Forecasting In-Hospital Mortality in ICU Patients

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AGENDA

- ❑ Introduction
- ❑ About the Dataset
- ❑ ML Implementation
- ❑ Results
- ❑ Conclusions

INTRODUCTION

Congestive Heart Failure (CHF)

It's a chronic and progressive condition where the heart muscle doesn't pump blood as effectively as it should. Can be a serious condition that, if left untreated or poorly managed, can lead to complications, including fatalities.

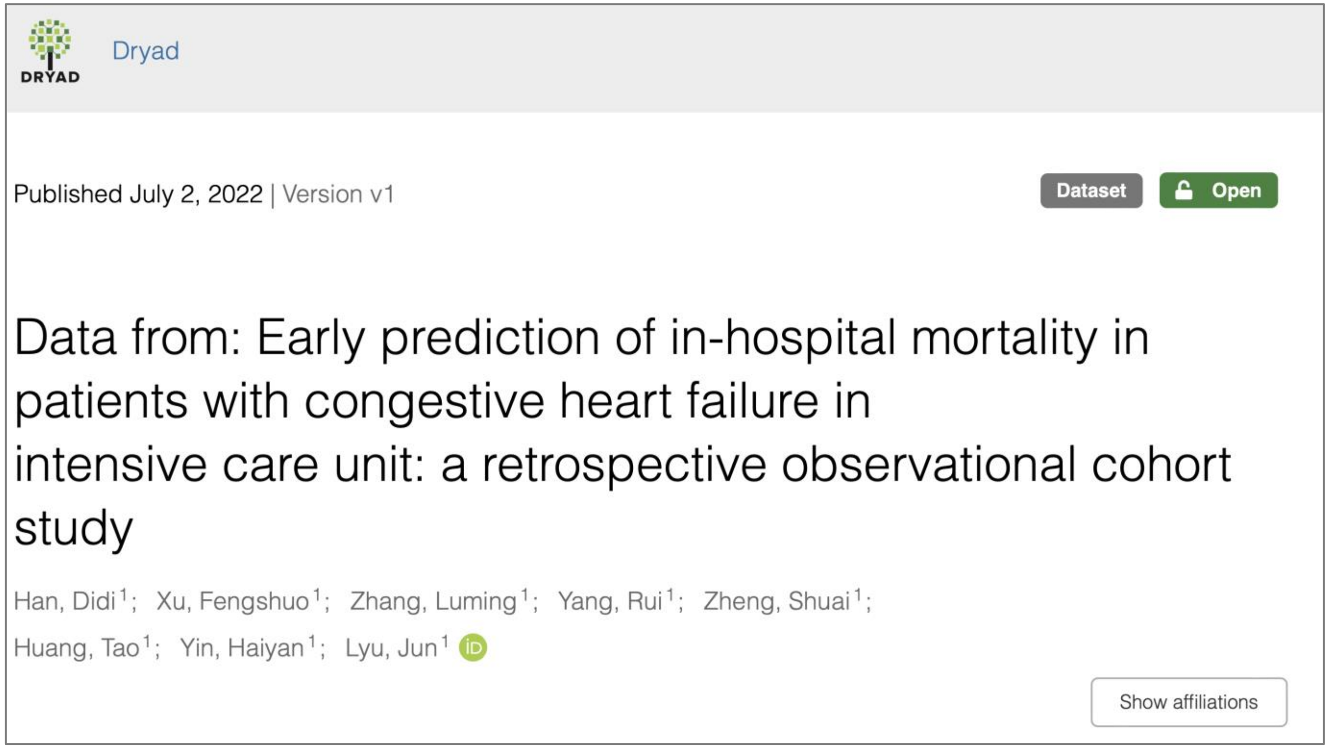
Our Objective

Comprehend the primary determining factors in a patient's history that could forecast the likelihood of mortality resulting from their past heart condition. This information is collected from a large, comprehensive dataset comprising clinical information such as vital signs, laboratory test results, procedures, and more (MIMIC).

ABOUT THE DATASET

ICU Mortality data obtained from MIMIC-IV database

- ❑ Data of study consists of 30,411 ***Congestive heart failure (CHF) patients stored in the Medical Information Mart of Intensive Care (MIMIC-IV) database.***
- ❑ Inclusion criteria (total number of records): **15,983 subjects** who's in-hospital mortality rate was **12.4%**.



