Dynamic Risk Prediction of Cardiac Inflammatory Syndrome

JiWon Woo1, Rebecca Mosier1, Rishima Mukherjee1, Kaashri Pruthi1, Wenyu Yang1, Bhargava Chinni2, Joseph Greenstein Ph.D.1, Casey Overby Taylor Ph.D.1, Brian McCrindle M.D.3, Cedric Manlhiot Ph.D.2

1Department of Biomedical Engineering, Johns Hopkins University Whiting School of Engineering, Baltimore, MD, USA
2Department of Pediatrics, Johns Hopkins University School of Medicine, Baltimore, MD, USA
3Department of Pediatrics, University of Toronto, Toronto, ON, Canada

Introduction

Cardiac Inflammatory Syndrome (CIS) is a difficult-to-diagnose, life-threatening condition that leads to long-term consequences in pediatric patients.

Early ICU admission has shown to significantly increase the survival rates for pediatric patients.

Objective

I. Develop machine learning models to predict ICU admissions for children with CIS to improve clinical outcomes.

II. Identify clinical features driving the risk associated with CIS.

Methods

The data used for this study is collected by the International Kawasaki Disease Registry Consortium (IKDR).

Results

I. Machine learning models can effectively predict if the patient will be admitted to ICU within 48 hours at the time of evaluation.

Snapshot Models use discrete time-point clinical features. Window Models use both discrete time-point and engineered time-series clinical features.

Result 1. Machine learning models can effectively predict if the patient will be admitted to ICU within 48 hours at the time of evaluation. Snapshot Models use discrete time-point clinical features. Window Models use both discrete time-point and engineered time-series clinical features. Areas under each curve are noted on the legend. (A) Receiver-operator characteristic curves of Snapshot Models. (B) Receiver-operator characteristic curves of Window Models with 3-day sampling window. (C) Precision-recall curves of Snapshot Models. (D) Precision-recall curves of Window Models with 3-day sampling window.

Result 2. XGBoost and Random Forest Window Models can be well calibrated via Bayesian optimization and 5-fold cross-validation.

Result 3. Machine learning models reveal the feature importance levels associated with CIS. The plot shows 15 most important features measured by Shapley Additive Explanations (SHAP) on 3-day XGBoost model. Blue represents discrete time-point clinical features. Yellow represents engineered time-series clinical features.

Result 4. Incorporation of time-series clinical features improve predictive performances independent of sampling time. PRAUC represents area under precision-recall curve. AUROC represents area under receiver-operator characteristic curve.

Conclusion

I. Machine learning models can accurately predict ICU admission for at-risk pediatric patients with CIS.

II. Incorporation of engineered time-series clinical features improves predictive performances of the machine learning models.

III. Machine learning models reveal clinical features that drive the risks associated with CIS.