BIOMEDICAL ENGINEERING

Predicting Liberation from Mechanical Ventilation in the Intensive Care Unit

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INTRODUCTION

The timing of patient liberation from ventilatory support is critical to avoid complications and reduce healthcare costs. **Models that accurately predict independence from mechanical ventilation would be pivotal in supporting clinician's informed decision-making, improving patient outcomes upon extubation, and decreasing ICU expenditures.**

Aim 1: Data Preprocessing

- **Inclusion/exclusion criteria**
- **Data Imputation and cleaning**
- **Sliding window definition**

Aim 2: Liberation Prediction

- **Predict whether the patient will have an extubation success or failure based on the status**

Aim 3: Duration Prediction

- **Predict whether the patient can be extubated within a week based on 6-hour sliding window**
- **Predict whether the patient can be extubated within which quantile time range**

DATASET

- 9781 patients with multiple 6-hour observation windows were pulled from the Precision Medicine Analytics Platform (PMAP) Dataset feature summary is shown below.
  - Heterogenous data of multiple modalities: demographic, vital measurements, lab results, and medical history
  - Predominantly consists of overweight, geriatric, white males with circulatory issues and cystic fibrosis

Table 1: Feature summary table

Type (144)*	Feature (N = 9781)	Statistic
Static (12)	Gender - Female, n (%)	4441 (45.4)
	Gender - Male, n (%)	5340 (54.6)
	Race - White, n (%)	6228 (63.7)
	Race - Black, n (%)	2578 (26.4)
	Race - Other, n (%)	975 (9.9)
History (68)	Blood and blood-forming organs, n (%)	1438 (14.7)
	Circulatory system, n (%)	6840 (69.9)
	Compromised, n (%)	2638 (27.0)
	Cystic fibrosis, n (%)	5460 (55.8)
	Digestive system, n (%)	3955 (40.4)
	Genitourinary system, n (%)	2001 (20.5)
	Mental disorders, n (%)	2570 (26.3)
	Model community acquired pneumonia group, n (%)	3026 (30.9)
	Musculoskeletal system and connective tissue, n (%)	2967 (30.3)
	Neoplasms, n (%)	3760 (38.4)
	Symptoms, signs, and ill-defined conditions, n (%)	3534 (36.1)
Dynamic (8)	Age, median [Q1,Q3]	65.0 [53.0,74.0]
	BMI, median [Q1,Q3]	27.9 [24.2,32.5]
	Current duration at MV Level, median [Q1,Q3]	34.7 [17.7,60.0]
	Extubation time, median [Q1,Q3]	76.3 [41.0,138.3]
	Height, median [Q1,Q3]	67.0 [64.0,70.0]
	Level, median [Q1,Q3]	1.0 [1.0,1.0]
	Num. of MV Instances, median [Q1,Q3]	11.0 [6.4,19.3]
	Weight, median [Q1,Q3]	81.2 [68.4,96.6]
Vital (36)	DBP, median [Q1,Q3]	68.1 [63.5,73.2]
	EtCO2, median [Q1,Q3]	33.0 [29.9,35.7]
	GCS, median [Q1,Q3]	14.8 [14.2,15.0]
	MAP, median [Q1,Q3]	89.3 [83.2,95.4]
	Pulse, median [Q1,Q3]	80.6 [73.3,88.0]
	Respiratory Rate, median [Q1,Q3]	17.6 [16.7,18.6]
	SBP, median [Q1,Q3]	126.1 [116.7,134.9]
	SpO2, median [Q1,Q3]	96.8 [95.8,97.8]
	Temperature, median [Q1,Q3]	36.6 [36.4,36.8]
Lab (20)	Anion gap, mean (SD)	13.4 (2.1)
	Calcium, mean (SD)	8.4 (0.5)
	Creatinine, mean (SD)	1.2 (1.2)
	Erythrocyte distribution width, mean (SD)	14.8 (2.1)
	Glucose, mean (SD)	135.9 (35.9)
	Glomerular filtration rate, mean (SD)	76.5 (30.8)
	Hematocrit, mean (SD)	31.7 (5.3)
	Hemoglobin , mean (SD)	10.4 (1.8)
	Sodium, mean (SD)	139.2 (2.8)
	Leukocytes, mean (SD)	10.3 (3.6)
	Urea nitrogen/Creatinine, mean (SD)	17.7 (6.9)
	Platelet mean volume, mean (SD)	10.4 (0.9)
	Nucleated erythrocytes/100 leukocytes, mean (SD)	0.0 (0.1)

*Not all features are shown in table for the sake of clarity.