Dryad

Published July 2, 2022 | Version v1

Dataset | Open

Data from: Early prediction of in-hospital mortality in patients with congestive heart failure in intensive care unit: a retrospective observational cohort study

Han, Didi[1]; Xu, Fengshuo[1]; Zhang, Luming[1]; Yang, Rui[1]; Zheng, Shuai[1]; Huang, Tao[1]; Yin, Haiyan[1]; Lyu, Jun[1]

Show affiliations

Number of Features: 38

Target variable: In-hospital mortality (Hstatus) → [0, 1]

Variables included in the datasets:

- ❑ Age, race and gender
- ❑ Any special condition of the patient: diabetes, hepatitis, vasopressin, mechanical ventilation, ...
- ❑ Vital signs: temperature, heart rate, blood pressure, ...
- ❑ Blood chemistry: creatinine, chloride, RDW (red cell distribution width, ...

Data Science Process

Data Exploration

Descriptive statistics
Distributions

Data Cleansing

Missing imputation
Hot encoding

Feature Selection

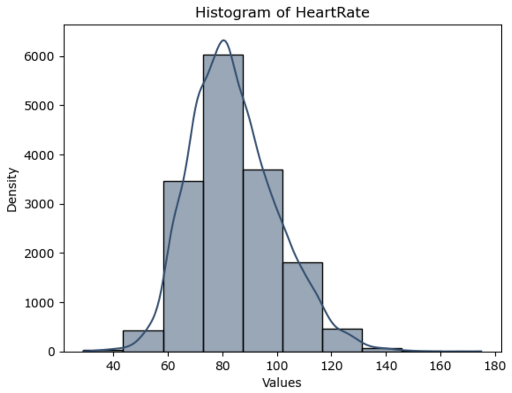
Applying different methodologies such as Variance Threshold, RFE, etc.

