

### Coma Predictor: Prediction of Neurological Trajectories in Non-Neurological ICU Patients



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### Background

**Decreased neurological responsiveness** is a cardinal manifestation of brain dysfunction, which occurs in ICU patients **without primary neurological disorders**. Brain dysfunction may be treatable or even preventable with limited means to predict responsiveness changes. There is an unmet need for models to **predict responsiveness outcomes in patients admitted to the ICU**.

### **Objectives**

- Predict neurological responsiveness trajectories of non-neurological ICU patients
- 2. Identify and rank predictive features associated with specific neurological responsiveness trajectories

#### Methods

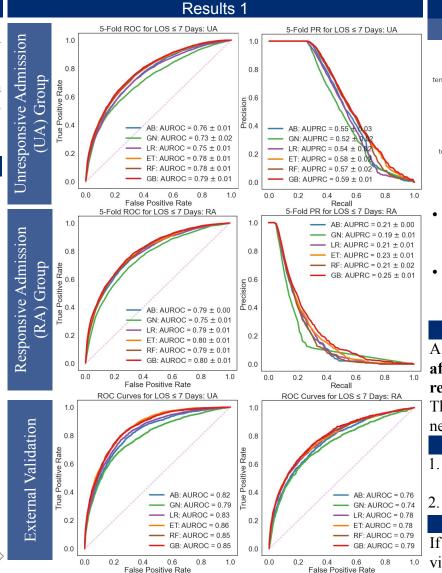
We used the **eICU** database (200,859 ICU stays) as training and testing set; the **MIMIC-IV** database (69,619 ICU stays) for external validation.

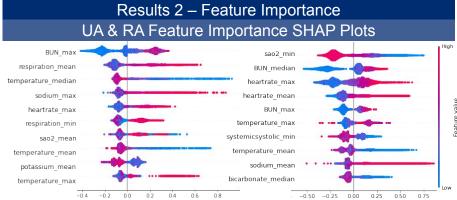
# Data Preprocessing Motor GCS Filter Motor GCS Filter Motor GCS Filter Motor GCS recorded <= 12 h of admission <= 24 h of discharge EICU 68,452 stays Unresponsive Admissions (UA Group, mGCS < 6) Filter Time & Age Filter Age >= 18 years LOS <= 7 days Diagnosis Filter Non-neurological diagni MIMIC-IV 37,546 stays Responsive Admissions (RA Group, mGCS = 6) Pure IIII MIMIC-IV 37,546 stays

### **Model Development**

Two classifications: **responsive admission** (RA) and **unresponsive admission** (UA) group.







- The mean (±SD) AUROC for predicting responsiveness was **0.80** (±**0.01**) for **RA Group** and **0.79** (±**0.01**) for **UA Group**. We chose **gradient boosting** models for best results.
- Top ranked features included physiological signals: respiratory rate, systemic blood pressure and heart rate; lab features: blood urea nitrogen and red blood cell count.

### Conclusions

A machine learning model trained with data collected in the **first 24h after ICU admission** can **accurately predict neurological responsiveness at discharge of patients in ICU for 7 days or less**. This information could be critical in identifying strategies to prevent neurological deterioration or enhance neurological recovery

### **Future Directions**

- 1. Develop neural network models for prediction and feature importance interpretation;
- 2. Explore additional features to enhance prediction accuracy

### Additional Information

If you have any other questions or comments, welcome to contact us via rstevens@jhmi.edu



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### Background

Loss of consciousness is a medical emergency that requires rapid and precise intervention to maximize the chances of survival, emergence, and neurological recovery. It is commonly associated with a primary neurological disorder, such as stroke or traumatic brain injury; however, impaired consciousness is also frequently seen in critically ill patients without a primary neurological disorder.

### Objectives

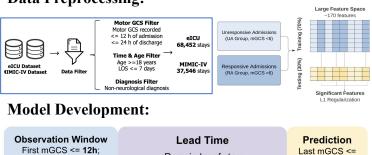
- 1. Use machine learning methods to develop models for coma prediction of non-neurological ICU patients.
- 2. Identify **the important clinical variables** contributing to coma onset based on data-driven methods.

### Methods

**Database**: **eICU database** (200,859 ICU stays) as training and testing set; **MIMIC-IV database** (69,619 ICU stays) for external validation.

### **Data Preprocessing:**

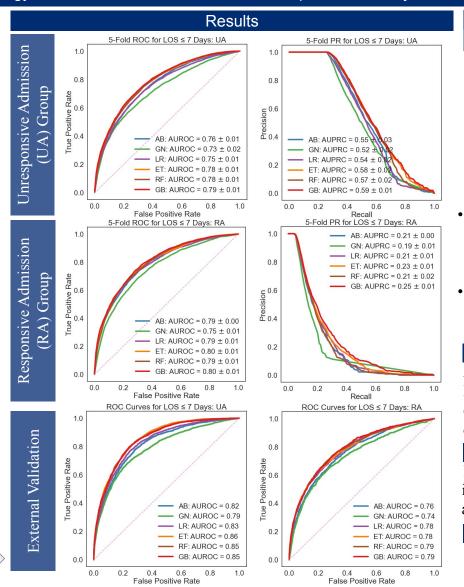
24h Data collection



Remainder of stav

Time

24h of discharge



### Result 2 – Feature Importance UA & RA Feature Importance SHAP Plots



- The mean (±SD) AUROC for predicting responsiveness outcome was **0.80** (±**0.01**) for **RA Group** and **0.79** (±**0.01**) for **UA Group**. We chose **gradient boosting** models to predict the level of responsiveness at ICU discharge.
- Highly ranked features included physiological signals: respiration rate, systemic blood pressure and heart rate; lab features: blood urea nitrogen and red blood cell count.

### Conclusions

A machine learning model using data collected in the **first 24h of ICU admission** can **accurately predict neurological function at discharge**, which informs strategies to prevent neurological deterioration or enhance neurological.

### **Future Directions**

1. Improve our neural network models for prediction and feature importance interpretation; 2. Include more features such as admission diagnosis.

### Additional Information

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