DUHS Inpatient General Decompensation Prediction

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Content

- Background & Significance
- Purpose of Study
- Design & Precedures
- NEWS Implementation & Future Plan

Content

Backgroud

- Patients in hospital may suffer decompensation
- Fail to detect:
  - Nurses have too much workload[3]
  - Constantly observable information is insufficient for decision making[4]
  - General ward is usually harder setting than ICU[5]

[3] Patricia R DeLucia, Tammy E Ott, and Patrick A Palmieri. "Performance in nursing". In: *Reviews of human factors and ergonomics* 5.1 (2009), pp. 1–40.

[4] Molly McNett et al. "Judgments of critical care nurses about risk for secondary brain injury". In: *American Journal of critical care* 19.3 (2010), pp. 250–260.

[5] Clemence Petit, Rick Bezemer, and Louis Atallah. "A review of recent advances in data analytics for post-operative patient deterioration detection". In: *Journal of clinical monitoring and computing* 32.3 (2018), pp. 391–402.

Backgroud

Reactions:

- Rapid Response Team (RRT)
- Transfer to ICU

Consequences:

- Unplanned transfers, delayed transfers[6] to ICU increase mortality and length of stay[7].

[6] Vincent Liu et al. "Adverse outcomes associated with delayed intensive care unit transfers in an integrated healthcare system". In: *Journal of hospital medicine* 7.3 (2012), pp. 224–230.

[7] Matthew M Churpek et al. "Association between intensive care unit transfer delay and hospital mortality: a multicenter investigation". In: *Journal of hospital medicine* 11.11 (2016), pp. 757–762.

Backgroud

Patients show physiologic derangement 6-24 hours prior to deterioration[8].

[8] Michael J Rothman, Steven I Rothman, and Joseph Beals IV. "Development and validation of a continuous measure of patient condition using the Electronic Medical Record". In: *Journal of biomedical informatics* 46.5 (2013), pp. 837–848.

Backgroud

Risk Scores:

- Early Warning Score (EWS)[9]
- Modified Early Warning Score (MEWS)[10]
- National Early Warning Score (NEWS)[11]
- Rothman Index (RI)[12]

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[9] Jennifer McGaughey et al. "Outreach and Early Warning Systems (EWS) for the prevention of intensive care admission and death of critically ill adult patients on general hospital wards". In: *Cochrane Database of Systematic Reviews* 3 (2007).

[10] J Gardner-Thorpe et al. "The value of Modified Early Warning Score (MEWS) in surgical in-patients: a prospective observational study". In: *The Annals of The Royal College of Surgeons of England* 88.6 (2006), pp. 571–575.

[11] Gary B Smith et al. "The ability of the National Early Warning Score (NEWS) to discriminate patients at risk of early cardiac arrest, unanticipated intensive care unit admission, and death". In: *Resuscitation* 84.4 (2013), pp. 465–470.

[12] Michael J Rothman, Steven I Rothman, and Joseph Beals IV. "Development and validation of a continuous measure of patient condition using the Electronic Medical Record". In: *Journal of biomedical informatics* 46.5 (2013), pp. 837–848.

Backgroud

- **Poor predictive capabilities**
  - result in alert fatigue[13]
- **Population-based not individual-based**
  - cannot fit specific patients
- **Personalized models in need**

[13] *Alert Fatigue*. https://psnet.ahrq.gov/primers/primer/28/alert-fatigue. Accessed: 2019-05-27.

Backgroud

- Machine Learning (ML) algorithms
  - prediction models
  - incorporate numerous predictor variables
- Methods applied[14]
  - Support Vector Machines (SVM)
  - Random forest
  - Artificial Neural Network (ANN), etc

[14] Clemence Petit, Rick Bezemer, and Louis Atallah. "A review of recent advances in data analytics for post-operative patient deterioration detection". In: *Journal of clinical monitoring and computing* 32.3 (2018), pp. 391–402.

