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Intelligent techniques and applications in liver disorders: a survey

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Abstract: Liver disease is one of the leading causes of mortality in India, as it is in rest of the world. This paper presents a survey on intelligent techniques applied to liver disorders between the years January 1995 and January 2013. Individual ITs include artificial neural network (ANN), data mining (DM), fuzzy logic (FL) etc. Integrated ITs combine methods as artificial neural network-case-based reasoning (ANN-CBR), artificial immune system-artificial neural network-fuzzy logic (AIS-ANN-FL) etc. The different types of liver disorders covered in the study are hepatitis, liver fibrosis, liver cirrhosis, liver cancer, fatty liver, liver disorders data set, hepatitis data set and hepatobiliary disorders data set. The study identifies which ITs are applied for what types of liver disorders and on which types of disorders maximum works has been done. Another imperative fact emerging from this survey is that large part of the research work on liver disorders has been done from 2007 onwards.

Keywords: ANNs; artificial neural networks; data mining; fuzzy logic; genetic algorithm; case-based reasoning; rule-based reasoning; artificial immune system; particle swarm optimisation; literature survey; liver disorders; intelligent techniques; biomedical engineering.

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1 Introduction

Modern era of computing has stretched its reach to the intensive and efficient usage of Intelligent Techniques (ITs) in bioinformatics. Owing to the uncertainty in medical data sets, deriving comprehensible information becomes a major challenge for physicians. This challenge can lead to erroneous diagnosis of a disease, which would further lead to improper treatment. Specifically, we can say that it would be favourable for patients if medical experts cross-check their assessment with the help of some decision-making systems. These systems are developed by using intelligent techniques, which resourcefully scrutinise complex and ambiguous data sets. Implementing these ITs for liver disorders is acting as a catalyst in overcoming the overheads and problems faced by doctors. ITs effectively prevail over the inadequacies, help in obtaining better accuracies and make the systems adaptable. ITs decrease the probability of occurrence of medical errors, and reduces the cost, time and effort needed. Going into more specific discussion, intelligent techniques that are applied to liver disorders discussed in this survey are as follows: Artificial Neural Network (ANN), data mining (DM), fuzzy logic (FL), genetic algorithm (GA), Artificial Neural Network-Case-Based Reasoning (ANN-CBR), Artificial Neural Network-Data Mining (ANN-DM), Artificial Neural Network-Fuzzy Logic (ANN-FL), Artificial Immune System-Fuzzy Logic (AIS-FL), Artificial Neural Network-Genetic Algorithm (ANN-GA), Artificial Immune System-Genetic Algorithm (AIS-GA), Artificial Neural Network-Particle Swarm Optimisation (ANN-PSO), Case-Based Reasoning-Data Mining (CBR-DM), Case-Based Reasoning-Genetic Algorithm (CBR-GA), Data Mining-Genetic Algorithm (DM-GA), Data Mining-Fuzzy Logic (DM-FL), Fuzzy Logic-Genetic Algorithm (FL-GA), Artificial Immune System-Artificial Neural Network-Fuzzy Logic (AIS-ANN-FL), Artificial Neural Network-Case-Based Reasoning-Rule-Based Reasoning (ANN-CBR-RBR), Artificial Immune System-Data Mining-Fuzzy Logic (AIS-DM-FL), Artificial Neural Network-Data Mining-Fuzzy Logic (ANN-DM-FL), Artificial Neural Network-Data Mining-Genetic Algorithm (ANN-DM-GA), Artificial Neural Network-Genetic Algorithm-Rule-Based Reasoning (ANN-GA-RBR), Case-Based Reasoning-Genetic Algorithm-Particle Swarm Optimisation (CBR-GA-PSO), Data Mining-Fuzzy Logic-Genetic Algorithm (DM-FL-GA) and Case-Based Reasoning-Data Mining-Fuzzy Logic-Genetic Algorithm (CBR-DM-FL-GA). Survey results confirmed the popularity and applicability of individual and integrated ITs used for liver disorders. Though, researchers had not shown much interest in combining two or more ITs before the year 2007.

Liver is the largest internal organ in a human body, which performs numerous metabolic functions (Li et al., 2012). It works to filter blood, aids in digestion of fats, makes proteins for blood clotting and most importantly detoxifies chemicals (Chuang, 2011). Liver has a vital importance to life but improper functioning of it may cause serious health consequences. Liver disease is usually caused by inherited disorders, contaminated food, damaged hepatocytes infected with viruses, bacteria or fungi, excessive fat accumulation, and excessive consumption of alcohol or drugs (Chuang, 2011). Liver disease is a serious area of concern in the universal set of medicine and is becoming the leading cause of deaths in India, as well as in other countries around the world (http://thelivercarefoundation.org, 26th November 2013). Liver resists early

detection, as it functions normally even when partially damaged, making the disease even more alarming because by then it might have suffered eternal damage. This indicates that an early diagnosis of liver disorders becomes a necessity so that in time treatment can be possible. During diagnosis, analysing complex data set of patients stretches the decision time of doctors. To reduce this time period and effort, decision-making systems are developed using numerous intelligent techniques.

This paper has made a contribution to medical field by presenting a study on intelligent techniques applied to liver disorders between the years January 1995 and January 2013. To the best of our knowledge, not a single attempt had been made to write any survey paper on liver disorders for the last 36 years (1977–2013). Numerous authors have written literature review sections but no complete article has found so far. This paper would be helpful for researchers in developing efficient decision-making tools, as one need to be well acquainted with the applicability of ITs to liver disorders and also which method is widely applied for what types of liver disorders. The different types of liver disorders covered in this study are: hepatitis, liver fibrosis, liver cirrhosis, liver cancer, fatty liver, liver disorders data set, hepatitis data set and hepatobiliary disorders data set (Table 26). This study has figured out which ITs are widely used and vice-versa, which ITs outperformed others in comparison and what are the attributes taken for experiments. This study also discovers the merits and demerits (if any) of medical systems developed using individual and integrated ITs.

The rest of this paper is organised as follows: Section 2 presents the survey on individual intelligent techniques which include ANN, DM, FL and GA. Section 3 covers various integrated intelligent techniques such as: ANN-CBR, ANN-DM, ANN-FL, AIS-FL, ANN-GA, AIS-GA, ANN-PSO, CBR-DM, CBR-GA, DM-GA, DM-FL, FL-GA, AIS-ANN-FL, ANN-CBR-RBR, AIS-DM-FL, ANN-DM-FL, ANN-DM-GA, ANN-GA-RBR, CBR-GA-PSO, DM-FL-GA and CBR-DM-FL-GA. In both Sections 2 and 3, information is listed in tabular form. Section 4 presents the observation. Finally, conclusions are drawn in Section 5.

2 Individual intelligent techniques

This section briefly introduces individual intelligent techniques which are applied to liver disorders. The survey is detailed in tabular form containing following information: author name, year of publication, attributes, intelligent techniques and other methods used, and result and application. Based on the literature survey, merits and demerits (if any) of IT-based proposed systems are also stated. Individual ITs discussed in this segment are ANN, DM, FL and GA.

2.1 Artificial Neural Networks (ANNs)

Artificial neural networks are a simulated view of human brain that is composed of artificial neurons or nodes. These neurons are made up of highly interconnected and interacting processing units (Lin and Chuang, 2010). The first design of ANNs was given by physiologists, McCulloch and Pitts in the year 1943. The basic structure of ANN

consists of input, hidden and output layers, which collectively work as a neuron of a human brain. Neurons in ANN communicate with each other with the help of impulses. These impulses could be of dual nature such as electrical or chemical. It works by acquiring raw data from the outer world for generalising the knowledge. ANNs have an immense ability to learn and derive meaning from intricate and imprecise data. It does not require any preceding knowledge of a problem. ANN has impactful applications in various fields such as pattern recognition, time series prediction, data processing, robotics and regression analysis. Apart from these fields, ANN has also spread its reach in medicine too. It has emerged as one of the most popular tools and provides promising results for medical data analysis. In medicine, ANN helps in diagnosis, radiology, medical image analysis, etc. Limitations of ANN are as follow: it requires lots of knowledge intake, ANN-based systems take lots of time to get fully trained and at time it is difficult to find adequate solution to a problem. Apart from this, choosing an appropriate knowledge set is yet again a major challenge.

ANNs have fascinated many researchers and have shown remarkable performance when applied to liver disorders. ANN-based systems are reliable, robust, more accurate, predictive, computationally simple, non -invasive and inexpensive (Ozyilmaz and Yildirim, 2003; Azaid et al., 2006; Bucak and Baki, 2010; Hashem et al., 2010; Icer et al., 2006; Autio et al., 2007). ANN speeds up the learning process and solves fast size-growing problem (Lee et al., 2005). Levenberg-Marquardt training algorithm of multilayer perceptron (MLP) network employing back propagation shows fair prediction and obtains lower mean square errors (Icer et al., 2006). Implementation of MLP networks trained by resilient back propagation algorithm is good in improving classification accuracy of small classes (Autio et al., 2007). Elizondo et al. (2012) proposed a method that detects differences in the complexity of classification problem. Sun et al. (2005) deployed fast discrete wavelet transform for decreasing time consumption in computation. Some limitations of ANN-based systems are: it is difficult to explain complex classification process as rules (Lee et al., 2005), classification accuracy for MLP is low (Ozyilmaz and Yildirim, 2003), Self-Organising Map (SOM) is unreliable to diagnose hepatitis virus (Ansari et al., 2011), implementation of pyramid neural network consumes a bit longer time in processing (Sun et al., 2005).

Hayashi et al. (2000) stated that overall accuracy rates obtained from NeuroLinear and NeuroRule were higher than those of Linear Discriminant Analysis (LDA) and Fuzzy Neural Networks (FNNs). Ozyilmaz and Yildirim (2003) found the accuracy of Conic Section Function Neural Network (CSFNN) was higher than C4.5 decision tree, Naive Bayes classifier, Bayesian network with naive dependence and feature selection (BNNF). Ansari et al. (2011) asserted that supervised model performs better as compared to unsupervised one. Perez et al. (2012) proposed an Associative Memory-Based Classifier (AMBC) method that achieves the highest classification accuracy among the methods such as AdaBoostM1, Bagging, BayesNet and Logistic. Generalised Regression Neural Network (GRNN) (Ansari et al., 2011) performed better than Feedforward Back Propagation Neural Network (FFNN). Revesz and Triplet (2010) compared classification of integration and data integration methods, both used Support Vector Machine (SVM) linear classifier, and found that the former was more accurate than latter in case of missing values in data. Two-Level Neural Network (2-LNN) method (Hayashi and

Setiono, 2002) achieved higher predictive accuracy than FNN and Fuzzy Multilayer Perceptron (FMLP). ANN (Hashem et al., 2010) attained better classification accuracy than decision tree and Multivariate Logistic Regression Analysis (MLRA). ANN (Hashem et al., 2010) performed better than MLRA in simulating non-linear relation between fibrosis grades and biomarkers. Radial Basis Functions (RBFs) network (Rouhani and Haghighi, 2009) outperformed all networks including GRNN, learning Vector Quantisation Network (LVQ), PNN and SVM, except for the one class (hepatitis B) in which the Probabilistic Neural Networks (PNN) performed better. SVM-SA (simulated annealing) based system (Sartakhti et al., 2012) achieved better accuracy than methods such as C4.5, Naive Bayes (NB), LDA, LVQ, GA-SVM, MLP, GRNN, and MLP with BP (back propagation). The survey on applicability of ANNs for liver disorders is listed in Table 1.