METHOD

25353 total ICU patients with mechanical ventilation record in PMAP

3640 patients deceased while during ICU stay

21713 patients alive at the end of ICU stay

2033 patients missing some type of static record

19680 patients with full static record

5417 patients missing more than 60% of dynamic record

14263 patients with both static demographic information recorded

Data Imputation & Data Cleaning

Data Imputation & Cleaning Details

1. **Data Imputation**
   Used KNN imputation with k = 10
2. **Selecting successfully extubated patients**
   Patients *successfully* extubated if they were not reintubated with 72 hours of the extubation event
3. **Data Cleaning**
   Removed erroneous values, extreme outliers, etc. from the data

9781 patients In total
Train: Validation: Test =
7825:978:978 patients

Apply **6-hour** observation window to each patient

Final Dataset 21985 windows
Train: Validation: Test =
17709:1978:2298 windows

Discretize the continuous extubation time into quantiles for binary classification
Used SMOTE for class imbalance

Apply Machine learning & Deep Learning Models

Model Details

Machine Learning Models:
- Logistic Regression (LR)
- RF
- XGBoost

Deep Learning Models:
- Transformer
- Recurrent Neural Network (RNN)
- Long Short-Term Memory Network (LSTM)
- Convolutional Neural Network (CNN)

Hyper parameter Finetuning based on the train and validation data set

Use F1, AU-ROC, AU-PR, and NPV to evaluate the model on the test data set

SHAP Analysis
To extract the most important feature with aim to help with the clinical decision