Backgroud

- Potentially useful input data[15]
  - demographics
  - clinical history
  - physical examination
  - presenting symptoms
  - laboratory data
  - ECG (short and long term heart rate variability measures)

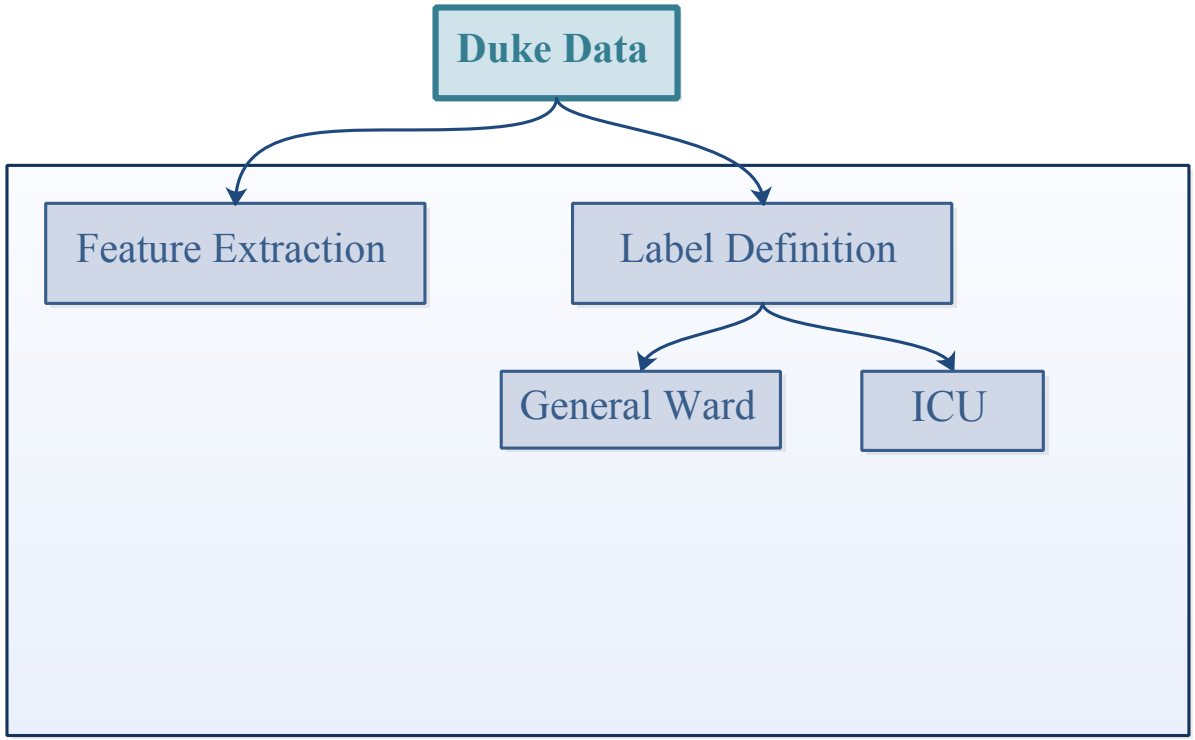
[15] Clemence Petit, Rick Bezemer, and Louis Atallah. "A review of recent advances in data analytics for post-operative patient deterioration detection". In: *Journal of clinical monitoring and computing* 32.3 (2018), pp. 391–402.

