Predicting Patient Deterioration Using Continuous Monitoring and Concepts from the Field of Sports

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Introduction

- Patients frequently demonstrate clinical signs of deterioration hours before a major event (transfers to intensive care unit or death).
- Continuous monitoring[1] may improve patient outcomes and reduce costs.
- With EarlySense™ **contact-free** piezoelectric sensor, we were able to gather **continuous** measurement of heart rate, respiration rate, and body motion.
- The goal of this study was to test whether machine learning models based on features from continuous monitoring data and sports concepts can improve established Early Warning Scores such as MEWS[2] (based on respiratory rate, heart rate, BP, urine output, temperature, and neurological signs).

Methods

Data Collection

- All patients hospitalized in five medical/surgical (non-ICU) units between April 2016 and April 2017 in a community hospital in Massachusetts, were monitored continuously with EarlySense contact free monitoring system.
- Monitoring included heart rate (HR), respiratory rate (RR), motion and bed presence at a 10 seconds resolution.

Feature Extraction

- Age-normalized features (based on maximal HR, calculated as 220-age) were calculated and compared against a threshold corresponding to HR zones, as utilized in the field of professional sports (see Fig 1). Similar definitions were used for the first time for respiration.
- Features to account for temporal patterns were extracted including: HR trend in last 3 hours, 80th percentile RR in last 6 hours, and standard deviation of HR in last hour.
- Features were calculated every hour.
- The target variable is a binary label, which is tagged as 'positive' in the 24 hours preceding to a major event.

