Treatment Response Prediction in Hepatitis C Patients using Machine Learning Techniques

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TREATMENT RESPONSE PREDICTION IN HEPATITIS C PATIENTS USING MACHINE LEARNING TECHNIQUES

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ABSTRACT:

The proper prognosis of treatment response is crucial in any medical therapy to reduce the effects of the disease and of the medication as well. The mortality rate due to hepatitis c virus (HCV) is high in Pakistan as well as all over the world. During the treatment of any disease, prediction of treatment response against any particular medicine is difficult. This paper focuses on predicting the treatment response of a drug: "L-ornithine L-Aspartate (LOLA)" in hepatitis c patients. We have used various machine learning techniques for the prediction of treatment response, including: "K Nearest Neighbor, kStar, Naive Bayes, Random Forest, Radial Basis Function, PART, Decision Tree, OneR, Support Vector Machine and Multi-Layer Perceptron". Performance measures used to analyze the performance of used machine learning techniques include, "Accuracy, Recall, Precision, and F-Measure".

Keywords—Treatment Response Prediction, Hepatis C, Machine Learning, Medical Data Mining

INTRODUCTION

Hepatitis is a dangerous and transmissible disease [1-4]. The virus of this disease can spread from one infected person to another healthy human being. This disease has already infected almost 17 million people in all over the world and the numbers are getting increased day by day [2-6]. The virus of hepatitis c needs to be treated as early as possible to control and reduce the effects of the disease. A proper and complete medical therapy is needed in order to bring down the effects of this disease. However, not one medical therapy is good for all the patients. Same medicine may have different effects on different people due to other known or hidden medical reasons of the patients [5-10]. This paper explores the importance of machine learning techniques to predict the treatment response of a drug: “L-ornithine L-Aspartate (LOLA)” in hepatitis c patients. Various machine learning techniques are used in this study for the prediction of treatment response, including: “K Nearest Neighbor, kStar, Naive Bayes, Random Forest, Radial Basis Function, PART, Decision Tree, OneR, Support Vector Machine and Multi-Layer Perceptron”. Performance of used machine learning techniques is analyzed and evaluated by various measures, including: “Accuracy, Recall, Precision, and F-Measure”.

RELATED WORK

Many researchers have used machine learning and data mining techniques in order to predict the treatment response. Researchers in [11] has built a hybrid framework to examine the similarity of drugs response using advanced K-means clustering. Researchers in [12] predict the response of Clozapine; a drug used for the treatment of psychiatric disease. They used a machine learning approach to predict the response of drug. In [13], a machine learning supported framework built by the team of researchers on post-marketing dataset for predicting the Anti-PD-1 treatment response. In [2], treatment response prediction is performed using the Artificial Neural Network and Decision Tree. In [14], researchers used Decision Tree (DT) to predict the early diagnosis of hepatitis C in the diabetic patients using the routine laboratory tests. In [15], researchers used different machine learning techniques to predict the drugs toxicity and its side effects, these side effects weaken the quality of life, which needs to be addressed on priority bases. In [16], researchers presented a machine learning based prediction for HIV medication resistance with a set of mutant features. The proposed algorithm first identify the protein structure then classify it based on sparse representation using Artificial Neural Network, Support Vector Machine and Regression. In [17], the researchers explored that the deep learning techniques played a vital role in cancer patients for identification the drugs response. The researchers critically examined the cancer cell in order to predict the drug response on them. Researchers in [18] uses Bayesian Network for predicting the esophageal disease which is an adverse effect, present in the disease of liver cirrhosis.

MATERIALS AND METHODS

This study explores the effectiveness of machine learning techniques in the prediction of treatment response in hepatitis c patients. Machine learning and data mining techniques have been widely and effectively used by many researchers in various domains and fields including: Sentiment/Polarity analysis [19-25], Rainfall/Weather Prediction [26-27], and Network Intrusion Detection/Network Security [28-29], Software Defect Prediction [30-38], Medical and Health data mining [39-47]. Machine learning techniques included in this study for the prediction of treatment response are: “K Nearest Neighbor, kStar, Naive Bayes, Random Forest, Radial Basis Function, PART, Decision Tree, OneR, Support Vector Machine and Multi-Layer Perceptron”. The machine learning techniques are used on the patient’s dataset collected from a hospital in city of Lahore, Pakistan. The dataset consists of various attributes regarding the medical information of the patient. The attribute which is predicted on the basis of medical information is the response, which consists of two categorical values: Respondent or Not Respondent. This attribute reflects that the particular patient is showing response against LOLA therapy or not. The used dataset is pre-processed before the classification. The pre-processing activities include: cleaning and normalization (Fig 1).