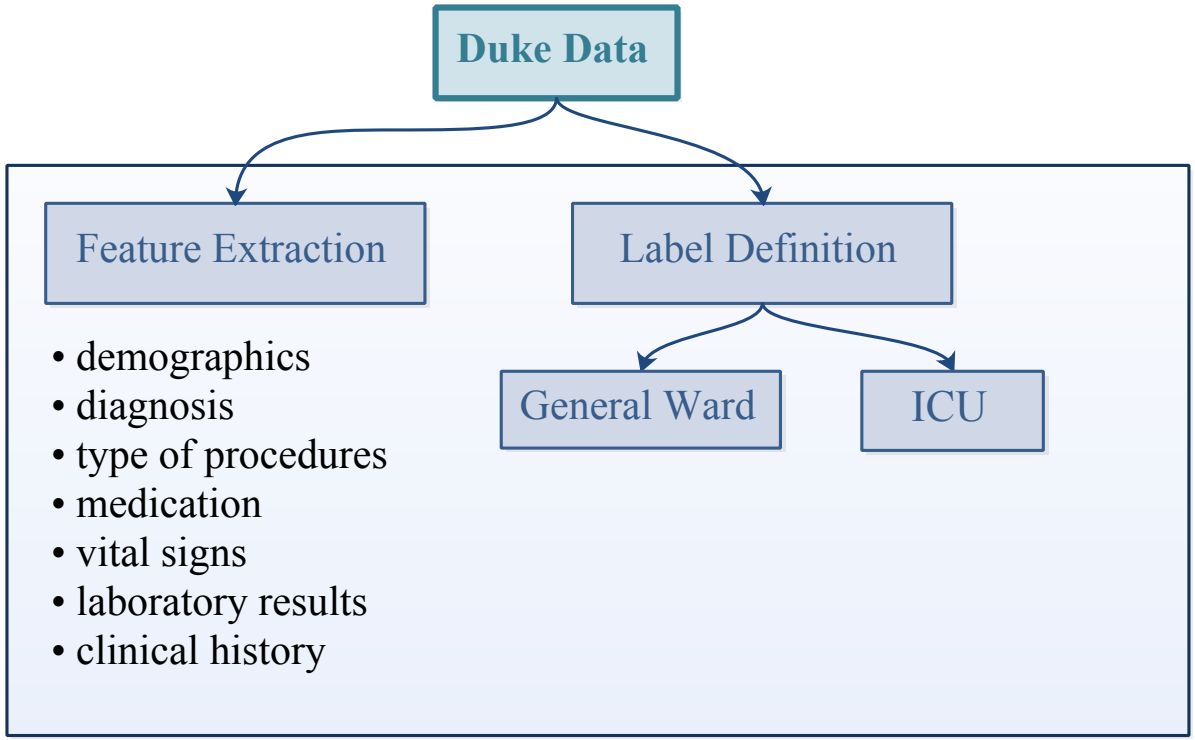
Content

Purpose of Study

1. Define decompensation
2. Create a state-of-the-art of the machine learning model applied for decompensation detection
3. Reduce deterioration and standardize response protocols

