SIIM CAIMI26
Conference on Artificial Intelligence in Medical Imaging
OCT 26-27 | University of Pennsylvania, Philadelphia, PA

AI-Enabled Prediction of Postoperative Sepsis in Hemodialysis Patients undergoing IR Interventions

Krishnaveni Parvataneni, Massachusetts General Hospital; David C. Schramm, MBBS; Jie Cui, MD; Christopher P. Bridge, DPhil; Dania Daye, MD, PhD

Introduction/Background

Patients with end-stage renal disease (ESRD) undergoing dialysis-related interventional procedures are at elevated risk for postoperative sepsis, yet existing risk prediction tools primarily target long-term outcomes rather than peri-procedural complications. Predicting short-term sepsis is challenging due to low event rates and complex interactions among demographic, laboratory, and procedural variables. We evaluated whether foundation models for tabular data could improve clinically actionable risk stratification in this high-risk population.

Methods/Intervention

A retrospective cohort of 5,077 patients undergoing dialysis-related procedures was identified from the American College of Surgeons National Surgical Quality Improvement Program (ACS-NSQIP, 2011–2018). A Tabular Prior-Data Fitted Network (TabPFN) and a random forest baseline were developed to predict 30-day postoperative sepsis using demographic, clinical, laboratory, and procedural variables. Performance was evaluated on contemporaneous and temporally distinct test cohorts using AUROC. Representation learning with Uniform Manifold Approximation and Projection (UMAP), topological data analysis (Mapper), and SHapley Additive exPlanations (SHAP) were used to characterize patient heterogeneity and interpret model predictions.

Results/Outcome

Postoperative sepsis occurred in 2.3% of patients. TabPFN achieved AUROCs of 0.69 in the contemporaneous test cohort and 0.86 in the temporally distinct validation cohort, outperforming the random forest baseline (0.63 and 0.85, respectively), with a significant improvement in the contemporaneous cohort (DeLong $p=0.031$). Representation learning demonstrated that sepsis risk was distributed across multiple interconnected patient phenotypes rather than a single high-risk cluster. Explainability analyses identified liver dysfunction, coagulation abnormalities, emergency presentation, contaminated wound classification, and markers of physiologic reserve as the strongest contributors to model predictions. Performance remained consistent across demographic and clinical subgroups.

Conclusion

Foundation models for tabular clinical data improve prediction of postoperative sepsis following dialysis-related procedures while providing interpretable insights into heterogeneous risk patterns. Combining foundation models with representation learning and explainability offers a framework for clinically actionable AI that may enable earlier identification of high-risk patients and support personalized peri-procedural management.

Statement of Impact

By integrating foundation models, representation learning, and explainability, this work provides an interpretable framework for predicting rare postoperative complications in medically complex patients. The approach advances clinically trustworthy AI by combining improved predictive performance with insights into heterogeneous disease phenotypes that can inform personalized clinical decision-making.

Keywords

Postoperative Sepsis; Risk Prediction; Hemodialysis; Tabular Machine Learning