Comparing Machine Learning Algorithms for Predicting ICU Patients’ Mortality

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Statement of the Problems

- Efforts have been made to identify Clinically relevant statistical methods and machine learning applications that are optimal in predict the ICU patients' mortality.
- The knowledge gaps are still in utilizing machine learning to help ICU physicians make optimal clinical decisions and early and accurate identification of ICU patients with a high risk of in-hospital deaths.
- The current study applied and evaluate the performance of four different machine learning algorithms in predicting ICU in-hospital deaths. My goal was to identify the best algorithm using demographic data, vital, and laboratory data, which can, in turn, improve the prognosis and clinical outcomes.

Clinical Questions

1. What are the features of patients’ demographic, lab visit and vital signs to predict ICU patients’ in-hospital death?
2. Which is the best machine learning model to predict the ICU patients’ mortality among XGboosting, logistic regression, decision tree and KNN?
3. What are the recommendation of the machine learning algorithm to the doctors and physician to best perform clinical interventions for critically ICU patients?

Methods, Metrics and Features

- Train ICU visit data: 91713 (size)
- Features: (103)
  - Patients Demographic (19)
  - Lab: min, max by day and hours (46).
  - Vital sign of min, max by day and hours (38)
- Predictors: Probability of Hospital Death('1'), Survival ('0')
- Predictive Modeling: four ML models
- Metrics: Accuracy score, Recall, F1 score, ROC AUC

Confusion Matrix

Supervised Learning Modeling (classifier)

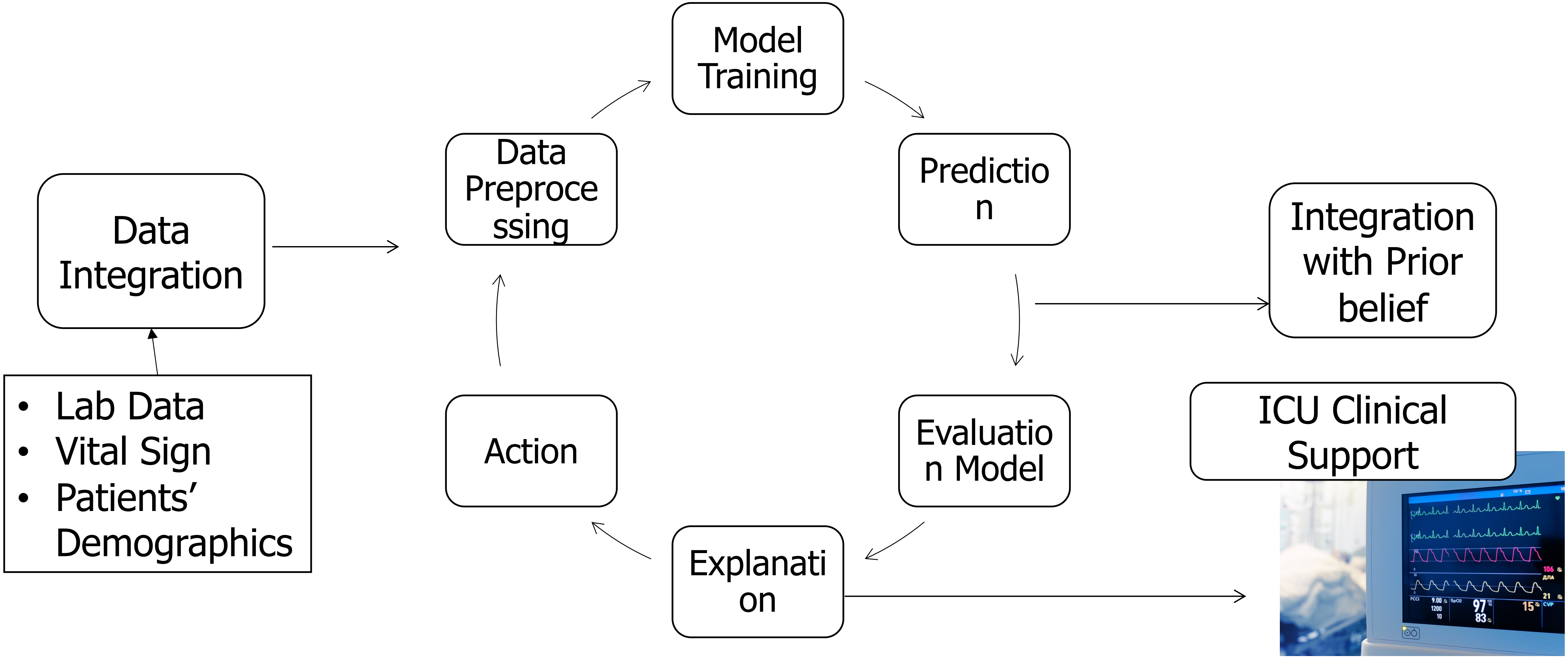
Logistic Regression: (tradition maximum likelihood estimate and independent Input)