Content


Duke Data
Feature Extraction
Label Definition
General Ward
ICU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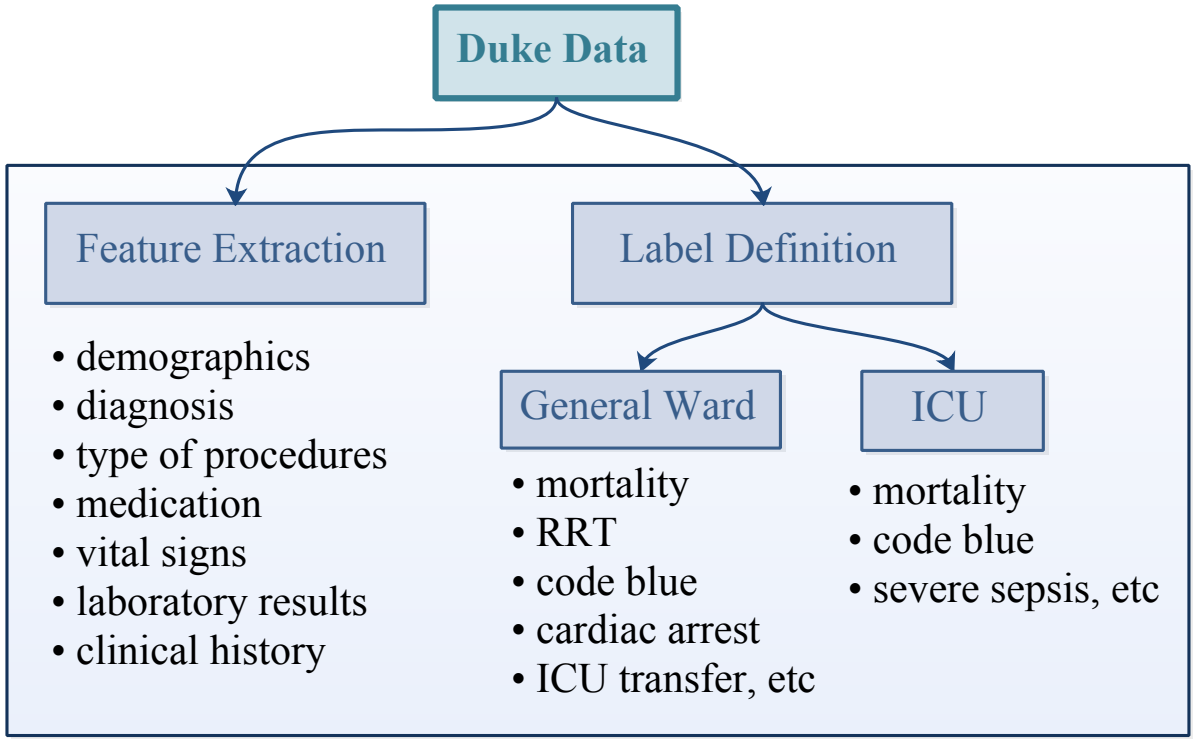
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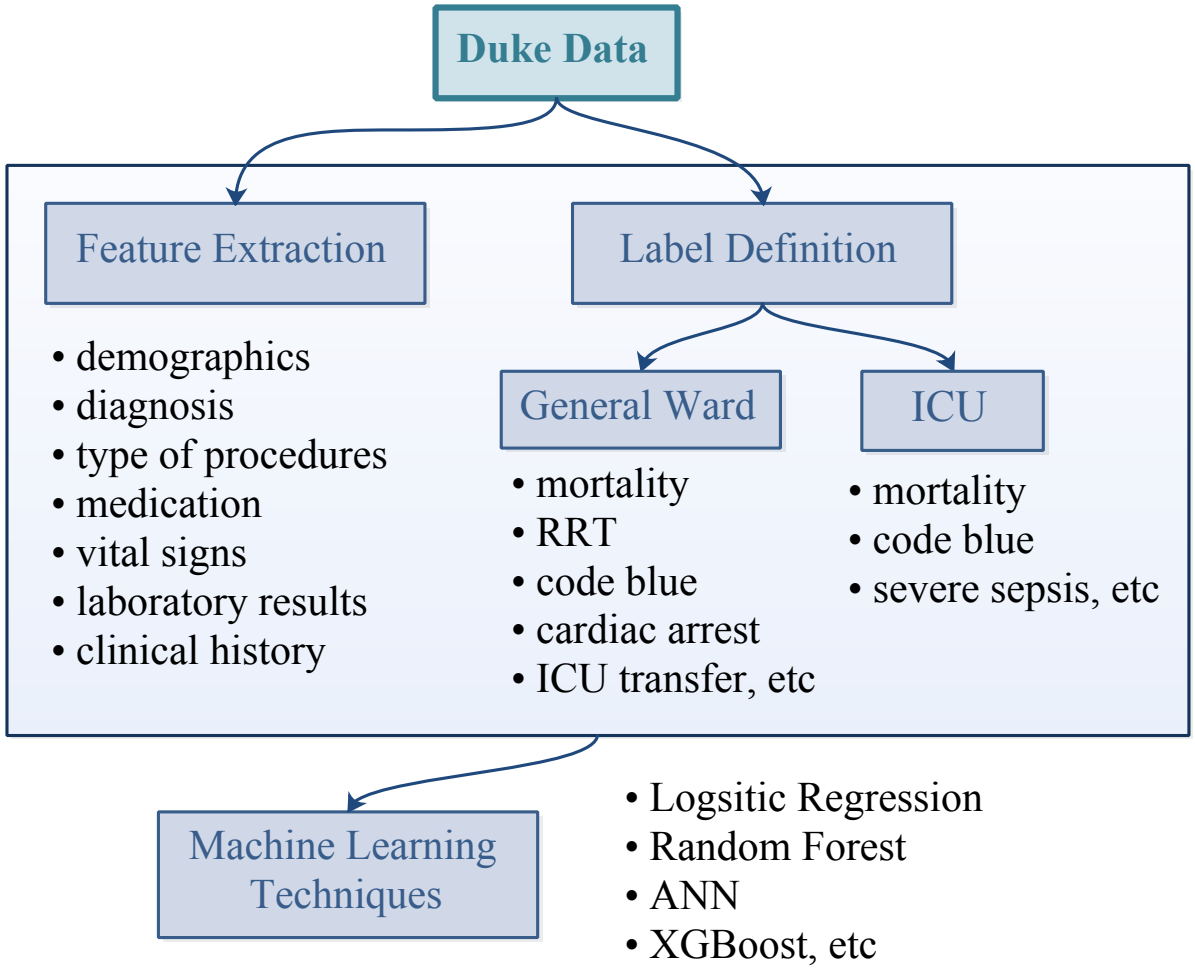
• RRT
• code blue
• cardiac arrest
• ICU transfer, etc
ICU
• mortality
• code blue
