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Capstone Presentation
Springboard School of Data
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Predicting Sepsis in ICU Patients

Earlier intervention for better health outcomes

Project GitHub Repository:

https://github.com/Aisling-C/Springboard/tree/main/CapstoneProject1/PredictingSepsis/notebooks

Problem Identification

Context
Sepsis is a leading cause of death in US hospital patients

Solution Space
Classification of pre and non sepsis patients

Success Criteria
Accurate classification of pre and non sepsis patients in test set

Data Source
Hourly data from 40,336 ICU patients in 2 hospitals

Problem Statement: Early intervention in sepsis patients can lead to better health outcomes. Is it possible to predict sepsis in ICU patients hours before clinical diagnosis?

Data Structure & Source

Time (Hours)	Vital Signs 1-8	Laboratory Values 9-34	Demographics 35-40	Sepsis Label 41
t_0	…	…	…	0
t_1	…	…	…	1
….	…	…	…	0
t_n	…	…	…	0

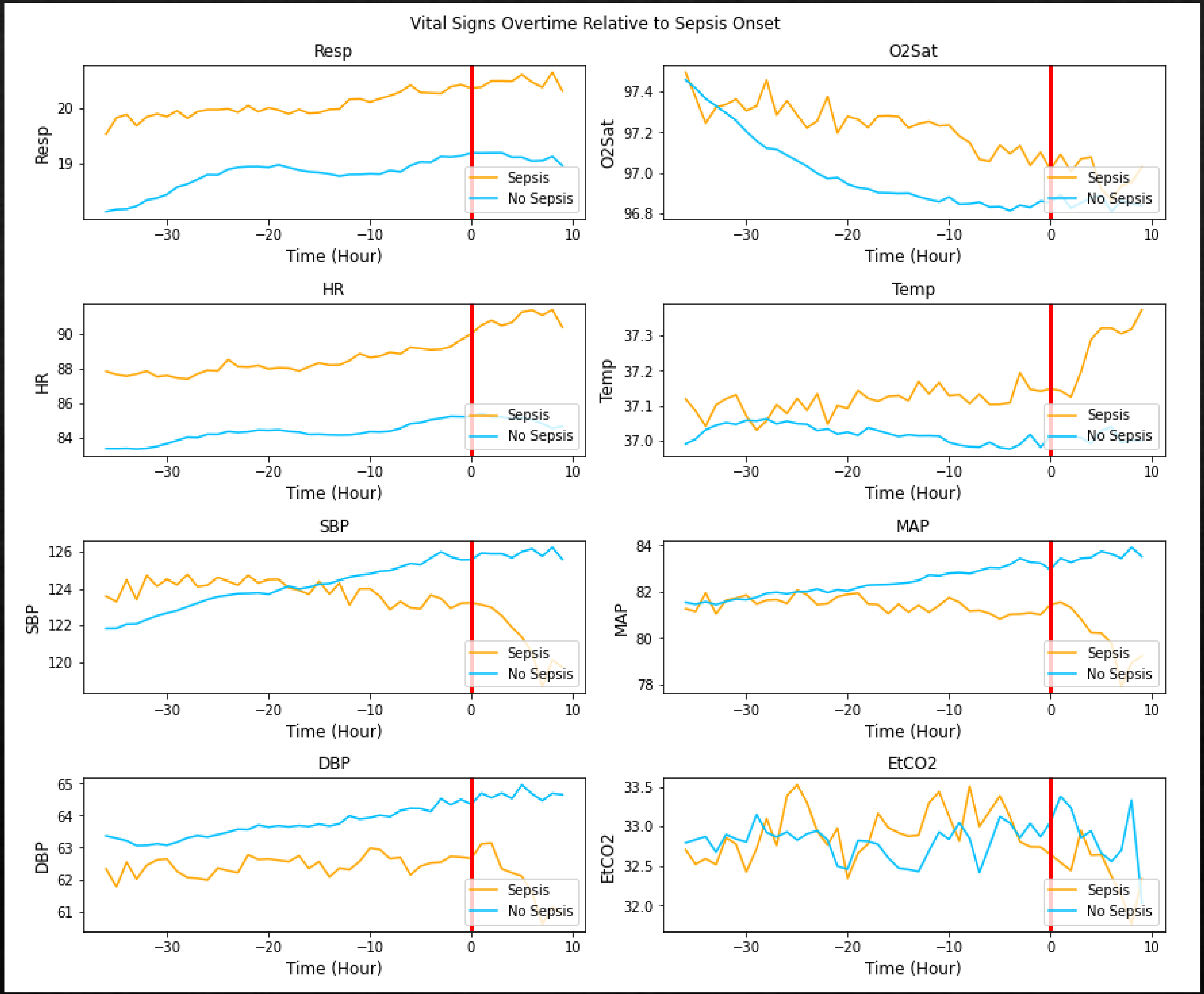
Data made available by Physionet Computing in Cardiology Challenge 2019

