Development of a Machine Learning Classification Model for ICU Admission Following Resuscitation at a Level I Trauma Center

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Background.

For the past 45 years the concept of the Golden Hour, which suggests improved patient outcomes with rapid transport to a definitive trauma center, has informed much of pre-hospital care design and trauma center availability and infrastructure [1-2]. While rapid arrival to a trauma center is generally seen as a definitive endpoint to improved mortality, there is a paucity of research on correlating subsequent trauma bay resuscitation time and efficiency to patient outcomes. What happens when a patient arrives at a level I trauma center is often thought of as a homogeneous resuscitation event due to the international systematization of the approach to the critically injured via the near universally adopted Advanced Trauma in Life Support (ATLS) curriculum [3]. Trauma patients, however, represent a spectacularly diverse and unique population where no two injured patients are exactly alike. Dynamic and often competing priorities in addressing their frequently multiple life-threatening injuries often disrupts timely adherence to existing ATLS protocol [4]. Our team created a novel machine learning model to predict ICU admission in a trauma patient based on collected trauma resuscitation metrics.

Methods.

Our model's training cohort is an all-comer adult trauma patient population from July 2021 to June 2022 at St. Joseph's Hospital in Phoenix, Arizona. Admission data included 361 features consisting of time to endpoints such as imaging, chest tube, CPR, as well as descriptive data such as type of trauma, site/type of injuries, vitals at arrival, neurological deficits, resuscitation fluid types and volume, medications administered, supportive care devices, and patient past medical/surgical history. We identified cases resulting in ICU admission following trauma activation. Features were accessed for completeness and plausibility as well as processed with standard scaling and categorical one-hot encoding. A total of 2148 patients and 120 admission features based on feature importance were included for final modelling. We compared the performance of classification models built using random forest, XGBoost distributed gradient boosting, and support vector machine algorithms with an 80/20 train/test split, balanced class weighting, and five-fold cross validation.

Results.

In our trauma cohort, 30.8% of cases resulted in ICU admission within 24 hours following trauma activation. The random forest classification yielded the most optimal performance (AUC = 0.88) of all algorithms tested with 1200 estimators, 10 minimum sample splits, 4 minimum leaf samples, and a max depth of 60 following hyperparameter tuning. The model testing average f1 score was 0.79 and the positive ICU admission sensitivity was 74%. The five most important features predictors in the model were neurosurgical consult, time to CT scan, mechanism of injury, time to vital signs, and time to secondary patient survey. Mean arterial pressure and pulse rate were the most predictive patient vital sign metrics.

Conclusion

Our model is designed to predict ICU admission for adult trauma patients. Our model aims to help identify patients most at risk for ICU admission, thus allowing clinicians to efficiently intervene on higher risk patients. Allowing clinicians to identify and act on those patients at greatest risk for developing adverse events we hope will aid in the furtherance of better patient outcomes and improve management of critical care resources.

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