K Nearest Neighbor: (non-parametric)

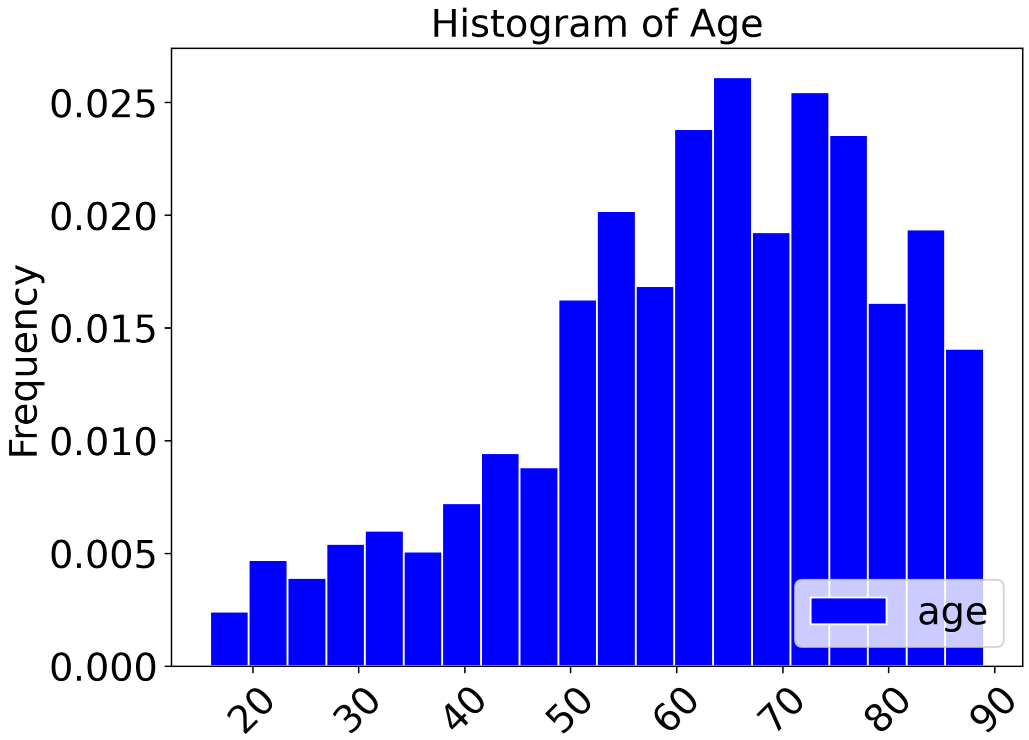
Decision Tree: (use gini and entropy to find the best break point)