Second classifier column, pre-sepsis, added

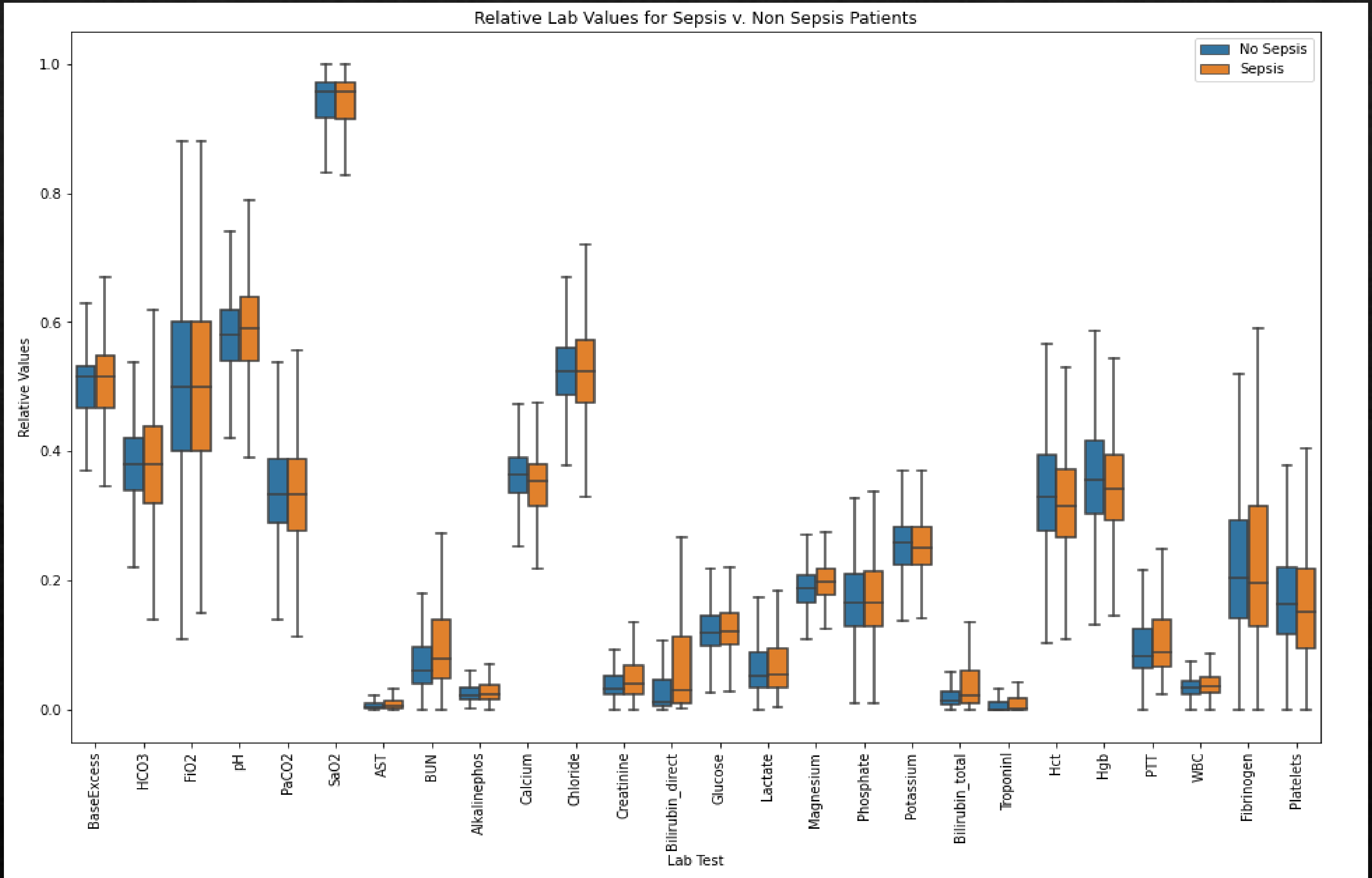
Sepsis Prevalence

Of **40,336** patients available in the data set, **7.27%** develop sepsis at some point during their hospital stay.

