# Impact of Tissue Oxygenation on Patients with Sepsis

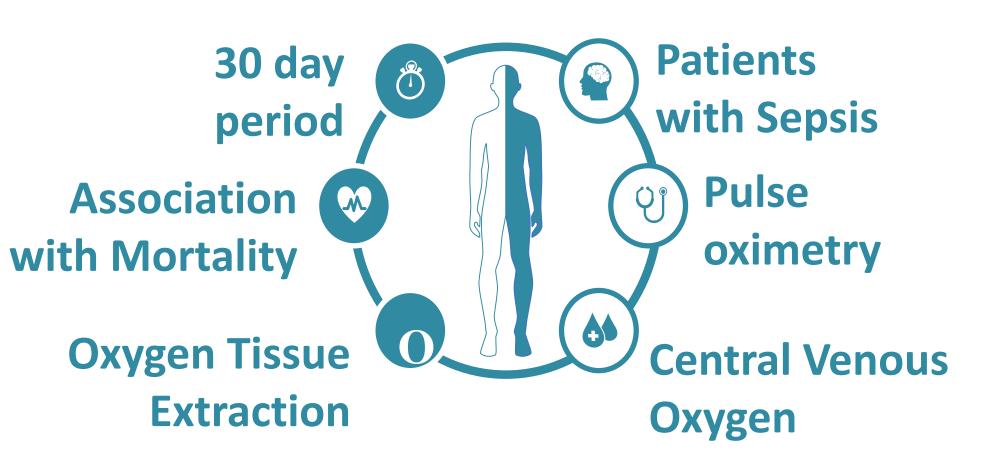
CSE 6242 Data & Visual Analytics Poster

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### Introduction

We aim to find the association between oxygen tissue extraction and mortality on a cohort of sepsis patients over 30 days from the MIMIC-III database

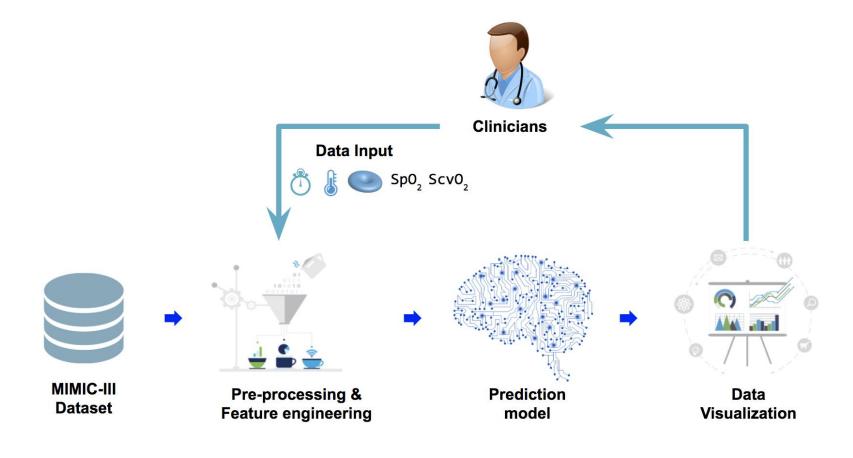


## **Mortality Rate for Sepsis Patients**



### Methods

The data obtained is preprocessed and additional features such as moving average and momentum are *engineered* in order to capture the effects of the time series data. The prediction models are trained on the data from the database and tuned to improve prediction. The *novelty* in our method stems from combining the time series data together with the Machine Learning Techniques.



### **Dataset**

Medical Information Mart for Intensive Care III (MIMIC-III)

The ICU Patient data is obtained from MIMIC-III.

