologist and physician. Although there exists “liver window view” option [8] in the advanced softwares, the appropriate usage of this view, rather than normal abdominal view, towards unsupervised classification of the liver diseases, is still an exigency. The target of classifying the different categories of liver diseases requires appropriate data space of features to be extracted, absolute selection of feature among the feature data space and choosing of impactful classifiers. The studies outline the advantages and disadvantages of using microarrays to predict disease outcomes. No headway has been achieved in the clinical application of gene signatures, despite the fact that they might greatly enhance our capacity for prognosis in patients with liver disease. Investigations utilizing more substantial data samples and sufficient validation are necessary prior to the application of gene expression profiling in clinical practice.

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This study solely presents research that has used k-NN, DT, SVM, NN 10, AdaBoost ML methods to simulate liver disease diagnosis and prognosis.

2. Soft Computing Techniques for Liver Decease Classification

Machine learning algorithms (MLA) such as ensemble [11], neural networks [9], Support Vector Machines (SVM) [10], and others are used for this task in order to categorise CLD according to content. Furthermore, for precise CLD classification, researchers choose MLA models such as SVM, Random Forests (RF), Artificial Neural Networks (ANN), and others [12–13]. In contrast, RF, which is a well-known predictor, could be exposed to weaknesses [14]. Although ANN is better at classifying liver diseases, it costs more to run and can overfit [15]. SVM can handle noise well and produces good classification results [16].

An analysis of 225 records (each containing 14 highlights) of liver capacity tests was conducted in [17]. These records were selected from a larger pool of 1,000 records, which included records from 25 patients with liver disease from various hospitals. By combining data visualization techniques with Support Vector Data Description (SVDD) and the Glow-worm Swarm Optimization (GSO) algorithm, the authors have improved diagnostic accuracy to 96% sensitivity, 86.28% specificity, and 84.28% accuracy.

In order to identify liver illness, a CAD framework was developed in [18] that made use of tumour characteristics gathered from multiphase CT scans. The immune system's memory and learning abilities were used by Liang and Peng [19] to identify liver illness. The detection of liver diseases required the application of a hybrid methodology that blended genetic algorithms and artificial immunological techniques. The architecture of the system is based on the artificial immune system, and it uses a learning technique based on genetic algorithms to infer the evolution of the antibody population. These findings suggest that the developed approach may prove to be a useful automated liver disease diagnostic tool. In order to identify fatty and cirrhosic liver from CT abdominal images, [20] performed a textural analysis of CT images and built three neural networks: a Probabilistic Neural Network (PNN), a Linear Vector Quantization (LVQ) neural network, and a back propagation neural network (BPN).

Neural networks are augmented by traditional image processing processes to accomplish the specified goal. A novel hybrid ensemble classifier was created to classify coronary plaque areas [21]. The SVM and ANN/Naive Bayes algorithms were utilized to classify liver disease, and it was shown that SVM performed better in comparison, as reported in a study [22]. The identification of left ventricular structural alterations from echo sequence was executed using Support Vector Machine (SVM) [23]. The implementation of Random Forest (RF) based similarity metrics for multi-modal classification has been demonstrated to outperform previous methods in the context of Alzheimer's disease [24]. Moreover, other classification methodologies have evolved and continue to develop in the present period.

The main goal of soft computing techniques is to provide a model that can be applied to tasks like estimate, prediction, classification, or other similar tasks. During the learning process, the most common activity is classification. This learning function, as previously said, groups the data item

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into one of several predefined categories. Building a classification model with ML approaches may lead to errors in training and generalisation. The first one deals with training data misclassification mistakes, while the second one discusses predicted testing data errors. All cases should be correctly classified by a competent classification model, and the model should fit the training set effectively. The phenomenon known as model overfitting happens when a model's test error rates start to rise despite a drop in their training values. The situation is related to the complexity of the model, which means that increasing the complexity of the model can lower the training errors. A model's optimal complexity, in order to prevent overfitting, is clearly the one that yields the best generalization error. To formally analyze a learning algorithm's expected generalization error, one can use the bias-variance decomposition. A learning algorithm's bias is a measure of how often the system makes mistakes. Another potential source of error that applies to all potential test sets and training sets of a given size is the variance of the learning process. A classification model's total anticipated error is equal to its bias plus its variance, as determined by the bias-variance decomposition.

