Using Machine Learning to Predict Extubation Readiness in Extreme Preterm Infants

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Problem and Motivation

- Nearly all extreme preterm infants need to undergo endotracheal intubation and mechanical ventilation (ETT-MV) in order to survive.
- **ETT-MV complications** ➔ pneumonia, air leaks, airway trauma, bronchopulmonary dysplasia (BPD)
- 1 wk ETT-MV ➔ 2.7 fold increase developing BPD
- Extubate **as early as possible** but possibility of **extubation failure** (needing reintubation)
- **Reintubation risks** ➔ tube blockage, traumatic injuries, lung or airway collapse, infections, severe bradycardia
- Cardiorespiratory and neurological injuries ➔ long-term disabilities

- **Extubation failure rates** ➔ 25-35%
- Determining extubation readiness: **imprecise scientific foundation**
- **Goal**: develop a tool to predict extubation readiness using cardiorespiratory and clinical data
- **Challenge**: exploit structure of time series used for prediction

Background and Related Work

- **Previous study** on extubation readiness done on 56 babies[4]
- **Features:** derived from various cardiorespiratory signals using AUREA[5], a system characterizing respiratory activity
- **Classifiers**: Support Vector Machines (SVM) (best) and Logistic Regression (LR)
- **Results (ROC curve with varying C and kernel width for SVM):**
  - ➔ Specificity: 83%
  - ➔ Sensitivity: 74%
- **Drawbacks:**
  - ➔ High number of false positives
  - ➔ Feature extraction did not leverage structure of time series
- 1 baby = 3,000 instances (1 minute at 50 Hz)

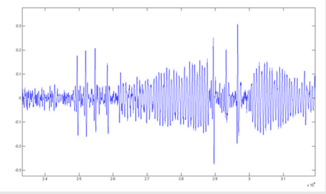
Approach

- Previous study: hardcoded scripts or code not recorded ➔ need for highly flexible pipeline
- **Pipeline for time series**:

Raw Signals

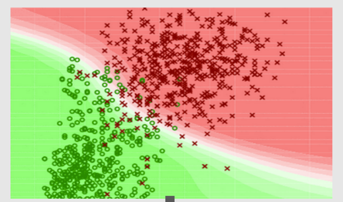
- ECG, PPG
- O2 saturation
- Respiratory movement (ABD, RCG)

Feature Extraction



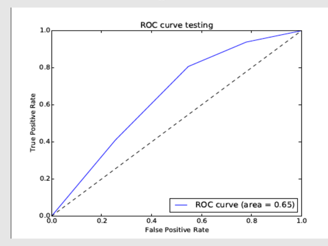
- Signal processing and analysis (AUREA)
- Dynamic Time Warping

Classification



- Support Vector Machines
- Logistic Regression
- Cross-validation opts (scikit-learn python package)

Analysis



- ROC Curves
- Heatmaps
- Predictions over time

Fig. 1: The pipeline for time series

- **Dynamic Time Warping** (DTW) ➔ measures difference between two time series. MATLAB implementation used to exploit time series structure

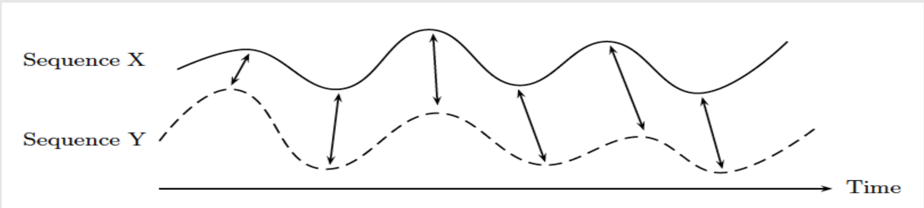


Fig. 2: A visualization of DTW

- **Spontaneous Breathing Trial** (SBT): 45 minutes after ETT-MV, patients are put on continuous positive airway pressure ventilation (CPAP), a lower ventilation setting, for 5 minutes
- **Compare** ETT-MV and ETT-CPAP metrics and signals using a sliding window ➔ new time series
- New dataset: only **33 babies**

Clinical Feature Selection and Classification

- Not taken into account in the previous study
- Number of features > Number of patients (55 vs 33) ➔ need to choose subset of features

1. Calculate mutual information (MI) between every feature and the labels, select features with MI > threshold (0.3)
2. Feature selection with linear SVM and L1 penalty
3. Run SVM with RBF kernel; generate ROC curves
4. Repeat 2 & 3

Results and Contribution

Time series

- FPRs & TPRs generated though a search on the regularization and kernel width by comparing true outcome to mode of the 3000 instances' predictions