Table 1 Details of ANN-based systems with their results and applications

Author, Year	*Attributes*	*Intelligent techniques and other methods*	*Result and application*
Hamamoto et al. (1995)	Preoperative aspartate aminotransferase, alanine aminotransferase, alkaline phosphatase, total bilirubin of the serum, hepaplastine test, $ICGR_{15}$, total liver volume, residual liver volume and number of platelet	Perceptron-type neural network, linear regression method, supervised learning based on back propagation method	Prediction of early prognosis of hepatectomised patient with hepatocellular carcinoma (liver cancer). Accuracy: 100%
Hayashi et al. (2000)	Hepatobiliary disorders data set	Standard feedforward network, line search algorithm, quasi Newton algorithm, BFGS method, NeuroLinear and NeuroRule rule extraction techniques	Diagnosis of hepatobiliary disorders. Accuracy: NeuroRule – 88.3% Neuro Linear – 90.2%
Hayashi and Setiono (2002)	Hepatobiliary disorders data set	Standard feedforward network with a single hidden layer	Diagnosis of hepatobiliary disorders. Accuracy of 2-LNN: 83.47% (using best choice criterion) and 91.41% (using second best choice criterion)
Ozyilmaz and Yildirim (2003)	Hepatitis data set	MLP trained with standard back propagation algorithm, RBF trained with OLS algorithm, CSFNN combined MLP and RBF, Gaussian bell function	Diagnosis of hepatitis disease. Accuracy: CSFNN – 90% RBF – 85% MLP – 81.375%

Table 1 Details of ANN-based systems with their results and applications (continued)

Author, Year	*Attributes*	*Intelligent techniques and other methods*	*Result and application*
Lee et al. (2005)	Contour of the liver cyst, contrast between liver tissues, grey levels of the liver tissues	BP-CMAC neural network (integrated with BP and CMAC)	Classification of liver disorders (liver cyst, hepatoma and cavernous haemangioma). Accuracy: 87%
Malal and Sadasivam (2005)	Computerised tomography images	Probabilistic neural network. Wavelet-based texture analysis: orthogonal wavelet transform, mean, standard deviation, contrast, entropy, homogeneity and angular second moment	Classification of diffused liver disorders (fatty liver and liver cirrhosis). Accuracy: 95% Sensitivity: 96% Specificity: 94%
Sun et al. (2005)	Ultrasonographicimages of cirrhosis	Pyramid neural network trained using ultrasonographic images of cirrhosis and using data judged by clinicians, fast discrete wavelet transform, steepest descent method	Diagnose the type of cirrhosis diseases.
Azaid et al. (2006)	Ultrasound images: mean grey level, variance of grey levels, skewness of grey level distribution, kurtosis	Multi-layer back propagation neural network trained on features (mean grey level, variance of grey level, skewness of grey level and kurtosis), quantitative tissue characterisation technique, square-shaped region technique	Classify liver disorders as fatty liver, liver cirrhosis, liver cancer. Accuracy: 96.125%
Revett et al. (2006)	Case number, days since registration, drug, age at initial registration, sex, days between study enrolment and a visit, presence of ascites, presence of hepatomegaly, presence of spiders, presence of oedema, serum bilirubin, serum cholesterol, albumin, alkaline phosphatase, SGOT, platelets, prothrombin time, histological stages of disease	Probabilistic neural network, approach based on Bayes formula, Taylor's polynomial approximation. Rough Sets: Rosetta implementation, entropy preserving or MDL (Minimal Description Length) algorithm, equivalence classes, genetic algorithm-based search technique	Mining a primary biliary cirrhosis data set. Accuracy: 87%

Table 1 Details of ANN-based systems with their results and applications (continued)

Author, Year	*Attributes*	*Intelligent techniques and other methods*	*Result and application*
Icer et al. (2006)	Power Spectral Densities (PSD) of Doppler signals	Feed forward multi-layer perceptron network, sigmoid transfer functions, training algorithms adopted were resilient propagation algorithm (RP), scaled conjugate gradient algorithm (SCG) and Levenberg–Marquardt algorithm (LM) employing back propagation, power spectral densities (PSD) of portal venous Doppler signals, short time Fourier transform (STFT) method	To determinate cirrhosis diseases with power spectral densities of portal venous Doppler signals. Accuracy: sensitivity and specificity was 100% with Levenberg–Marquardt training algorithm
Autio et al. (2007)	Liver disorders data set	Multi-layer perceptron networks trained with resilient back propagation algorithm, logarithmic sigmoid function, root mean square formula, least gradient technique, tenfold cross-validation	Classification of liver disorders as sick and healthy. Accuracy: 71%
Dong et al. (2008)	Liver disorders data set	Support vector machines, tenfold cross-validation	To calculate optimal value of cost parameter in order to minimise classification error. Accuracy: 68.12%
Su and Yang (2008)	Liver disease data set collected from department of health examination, Chang gung memorial hospital, Tao-Yuan, Taiwan	Support vector machine model, polynomial kernel, Gaussian radius base function kernel and combined kernel functions, L-J method for feature selection	Classification of liver disorders. Accuracy (kP.G): 77% (with 100% features)
Rouhani and Haghighi (2009)	Sex, age, ALK, AST, SGOT, ALT, SGPT, Bi, T, Bi, D, G.G.T, HBSAg, Alb, LHD, PT, FBS, CHO and HCVAb	RBF networks: two-layer structure, linear activation function, Gaussian function GRNN: radial basis layer and a special linear layer PNN: structure was alike RBF networks, Gaussian distribution, competitive transfer function LVQ networks: competitive layer and a linear layer SVM: polynomial kernel function	Diagnosis of hepatitis disease. Accuracy (RBF): 96.4%

Table 1 Details of ANN-based systems with their results and applications (continued)

Author, Year	*Attributes*	*Intelligent techniques and other methods*	*Result and application*
Uttreshwar and Ghatol (2009)	Hepatitis B surface antigen (HBsAg), hepatitis B surface antibody (HBsAb), hepatitis B e-antigen (HBeAg), hepatitis B DNA	Generalised regression neural networks, kernel-based approximation, logical inference, IF-Then rules	Diagnosis of hepatitis B. Accuracy: 86.3237%
Bucak and Baki (2010)	AST, ALT, AST/ALT, albumin, protein, platelet, and prothrombin time	CMAC neural network, supervised learning, quantisation, least mean square (LMS)	Diagnosis of liver disorders (hepatitis B, hepatitis C, cirrhosis A, cirrhosis B and C). Accuracy: 100%
Hashem et al. (2010)	Routine work tests: platelets count, haemoglobin, WBCs, RBCs, alanine aminotransferase, aspartate aminotransferase, alkaline phosphatase, serum albumin, total bilirubin, prothrombin concentration, alfa-fetoprotein, thyroid stimulating hormone, creatinine, urea, and blood glucose. Fibrotic markers: matrix metalloproteinase-1, metalloproteinase-2, hyaluronic acid, tissue inhibitor of metalloproteinase-1, tissue growth factor beta1, α2-macroglobulin, haptoglobin, apolipoprotineA1	ANN: simulate non-linear relation between fibrosis grades and biomarkers Analysis of variance (ANOVA), Tukey–Kramer and Bonferroni multiple comparison tests, sequential R-square measure, box plots	Prediction of the degree of liver fibrosis (predict the hepatic fibrosis extent in patients with HCV). Accuracy: 93.7% Sensitivity: 92.5% Specificity: 94.8% Area under ROC curve: 0.974
Revesz and Triplet (2010)	Case number, days between registration and earliest of death, transplantion or study; age in days, gender, ascites present, hepatomegaly present, spiders present, oedema, serum bilirubin, serum cholesterol, albumin, urine copper, alkaline phosphatase, SGOT, triglicerides, platelets, prothrombin time in seconds, status, drug, histological stage of the disease	SVM, linear kernel, used SVM implementation from SVMLib	Liver disorder classification (primary biliary cirrhosis)

Table 1 Details of ANN-based systems with their results and applications (continued)

Author, Year	*Attributes*	*Intelligent techniques and other methods*	*Result and application*
Ansari et al. (2011)	Hepatitis data set	FFNN: Levenberg–Marquardt back propagation algorithm, mean square error (MSE) formula. GRNN: kernel function, radial basis transfer function, linear transfer function, Euclidean distance weight function. SOM: competitive learning approach, Euclidean distance, link distance function.	Diagnosis of hepatitis virus. Accuracy: FFNN-91.3%, GRNN-92%
Arsene and Lisboa (2012)	Time, triglicerides, SGOT, serum cholesterol, alkaline phosphatase, ascites, platelets, urine copper, spiders, bilirubin, albumin, age, gender, presence of oedema, prothrombin time, hepatomegally, histological stage of disease, drug	Bayesian neural network, partial logistic artificial neural network (PLANN) and automatic relevance determination (ARD), Bayesian regularisation framework, hessian matrix of the total error function, local and a global compensation mechanism	Medical survival analysis of primary biliary cirrhosis (PBC)
Perez et al. (2012)	Liver disorders data set and Hepatitis data set	Associative memory based classifier (AMBC): learning phase, learning reinforcement phase and classification phase, Integer To Vector operator. Cross-validation: 50–50 training-test split, 70–30 training-test split, tenfold cross-validation and leave-one-out cross-validation	Diagnosis of liver disorders. Classification accuracy using 50–50 training-test split: BUPA – 65.40% Hepatitis – 83.76% Classification accuracy using 70–30 training-test split: BUPA – 59.593% Hepatitis – 84.86% Classification accuracy using 10 fold cross-validation: BUPA – 65.50% Hepatitis – 85.16% Classification accuracy using leave-one-out cross-validation: BUPA – 60.57% Hepatitis – 85.16%

Table 1 Details of ANN-based systems with their results and applications (continued)

Author, Year	*Attributes*	*Intelligent techniques and other methods*	*Result and application*
Elizondo et al. (2012)	Hepatitis data set	Recursive deterministic perceptron (RDP) neural network, simplex method for testing linear separability, ANOVA analysis	Quantifying the level of complexity of classification data sets
Sartakhti et al. (2012)	Hepatitis data set	SVM, RBF kernel, simulated annealing, k-fold cross-validation	Hepatitis diseases diagnosis. Accuracy: 96.25%
Babu and Suresh (2013)	Liver disorders data set	PBL-McRBFN: cognitive component and meta-cognitive component, Gaussian activation function, sample delete strategy, neuron growth strategy, parameter update strategy, sample reserve strategy	Classification performance on liver disorders data set. Accuracy: 72.63%
Jeon et al. (2013)	Ultrasound images: characteristics of lesions including internal echo, morphology, edge, echogenicity and posterior echo enhancement	SVM, multiple ROI selection, feature extraction, feature-level fusion method to combine features, tenfold cross-validation	Focal liver lesion classification. Accuracy for classification of cysts and haemangioma: 93.77% Accuracy for classification of cysts and malignancies: 92.13% Accuracy for classification of haemangioma and malignancies: 69.38% Accuracy for classification of haemangioma and malignancies: 80% (with feature selection algorithm)

Notes: CMAC: Cerebellar Model Articulation Controller, PBL: Projection-Based Learning, McRBFN: Meta-cognitive Radial Basis Function Network, ROI: Region of Interest.

Liver disorders data set attributes are: MCV (mean corpuscular volume), Alkphos (alkaline phosphotase), SGPT (alamine aminotransferase), SGOT (aspartate aminotransferase), gamma-GT (gamma-glutamyl transpeptidase), drinks (number of half-pint equivalents of alcoholic beverages drunk per day).

Hepatitis data set attributes are: age, sex, steroid, antivirals, fatigue, malaise, anorexia, liver big, liver firm, spleen palpable, spiders, ascites, varices, bilirubin, alk phosphate, sgot, albumin, protime, histology.

Hepatobiliary disorders data set attributes are: Glutamic Oxalacetic Transaminate (GOT, Karmen unit).

Glutamic Pyruvic Transaminase (GPT, Karmen Unit), Lactate Dehydrase (LDH, iu/l), Gamma Glutamyl Transpeptidase (GGT, mu/ml), Blood Urea Nitrogen (BUN, mg/dl), Mean Corpuscular Volume of red blood cell (MCV, fl), Mean Corpuscular Haemoglobin (MCH, pg), Total Bilirubin (TBil, mg/dl) and Creatinine (CRTNN, mg/dl).

2.2 Data mining (DM)

Data mining is a process of identifying hidden relationships and discovering new knowledge from large data sets. The term 'data mining' was originated in the year 1990, but work on this started a bit earlier. DM helps in processes such as classification, clustering, regression and summarisation, which generate hidden facts from historical data. Some issues in DM which needs to be taken care are: quality of data to mine, the extent up to which data needs to be cleaned, and interoperability (data from heterogeneous sources needs to combine and analyse). DM-based system has the capability of replacing liver biopsy in liver disorders diagnosis (Floares, 2009). Yan et al.'s (2008) C4.5 decision tree-based proposed method can be efficiently integrated with algorithm like boosting to enhance prediction. Eastwood and Gabrys (2012) mentioned advantages of a single tree classifier: simple model structure, small memory requirement and quick calculation of predictions. Kohara et al. (2010) has done something very interesting and out of the box by proving the feasibility to diagnose liver cirrhosis using PCA-based statistical shape model of the liver.