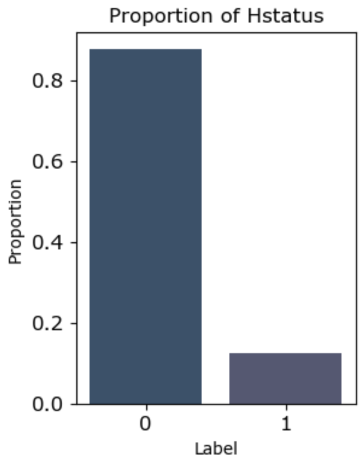
Modeling

Application of several ML classifier algorithms

Predictions

Prediction of out-of-sample data





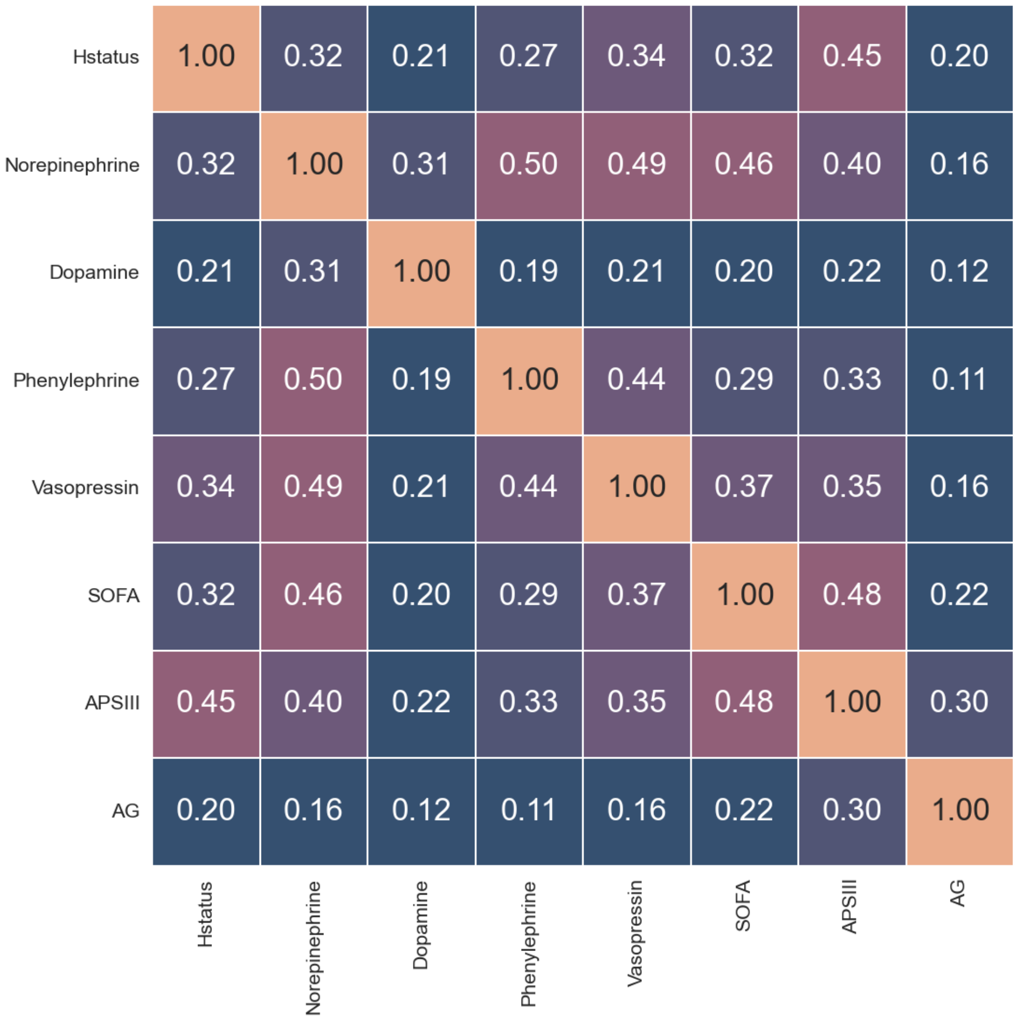
- ❑ Phase 1:
Generation of multiple combination of feature selection– feature scaling – model algorithm.

