A CASE STUDY OF ELECTRONIC MEDICAL RECORDS USE FOR PREDICTING KIDNEY INJURY

Davide Passaro [1], Luca Tardella [1], Giovanna Jona Lasinio [1], Tiziana Fragasso [2], Valeria Raggi [2] and Zaccaria Ricci [3]

[1] Department of Statistical Sciences, Sapienza University of Rome, (e-mail: davide.passaro@uniroma1.it)

[2] Department of Cardiology and Cardiac Surgery, Pediatric Cardiac Intensive Care Unit, Bambino Gesù Children's Hospital, IRCCS, Rome, Italy

[3] Meyer University Hospital, University of Florence, Italy

ABSTRACT: We present a case study concerning the use of electronic medical records (EMRs) acquired in an intensive care Unit (ICU). In particular, we focus on the problem of exploiting this emerging new type of data for predicting Acute Kidney Injury (AKI), a frequent complication in hospitalized patients during patient stay using data collected in the Pediatric Cardiac Intensive Care Unit of Bambino Gesù Childen's Hospital. We discuss the methodological issues related to pre-processing the available EMR data, analyze the possible alternative ways of defining the outcome and use different tools for making predictions.

KEYWORDS: 'EMR', 'classification', 'forecast', 'predictive model'.

1 The challenges of electronic medical records

In the last thirty years, the development of technologies has favored the development of Electronic Medical Records (EMRs). EMRs are the digital version of a patient's paper chart. EMRs are real–time, patient–centered records that make information available instantly and securely to authorized users. A database with Electronic Health Records contains patient data recorded to varying levels of granularity.

The trend of adoption of digital health record systems in hospitals seems to be clear and no longer deferrable (Collins & Tabak, 2014). The increasingly widespread presence of this new type of data has involved the development of research with the aim of using this data to support doctors' decisions.

Hodgson *et al.*, 2019 observe that, within health care, clinical decision support systems (CDSS) are increasingly being introduced with the aim to provide pertinent information, intelligently filtered or presented at appropriate times, to enhance care and potentially improve outcomes.

Indeed, Electronic health records contain valuable data for identifying health outcomes, but these data also present numerous challenges. In fact, despite the progress realized in recent years, the EMRs data suffer yet of no standardization problem in measurements acquisition in the particular case of Intensive Care Unit (ICU).

Statistics and Machine learning methods could help with some of these challenges (Wong *et al.*, 2018). As highlighted by Shafaf & Malek, 2019, the use of statistical methods as well as artificial intelligence and machine learning techniques in different medical fields are rapidly growing, in particular for the case of prediction and early detection of disease.

We describe a case study of use of EMRs using the data collected by the Pediatric Cardiac Intensive Care Unit (PCICU) of Bambino Gesù Childen's Hospital focusing on the problem of predicting Acute Kidney Injury (AKI) beforehand. Our study involved patient records extracted from January 2018 to February 2020. All the data extracted by the EMR have been anonymized.

2 The case of acute Kidney injury prediction

AKI is an increasingly common clinical problem associated with mortality, length of stay, and healthcare cost. In light of the impact of AKI on short and long-term outcomes, it is of high importance to develop methods to identify when patients are at risk for AKI and to diagnose subclinical AKI in order to improve patient outcomes.

For these reasons, we focus our work on the objective of predicting the AKI defined according to the AKI stage criteria (described in Khwaja, 2012). We adopt a continuous forecasting approach of the state of AKI throughout the hospital stay with a time advance of 48 hours.

In the initial phase, we work on data selection, extraction, and management of missing data. In particular, according to the literature and the clinicians, we use a selection of objectively collected variables available in the EMR data grouped into the following groups: admission and post-surgical data, vital signs, fluids, blood gas analysis, laboratory analysis, and therapies administered. Since a pediatric patient admitted to intensive care can be subjected, although not frequently, to more than one surgical and/or hemodynamic procedure during the same hospitalization we decided to select the following subset of the dataset:

- only patient in pediatric age ($\leq$ 18 years) with a length of hospitalization greater than 48h

	RF (all var)	RF using RFE	GAM (all var)	BN (all var)	BN (MMPC)
AUC bin AKI	0.93 (0.92-0.94)	0.95 (0.94-0.96)	0.87 (0.85-0.89)	0.90 (0.88-0.92)	0.90 (0.88-0.92)
AUC severe AKI	0.99 (0.98-1)	0.98 (0.97-0.99)	0.94 (0.92-0.96)	0.97 (0.96-0.98)	0.97 (0.96-0.98)
Accuracy Max AKI	0.92 (0.91-0.93)	0.93 (0.92-0.93)	0.87 (0.86, 0.89)	0.88 (0.87-0.89)	0.87 (0.86-0.88)
Accuracy Mode AKI	0.95 (0.94-0.96)	0.96 (0.95-0.97)	0.90 (0.89, 0.91)	0.92 (0.91-0.93)	0.92 (0.91-0.92)

Table 1. *Summary of results of AKI prediction using RF, GAM, BN.*

- only the temporal data between admission and discharge date from PCICU or before the start of a second surgery.