• severe sepsis, etc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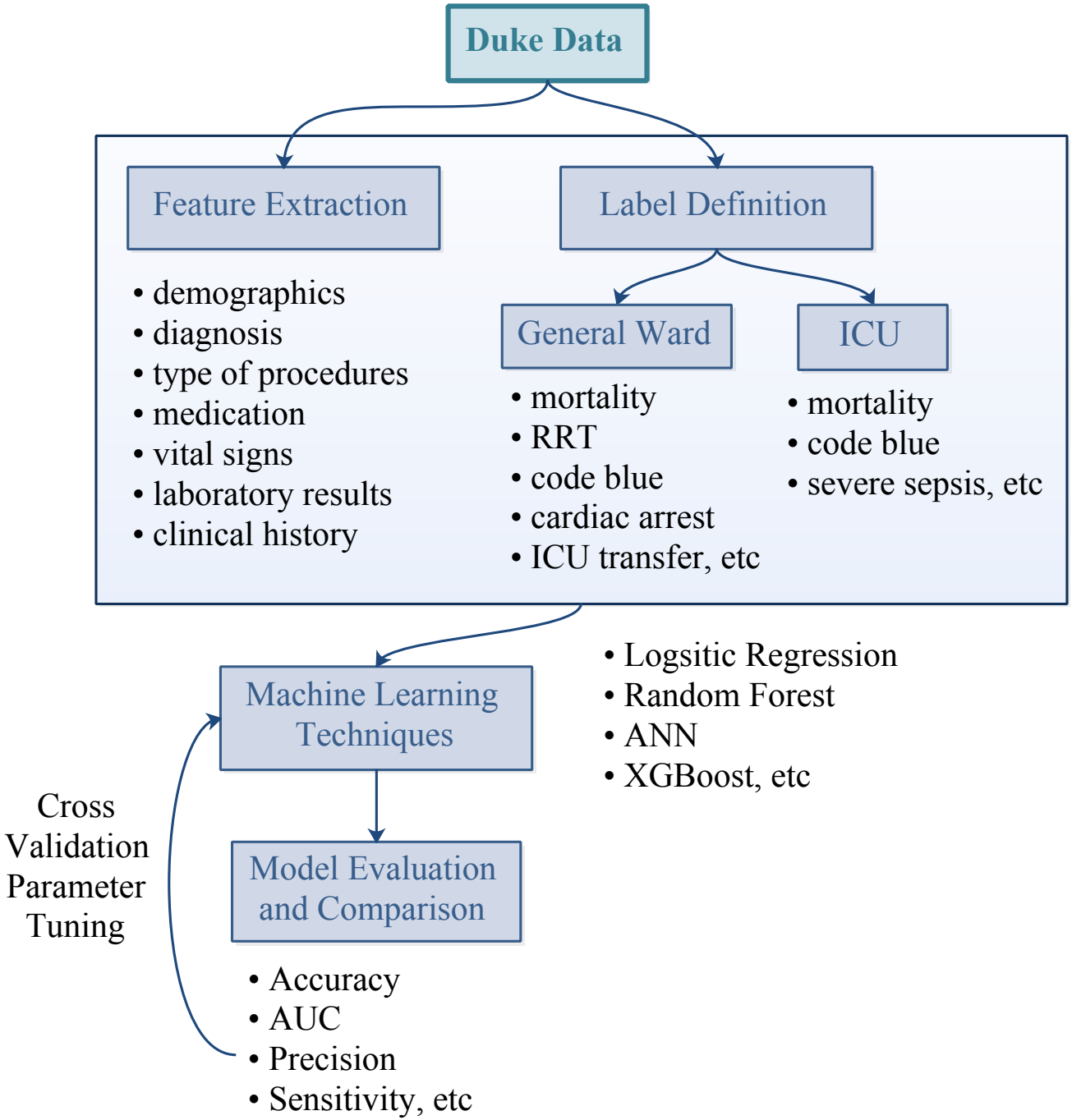
• Random Forest
• ANN
• XGBoost, etc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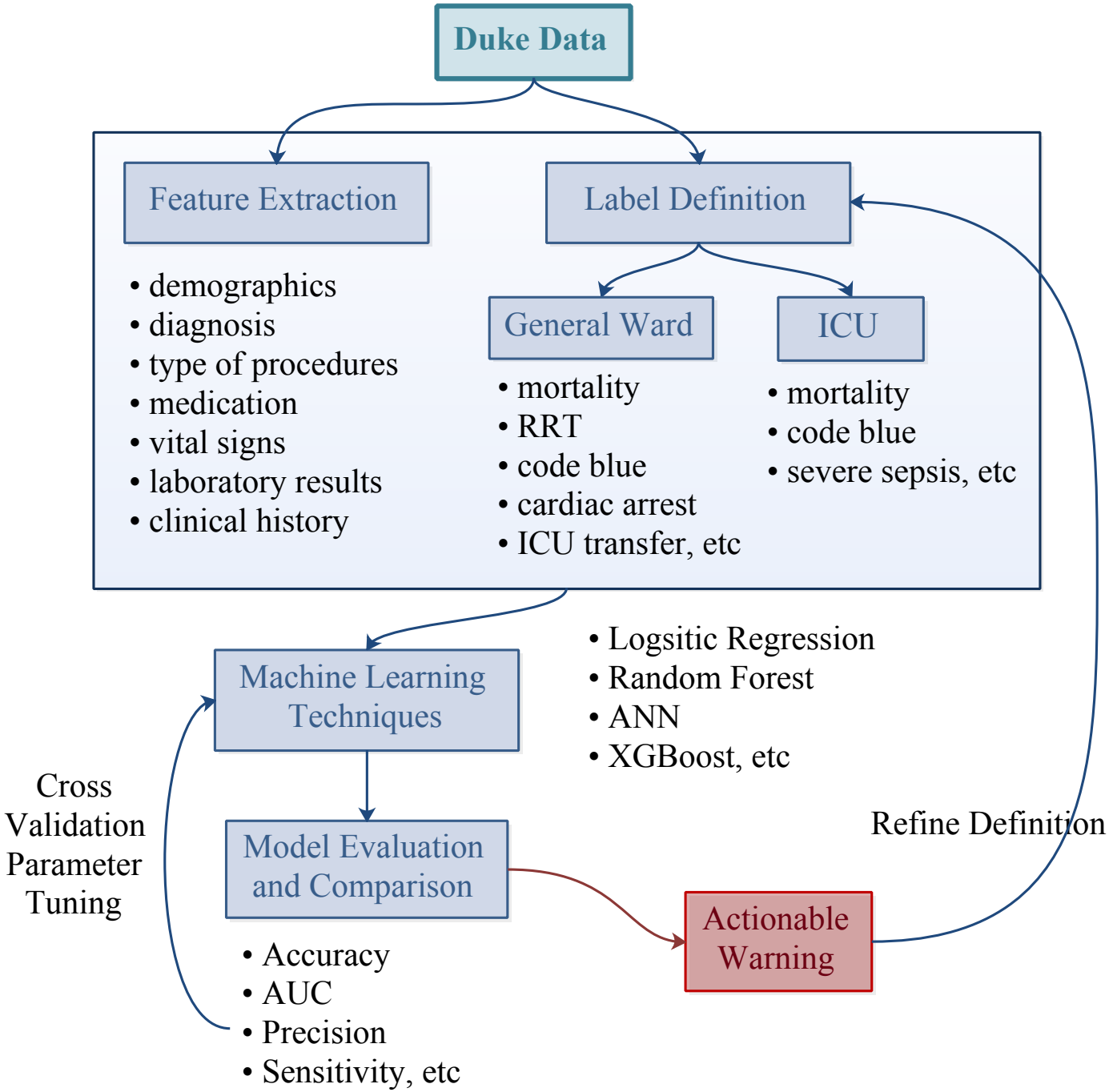
Cross Validation Parameter Tuning
Model Evaluation and Comparison
• Accuracy
• AUC
• Precision
• Sensitivity, etc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Actionable Warning
Refine Definition

