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A Federated Learning Model for the Prediction of Blood Transfusion in Intensive Care Units

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Abstract. Accurate prediction of blood transfusion requirements is crucial for patient outcomes and resource management in clinical settings. We developed a machine learning model using XGBoost to predict the need for a blood transfusion 2 hours in advance based on up to 7 hours of prior data from two large databases, MIMIC-IV and eICU-CRD. Our federated model showed promising results, with F1 scores of 0.72 and 0.66, respectively.

Keywords. Federated Learning, ICU, Flower framework, blood transfusion, OMOP CDM

1. Introduction

Predicting blood transfusion (BT) requirements in clinical settings has received considerable attention due to its impact on patient outcomes and resource management. Recent studies apply machine learning (ML) to improve prediction accuracy [1–3], while federated learning (FL) offers privacy-preserving solutions with improved generalizability [4]. Since the average time from requesting to starting a BT is 135 min [5], the objective of this study is to predict BT 2 hours in advance based on an observation window of up to 7 hours using FL.

2. Methods

This study was conducted using two databases, MIMIC-IV [6] and eICU-CRD [7]. The datasets included are IRB-exempt. All patients over 18 years of age were included. MIMIC-IV included a total of 47,779 patients with a BT rate of 21.15%, while eICU-CRD included 42,252 patients with a BT rate of 16.67%. To control for class imbalance, the eICU-CRD cohort without BT was downsampled. Prior to modeling, outliers were removed by replacing values below the 2nd percentile and above the 98th percentile with NaN for each feature. Finally, the data were transformed from a long format to a wide format. We used 21 relevant clinical variables. The primary objective was to predict the occurrence of BT within a 2-hour window, based on up to 7 hours of preceding data.

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XGBoost was used with an 08/20 train-test split. The Flower framework [8] was implemented in a dockerized environment to simulate a federated scenario. The Observational Medical Outcomes Partnership (OMOP) Common Data Model (CDM) was used to standardize the data for FL.

3. Results

The performance of the classification model on MIMIC-IV and eICU-CRD datasets was evaluated using four metrics: F1 score, AUCPR, precision, and recall. The F1 score for MIMIC-IV was 0.72, while for eICU it was 0.66. The AUCPR for MIMIC-IV was 0.80, and for eICU-CRD 0.73. Precision was higher on MIMIC-IV at 0.74 compared to eICU-CRD's 0.67. Recall was also higher on MIMIC-IV at 0.70 compared to eICU-CRD's 0.64.

4. Discussion and Conclusions

We developed a model to predict BT needs, which can enhance outcomes for critically ill patients and optimize resource management in healthcare. This study expands on previous work by predicting BT for a broader patient cohort and extending FL to more diverse use cases. The classification model shows promising results as our federated results are comparable to those of [9]. Future work will focus on an external validation to quantify the benefits of FL.

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