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Developing and evaluating a machine learning based algorithm to predict the need of pediatric intensive care unit transfer for newly hospitalized children

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ABSTRACT

Background: Early warning scores (EWS) are designed to identify early clinical deterioration by combining physiologic and/or laboratory measures to generate a quantified score. Current EWS leverage only a small fraction of Electronic Health Record (EHR) content. The planned widespread implementation of EHRs brings the promise of abundant data resources for prediction purposes. The three specific aims of our research are: (1) to develop an EHR-based automated algorithm to predict the need for Pediatric Intensive Care Unit (PICU) transfer in the first 24 h of admission; (2) to evaluate the performance of the new algorithm on a held-out test data set; and (3) to compare the effectiveness of the new algorithm's with those of two published Pediatric Early Warning Scores (PEWS).
Methods: The cases were comprised of 526 encounters with 24-h Pediatric Intensive Care Unit (PICU) transfer. In addition to the cases, we randomly selected 6772 control encounters from 62516 inpatient admissions that were never transferred to the PICU. We used 29 variables in a logistic regression and compared our algorithm against two published PEWS on a held-out test data set.
Results: The logistic regression algorithm achieved 0.849 (95% CI 0.753–0.945) sensitivity, 0.859 (95% CI 0.850–0.868) specificity and 0.912 (95% CI 0.905–0.919) area under the curve (AUC) in the test set. Our algorithm's AUC was significantly higher, by 11.8 and 22.6% in the test set, than two published PEWS.
Conclusion: The novel algorithm achieved higher sensitivity, specificity, and AUC than the two PEWS reported in the literature.

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1. Introduction

Failure to rescue hospitalized patients from complications of disease or treatment is the source of substantial morbidity and death.[1,2] A cardiopulmonary arrest or code outside the intensive care unit (ICU) is a profound consequence of failure to rescue that is associated with a poor prognosis in hospitalized children and adults.[3] As clinical antecedents are present before most codes, rapid response systems (RRS) have been designed, tested, and implemented to detect deterioration early and to rapidly intervene.[4,5] One challenge with RRS is failure to activate or trigger the afferent limb.[6] Early warning scores (EWS) are designed to address this challenge by combining physiologic and/or laboratory measures into a quantified score that can then be linked to clear, expected action such as increased nursing assessments or activation of RRS.[7–18] The most commonly used Pediatric EWS (PEWS) combine scores in 3–7 sub-scales to generate a score between 0 and 26.[12,15,16] Initial development and validation of these scores, which are designed to be tabulated by hand by nurses, occurred before widespread implementation of electronic health records (EHR) and therefore leverage only a small fraction of the EHR content.

The predictive validity of two commonly used PEWS scores[12,15,16] has been examined using the outcome of subsequent transfer to the PICU. The Bedside PEWS is the most extensively validated to date and includes seven components: heart rate, systolic blood pressure, capillary refill time, respiratory

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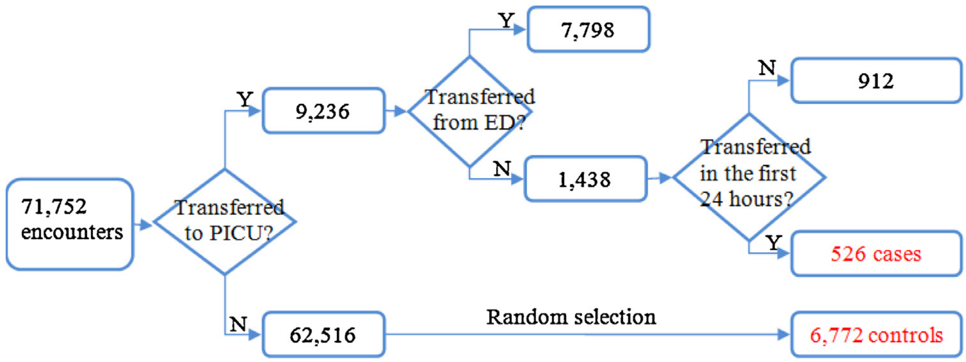

Fig. 1. Steps to generate cases and controls.

rate, respiratory effort, transcutaneous oxygen saturation, and oxygen therapy.[15] A score of 0, 1, 2, or 4 is generated from each category and aggregated to a total score, which has an area under the receiving operating characteristics curve (AUC) of 0.91 in its derivation cohort and AUC of 0.87 and 0.73 in two separate validation cohorts.[12,15,17]