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National Early Warning Score

Table: NEWS scoring criteria as a aggregate weighted system[16].

Score	3	2	1	0	1	2	3
Respiration Rate	≤ 8		9-11	12-20		21-24	≥ 35
Oxygen Saturations	≤ 91	92-93	94-95	≥ 96			
Supplemental Oxygen		Yes		No			
Systolic BP	≤ 90	91-100	101-110	111-219			≥ 220
Heart Rate	≤ 40		41-45	51-90	91-110	111-130	≥ 131
Temperature	≤ 35		35-36	36-38	38-39	≥ 39	
Level of Consciousness				A			V,P,U

[16] Ariel L Shiloh et al. "Early warning/track-and-trigger systems to detect deterioration and improve outcomes in hospitalized patients". In: *Seminars in respiratory and critical care medicine*. Vol. 37. 01. Thieme Medical Publishers. 2016, pp. 088–095.

Experimental Setting

- **Data Source**
  - MIMIC III[17]
  - Tables used: patients, icustays, chartevents, etc
- **Cohort**[18]
  - exclude age less than 16
  - exclude ICU stay less than 4 hours
- **Features**
  - respiration rate, SpO_2, temperature, $sysBP$, heart rate
- **Outcome**
  - 30−day mortality after ICU admission

[17] Alistair EW Johnson et al. "MIMIC-III, a freely accessible critical care database". In: *Scientific data* 3 (2016), p. 160035.