The next step, after acquiring a classification model via ML methods [25], is to assess the performance of the classifier. Each model's performance is evaluated using four metrics: sensitivity, specificity, accuracy, and area under the curve (AUC). The sensitivity of a classifier is its ability to accurately detect real positives, while the specificity is its ability to correctly identify true negatives. Two quantitative metrics are used to assess a classifier's overall performance: accuracy and AUC. A statistic called precision is related to the total number of accurate forecasts. On the other hand, the receiver operating characteristic (ROC) curve, which illustrates the trade-offs between sensitivity and 1-specificity, yields the area under the curve (AUC), a model performance indicator (Figure 2).

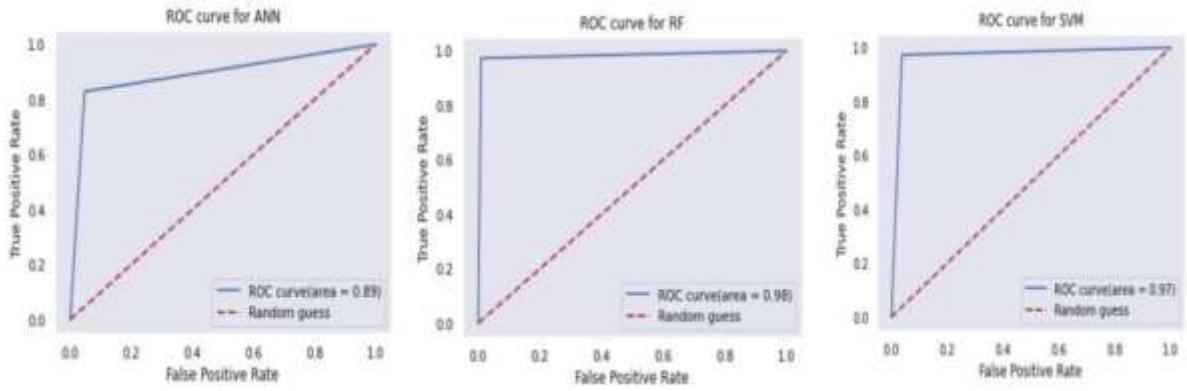

Figure 2: Predition Results of various Soft computing Techniques

In order to evaluate the six-machine learning classifier for the liver disease dataset, Measurement of Classification Techniques [26] took into account various analyses. With a score of 75%, LR was the most accurate, while NB scored 53%, the lowest. The best score was 91% for LR in terms of accuracy, while the worst score was 36% for NB. Taking sensitivity into account, SVM got the best result at 88% while KNN got the poorest at 76%. On the other hand, Logistics Regression achieved the highest performance (83% on the f1 measure) while NB achieved the lowest performance (53%). For specificity, DT got 48% while LR got 47%. When compared to other classifiers, the LR classification method for chronic liver disease prediction performed better based on these evaluation