MODEL PERFORMANCE

Figure 1: Model Comparison

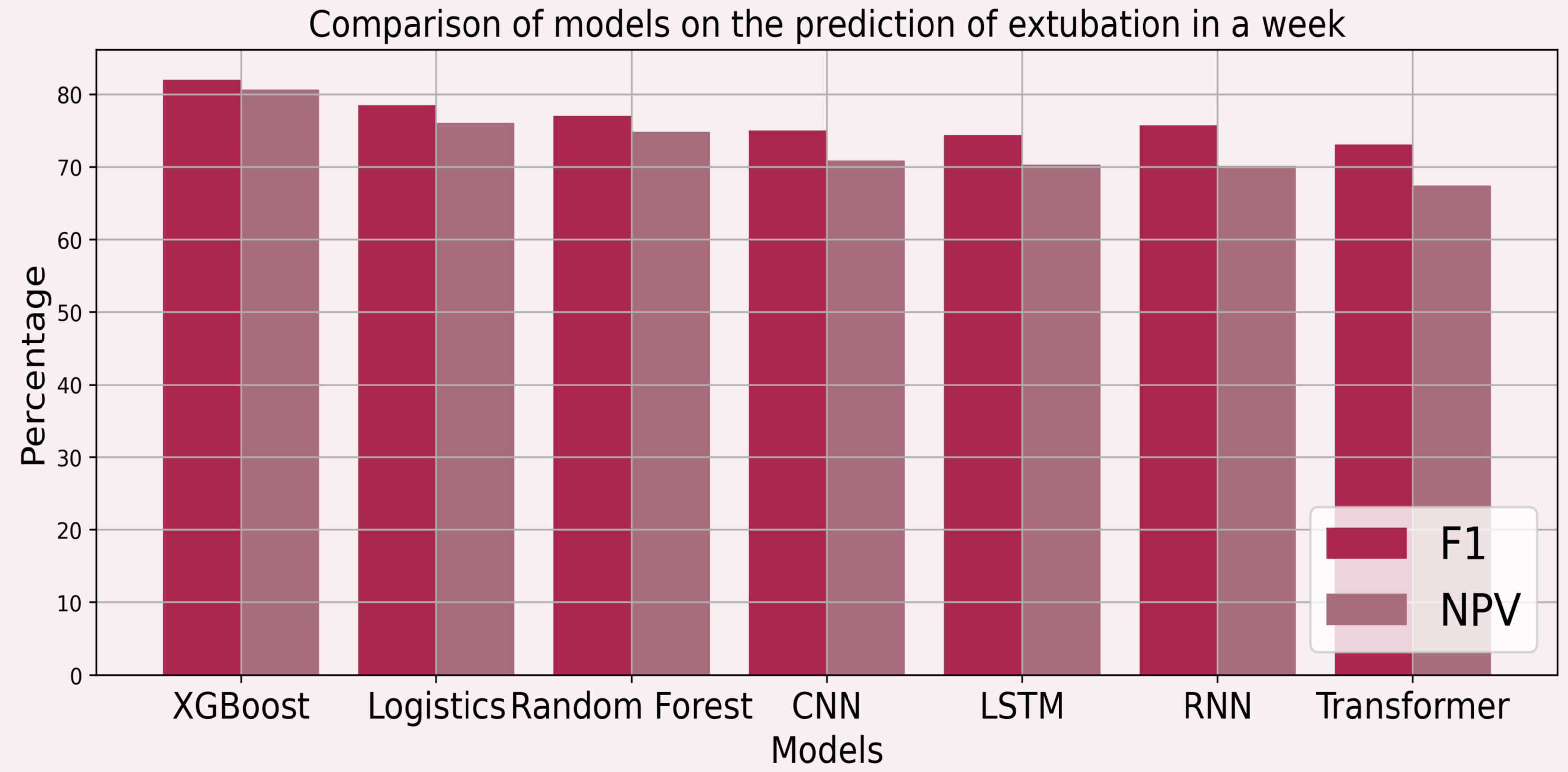

Table 2: Model Comparison with respect of AU-ROC, AU-PR, F1, NPV scores on Binary

	Machine Learning Models			Deep Learning Models			
	XGBoost	Logistics	Random Forest	CNN	LSTM	RNN	Transformer
ROC-AUC	**0.8631**	**0.8357**	0.8179	0.8336	0.7598	0.8325	0.8215
PR-AUC	**0.8657**	**0.8483**	0.8363	0.8336	0.75.98	0.8325	0.8215
F1	**0.8203**	**0.7851**	0.7707	0.7816	0.74.52	0.7573	0.7666
NPV	**0.8062**	**0.7609**	0.7480	0.7480	0.7052	0.7014	0.7120