[18] Alistair EW Johnson and Roger G Mark. "Real-time mortality prediction in the Intensive Care Unit". In: *AMIA Annual Symposium Proceedings*. Vol. 2017. American Medical Informatics Association. 2017, p. 994.

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Table: Summary statistics of extracted patients.

Class	expire flag = 1	expire flag = 0
#Features	5	
#Total Samples	51996	
#Samples	7526	44470
#Proportion	14.5%	85.5%

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- **Features**
  - respiration rate, SpO_2, temperature, $sysBP$, heart rate
- **Outcome**
  - 30−day mortality after ICU admission
- **Algorithm**
  - NEWS scoring system
  - time window: first 24 hours during ICU stay

Performance

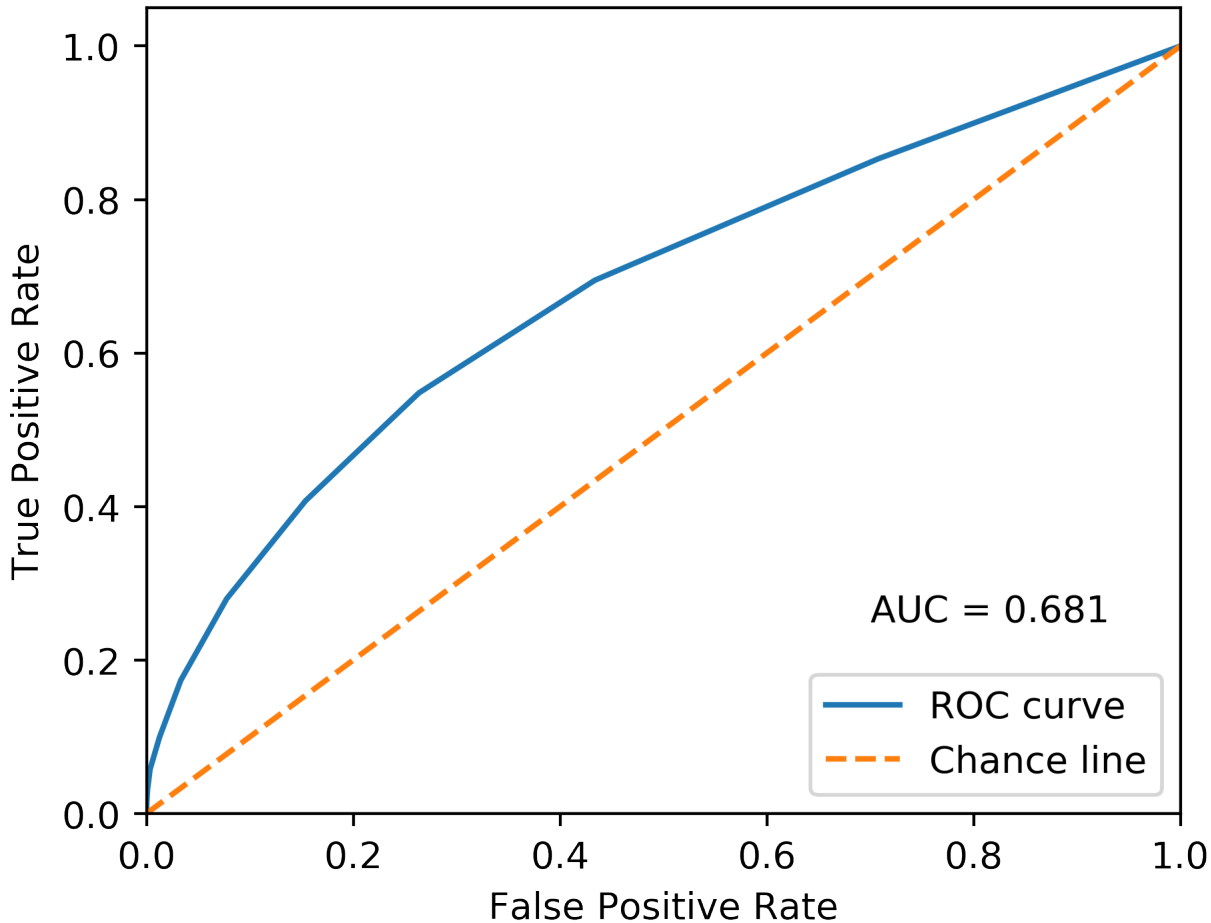

Figure: Receiver operating characteristic. (Area under curve: 0.681)

