

Read-ICU: An Ensemble Deep Learning Model for ICU Readmission Prediction

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INTRODUCTION

Intensive Care Unit (ICU) readmissions are linked to increased morbidity, mortality, and healthcare costs [1]. The correct timing of ICU discharge is critical to prevent these adverse outcomes. Traditional predictive models have limited accuracy, while deep learning (DL) models offer potential improvements by extracting richer information from multimodal electronic health record data [2].

OBJECTIVES

To enhance ICU readmission prediction task accuracy by developing READ-ICU, an ensemble DL model trained on harmonized multi-institutional data.

METHODS

We identified standardized, publicly available ICU datasets from different institutions and geographical regions. Existing pipelines to merge and pre-process the datasets were searched. A previously conducted systematic review and meta-analysis informed the selection of DL architectures, outcome definitions, and predictors [3]. Bayesian Model Averaging (BMA) was chosen to ensemble the retrieved DL models whose code was publicly available [4]. The area under the receiving operating curve (AUROC) served as the primary performance metric, which guided the training and fine-tuning process. To improve the explainability of the resulting model, we applied an explainable artificial intelligence (XAI) technique able to identify key predictors influencing model output. Analyses were conducted using Python v. 3.10.12.

RESULTS

We gained access to MIMIC-III, MIMIC-IV, the multi-center eICU US datasets, and the European AmsterdamUMCdb [6-9]. We harmonized the four datasets through the BlendedICU pipeline [10]. The 48-hour readmission interval was selected as the outcome measure due to its stronger association with ICU care quality [11]. Recurrent neural networks (RNNs), long short-term memory (LSTM) networks, and convolutional neural networks (CNNs) were retrieved from the selected articles and were integrated into the ensemble READ-ICU model. Key predictors included static variables (e.g., demographics, length of ICU stay, admission source, comorbidities) and time-dependent variables from the last 48 hours of ICU stay (e.g., vital signs, laboratory test results, diagnosis codes, medications), which improved predictive performance in previous models [12].

CONCLUSIONS

DL enables innovative predictive models that may outperform traditional prognostic tools for ICU readmissions. Our systematic review identified promising DL models and challenges, though further efforts are required to optimize performance through multimodal data integration. This study highlights the potential of using ensemble DL techniques, multi-institutional datasets, and XAI techniques to improve the prediction of important outcomes in critical care.

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