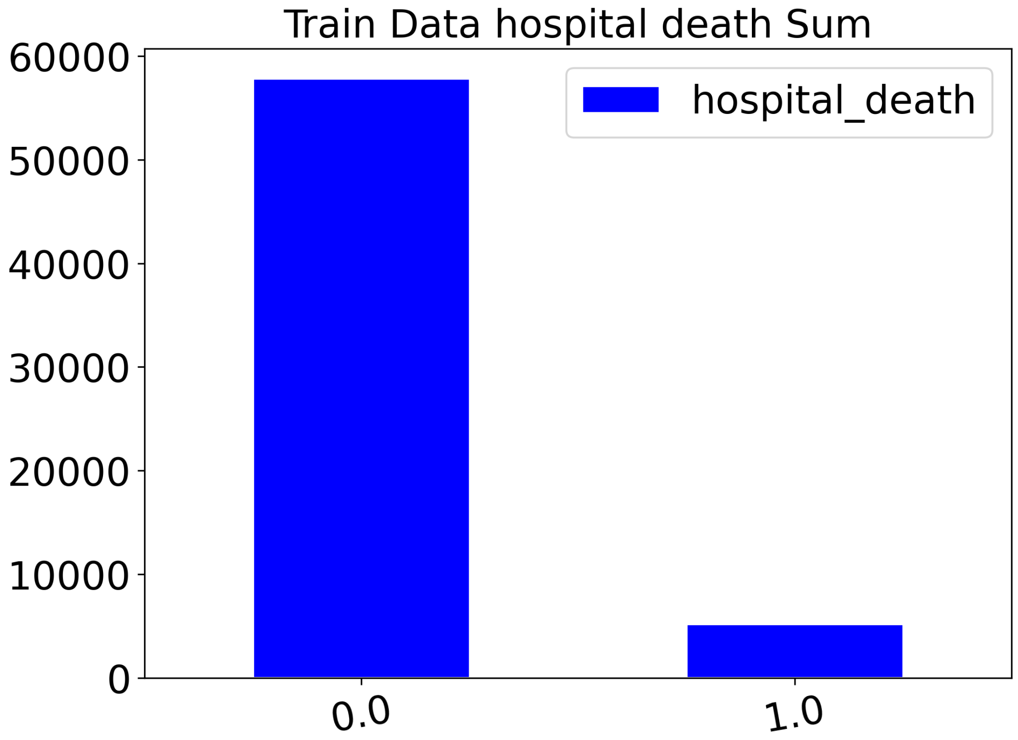
XGboosting: (optimize number of features)

Methods


Data Integration
Lab Data
Vital Sign
Patients' Demographics
Data Preprocessing
Model Training
Prediction
Evaluation Model
Explanation
Action
Integration with Prior belief
ICU Clinical Support

