

PINNAC: Theory-Trained Neural Networks for Robust Arrhythmia Classification

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ABSTRACT

Electrocardiogram (ECG) based arrhythmia screening needs to maintain robustness against physiologic artifacts, data imbalance and distribution shift. PINNAC is a theory-trained neural network for arrhythmia classification, which combines a standard neural backbone (MLP/CNN) with physics-informed compact excitable-cell surrogates governed by the Aliev Panfilov and FitzHugh Nagumo biophysical models. The electrophysiology modules impose constraints or distillation losses through differentiable solutions, so the resulting latent states are then concatenated to learned features for classification. They developed a confidence-weighted, warm-up schedule to balance the physics and data terms during training, and used test-time aggregation to reduce prediction variance. We assess PINNAC on the MIT-BIH Arrhythmia Database and Noise Stress Test Database in clean, noisy, and reduced-training settings, as well as on a feature-engineered tabular version with Gaussian perturbations. The physics-informed models consistently surpass robust baselines, demonstrating superior accuracy and enhanced class-balanced performance in the presence of noise and data scarcity. Compared to constraints from a single model, the ablation analyses reveal that joint use of both physics priors boosts generalization and robustness. Our results show that incorporating compact electrophysiology priors into deep neural network classifiers enhance robustness against signal corruption, facilitate interpretable latent dynamics and provide a pragmatic path towards robust physiology-aware ECG diagnostics.