In comparison, Yan et al. (2008) proposed C4.5 algorithm that has better classification rate than other methods such as ID3 decision tree, RBF NN, BayesNet and logistic. Based on the results achieved, Yan et al. (2008) claimed that if a patient has gotten cirrhosis, he must has symptoms like lassitude and fatigue, chill and cold limbs, tarnish complexion, yellow eyes or yellow body or yellow urine. Floares (2009) developed a C5.0 decision tree and boosting-based system which has outperformed other methods such as SVMs, Bayesian networks, neural networks of various types and architectures, and classification and regression trees. The survey on applicability of data mining techniques for liver disorders is listed in Table 2.

2.3 Fuzzy logic (FL)

FL-based models have been developed and utilised by numerous researchers for handling liver disorders. The concept of fuzzy logic was introduced by Lotfi A. Zadeh in the year 1965 and was applied in medical systems approximately after 20 years. FL employs linguistic rules in the form of IF-Then statements. FL deals with uncertainty and also assists computer in interpreting statements which consists of intermediate constructs. For example, if glass is half-full then pour some water. The semantic of this statement does not correspond to any truth value, either true/false. FL-based systems are faster, liable, cheaper (Neshat et al., 2008), robust, flexible, customisable, interpretable and easy to train (Gadaras and Mikhailov, 2009). FL-based system also has flexible initialisation, fast convergence and robust segmentation (Li et al., 2012). FL-based system efficiently deals with uncertainty, ambiguous information and imprecise data (Obot and Udoh, 2011). Ming et al.'s (2011) fuzzy-based framework uses global k-means algorithm to determine actual number of cluster needed for different data sets and fast global k-means to improve computation time taken by global k-means algorithm. This model was based on enhanced supervised fuzzy clustering algorithm, which effectively handles small size data that is noisy and atypical. Sometimes fuzzy-based systems also require more simulation and fine tuning.

Table 2 Details of DM-based systems with their results and applications

Author, Year	*Attributes*	*Intelligent techniques and other methods*	*Result and Application*
Yan et al. (2008)	Lassitude and fatigue, chill and cold limbs, tarnish complexion, yellow eyes or yellow body or yellow urine	C4.5 decision tree, tenfold cross-validation	To analyse relationship between child-pugh degree and examinations of traditional Chinese medicine based on liver cirrhosis. Accuracy: 85.67 % (for child pugh A)
Floares (2009)	Age, aspartate aminotransferase, gamma-glutamyl-transpeptidase, cholesterol, triglycerides, thickness of the gallbladder wall, spleen area and perimeter, left lobe and caudate lobe diameter, liver homogeneity, posterior attenuation of the ultrasound, liver capsule regularity, spleen longitudinal diameter, the maximum subcutaneous fat, perirenal fat	C5.0 decision tree and boosting (AdaBoost)	Liver disorders classification (chronic hepatitis C and B). Accuracy: 100%
Kohara et al. (2010)	Components of shape feature vector	Principal component analysis (PCA), marching cube algorithm, Chui method	Diagnosis of liver cirrhosis
Luo et al. (2011)	Jaundice, poor appetite, fatigue, yellow urine and hypochondriac pain	Cluster analysis: DBScan algorithm Association rules: Apriori algorithm	Preventing and treating viral hepatitis
Eastwood and Gabrys (2012)	Liver disorders data set	Standard decision tree induction, re-sampling (bootstrapping), linear discriminant analysis, model level combination method, pessimistic pruning and error-based pruning, 10 × 10fold cross-validation	Proposed pruning criteria (Liver disorders UCI database for the empirical investigation of proposed method).
Jen et al. (2012)	Systolic pressure, diastolic pressure, glutamate-pyruvate transaminase, alpha-fetoprotein	K-nearest neighbour, linear discriminant analysis with sequential forward selection (a bottom-up search procedure)	Used risk factors of chronic diseases (disease of the liver) to build early warning criteria. Accuracy: 82.65%

Based on the comparisons, Badawi et al. (1999) proposed fuzzy-based classification that attains higher sensitivity than neural network classification, and higher sensitivity and specificity than statistical classification techniques. Obot and Udoh (2011) stated that FL ability to work from approximate reasoning and finding precise solution makes it superior to other methods such as ANN, RBR and CBR. Neshat et al. (2008) proposed fuzzy system that obtains higher accuracy than other traditional diagnostic systems such as RULES-4, C4.5, Naive Bayes, BNND, BNNF, SVM with GP, SSVM, RSVM, MLP, PNN, GRNN, RBF, AIRS and FW-AIRS. Gadaras and Mikhailov (2009) proposed fuzzy classification framework that achieves higher accuracy than other techniques mentioned in the literature such as FBP-NN, BZ, GF-SVM and NF-BSP. Ming et al. (2011) proposed a deterministic and autonomous algorithm (enhanced supervised fuzzy clustering) which attains higher mean accuracy than supervised fuzzy clustering method. Luukka (2011) proposed fuzzy bean-based classifier that obtains higher accuracy than classifiers such as CN2, MLP, DIMLP and SIM. The survey on applicability of FL for liver disorders is listed in Table 3.

Table 3 Details of FL-based systems with their results and applications

Author, Year	*Attributes*	*Intelligent techniques and other methods*	*Result and Application*
Badawi et al. (1999)	Mean grey level, contrast, angular second moment, entropy, correlation, attenuation and speckle separation	Fuzzy rules, MIN compositional rule of inference, bell membership function	Differentiate diffuse liver disorders. Results of fuzzy rule-based classification: Specificity: 92% Sensitivity for liver cirrhosis: 94% Sensitivity for fatty liver: 96%
Neshat et al. (2008)	Liver disorders data set	Fuzzy rules, triangular or trapezoidal fuzzifier, centre of gravity defuzzifier formula	Liver disorders diagnosis (healthy and unhealthy liver). Accuracy: 91%
Gadaras and Mikhailov (2009)	Liver disorders data set	Fuzzy rules, min-max method, trapezoid membership function	Classification performance on liver disorders data set. Accuracy: 89.9%
Luukka (2011)	Liver disorders data set	Fuzzy beans, Bocklisch membership function, differential evolution algorithm	Liver disorders diagnosis. Accuracy: 73.9%
Ming et al. (2011)	Hepatobiliary disorders data set	Enhanced supervised fuzzy clustering algorithm, k-means algorithm, fast global k-means, unsupervised Gath–Geva algorithm	Liver disorders classification (alcoholic liver damage, primary hepatoma, liver cirrhosis and cholelithiasis). Accuracy: 58.78%

Table 3 Details of FL-based systems with their results and applications (continued)

Author, Year	*Attributes*	*Intelligent techniques and other methods*	*Result and Application*
Obot and Udoh (2011)	Nausea, vomiting, fever, body weakness, loss of appetite, diarrhoea, itching, convulsion, stupor, headache, tremors, skin discoloration, eye discoloration, liver tenderness, bile in urine, jaundice	Fuzzy rules, max-min method, centre of gravity (CoG) method, fuzzified with membership functions	Diagnosis of hepatitis
Li et al. (2012)	Contrast-enhanced computed tomography images	Unsupervised fuzzy clustering, fuzzy c-means	Semi-automatic liver tumour segmentation

2.4 Genetic algorithm (GA)

The genetic algorithm was proposed in 1975 by John Holland (Ozsen and Gunes, 2009) at University of Michigan, USA. GA is a branch of evolutionary algorithm which imitates the process of natural evolution and survival of the fittest (Zhang and Rockett, 2011). GA finds the optimum solution from the set of candidate solutions. GA uses a fixed-length chromosome structure and is aimed at solving optimisation or search problems. The basic requirements of GA are a genetic representation of solution set and a fitness function to test and evaluate the solution set. Primary genetic operators used by GA are selection, crossover and mutation. GA has several limitations, which are: implementation of fitness function to evaluate the solution set is quite expensive, shows less efficiency as the complexity of the problem increases and does not operate well on dynamic data sets. Despite this, usage of GA for optimising parameters makes the diagnostic systems robust and invariant (Tan et al., 2003). Falco (2013) proposed a tool that extracts knowledge in the form of IF-Then rules from databases. This is simple, faster, robust, reliable and easy to implement. It also helps users in medical diagnosis and gives explanation of evidences on why a patient is suffering from a specific disease.

In comparison, Tan et al. (2003) proposed a two-phase hybrid evolutionary classification technique which performed better than methods such as C4.5 (decision tree program), PART (rule-learning scheme) and is comparable to Naive Bayes (utilises the Bayesian techniques). Zhang and Rockett (2011) proposed feature extraction method that proves its superiority to competitive methods such as RBF, logistic (modified multinomial logistic regression model), nearest-neighbour-like algorithm, Bayes network classifier using K2 learning algorithm, instance-based learning algorithm, ADTree (the alternating decision tree learning algorithm), Sequential Minimal Optimisation (SMO) algorithm and C4.5 decision tree algorithm. This method also records the lowest mean error. Wu et al. (2012) presented a GA-based feature selection algorithm, which selects a better feature subset than serial feature combination and serial feature fusion schemes. This algorithm performs better, in selecting feature subsets, than NMIFS (Normalised Mutual Information Feature Selection) and GAMIFS (a hybrid filter/wrapper method

called GAMIF). Falco (2013) proposed a tool that is superior to Bayes Net, Naive Bayes, IB 1, FLR (Fuzzy Lattice Reasoning), VFI (Voting Feature Interval), OneR, Part, and inferior to MLP, RBF, KStar, AdaBoostM1, Bagging, Ridor (ripple down rule), J48, NBTree. It also requires the lowest number of rules in comparison to other rule-based classification methods (Part, OneR and Ridor). In spite of these excellent features, this tool has a limitation of not taking uncertainty into account. The survey on applicability of GA for liver disorders is listed in Table 4.

Table 4 Details of GA-based systems with their results and applications

Author, Year	*Attributes*	*Intelligent techniques and other methods*	*Result and Application*
Tan et al. (2003)	Hepatitis data set	Tournament selection scheme, genetic programming tree-based chromosome representation, two Boolean operators (AND and NOT) were adopted, ramped-half-and-half approach, fixed-length real-coding chromosome structure, standard tree-based crossover and mutation operators, standard single-point crossover, covering algorithm, knowledge presented as multiple IF-Then rules, Michigan coding approach, Pittsburgh coding approach, Pittsburgh-like approach, paired t-test	Predict whether a patient with hepatitis will live or die. Average Accuracy: 83.92% Best Accuracy: 94.34%
Zhang and Rockett (2011)	Liver disorders data set	Binary tournament selection, depth-fair operator, roulette wheel selection, non-destructive, depth dependent crossover and mutation operators, minimisation of vectors, three-dimensional fitness vector compromising tree complexity, misclassification error and Bayes error	Classification performance on liver disorders data set
Wu et al. (2012)	Ultrasonic liver image data set	Two-point crossover and mutation, roulette wheel selection scheme, k-nearest neighbour method, threefold cross-validation	Ultrasonic liver tissue characterisation (cirrhosis, hepatoma, and normal). Accuracy: 96.62 %
Falco (2013)	Liver disorders data set	Differential evolution method, tenfold cross-validation mechanism	Automatic classification of items in medical databases. Accuracy in case of liver disorders data set: 64.74% Specificity: 45.08% Sensitivity: 79.84% ROC curve area: 62.46

3 Integrated intelligent techniques

This section presents the survey results of integrated intelligent techniques applied to liver disorders. The study is detailed in tabular form containing following information: author name, year of publication, attributes, intelligent techniques and other methods used, and result and application. Integrated ITs combine methods in one of the two ways: either the techniques are applied sequentially, in which one technique is used to accomplish a specific task that is followed by second technique and so on, or all the techniques are applied simultaneously. For example, sometimes integration of both ANN and CBR is used to identify the existence of liver disorders; whereas in integration ANN is used to identify the existence of liver disorders and CBR is used to find the types of liver disorders. It could also be possible that researchers might have used some methods that are not considered for this survey but we have mentioned those methods, in the table, wherever possible. This section also enlightens the benefits of integrated IT-based systems when used for liver disorders. Integrated intelligent techniques focused in this segment are: ANN-CBR, ANN-DM, ANN-FL, AIS-FL, ANN-GA, AIS-GA, ANN-PSO, CBR-DM, CBR-GA, DM-GA, DM-FL, FL-GA, AIS-ANN-FL, ANN-CBR-RBR, AIS-DM-FL, ANN-DM-FL, ANN-DM-GA, ANN-GA-RBR, CBR-GA-PSO, DM-FL-GA and CBR-DM-FL-GA.

