Ho, E et al 2017 Predicting Readmission at Early Hospitalization Using Electronic Health Data: A Customized Model Development. *International Journal of Integrated Care*, 17(5): A506, pp. 1-8, DOI: dx.doi.org/10.5334/ijic.3826

POSTER ABSTRACT

Predicting Readmission at Early Hospitalization Using Electronic Health Data: A Customized Model Development

17th International Conference on Integrated Care, Dublin, 08-10 May 2017

Emily Tse Lin Ho[1], Ivan En-Howe Tan[2], Ian Lee[2], Phoebe Yubai Wu[2], Hon Fah Chong[3]

1: SingHealth Regional Health System, Singapore;

2: SingHealth Office for Insights and Analytic, Singapore;

3: Government Technology Agency of Singapore, Singapore

Introduction: Frequent admitters to hospitals are high-cost patients who strain finite healthcare resources. Several predictive models for readmission have been developed, however these are limited in generalizability to other health systems due to their unique variables. Moreover some indexes can only be calculated at the point of discharge and are not validated in our local population.

Objective: A frequent admitter in our context is defined as a patient who has three or more inpatient admissions within a 12 month period. Our objective is to develop a localized automated readmission risk predictive tool to identify these high risk patients at the point of hospital admission for early intervention.

Methods: Retrospective cohort data was extracted via electronic medical records of a tertiary academic hospital. Death after discharge, elective admissions and oncologic admissions with high rates of elective chemotherapy were excluded. Final data set included 144,494 patient admissions from Jan 2011 to Oct 2013 of which 40,747 were known frequent admitter admissions. Variables included data from inpatient, outpatient, emergency department and government based primary care visits, demographics and basic socioeconomic information, clinical diagnoses and laboratory results. Three models were developed using logistic regression, random forest and gradient boosting, and compared to the LACE index as a benchmark. Derived model performances were compared using the Area under the Receiver Operating Characteristic (AUROC) curves. A hold out set of data from Oct 2013 to April 2014 comprising 26,767 admission records was used to validate the final predictive model.

Results and Discussion: Using the LACE index we obtained an AUROC of 0.6653 with our data, the Logistic Regression model 0.866, Random forest model 0.877 and the XGBoost model (extreme gradient boosting) 0.876 (for AUROC, 0.5 represents random classifications and 1 represents perfect classifications). Based on performance, the final XGBoost algorithm was chosen. The final model performance has a Precision-Recall area under curve (PR AUC) of 0.741 with a Recall at 80% precision of 41.5%. On evaluation with the hold out data set, the model showed a better PR AUC of 0.76 and Recall at 80 % precision of 46.3%.

Conclusion: We develop a customized high performing predictive model for hospital readmission to identify patients during early hospitalization. When incorporated into the working electronic health system, a score generated at point of admission facilitates early identification by clinicians and mobilization of transitional care services for patients who will benefit the most.

Lessons learned: Strong predictors found for readmissions were age, a previous hospitalization, patients with diabetes complications (retinopathy and amputations), cardiac and chronic hepatic conditions. Implementation of this model clinically and external validation are needed to ensure reproducibility.

Limitations: Variables used in the data set are limited to those collected on electronic health records and hospital database. Information not captured electronically, such as detailed social economic history, behavioural, functional status and caregiver availability could have improved performance of the model. We are also unable to prove causal relationship between predictor variables and hospital admissions.

Keywords: hospital readmissions; predictive modelling