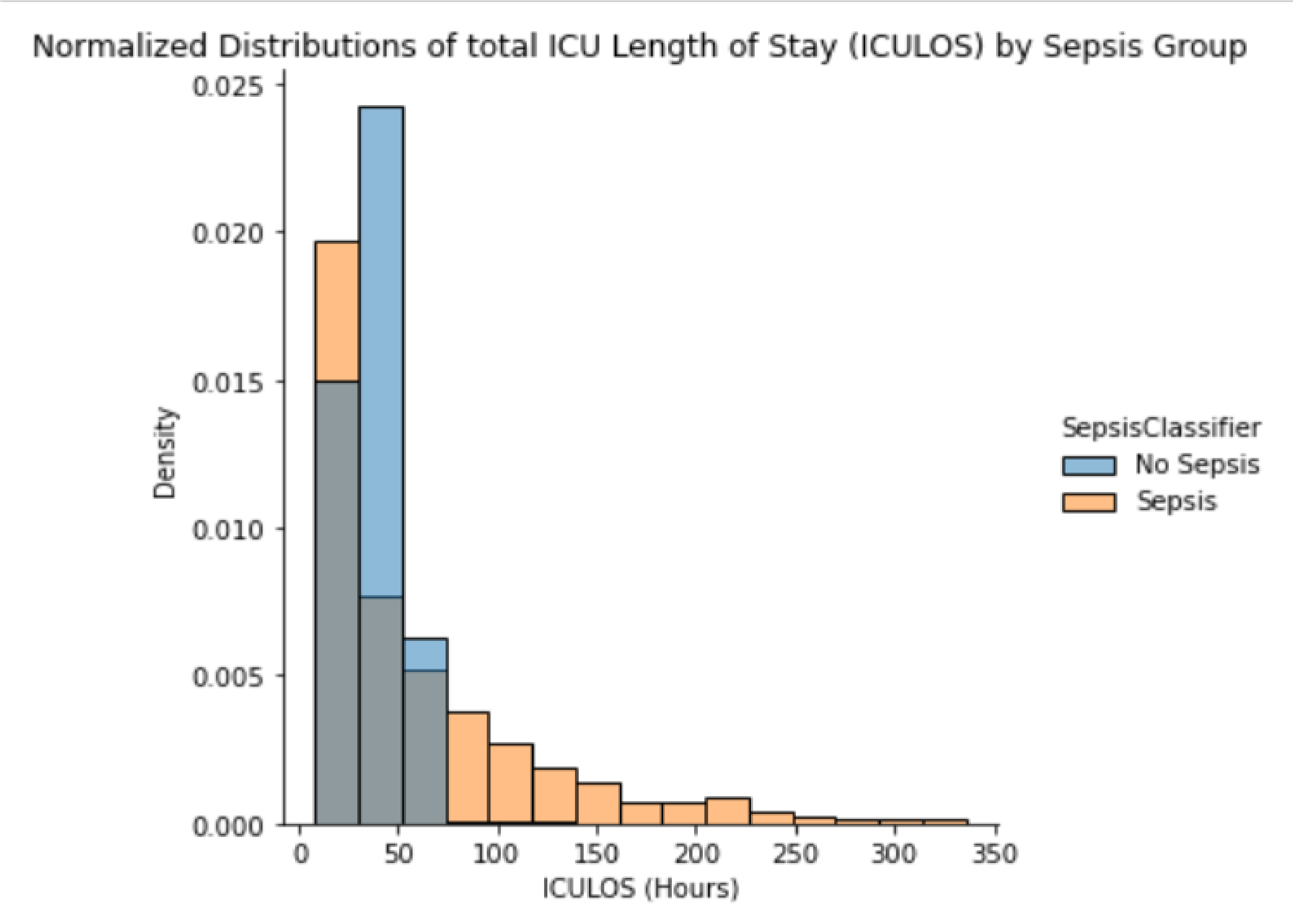
Exploratory Data Analysis: Vital Signs



Exploratory Data Analysis: Normalized Lab Values



Exploratory Data Analysis: ICU Length of Stay



Feature Engineering

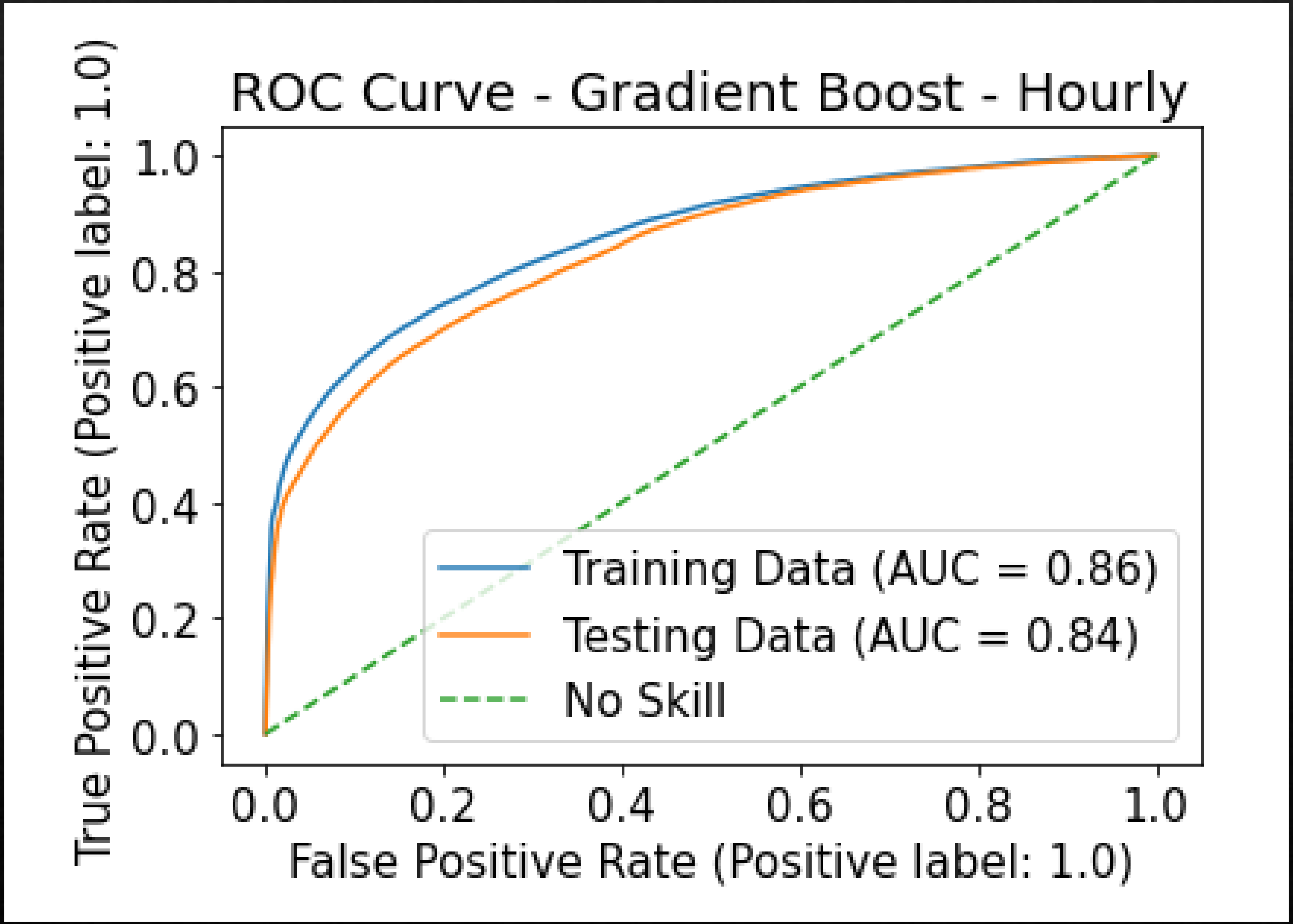
- Interpolation & forward filling
  - Lab & Vital Sign Data
- Changes in vital sign column
  - Past 1, 2, 3 Hours
- Lab value indicator, forward filled