#### MIMIC-III

- Large, freely-available database
- Over 40,000 patients

#### **Server Hosting**



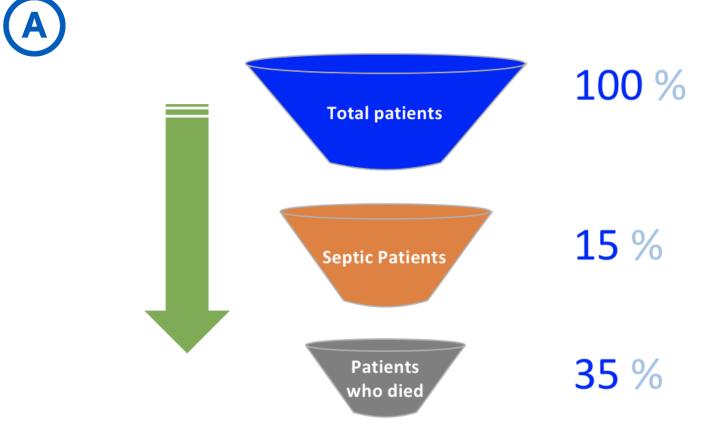


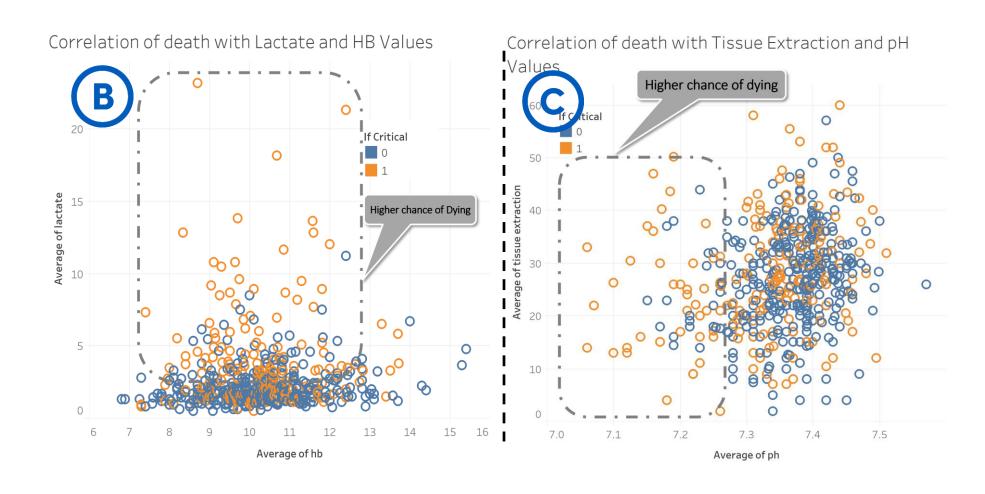


## **Data Analysis**

The data contains 5,500 instances of 528 unique Sepsis patients. The death rate of ICU patients is approximately 35%, which complies with what we see in the critical care literature for death rate amongst Sepsis patients. Analysis on the data was conducted and observed:

- A. Shows the breakdown of the number of Sepsis patients and those who are critical.
- B. Shows that Sepsis patients with higher lactate values have higher a mortality rate.
- C. Shows that Sepsis patients with lower pH values have a lower mortality rate.

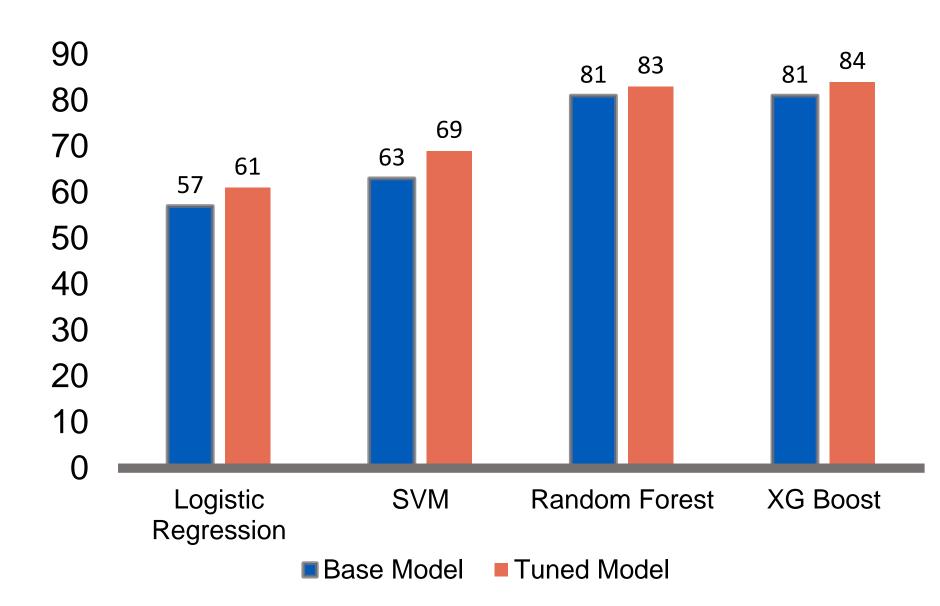




#### MODEL IMPROVEMENT USING CROSS VALIDATION

A significant lift in AUC values for logistic regression and SVM is achieved. However, XG Boost is chosen as the final model due to highest AUC and Recall values.