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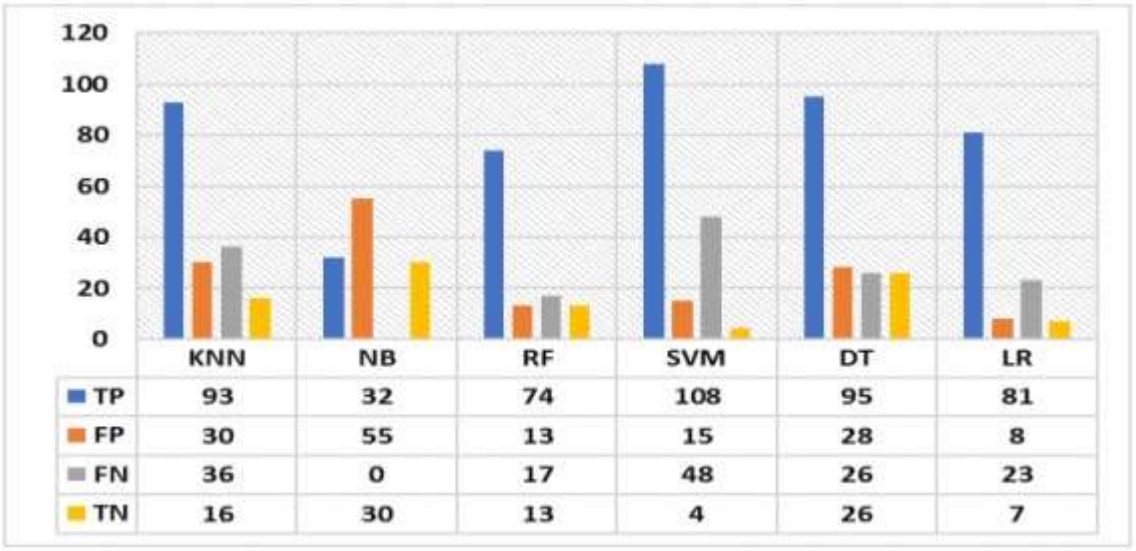
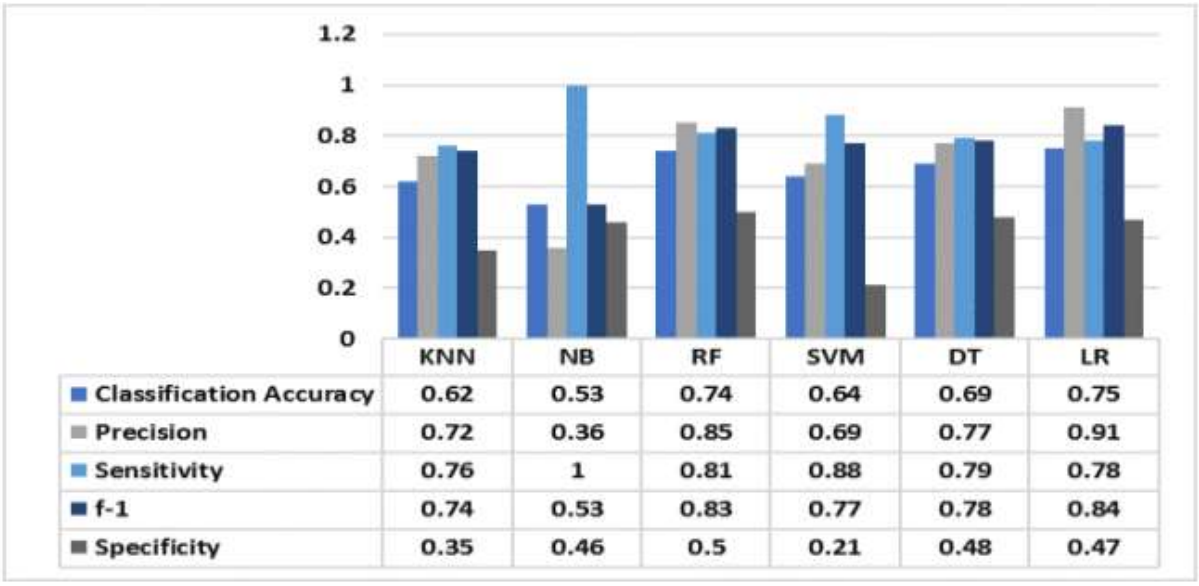
criteria. In Figure 2 we can see the prediction results confusion matrix. The results of six different supervised machine learning methods are shown in figure 3.



	KNN	NB	RF	SVM	DT	LR
TP	93	32	74	108	95	81
FP	30	55	13	15	28	8
FN	36	0	17	48	26	23
TN	16	30	13	4	26	7

Figure 2: Predition Results of various Soft computing Techniques



	KNN	NB	RF	SVM	DT	LR
Classification Accuracy	0.62	0.53	0.74	0.64	0.69	0.75
Precision	0.72	0.36	0.85	0.69	0.77	0.91
Sensitivity	0.76	1	0.81	0.88	0.79	0.78
f-1	0.74	0.53	0.83	0.77	0.78	0.84
Specificity	0.35	0.46	0.5	0.21	0.48	0.47