- ❑ Phase 2:
Generation of the ML pipeline to be exported as a pickle file for future predictions.

MOSTLY·AI

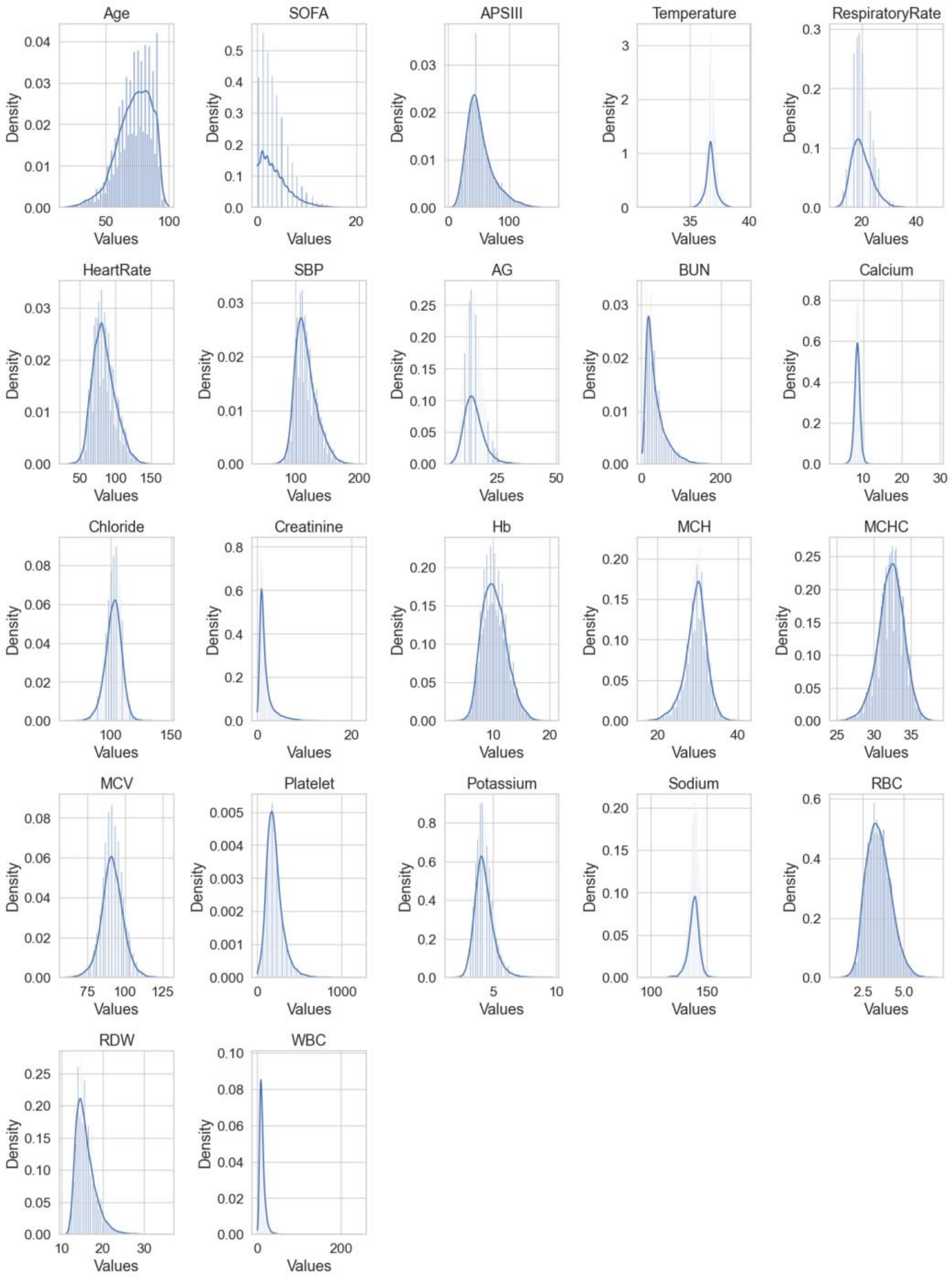
An online platform to generate synthetic data with AI capabilities.