Table 5 Details of ANN-CBR-based systems with their results and applications

Author, Year	*Attributes*	*Intelligent techniques and other methods*	*Result and Application*
Lin and Chuang (2010)	Hepatitis test: HBsAg, HBeAg, Anti-HBs, Anti-HBe, Anti-HBc Anti-HCV Liver function test: AST (SGOT), ALT, T-Bil, ALB, ALP, r-GT. Tumour marker: α-AFP Basic information: gender, marriage, blood type, age, education, occupation. Lifestyle habit: tattoo, smoking, chewing betel-nut, alcohol. Lifestyle: Fatigue, sleep, nap, exercise, breakfast habit, vegetables, fruits, food date mark, food composition, low-salt, low-sugar. Health condition: healthy status, weight, response to physical discomfort, healthy examination, acupuncture, blood donation.	ANN: BPN trained with gradient steepest descent algorithm. CBR: retrieve most similar case, vector of features, case indexing, case retrieval, assigning weights to attributes, nearest neighbour method. AHP: structure decision hierarchy, pair wise comparisons, initiate prioritisation evaluated consistency, means of a consistency ratio, compute relative weights, geometric mean. Fivefold cross-validation	To examine the existence of liver disorders and to determine the types of liver disorders. Accuracy: ANN (diagnosis of liver disorders): 98.04% AHP-weighted CBR (discovers the types of liver disorders): 94.57% Types of liver disorders: 90.2% for chronic hepatitis, 19.6% for liver cirrhosis, 60.2% for B hepatitis and 10% for alcohol hepatitis

Table 5 Details of ANN-CBR-based systems with their results and applications (continued)

Author, Year	*Attributes*	*Intelligent techniques and other methods*	*Result and Application*
Chuang (2011)	Hepatitis test: HBsAg, HBeAg, Anti-HBs, Anti-HBe, Anti-HBc Anti-HCV. Liver function test: AST (SGOT), ALT, T-Bil, ALB, ALP, r-GT. Tumour marker: α-AFP Basic information: Gender, marriage, blood type, age, education, occupation. Lifestyle habit: Tattoo, smoking, chewing betel-nut, alcohol. Lifestyle: Fatigue, sleep, nap, exercise, breakfast habit, vegetables, fruits, food date mark, food composition, low-salt, low-sugar. Health condition: Healthy status, weight, response to physical discomfort, healthy examination, acupuncture blood donation.	ANN: BPN implemented using NeuroShell 2.0, gradient steepest descent training algorithm. CBR: Euclidian distance to extract similar cases, nearest neighbour method. Tenfold cross-validation, sampling using the Bernoli method	Liver disorders diagnosis. Accuracy: BPN-CBR: Accuracy: 95% Sensitivity: 98% Specificity:94% AUC: 96% BPN: Accuracy: 93%, Sensitivity: 91% Specificity: 96% AUC: 93% CBR: Accuracy: 89% Sensitivity: 90% Specificity: 88%, AUC: 89%

Notes: BPN: Back propagation neural network, AHP: Analytic hierarchy process.

3.1 ANN-CBR

ANN-CBR methodology was used by Lin and Chuang (2010), where ANN is deployed to examine the existence of liver disorders and AHP-weighted CBR is used to discover the types of liver disorders, and by Chuang (2011), where ANN-CBR integration is deployed to obtain enhanced accuracy in diagnosis. The integration of ANN-CBR makes the diagnosis more accurate and comprehensive (Chuang, 2011), decreases the occurrence of false diagnosis and avoids postponement of treatment (Lin and Chuang, 2010). Chuang (2011) made it evident that proposed ANN-CBR model achieves better diagnostic accuracy than BPN (back propagation neural network), CART (classification and regression tree), DA (discriminatory analysis), LR (logistic regression), CBR, LR-CBR, DA-CBR, and CART-CBR. Lin and Chuang (2010) used AHP-weighted CBR instead of CBR because it reduces diagnostic errors, accelerates the medical treatment and most importantly has obtained better accuracy. AHP allocates weights to the attributes. One appealing fact in this study (Lin and Chuang, 2010) is identifying types of liver disorders as most of the literature work had not moved beyond diagnosis. The survey on applicability of ANN-CBR for liver disorders is listed in Table 5.

3.2 ANN-DM

ANN-DM methodology was used by Bologna (2003), where DM is used for extraction of rules and ANN is used for classification, and by Calisir and Dogantekin (2011), where DM is used for feature extraction and feature reduction and ANN is used for classification. ANN-DM-based systems in medical domain have reliability, more accuracy, small-sample problem-solving ability, correct recognition rates, simple structure and good generalisation (Bologna, 2003; Calisir and Dogantekin, 2011; Hashem et al., 2012). PCA-LSSVM method (Calisir and Dogantekin, 2011) achieved higher accuracy than methods such as Weighted9NN, 18NN, ASI, MLP+BP (Tooldiag), LDA, MLP, RBF (Tooldiag), 1NN, RBF, FS-AIRS, 15NN, FSM with rotations, FSM without rotations, MLP with BP, QDA, Naive Bayes, Fisher discriminant analysis, LVQ, GRNN, ASR, IncNet, CART (decision tree), PCA-AIRS, and LFC. Bologna (2003) proposed DIMLP model that is appreciably more accurate than CN2 induction algorithm on most of the problems. The survey on applicability of ANN-DM for liver disorders is listed in Table 6.

Table 6 Details of ANN-DM-based systems with their results and applications

Author, Year	*Attributes*	*Intelligent techniques and other methods*	*Result and Application*
Bologna (2003)	Hepatitis data set and Liver disorders data set	ANN: discretised interpretable multi-layer perceptron (DIMLP) model, staircase activation function, weighted sum of inputs and weights, sum squared error (SSE) function, gradient was determined using sigmoid functions, trained by back propagation with default parameters, bagging and arcing methods based on re-sampling techniques, relevance hyperplane criterion. DM: C4.5 decision trees, IF-Then rules. Tenfold cross-validation, t-statistic test, two tailed test	Diagnosis of liver disorders. Average predictive accuracy: Hepatitis: 79.1% Liver disorders: 70.15%
Calisir and Dogantekin (2011)	Hepatitis data set	ANN: least square support vector machine (LSSVM) classifier, maximum Euclidean distance, parameters includes width of Gaussian kernels and regularisation factor. DM: principle component analysis (PCA)	Diagnosis of hepatitis diseases. Accuracy: 96.12%

Table 6 Details of ANN-DM-based systems with their results and applications (continued)

Author, Year	*Attributes*	*Intelligent techniques and other methods*	*Result and Application*
Hashem et al. (2012)	HA, TGF-β1, α2-macroglobulin, MMP2, ApoA1, urea, TIMP, MMP1 and haptoglobin	Single-stage classification model: ANN: tangent sigmoid transfer function. DM: decision tree, chi-square, entropy reduction, Gini reduction splitting criteria. Multivariate logistic regression analysis (MLRA), nearest neighbourhood (KNN). A multistage stepwise classification model: ANN: linear, tangent sigmoid and logarithmic sigmoid, back propagation algorithms (gradient descent, gradient descent with momentum, conjugate-gradient, quasi-Newton and Levenberge–Marquardt), mean square error). DM: decision tree, entropy, Gini index, chi-square test support and confidence measures. Multivariate logistic regression analysis, likelihood ratio test, Hosmer and Lemeshow Chisquare goodness of fit tests, variance inflationary factor (VIF) test	Prediction of liver fibrosis degree in patients with chronic hepatitis C infection. Accuracy: Single staged model: 82.8% (training), 71.2% (testing) Multistage model: 85.6% (testing), 81.9% (training)

3.3 ANN-FL

ANN-FL has emerged as one of the highly used integration method applied to liver disorders. The literature work shows integration of ANN-FL as one of the best model, which has several benefits such as enhanced accuracy (Comak et al., 2007), flexibility, improved decision ability (Neshat and Zadeh, 2010), robustness (Dogantekin et al., 2009; Celikyilmaz et al., 2009) and simplicity and clarity (Ceylan et al., 2011). This integration also makes the system reliable, rapid, more accurate, easy to operate, non-invasive, more economical and more efficient (Neshat and Zadeh, 2010; Ceylan et al., 2011; Dogantekin et al., 2009; Celikyilmaz et al., 2009). ANN-FL methodology was used by Comak et al. (2007), where FL is used to pre-process liver disorders data set and ANN is used to classify, by Dogantekin et al. (2009), where fuzzy inference system-based ANN is used for classification, by Li et al. (2010), where FL is used to compute new attribute values and ANN is used to classify, by Ceylan et al. (2011), where FL is used to reduce the number of segments in training pattern and ANN is used for classification, by Neshat and

Zadeh (2010), where FL is used for clustering and ANN is used for classification, by Li and Liu (2010), where FL is applied to calculate the similarity of paired data for every class and attribute and ANN is used to classify, by Celikyilmaz et al. (2009), where ANN is used to approximate fuzzy classification function parameters of each cluster and FL is used to classify, and by Kulluk et al. (2013), where the proposed approach extracts brief and accurate fuzzy classification rules (FCR) from ANNs.

Neshat and Zadeh's (2010) fuzzy Hopfield neural network approach has fast computational power and gains better accuracy than other neural networks such as MLP, RBF, GRNN, PNN, LVQ and Hopfield. Li et al. (2010) proved that its method is superior to SVM and C4.5 decision tree in terms of classification accuracy. As class imbalance problem in medical data sets diminishes the classification performance of traditional techniques, ANN-FL-based approach (Li et al., 2010) balances the data size by over-sampling the minority class and under-sampling the majority class. Comak et al. (2007) proposed medical a decision-making system that attains higher classification accuracy than those of methods mentioned in the literature include, RULES-4, C4.5, Naive Bayes, BNND, BNNF, SVM with GP, SSVM, RSVM, MLP, PNN, GRNN, RBF, and AIRS. Dogantekin et al. (2009) proposed an automatic diagnosis system that has better classification performance than other methods which includes RBF, FS-AIRS with fuzzy, FSM with rotations, FSM without rotations, MLP with BP, QDA (quadratic discriminant analysis), Weighted9NN, 18NN, ALI, MLP+BP, LDA, MLP, RBF, 1NN, Na Bayes and semi-NB, Fisher discriminant analysis, LVQ, GRNN, ASR, IncNet, CART (decision tree), PCA-AIRS and LFC. Li and Liu (2010) proposed kernel on SVM that attains improved classification accuracy than polynomial and Gaussian kernels. Kulluk et al. (2013) proposed a fuzzy DIFACONN-miner algorithm that yields higher accuracies than other fuzzy rule-based classification algorithms, namely $2SLAVE_{sum}$, $FRBCS\_GP_{sum}$, and $GP\text{-}COACH_{sum}$. It also minimises a few complexity problem. The survey on applicability of ANN-FL for liver disorders is listed in Table 7.