Figure 3: Performance Comparison of various soft computing techniques

3. Soft Computing and Liver Prediction / Prognosis

In paper [27] classification algorithms FT growth and Naïve Bayes were used to find out their accuracy. 54 instances with 12 attributes were used by the authors. The Naïve Bayes correctly classified 23 instances from 29 instances and its kappa statistics was 0.67% and the accuracy was 75.54%. Whereas FT Tree was classified 19 instances correctly and kappa statistics was 0.0794% and the accuracy was 72.66% using WEKA tool. 29 training datasets were used with 12 attributes for performing experiments. The Naïve Bayes gave better results. The paper [28] entails FT Tree, Naïve Bayes and Kstar algorithms were used on BUPA liver disorder dataset. These algorithms

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were evaluated using 10-fold cross validations. FT tree accuracy was best compared with Naïve Bayes and Kstar algorithms. The paper [29] deals with liver Liver decease treatment in light of CT scans. It was based on textual analysis applying neural networks and genetic algorithm. In fact, genetic algorithm provided good results in diagnosis of liver Liver decease. Many algorithms could be applied effectively for texture feature algorithm. The study [30] described miner classes to compensate the insufficiency liver disorder using oversampling method. Decision tree was not provided as high priority for miner classes because of duplication in BUPA liver disorder. To increase the minor classes and to proceed the decision tree algorithms CART and C4.5 provided good results using oversampling. In the work [31] new approaches were used for diagnosis of liver diseases employing soft computing. It was completed in three phases, in the first phase it categorized the disease using ANN classification, secondly LEM algorithm was used for generating classification rules to reduce the shortcoming of MLP and to improve the accuracy finally fuzzy rules were applied to recognize liver diseases. LEM algorithm was generated by six rules that classified data with 96% accuracy. It improved the classification rate by 6% more than the MLP. It recognized disease using four rules.

4.1 Survey on Static Machine Learning Classifier

According to the research conducted in [32], a particular classification algorithm was examined to determine its relative performance and practical utility on various healthcare datasets. Additionally, in [33], a 'Probabilistic Neural Network' was suggested and put into practice for automated brain tumor classification using image and data processing techniques.

The dataset from the prior study by the CDC Chronic Fatigue Syndrome Research Group was used by the authors of publication [34]. They also used three methods for classification: the C4.5 decision tree algorithm, the support vector machine algorithm, and the naive Bayes algorithm.

In order to test the classification capabilities of thirty different machine learning algorithms, the authors of [35] created rotation forest (RF) ensemble classifiers. They used Parkinson's diabetes and heart diseases as examples to evaluate the performance of these algorithms. The results of experiments show that RF, which is a recently suggested ensemble technique, has proven to be effective in considerably improving the accuracy of classifiers while also being efficient.

In [36], a unique approach for the diagnosis of Parkinson's disease (PD) was presented. This method is based on the examination of the dynamic response of the vestibular system, and multivariate analysis of variance is used to choose pairs of features that exhibit the most significant differences between the groups.

In order to conduct an analysis of the power spectrum of the EEG data, the author [37] utilized the spectrum estimation technique that is based on matrix Eigen decomposition. The results of their experiments demonstrate that it is possible to use the eigenvector approach to extract the characteristics of the power spectrum as input vectors of the classifier. This method has been successful in achieving spontaneous EEG classification and has produced a more favourable effect.

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Using both supervised and unsupervised methods, the study team conducted experimental investigations to classify genomic sequences [38]. The results show that both supervised and unsupervised classification have good performance, but that supervised classification is quicker and unsupervised is better.

The study in [39] examines how well five popular classification techniques function. These include the following: Fisher's linear discriminant (FLD), stepwise linear discriminant analysis (SWLDA), and four linear methods: Pearson's correlation method (PCM), a nonlinear approach, and Gaussian kernel support vector machine (GSVM). The P300 Speller paradigm was used to gather the data.

A synthetic discriminant function network (SDFN), which sorts objects statistically by analysing them with the best spatial filters, and a radial basis function network (RBFN), an artificial neural network, were the two methods of object recognition that were compared in the study [40].

The aforementioned paper [41] included several supervised ANN models for RGB index-based plaque categorization. The Levenberg Marquardt feed forward, the back propagation, and the radial basis function approach are used to design and implement these models.