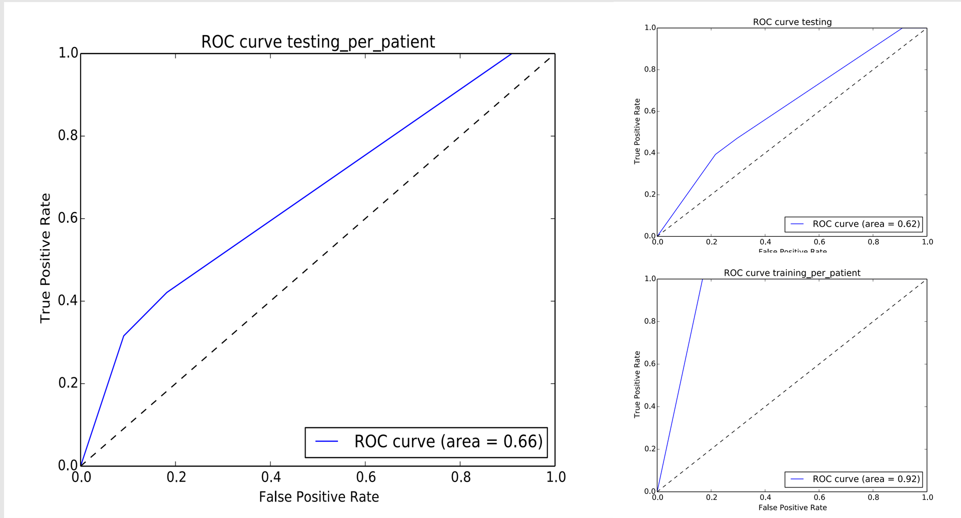


Fig. 3: SVM with respiratory metrics only

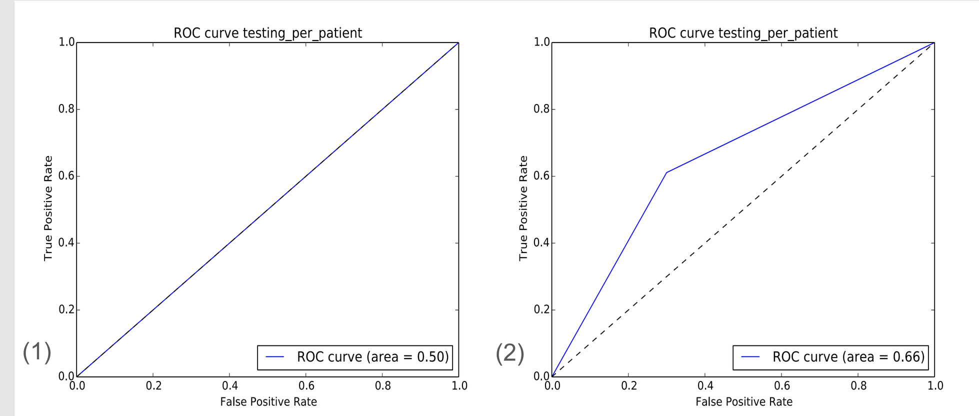


Fig. 4: LR with SVM without (1) and with (2) DTW

- SVM classification with cardiorespiratory metrics performed relatively well, but no improvement with DTW features addition
- DTW as new feature improves LR and gives us the best classifier ➔ worth investigating further

Clinical Feature Selection (FS) & Classification

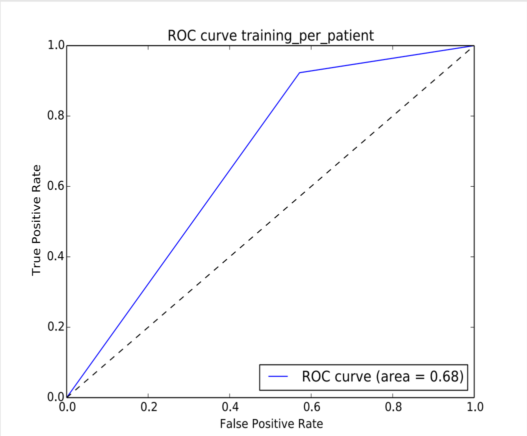


Fig. 5: Linear SVM with L1 penalty for classification

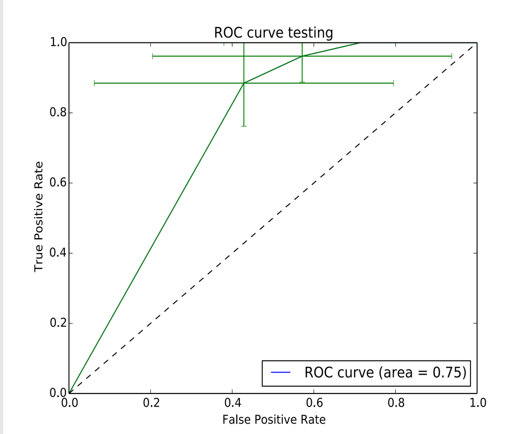


Fig. 6: Linear SVM with L1 penalty for FS, SVM RBF kernel for classification

- FS: L1 Penalty with linear SVM & Classification: SVM with RBF kernel performed better than SVM with RBF kernel only
- Still overfitting problems → small dataset

Selected features for 2nd pass of SVM, L1 penalty

Feature	Nb sel.
Tidal volume	33
PCA	33
pH	33
Age at intubation	32
pCO_2	5
Birth Weight	3

pH analysis:

- always selected on all folds of cross validation
- Aggregation of failures for low pH
- Low pH associated with respiratory acidosis → can be caused by various breathing and ventilation problems [7]

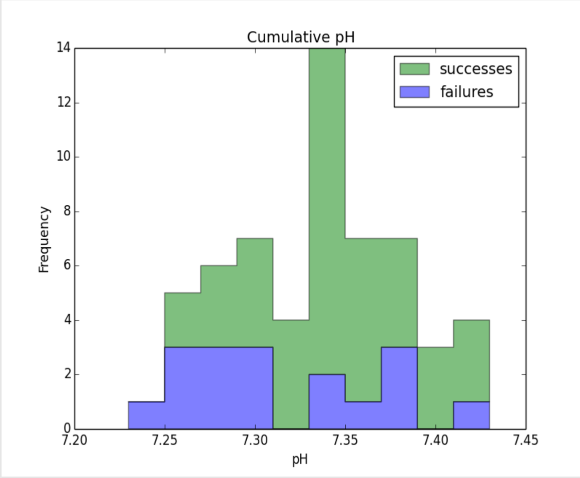


Fig. 7: distribution of blood gas pH for extubation successes and failures

Future Work

- Growing dataset (ongoing collection)
- Mixture of experts to combine time series and clinical data classifiers
- Exploring new classifiers such as random forests
- Develop a confidence measure to give a probabilistic prediction of extubation readiness in lieu of a binary prediction outcome

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The scikit-learn (python) and DTW (MATLAB) packages were used.