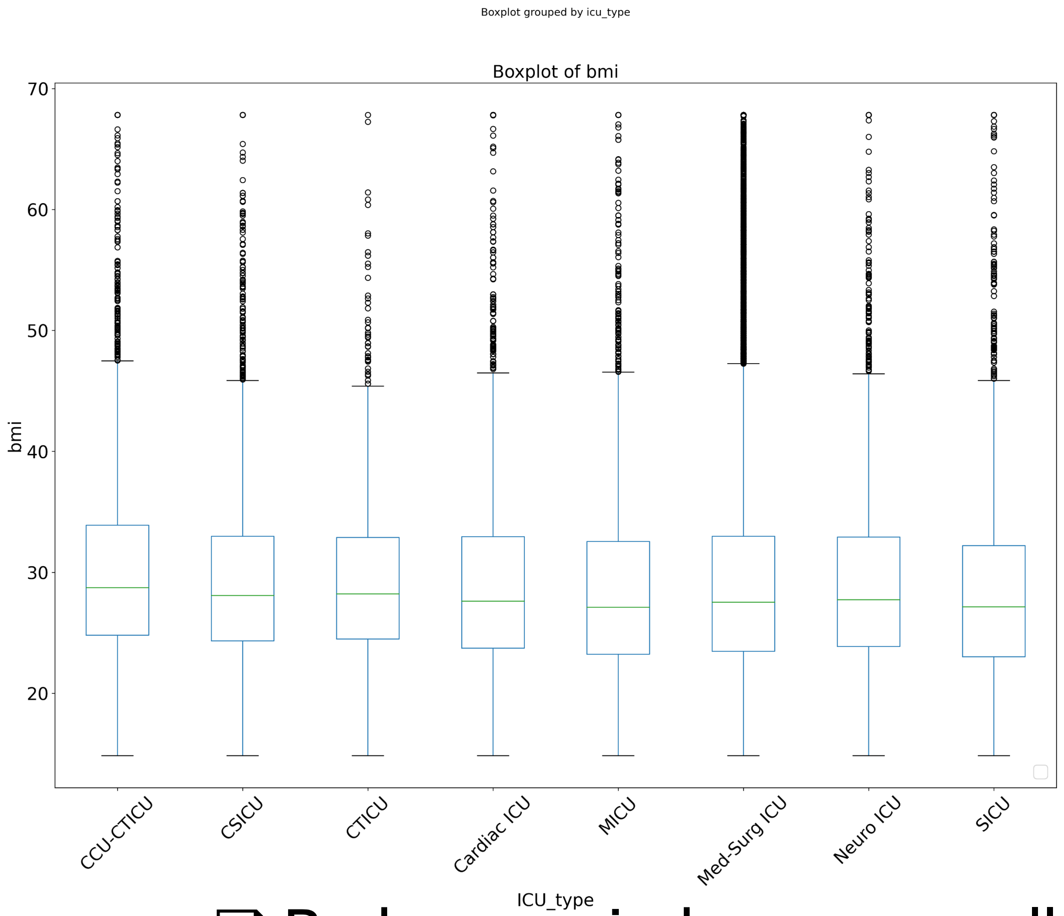
Exploratory Data Analysis

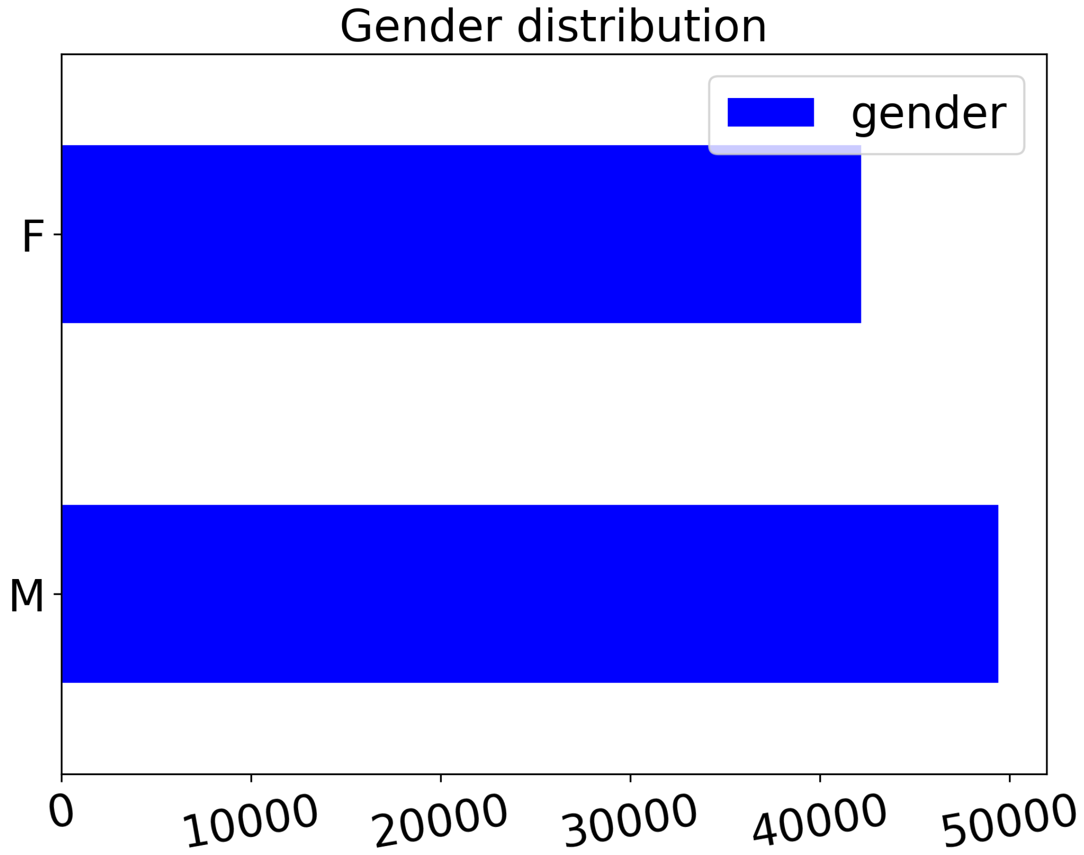




- ❑ Patients’ age over 90 are excluded from the data
- ❑ Imbalanced data of deaths and survival in training data