Performance

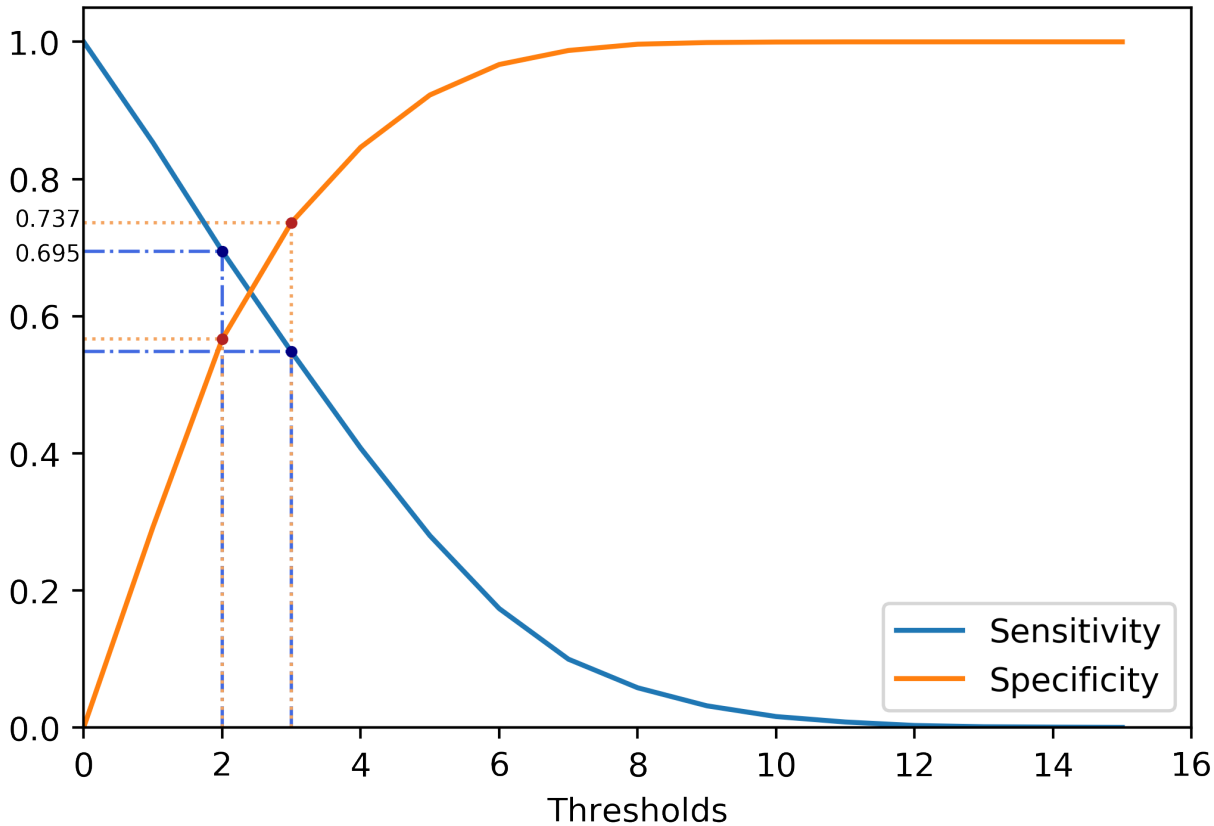

Figure: Sensitivity and specificity values plotted along thresholds. (Optimal sensitivity: 0.695, Optimal specificity: 0.737)

Future Work

- Refine NEWS Implementation
- Data Exploration
- Test Models
  - traditional risk scores
  - common machine learning algorithms
- Incorporate Real-time Techniques
  - set random time points[19]
  - Gaussian process, Recurrent Neural Network[20]

[19] Alistair EW Johnson and Roger G Mark. "Real-time mortality prediction in the Intensive Care Unit". In: *AMIA Annual Symposium Proceedings*. Vol. 2017. American Medical Informatics Association. 2017, p. 994.

[20] Joseph Futoma, Sanjay Hariharan, and Katherine Heller. "Learning to detect sepsis with a multitask Gaussian process RNN classifier". In: *Proceedings of the 34th International Conference on Machine Learning-Volume 70*. JMLR. org. 2017, pp. 1174–1182.

Thank you for listening!

Q&A