Graph-Based Multimodal Learning for Early Sepsis Prediction in Resource-Constrained Clinical Settings

Keywords: Graph Neural Networks, Multimodal fusion, Sepsis prediction, Temporal modeling, Cross-patient reasoning

Sepsis continues to represent a major challenge in intensive care units (ICUs), with mortality risk increasing by 4–8% for every hour of delayed intervention [1]. While recent deep learning approaches have shown promise in predicting sepsis onset from electronic health records and physiological time series [2,3], their reliance on complete, regularly sampled data renders them ill-suited to real-world low resource settings characterized by heterogeneous, asynchronous, and frequently missing modalities [4]. Moreover, existing multimodal fusion methods often neglect temporal irregularities and inter-modality dependencies that are central to clinical reasoning [5].

To address these limitations, we introduce a graph-based multimodal framework that explicitly models both temporal dynamics and cross-modality relationships. Each patient is represented as a temporal-modality graph in which clinical variables—including vital signs, laboratory biomarkers, demographic attributes, and chest radiographs—form modality nodes connected by edges encoding temporal proximity and physiological correlation. We develop a time-aware, resource-weighted message passing mechanism that adaptively prioritizes recent and reliable modalities, thereby mitigating the information loss associated with irregular sampling. In addition, a cross-patient graph propagation layer leverages population-level similarities to enhance prediction under severe modality sparsity, a scenario frequently observed in low- and middle-income healthcare systems.

We evaluate the framework on a curated dataset integrating MIMIC-IV and MIMIC-CXR, encompassing 1,248 patients with balanced positive and negative sepsis outcomes. The proposed model achieves an AUROC of 0.945 and an AUPRC of 0.918, substantially outperforming strong baselines including dynamic temporal GNNs, interpretable sepsis risk scores, and static multimodal graph models. Ablation studies confirm that time-aware message passing, modality-level attention, and cross-patient reasoning each provide significant performance, with the latter proving essential for robustness under missing data. Importantly, the model maintains superior performance even when 50% of modalities are absent, underscoring its applicability in resource-constrained clinical workflows.

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