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A Multimodal Transformer-Based LLM for Predicting Clinical Outcomes in Critically Ill Cardiac Patients

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Introduction

Accurate risk prediction in Cardiac Intensive Care Units (CICUs) is critical for optimizing patient management and improving survival outcomes. Traditional clinical models struggle to integrate the complex and heterogeneous data generated in ICU settings, including high-resolution ECG waveforms, echocardiography images, continuous vital signs, static clinical data, and unstructured clinical notes. This study presents a multimodal deep learning (DL) model incorporating a transformer-based Large Language Model (LLM) to predict key cardiac ICU outcomes, including mortality, length of stay (LOS), cardiac arrest, hemodynamic instability, and shock. Additionally, the model predicts echocardiographic findings from ECG waveforms, offering a cost-effective and non-invasive alternative to imaging in resource-limited settings.

Materials & Methods

This study utilized a multimodal deep learning framework to integrate structured and unstructured data for predicting clinical outcomes in CICU patients. The dataset included ECG waveforms, vital signs, laboratory values, echocardiographic images, and physician notes. Preprocessing involved imputation of missing data, feature extraction, and embedding techniques for different modalities. A transformer-based architecture processed ECG and time-series data, while a Vision Transformer analyzed echocardiographic images. Clinical notes were embedded using a fine-tuned ClinicalBERT model. A late-fusion layer combined these representations to predict mortality, length of stay, cardiac arrest, hemodynamic instability, and shock.

Results

The models multimodal fusion architecture contributed to its robustness, particularly in cases where certain data modalities were missing. Ablation studies confirmed that integrating ECG, vitals, and clinical notes yielded the highest performance, while image data further improved predictive accuracy. Overall, this multimodal transformer-based framework offers a highly effective solution for real-time ICU decision support, personalized patient management, and early intervention strategies, showcasing its potential to transform cardiac critical care through AI-driven analytics. Results of performance will be presented in different metrics and will be made available for use at different hospital units

Conclusion

The results of the model will be shown at the conference as the model is still being fine-tuned. The model promises to enhance patient management using multimodal techniques.