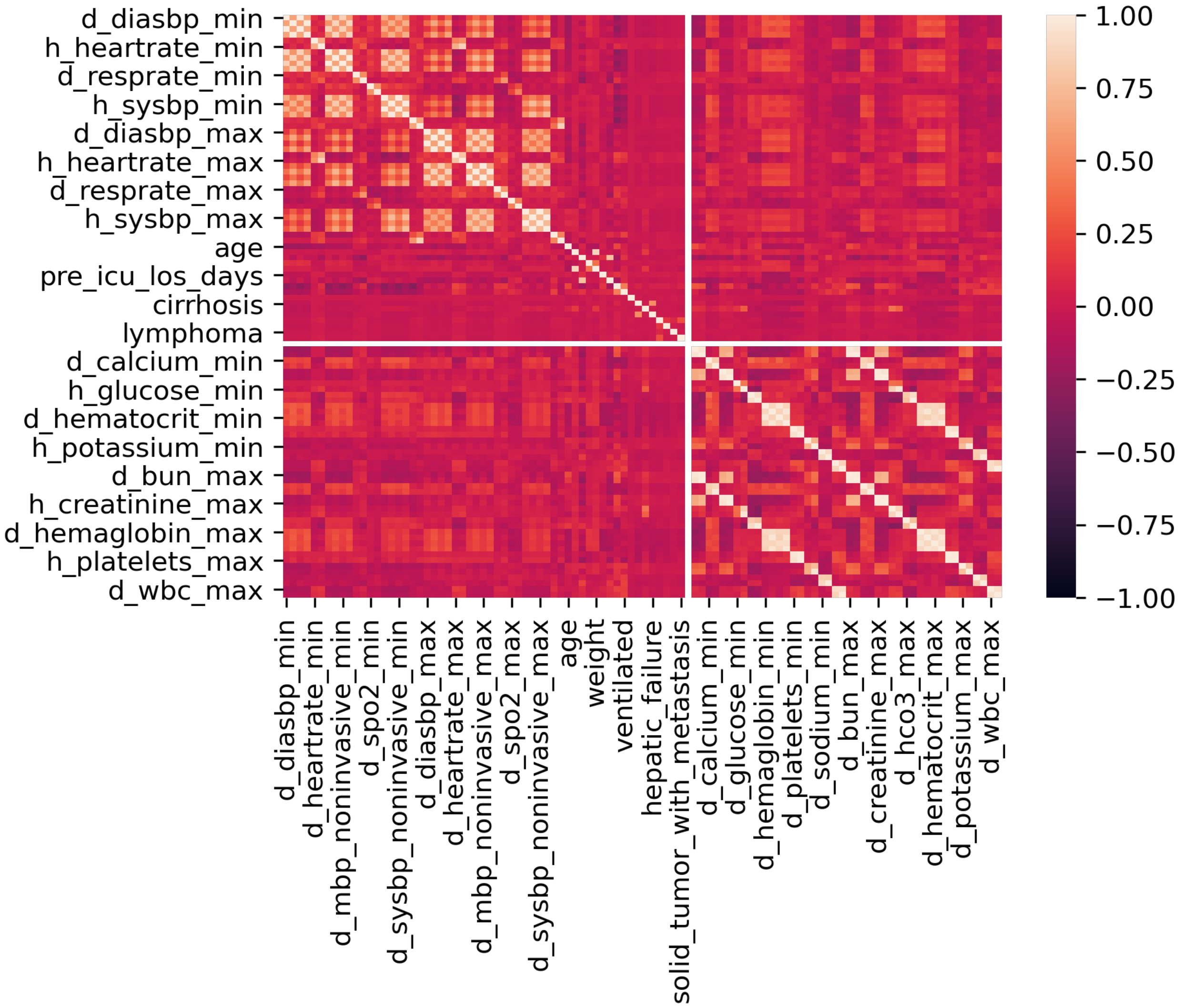
Exploratory Data Analysis





- ❑ Body mass index are equally distributed in the ICU Types.
- ❑ Gender data are balanced.

