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Digital signatures for early traumatic brain injury outcome prediction in the intensive care unit

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Traumatic brain injury (TBI) is a leading neurological cause of death and disability across the world. Early characterization of TBI severity could provide a window for therapeutic intervention and contribute to improved outcome. We hypothesized that granular electronic health record data available in the first 24 h following admission to the intensive care unit (ICU) can be used to differentiate outcomes at discharge. Working from two ICU datasets we focused on patients with a primary admission diagnosis of TBI whose length of stay in ICU was ≥ 24 h (N = 1689 and 127). Features derived from clinical, laboratory, medication, and physiological time series data in the first 24 h after ICU admission were used to train elastic-net regularized Generalized Linear Models for the prediction of mortality and neurological function at ICU discharge. Model discrimination, determined by area under the receiver operating characteristic curve (AUC) analysis, was 0.903 and 0.874 for mortality and neurological function, respectively. Model performance was successfully validated in an external dataset (AUC 0.958 and 0.878 for mortality and neurological function, respectively). These results demonstrate that computational analysis of data routinely collected in the first 24 h after admission accurately and reliably predict discharge outcomes in ICU stratum TBI patients.

Traumatic brain injury (TBI) is a leading cause of death and disability, with more than 50 million cases reported annually worldwide[1]. Among TBI patients admitted to the Intensive Care Unit (ICU), an estimated two thirds die or have neurological disability at 6 months[2]. To develop therapeutic interventions that improve outcomes, effective methods are needed to characterize TBI severity and predict clinical outcomes in the acute phase[3,4]. Established TBI prognostic scores such as the Corticosteroid Randomization After Significant Head Injury (CRASH) and International Mission for Prognosis and Analysis of Clinical Trials in TBI (IMPACT) combine clinical features (core models) or clinical features combined with head CT and laboratory or physiological variables (extended models) in multivariable logistic regression models[5,6]. These models have been tested and validated extensively and discriminate moderately well with areas under the receiver operator characteristic curve (AUC) of 0.82 and 0.79 across studies for CRASH and IMPACT respectively[7]).

One potential limitation of existing models is that they do not capture some important predictive features in this population. A more granular analysis of physiological signals (e.g. curve shape, local averages) may reveal important information about a patient's clinical trajectory. Moreover, recent research indicates that prediction of clinical outcomes and physiological state transitions might be enhanced by training machine learning classifiers because they can effectively model granular relationships in high-dimensional spaces[8,9].

Here, we explored electronic health record data to test the hypothesis that early data signatures can differentiate short-term clinical trajectories of TBI patients admitted to the ICU. We demonstrate that information available in the first 24 h of intensive care is predictive of mortality and neurological function at ICU discharge, and that machine learning models can accurately model this relationship. We found that model performance was robust and validated effectively in an independent external population.

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