A Machine Learning Model to Predict Responsiveness in Non-Neurological ICU Patients

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Introduction:

The acute loss of responsiveness is a frequent medical emergency that requires rapid and precise intervention to maximize the chances of survival, awakening, and neurological recovery. It is commonly associated with a primary neurological disorder, such as stroke or traumatic brain injury; however, decreased responsiveness is also frequently seen in critically ill patients without a primary neurological disorder.

Objectives:

To predict the level of responsiveness at discharge in patients admitted to the ICU without a primary neurological diagnosis. We hypothesized that accurate prediction can be achieved by training machine learning classifiers with high-resolution data acquired in the first 24 hours following ICU admission.

Methods:

We leveraged the eICU database (200,859 ICU stays) as a train-and-test set and the MIMIC-IV database (69,619 ICU stays) for external validation. We included adult patients who did not have a primary neurological diagnosis at ICU admission and whose ICU length of stay was at least 2 days and no more than 7 days. The level of responsiveness was evaluated using the motor subscore of the Glasgow Coma Scale (mGCS). Binary classification models were trained on the full population and subgroups classified by the responsiveness levels at ICU admission: responsive admissions (mGCS = 6; RA Group), and unresponsive admissions (mGCS < 6; UA Group). Feature selection removed features with coverage < 85% and imputed the remaining with medians. The final feature space contained physiological signals, lab values, medications, and demographics extracted from the first 24 hours of ICU stay. After performance comparisons, we chose gradient boosted decision trees (GB) to predict the level of responsiveness at ICU discharge.

Results:

The preprocessed dataset consisted of 37,568 ICU stays (RA Group: 28,905; UA Group: 8,663) for eICU and 20,127 ICU stays (RA Group: 12,559; UA Group: 7,568) for MIMIC-IV. After 5-fold cross validation, we evaluated the models with median AUROC, and GB trained on the full population had the best performance (Fig. 1). Other model performance metrics are provided in Table 1. Predictive features which were consistently highly ranked included physiological signals such as respiration rate, systemic blood pressure and heart rate, and lab features, including blood urea nitrogen and red blood cell count.

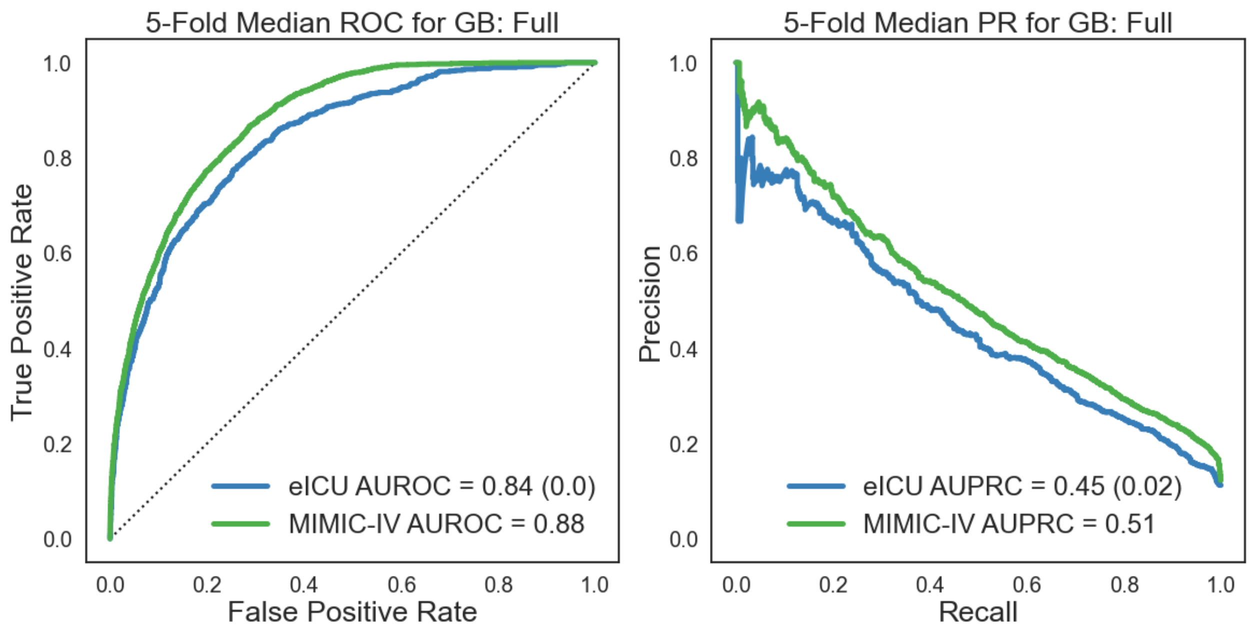

Figure 1. 5-fold Median Performance Curves for Full Population.

Performance Metrics	RA Group		UA Group		Full Population	
	eICU Test	MIMIC-IV Validation	eICU Test	MIMIC-IV Validation	eICU Test	MIMIC-IV Validation
Sensitivity	0.77	0.85	0.69	0.76	0.77	0.78
Specificity	0.71	0.82	0.72	0.75	0.75	0.79
PPV	0.15	0.22	0.45	0.41	0.27	0.31
NPV	0.98	0.99	0.88	0.93	0.97	0.97
Brier Score	0.05	0.18	0.15	0.12	0.07	0.07

Table 1. 5-fold Median Performance Metrics for Population Groups.

Conclusions:

In patients admitted to the ICU with a non-neurological diagnosis, a machine learning model using data collected in the first 24 hours of ICU admission can accurately predict responsiveness at discharge. These predictions could inform strategies to prevent neurological deterioration or enhance neurological function during critical illness.

Reference(s):

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