For groups of variables for which there was missing data (blood gas analysis and vital signs) we assume the origin of the missing data is missing at random (MAR). Starting this assumption we use a nonparametric missing value imputation using Random Forest provided by MissForest R Package (Stekhoven & Bühlmann, 2011). We discretize all the different acquisition frequencies in a common sample frequency of $\Delta t = 6$ hours. Finally, we define different types of outcome grouping the AKI stage in the binary and multiclass way.

In the second phase, we develop different classification models: random forest (RF), Generalized Additive Method (GAM), and Bayesian Network (BN). In all the cases we split the dataset into train (70%) and test (30%) sets. The former is used to fit the classification model, whereas the latter is employed to evaluate its performance. In splitting the data, we preserve the percentages of each class in train and test sets.

The overall performances reported in Table 1 are evaluated using the standard measures as Area under the ROC Curve (AUC-ROC) for binary cases and accuracy and kappa for the multiclass cases. The obtained results are always good compared with other recent attempts in the literature (Gameiro *et al.*, 2020).

We use, furthermore, different techniques of variable selection. In the case of RF, we applied Recursive Feature Elimination RF as described in Chen *et al.*, 2020. In BN cases we use the Max-Min Parents and Children algorithm (MMPC) as described in Lagani *et al.*, 2017. The list of the most important variables obtained in the various classifications confirm the importance of some of the variables (such as creatinine) reported in other studies in the literature but also highlights the presence of variables that are specific to pediatric patients under examination (such as Pediatric Index of Mortality).

All implemented models confirm the possibility of making an accurate prediction of the AKI stage using the PCICU. These models can be potentially included in a web interface and, in perspective, be integrated into the EMR of PCICU. This tool would allow the doctors to predict prospectively the patient's stage of AKI and evaluate how to intervene if necessary. In order to proceed with this, it would be necessary for the future to implement the export of a larger dataset adding new data acquired in the meantime in PCICU.

References

CHEN, RUNG-CHING, DEWI, CHRISTINE, HUANG, SU, & CARAKA, REZZY. 2020. Selecting critical features for data classification based on machine learning methods. *Journal Of Big Data*, **7**(07), 26.

COLLINS, F., & TABAK, L. 2014. Using machine learning to identify health outcomes from electronic health record data. *Nature*, **505**, 612–613.

GAMEIRO, JOANA, BRANCO, TIAGO, & LOPES, JOSÉ. 2020. Artificial Intelligence in Acute Kidney Injury Risk Prediction. *Journal of Clinical Medicine*, **9**(03), 678.

HODGSON, LUKE, SELBY, NICHOLAS, HUANG, TAO-MIN, & FORNI, LUI. 2019. The Role of Risk Prediction Models in Prevention and Management of AKI. *Seminars in Nephrology*, **39**(09), 421–430.

KHWAJA, A. 2012. KDIGO Clinical Practice Guidelines for Acute Kidney Injury. *Nephron Clin Pract*, 179–184.

LAGANI, VINCENZO, ATHINEOU, GIORGOS, FARCOMENI, ALESSIO, TSAGRIS, MICHAIL, & TSAMARDINOS, IOANNIS. 2017. Feature Selection with the R Package MXM: Discovering Statistically Equivalent Feature Subsets. *Journal of Statistical Software*, **80**(7), 1–25.

MAKOUL, G., CURRY, H., R., & TANG, P. C. 2001. The use of electronic medical records: communication patterns in outpatient encounters. *Journal of the American Medical Informatics Association : JAMIA*, **8**(6), 610–615.

SHAFAF, NEGIN, & MALEK, HAMED. 2019. Applications of Machine Learning Approaches in Emergency Medicine; a Review Article. *Archives of academic emergency medicine*, **7**(06), 34.

STEKHOVEN, DANIEL J., & BÜHLMANN, PETER. 2011. MissForest—non-parametric missing value imputation for mixed-type data. *Bioinformatics*, **28**(1), 112–118.

WONG, J., M., HORWITZ M., ZHOU, L., & TOH, S. 2018. Using machine learning to identify health outcomes from electronic health record data. *Current epidemiology reports*, **5**(4), 331–342.