Early Dynamic Prediction of Cardiovascular System Deterioration in ICU Patients

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Introduction

Cardiovascular failure is a life-threatening condition characterized by inadequate effective blood flow and reduced tissue perfusion with decreased delivery of oxygen to the capillaries. The reduction in oxygen delivery leads to impaired oxidative metabolism, lactic acidosis, and cell death.

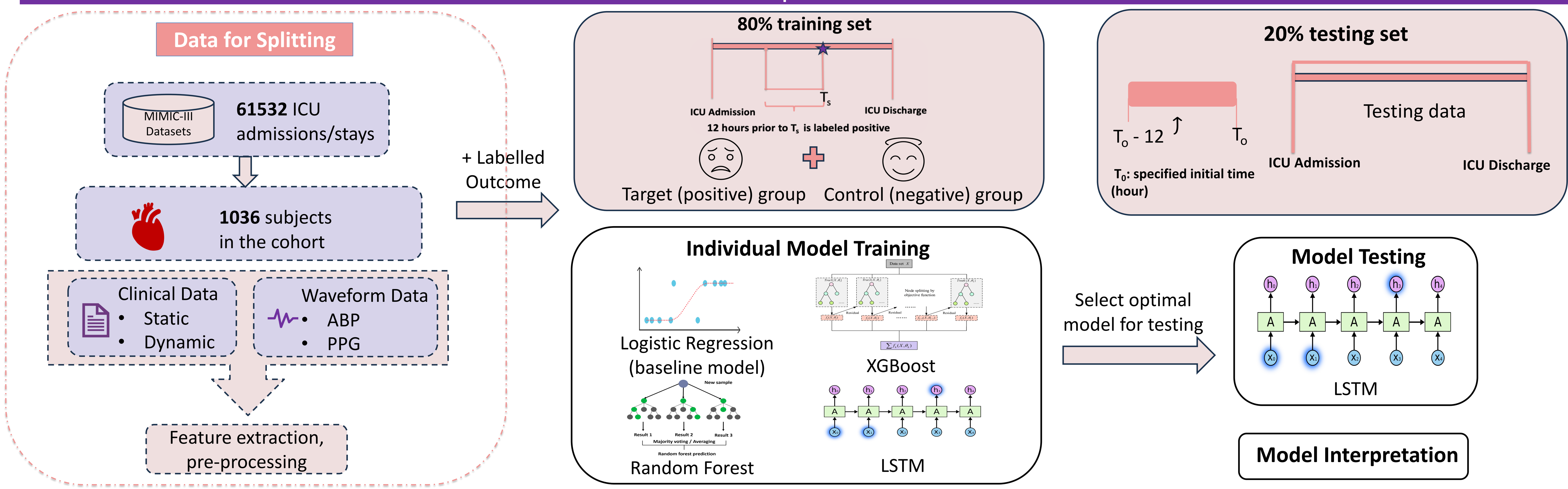
- The effects of cardiovascular failure are initially reversible in most patients, but repeated or prolonged episodes of hypotension may worsen the prognosis.
- Early prediction of **cardiovascular deterioration events** may **significantly enhance survival rates** by enabling timely interventions.

Objectives

Build prognostic model for cardiovascular organ deterioration.

- **Feature extraction and preprocessing**
  - Cohort Identification (Mean Arterial Pressure (MAP) < 65mmHg)
  - Labeling the outcome
  - Feature extraction and preprocessing
- **ML model implementation on EHR and EHR + Waveform dataset**
  - Train & Test Logistic Regression, XGBoost, Random Forest, and LSTM & Test model for dynamic prediction.
- **Model interpretation using SHAP**

Pipeline



Methods

Cohort Identification:(1) age ≥ 18 years, (2) length of ICU stays ≥ 48 hours, (3) patients with vital signs, lab measurements taken ≥ 6 hours, (4) Had waveform data taken ≥ 30 mins

Labeling Outcome:
(1) Subjects with Event - MAP<65mmHg for more than 15 mins (indication of hypotension).
(2) Labeled 12-Hour Window Prior to Event Start as class 1, target group.
(3) Remain as class 0, control group.