Scholars [42] assessed two approaches: partial least squares discriminant analysis (PLSDA) and Bayesian regularised artificial neural network (BRANN) for human drug metabolising enzyme substrate and non-substrat classification. Another option was the support vector machine (SVM).

4.2 Survey on Ensemble Classifier Comparison

A new approach to creating ensemble members using the 'learning from mistakes' paradigm was suggested and tested by the authors in [43]. In comparison to ensembles constructed using AdaBoost, MAdaBoost, Bagging, and Arc-x4SVM, the constructed ensemble has superior accuracy.

For each possible combination of the many low-level features used by the Multimedia Content Description Interface in images, researchers [44] built multi-class classifiers.

In order to classify liver decease data, a novel ensemble approach was suggested in [45]. Prior to feature extraction, the gene expression data undergoes pre-processing for normalization using Kernel Independent Component Analysis (KICA). When compared to other state-of-the-art artificial approaches, the results demonstrate that the suggested method achieves a respectable recognition rate.

SCECM, an ensemble classifier model for imbalanced datasets in a heterogeneous classifier fusion environment, was proposed by [46]. It is based on an upgraded Adaboost algorithm with differentiated re-sampling technology (DSRA). Results from controlled experiments demonstrate that the suggested method boosts minority class performance without compromising recognition of majority class samples.

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The supervised learning algorithm XGBoost uses a technique known as boosting to produce reliable models. In order to infer a predictive model, supervised learning uses a set of prominent training examples [47]. We employed forty estimators in this case. The number of boosting stages that are performed is an estimator. Here, 0.7 was the subsample and 12 was the depth. The proportion of samples that are suitable for the basic learners is called the subsample.

AdaBoost is an abbreviation for the term "adaptive boosting." AdaBoosting is a highly efficient method for predicting outcomes, particularly in the context of double-order boosting. As a means of enhancing intellectual capacity, it is the optimal place of departure. AdaBoost is employed for short decision trees. Furthermore, the main tree is generated by utilizing the tree visualization for each preparation event. The purpose of this is to measure the extent to which the tree in question is considered [48]. For this work, we employed a total of 30 estimators, with a learning rate set at 1. An estimator refers to the comprehensive compilation of sub-estimators.

Using the ILPD (Indian Liver Patient Dataset), this study examines and contrasts the outcomes of several ensemble-based ML algorithms. An innovative method for making predictions, the Ensemble technique combines various machine learning models—including decision trees, logistic regression, support vector machines, and more—into a single model [49]. Base estimators and base learners are the names given to the models that make up ensemble models. Compared to more conventional models, ensemble models have many advantages.

The base estimators used by stacking methods train on the full dataset [50]. A meta-learner is constructed from the various models after the base learners have been trained, with the output of the base learners being utilized to train the meta-learners [50]. With this method, a heterogeneous ensemble is formed by using various algorithms as foundation learners. [50]

4.3 Survey on other Soft Computing Approaches

S.No	Problem	Methods Used	Ref.
.1	Fatty liver detection using biopsy and qualitative biomarkers	Fatty liver detection at the early stage to recognize fat-related abnormalities.	[51]
2	Ultrasonography for reliable detection of moderate and severe fatty liver	Histology is less accurate than ultrasonography for moderate-severe fatty liver. Kappa values for ultrasound-detected fatty liver ranged from 0.54 to 0.92 intrarater and 0.44 to 1.00 interrater.	[52]
3	The liver surface nodularity score measurement.	Hepatic fibrosis staging by random liver biopsy leads to sampling errors. Liver stiffness measurement using magnetic resonance imaging and ultrasound for hepatic fibrosis detection.	[53]

