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Electronic Medical Record-Based Predictive Model for Acute Kidney Injury in an Acute Care Hospital

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Abstract. Patients with acute kidney injury (AKI) are at risk for increased morbidity and mortality. Lack of specific treatment has meant that efforts have focused on early diagnosis and timely treatment. Advanced algorithms for clinical assistance including AKI prediction models have potential to provide accurate risk estimates. In this project, we aim to provide a clinical decision supporting system (CDSS) based on a self-learning predictive model for AKI in patients of an acute care hospital. Data of all in-patient episodes in adults admitted will be analysed using "data mining" techniques to build a prediction model. The subsequent machine-learning process including two algorithms for data stream and concept drift will refine the predictive ability of the model. Simulation studies on the model will be used to quantify the expected impact of several scenarios of change in factors that influence AKI incidence. The proposed dynamic CDSS will apply to future in-hospital AKI surveillance in clinical practice.

Keywords. Acute Kidney Injury, Electronic Medical Records, Data Mining, Clinical Decision Support System, Risk Prediction

1. Introduction

Acute kidney injury is a sudden decline in a person´s kidney function. It affects up to 15% of all patients admitted to hospitals, carries a substantially increased risk of individual morbidity and mortality.[1, 2] Although the implications of the disorder have become widely appreciated, no specific therapy for AKI has been demonstrated. Efforts to improve clinical outcomes for AKI have focused on early diagnosis and tailored treatment including drug dose adjustment, nephrotoxin avoidance and attention to fluid balance.[3, 4] Up to 30% cases could be prevented with appropriate recognition and timely intervention.[5] The electronic medical record (EMR) has become an integrated part of medical practice and its appropriate use improves patients´ care.[6-8] In recent years, EMR has been used as a platform to identify patients who have or may develop AKI and active surveillance for changes in creatinine has been shown to increase the timeliness of interventions and improve outcomes.[9, 10] However, the utilities of the EMR in AKI should go beyond a rule-based detection of AKI as a syndrome.[11] AKI forecasting models incorporated in advanced algorithms for

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clinical assistance have the potential to provide accurate risk estimates for AKI. In this project, we aim to develop a clinical decision supporting system based on a self-learning predictive model of AKI in patients from an acute care hospital. The specific objectives are: 1. to develop a clinical decision supporting system for AKI risk estimation: a) to construct a new predictive model for AKI and evaluate the quality of the predictions; b) to optimize the performance of the model over time applying a machine-learning process; 2. to define strategies for prevention of AKI in the institution based on simulation studies on the developed model.

2. Methods

2.1. Setting, data source and outcome

We are going to study hospitalization episodes of adult patients, admitted due to acute medical or surgical conditions. For analysis, we will solely use structured data obtained from EMR In 2012, an in-hospital data warehouse (HVITAL) was built, which is an on-line analytical processing tool that integrates disperse information in different in-hospital systems and provides historical data consolidated for analysis. For the model development and simulation study, we will use EMR of in-patient episodes from 2014 and 2015, while for the machine-learning process, data of patients admitted in 2016 and 2017. We will exclude episodes of patients under chronic renal replacement therapy, those admitted due to primary acute kidney diseases and women from the obstetrics department. Three different sets of criteria for AKI: the Risk, Injury, Failure, Loss and End-stage Kidney (RIFLE)[12], the AKI Network (AKIN)[3] and the Kidney Disease Improving Global Outcomes (KDIGO)[13] will be compared to choose the system with the best prognostic performance in our sample.

2.2. Clinical Decision Supporting System

Eligible patient episodes will be randomly partition into two sets of 70% for training and 30% for test. The model building strategy will combine a priori knowledge on the determinants of AKI with data mining algorithms. The data mining approach will allow for the recognition of unanticipated patterns (cluster analysis, principal components analysis and latent variables models), even among constructs that are known to be important. We will compare several established data mining algorithms, known as classifiers for supervised learning (artificial neural networks, k-neighbourhoods, decision trees and logistic regression) to estimate their performance and find the best set of parameters for feature ranking.

Subsequently, the predictive ability of the model will be examined in a test dataset by comparing the model's prediction with the observed outcome in new patients, estimating the model's sensitivity, specificity, overall accuracy and area under the ROC curves.

For further optimization of the prognostic performance, the machine-learning process will be introduced into the model. In the offline mode, new observations will be sequentially incorporated in the dataset where two advanced algorithms for data stream and concept drift are intended to refine the predictive ability of the model.

2.3. Simulation studies

The model will be used in simulation studies to examine the expected change in the incidence of AKI under the following scenarios: 1. preventing hospital-acquired infections (15% relative reduction); 2. avoiding or limiting exposure to nephrotoxic drugs (25% reduction in exposed); 3 applying prophylaxis in patients submitted to intravascular contrast media for imaging tests (all patients, unless contraindicated).

In this project, we present a comprehensive approach to a real problem, which is AKI incidence in a hospital setting. We will combine "data mining" techniques and cutting-age machine-learning algorithms to develop a dynamic support tool for the most accurate prediction of risk of AKI. It is our intention that the proposed CDSS applies for future in-hospital AKI surveillance. Integrated with the already operating on-line HVITAL, it would provide a real-time, individual risk prediction of AKI for future patients and allow for timely and adequate intervention. The research contributes in extending actual medical and health knowledge, underlying the essential role of Medical Informatics in contemporary research and health care organization. In this multidisciplinary approach, we join current Medical Informatics achievements, epidemiological concepts, the latest knowledge on AKI and relevant statistical methods to provide a valid answer to a specific problem. Furthermore, this study promotes the application of Medical Informatics in clinical practice.

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