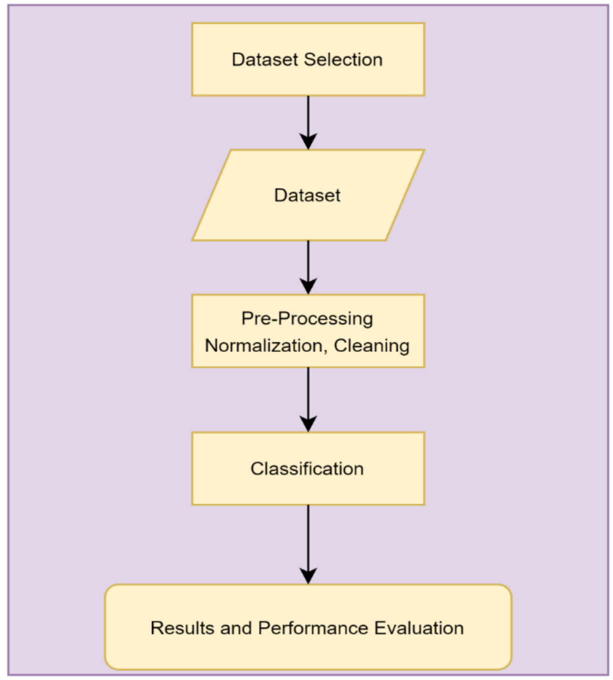

Fig 2 Treatment Response Prediction using Machine Learning Techniques

RESULTS AND DISCUSSIONS

Evaluating the performance of used machine learning techniques is a crucial stage where we have to compare the accuracy measures of used algorithms in order to select the best one for future use [48-50]. Performance of used machine learning techniques is analyzed and evaluated by various measures, such as: “Accuracy, Recall, Precision, and F-Measure”. The parameters used in the formulas of performance measures came from the confusion matrix (Fig 2), which is the ultimate result of classification/prediction. The Parameters used in the confusion matrix are: TP, FN, TN and FP [30-38].

The formulas of the TP, FN, TN and FP has given below.

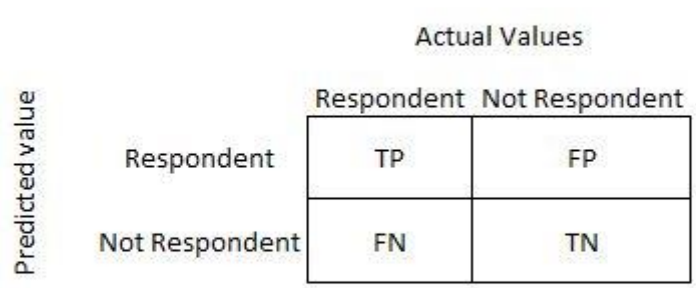

Fig 2 Confusion Matrix

$$Precision = \frac{TP}{(TP+FP)}$$

$$Recall = \frac{TP}{(TP+FN)}$$

$$F\text{-}Measures = \frac{Precisin * Recall * 2}{(Precisin + Recall)}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

The Weka tool is used to conduct the experiments. All of the used performance measures are provided by the WEKA tool. Table 1 reflects the results on training dataset with all of the used classification algorithms.

Table 1: Results with Training Dataset

Classifier	Class	Precision	Recall	F-Measure
NB	Respondent	0.893	0.895	0.894
	Not Respondent	0.622	0.618	0.62
MLP	Respondent	0.914	0.953	0.933
	Not Respondent	0.803	0.681	0.737
RBF	Respondent	0.878	0.922	0.9
	Not Respondent	0.661	0.542	0.595
SVM	Respondent	0.89	0.922	0.906
	Not Respondent	0.68	0.59	0.632
KNN	Respondent	0.963	0.901	0.931
	Not Respondent	0.712	0.875	0.785
K*	Respondent	0.924	0.944	0.934
	Not Respondent	0.782	0.722	0.751
OneR	Respondent	0.892	0.911	0.901
	Not Respondent	0.654	0.604	0.628
PART	Respondent	0.931	0.913	0.922
	Not Respondent	0.708	0.757	0.732
DT	Respondent	0.692	0.625	0.657
	Not Respondent	0.898	0.922	0.91
RF	Respondent	0.931	0.936	0.933
	Not Respondent	0.766	0.75	0.758

Table 2 shows the results on testing dataset. It can be seen that the accuracy measures are different on both the datasets.

Table 2: Results with Testing Dataset

Classifier	Class	Precision	Recall	F-Measure
NB	Respondent	0.885	0.865	0.875
	Not Respondent	0.552	0.597	0.574
MLP	Respondent	0.873	0.865	0.869
	Not Respondent	0.531	0.548	0.54
RBF	Respondent	0.882	0.91	0.896
	Not Respondent	0.636	0.565	0.598
SVM	Respondent	0.873	0.932	0.902
	Not Respondent	0.681	0.516	0.587
KNN	Respondent	0.9	0.811	0.853
	Not Respondent	0.5	0.677	0.575
K*	Respondent	0.898	0.874	0.886
	Not Respondent	0.588	0.645	0.615
OneR	Respondent	0.888	0.932	0.91
	Not Respondent	0.706	0.581	0.637
PART	Respondent	0.9	0.851	0.875
	Not Respondent	0.554	0.661	0.603
DT	Respondent	0.889	0.937	0.912
	Not Respondent	0.72	0.581	0.643
RF	Respondent	0.895	0.883	0.889
	Not Respondent	0.6	0.629	0.614

Accuracy of the training dataset and testing dataset is reflected in Table 3. The accuracy in the training dataset is highest in KNN, K* and Random Forest. On the other hand, Decision Tree shows the highest accuracy in the test dataset.

Table 3: Accuracy Comparison

Classifier	Training Accuracy	Test Accuracy
NB	83.4598	80.6338
MLP	89.3778	79.5775
RBF	83.915	83.4507
SVM	84.9772	84.1549
KNN	89.5296 (Highest)	78.169
K*	89.5296 (Highest)	82.3944
OneR	84.3703	85.5634
PART	87.8604	80.9859
DT	85.736	85.9155 (Highest)
RF	89.5296 (Highest)	82.7465

CONCLUSION:

This paper presented a comparative analysis of various machine learning techniques on the prediction of treatment response in hepatitis c patients. The machine learning techniques used in this study include: “K Nearest Neighbor, kStar, Naive Bayes, Random Forest, Radial Basis Function, PART, Decision Tree, OneR, Support Vector Machine and Multi-Layer Perceptron”. The performance of these algorithms is measures by different evaluation measures such as “F-measures, Precision, Accuracy and Recall”. It is observed that in the accuracy measure, training data, KNN, K* and RF performed well where as in test data DT performed well.

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