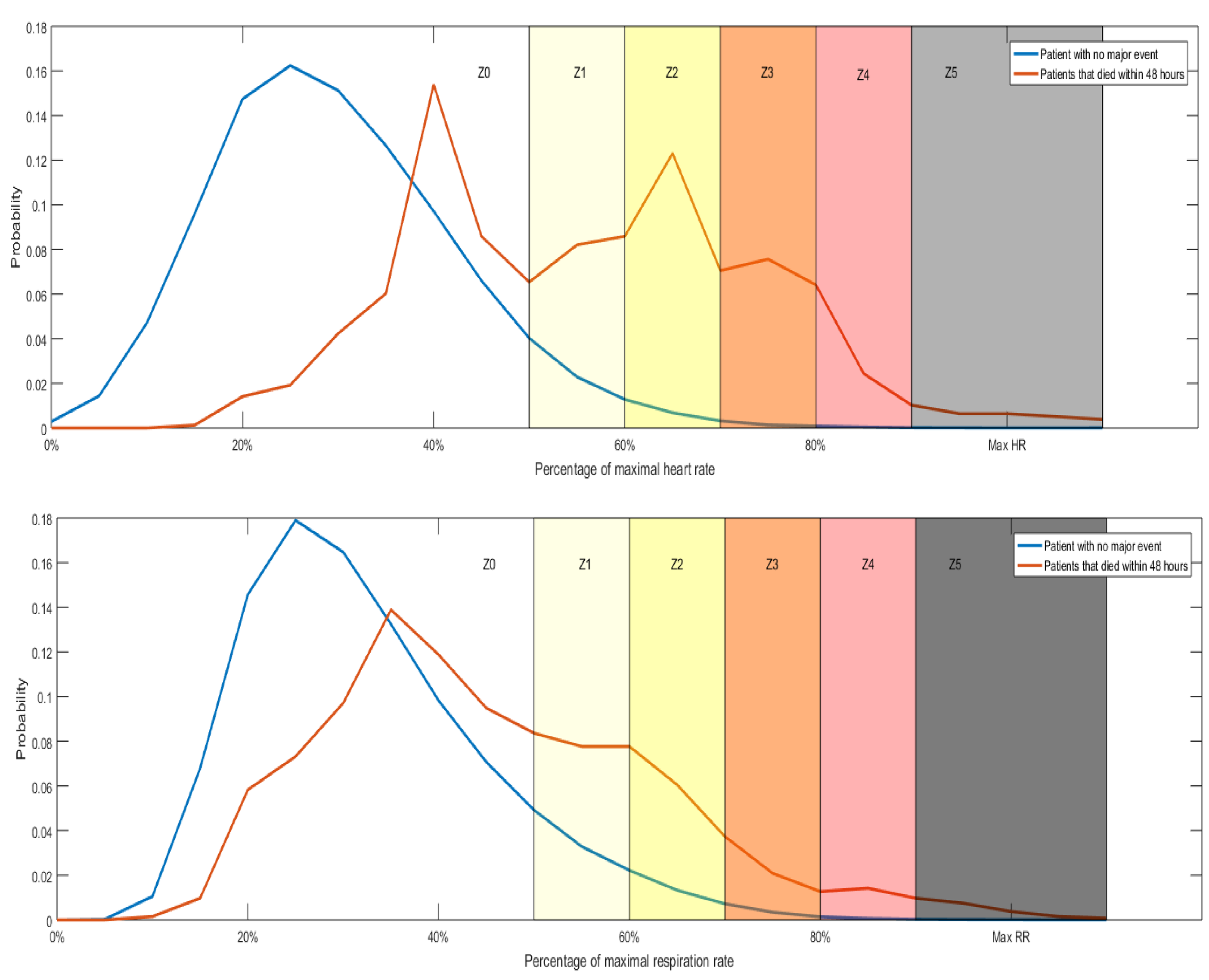

Figure 1: Normalized HR (top) and RR (bottom), from continuous monitoring of patients that expired, compared to patients with no major event in general ward patients. This difference in distribution motivated us to use these rates as model features.

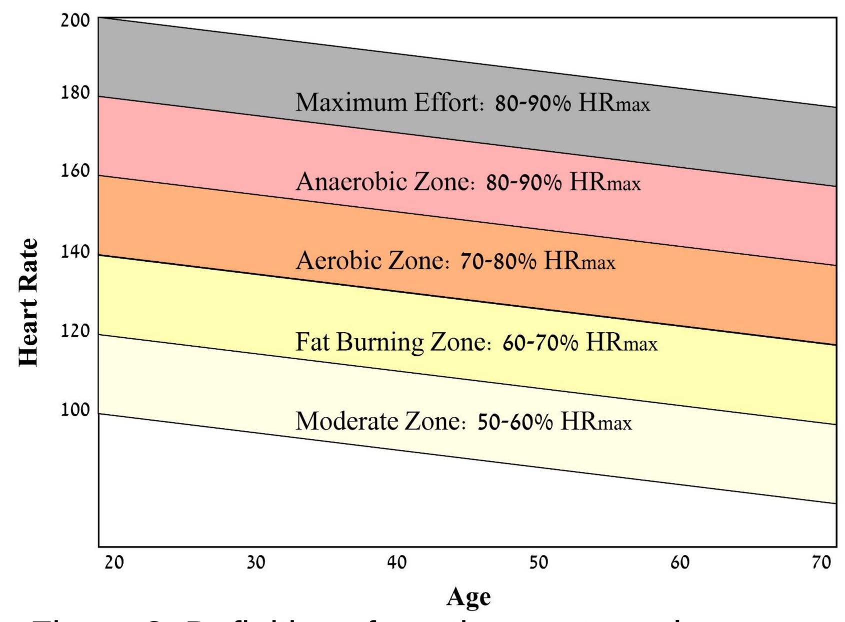

Figure 2: Definitions from the sports realm.

$$HR_{min} = 40$$
$$HR_{max} = 220 - age$$
$$HR_{norm} = \frac{HR - HR_{min}}{HR_{max} - HR_{min}}$$
$$RR_{min} = 4$$
$$RR_{max} = \frac{220 - age}{3}$$
$$RR_{norm} = \frac{RR - RR_{min}}{RR_{max} - RR_{min}}$$