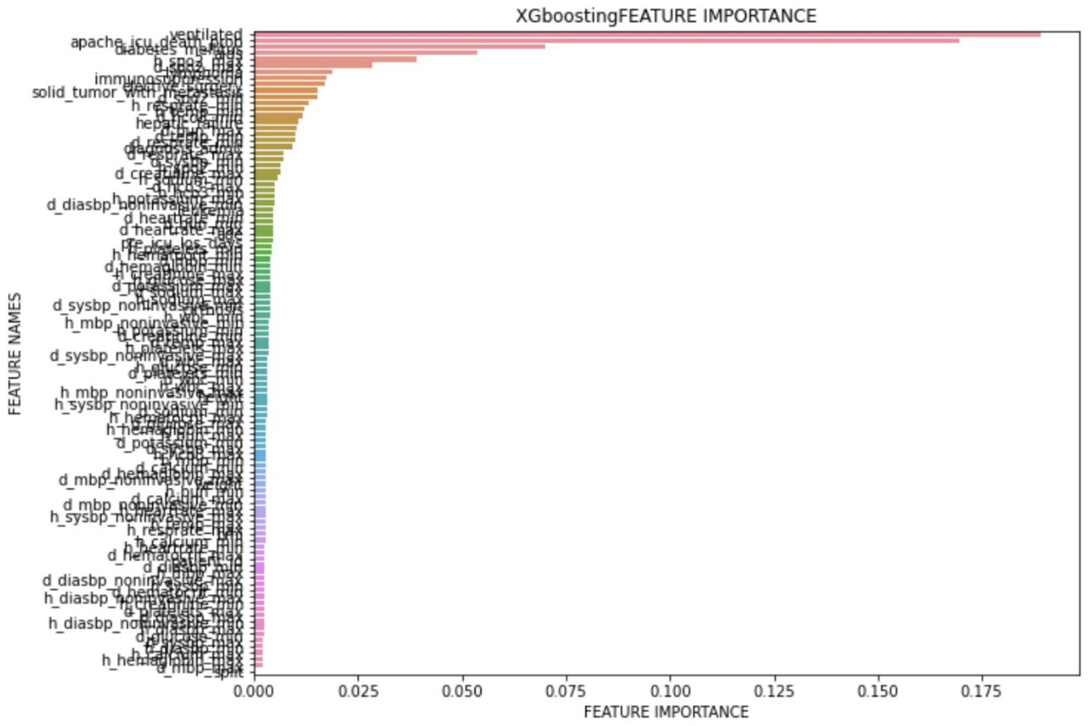
Feature Correlation & Sig Predictors



- Heat map identifies the features of high or low correlation features.
- Solid tumor metastasis, lymphoma, day_diasbp_min, and day_mbc_max are removed from the model for high correlation with any other features.
- Cirrhosis is removed due to the none correlation to other features

Feature Importance Ranking

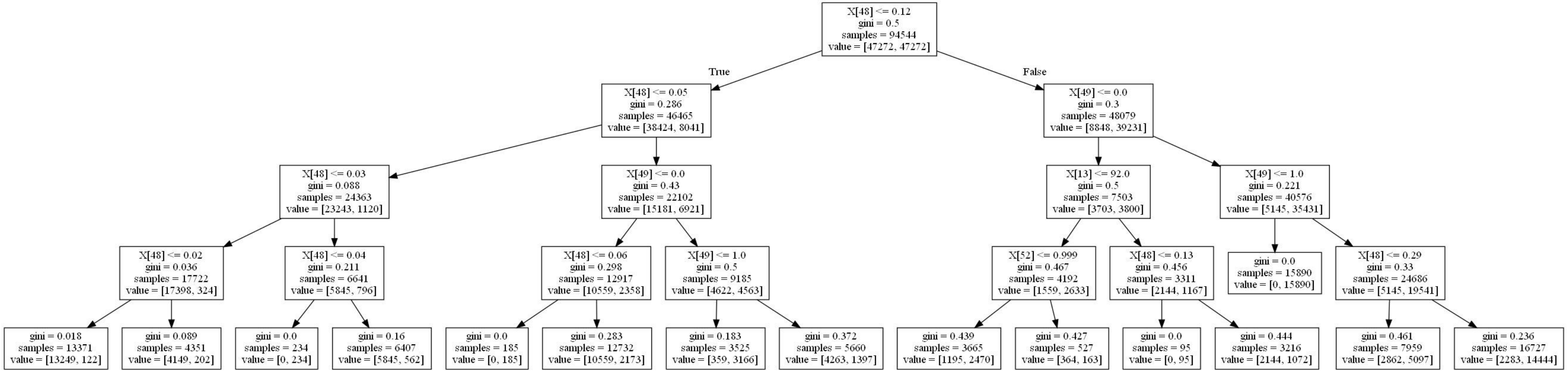
- The outcomes only stands out four features, Other features show no effect thus remove from the model.
- Hyperparameter tuning is applied to use only four features that have the importance to the model



