Using Machine Learning to Predict Respiratory Decompensation

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Conflict of Interest/Funding

• Past: Grant funding from Medtronic to study inpatient respiratory monitoring
• Current: NIH-NCATS 1KL2TR002245, AHRQ R18-HS026616

Learning Objectives

• At the conclusion of this activity, participants will be able to demonstrate an improved understanding of the state of the science in applying machine learning techniques to the clinical problem of respiratory decompensation
Overview

• Prevention
• Detection (with better monitors—passive and active surveillance)
• Treatment/Early Intervention
• Better Documentation

Respiratory Decompensation

• Definition:

  • “I know it when I see it” — Justice Potter Stewart
Temporality

- Sudden/abrupt
- Gradual
- Unclear if changed at all (baseline)

Often difficult to determine when

Evidence of Pathology

- Pneumonia
- “Atelectasis”
- Tachypnea/bradypnea
  – Capnography?
- Desaturation
- P:F ratio, S:F ratio

Evidence of Treatment

- Breathing treatment
- Increased oxygen requirement
- Change in means of oxygen delivery
- Positive pressure ventilation
- Intubation
  – Gabel A+A 2017
- ICU stay
- RRT activation
RRTs

- 2,399 RRTs 2010-16; 566 were respiratory (24%), median time to event 48 hours (late)

Classical regression

- Derivation
- Validation
- Calibration/discrimination
- Publication

- Need an algorithmically-definable outcome

- Machine learning?

Supervised Machine Learning

- Classification: “The problem of identifying to which of a set of categories a new observation belongs” –Wikipedia
- Assumes that category membership is known in the training dataset
- Need an algorithmically-definable outcome
- Adjustment for noise/human error
Unsupervised Machine Learning

- Clustering—grouping similar objects

An Unsupervised Approach to Bananas

Clusters of Decompensation

- Heterogeneity of population
- Varying severity
- Unclear definitions
- Much more complicated than bananas
- Need better phenotyping first
Predicting Decompensation in Cancer Patients

- 1.6 million new cases in US annually
- Largely outpatient treatment; radio/chemotherapy
- Unplanned hospitalization rates 14-37%
- 50% of chemo patients have severe treatment toxicity
- 80% of patients have non-routine adverse events

Multimodal Surveillance and Response System

- Passive and active surveillance
  - Smartphone application to report problems
  - EHR-derived data collection based in Epic
  - FitBit sensors
    - Overall activity
    - Heart rate variability
    - Geolocation
  - Routine structured interviews with patients, families
How to Provide Value

• Critical need to generate algorithm(s) that accurately categorize respiratory decompensation

Future steps:

• Prevention
• Detection (with better monitors—passive and active surveillance)
• Treatment/Early Intervention
• Better Documentation

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