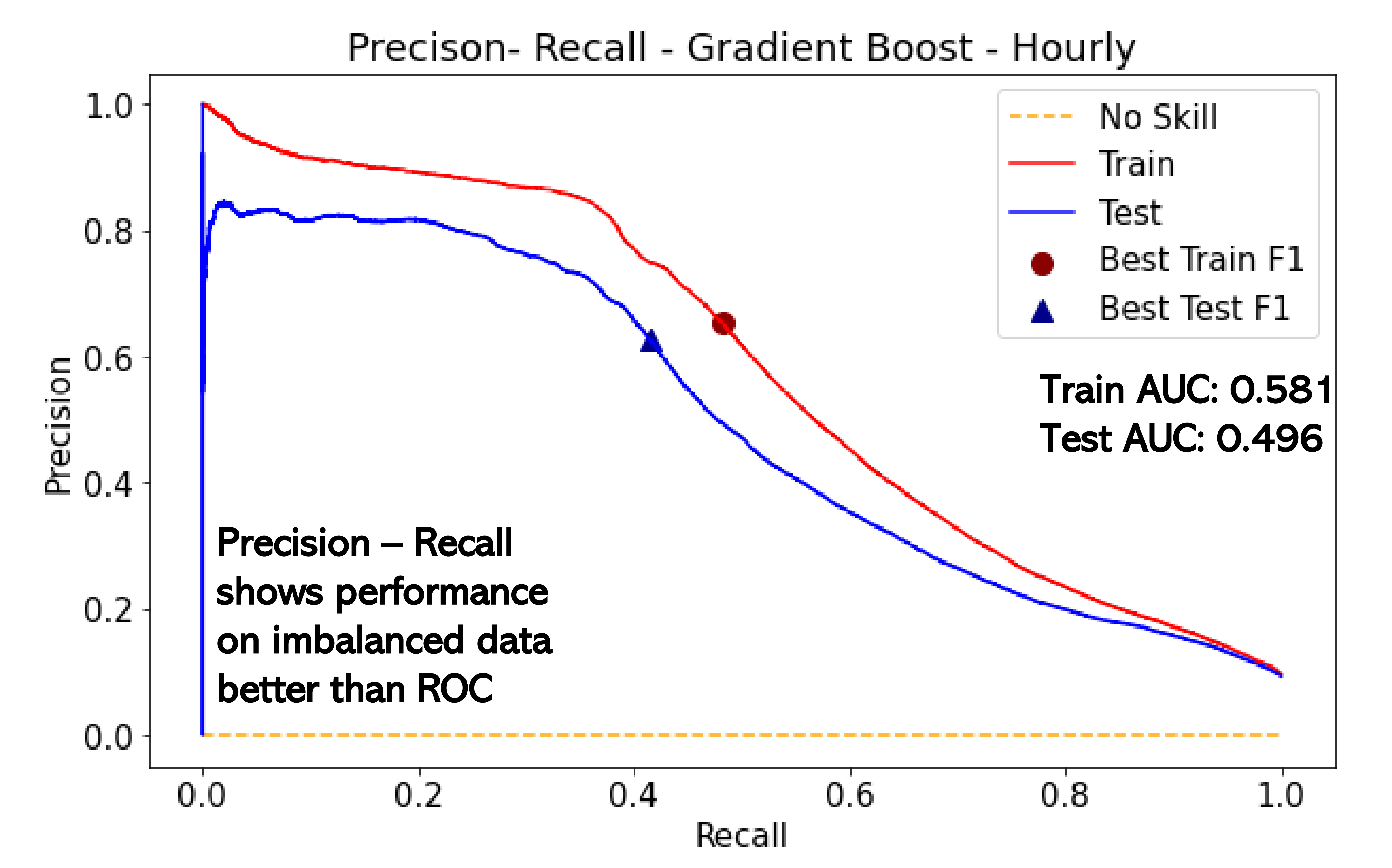
	d3_HR	d2_HR	d1_HR	HR
0	0.0	0.0	0.0	97.0
1	0.0	0.0	0.0	97.0
2	0.0	-8.0	-8.0	89.0
3	-7.0	-7.0	1.0	90.0
4	6.0	14.0	13.0	103.0
5	21.0	20.0	7.0	110.0
6	18.0	5.0	-2.0	108.0
7	3.0	-4.0	-2.0	106.0
8	-6.0	-4.0	-2.0	104.0
9	-6.0	-4.0	-2.0	102.0
10	-2.0	0.0	2.0	104.0

