Early Detection of Hepatorenal Syndrome with Cirrhosis Patient Medical Records

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Abstract

Hepatorenal syndrome (HRS) is a type of kidney failure that occurs in advanced cirrhosis (liver dysfunction). The 3-month survival rate of patients with HRS is 15%. However currently the biomarkers, precipitating factors, and useful prognosis criteria are not yet discovered. Also there is no correlation with liver function such as Child-Pugh classification. Fortunately early treatments are effective so early prediction of HRS is significant. In this work, I used Random Forest to predict an onset of HRS with the cirrhosis patients’ medical records at the time of hospitalization from MIMIC2 public database. As a result, my prediction achieved 0.81 as AUC. This prediction is the first prediction of HRS and can be done from extremely early phase.

1 Introduction

Hepatorenal syndrome (HRS) is a unique type of kidney failure that occurs in advanced cirrhosis as a liver complication. It is characterized by functional impairment of the kidneys due to vasoconstriction of the renal arteries in the absence of histologic abnormalities and tubular dysfunction. Reported incidence of HRS is 10% among hospitalized patients with cirrhosis. In decompensated cirrhotics, the probability of developing HRS with ascites ranges between 8-20% per year and increases to 40% at 5 years [1]. After the onset of HRS, the 3-month survival rate of patients with cirrhosis is 15% [2]. It has become evident that the HRS is originated from circulatory system. The circulatory system is strongly affected by liver function. Since HRS is reversibility, the normalization or improvement in kidney function is important such as liver transplant [3,4], or pharmacologic treatment with vasoconstrictors and albumin [5]. However if they were not treated appropriately, the hospital mortality rate would be 100% [6,7,8]. Moreover procedure of liver transplantation takes long time. Due to these reasons, early diagnosis, treatment, and decision are significant.

1.1 Related Work

The definition of acute kidney injury (AKI) proposed by the Acute Kidney Injury Network (AKIN) is close to definition of HRS. So it appears to be effective to use AKI classification. However this classification has not been validated in patients with cirrhosis. Therefore, it is reasonable to keep the term HRS for the unique form of kidney failure [9].

Several factors have been suggested to be linked to an increased risk of HRS, including severe sodium retention, hypervolemic hyponatremia, low mean arterial blood pressure and low cardiac output. However interestingly HRS is the liver complication; there is no distinguished correlation with either the extent of liver failure, gauged by standard assessments of liver function (serum bilirubin, albumin, and prothrombin time) or
Child-Pugh classification [10,11,12]. There only exists a criterion of HRS for after the onset of HRS [2]. Such criterion takes account of noticeable features such as creatinine, shock, ascites, and urinary volume. Therefore under the current circumstances, there is no useful criteria or classification. So prediction of HRS before onset is required to early treatment and save lives.

2 Methodology

My interest is whether machine-learning algorithm can predict the onset of HRS from the medical records at the time of patients’ hospitalization. I gathered data from MIMIC-2 [13]. The MIMIC-2 database was collected from the Beth Israel Deaconess Medical Center between 2001-2008 from over 17,000 adult ICU patients. In this case, there are over 1000 cirrhosis patients and 150 of 1000 patient had HRS. Some of the targeted patients have missing records so I excluded them from my training data. As a result, there are 600 cirrhosis patients and 124 of them caused HRS.

2.1 Feature Extraction

The other major contribution of this work is in building good features for prediction of the onset of HRS. As mentioned in above, the current criteria of HRS are noticeable features such as ascites and creatinine. Such features are useless for early diagnosis. In this work, we take other features into consideration: AST, Blood Pressure, Bun, Heart Rate, Bilirubin, Potassium, Sodium, White Blood Cell.

2.2 Evaluation

I used classification method called Random Forest to predict whether the cirrhosis patients cause HRS. The number of cirrhosis patients with HRS is small comparing to cirrhosis patients without HRS. So in evaluation, I set the same number of patients randomly in both groups. 90% of patients are for training and the rest are for testing in random. I iterated 100 times for evaluation. Random Forest is borrowed from scikit-learn based on Python [14].

3 Results

We were able to predict HRS with $0.81 \pm 0.01$ AUC with 95% CI on my test data from MIMIC-2. Also precision rate is around $70 \pm 2\%$ and recall rate is $76 \pm 2\%$ with 95% CI. Currently there are no prediction criteria or prognosis classification of HRS in clinical settings. Thereby my prediction algorithm is useful.

4 Conclusions

In my study, I showed that I can use Random Forest to create an early warning prediction system for Hepatorenal Syndrome. This allows hospital staff and doctors the ability to reduce the opportunity to rush for sudden onset of HRS and save valuable lives. I also found that this prediction can be useful at the time of patients’ hospitalization. More importantly, I take 9 features into consideration, which are not common in present criteria. I suggest the 9 features are useful for early diagnosis. As a future work, I am currently working with Japanese hospitals to obtain Japanese patients medical records and verify my model.

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References