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4	The Fibrosis-4 stage of human NAFLD is linked to gut microbiota. Advanced fibrosis detection is achieved with a gut microbiome panel based on the metagenome.	Whole-genome shotgun sequencing is used to analyse the composition of the gut microbiome using DNA extracted from stool samples. To differentiate between stage 4 fibrosis and mild and moderate Non-Alcoholic Fatty Liver Disease (NAFLD), a Random Forest classifier model is employed.	[54]
5	In order to detect fibrosis, transient elastography (TE) and magnetic resonance elastography (MRE) are compared, and steatosis is detected by comparing the TE-based controlled attenuation parameter (CAP) with MRI-based proton density fat fraction (MRIPDFF).	For NAFLD patients who are not candidates for surgery, steatosis and scarring are detected using transient elastography (TE) and magnetic resonance imaging (MRI) based on ultrasonography. MRE detected any stage 1 fibrosis with an area under the receiver operating characteristic curve (AUROC) of 0.82, greater than TE's AUROC of 0.67.	[55]
6	For liver fibrosis evaluation diagnostic accuracy, use APRI, FIB-4, BARD score, NAFLD fibrosis score NFS, FibroScan M, FibroScan XL, Shear Wave Elastography, and Magnetic Resonance Elastography.	The specificity, sensitivity, positive predictive value, negative predictive value, and area under the curve (AUROC) of several non-invasive methods for the diagnosis of fibrosis, advanced fibrosis (AF), and cirrhosis are evaluated.	[56]
7	examination of fibrosis and steatosis using FibroScan: measurement of liver stiffness and controlled attenuation parameter.	FibroScan is used for measuring liver stiffness and controlled attenuation; the area under the receiver operating curve (AUC) is used to identify steatosis and fibrosis in the liver.	[57]
8	Semantic fused feature and long short-term memory based rapid cardiac view categorization	A method that uses deep learning to sort ECG images into groups that can be used to find the subject's physiological position. The echomotion takes each picture and pulls out the spatial convolutional neural network features. The neutrosophic temporal motion properties are obtained after echo-motion activity. Using the features concatenation technique, we integrated the spatial and neutrosophic temporal CNN features..	[58]

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9	Forecast the prognosis of a patient with hepatitis, indicating whether they will survive or succumb.	Two Boolean operators (AND and NOT) were used in a tree-based chromosomal representation in the genetic programming. The first population was created using the ramped-half-and-half method. Real-coding was applied in the fixed-length chromosomal structure. typical single-point crossover as well as typical tree-based crossover and mutation operators were applied. Multiple IF-Then rules were supplied as knowledge, which was handled using a covering method. We used the Pittsburgh and Michigan coding approaches in addition to a Pittsburgh-like technique. There were paired t-tests performed.	[59]
10	Evaluation of classification accuracy on liver diseases dataset	The user's text describes many techniques and concepts used in evolutionary algorithms. These consist of minimization of vectors, depth-fair operator, roulette wheel selection, binary tournament selection, non-destructive crossover and mutation operators, and a three-dimensional fitness vector that takes into account Bayes error, misclassification error, and tree complexity.	[60]
11	Characterization of liver tissue using ultrasonic imaging to distinguish between cirrhosis, hepatoma, and normal tissue.	k-nearest neighbour approach, threefold cross-validation, roulette wheel selection system, two-point crossover and mutation	[61]
12	Liver fibrosis diagnosis and prognosis in long-term hepatitis C patients.	Model for one-stage classification: The tangent sigmoid transfer function is an ANN algorithm. DM: criterion for splitting, decision tree, chi-square, entropy reduction, Gini test. Nearest Neighbor (KNN), Multivariate Logistic Regression Analysis (MLRA).	[62]

5. Prediction of Liver Susceptibility

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Using information from several liver disease datasets, the study's authors [63] investigated the area under the curve (AUC), sensitivity, specificity, and accuracy of ANN and SVM models. In contrast, artificial neural networks yielded results with an accuracy of 57.28%, a sensitivity of 75.00%, a specificity of 32.56%, and an area under the curve (AUC) of 53.78% for the BUPA liver disorder training set. SVM produced results with an accuracy of 63.11%, a sensitivity of 36.67%, a specificity of 100.0%, and an AUC of 68.34%.

The paper [64] states that the accuracy, sensitivity, specificity, and area under the curve (AUC) of ANN and SVM were evaluated on a variety of liver disease datasets. The BUPA liver disorder training set yielded the following findings after analysis: 57.28% accuracy, 75.00% sensitivity, 32.56% specificity, and 53.78% AUC for Artificial Neural Networks and 70% accuracy, 36.67% sensitivity, 100% specificity, and 68.34% area under the curve (AUC) for SVM.