Equation 1: Normalization

Model Training and Evaluation

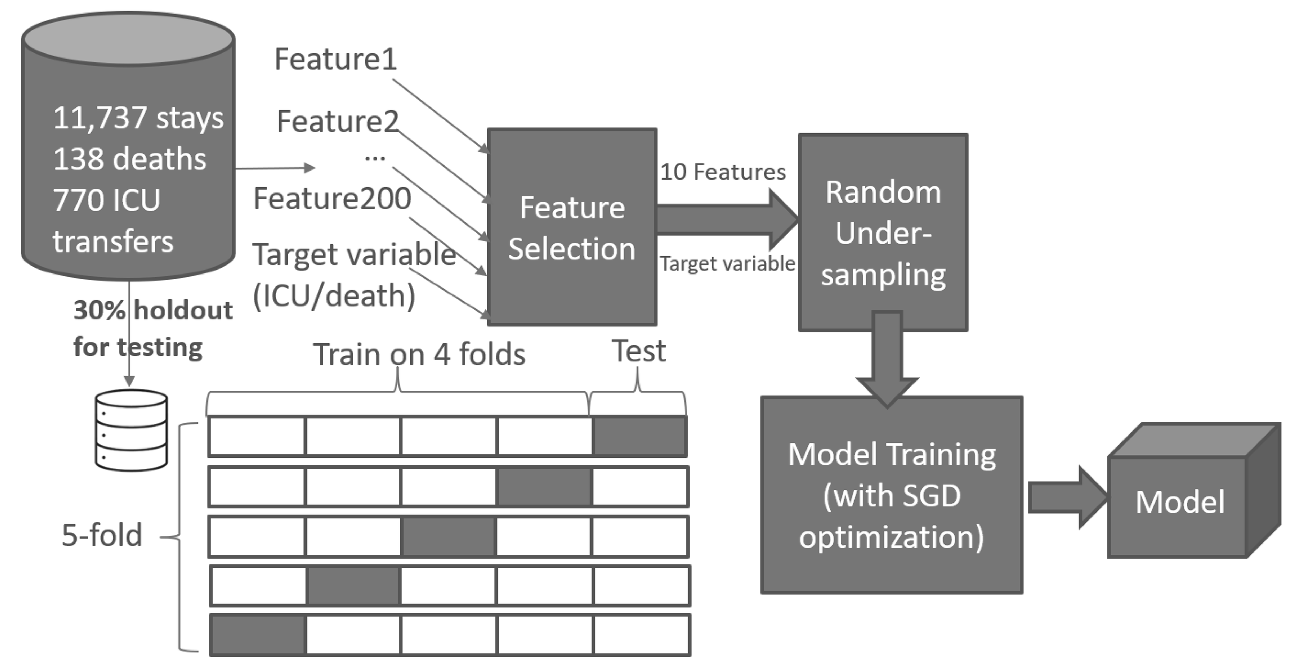

Figure 3: The process of feature extraction and model training, with 5-fold cross validation.

- Stratified splitting was used for creating training and test sets. In addition, it was ensured there are no samples from the same stay both in the train and in the test sets.
- Models were compared in testing cohort using the area under the receiver operating characteristic curve (AUC).

Results

Testing model AUCs outperformed or were as good as MEWS[2] AUC for the same data set. For ICU, the model's AUC vs. MEWS' AUC measures were 0.73 vs. 0.68 respectively. For mortality, MEWS and the model performed equally well, at 0.88.

This work supports the premise that continuous monitoring benefits patient outcomes, while minimizing the need for cumbersome manual work needed for MEWS[2].

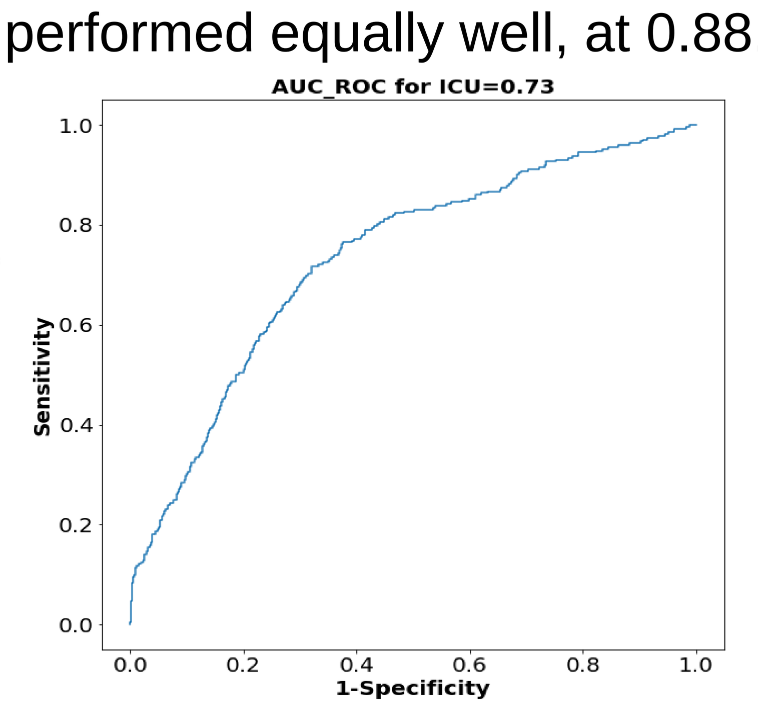

Figure 4: Receiver operating characteristics curve – measuring model performance for predicting ICU transfers.

Conclusions

This work is novel in three ways:

1. We developed an early warning score based on continuous monitoring, that outperform or perform as well as the commonly used MEWS[2] score
2. We applied professional sports terminology to hospital medicine using an individual calibration of HR based on age and resting baseline
3. We offer an analogy for the calibration of respiratory rate.

Bibliography

1. Downey CL, Chapman S, Randell R, Brown JM, Jayne DG. The impact of continuous versus intermittent vital signs monitoring in hospitals: A systematic review and narrative synthesis. Int J Nurs Stud. 2018; 84:19-27.
2. Gardner-Thorpe J, Love N, Wrightson J, Walsh S, Keeling N. The value of Modified Early Warning Score (MEWS) in surgical in-patients: a prospective observational study. Ann R Coll Surg Engl 2006;88:571–5.