Figure 2: PR Curves

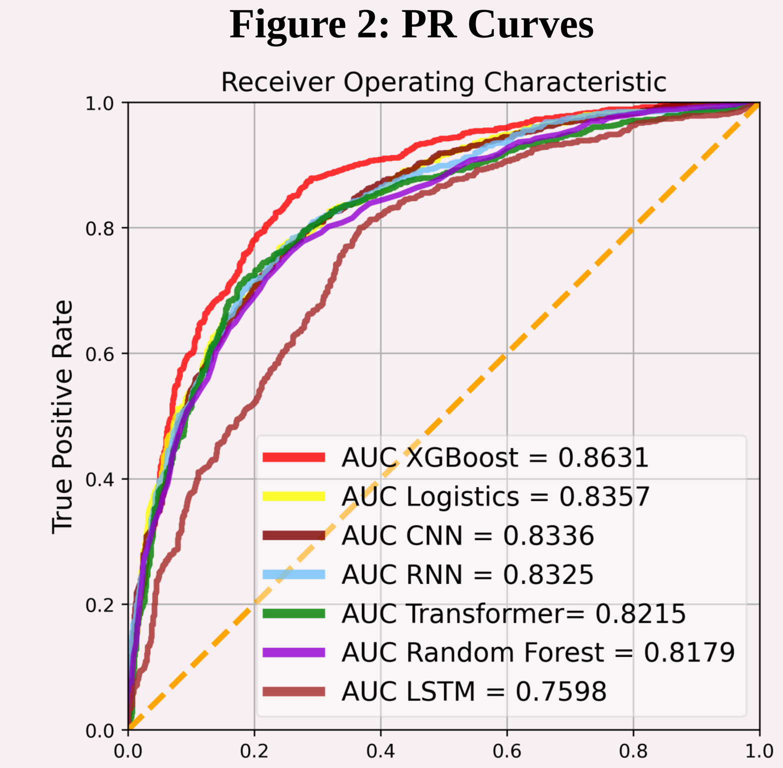

Figure 3: ROC Curves

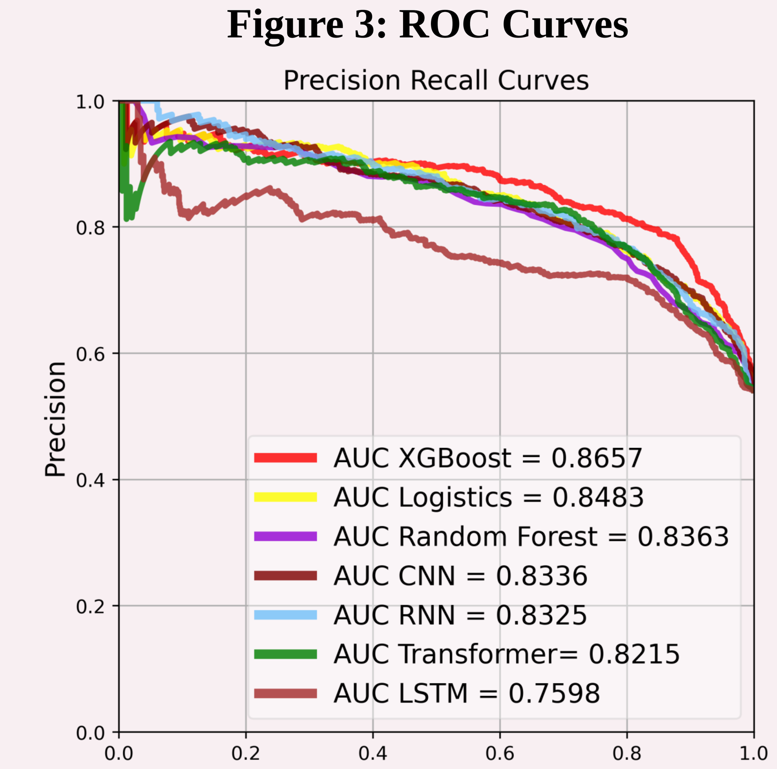

Table 3: Model Comparison with respect F1 scores on Quantile Classification

F1 score Extubation Range	Machine Learning Models			Deep Learning Models			
	XGBoost	Logistics	Random Forest	CNN	LSTM	RNN	Transformer
[0-72)	**0.5313**	0.5204	0.5087	0.5322	0.5209	0.4878	**0.5225**
[72-168)	**0.4850**	0.4626	0.4499	0.4610	0.4650	0.4510	**0.4740**
[168-336)	**0.3395**	**0.3397**	0.3028	0.2782	0.3139	0.4186	0.3105
[336,inf)	0.4402	**0.4434**	0.3794	0.3599	0.3612	0.4912	0.3924

FEATURE IMPORTANCE

The top three critical features in lab data according to the SHAP analysis were **platelets in blood, nucleated erythrocyte/100 leukocytes ratio, and erythrocyte distribution width**. Several studies have found that platelets and erythrocytes may serve as biomarkers to predict extubation time or respiratory failure in the ICU, which is consistent with our findings [1-5].

