Generative AI for Cardiac Arrest Prediction

Cardiac arrest is a leading cause of morbidity and mortality in the U.S. There are approximately 300,000 in-hospital and 250,000 out-of-hospital cardiac arrests each year. In-hospital cardiac arrest requires immediate resuscitative interventions to improve the chances of survival and intact neurologic function. Yet, only about 25% of patients survive to discharge. Clinical studies highlight the need for enhanced predictive algorithms to identify patients at risk for impending cardiac arrest in the minutes to hours before arrhythmia onset. Current monitoring systems in the ICU are unable to identify impending cardiac arrests despite post-hoc analysis by cardiologists revealing high-risk signs. Moreover, cardiac telemetry algorithms suffer from a high burden of false alarms that lead to alarm fatigue.

To address this gap, we propose a cross-disciplinary initiative that combines advanced AI modeling with high-resolution, real-time, cardiac telemetry ECG waveform data from patients admitted to the ICU. Our goal is to develop AI-driven models that provide timely, clinically actionable predictions while substantially reducing false alarms. The potential for real-world impact is high. ICU systems already provide continuous multi-lead ECG monitoring. The high-frequency nature of these signals offer the potential to identify warning signatures that could enable clinical response teams to intervene rapidly on critically ill patients prior to cardiac arrest. ECG waveforms are standard measures of a patient's electrophysiologic health and are generalizable across patient populations.

The team comprises Penn Engineering researchers *Rajeev Alur, Mayur Naik*, and *Eric Wong*, who specialize in safe, explainable, and trustworthy AI, and work in close coordination with leading cardiovascular experts *Dr. Rajat Deo* and *Dr. Sameed Khatana* at Penn Medicine. Their approach comprises three fundamental pillars: (1) generating the largest high-quality long-horizon ECG dataset; (2) building accurate and explainable predictive AI models; and (3) translational integration and clinical validation. In contrast to domains like code generation or protein folding where AI has been remarkably successful due to abundantly available data, public ECG datasets offer only 10-second or single-lead waveforms, which are inadequate to build a generative ECG model let alone predict cardiac arrest sufficiently in advance. This in turn has led to the prevalence of older architectures like tree-based ensembles whose performance is significantly inferior to modern deep learning approaches. Lastly, many efforts in this space suffer from a disconnect between clinical realities and technical development, hindering translational integration.

Our approach will leverage novel, high-resolution, long-horizon ECG data at Penn Medicine, collected from monitoring 10,000 patients. These data, sampled at 250Hz, will provide the crucial fine-grained information that are unavailable in any public dataset. The core challenge in developing prognostic models relates to the ability to distinguish between clinically informative ECG patterns and noise over long-horizon data. Our target is less than 1 false alarm per 3 hours per hospitalized patient and to identify impending cardiac arrest minutes to hours prior to the event. The team has unique expertise in neurosymbolic AI—an approach that blends deep learning's ability to detect complex physiological patterns with symbolic reasoning that provides guardrails by grounding predictions in clinical reality. Their work is rooted in mathematical rigor, systems engineering, and state-of-the-art methods for reliability and interpretability—making them uniquely equipped to build models that are not only accurate but also deployable in high-stakes settings. Our clinical colleagues have extensive expertise in developing and validating prognostic models for sudden cardiac death and fatal cardiovascular disease. Consequently, this collaboration is deeply integrated across both domains—from acquiring and interpreting raw telemetry data to designing models that support clinical decision-making. Our designs are modularly integrated into platforms for clinical evaluation. This initiative will include a shared computational platform for generative design and automated experimental facilities for high-throughput analysis, with the ultimate goal of translating our findings directly into improved patient outcomes. The infrastructure for interdisciplinary collaboration already exists through Penn Engineering's ASSET Center for Trustworthy AI.