Decision Tree Feature Importance

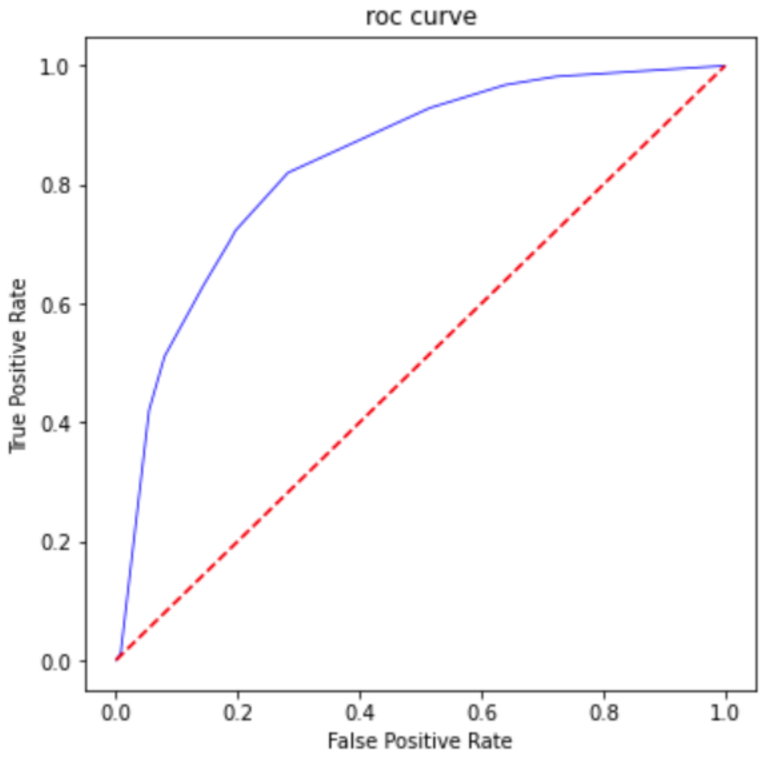
	Features	Coefficient
48	apache_icu_death_prob	0.785
49	ventilated	0.191
52	diabetes_mellitus	0.023
15	d_sysbp_min	0.001