Final Model Results

Classification Scheme 1: Hourly Classification

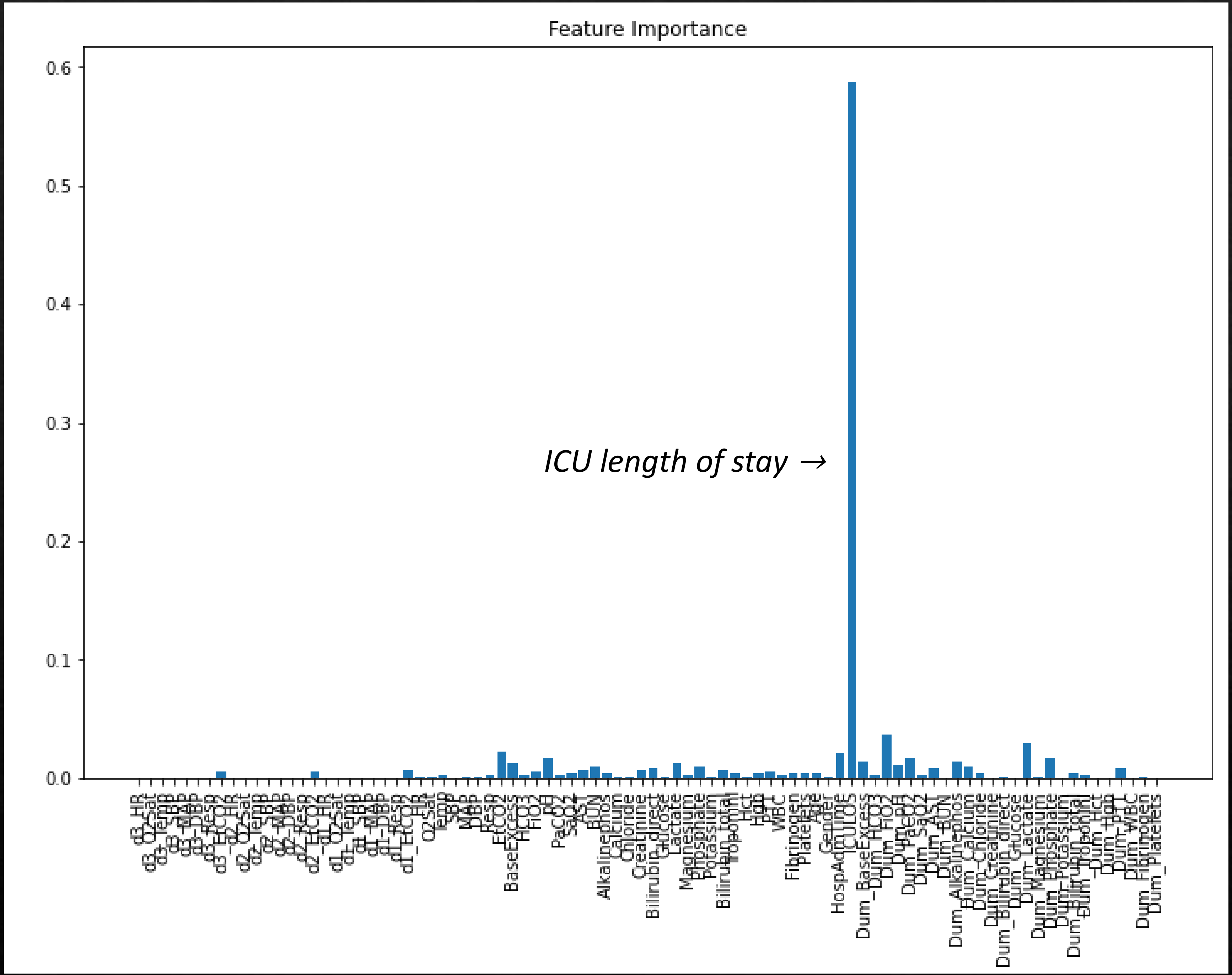
- Hour by hour classification of a patient being in the pre-sepsis period or not.