Feature extraction and preprocessing:

MIMIC-III Clinical Database

Static Features

- Demographics
  - Age
  - Gender
  - Ethnicity
  - Hospital expire flag
  - BMI
- Comorbidities
  - 30 selected from Charleson and Elixhauser Indices
- Severity Scores on Admission
  - SOFA score
  - OASIS score

Dynamic Features

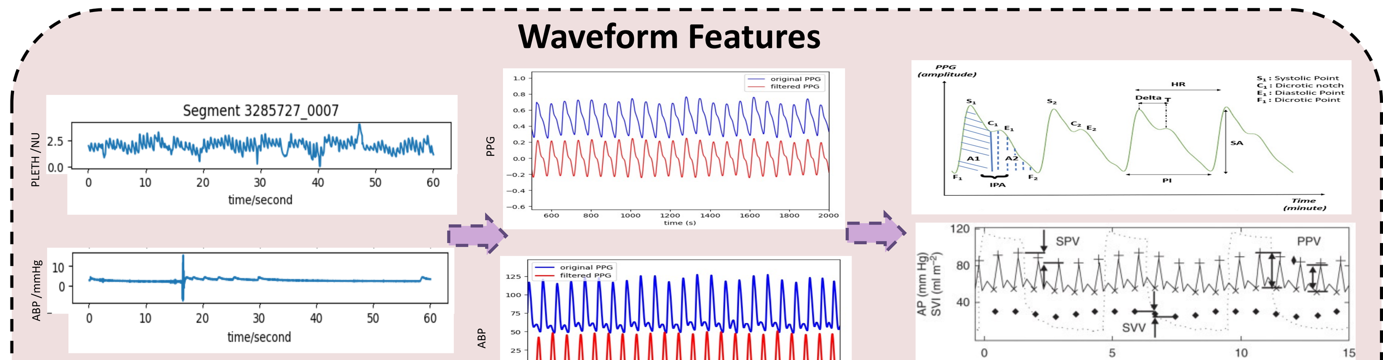
Collected every hour (max value) for entire duration of ICU stay

- Vital Signs
  - Temperature
  - Heart rate (HR)
  - Systolic BP
  - Diasystolic BP
  - Mean Arterial BP
  - Respiratory Rate
  - spO2
  - Glucose Level
- Metabolic and Electrolyte Parameters
  - Lactate
  - Creatinine
  - Anion Gap
  - Bicarbonate
  - Sodium
  - Chloride
  - Potassium
- Hematological Parameters
  - Hemoglobin
  - Platelet
  - Hematocrit
  - White Blood Cells (WBC)
  - Partial Thromboplastin Time (PTT)
  - International normalised ratio (INR)
  - Prothrombin Time (PT)

- Imputed using forward and backward fill
- Lactate imputed by median for specific patient

MIMIC-III Waveform Database Matched Subset

Waveform Features



First segment for each subject that had PLETH, ABP waveforms*

Filtered and handled outlier (Iqbal, T.et. al, 2022)

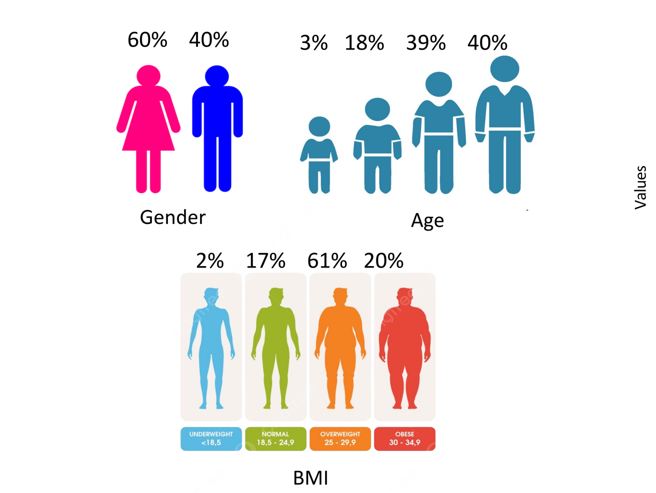
Feature extraction
PPG: SPO2, Respiratory Rate, HRV
ABP: CO, SV, BP, etc.