The Monaghan's PEWS used in our institution combines subscores in behavior, cardiovascular, and respiratory domains, with added points for nebulizers ¼ hourly or vomiting following surgery to create a 0–9 overall score. While less extensively validated, this score had AUC of 0.89 when prospectively evaluated.[16] Since an EWS will only succeed in preventing deterioration when it is tied to clear action, each score has cut points where associated algorithms call for specific actions to be taken. The Bedside PEWS has most commonly been studied using a cut point of 8, while the Monaghan's PEWS commonly uses a score >2 for increased nurse and physician evaluation.[15,16]

The planned widespread implementation of EHRs brings the promise of abundant data resources for research purposes via secondary use of EHR data, including better prediction of clinical deterioration.[19] As noted, EHRs and EHR-based research can transform health care delivery through advanced clinical decision support.[20] However, many of the grand challenges in developing clinical decision support are still barely addressed.[21] One of these challenges is to mine large clinical data sets to develop new clinical decision support systems to improve clinical outcomes. In our study we aim to contribute to achieving this exact goal by using the data collected in the EHR during routine clinical care to derive and evaluate a prediction algorithm for PICU transfer for children in acute care wards within the first 24 h of admission.

2. Methods

2.1. Definition of cases and controls

Cincinnati Children's Hospital Medical Center's (CCHMC) Institutional Review Board approved the protocol for our retrospective study. We extracted EHR data that were generated by clinical providers between January 1, 2010 and August 31, 2012. During this period, CCHMC had 71,752 admissions to its inpatient wards. Of these, 1438 admissions were later transferred from the general wards to the PICU. Our unit of analysis was the encounter and not the patient. For each inpatient encounter, we defined the first 24 h of admission as the study period for three reasons. First, we attempted to determine which patients might need more attention and resources at the start of their inpatient stay. Second, as presented below, the PICU transfers that occurred in this scope covered a large percentage of total PICU transfers (i.e., 36.6%). Third, the algorithm developed in this scope could be generalized and tested in other scopes. We identified 526 case and 6772 control encounters (Fig. 1).

Cases and controls were split into two experimental datasets, a training set with 90% of cases (including 473 cases and 473 controls) and a test set with 10% of cases (consisting of 53 cases and 6299 controls). The 119:1 ratio of "no-PICU transfer": "24-h PICU transfer" was maintained in the test set to preserve the generalizability of the study's findings.

2.2. Identification and selection of predictive clinical elements for the machine learning algorithm

We collected over 300,000,000 data points from all 71,752 encounters that occurred between January 1, 2010 and August 31, 2012. The data set included 7587 unique clinical elements as candidate predictors. Through a six-step process (Fig. 2), we selected the predictive clinical elements from this data set.

In the first step, we sorted the clinical elements by their frequency. In the next step we filtered out the elements that were measured in less than 20% of clinical encounters and retained the top 400 most frequent elements. In the third step, a pediatric hospitalist manually reviewed the 400 clinical elements and generated a list of 16 candidate clinical elements with predictive potential. To create independent variables, we collected all measurements for the 16 clinical elements recorded in the EHR until 1 h before the transfer event for cases and measurements recorded in the first 24 h for

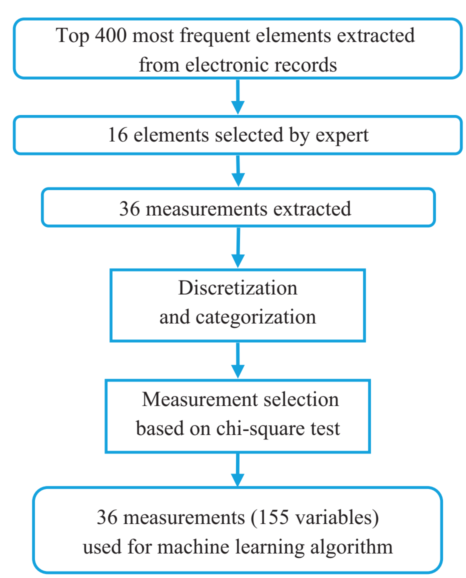

Fig. 2. Identification and selection procedure of clinical elements for machine learning algorithm.

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