Table 7 Details of ANN-FL-based systems with their results and applications

Author, Year	*Attributes*	*Intelligent techniques and other methods*	*Result and Application*
Comak et al. (2007)	Liver disorders data set	ANN: least square support vector machine (LSSVM), set of linear equations for training. FL: fuzzy weighting pre-processing, triangular (input and output) membership functions, fuzzy IF-Then rules	Diagnosing liver disorders. Accuracy: 94.29% Sensitivity: 95% Specificity: 93.33%
Celikyilmaz et al. (2009)	Liver disorders data set	ANN: SVM, Platt's probability method. FL: classical fuzzy c-means (FCM) clustering. Semi-non-parametric inference mechanism, posterior probabilities from logistic regression (LR), three-way data split cross validation method	Liver disorders diagnosis. Accuracy: 77%

Table 7 Details of ANN-FL-based systems with their results and applications (continued)

Author, Year	*Attributes*	*Intelligent techniques and other methods*	*Result and Application*
Dogantekin et al. (2009)	Hepatitis data set	ANN: hybrid learning algorithm (back propagation for non linear parameters and least square errors for linear parameters) FL: fuzzy IF-Then rules, bell-shaped membership function.	Diagnosis of hepatitis. Accuracy: 94.16% Sensitivity: 96.66% Specificity: 91.66%
Neshat and Zadeh (2010)	Liver disorders data set	ANN: Hopfield neural network, discrete and continuous models, sigmoid activating function. FL: fuzzy c-means	Liver disorders diagnosis. Accuracy: FHNN –92% HNN – 88.2%
Li et al. (2010)	Liver disorders data set	ANN: support vector machine classifier. FL: Gaussian type fuzzy membership function and α-cut to reduce data size, mega-trend diffusion membership function. Tenfold cross-validation	Deal with class imbalance problem with medical data sets and to enhance classification accuracy in BUPA liver disorders data set. Accuracy: 86.36%
Li and Liu (2010)	Liver disorders data set	ANN: support vector machine, class probability based kernel, kernel based on Gaussian membership function, decomposition principle, diffusion function technique, mega-trend diffusion technique. FL: triangular type membership function	Classification performance on liver disorders data set. Accuracy: 70.78%
Ceylan et al. (2011)	Doppler signals of 90 subjects (each subject includes 40 samples)	ANN: complex-valued artificial neural network (CVNN), complex back propagation (CBP) algorithm, complex-valued activation function, real and imaginary components. FL: fuzzy clustering, calculation of FFT (Fast Fourier Transform) values, FCM clustering	Liver disorders classification (identify liver as healthy or cirrhosis). Accuracy: 100% Sensitivity: 100% Specificity: 100%
Kulluk et al. (2013)	Liver disorders data set	ANN: feedforward and recurrent ANNs, trained using differential evolution algorithm. FL: triangular membership function generates fuzzy rules by touring ant colony optimisation (TACO) algorithm, fixed length binary encoding scheme to represent rules. Tenfold cross-validation, fitness evaluation by minimum deviation method (MDM)	Classify liver disorders. Accuracy: 85.60%

Notes: FHNN: Fuzzy Hopfield Neural Network, HNN: Hopfield Neural Network, FCM: Fuzzy C-Means.

3.4 AIS-FL

AIS-FL methodology was used by Polat et al. (2007), where FL is used for resource allocation and AIS is used for classification, by Mezyk and Unold (2011), where AIS is used for induction of fuzzy rules. Polat et al. (2007) proposed a fuzzy-artificial immune recognition system that obtained the highest classification accuracy among classifiers such as RULES-4, C4.5, Naïve Bayes, BNND, BNNF, SVM, SSVM, RSVM, MLP, PNN, GRNN, AIRS and RBF. It has taken less time in computation, effectively solves problems having large dimensioned feature space and too many classes; and required fewer resources than traditional AIRS, which makes it more beneficial. Mezyk and Unold (2011) proved that IFRAIS method is superior to classifiers such as C4.5, Naive Bayes, K*, Meta END, JRip, and Hyper Pipes in terms of classification accuracy. The survey on applicability of AIS-FL for liver disorders is listed in Table 8.

Table 8 Details of AIS-FL-based systems with their results and applications

Author, Year	*Attributes*	*Intelligent techniques and other methods*	*Result and Application*
Polat et al. (2007)	Liver disorders data set	AIS: artificial immune recognition system (AIRS) supervised learning algorithm, resource competition, clonal selection, affinity maturation, memory cell formation. FL: fuzzy resource allocation, IF-Then rules. k-nearest neighbour algorithm, k-fold cross-validation, tenfold cross-validation method	Liver disorders classification. Accuracy: 83.36%
Mezyk and Unold (2011)	Hepatitis data set and Liver disorders data set	Induction of Fuzzy Rules with an Artificial Immune System (IFRAIS): sequential covering algorithm and clonal selection algorithm, fuzzy partition inferring based on clonal selection algorithm, only continuous attributes were fuzzified, IF-Then fuzzy rules, paired *t*-test	To assess prediction accuracy of liver disorders in patients. Accuracy: Hepatitis: 93.87% BUPA data set: 72.34%

3.5 ANN-GA

GA is used with ANNs to enhance classification performance of medical systems (Gorunescu et al., 2012). GA eliminates irrelevant and noisy features, which decreases the size of network (Dehuri and Cho, 2010). Integration of ANN-GA overcomes the non-linearity problems and solves the complexity problems of each other (Dehuri and Cho, 2010). ANN-GA-based framework has low-computational complexity and simplicity of architecture (Dehuri and Cho, 2010). Gorunescu et al. (2012) replaced back propagation algorithm with GA-based learning to optimise MLP's weights. ANN-GA methodology was used by Dehuri and Cho (2010), where GA is used to select pertinent features and ANN is used to classify, and by Gorunescu et al. (2012), where GA is used to optimise the ANNs synaptic weights and ANN is used to classify. Gorunescu et al. (2012) proposed an intelligent system that attains improved accuracy, for both complete data set

and reduced data set, than other machine learning techniques accounted in the literature including LN, PNN, RBF, 3-MLP and 4-MLP. This intelligent system is even faster and more effective than 3-MLP and 4-MLP. Results (Dehuri and Cho, 2010) demonstrated that proposed method named as HFLNN outperforms other competing classification methods such as Radial Basis Function Network (RBFN) and Functional Link Neural Network (FLNN) with back propagation learning. The survey on applicability of ANN-GA for liver disorders is listed in Table 9.

Table 9 Details of ANN-GA-based systems with their results and applications

Author, Year	*Attributes*	*Intelligent techniques and other methods*	*Result and Application*
Dehuri and Cho (2010)	Liver disorders data set	ANN: back propagation learning and genetic optimisation, trigonometric function. GA: single point crossover operator, mutation operator, selection. Twofold cross-validation, parametric *t*-test, non-parametric Wilcoxon signed rank test	Diagnosis of liver disorders. Accuracy: 77.6820%
Gorunescu et al. (2012)	Complete data set: stiffness, sex, body mass index, glycaemia, triglycerides, cholesterol, HLD cholesterol, aspartate aminotransferase, alanin aminotransferase, gama glutamyl transpeptidase, total bilirubin alkaline, phosphatase, prothrombin index, quiq time, prothrombin time ratio, prolonged activ. partial thromboplastin time, haematids, haemoglobin, hematocrit, medium erytrocity volume, avg. erytrocitary haemoglobin, avg. concentration of haemoglobin in a red blood cell, thrombocytes, sideraemia, interquartile range. Reduced data set: stiffness, aspartate aminotransferase, prothrombin index, thrombocytes, sideraemia, interquartile range	ANN: multi-layer perceptron architecture. GA: crossover and mutation. Tandem feature selection mechanism, statistical procedures, and sensitivity analysis, discriminant function analysis, multiple (linear) regression model (both forward stepwise and backward stepwise), analysis of correlation matrix, tenfold cross-validation, binary tournament selection, total arithmetic recombination	Classify liver fibrosis stadialisation in chronic hepatitis C. Accuracy: 61.16% (complete data set) 65.21% (reduced data set)

3.6 AIS-GA

AIS-GA methodology was used by Ozsen and Gunes (2009), where GA is used to determine the weights of attributes that gives minimum classification error and then these weights are used in their own previously developed AIS-based system. The classification accuracy of GA-AWAIS-based system is superior to both AWAIS and other traditional classifiers mentioned in the literature such as Fuzzy-AIRS, AIRS, RSVM, MLP, SSVM, SVM with GP, C4.5, GRNN, Naive Bayes, BNNF, BNND, RBF, RULES-4 and PNN. The survey on applicability of AIS-GA for liver disorders is listed in Table 10.

Table 10 Details of AIS-GA-based systems with their results and applications

Author, Year	*Attributes*	*Intelligent techniques and other methods*	*Result and Application*
Ozsen and Gunes (2009)	Liver disorders data set	AIS: attribute weighted artificial immune system (AWAIS). GA: single point crossover, hypermutation, selection. Tenfold cross validation	Classification performance on liver disorders data set. Accuracy: 85.21%

3.7 ANN-PSO

ANN-PSO methodology was used by Qasem and Shamsuddin (2011), where TVMOPSO-based RBF networks are developed. TVMOPSO extends the algorithm to handle multi-objective optimisation problems. TVMOPSO is simple, robust, easy to use and easy to implement. Classification accuracy of proposed adaptive evolutionary RBF network algorithm is superior to HMOEN_L2, HMOEN_HN and inferior to RBF network based on MOPSO and NSGA-II algorithms. Advantages of this integration method are: stability, consistency, simplicity, enhanced accuracy, better convergence and small standard deviations. The survey on applicability of ANN-PSO for liver disorders is listed in Table 11.

Table 11 Details of ANN-PSO-based systems with their results and applications

Author, Year	*Attributes*	*Intelligent techniques and other methods*	*Result and Application*
Qasem and Shamsuddin (2011)	Hepatitis data set	ANN: RBF network, centres of RBF network in hidden layer are initialised from k-means clustering algorithm, weights of RBF network are initialised from the least mean squared (LMS) algorithm, crowding distance operator. PSO: time variant multi-objective particle swarm optimisation (TVMOPSO)	Diagnosis of hepatitis diseases. Accuracy: 82.26% Sensitivity: 88.47% Specificity: 41.92% AUC: 0.652

3.8 CBR-DM

CBR-DM methodology was used by Lin (2009), where DM is used to find existence of liver disorders and CBR is used to identify types of liver disorders. CBR participated in problem-solving by reducing diagnostic errors and meliorating quality of treatment. Though both CBR and DM could be used in first phase for identifying the presence of liver disorder, but Lin (2009) choose DM technique as it obtained better results in terms of accuracy, sensitivity and specificity. Then in second phase, CBR performed reasonably well in identifying the types of liver disorders. The survey on applicability of CBR-DM for liver disorders is listed in Table 12.

Table 12 Details of CBR-DM-based systems with their results and applications

Author, Year	*Attributes*	*Intelligent techniques and other methods*	*Result and Application*
Lin (2009)	Age, aspartate aminotransferase, alanine aminotransferase, alkaline phosphatase, total bilirubin, direct bilirubin, total protein, albumin, gamma-glutamyl transpeptidase, alpha-fetoprotein, sex, blood type, HBsAg, HBeAg, Anti-HBs, Anti-HBe, Anti-HBc, Anti-HCV	CBR: retrieve most similar cases, reuse cases, revise potential solution, retain new solution, assign indices and weights, case adaptation (through inclusion, removal, substitution or transformation). DM: CART, tree-building method, binary tree structure, recursive binary splitting, tree growing and tree pruning stages, Gini diversity index Fivefold cross-validation methodology	Phase 1: Liver disorders diagnosis Phase II: Identify types of liver disorders (chronic hepatitis, alcohol hepatitis, liver cirrhosis and B hepatitis. Accuracy: Phase I (CART): Accuracy: 92.94% Sensitivity: 96.00% Specificity: 88.57% AUC: 0.928 Phase II (CBR): Accuracy: 90.00% Sensitivity: 91.09% Specificity: 88.41% AUC: 0.889

3.9 CBR-GA

The CBR-GA methodology was used by Parka et al. (2011), where CBR uses GA to find optimal cut-off distance and cut-off classification point. This integration overcomes the limitation of conventional CBR of being deficient in reflecting asymmetric misclassification cost. It has been found that average total misclassification cost of proposed method (Parka et al., 2011) is considerably less than C5.0 and CART cost-sensitive learning methods for a number of data sets. The survey on applicability of CBR-GA for liver disorders is listed in Table 13.

