Using ML for Perfusionists' Decision Prediction for Robotic-Assisted Cardiopulmonary Bypass in Cardiac Surgery

Zhaoxin Li[1], Manisha Natarajan[1], Letian Chen[1], Zixuan Wu[1], Paul Ogara[3], Paulo Borges[2], Geoff Rance[4], Rithy Srey[5], Ryan E. Harari[2], Marco A. Zenati[2,3], Roger D. Dias[2], Matthew Gombolay[1]

[1]*School of Interactive Computing, Georgia Institute of Technology, USA*
[2]*Mass General Brigham, Divisions of Cardiac Surgery and Emergency Medicine, USA*
[3]*Division of Cardiac Surgery, VA Boston Healthcare System, USA*
[4]*Cape Code Healthcare, USA* [5]*InvoCirc, Inc., USA*
zli3088@gatech.edu

INTRODUCTION

Cardiopulmonary bypass (CPB) is an essential part of most cardiac surgeries and is managed by Perfusionists. Unfortunately, preventable errors occur due to the interplay of stress, task complexity, information overload, team coordination, and communication with surgeons, anesthesiologists, and nurses. To enable robotic-assisted CPB, an adaptive decision support system (DSS) to support perfusionists with time- and safety-critical intraoperative decision-making. We developed a prototype for such a DSS that can recommend optimal actions to perfusionists in complex clinical scenarios. The system leverages machine learning (ML) models trained on a retrospective dataset of *expert* perfusionists exhibiting real-world decision making; the goal is to predict what an expert perfusionist would likely do in a prospective scenario. We collect a novel dataset of expert perfusionists' decision-making in the operating room with real patients, and we demonstrate that our ML models can predict experts' actions.

MATERIALS AND METHODS

We recruited three patients and two perfusionists at an academic tertiary cardiac surgery service in the USA. Participants were consented under IRB. We collected 492 minutes of time-series data for arterial flow, arterial line pressure, arterial revolutions per minute (Art RPM) of the centrifugal pump, and indexed delivery of oxygen (DO_2i) with a sampling rate between 0.1-1Hz. We linearly smoothed the data to 0.1 Hz resulting in 2,957 data points. Our model predicts the perfusionist action (i.e., Art RPM) with physiological inputs. Due to data imbalance (i.e., most timesteps involve no perfusionist actions), we used a hierarchical approach to first predict 1) whether the Art RPM changes (a multi-layer perceptron (MLP) neural network with three hidden layers [64, 64, and 32 with Rectified Linear Units (ReLU)] taking as input physiological data at a specific time step and a binary cross-entropy loss), and 2) what the new value should be (a Long, Short-term Memory (LSTM) neural network with using one, four-unit hidden and ReLU activations taking as input the last ten time steps of data) at each timestep. We also use MSMOTE [1] to address the imbalance. We only consider the change of the Art RPM > 1.0 as a perfusionist action to denoise.

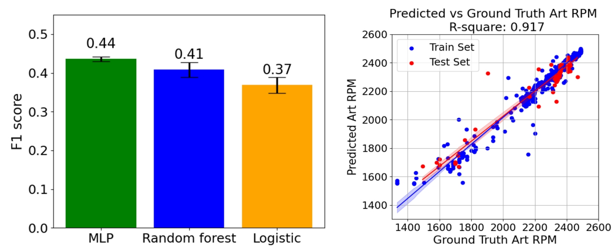

Fig. 1 (Left) F1 scores for predicting action vs. no action. (Right) Scatter plot: predicted vs. ground-truth Art RPM.

RESULTS

First for predicting whether Art RPM changes, we showed our MLP outperformed random forest and logistic regression models (Figure 1). The LSTM model for predicting the new Art RPM achieved an $R^2 = 0.917, F(1, 285) = 19.9, p = 1.20 \times 10^{-5}$.

DISCUSSION

From limited data, the MLP and LSTM models have demonstrated potential for predicting perfusionist's actions. We aim to collect a larger dataset and build machine-learning models to assist perfusionists with higher accuracy in the future.

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REFERENCES

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