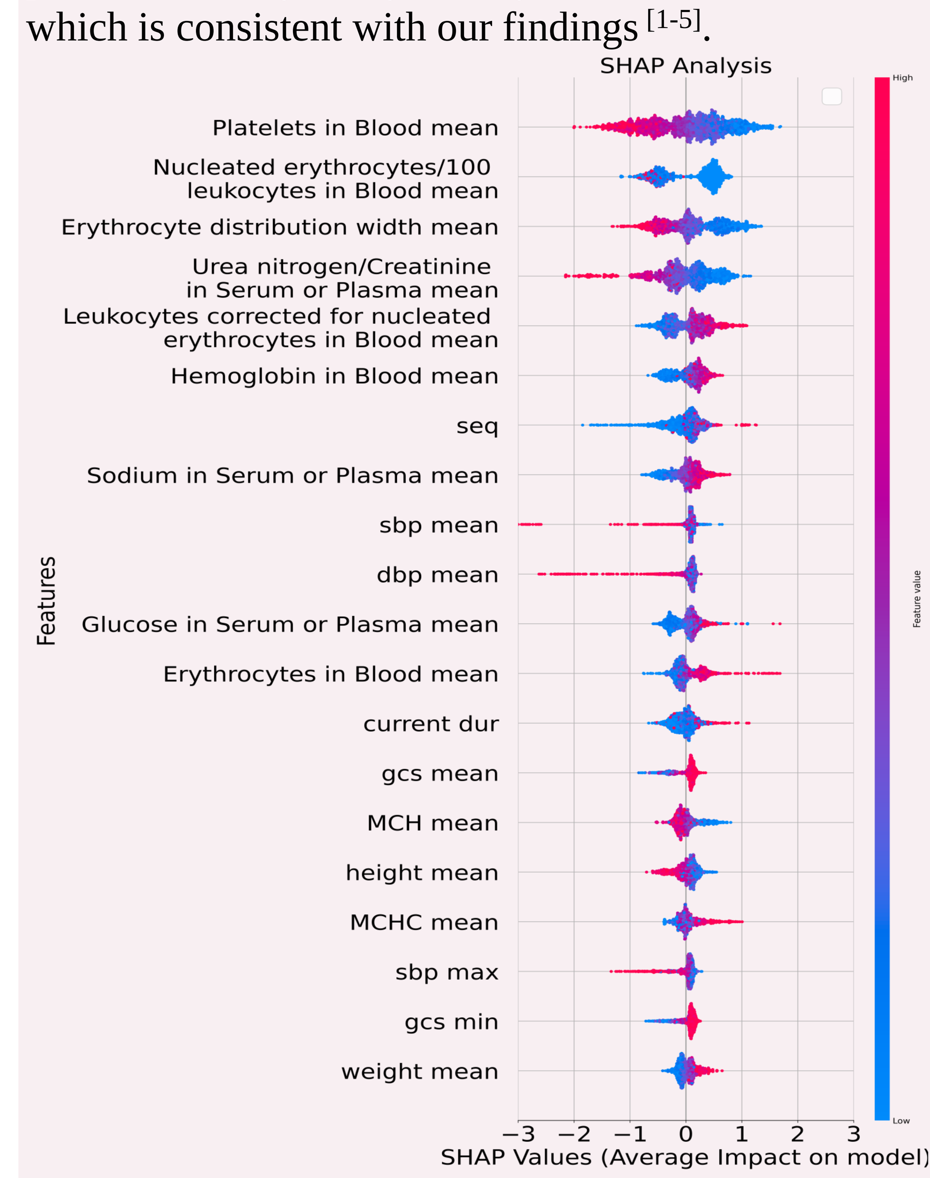

Figure 4: SHAP Analysis on binary prediction of extubation time

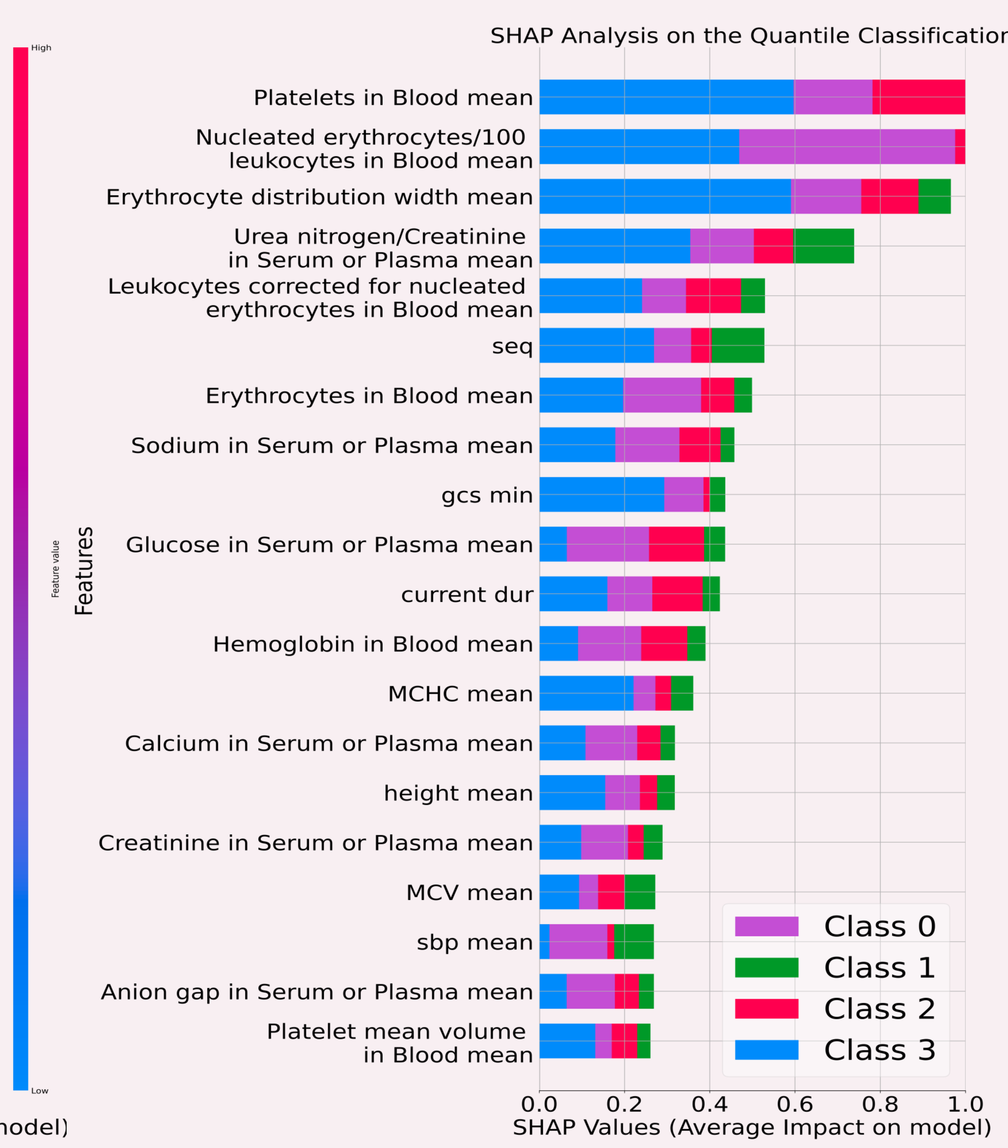

Figure 5: SHAP Analysis on quantile prediction of extubation time

CONCLUSION

- We created the data set from PMAP for the prediction of patient's extubation time using 6-hour observation window, which consists of **9781 patients with multiple features**.
- We compared 3 machine learning models and 4 deep learning models on the data set and found **XGBoost performed the best on both binary and quantile prediction.**
- We conducted SHAP analysis using the trained XGBoost model. We found that lab data is highly relevant to the prediction of extubation time in addition to vital data like blood pressure and Glasgow coma scale. We found **platelets in blood, ratio of nucleated erythrocytes to 100 leukocytes**, and **erythrocyte distribution width** are the **top 3 most important features in the prediction of extubation time.**
- Future work can be done in creating a classifier that outputs a continuous time-forecast for the end of a mechanical ventilation instance.

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