The study [65] utilized a dataset consisting of 78% of liver disease patients with cirrhosis, split evenly between those with HCC and those without tumors, and used this data for both training and testing. The K-nearest neighbor approach was used to eliminate the missing values. Using principal component analysis, the creator of this method improved a fuzzy neural network and then compared its findings to those of the GA search. Using a smaller number of genes allowed FNN-PCA to achieve a 95.8% accuracy rate.

This approach was used to classify the dataset for liver and non-liver illnesses [66]. C4.5 and the Naïve Bayes classifier were used to prepare the medical data from the Chennai medical hospital for analysis. There were fifteen attributes in the data collection. In accuracy, C4.5 performed better than the Naïve Bayes method.

In the publication [67], the algorithms C4.5 and Random Tree were chosen for examination. Both algorithms performed impressively when it came to liver problem diagnosis.

S.no	Techniques Used	Problem Type	Compared methods	Metrics Used	Ref.
1	Generalised Regression Neural Network (GRNN)	Liver Disorder	FFNN ANN	Accuracy Learning Rate	[68]
2	Levenberg-Marquardt algorithm	Liver Disorder	MLP	MSE Accuracy	[69]
3	SOM	hepatitis virus		Accuracy	[70]
4	LDA – FNN	NeuroLinear and NeuroRule	FNN	Accuracy Learning Rate	[71]
5	CSFNN - Conic Section		C 4.5 DT	Accuracy Feature Selection	[72]

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	Function Neural Network				
6	AMBC Associative Memory-Based Classifier	Diagnosis of liver disorders	AdaBoostM1 Bagging BayesNet Logistic	Accuracy MSE MMRE	[73]
8	2 LNN		FNN FMLP	Accuracy	[74]
9	ANN	simulating non-linear relation between fibrosis grades and biomarkers	DT MLRA	Accuracy	[75]
10	RBF	Hepatitis B	GRNN LVQ PNN SVM	Accuracy Learning Rate MSE	[76]
12	2 LNN	Diagnosis of hepatobiliary disorders	FFN Single Layer	Accuracy	[77]
13	CSFNN	Diagnosis of hepatitis disease	RBF MLP	Accuracy	[78]
15	RDP – NN	Diagnosis of hepatitis virus	ANOVA	Classification Accuracy	[79]
16	PBL-McRBFN	Liver disorders	ML	Accuracy	[80]
17	SVM	Focal liver lesion classification	Feature Selection Algorithms	Accuracy	[81]
18	ANN	Diagnosis of liver diseases.	BPN CBR	Accuracy Sensitivity Specificity AUC	[82]
19	DIMLP	Diagnosis of liver disorders.	C4.5 DT	Accuracy	[83]
20	FL	Diagnosis of hepatitis.	BPN ANN	Accuracy Sensitivity Specificity	[84]

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21	FL – ANN	Liver disorders diagnosis.	FHNN HNN	Accuracy	[85]
22	CVNN	Classification of liver problems involves the identification of whether the liver is in a healthy state or if it has developed cirrhosis.	CBP FL FFT FCM	Accuracy Sensitivity Specificity	[86]
24	IFRAIS	In order to evaluate the precision of predicting liver problems in individuals.	FL	Accuracy	[87]
25	GA	Mark the stages of stadialization in chronic hepatitis C-related liver fibrosis.	ANN MLP	Accuracy	[88]
26	AWAIS	Efficiency of classification on a dataset containing information on liver illnesses.	GA FL	Accuracy	[89]
27	LMS	Diagnosis of hepatitis diseases.	ANN RBF TVMOPSO	Accuracy Sensitivity Specificity AUC	[90]
28	CBR	Classify liver diseases according to their symptoms and signs; they	DM CART	Accuracy AUC Sensitivity Specificity	[91]

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		include alcohol hepatitis, chronic hepatitis, cirrhosis of the liver, and HCV.			
29	GA	The overall expense of incorrectly classifying CSCBR results in medical databases (hepatitis).	CSCBR	Accuracy	[92]

6. Observation and Discussion

Our main goals in this study are to define and categorise intelligent treatments for liver illnesses and to determine the correctness of each model. Table was generated following a thorough evaluation of every search result. This table explained the various metrics (hepatitis, fibrosis, cirrhosis, cancer, fatty liver, liver disorders data set, hepatitis data set, hepatobiliary diseases data set, and others) used to specify each model to predict liver problems. The five models—k-NN, DT, SVM, NN 10, and Ada-Boost—are shown in the table. In the "others" section to be placed.