* Limited computational Resources

Results

- Identified 1036 subjects with 865 labelled as class 1, and 171 as class 0 for Cardiovascular Organ Deterioration.
- 64 features extracted from clinical dataset (EHR), and 76 feature from EHR + waveform dataset.
- 53 subjects out of 100 with waveform dataset met the inclusion criteria.

Population Characteristics and Exploratory Data Analysis



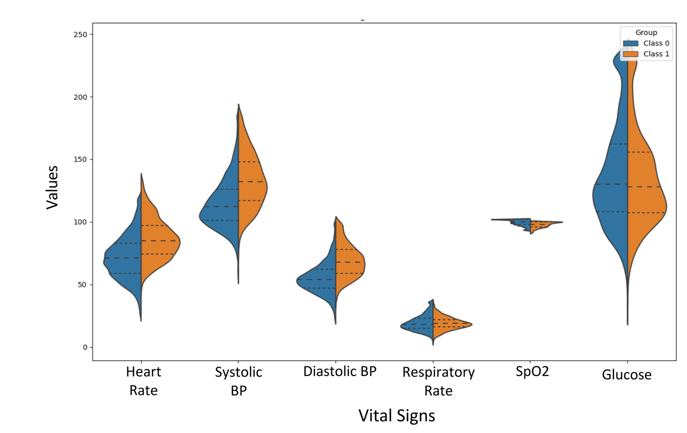


Figure 1: Vital signs comparison between control and target population

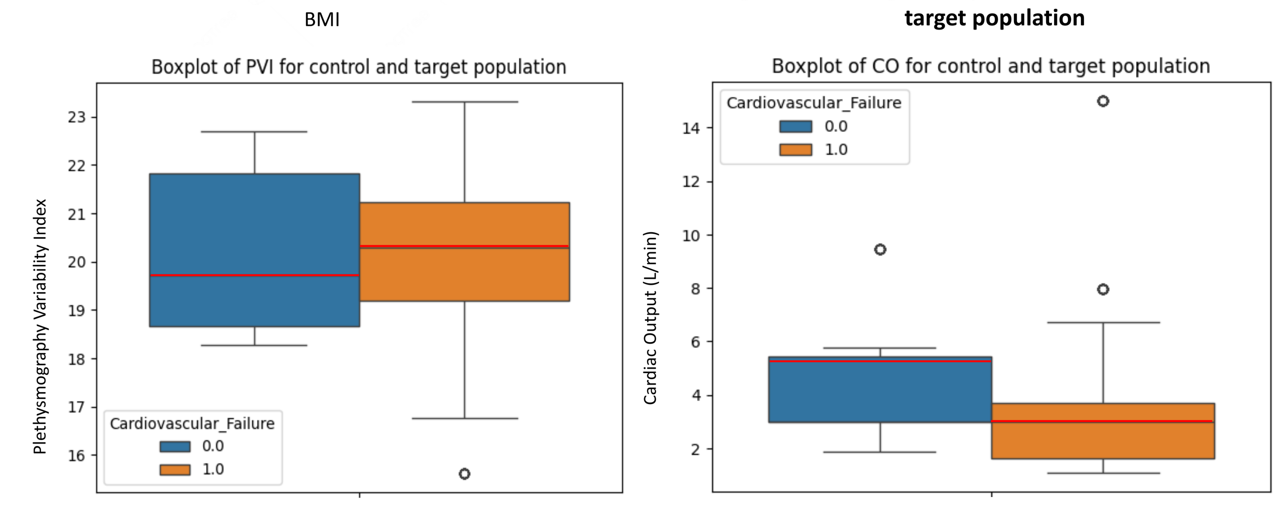
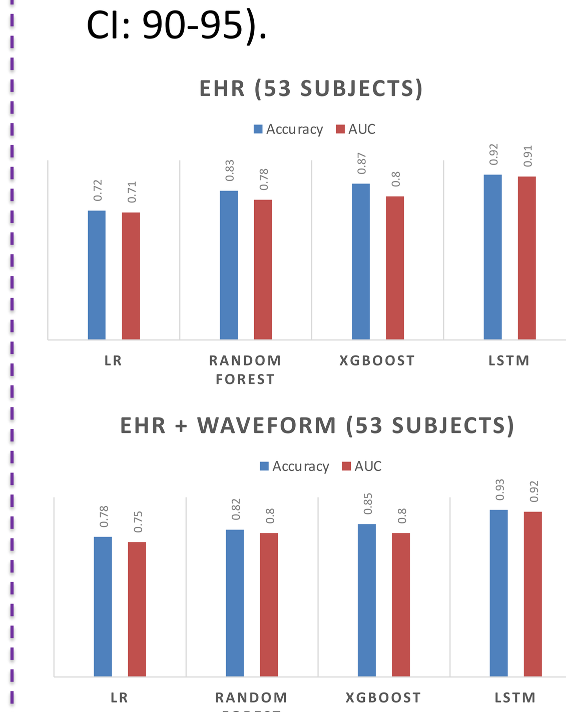


