Objectives/Aims

Clinical Trials (IMPACT) and Corticoid Randomization After Significant Head injury (CRASH) indirect medical costs) in 2010 was $76.5 billion. hospitalizations per year and 57,000 deaths. the United States alone, TBI accounts for about 30% of all injury related deaths with about 300,000 but also cognitive impairment and reduced quality of life in a significant proportion of survivors. mortality, and 2. neurological outcome based on dichotomized motor Glasgow Coma score. The signals will significantly improve clinical outcome prognostication of ICU stratum TBI patients. Two short-term hospital discharge endpoints were evaluated and modeled: 1. in-hospital discharge as clinical endpoints. 2. hospitalization. The estimated economic burden of TBI (direct and indirectly derives features. We see that of the top 50 features, 22 beta coefficients were PTS derived features. We were able to observe the clear discriminative benefits of PTS derived variables in combination with EHR derived variables. Conclusions & Future Work

Our results demonstrate that physiology-driven ML approaches significantly outperform IMPACT and CRASH logistic regression models for both neurological outcome and mortality prediction for ICU admission TBI patients. These models, established using the multi-center eICU-CRD cohort, outperform successful external validation in the MIMIC-III single center TBI cohort and provides increasing confidence in the multicenter model’s generalizability. Results suggest that a data-driven approach incorporating PTS derived features captures prognostically relevant information on TBI patients which may be overlooked in existing TBI prediction systems. Further work is being conducted to extend the TBI external validation analysis to MIMIC-IV, Amsterdam University Medical Center (AUMC), and Johns Hopkins Medicine patient datasets. This will help provide further evidence that our eCU developed model can be generalized to multiple adult TBI populations, especially two European cohorts and another large single center education medical institute.

Methods

In a multi-disciplinary clinical database of 208 institutions in the US (eICU), we identified patients admitted to the ICU with a diagnosis of TBI (n=4450). Predictive features of interest were clinical variables, laboratory results, and physiologic time series data (PTS), i.e., high frequency monitoring data including heart rate, SaO2, respiratory rate, and blood pressure). Three different machine learning (ML) algorithms were trained on a generalized linear models (GLM) baseline, random forest (RF), and XGBoost (XG) tree, were trained on a statistically pruned feature space of 147 derived variables using mortality and neurological outcome at hospital discharge as clinical endpoints.

ML models performed well for both neurological outcome prediction and for mortality prediction (Figure 2, Table 2). ML model performance was significantly higher for IMPACT and CRASH for neurological outcome and mortality at discharge. Additionally, published AUROC for IMPACT and CRASH models ranged from 0.79 to 0.82 for mortality and 0.77 and 0.78 for neurological outcome prediction. Our IMPACT and CRASH AUROCs were well within the literature review and previous comparison consistency of our eCU and MIMIC III TBI population to prior works. External validation utilizing MIMIC III corroborated the results from eICU for both neurological outcome and mortality. Our eCU developed model was generalizable to the MIMIC III TBI cohort as observed by an increase in performance metrics for both clinical outcomes.

The value of integrating PTS derived features was clearly observed in features ranked by beta coefficients of our trained GLM model. Figure 4 shows the rankings for neurological outcome prediction. We see that of the top 50 features, 22 features were PTS derived features. Similar importance of PTS features was seen for mortality prediction (not shown). 24 of the top 50 bedside monitoring variables were PTS derived features. We were able to observe the clear discriminative benefits of PTS derived variables in combination with EHR derived variables.

A Physiology-Driven Machine Learning Model for Traumatic Brain Injury Outcome Prediction Using a Large Multi-Center Database

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Conclusions & Future Work

Our results demonstrate that physiology-driven ML approaches significantly outperform IMPACT and CRASH logistic regression models for both neurological outcome and mortality prediction for ICU admission TBI patients. These models, established using the multi-center eICU-CRD cohort, outperform successful external validation in the MIMIC-III single center TBI cohort and provides increasing confidence in the multicenter model’s generalizability. Results suggest that a data-driven approach incorporating PTS derived features captures prognostically relevant information on TBI patients which may be overlooked in existing TBI prediction systems. Further work is being conducted to extend the TBI external validation analysis to MIMIC-IV, Amsterdam University Medical Center (AUMC), and Johns Hopkins Medicine patient datasets. This will help provide further evidence that our eCU developed model can be generalized to multiple adult TBI populations, especially two European cohorts and another large single center education medical institute.

References