Unsupervised Machine Learning Models for Characterization of Risk for Pediatric Severe Critical Events from Anesthesia Using the Wake-Up Safe Registry

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Introduction: Despite improvements in anesthesia safety, patients continue to experience unintended harm related to anesthesia and surgical care.[1] Characterization of these serious adverse events in children remains an ongoing challenge due to their relative infrequency. Wake Up Safe (WUS), a national pediatric anesthesia collaborative supported by the Society of Pediatric Anesthesia launched in 2008, with the goal to make anesthesia safer for children. The registry represents one effort to better understand and reduce the incidence of serious adverse event. This study applies unsupervised machine learning methods to characterize risks for severe critical events from anesthesia and provide useful tools for clinical decision making and risk stratification. These tools help facilitate better use of the WUS registry in the clinical setting.

Methods: Two datasets are made available from WUS, one for billing data and one for critical events data. The billing dataset has relatively few features collected (Age, ASA Score, ICD, CPT, ASA Emergency Status), while the events dataset contains detailed information on each critical event. The absence of a direct link between the events dataset and the billing dataset, as well as the substantial discrepancy in the features contained in each dataset, prohibit directly combining them into a single dataset for predictive modeling. To overcome this issue, a novel strategy to indirectly link the two together is devised. The approach is as follows: first the billing dataset is clustered using the k-prototypes algorithm.[2] A fuzzy record matching algorithm is then applied to match the entries from the events dataset to clusters in the billing dataset. Then, the probability of different events is calculated for each cluster. This can be used to predict patient risk given diagnosis, procedure and demographics.

Results: Table 1 shows cluster statistics. Four clusters were identified as optimal (data not shown). Cluster 1 had young, complex patients (ASA IV/V majority), with majority male. Cluster 2 contained older, moderately complex patients (ASA III majority). Cluster 2 contained the highest number of ASA emergency designations. Cluster 3 was composed of preschoolers who were medically stable (ASA I majority), predominantly nonemergency ASA status and female. Cluster 4 was composed of grade-schoolers who were moderately stable (ASA II majority).

Table 1. Cluster Statistics.

Cluster	Age	ASA					Emergency Status		Gender	
		I	II	III	IV	V	Non.	Emerg.	Male	Female
1	1.26 (0.89)	24.71	39.20	26.61	**9.15**	**0.32**	95.02	4.98	**64.91**	35.09
2	14.79 (1.90)	22.56	45.02	**29.27**	3.02	0.13	93.15	**6.85**	53.07	46.93
3	4.85 (1.17)	**25.74**	45.20	26.46	2.54	0.07	**95.43**	4.57	43.66	**56.34**
4	9.07 (1.35)	23.00	**46.65**	27.83	2.43	0.09	93.21	6.79	62.18	37.82

The largest number of critical events occurred in Cluster 1 (N=1645), with Airway complications (N=135), Cardiac Arrest (N=396), Cardiovascular Support (N=195), Malignant Hyperthermia (N=5), Perioperative death (N=111) and Respiratory events (N=455) found most frequently in this group out of all groups. Cluster 2 had the second highest number of events (N=1308), with the highest number of Airway Injury (N=39), Cutaneous/Musculoskeletal (N=37), Eye Injury (N=19), Medication Event (N=197), Nervous System Injury (N=71), Other Injuries (N=52), Under General Anesthesia (N=8) and Wrong Side Sites (N=11) occurring in this group. Cluster 3 had the second lowest number of events (N=1289), with Blood Transfusion complications (N=16) occurring with the highest frequency in this cluster. Cluster 4 had the lowest number of events (N=914). Respiratory events (N=1477) represented the most commonly occurring critical events, while Malignant Hyperthermia (N=10) was the least common.

Conclusion: Application of unsupervised ML techniques along with matching facilitated development of a model with clinical utility from a dataset not amicable to advanced data use. Patient characteristics were identified from the clusters, while the type and frequency of several critical events was determined using matching. Young, medically complex patients were most likely to suffer from Respiratory events. Older, moderately complex patients undergoing emergency procedures were most likely to suffer from medication events when compared to all patient groups. This work provides insight into leveraging a complex dataset for better characterization of patient groups suffering from severe critical adverse events.

References

1. Kurth CD, Tyler D, Heitmiller E, Tosone SR, Martin L, Deshpande JK. National Pediatric Anesthesia Safety Quality Improvement Program in the United States. *Anesthesia and Analgesia.* 2014;119(1):112-121.
2. Huang ZX. Extensions to the k-means algorithm for clustering large data sets with categorical values. *Data Mining and Knowledge Discovery.* 1998;2(3):283-304.