Augmenting Sepsis Prediction with Machine Learning

Kathleen Fort, Maria Jorge, Dylan Sain, Alin Navas, Catherine Mooney

Introduction

Machine learning implementation has great potential to aid in sepsis prediction by decreasing the time of diagnosis and treatment by clinicians. To implement machine learning algorithms in a clinical setting, the user interface must:

- Be explainable and understandable
- Avoid eye strain and fatigue
- Have minimal feature inputs
- Implement seamlessly into clinical workflow

These considerations, along with the use of Explainable AI (XAI) were critical in the creation of the user interface for our ML tool.

SOFA Scores & Model Improvements

The current sepsis prediction protocol relies on the SOFA score, which assesses patient risk based on respiration, coagulation, liver, cardiovascular, central nervous, and renal system readings. By incorporating additional laboratory data, including white blood cell count, pO2 levels, and pH, our machine learning model demonstrates improved predictive power. We also integrate raw data on platelet count and creatinine levels, along with coagulation and renal scores. Race and gender data are collected solely for model bias assessment and are not used as predictive factors.

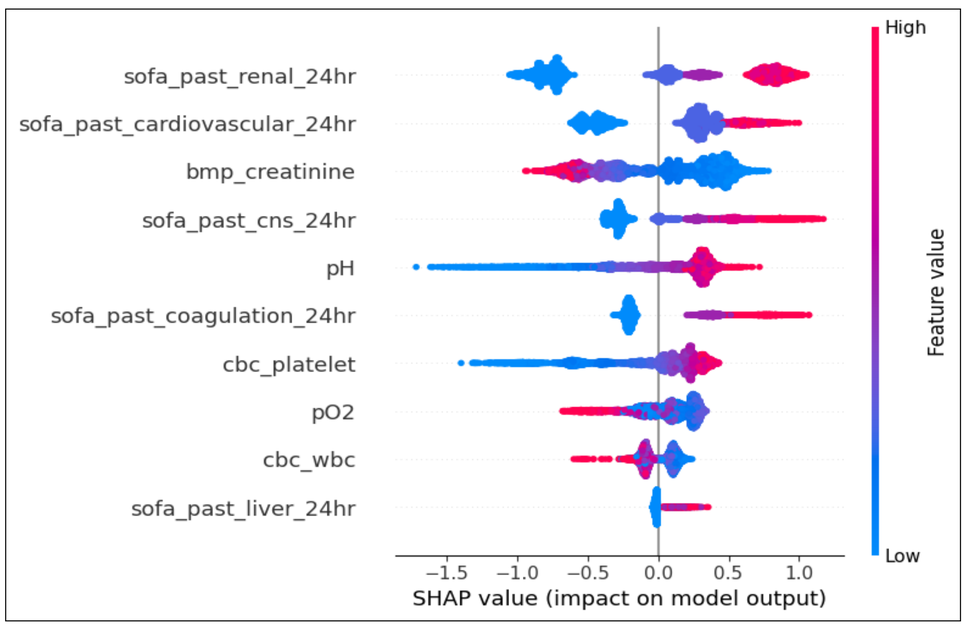
Explainable AI

Explainability is essential in our machine-learning tool in order to:

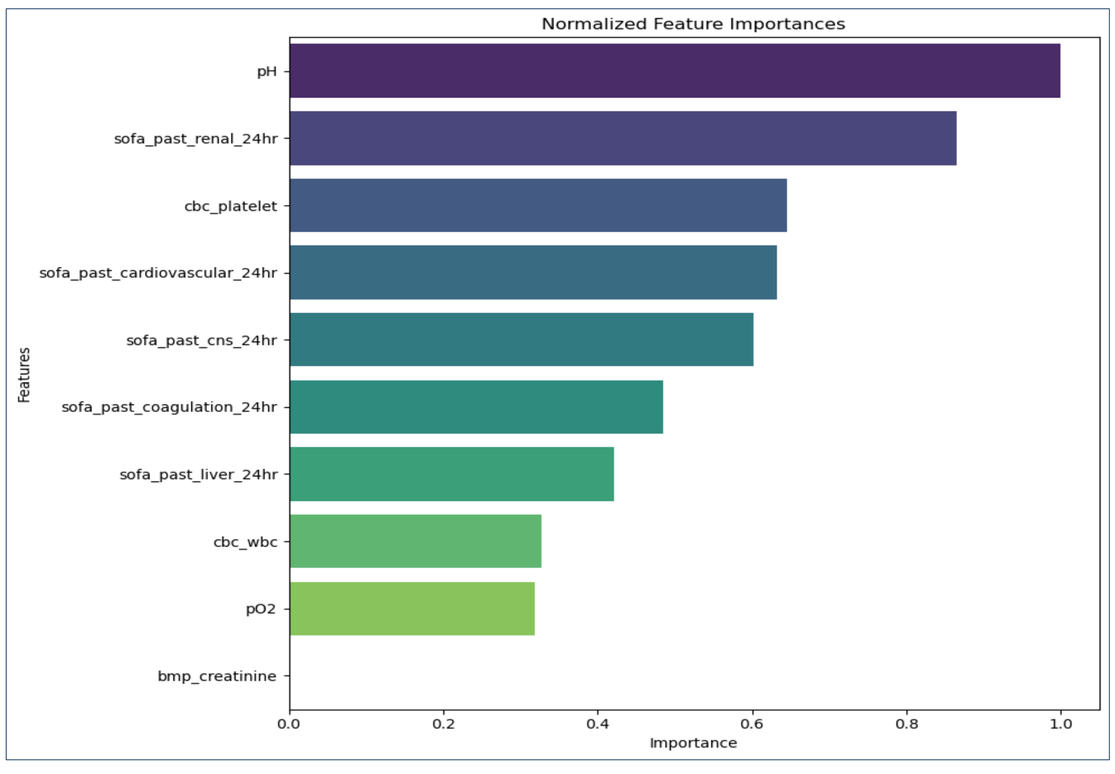
- Allow clinicians to build trust in the algorithm
- Identify flaws and biases in the model
- Resolve disagreements between the model output and clinical decision-making