Figure 2: Waveform features comparison between control and target population

- Majority of the diagnoses and comorbidities at admission were related to the cardiovascular organ system.
- Average Stroke Volume of target population was lower compared to the control group (p<0.05)

Training the models for EHR and EHR+Waveform Dataset

- Including features extracted from **waveform data do not increase the accuracy, AUC score** by large margin.
- Best accuracy on complete EHR dataset (1036 subjects) was **93% by LSTM**, with an AUC score of 0.90 (95% CI: 90-95).



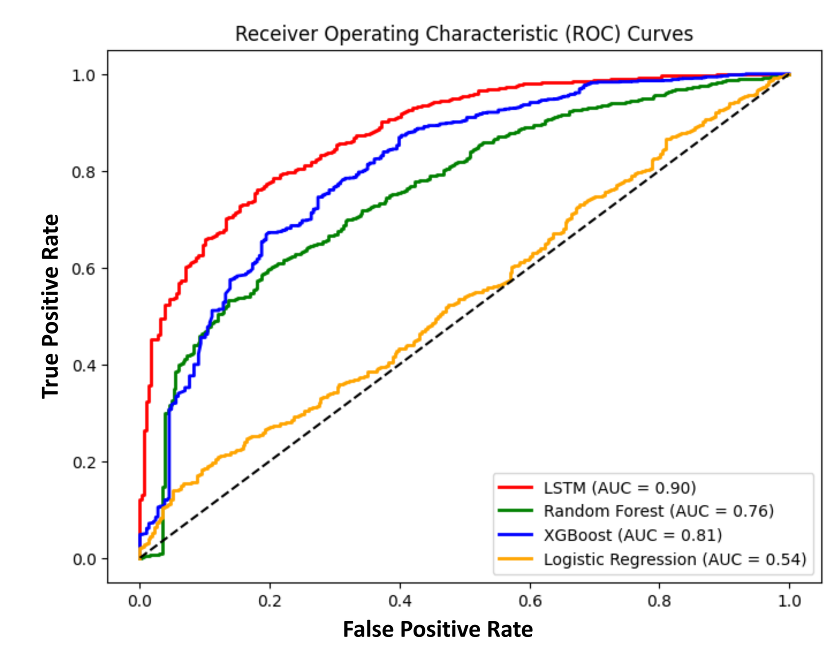


Figure 3: AUC ROC for EHR data (1036 Subjects)

