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Seyedmostafa Sheikhalishahi, Johanna Schwinn, Matthaeus Morhart, Mathias Kaspar, Ludwig Christian Hinske

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Federated Learning for Predictive Analytics in Weaning from Mechanical Ventilation

Seyedmostafa SHEIKHALISHAHI [a], Johanna SCHWINN[a], Matthaeus MORHART[a], Mathias KASPAR[a,1], and Ludwig Christian HINSKE[a]
[a] *Digital Medicine, University Hospital of Augsburg, Augsburg, Germany*
ORCiD ID: Seyedmostafa Sheikhalishahi: https://orcid.org/0000-0002-0121-0160

Abstract. Mechanical ventilation is crucial for critically ill patients in ICUs, requiring accurate weaning and extubations timing for optimal outcomes. Current prediction models struggle with generalizability across datasets like MIMIC-IV and eICU-CRD. We propose a federated learning approach using XGBoost with bagging aggregation to improve weaning predictions while ensuring patient data privacy, compliant with GDPR and HIPAA. Using the OMOP Common Data Model, our method integrates machine learning techniques across three ICU databases, encompassing over 33,000 patients. Our model achieved robust performance with 77% AUC and 73% AUPRC. Planned pilot studies in Germany will further refine and validate our approach. This study demonstrates the potential of federated learning to enhance critical care by providing personalized, data-driven insights for ventilation management.

Keywords. Federated Learning, Intensive Care Unit, Weaning, Mechanical Ventilation

1. Introduction

Mechanical ventilation is an important treatment for critically ill patients in the intensive care units. Precisely managing the timing of weaning and extubations from mechanical ventilation is essential for ensuring patient safety and enhancing recovery outcomes [1]. Various approaches are used to forecast weaning; these include direct predictions of complete extubations and the more gradual approach of first anticipating an easing in ventilation requirements. Our recent analysis on the Medical Information Mart for Intensive Care IV (MIMIC-IV) and the eICU Collaborative Research Database (eICU-CRD) highlighted challenges in developing models that are generalizable and perform consistently well across both datasets. In this study we propose a federated learning (FL) approach to improve predictive analytics for weaning patients from mechanical ventilation, to ensure privacy standards that are crucial to handle sensitive health care data and tries to create more generalizable models.

2. Methods and Results

Our study leverages data from three ICU databases: MIMIC-IV, eICU-CRD, and the University Hospital of Augsburg (UKA). This diverse dataset, encompassing over

[1] Corresponding Author: Dr. Mathias Kaspar; E-mail: mathias.kaspar@uni-a.de.

33,000 patients across multiple institutions and geographical regions, providing a robust foundation for training and validating our federated learning model. We converted an existing validated weaning algorithm [2] to a FL scenario. Our FL setup is based on Flower [3] and allows healthcare institutions to collaboratively train models without sharing patient data to better comply with GDPR and HIPAA. We use the OMOP Common Data Model at each Flower client site, into which all source data is transformed. The OMOP transformation achieved 85% accuracy with minimal manual corrections required, ensuring data compatibility across institutions. Using a specialized data extraction tool, we automate the data selection and provision to both conventional machine learning and advanced deep learning techniques.
We implemented a federated learning approach using XGBoost with bagging aggregation, where each institution trains local models that are aggregated without sharing patient data. Model performance was evaluated using multiple metrics: Area Under the Receiver Operating Characteristic curve (AUC), Area Under the Precision-Recall Curve (AUPRC), Precision, and Recall, providing a comprehensive assessment of the binary classification performance for weaning success prediction. The federated model achieved an AUC of 77%, AUPRC of 73%, with precision and recall of 65% and 80% respectively, demonstrating robust performance across diverse patient populations.

3. Discussion and Conclusions

Our initial results indicate that FL has the potential to enhance the performance of an algorithm on single databases (balance) while using different databases [4] and to have potentials to reduce mechanical ventilation duration. Accurate predictions help avoid premature extubations risks, improving patient safety and recovery rates. The model's adaptability to different protocols without direct data transfer is a significant advancement. Implementation challenges include handling heterogeneous ICU data formats, integrating predictions into existing clinical decision support systems, and aligning with varying institutional protocols. Pilot studies in German ICUs will refine algorithms, validate effectiveness, and assess patient management impact. These studies will analyze the implementation processes for FL in clinical settings. Integrating this machine learning tool into clinical workflows marks a significant step towards personalized, data-driven patient care, providing clinicians with reliable tools for informed ventilation management decisions.

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