Data Exploration and Data Cleansing



Highest correlations:

- **Norepinephrine**: used as a medication to increase blood pressure.
- **Dopamine**: improves heart function and increase blood pressure.
- **Phenylephrine**: raise blood pressure in cases of hypotension.
- **Vasopressin**: regulates water balance in the body and can constrict blood vessels.
- **SOFA**: scoring system used to track a patient’s status in ICU.
- **APSIII**: scoring systems to assess illness severity.
- **AG (Anion Gap)**: used for metabolic disorders diagnosis.



Skewed variables:

- PSIII (Acute Physiology Score III)
- Temperature.
- AG (Anion Gap)
- BUN (Blood Urea Nitrogen)
- Calcium
- Creatinine
- Platelet
- Potassium
- Sodium
- RDW (Red Cell Distribution Width)
- WBC (White Blood Cell Count)

ML IMPLEMENTATION

Implementation

Feature Selection	Feature Scaling	ML Model
❑ Variance Threshold ❑ SelectKBest method ❑ SelectFromModel method (Logistic Regression) ❑ Random Forest (Feature Importance) ❑ Recursive Feature Elimination ❑ Generalized Linear Model	❑ Standard Scaling ❑ Min-Max Scaling ❑ Robust Scaling	❑ Logistic Regression ❑ Random Forest ❑ Decision Tree ❑ Gaussian Naïve Bayes ❑ Multinomial Naïve Bayes ❑ XGBoost

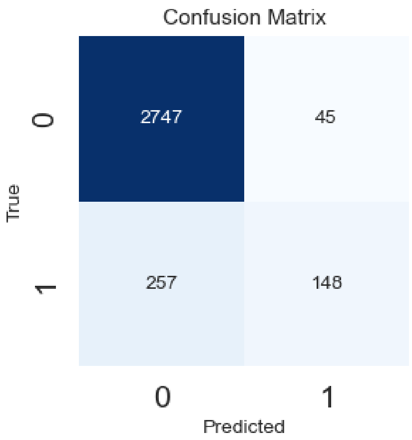
- ❑ First step: Apply all combinations of these 3 steps without using *sklearn* pipelines (*309 combinations tested*).
- ❑ Second step: Pick the best combination and execute them through *sklearn* pipeline for the ML deployment

Let´s see how it works!