Our tool utilizes global XAI methods, including Permutation Feature Importance (PFI), Shapley Additive Explanations (SHAP), and Local Interpretable Model-Agnostic Explanations (LIME). Additionally, the user interface displays SHAP local XAI to clarify the categorization of individual patients for clinicians.

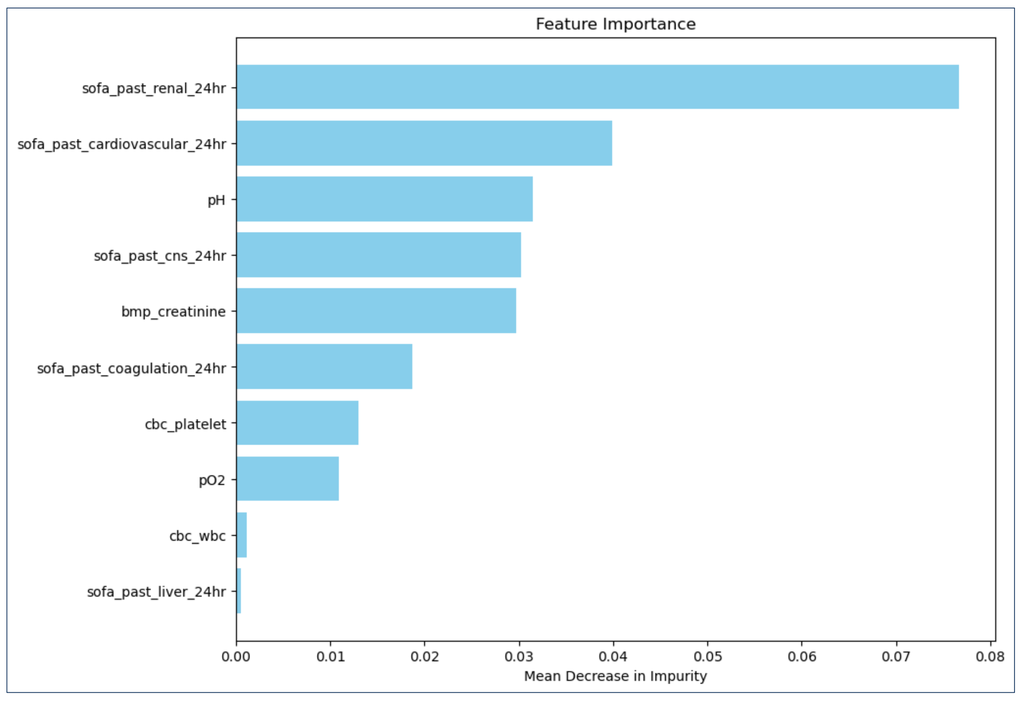
SHAP Global Explainability



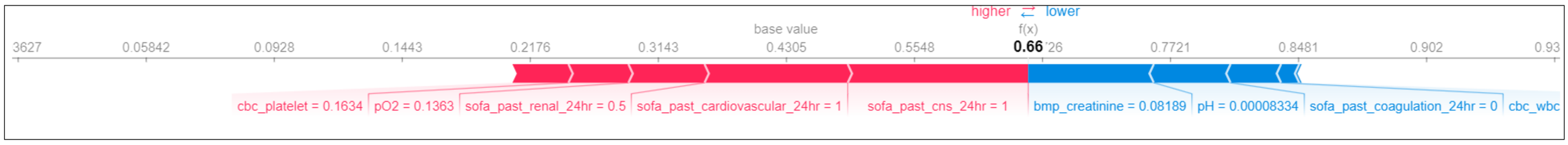
LIME Global Explainability



PFI Global Explainability



SHAP Local Explainability



Clinical User Interface Considerations

Electronic interfaces in clinical settings often cause emotional fatigue, frustration, and eye strain, which can increase clinical errors and the time spent on individual patient cases. It is crucial that our ML tool minimizes user fatigue and integrates seamlessly into the hospital workflow. To achieve this, our tool reduces the number of required input features and incorporates user-friendly elements like drop-down menus and radio buttons, ensuring ease of use and intuitive operation.

Conclusion

Our research aims to enhance sepsis prediction with machine learning, focusing on accuracy, explainability, and user-friendliness. By integrating additional lab data, our model's performance increases. We employed XAI techniques like PFI, SHAP, and LIME to build clinician trust and transparency. Our user interface minimizes fatigue with streamlined inputs and intuitive design. This work is crucial for timely and accurate sepsis diagnosis, improving patient outcomes and demonstrating effective integration of AI in clinical workflows.

ARCADIA ABROAD

katie_fort@outlook.com

UCD School of Computer Science