Table 13 Details of CBR-GA-based systems with their results and applications

Author, Year	*Attributes*	*Intelligent techniques and other methods*	*Result and Application*
Parka et al. (2011)	Hepatitis data set	CBR: cost-sensitive case-based reasoning (CSCBR), case retrieval. GA: integration with nearest neighbour method, reproduction, crossover and mutation operators. Tenfold cross-validation, paired *t*-test	Total misclassification cost of CSCBR in medical data sets (Hepatitis). Total Cost: 7.0600

Note: CSCBR: cost-sensitive case-based reasoning.

3.10 DM-GA

DM-GA methodology was used by Sarkar et al. (2012), where DM is used for producing rules from training data set and GA is used for handling interpretability problem, and by Stoean et al. (2011b), where DM is used to extract features and GA is used to build rules for establishing the diagnosis. In comparison, proposed learning system called DTGA (decision tree and genetic algorithm) is more accurate than classifiers such as neural network, Naive Bayes, C4.5, rough-set based rule inducer; and is less sensitive to missing data compared to NN and C4.5 (Sarkar et al., 2012). This integration system also enhances the performance over volumetric data and has less time complexity compared to the majority of GA-based approaches. Cooperative Co-Evolutionary Algorithm (CCEA) based proposed technique (Stoean et al., 2011a) has attained smallest standard deviation and highest accuracy among classification techniques such as SVM, NN, SVM + PCA and NN + PCA. The survey on applicability of DM-GA for liver disorders is listed in Table 14.

Table 14 Details of DM-GA-based systems with their results and applications

Author, Year	*Attributes*	*Intelligent techniques and other methods*	*Result and Application*
Stoean et al. (2011)	Stiffness, sex, body mass index, glycemia, triglycerides, cholesterol, HDL cholesterol, aspartate aminotransferase, alanin aminotransferase, gama glutamyltranspeptidase, total bilirubin, alkaline phosphatase, prothrombin index, TQS (Quiq Time) INR (prothrombin time ratio), prolonged activated partial thromboplastin time. haematids (erythrocytes), haemoglobin, hematocrit, medium erytrocity volume, avg. erytrocitary haemoglobin, Avg. concentration of haemoglobin in a red blood cell, thrombocytes, sideraemia	DM: PCA for feature extraction, IF-Then rules. GA: mutation operator, cooperative co-evolutionary algorithm (CCEA). Hill climbing algorithm	Liver fibrosis diagnosis (differentiate between five degrees of liver fibrosis). Accuracy: 62.11%

Table 14 Details of DM-GA-based systems with their results and applications (continued)

Author, Year	*Attributes*	*Intelligent techniques and other methods*	*Result and Application*
Sarkar et al. (2012)	Liver disorders data set	DM: C4.5 decision tree based rule inducer algorithm, IF-Then rules.	To improve prediction accuracy for liver disorders irrespective to domain and size.
		GA: selection, single point crossover, mutation	Accuracy: 80.02%

Note: PCA: Principal component analysis.

3.11 DM-FL

The DM-FL methodology was used by Luukka and Leppalampi (2006), where DM is used for dimension reduction and fuzzy similarity model is used for classification, by Luukka (2009), where fuzzy robust PCA algorithm is used for data pre-processing and similarity classifier for classification, and by Torun and Tohumoglu (2011), where DM is used to group the data and FL is used for classification. The DM-FL integration-based systems are robust and effective in diagnosis. These systems also provide semantic information about classification task (Luukka and Leppalampi, 2006) and have obtained improved accuracies (Luukka, 2009). Luukka and Leppalampi's (2006) fuzzy similarity model performed fairly well as compared to other classifiers such as C4.5-1 (C4.5 with default learning parameters) and C4.5-3 (C4.5 with parameter c equal to 95). Classification accuracies are obtained using both dimension reduction methods: PCA and entropy minimisation. The mean classification result is a bit higher using PCA than using entropy. Luukka (2009) proposed FRPCA classification method which shows higher accuracy when compared with those of conventional PCA and similarity classifier. Torun and Tohumoglu (2011) proposed simulated annealing and subtractive clustering-based fuzzy classifier (SASCFC) in four different versions (SASCFC Type 1, Type 2, Type 3, and Type 4). Classifications results obtained from different versions are compared among each other and it is found that SASCFC-Type 4 is superior. The survey on applicability of DM-FL for liver disorders is listed in Table 15.

3.12 FL-GA

FL-GA methodology was used by Wang et al. (1998), where GA is used for generating optimal set of fuzzy rules and membership functions, and by Chowdhury et al. (2007), where GA is used to simultaneously integrate multiple fuzzy rule sets and their membership function sets. The proposed genetic algorithm-based fuzzy-knowledge integration framework needs no human intervention during integration process and is scalable (Wang et al., 1998; Chowdhury et al., 2007). Accuracy of the framework increases with increase in data size (Chowdhury et al., 2007). The shortcomings of the framework are limited precision, and several unresolved issues in the field of knowledge verification (Wang et al., 1998). In terms of classification accuracy, proposed genetic algorithm-based fuzzy-knowledge integration framework (Wang et al., 1998) triumphs over other learning methods mentioned in the literature such as CN2, C4, IR*, Bayes, Assistant-86, and Diaconis and Efron. The survey on applicability of FL- GA for liver disorders is listed in Table 16.

Table 15 Details of DM-FL-based systems with their results and applications

Author, Year	*Attributes*	*Intelligent techniques and other methods*	*Result and Application*
Luukka and Leppalampi (2006)	Liver disorders data set	DM: PCA and entropy minimisation method. FL: fuzzy similarity model, Lukasiewicz structure for defining memberships of objects	Detection of liver disorders. Accuracy: 66.50% (PCA) 66.06% (entropy)
Luukka (2009)	Liver disorders data set	Data was pre-processed using Fuzzy robust PCA algorithms (FRPCA), similarity classifier for classification	Classification accuracy on liver disorders data. Accuracy: 70.25%
Torun and Tohumoglu (2011)	Liver disorders data set	FL: fuzzy IF-Then rules, fuzzy inference system (FIS). DM: subtractive clustering, wrapper type feature selection approach. Simulated annealing, least square estimation, k-fold cross-validation	Liver disorders classification. Accuracy: SASCFC-Type 1:73.6% SASCFC-Type 2:73.9% SASCFC-Type 3:73.93% SASCFC-Type 4:74.13%

Notes: PCA: Principal Component Analysis, SA: Simulated Annealing, SC: Subtractive Clustering.

Table 16 Details of FL-GA-based systems with their results and applications

Author, Year	*Attributes*	*Intelligent techniques and other methods*	*Result and Application*
Wang et al. (1998)	Hepatitis data set	FL: fuzzy knowledge encoding, fuzzy knowledge integration, IF-Then rules, isosceles-triangle functions, Parodi and Bonelli parameters to represent each membership function. GA: two-substring crossover operator, two-part mutation operator, Pittsburgh approach	Hepatitis diagnosis. Accuracy: 91.61%
Chowdhury et al. (2007)	Age, bilirubin, alk phosphate, SGOT, albumin and protime	FL: fuzzy knowledge encoding and fuzzy knowledge integration, fuzzy rules, isosceles-triangle functions, Parodi and Bonelli parameters to represent each membership function. GA: SBMAC (sub population based max-mean arithmetical crossover), dynamic time-variant mutation (TVM), insertion mutation, deletion mutation, novel evolutionary strategy algorithm	Hepatitis diagnosis. Accuracy: 96.33%

3.13 AIS-ANN-FL

AIS-ANN-FL methodology was used by Kahramanli and Allahverdi (2009), where AIS algorithm is deployed to extract rules from hybrid neural network. Generated rules are very accurate but are large in numbers. Classification accuracy of the proposed integration approach is superior to other classification techniques mentioned in the

literatures such as C-MLP2LN, FSM and CART. The survey on applicability of AIS-ANN-FL for liver disorders is listed in Table 17.

Table 17 Details of AIS-ANN-FL-based systems with their results and applications

Author, Year	*Attributes*	*Intelligent techniques and other methods*	*Result and Application*
Kahramanli and Allahverdi (2009)	Hepatitis data set	Hybrid neural network: artificial neural network, fuzzy neural network, trained with back propagation algorithm, fuzzification, defuzzification, weight update method of back propagation algorithm. Artificial immune systems (AIS) algorithm: extracting rules from hybrid neural network, IF-Then rules	Liver disorders classification on hepatitis data set. Accuracy: 96.78% Sensitivity: 97.56% Specificity: 93.75%

3.14 ANN-CBR-RBR

ANN-CBR-RBR methodology was used by Obot and Uzoka (2009), where case-based technique outputs constitute an input to ANN and results obtained from ANN are assisted to form rule base. Finally, a hybrid inference engine has been built to obtain accuracy through rule base. This hybrid system (Obot and Uzoka, 2009) provides high diagnostic accuracy and high speed for retrieval of information. Limitations of the system are: restricted explanation capability, ineffective in managing noisy data due to fragility of rules, and it would not like the insertion of new knowledge. The survey on applicability of ANN-CBR-RBR for liver disorders is listed in Table 18.

Table 18 Details of ANN-CBR-RBR-based systems with their results and applications

Author, Year	*Attributes*	*Intelligent techniques and other methods*	*Result and Application*
Obot and Uzoka (2009)	Nausea, vomiting, fever, body weakness, loss of appetite, diarrhoea, itching, convulsion, stupor, headache, tremors, skin discoloration, eye discoloration, liver tenderness, bile in urine, jaundice	ANN: trained with multi-layer perceptron back propagation neural networks (MLPBPNN). CBR: retrieval using binary search algorithm, adaptation. RBR: IF-Then rules	Diagnosis of hepatitis disease

3.15 AIS-DM-FL

AIS-DM-FL methodology was used by Polat and Gunes (2007a), where DM is used for dimensionality reduction, FL is used for data-weighted processing and AIS for classification, and by Polat and Gunes (2007b), where DM is used for feature reduction, FL is used for weighting the whole data set and AIS for classification. Advantage of deploying AIRS is that it is not necessary to know the appropriate settings for the classifier. In terms of classification accuracy, Polat and Gunes (2007a) proposed a hybrid

approach that triumphs over other learning methods such as MLP, RBF (ToolDiag), MLP + BP (ToolDiag) and GRNN. Polat and Gunes (2007b) proposed a machine learning approach that obtains very promising results, which are effective, accurate and superior to weighted 9-NN, 18-NN, 15-NN, FSM with rotations, FSM without rotations, RBF (ToolDiag), LDA, Naive Bayes, QDA, 1-NN, ASR, Fisher discriminant analysis, LVQ, CART (decision tree), MLP with BP, ASI, LFC, IncNet, MLP, RBF and GRNN. The survey on applicability of AIS-DM-FL for liver disorders is listed in Table 19.

Table 19 Details of AIS-DM-FL-based systems with their results and applications

Author, Year	*Attributes*	*Intelligent techniques and other methods*	*Result and Application*
Polat and Gunes (2007a)	Hepatitis data set	DM: C4.5 decision tree algorithm, wrapper approach, filter-based feature selection. FL: fuzzy weighted pre-processing, triangular membership functions, fuzzy IF-Then rules. AIS: AIRS supervised learning algorithm, immune mechanisms used are resource competition, clonal selection, affinity maturation and memory cell formation, stages of AIRS includes initialisation, memory cell identification and ARB generation	Diagnosis of hepatitis disease. Accuracy: 81.82% Sensitivity: 55.56% Specificity: 83.82%
Polat and Gunes (2007b)	Hepatitis data set	DM: C4.5 decision tree algorithm. FL: weighted with fuzzy weighted pre-processing, triangular membership functions, fuzzy IF-Then rules. AIS: AIRS, immune metaphors used are antibody-antigen binding, affinity maturation, clonal selection process, resource distribution and memory acquisition, learning algorithm consists of initialisation, memory cell recognition, resource competition and revision of resulted memory cells. tenfold cross-validation	Diagnosis of hepatitis disease. Accuracy: 94.12% Sensitivity: 100% Specificity: 92.85% ADR: 96.42%

Notes: AIRS: Artificial Immune Recognition System, ARB: Artificial Recognition Balls.