RESULTS

Best Model – Criteria Accuracy

- **Feature Selection Method:** Random Forest feature importance
- **Feature Scaling:** standard scaling
- **ML Model: Random Forest** (min sample split = 5 – number of estimators: 500)

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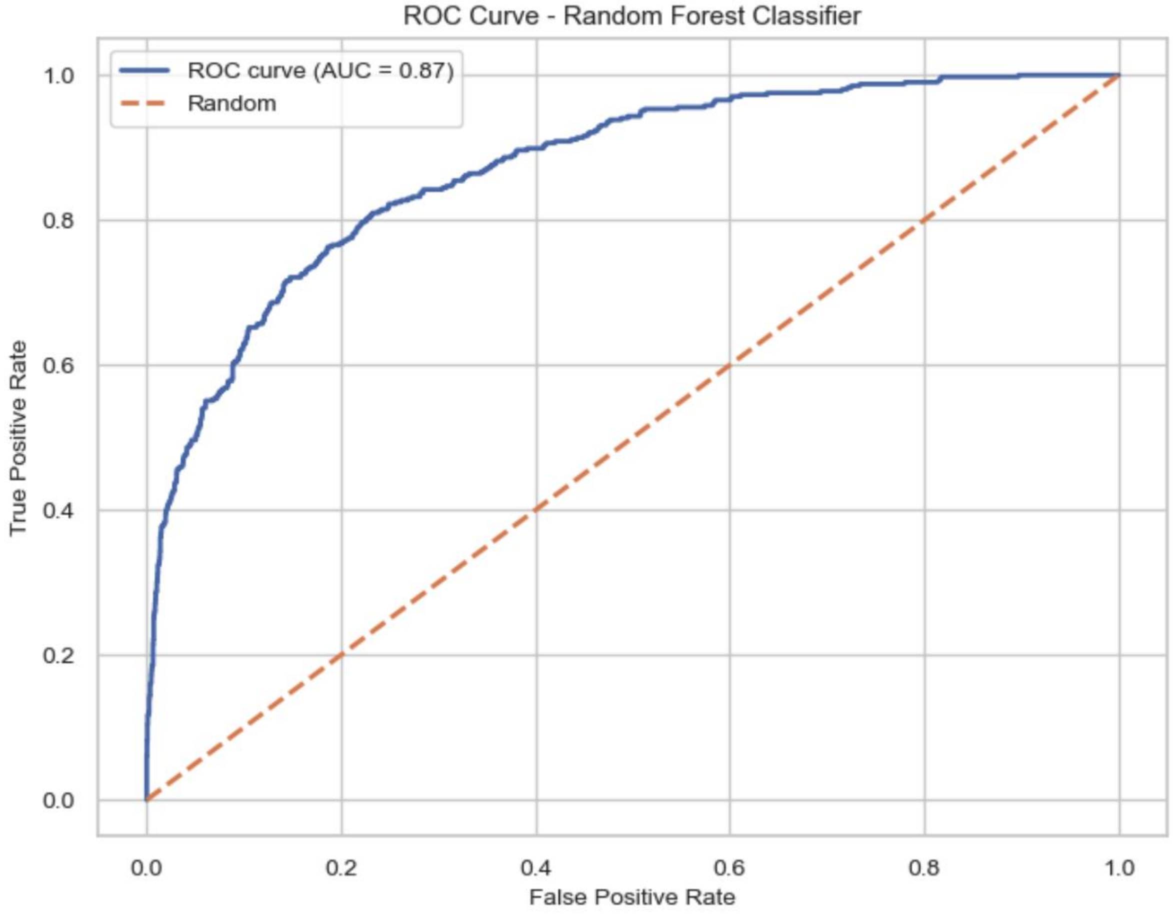
Evaluation Metrics on Test Set:
Accuracy: 0.9055
Precision: 0.7668
Recall: 0.3654
F1-Score: 0.4950
```

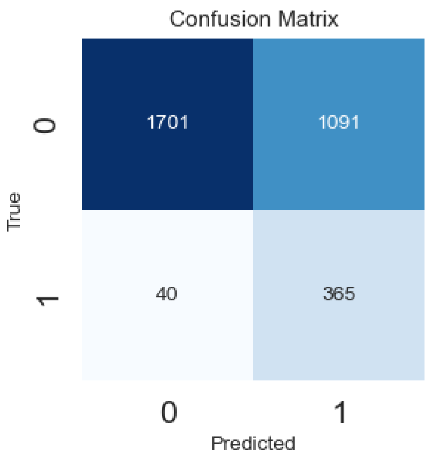


Selected features

Vasopressin, Age, SOFA, APSIII, Temperature, RespiratoryRate, HeartRate, SBP, AG, BUN, Calcium, Chloride, Creatinine, Hb, MCH, MCHC, MCV, Platelet, Potassium, Sodium, RBC, RDW, WBC

Best Model – Criteria Recall

- ❑ **Feature Selection Method:** Recursive Feature Elimination (Decision Tree Estimator)
- ❑ **Feature Scaling:** standard scaling
- ❑ **ML Model: XGBoost** (learning_rate= 0.01 - max_depth=3 - n_estimators= 300)

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Evaluation Metrics on Test Set:
