Adoption of a Deep Learning "Risk Scale" Predictive Model to Reduce 7-day Readmission of Respiratory Patients at a Pediatric Center

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Background: A hospital readmission occurs when a second admission to hospital within a short period occurs for an individual patient. Some readmissions are inevitable and may be unrelated to the index admission, but it is accepted that some are preventable[1]. Reducing these preventable readmissions improves quality of care and reduces patient harm. The Affordable Care Act also reduces Medicare payments to hospitals with excessive readmission rates[2].

Several recent publications have reported the development of models to predict a patient's risk of readmission. However, few of these articles report meaningful integration into the day-to-day clinical workflow. This may be because the data science processes involved are not adapted for the use of real-world data and focus on all-cause readmission instead of beginning with a smaller specific cohort. We report on the development of a deep learning model and associated data pipeline using near-real-time, real-world data as part of a hospital clinical intervention initiative that aims to reduce pediatric respiratory readmissions by 10-20% over one year.

Methods: We first established an AI care team comprising physician champions, data scientists, a project manager, database analysts, the data warehouse manager, biostatisticians, IT support staff and patient case managers. We engaged frontline staff in the development process so that our machine learning model had full clinical applicability. Clinician involvement in the development of technology for medicine is crucial to uphold the social trust in medicine[3]; physician champions are also able to educate their peers in use of the new techniques.

We embarked on exploration of the real-world hospital data that would be available to the model and on establishment of ground truth. During this process, we found three separate 7-day readmission rates reported by the hospital system. We were able to work with stakeholders to consolidate the information into one group that became the single source of truth for the entire hospital's reporting metrics.

We focused on respiratory cohort patients as they are a large group with one of the highest readmission rates. We used 3 years (July 2016 to June 2019) of patient encounter data from our electronic medical record to train, validate, and test a model to prospectively identify a real-world patient's risk for 7-day readmission. The dataset comprised 4947 patients, 127 patients (2.5%) of whom were readmitted within 7 days and 323 patients (6.5%) who were readmitted between 7 and 30 days after the index discharge. The dataset included demographic, insurance and illness severity information for both inpatient and observation patients, but different variables were available for these two groups. We first divided the dataset into training (70%) and test (30%) sets. We then divided the training set into inpatient (n=2641) and observation (n=821) subsets. For both patient groups, we developed a deep neural network with 3 hidden layers and used Bayesian optimization to find the optimal hyperparameters. We used batch normalization in hidden layers to scale the data between layers. We also used dropout technique and L2 regularization of hidden layers to avoid overfitting.

Results: The developed models show an average area under receiver operating characteristic curve (AUROC) of 0.76 with AUROC for detection of 7-day readmission of 0.77. Recall for prediction of 7-day and 30-day readmission is 0.55 and 0.60 respectively. The overall accuracy of the models is 0.82.

We developed an automated data pipeline process that creates both a daily output score and a record of the main factors that contribute to the score, to aid in clinical trust and model explainability. We built a practical visual analytics interface to present the daily results to clinicians via email. A traffic light system of green, amber or red indicates low, medium or high risk for readmission. Hospitalists and patient care managers are able to see which patients will benefit most from application of the interventions introduced by the overall project. These interventions include homecare nursing support, increased patient case manager support and the introduction of a transition of care handoff tool.

Conclusion: In an area where there is currently minimal evidence for how to use a predictive risk assessment tool in clinical practice, we successfully introduced a high performance deep learning model to the clinical workflow. We defined the success of the introduction of our ML model as- a reliable tool that uses real-world, near-real-time data, that can be organically used by the care team to make informed decisions about how to allocate targeted, supportive resources to the patients at highest risk of readmission. In the future, we look forward to assessing the impact of our project on both the rate of readmission and on improvements in patient care. We also look forward to comparing the tool's predictive ability against that of the experienced clinicians who make decisions on behalf of the patient.

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