#### **AUC Comparison - Tuned VS Base Models**



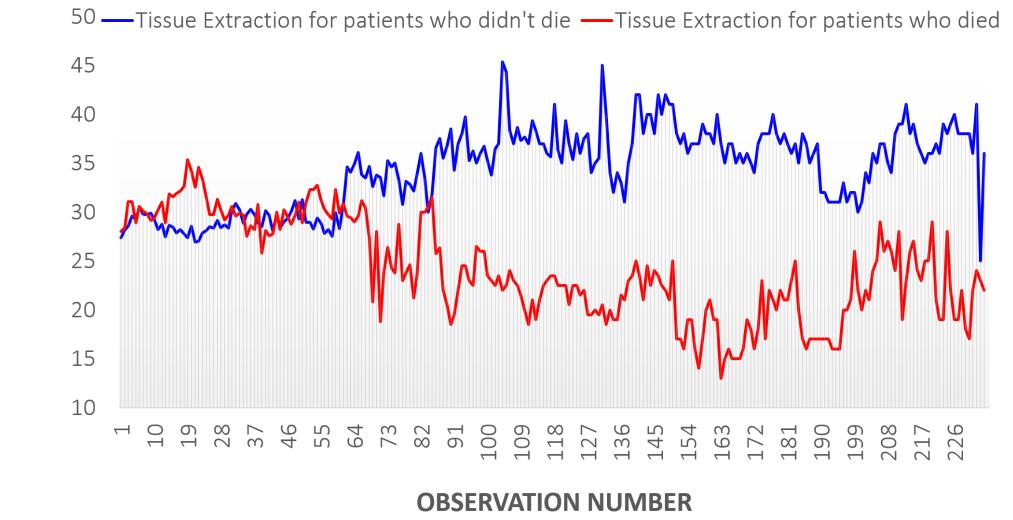
	Logistic Regression	Support Vector Machine	Light GBM	Random Forest	XG Boost
AUC	60.9	69.3	81.2	82.7	83.5
F-Score	46.5	57.5	75.2	77.3	77.9
Test Accuracy	65.6	73.0	85.1	87.3	87.0
Precision	44.5	55.5	83.2	85.3	81.5
Recall	48.8	59.8	68.1	70.7	74.6

Performance of fine-tuned models

## **Results**

#### **TISSUE OXYGEN EXTRACTION**

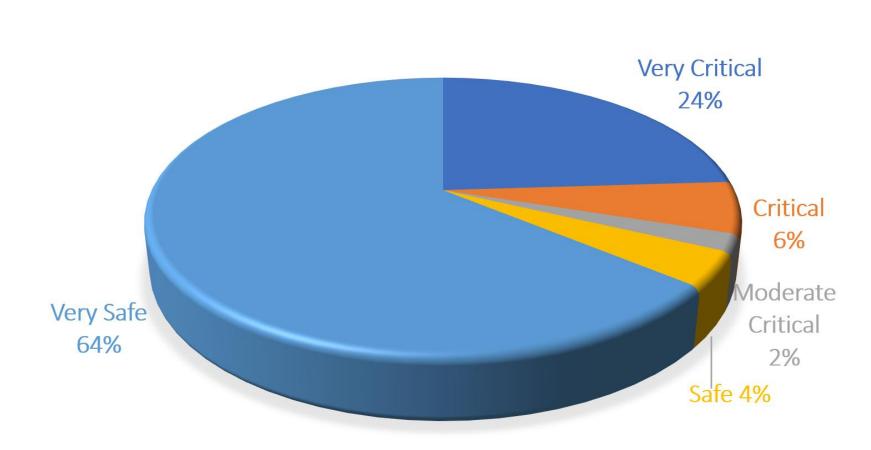
We observed a decreasing trend for the oxygen extracted by tissues for those patients who died within a 30-day period. The oxygen tissue extraction for the patients who survived was consistently higher with increasing observations.



#### **CRITICALITY BREAKDOWN**

From the data, the models were able to analyze, interpret and determine the various levels of criticality of the ICU patients. The statistics are shown below:

#### Criticality distribution of Patients



## Conclusion

We believe our analysis will help further critical care research and aid clinicians in identifying patients with highest risks in ICU. By doing so, we hope to reduce the number of deaths in ICU.

## References

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