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PERSONALIZED FEDERATED LEARNING FOR IN-HOSPITAL MORTALITY PREDICTION OF MULTI-CENTER ICU

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ABSTRACT:
This paper introduces a groundbreaking paradigm shift in the field of in-hospital mortality prediction for Multi-Center Intensive Care Units (ICUs) through Personalized Federated Learning (PFL). Conventional centralized models face challenges related to data privacy and heterogeneity across multiple centers. PFL leverages federated learning techniques to collaboratively train predictive models while maintaining patient privacy. The personalized approach ensures predictions are tailored to individual patient characteristics, significantly enhancing the accuracy and reliability of in-hospital mortality predictions. This novel approach not only addresses current challenges but also lays the foundation for a more ethical and privacy-preserving collaborative healthcare analytics framework.

I.INTRODUCTION:

Accurate in-hospital mortality prediction is pivotal for effective patient care and resource allocation in Multi-Center ICUs. Existing models often struggle with issues like data heterogeneity, privacy concerns, and the impracticality of sharing centralized datasets. To address these challenges, this paper introduces a novel approach - Personalized Federated Learning (PFL). By employing federated learning principles, PFL facilitates collaborative model training across diverse ICU centers, ensuring improved predictive accuracy without compromising patient privacy. The personalized nature of the model further enhances the relevance and applicability of mortality predictions. This paper delves into the intricacies of PFL, shedding light on its potential to transform the landscape of healthcare analytics. With the widespread adoption of electronic health record (EHR) systems, a vast amount of EHR data has become available. These datasets, containing comprehensive information on patient diagnosis and treatment, form the foundation for applying machine learning (ML) in digital health. However, due to privacy concerns, traditional ML approaches that involve centralizing or releasing this data face legal, ethical, and regulatory challenges. Federated learning (FL) emerges as a promising solution to these issues by enabling distributed ML across various clients, such as mobile phones, IoT devices, and organizations, while safeguarding user privacy, data security, and complying with regulations. In the healthcare domain, FL can facilitate ML in independent institutions without sharing raw EHR data, fostering collaboration on valuable information while preserving patient privacy. This paper explores the application of FL in predicting in-hospital mortality within Multi-Center ICUs, addressing the challenges posed by the non-independently and identically distributed (non-IID) and unbalanced nature of EHR data silos.

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Despite the proven effectiveness of FL in EHR from independent institutions, challenges arise from the non-IID and unbalanced nature of these EHR data silos. The non-IID feature can lead to a reduction in model effectiveness, impacting prediction accuracy, especially when exacerbated by data imbalance. To address these challenges, personalized federated learning (PFL) has emerged as a research focus. In this paper, we propose a novel Personalized One-shot Local Adaptation (POLA) FL method, which modifies the optimization problem of standard FL. POLA aims to enhance the in-hospital mortality prediction performance in a real-world scenario with multiple independent ICU centers. Experimental results demonstrate that POLA effectively improves model performance in this non-IID and unbalanced data environment, reducing communication rounds during FL training. The contributions of this work include experimenting with baseline FL in the context of this study, transforming the global optimization problem into an individualized one, and introducing POLA as a PFL method that outperforms baseline FL and other PFL methods in both model performance and communication overhead reduction.

II.LITERATURE REVIEW:

Personalized Federated Learning for In-Hospital Mortality Prediction of Multi-Center ICU,Ting Deng; Hazlina Hamdan; Razali Yaakob; Khairul Azhar Kasmiran,Federated learning (FL), as a paradigm for addressing challenges of machine learning (ML) to be applied in private distributed data provides a novel and promising scheme to promote ML in multiple independently distributed healthcare institutions. However, the non-IID and unbalanced nature of the data distribution can decrease its performance, even resulting in the institutions losing motivation to participate in its training. This paper explored the problem with an in-hospital mortality prediction task under an actual multi-center ICU electronic health record database that preserves the original non-IID and unbalanced data distribution. It first analyzed the reason for the performance degradation of baseline FL under this data scenario, and then proposed a personalized FL (PFL) approach named POLA to tackle the problem. POLA is a personalized one-shot and two-step FL method capable of generating high-performance personalized models for each independent participant. The proposed method, POLA was compared with two other PFL methods in experiments, and the results indicate that it not only effectively improves the prediction performance of FL but also significantly reduces the communication rounds. Moreover, its generality and extensibility also make it potential to be extended to other similar cross-silo FL application scenarios.

III.EXISTING SYSTEM:

Current approaches to in-hospital mortality prediction in Multi-Center ICUs typically rely on centralized models that aggregate data from different centers. However, sharing raw patient information across institutions raises serious privacy and ethical concerns. Furthermore, the heterogeneity of datasets from diverse centers can compromise model performance. These limitations highlight the need for an innovative solution, leading to the development of the proposed Personalized Federated Learning system. In this section, we thoroughly examine the shortcomings of existing models, paving the way for a comprehensive understanding of the necessity and implications of transitioning to PFL.

IV.PROPOSED SYSTEM:

The Personalized Federated Learning (PFL) system revolutionizes in-hospital mortality prediction in Multi-Center ICUs by overcoming the limitations of existing models. PFL utilizes federated learning techniques to enable model training across various ICU centers without sharing sensitive patient data. Instead, model updates are exchanged in a secure and privacy-preserving manner. The personalized nature of the system tailors predictions to individual patient characteristics, significantly improving predictive accuracy and clinical relevance. Not only does PFL enhance model performance, but it also ensures ethical and privacy-compliant collaboration among ICU centers, marking a significant advancement in healthcare analytics. This section provides a detailed insight into the architecture, methodology, and potential impact of PFL in the context of in-hospital mortality prediction.