3.16 ANN-DM-FL

ANN-DM-FL methodology was used by Su et al. (2006), where fuzzy ART neural network is employed to construct information granules and DM is used to extract knowledge rules from the granules, and by Li et al. (2011), where fuzzy-based non-linear

transformation method is applied to extend classification-related information, DM is used for extracting the optimal subset of features and ANN is used for classification. The hybrid model (Su et al., 2006) effectively deals with imbalanced data sets. Obtained simulated results prove superiority of proposed fuzzy-based non-linear transformation method (Li et al., 2011) over PCA and Kernel Principal Component Analysis (KPCA); and superiority of proposed knowledge acquisition via information granulation model (Su et al., 2006) over C4.5 and SVM. The survey on applicability of ANN-DM-FL for liver disorders is listed in Table 20.

Table 20 Details of ANN-DM-FL-based systems with their results and applications

Author, Year	*Attributes*	*Intelligent techniques and other methods*	*Result and Application*
Su et al. (2006)	Liver disorders data set	ANN: Fuzzy ART (Adaptive Resonance Theory) neural network. DM: knowledge acquisition via C4.5 decision tree	Improve classification performance by solving class imbalance problems. Accuracy (KAIG): 70% Data type: Information granules
Li et al. (2011)	Liver disorders data set	FL: fuzzy-based non-linear transformation method, triangle shape membership function, a fuzzy membership computational approach. DM: principal component analysis. ANN: SVM, megatrend diffusion (MTD) function, polynomial and Gaussian kernel. *t*-test, Friedman test, ANOVA test, Demsar's proposed method	To increase classification performance with small medical data sets. Accuracy: SVM (poly): 54.21% SVM (gaus): 54.13%

3.17 ANN-DM-GA

ANN-DM-GA methodology was used by Stoean et al. (2011b), where GA is used to dynamically concentrate search only on the most relevant attributes, DM is used to reduce the data dimensionality, and ANN makes the novel model flexible and good performer. Proposed evolutionary approach also obtained better classification accuracy than traditional SVMs. ESVM is deployed instead of SVM because it has successfully resolved complexity of SVM. ESVM has more simplicity, stability, flexibility, robustness, transparency, adaptability and operability, but ESVM training is a bit slow than standard SVMs. The survey on applicability of ANN-DM-GA for liver disorders is listed in Table 21.

3.18 ANN-GA-RBR

ANN-GA-RBR methodology was used by Ramirez et al. (2012), where RBR is used for decision-making, GA is used for obtaining new offspring and ANN is used for classification. Liver transplantation is the only treatment for patients having incurable liver disorders. Availability of donors is less due to number of requirements; and

transplantation is solely dependent on the availability of liver donors. This disproportion may result in countless deaths. Ramirez et al. (2012) did a fruitful research work by developing a donor-recipient decision system for liver transplantation, which prioritises recipients in queue. The tool is intelligible and sensible for physicians. The survey on applicability of ANN-GA-RBR for liver disorders is listed in Table 22.

Table 21 Details of ANN-DM-GA-based systems with their results and applications

Author, Year	*Attributes*	*Intelligent techniques and other methods*	*Result and Application*
Stoean et al. (2011)	Stiffness, sex, BMI (body mass index), glycemia, triglycerides, cholesterol, HDL cholesterol, aspartate aminotransferase, alanin aminotransferase, gama glutamyl transpeptidase, total bilirubin, alkaline phosphatase, prothrombin index, quiq time, prothrombin time ratio, prolonged activated partial thromboplastin time, haematids, haemoglobin, hematocrit, medium erytrocity volume, avg. erytrocitary haemoglobin, avg. concentration of haemoglobin in a red blood cell, thrombocytes, sideraemia	ANN: evolutionary-powered support vector machines (ESVM). DM: principal component analysis. GA: tournament selection method, reproduction (randomly selected), recombination (randomly generated), mutation (randomly generated)	Determining the degree of liver fibrosis in chronic hepatitis C. Accuracy: 77.31%

Table 22 Details of ANN-GA-RBR-based systems with their results and applications

Author, Year	*Attributes*	*Intelligent techniques and other methods*	*Result and Application*
Ramirez et al. (2012)	A liver transplant data set composed of 1001 patterns is used for experimentation	ANN: feedforward neural network, linear basis function, probabilistic function, radial basis function neural network, probability density function of generalised Gaussian distribution, trained with a multi-objective evolutionary learning algorithm (MOEA) called MPENSGA2. GA: multi-objective evolutionary algorithms, structural and parametric mutation operators. RBR: rule-based system designed using two ANN models named asMPENSGA2-E and MPENSGA2-MS, IF-Then rules.	Liver transplantation decision

Notes: MPENSGA2: Memetic Pareto Evolutionary NSGA2).

3.19 CBR-GA-PSO

CBR-GA-PSO methodology was used by Chang et al. (2012), where CBR is used to pre-process data set, GA is used to evolve weights of each attribute in PSO and PSO is used to construct the medical classification system. The proposed framework generates more

precise, effective and intelligible results. Advantage of using PSO is its capability to overcome overlapping situation of data set. Simulated results (Chang et al., 2012) compared with other forecasting models such as SVM, KNN, Naive Bayes, FDT, RULES-4, C4.5, BNND, BNNF, SVM with GP, SSVM, RSVM, MLP, PNN, and GRNN demonstrate the superiority of proposed model (CBRPSO). It is also proved that this model has the capability to produce high compact clustering than methods such as PSO and K-means. Different PSO-based approaches have been compared in which GA-CBRPSO outperforms PSO and CBR-PSO. The survey on applicability of CBR-GA-PSO for liver disorders is listed in Table 23.

Table 23 Details of CBR-GA-PSO-based systems with their results and applications

Author, Year	*Attributes*	*Intelligent techniques and other methods*	*Result and Application*
Chang et al. (2012)	Liver disorders data set	CBR: case base weighted cluster algorithm, weight vector, gradient method, feature evaluation function. GA: selection, crossover, mutation, replacement. PSO: PSO tool evolved by genetic algorithm, PSO-clustering algorithm, global searching stage, local refining stage, k-means algorithm	Liver disorders diagnosis. Accuracy: 76.8%

3.20 DM-FL-GA

DM-FL-GA methodology was used by Leung et al. (2011) where a DM-based framework is introduced in which GA is used for searching and optimisation and FL is used to increase performance. Proposed data mining framework obtains much better results than other forecasting models mentioned in the literature such as SVM, C5.0 decision tree, neural network and Naive Bayes. The survey on applicability of DM-FL-GA for liver disorders is listed in Table 24.

Table 24 Details of DM-FL-GA-based systems with their results and applications

Author, Year	*Attributes*	*Intelligent techniques and other methods*	*Result and Application*
Leung et al. (2011)	Genomic sequences: HBV DNA sequences, either genotype B or C over 200 patients	DM: molecular evolution analysis, clustering, feature selection, classifier learning and classification, phylogenetic tree analysis, information gain criterion, rule learning based on evolutionary algorithm. GA: generic genetic programming (GGP). FL: fuzzy measure for good performance of classification method. 10 K-fold method	To classify the HBV DNA data into liver cancer (HCC) and normal (CON, control) classes

3.21 CBR-DM-FL-GA

CBR-DM-FL-GA methodology was used by Chang et al. (2010), where CBR is used for decomposing the database into a set of smaller database, fuzzy decision tree is used to classify data and GA is used for selecting optimal fuzzy terms which in long-term improves accuracy, and by Fan et al. (2011), where CBR is used for clustering the data set, fuzzy decision tree is used to classify data and GA is used for further improving the classified result by evolving the number of fuzzy terms. These integrated systems are more precise and effective and also productively assisting doctors in diagnosis (Chang et al., 2010; Fan et al., 2011). It has been noticed that CBR-FDT model (Chang et al., 2010) reaches the highest classification accuracy among other benchmark classifiers such as improved particle swarm optimisation model (KNMPSO), SVM, K-nearest neighbour (KNN), SVMS, RMSVM and back propagation neural networks (BPN). Average hit rate of this model is highest also among all mentioned approaches on different database classification applications. Proposed CBFDT model (Fan et al., 2011) also shows promising performance and obtains higher classification accuracy when compared with RULES-4, C4.5, BNND, BNNF, SVM with GP, SSVM, RSVM, KNN, Naive Bayes, MLP, PNN GRNN, HNFB and SVM. The survey on applicability of CBR-DM-FL-GA for liver disorders is listed in Table 25.

Table 25 Details of CBR-DM-FL-GA-based systems with their results and applications

Author, Year	*Attributes*	*Intelligent techniques and other methods*	*Result and Application*
Chang et al. (2010)	Liver disorders data set	CBR: case-based weighted cluster algorithm.	Liver disorders diagnosis.
		DM and FL: fuzzy decision tree (FDT) generated from ID 3 algorithm based on recursive binary partitioning algorithm, data fuzzification, triangle membership functions, fuzzy rules.	Accuracy: 81.6%
		GA: reproduction/selection, replacement.	
		Stepwise regression analysis (SRA) model	
Fan et al. (2011)	Liver disorders data set	CBR: case-based weighted cluster algorithm, clustering method used was k-means algorithm.	Liver disorders diagnosis.
		DM and FL: fuzzy decision tree (FDT) generated from ID 3 algorithm based on recursive binary partitioning algorithm, triangle membership functions, fuzzy rules	Accuracy: 81.6% (Average) 90.40% (Best)
		GA: representation and selection(tournament method), two-point crossover method, two-point mutation method, binary code was adopted, de-coding, tournament method, replace, terminate	
		Stepwise regression analysis (SRA) model	

Note: ID: Iterative Dichotomiser.

4 Observation

We have already mentioned that the important goals of this paper are to survey and classify intelligent techniques applied to liver disorders and identify which intelligent techniques are applied to what types of liver disorders. The database search covers the papers that had been published till January 2013. All the articles are carefully studied, sorted and classified based on implementation of intelligent techniques. Individual ITs include ANN, DM, FL and GA. Integrated ITs combine methods such as ANN-CBR, ANN-DM, ANN-FL, AIS-FL, ANN-GA, AIS-GA, ANN-PSO, CBR-DM, CBR-GA, DM-GA, DM-FL, FL-GA, AIS-ANN-FL, ANN-CBR-RBR, AIS-DM-FL, ANN-DM-FL, ANN-DM-GA, ANN-GA-RBR, CBR-GA-PSO, DM-FL-GA, and CBR-DM-FL-GA.

Based on all the search results Table 26 have been prepared. This table detailed the applicability of intelligent techniques to different types of liver disorders (hepatitis, liver fibrosis, liver cirrhosis, liver cancer, fatty liver, liver disorders data set, hepatitis data set, hepatobiliary disorders data set and others). Liver disorders data set is used to diagnose liver disorders that might arise from excessive alcohol consumption. Hepatobiliary disorders data set is used to diagnose Alcoholic Liver Damage (ALD), primary hepatoma (PH), liver cirrhosis (LC) and cholelithiasis (C). Table 26 presents the five articles in total out of which three are ANN-based (Lee et al., 2005; Jeon et al., 2013; Su and Yang, 2008), one is DM-based (Jen et al., 2012) and one is ANN-GA-RBR-based (Ramirez et al., 2012). Either of the two conditions have been checked before classifying an article in 'others' column: first, if it has neither used liver disorders data set, hepatitis data set and hepatobiliary disorders data set nor it has covered the types of liver disorders which are considered for this survey. Second, if the work is related to liver other than diagnosis.

Table 26 presents which individual and integrated ITs are appreciably used for what types of liver disorders. For hepatitis liver disorders ANN, DM, FL, ANN-CBR, CBR-DM, FL-GA and ANN-CBR-RBR are used; for liver fibrosis ANN, ANN-DM, ANN-GA, DM-GA and ANN-DM-GA are applied; for liver cirrhosis ANN, DM, FL, GA, ANN-CBR, ANN-FL and CBR-DM are used; for liver cancer ANN, FL, GA and DM-FL-GA are applied; for fatty liver ANN and FL are used; for liver disorders data set ANN, DM, FL, GA, ANN-DM, ANN-FL, AIS-FL, ANN-GA, AIS-GA, DM-GA, DM-FL, ANN-DM-FL, CBR- GA-PSO and CBR-DM-FL-GA are applied; for hepatitis data set ANN, GA, ANN-DM, ANN-FL, AIS-FL, ANN-PSO, CBR-GA, FL-GA, AIS-ANN-FL and AIS-DM-FL are used; for hepatobiliary disorders data set ANN and FL are applied.