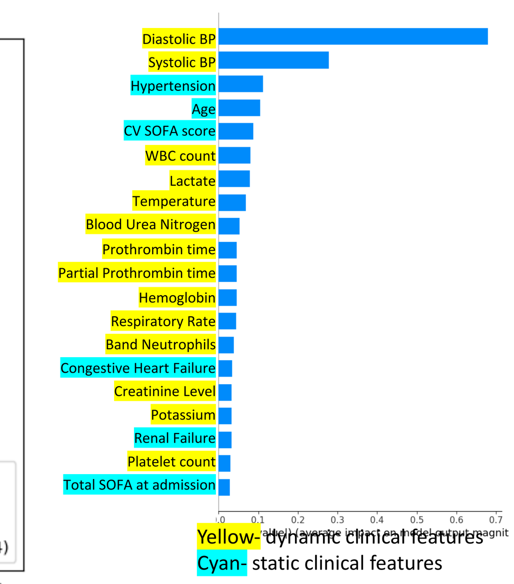


Figure 4: SHAP Analysis of static and clinical features

Testing using LSTM for Dynamic Prediction

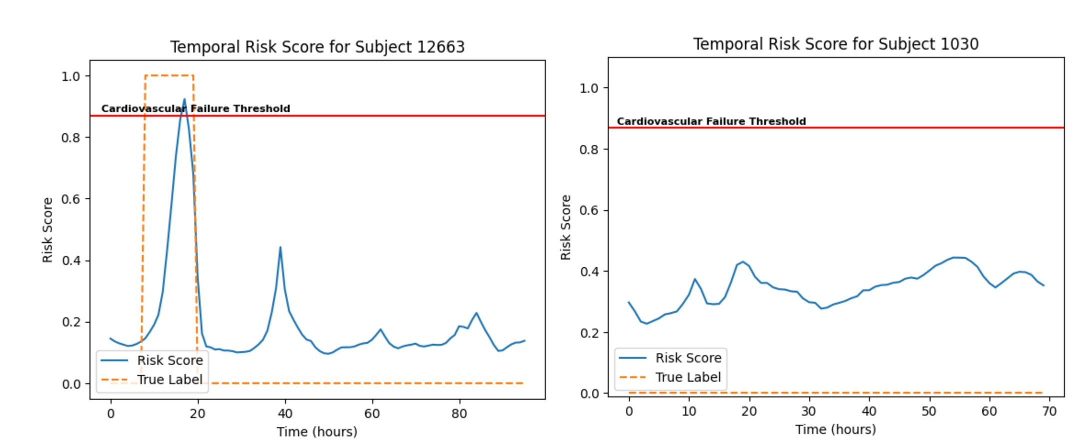


Figure 5: Dynamic risk score for target (left) and control (right) patients

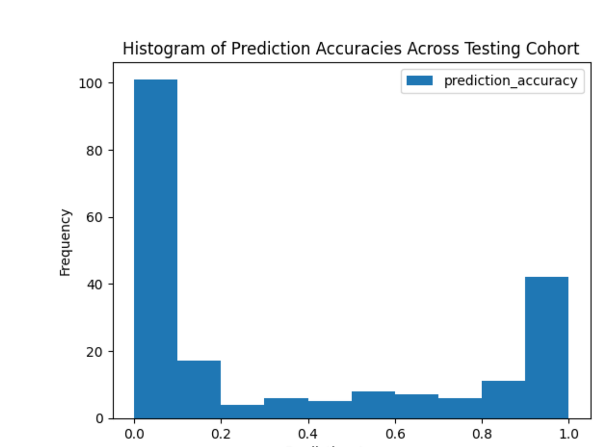


Figure 6: Histogram of point-wise agreement between prediction and label across testing cohort

Conclusions and Future Directions

- LSTM models, when applied to dynamic EHR data, may be successfully trained to detect changes in physiological features indicative of cardiovascular organ system deterioration in the ICU.
- Dynamic prediction of risk score using a 12-hour rolling window with 1 hour data censorship yielded temporally accurate predictions of cardiovascular organ system deterioration, providing early warnings for target group.

Future work:

- Training and testing models from this study, especially LSTM, to predict respiratory system organ deterioration in patients from the MIMIC-III clinical and matched waveform subset databases.
- Understand the model results using SHAP analysis.
- Exploring other time window and buffer times, as well as other data scaling methods between training/ internal validation and external validation datasets.

References/Additional Information