Predicting pediatric extubation failure with machine learning methods through an innovative tandem approach

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Pediatric cardiac critical care providers are often challenged with the equally important but often conflicting goals of minimizing patients' exposure to mechanical ventilation and preventing extubation failure. Extubation failures have been associated with adverse outcomes including increased duration of hospital stay, cardiac arrest, and mortality. Though these outcomes in part reflect overall illness severity and are not exclusively the result of extubation failure, patients may suffer downstream complications of extubation failure such as airway injury, prolonged mechanical ventilation, and the numerous consequences of prolonged exposure to critical care therapies. As such, efforts to reduce extubation failure events may lead to great benefits for patients. Reliable measures of extubation readiness, while validated in adult patients, remain elusive in pediatric cardiac critical care. Patients in the cardiac intensive care unit (CICU) have heterogeneous pathophysiology, and failure to breathe without assistance from a ventilator can be the result of primary respiratory or cardiac failure, or a mixed etiology. Our previous work also demonstrates wide variation in case mix-adjusted extubation failure rates across pediatric CICUs, further suggesting that practice and outcomes vary due to existing knowledge gaps. Physicians and nurses need new prediction tools to help with clinical decision making when assessing children in the CICU for extubation readiness.

We have previously investigated how patient, disease, and hospital factors associate with the risk of extubation failure using data from a large clinical registry of over 32 institutions from North America (Pediatric Cardiac Critical Care Consortium: PC4) using a traditional regression approach. An innovative software platform currently in use in our CICU at the University of Michigan (UM) C.S. Mott Children's hospital captures all data from CICU monitors and devices at 1 minute intervals. This data source allows us the opportunity to study physiologic parameters during the key period when patients are evaluated for extubation readiness. Machine learning methods that utilize large-scale shallow data from the PC4 registry in tandem with small-scale deep physiologic data from CICU monitors hold the possibility of unlocking patterns that even the most experienced clinicians may fail to recognize.

In this project we developed methods to combine large-scale, shallow EHR data with small-scale, deep patient data to improve prediction. The idea is to perform sequential classification: first using widely available covariates for risk stratification and subsequently refining prediction using deep data for a subgroup of patients. We propose three approaches to select which patients move onto a second stage prediction refinement using deep data. Our approaches select patients with poor predictive properties and intermediate risk based on the first stage classification. At each step of the sequential classification, we use a toolbox of machine learning methods. The predictions from the first two steps are combined to produce a tandem prediction. We developed a novel approach to extract important features from the patient's CICU physiologic trends to use as inputs in our machine learning classifiers. Features were extracted using simple summary statistics and time-series models.