Machine Learning Prediction of Responsiveness Phenotypes in Non-Neurological ICU Patients

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INTRODUCTION/HYPOTHESIS:

A significant number of patients admitted to ICU for a non-neurological illness develop an encephalopathy characterised by decreased levels of responsiveness. We hypothesized that features available on the first day of intensive care would be associated with the responsiveness phenotype at the time of discharge.

METHODS:

The eICU and MIMIC-IV datasets were used for train-and-test and external validation, respectively. We selected adult patients whose ICU length of stay was ≥ 2 and ≤ 7 days, focusing exclusively on data available in the first 24h after ICU admission. Responsiveness was determined on ICU admission and discharge with the motor subscore of the Glasgow Coma Scale (mGCS), with responsive and unresponsive phenotypes defined as mGCS = 6 and mGCS < 6, respectively. Binary classifications were trained on the full population and on the subsets who were responsive on admission (RA), and unresponsive on admission (UA). A gradient boosted (GB) decision tree model was selected as the classifier. After 5-fold cross validation, model discrimination was evaluated by area under the receiver operating characteristic (AUROC) analysis.

RESULTS:

The final dataset consisted of 37,568 admissions in eICU. The GB models had an AUROC(SD) for prediction of discharge responsiveness phenotypes of 0.86 (0.00), 0.84 (0.00), and 0.79 (0.01) in the entire sample, RA subset and UA subset, respectively. Features strongly associated with unresponsiveness at discharge were higher heart rate, lower systemic blood pressure, higher blood urea nitrogen and higher red blood cell count. External validation conducted with data from 20,127 admissions in MIMIC-IV revealed an AUROC(SD) of 0.88 (0.00), 0.86 (0.01), and 0.83 (0.01), respectively.

CONCLUSIONS:

In patients admitted to the ICU with a non-neurological illness, machine learning models trained with data collected in the first 24 hours of ICU stay accurately predicted responsiveness at discharge. The predictions were validated externally in an independent dataset, and they were interpretable. Results suggest data-driven computational approaches that could inform strategies to ameliorate neurological function during critical illness.