Table Intelligent approaches' suitability for various liver problems

Method	AUC	CA	F1	Precision	Recall
kNN(EQUL)	0.883	0.803	0.803	0.803	0.803
Tree	0.863	0.878	0.878	0.878	0.878
SVM	0.873	0.773	0.759	0.789	0.773
NN 10	0.967	0.911	0.911	0.911	0.911
AdaBoost	0.863	0.868	0.869	0.869	0.868

Figure A comparison of the quantity of published articles based on individual intelligent techniques produced between 2010 and 2023

7. Conclusion

This work provides an overview of the research published between January 1995 and January 2013 that addresses the use of intelligent methods in the treatment of liver diseases. The articles were sorted according to the intelligent techniques applied and which techniques are used for which types of liver disorders. The articles were searched using various keyword indices, including "liver disorders," "liver disorders diagnosis," "hepatitis," "liver fibrosis," "liver cirrhosis," "liver cancer," "fatty liver," "ANN used for liver disorders," "AIS used for liver disorders," "CBR used for liver disorders," "DM used for liver

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disorders," "FL used for liver disorders," "GA used for liver disorders," "PSO used for liver disorders," and "RBR used for liver disorders." According to the survey tables, there was a gradual application of all intelligent procedures to liver problems between 2007 and 2013. Intelligent approaches are utilised in the development of systems that manage imprecise, unstructured, and dynamic patient data. These systems also aid clinicians in diagnosing liver problems by serving as a second opinion resource.

When generating decisions using ML classifiers for diagnostic pathways, the machine learning algorithms described in this work can assist medical professionals; nonetheless, they are not a substitute. These techniques can lessen a number of the healthcare system's drawbacks, including inaccurate diagnosis, incomplete data, expense, and waiting times. By increasing the identification of risk factors and diagnostic variables, the application of machine learning techniques can contribute to a reduction in the overall impact of liver disease on global public health. More significantly, ML's ability to identify liver illness in concealed cases or at an earlier stage could reduce the need for liver transplants, hospital stays, and/or mortality associated with liver disease. The prognosis is improved by early discovery since therapy can begin before the disease progresses to later stages. Biopsies and other invasive testing would also be less common under this situation. It is possible that the techniques can be applied to differentiate various forms of liver disease from healthy persons, even though the study concentrated on hepatitis and chronic liver disease factors for machine learning training. By implementing all of the aforementioned techniques in additional medical fields, AI/ML-assisted diagnosis may become possible.

In an optimistic sense, this study has fulfilled the purpose of a survey by offering comprehensive information on the publications that were published about liver illnesses between 1995 and 2013; It provides details on which individual and combined techniques are applied to which kinds of liver disorders; it lists the articles that have been published along with their findings and applications; it accurately describes the features of ITs and contrasts how they are used; it helps researchers focus their work by educating them about the advantages and disadvantages of intelligent techniques; and it is essential for developing research hypotheses, planning research designs, and gathering and analysing data.

It is advised that inexperienced researchers use widely accepted methodologies like ANN and ANN-FL, which have produced higher accuracy results. Alternatively, they can select less-explored techniques like AIS and PSO, which can produce better results when used alone or in conjunction with other clever techniques. ANN and ANN-CBR would be more appropriate for diagnosing hepatitis; ANN and DM would be more appropriate for diagnosing liver cirrhosis; ANN would be more appropriate for diagnosing liver cancer and fatty liver; ANN-FL would be more appropriate for diagnosing liver disorders; and ANN would be more appropriate for diagnosing hepatitis and hepatobiliary disorders. However, there are a number of additional integration approaches that have not yet been widely used, including AIS-GA, ANN-PSO, CBR-DM, and CBR-GA. Therefore, the choice of which approaches to use is entirely up to the researcher, taking into account both his prior knowledge and the data he obtained from this study. It is hoped and anticipated that the modest effort put into this study would help achieve the goal of creating precise and reliable instruments for liver disease diagnosis.

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