ROC Curve - Gradient Boost - Hourly
True Positive Rate (Positive label: 1.0)
False Positive Rate (Positive label: 1.0)
0.0
0.2
0.4
0.6
0.8
1.0
Training Data (AUC = 0.86)
Testing Data (AUC = 0.84)
No Skill


Precison- Recall - Gradient Boost - Hourly
No Skill
Train
Test
Best Train F1
Best Test F1
Train AUC: 0.581
Test AUC: 0.496
Precision – Recall
shows performance
on imbalanced data
better than ROC
Precision
Recall
0.0
0.2
0.4
0.6
0.8
1.0

Confusion Matrix: Hourly

Actual	Predicted					
	0	1	0	1	0	1
0	82%	17.9%	97.5%	2.5%	98.4%	1.6%
1	32.1%	67%	58.5%	41.5%	62.9%	37%
Threshold	10%		21.6%		30%	

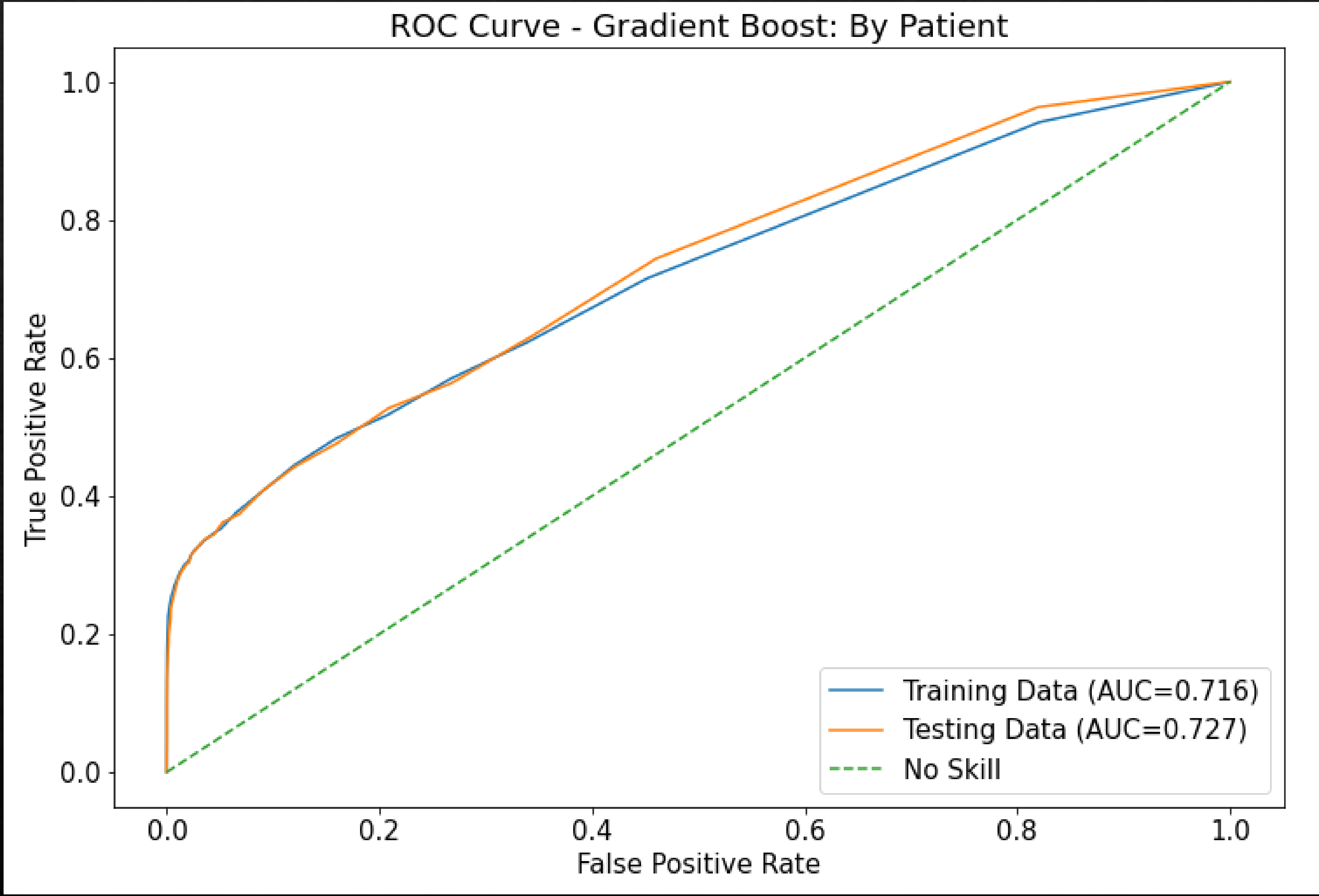

Feature Importance
0.6
0.5
0.4
0.3
0.2
0.1
0.0
ICU length of stay →

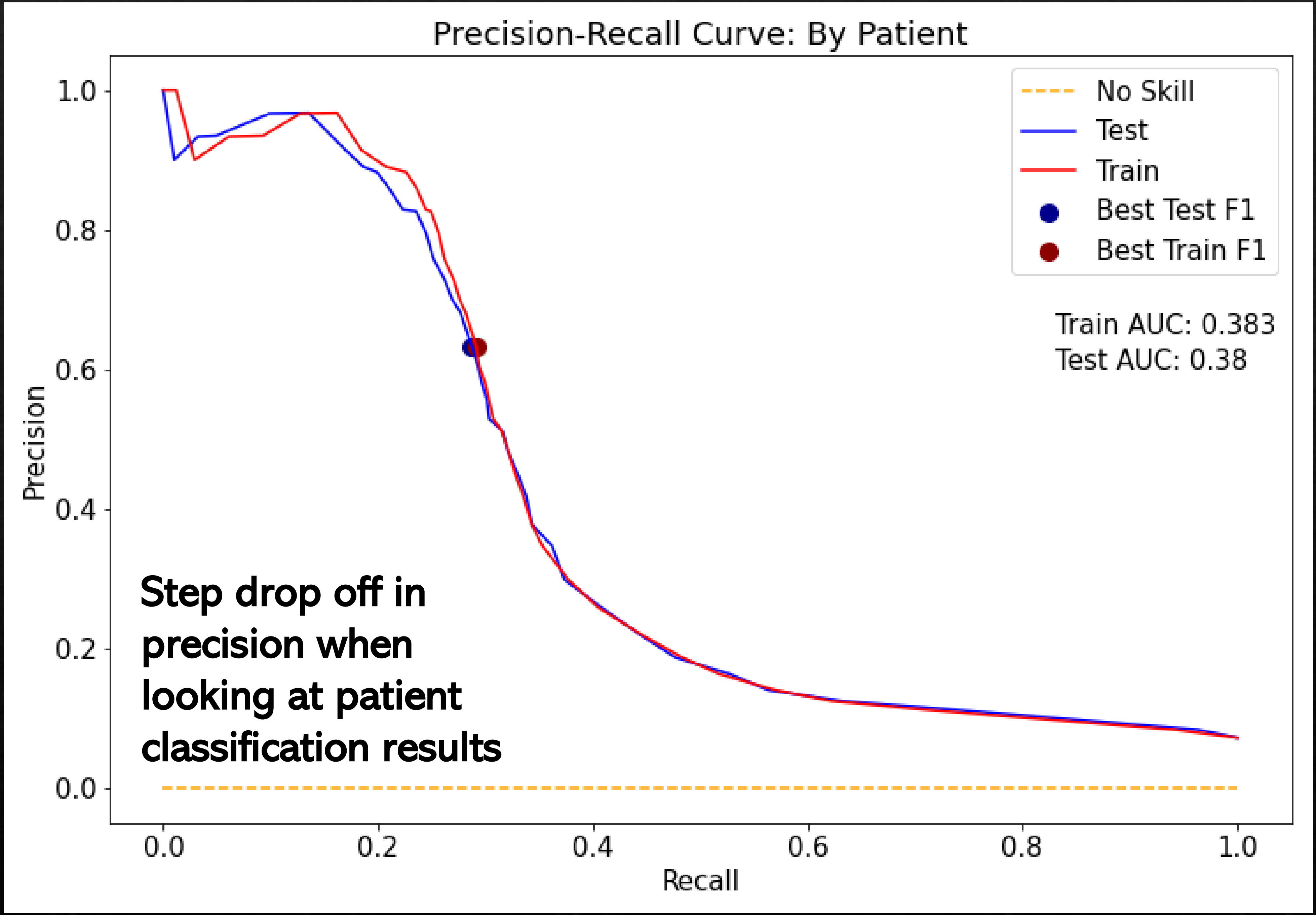
Final Model Results

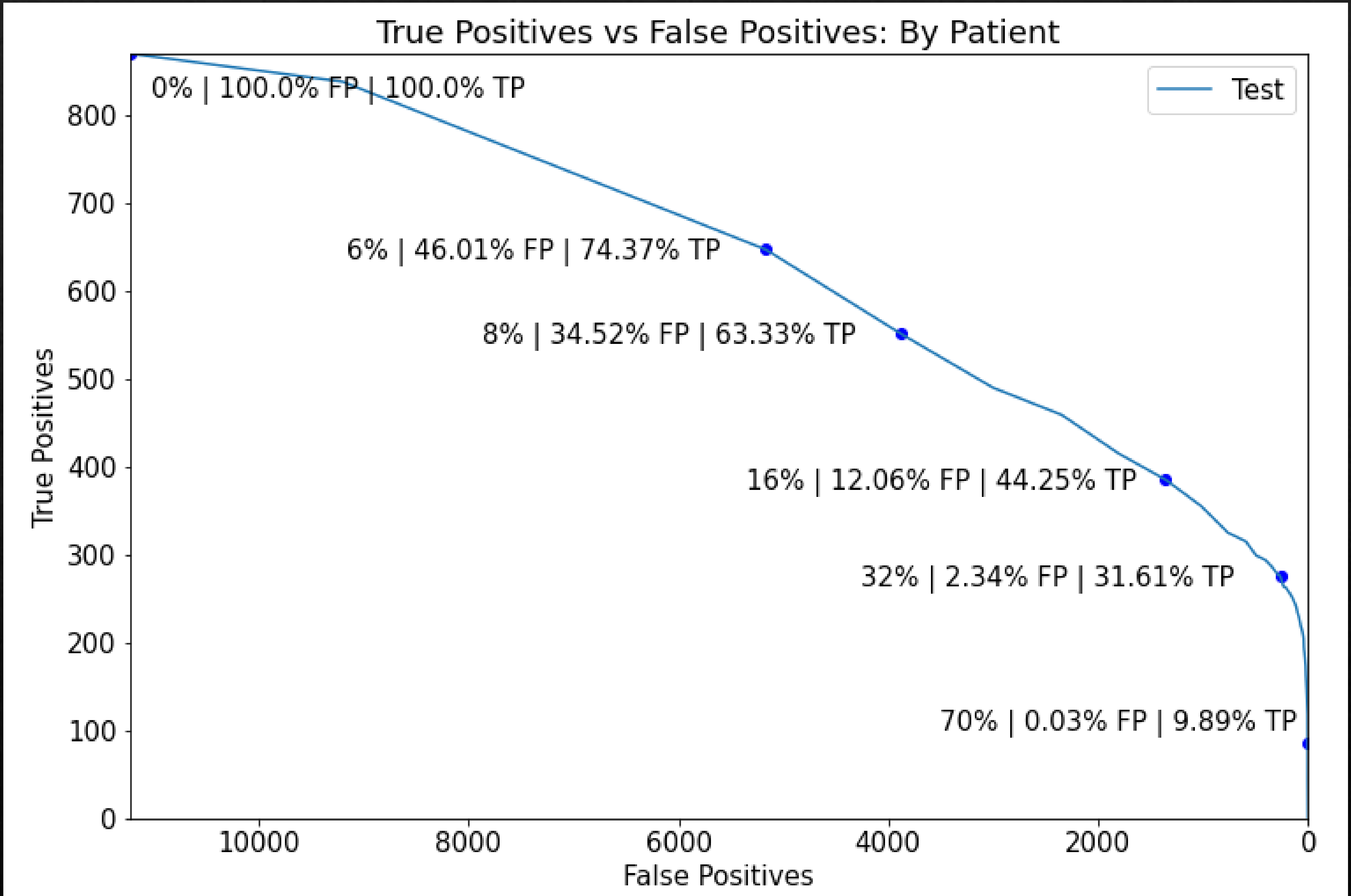
Classification Scheme 2: By-Patient Classification

- Non-sepsis patient classified with any positive hourly predictions, or a sepsis patient with positive prediction at any point in pre-sepsis period : 1

- Non-sepsis patient with no positive predictions, or a sepsis patient with positive prediction only during/after sepsis or not at all: 0


