Predicting hypoxemia for patients in the ICU

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INTRODUCTION

Hypoxemia is a life-threatening condition involving abnormally low levels of oxygen in arterial blood and is commonly diagnosed among general ICU patients with a prevalence around 54%. Since there is currently no way to anticipate this condition, we aim to predict near future hypoxemia which will enable timely intervention by clinicians to prevent hypoxemia.

METHODS

Hypoxemia event: SpO₂ level below 92% for a certain period of time.

Data source: Demographic data and time-series data from MIMIC-III database

Sampling: Select negative samples from points far away from events and positive samples from sliding prediction windows prior to events (Fig 1).

RESULTS

1. The models perform better with prediction windows closer to events (Fig 2).

2. Filtering out short events significantly increases AUC of GLM models (Table 1).

3. SpO₂ is the primary factor responsible for the functioning of the model (Fig 3).

4. Tracing back 2 hours before hypoxemia events, vital sign trends diverge between hypoxemia and non-hypoxemia instances.

Feature extraction: Filtering, Derivative approximation, Spectral Entropy, Exponentially weighted moving variance

CONCLUSION

Our results on balanced dataset (AUC ≥ 0.74 for any prediction window) suggest that it is promising to build a real-time hypoxemia prediction system using vital signs such as SpO₂, heart rate, pulse, and blood pressure that are frequently monitored in the ICU. Prolonged hypoxemia events are easier to predict than with shorter ones. Among vital signs, SpO₂ shows a dominant role in all models regardless of prediction window and event duration.

FUTURE DIRECTION

1. Minute-to-minute real-time prediction
2. Integrate more clinical features, such as ventilation and lab tests, into models