Prediction of Critical Pediatric Perioperative Adverse Events using the APRICOT Dataset

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Background: Despite the unparalleled safety of modern anesthesia techniques, it is possible, but rare, for a perioperative adverse event (PAE) that causes complications leading to long term disability or even the death of a child. The safety of children's anesthesia could be improved by having the ability to personalize a prediction for an individual patient, to highlight in when PAEs are more likely to happen and assist in perioperative planning.

Previous studies[1] on perioperative events comprise clinical audits or single institution studies, with insufficient dataset size to sufficiently power the study of rare adverse events. Existing predictive models for PAE in pediatric anesthesia are classic decision tree based models that use a very limited number of inputs and focus on risk stratification for individual conditions[2,3]. In this project, we used the largest pre-existing pediatric perioperative dataset of its type in the world to produce a sophisticated machine learning model that can accurately predict the risk of any PAE for every child undergoing an anesthetic procedure.

Methods: The Anesthesia PRactice In Children Observational Trial[4] (APRICOT) collected the primary endpoint of incidence of perioperative severe critical events in 30 874 children undergoing 31 127 anesthetic procedures in 261 participating centers across 33 European countries. The data includes information about demographics, medical history, surgery and anesthesia. We identified 57 fields from the case report form as input variables, based on known risk factors and consensus from clinical expert opinion. Out of these, six had no data entered and hence we excluded those variables from the study.

The severe critical events defined by APRICOT were laryngospasm, bronchospasm, pulmonary aspiration, drug error, anaphylaxis, cardiovascular instability, neurological damage, perianesthetic cardiac arrest and post-anesthetic stridor. The critical event rate across the study was 4.74%, meaning that 1 463 patients had at least one critical event reported. The occurrence of each individual type of event was therefore very rare, so we decided to initially use an aggregation of these events as the outcome for our deep learning model. Hence, we assigned a binary outcome of 1 if a patient was reported to have any critical event and 0 if no critical events were reported.

We chose to use a deep neural network (DNN) and used stratified random split to divide the data into 70% training and validation and 30% testing, ensuring relatively equal rates of positive outcome for the training and testing data (4.73% training, 4.74% testing). To address the significant class imbalance, we used oversampling of the minority class to increase the positive incidence rate to 25% in the training and validation sets. We used 15% of the training data for validation and monitored validation loss during training as a performance metric. Bayesian optimization was used to optimize the model's hyper-parameters.

Results: The best performing model for the prediction of individual risk of perioperative severe critical events in children demonstrated accuracy of 0.82, recall of 0.53, and AUROC 0.75 for the test set. For an imbalanced dataset such as APRICOT, these results show the promise of deep learning in prediction of individual patient outcomes.

Conclusion: Individually identifying patients at high risk of severe critical PAE has clinical utility through helping clinicians to improve outcomes by highlighting a need to consider modifying their routine standard of care. It will also give a common and objective risk score to aid communication with patients and their families and between members of the surgical care team. In this presentation, we demonstrate the application of DNN methodology for this problem with a successful secondary use of the largest observational trial dataset of its kind in the world. We look forward to further developing our work with front line clinicians to give more detail in predicting those patients most at risk, including the development of interpretability for the model and further delineating the physiological system affected by the PAE, such as respiratory or cardiovascular. We aim to work to produce a calculator and intuitive user interface using visual analytics methods, enabling front line clinical staff in using our work to inform their patient care in real-time.

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