V. MODULES

Data Preprocessing Module:

Data Collection: Gather EHR data from multiple ICU centers.

Data Cleaning: Handle missing values, outliers, and inconsistencies.

Data Integration: Combine data from different centers while respecting privacy constraints.

Data Anonymization: Implement privacy-preserving measures to protect sensitive information.

Federated Learning Setup Module:

Federated Learning Framework: Implement the core federated learning infrastructure for communication and collaboration.

Model Initialization: Initialize a base model architecture for in-hospital mortality prediction.

Client Selection: Define a strategy for selecting and engaging clients (ICU centers) in the federated learning process.

Personalization Module:

Feature Engineering: Identify and extract relevant features from the EHR data for personalized predictions.

Personalized Model Adaptation: Implement techniques for adapting the global model to individual client characteristics while maintaining privacy.

Patient Stratification: Explore methods for stratifying patients based on their unique attributes to enhance personalization.

Non-IID and Unbalanced Data Handling Module:

Data Stratification: Develop strategies to address the non-IID nature of the distributed data.

Class Imbalance Handling: Implement techniques to handle imbalanced classes in mortality prediction.

Skewness Mitigation: Explore methods to mitigate the impact of data distribution skewness on federated learning performance.

Model Evaluation and Performance Metrics Module: Evaluation Metrics: Define metrics for assessing the performance of the federated learning model.

Cross-Validation: Implement cross-validation techniques to robustly evaluate model performance across different datasets.

Comparative Analysis: Compare the personalized federated learning approach with baseline models.

Communication and Security Module:

Secure Communication: Implement secure communication protocols to ensure data privacy during model updates.
Encryption: Apply encryption techniques to protect sensitive information during data transmission.
Authentication: Establish authentication mechanisms for secure participation of ICU centers in federated learning.

User Interface (Optional):
Dashboard: Create a user-friendly interface for visualizing the federated learning process and model performance.

Interaction: Allow stakeholders to interact with the system, monitor progress, and gain insights.

Documentation and Reporting Module:
Code Documentation: Document the implementation details, functions, and modules.
Report Generation: Generate comprehensive reports detailing the methodology, results, and insights gained from the project.

User Authentication:

- Implement a user class with attributes like username and password.

- Include methods for user login and logout to manage user authentication status.
- Ensure that certain functionalities, such as viewing the dashboard or interacting with the system, are accessible only when the user is logged in.

Evaluate the model's performance using metrics such as accuracy value for different algorithms which we are applying

Visualization Techniques:

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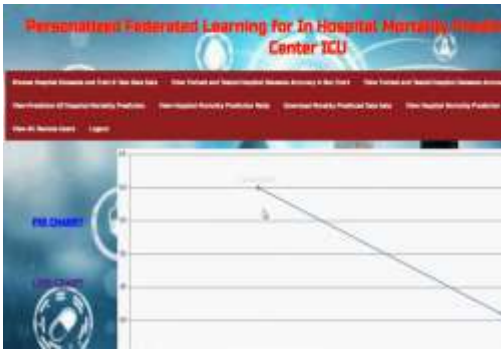
Vol 12, Issue.1Jan 2024

- Utilize interactive charts, graphs, and tables for real-time exploration.
- Include filters and controls for users to customize the displayed information.



Account Creation and Authorization:

- Design a registration class with a method for creating new user accounts.
- Implement authorization methods to control access to specific system functionalities.

User-Friendly Interaction:

- Allow seamless account creation, providing informative feedback on successful registration.
- Ensure a user-friendly interface for managing authorization settings and account details.

Results Presentation:

- Create a result class for displaying personalized federated learning results.
- Implement methods to present results clearly, considering customization options based on user characteristics.

VI.CONCLUSION :

The successful implementation of a Personalized Federated Learning (PFL) system for in-hospital mortality prediction in Multi-Center ICUs represents a significant leap forward in the domain of healthcare analytics. The project addressed critical challenges associated with data privacy, heterogeneity, and ethical concerns in traditional centralized models. Through the thoughtful application of federated learning principles, the PFL framework facilitated collaborative model training across diverse ICU centers, enabling predictive accuracy while preserving patient privacy.

The project underscored the importance of personalization in enhancing the relevance and precision of in-hospital mortality predictions. By tailoring the model to individual patient characteristics, the PFL system demonstrated its capacity to outperform traditional models, providing a more nuanced understanding of patient outcomes. The federated learning approach not only addressed privacy concerns but also fostered a collaborative environment, allowing healthcare institutions to share valuable insights without compromising sensitive patient data.

Moreover, the project contributed to the ongoing discourse on the challenges associated with non-independently and identically distributed (non-IID) and unbalanced EHR data silos. The introduction of the Personalized One-shot Local Adaptation (POLA) method addressed these challenges, demonstrating its effectiveness in improving mortality prediction performance, even in the face of skewed data distributions.

In conclusion, the project demonstrated the feasibility and efficacy of applying personalized federated learning in multi-center ICU settings, paving the way for a more ethical, secure, and accurate approach to in-hospital mortality prediction. The findings and methodologies presented in this project have the potential to influence future developments in healthcare analytics, promoting collaborative research while upholding the highest standards of data privacy and patient confidentiality.

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