ROC Curve - Gradient Boost: By Patient
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
Training Data (AUC=0.716)
Testing Data (AUC=0.727)
No Skill


Precision-Recall Curve: By Patient
No Skill
Test
Train
Best Test F1
Best Train F1
Train AUC: 0.383
Test AUC: 0.38
Precision
Recall
0.0
0.2
0.4
0.6
0.8
1.0
Step drop off in precision when looking at patient classification results


True Positives vs False Positives: By Patient
Test
0% | 100.0% FP | 100.0% TP
6% | 46.01% FP | 74.37% TP
8% | 34.52% FP | 63.33% TP
16% | 12.06% FP | 44.25% TP
32% | 2.34% FP | 31.61% TP
70% | 0.03% FP | 9.89% TP
True Positives
0
100
200
300
400
500
600
700
800
False Positives
10000
8000
6000
4000
2000
0

Confusion Matrix: Patient Level

Actual	Predicted					
	0	1	0	1	0	1
0	18.1%	81.9%	76%	24%	97.9%	2.1%
1	3.7%	96.3%	45.9%	54.1%	69.7%	30.3%
Threshold	4%		11%		34%	

Use Cases

The by-patient classification schema is used because it more accurately reflects how the model will perform across all patients, regardless of ICU length of stay. It is used for the following scenarios.

Sepsis Concern Eliminator
4% | TPR .96| FPR .81

Indicates if a patient is very unlikely to develop sepsis

Elevated Sepsis Intervention Warning
11% | TPR .54| FPR .24

Sepsis risk elevated; patient should be monitored closely

Critical Sepsis Intervention Warning
34% | TPR .30| FPR .02

Sepsis eminent; clinician should treat for sepsis

Conclusions & Future Directions

- Sepsis is known to manifest very differently in different people
- Nonetheless, the selected gradient boost model had skill in distinguishing groups
- The elevated sepsis intervention use case is the most feasible, because it could augment clinician’s decisions, while not being relied upon too greatly
- For actual clinical use, a model that could predict sepsis onset with greater precision and within a specific time frame is needed
- Recurrent neural net models have seen more success in this, as they can process sequences of data[1]

[1] Liu, L., Wu, H., Wang, Z., Lieu, Z, Zhang, M. Early Prediction of Sepsis From Clinical Data via Heterogeneous Event Aggregation. arXiv.org. 2019 Oct 12; 1910.06792v1.