For comparison among individual ITs, Figure 1 is presented which shows the number of ANN, DM, FL and GA based studies. Figure 2 illustrates the preference of integrated ITs compared to others. It is observed from Figures 1 and 2 that most of the researchers have preferred to use ANN and ANN-FL methodologies compared to other techniques. It has also found that ANN is mostly integrated with DM and FL, and vice versa. Figure 3 gives graphical representation about the usage of single and integrated ITs after every few years. The most surprising fact is the negligible applicability of integrated ITs to liver disorders before the year 2007. If we talk in percentage than 80% usage of integrated techniques is after 2007 with just 20% usage till 2006 (Figure 4). Another message emerging from the study is that not even a single intelligent technique had been applied between 1999 and 2002.

Table 26 Applicability of intelligent techniques to different types of liver disorders

	Liver Disorders									*Total*
	Hepatitis	*Fibrosis*	*Cirrhosis*	*Cancer*	*Fatty*	*Liver disorders data set*	*Hepatitis data set*	*Hepatobiliary disorders data set*	*Others*	
ANN	3	1	8	4	2	4	5	2	3	32
DM	2		2			1			1	6
FL	1		1	1	1	3		1		8
GA			1	1		2	1			5
ANN-CBR	2		1							3
ANN-DM		1				1	2			4
ANN-FL			1			6	1			8
AIS-FL						2	1			3
ANN-GA		1				1				2
AIS-GA						1				1
ANN-PSO							1			1
CBR-DM	1		1							2
CBR-GA							1			1
DM-GA		1				1				2
DM-FL						3				3
FL-GA	1						1			2
AIS-ANN-FL							1			1
ANN-CBR-RBR	1									1
AIS-DM-FL							2			2
ANN-DM-FL						2				2
ANN-DM-GA		1								1
ANN-GA-RBR									1	1
CBR-GA-PSO						1				1
DM-FL-GA				1						1
CBR-DM-FL-GA						2				2

Figure 1 Comparison of the numbers of individual intelligent techniques based published papers between the years 1995 and 2013

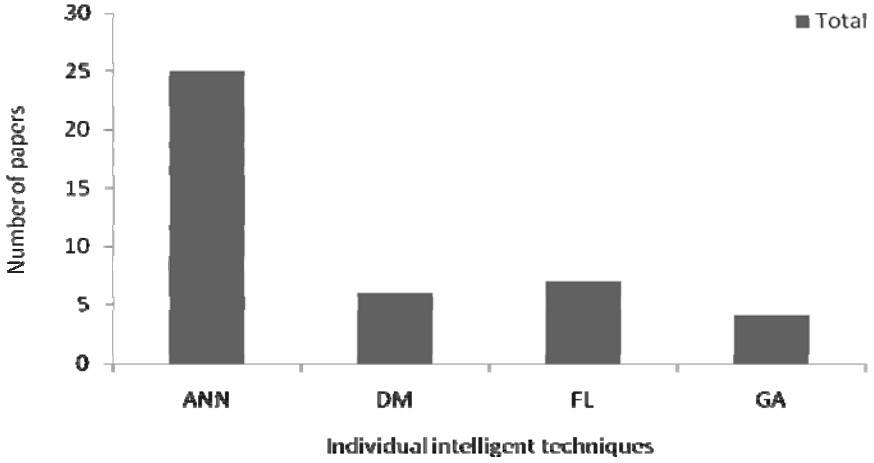


Figure 2 Comparison of the numbers of integrated intelligent technique-based published papers between the years 1995–2013

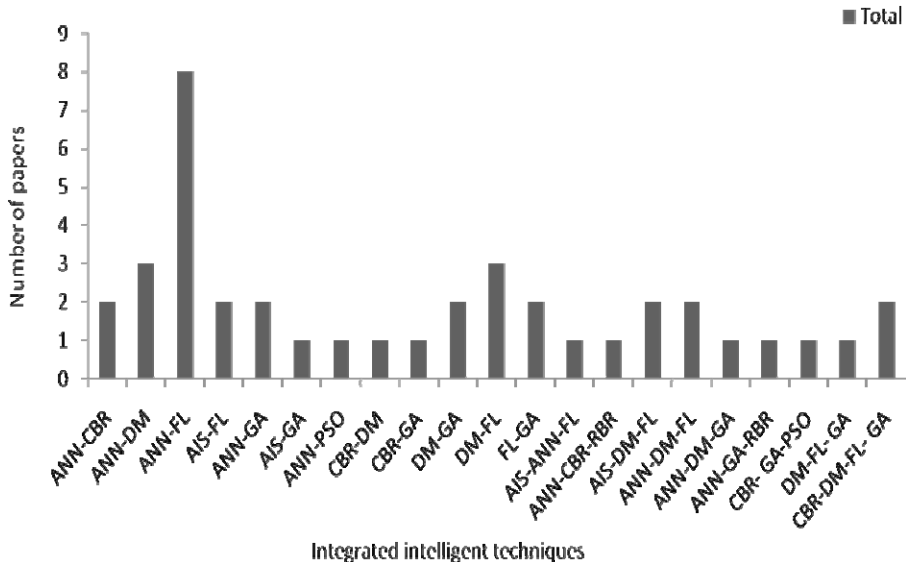


Figure 3 Comparison of the numbers of individual and integrated intelligent technique-based published papers between the years 1995 and 2013

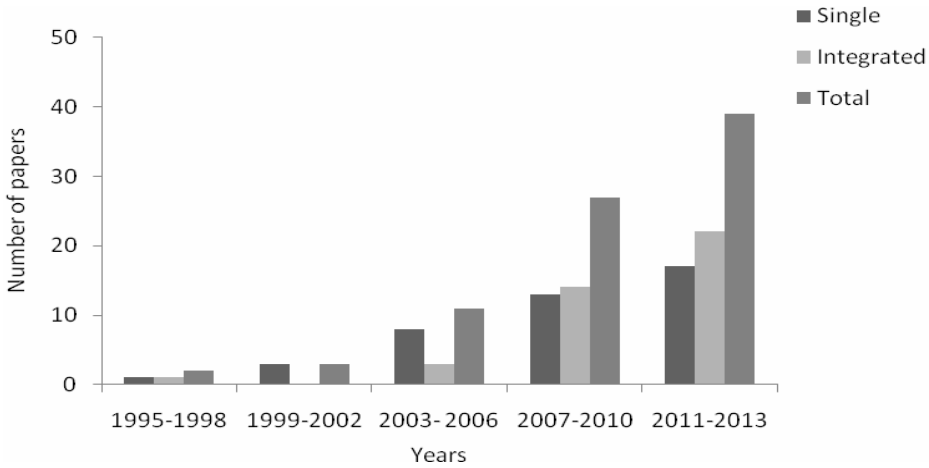
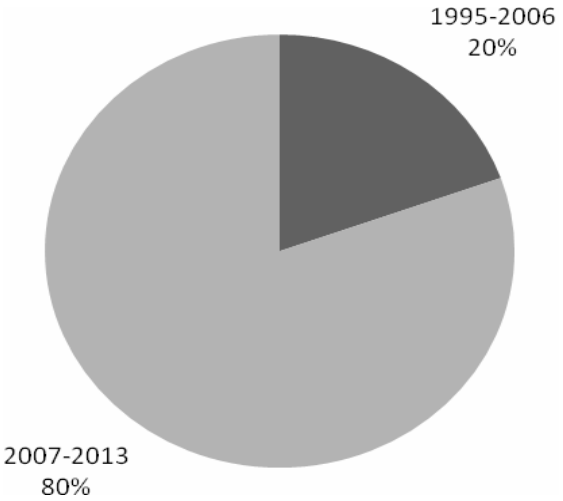


Figure 4 Comparative view of percentage use between the intervals 1995–2006 and 2007–2013



On computed relative comparison, it has been found that ANN method is most significantly used with its 60% rate, FL method is in the second rank with its 17% rate, DM method is in the third rank with its 14% rate, and GA method is the last one with only 9% rate. In integrated intelligent techniques, mostly used methodology is ANN-FL with 20% rate, then ANN-DM, DM-FL with 8% rate, then AIS-FL, ANN-GA, ANN-CBR, DM-GA, FL-GA, AIS-DM-FL, ANN-DM-FL, CBR-DM-FL-GA with 5% rate and the last ones are AIS-GA, ANN-PSO, CBR-DM, CBR-GA, ANN-CBR-RBR, AIS-ANN-FL, ANN-DM-GA, ANN-GA-RBR, CBR-GA-PSO, DM-FL-GA with 2% rate.

During this survey, we have found that the term intelligent techniques is not used well enough as a keyword in articles. Terms like ANN, AIS, CBR, DM, FL, GA, PSO, RBR, hybrid systems and integrated systems are mostly chosen instead of ITs. So we have introduced a new keyword 'intelligent techniques' which refers to all methodologies mentioned in this study. Along with number of benefits, writing a survey paper also has several limitations like author's limited knowledge as one needs to have extensive background knowledge for accumulating, studying and classifying articles; number of papers may have used intelligent techniques but still left out due to some indexing problems; publications using languages other than English cannot be included; it is difficult to cite all academic articles that are listed in Science Citation Index (SCI) as the amount of available text is increasing rapidly; and we have limited access to online database and also bounded by time constraint.

Hopefully, this study would be productive for neophyte researchers, about what to do and what not to, in developing medical decision-making systems which assist physicians in handling liver disorders. Novice researchers can either use methodologies like ANN, ANN-FL which has wide acceptance and has obtained higher accuracy results or can choose techniques such as AIS and PSO which have not been explored enough hitherto and can give improved results either alone or when integrated with some other intelligent techniques. For hepatitis diagnosis, ANN and ANN-CBR would be more suitable; for liver cirrhosis diagnosis, ANN and DM would be more suitable; for liver cancer and fatty liver diagnosis, ANN would be more suitable; for liver disorders data set, ANN-FL would be more suitable; for hepatitis data set and hepatobiliary disorders data set, again ANN would be more suitable.

5 Conclusion

This paper presents a survey of literature concerned with intelligent techniques applied to liver disorders between the January 1995 and January 2013. Articles were searched using different keyword indices such as '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 disorders', 'FL used for liver disorders', 'GA used for liver disorders', 'PSO used for liver disorders' and 'RBR used for liver disorders'; and then classified based on intelligent techniques applied and which techniques is used for what types of liver disorders. The trends indicating from the survey tables are that all intelligent techniques were being progressively applied, from 2007 to 2013, to liver disorders. Systems developed using intelligent techniques to handle imprecise, unstructured and dynamic data of patients, and also assist physicians by acting as a second opinion tool in decision-making process for liver disorders diagnosis.

Optimistically, this study has attained the objective of a survey in the following manner: it provides detail about the articles published for liver disorders from 1995 to 2013; it presents the information about which individual and integrated techniques are used for what types of liver disorders; it specifies the articles published with their results and applications; it portrays accurately the characteristics of ITs and compares their usage among each others; it narrows the researcher's work as they become aware with

pros and cons of the intelligent techniques; it also plays a fundamental role in formulating research hypothesis, preparing research design, and collecting and analysing the data.

It is suggested that novice researchers can use methodologies such as ANN, ANN-FL which have wide acceptance and have obtained higher accuracy results or can choose techniques such as AIS and PSO which have not been explored enough hitherto and can give improved results either alone or when integrated with some other intelligent techniques. For hepatitis diagnosis, ANN and ANN-CBR would be more suitable; for liver cirrhosis diagnosis, ANN and DM would be more suitable; for liver cancer and fatty liver diagnosis, ANN would be more suitable; for liver disorders data set, ANN-FL would be more suitable; for hepatitis data set and hepatobiliary disorders data set, again ANN would be more suitable. Though there are a number of other integration methodologies such as AIS-GA, ANN-PSO, CBR-DM and CBR-GA which have not been widely implemented until now. So, it is completely a researcher's decision to decide with which techniques to proceed based on his background knowledge and information he had grabbed from this study. It is hoped and anticipated that the humble effort made in this study will assist in the accomplishment of developing accurate and precise decision making tools to diagnose liver disorders.

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