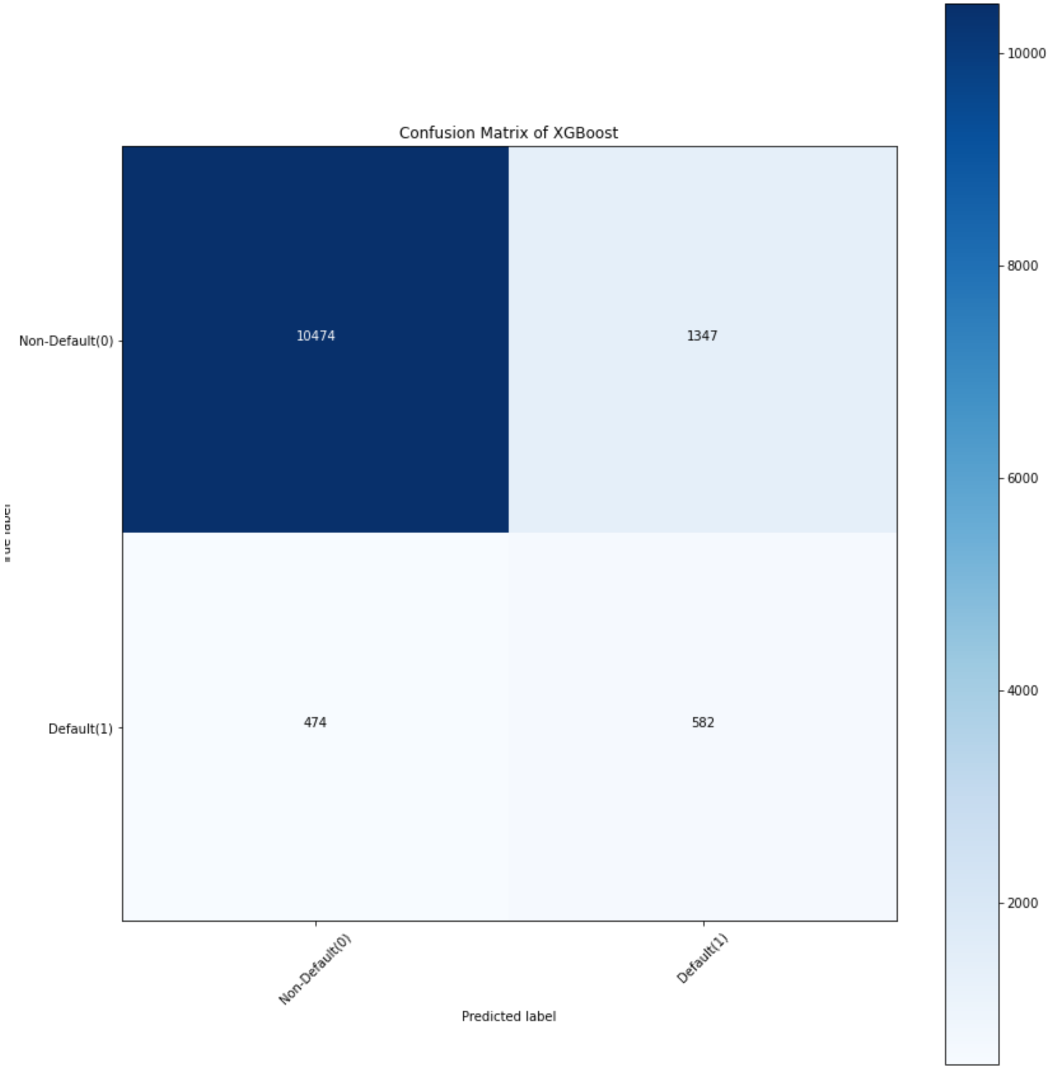
Decision Tree for Clinical Implication



- Calibration: APACHE <= 0.12
- Clinical Critical Value:
  - Ventilated < 0
  - diabetes_mellitus: <= 0.99,
  - systolic blood pressure: <= 92.0

Hyperparameter Tuning





Models Performance Comparison

	5- Folds Cross validation Mean accuracy sore	F1 Score	Recall Confusion Matrix (TPR)	AUC ROC curve	Confusion Matrix (FPR)
Decision Tree	0.79	0.36	0.73 **	0.84	0.20
KNN	0.91	0.36	0.42	0.62	0.08
Logistic Regression	0.92	0.41	0.68	0.78	0.15
XGboosting	0.93 **	0.68 **	0.55	0.88 **	0.11**

Findings & Implication

- The machine learning-based models developed in this study are compared to their prediction performance on each metric. Amongst them, XGboosting showed the best performance in predicting the risk of in-hospital death.
- The model provides the calibration of the APACHE probability and control of ventilated levels to protect the patients at risk. Other features like diabetes mellitus can be used as a reference to prioritize the patients at risk.
- It has the potential to assist physicians in the ICU to perform appropriate clinical interventions for critically ill patients and thus may help improve the pre-diagnostic of patients in the ICU.

Questions & Answers

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