Chapter 81
Diagnosis of Liver Disease by Using Least Squares Support Vector Machine Approach

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ABSTRACT

A healthy liver leads to healthy life. In India, as well as in other parts of the world, liver disease is one of the principle areas of concern in medicine. For this study, diagnosis of liver disease is performed by deploying classification methods include linear discriminant analysis (LDA), quadratic discriminant analysis (QDA), feed-forward neural network (FFNN) and support vector machine (SVM) based approaches. Experimental results concluded that SVM based approaches outperformed all other classification methods in terms of diagnostic accuracy rates. Furthermore, least squares support vector machine (LSSVM) with gaussian radial basis kernel function based machine learning approach had emerged as the as the best predictive model by reducing inefficiencies caused by false diagnosis. LSSVM also performed better than linear SVM, polynomial SVM, quadratic SVM and multilayer perceptron SVM despite the uneven variance in attribute values in the health examination data.

INTRODUCTION

Liver is a vital and largest internal organ in the human body. It is responsible for many key processes that keep us alive. It performs several imperative metabolic functions like enzyme production for digestion, storage of vitamins and iron, manufactures cholesterol and triglycerides, makes blood clotting factors, regenerates liver tissues and most prominently detoxifies harmful chemicals (Bucak & Baki, 2010). Improper working of any of the function leads to liver disease which further directed to serious health ramifications. Liver disease is generally caused by long term alcohol consumption, excess accumulation of fat, contaminated food, inherited disorders and overdose of drugs (Chuang, 2011; Lin & Chuang,

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2010; Lin, 2009). Liver diseases are categorized into more than hundred types out of which alcoholic liver disease, nonalcoholic fatty liver disease, viral hepatitis, fibrosis, cirrhosis and liver cancer are commonly prevalent (Singh & Pandey, 2014). Presence of liver disease is steadily increasing over the years. It has been ranked as the fifth most common cause of death by national statistics. Its timely detection and proper treatment is extremely crucial.

Data analysis methods and machine learning algorithms have been widely deployed to develop decision making systems for clinical purposes. The methods such as, artificial neural networks (ANNs), fuzzy logic (FL), generic algorithm (GA), case-based reasoning (CBR), particle swarm optimization (PSO), artificial immune system (AIS), or rule-based reasoning (RBR) are incorporated for data optimization and non-invasive diagnosis of liver disease (Singh & Pandey, 2014). ANN is one of the extensively used machine learning algorithm for predictions as it has shown finest learning capabilities (Jeon et al., 2013). Liver imaging and live biopsy are the major authorized standards for detection and confirmation of liver disease. However, the cost of these standard methods is essentially high and could not be afforded by patients at large. To reduce this expense, substantial research efforts have been done to develop efficient decision making systems for the assessment of liver diseases and its types.

Literature study proved the wide applicability of individual and integrated classification techniques to diagnose and classify liver disease. In individual methods, ANN, FL and decision trees were broadly implemented. ANN based systems were found reliable, robust, more accurate. These systems showed enhanced performance by taking less time in the learning process and decreasing the complexity in fast size growing problems (Autio et al., 2007; Azaid et al., 2006; Bucak & Baki, 2010; Elizondo et al., 2012; Hashem et al., 2010; Icer et al., 2006; Lee et al., 2005; Ozyilmaz & Yildirim, 2003). ANN based systems have been implemented to predict early prognosis of hepatectomised patient with hepatocellular carcinoma (Hamamoto et al., 1995), to diagnose hepatobiliary disorders (Hayashi et al., 2000), to diagnose hepatitis disease (Ozyilmaz & Yildirim, 2003; Sartakhti et al., 2015), to classify liver disorders as liver cyst, hepatoma and cavernous haemangioma (Lee et al., 2005) and to mine primary biliary cirrhosis dataset (Revett et al., 2006). FL based systems have been used to perform semi-automatic liver tumour segmentation (Li et al., 2012), to diagnosis hepatitis disease (Obot & Udoh, 2011) and to classify liver disorders as alcoholic liver damage, primary hepatoma, liver cirrhosis and cholelithiasis (Ming et al., 2011). C5.0 decision tree and boosting (AdaBoost) was used to classify liver disorders as chronic hepatitis C and B (Floares, 2009), C4.5 decision tree was used to analyse relationship between child-pugh degree and examinations of traditional chinese medicine based on liver cirrhosis (Yan et al., 2008).

In integrated methods, ANN-CBR, ANN-FL, AIS-FL, ANN-GA, FL-GA, AIS-ANN-FL and ANN-GA-RBR were significantly implemented for liver disease diagnosis. ANN-CBR was used to examine the existence of liver disorders and to determine the types of liver disorders (Chuang, 2011; Lin & Chuang, 2010). ANN-FL was used to diagnose liver disorders (Celikyilmaz et al., 2009; Comak et al., 2007; Kulluk et al., 2013; Li & Liu, 2010; Neshat & Zadeh, 2010), to deal with class imbalance problem with medical datasets and to enhance classification accuracy for liver dataset (Li et al., 2010). AIS-FL was used to classify liver disorders and to assess prediction accuracy of hepatitis disease (Mezyk & Unold, 2011; Polat et al., 2007). ANN-GA was used to diagnosis liver disorders and to classify liver fibrosis stadialisation in chronic hepatitis C (Dehuri & Cho, 2010; Gorunescu et al., 2012). FL-GA was used to diagnose liver disorder (Luukka, 2009; Torun & Tohumoglu, 2011). AIS-ANN-FL was used to diagnose hepatitis disease (Kahramanli & Allahverdi, 2009) and ANN-GA-RBR was used to take decision on liver transplantation (Cruz-Ramirez et al., 2012).