Accuracy: 0.6462
Precision: 0.2507
Recall: 0.9012
F1-Score: 0.3923
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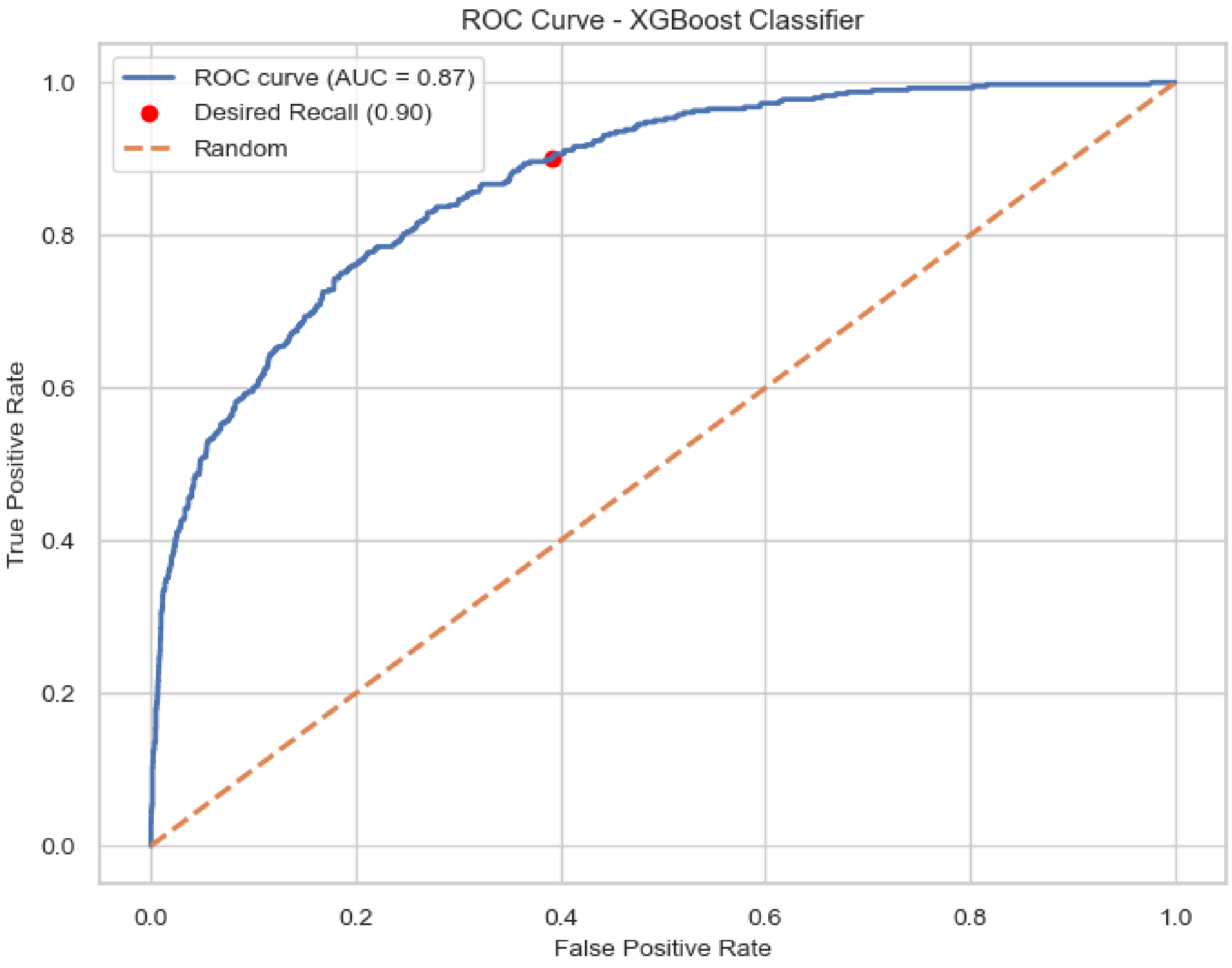

Selected features

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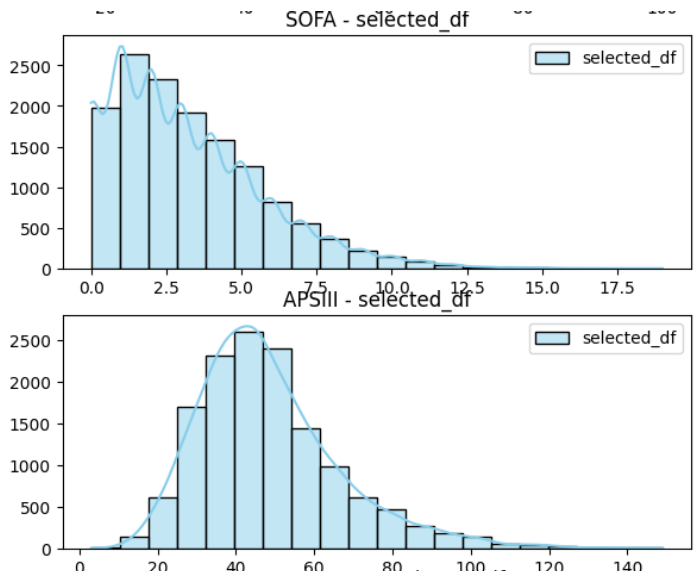
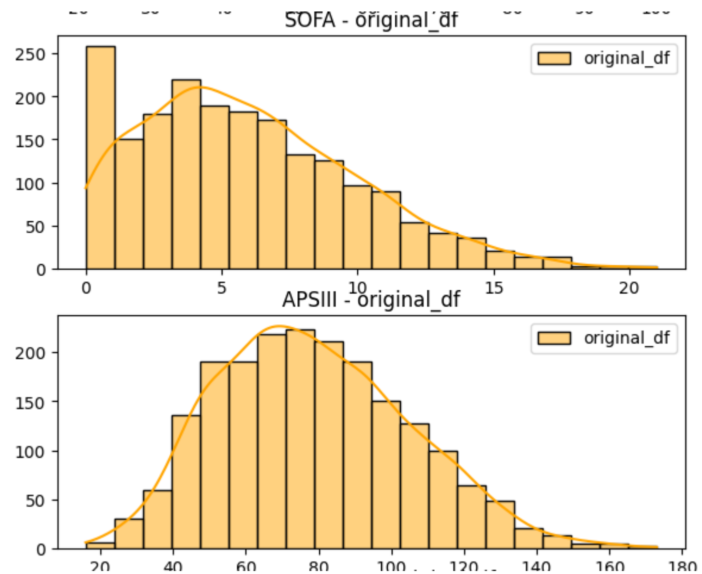
Hstatus 1



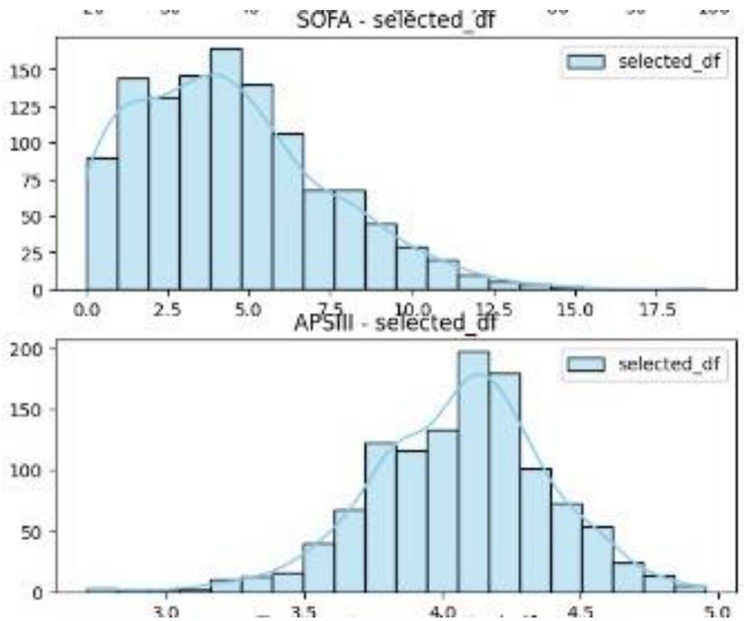
Hstatus 0



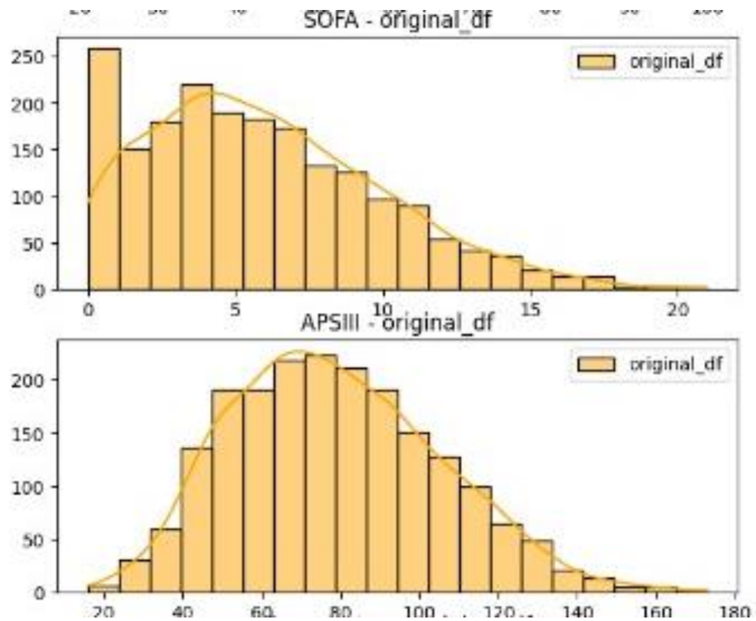
Mortality / Non-mortality

True Positive vs False Positive

Hstatus 1 – True Positive



Hstatus 1 – False Positive



CONCLUSIONS

Final selected features

- **Vital Factors**: Vasopressin, Age, SOFA, and APSIII emerged as pivotal factors influencing the prediction of CHF outcomes, showcasing their substantial predictive strength.
- **Physiological Indicators**: Temperature, Respiratory Rate, Heart Rate, and Systolic Blood Pressure (SBP) provided significant insights, reflecting their relevance in predicting CHF outcomes.
- **Metabolic Markers**: AG, BUN, Calcium, Chloride, Creatinine, and Potassium played crucial roles, highlighting the impact of metabolic indicators on predicting CHF-related mortality.
- **Hematological Insights**: Platelet count, Sodium, Red Blood Cell (RBC) characteristics (MCH, MCHC, MCV), RDW, and White Blood Cell count (WBC) contributed notably, indicating the significance of hematological parameters in outcome predictions for CHF.

Future work

- Explore deep learning algorithms such as Convolutional Neural Networks and LSTM (Long short-term memory).
- Increase the infrastructure capabilities to execute more robust algorithms (e.g. AWS Sagemaker, Azure Notebooks, Databricks).
- In clinical healthcare, enhancing model recall is crucial for accurately identifying patients at risk of not surviving ICU stays. Prioritizing patients who may need intensive care relies on the probability of requiring an ICU bed, considering the limited capacity of such facilities.

THANK YOU!