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

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ABSTRACT

Federated learning (FL) presents a promising solution for addressing the challenges of applying machine learning (ML) to privately distributed data, particularly in healthcare settings with multiple independently operated institutions. However, the inherent non-IID (non-identically distributed) and unbalanced nature of data distribution can hamper FL's performance and deter institutions from participating in training. This study investigates these challenges using real-world multi-center ICU electronic health record data, preserving the original non-IID and unbalanced distribution. Initially, the paper examines why baseline FL performs poorly under these conditions before introducing a personalized FL (PFL) approach called POLA to mitigate these issues. POLA is a personalized one-shot, two-step FL method designed to produce high-performance personalized models for each participant. Comparative experiments with two other PFL methods demonstrate that POLA not only enhances prediction accuracy and reduces communication rounds but also exhibits potential for application in similar cross-silo FL scenarios. Its versatility and scalability suggest broader applicability across diverse domains beyond healthcare.

I.INTRODUCTION

The utilization of machine learning techniques for predicting in-hospital mortality in intensive care units (ICUs) holds immense potential for enhancing patient care and clinical decision-making. However, traditional approaches face significant challenges when applied to healthcare data distributed across multiple independent institutions, including issues related to data privacy, heterogeneity, and imbalance. Federated learning (FL) has emerged as a promising paradigm for addressing these challenges by enabling collaborative model training without centralizing sensitive data.

In the context of in-hospital mortality prediction in multi-center ICUs, the non-identically distributed (non-IID) and unbalanced nature of patient data distribution poses unique obstacles to the effectiveness of FL. This project aims to explore and address these challenges through the development of a personalized federated learning (PFL) framework tailored specifically for in-hospital mortality prediction tasks.

Using a real-world multi-center ICU electronic health record database, we investigate the performance degradation of baseline FL methods under the original data distribution. Subsequently, we introduce a novel PFL approach named POLA (Personalized One-shot Learning Approach) designed to generate personalized models for each participating institution while mitigating the impact of non-IID and data imbalance.

Through comparative experiments with alternative PFL methods, we evaluate the efficacy of POLA in improving prediction accuracy and reducing communication overhead. Additionally, we assess the generalizability and scalability of POLA, considering its potential applicability to similar cross-silo FL scenarios beyond healthcare.

By addressing the challenges inherent in multi-center ICU data, this project aims to advance the state-of-the-art in personalized federated learning for in-hospital mortality prediction, ultimately contributing to improved patient outcomes and healthcare decision support in critical care settings.

II.EXISTING SYSTEM

In recent years, there has been a surge in research focusing on Personalized Federated Learning (PFL). This surge has been driven by the recognition of the limitations of the unified global model in Federated Learning (FL) to effectively generalize across heterogeneous data sources. Various PFL strategies have emerged to tackle this challenge. These strategies encompass techniques such as model fine-tuning, local loss regularization, meta-learning, multi-task learning, transfer learning, and knowledge distillation.

Model fine-tuning involves adjusting the parameters of the global model using local data from individual clients. Local loss regularization addresses data heterogeneity issues by introducing regularization loss during local training, thereby improving model performance. Meta-learning, exemplified by algorithms like MAML and Reptile, entails training a parameterized model through FL and then swiftly adapting it to individual clients' needs. Multi-task learning aims to simultaneously learn models for multiple related tasks, aligning with the concept of local adaptation in FL. Transfer learning facilitates knowledge transfer between related domains, aiding in personalized model development within FL settings. Knowledge distillation (KD) plays a crucial role in enhancing model personalization within FL. By distilling knowledge from the global model into local client models, KD helps personalize both model structure and parameters, as well as hyperparameters. As the goal of PFL is to maximize model personalization for performance enhancement in FL, KD emerges as a promising technique due to its potential to achieve this objective. Consequently, this study focuses on exploring the applications of KD within FL, aiming to further personalize FL models and improve their performance.

Disadvantages

- An existing system utilized a heuristic algorithm involving automated machine learning (AutoML) in the optimization of personalized models, which may be confused with existing comparable studies.
- By reviewing the existing federated AutoML research, it can be found that almost all of them focus on the NAS of DNN models, especially convolutional neural networks (CNNs). Because the structure of the DNN model has a great impact on the communication overhead and the performance of FL, its automatic design and optimization can bring the most considerable benefits.

III.PROPOSED SYSTEM

The primary objective of our study is to enhance the accuracy of in-hospital mortality prediction within a real-world setting encompassing multiple independent Intensive Care Units (ICUs). To validate the efficacy of our approach, we systematically partitioned the distributed ICU datasets into different configurations, thereby creating ICUs with varying degrees of non-IID data skewness while maintaining the original data distribution. Our experiments highlight that our proposed method,

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named POLA, not only boosts the mortality prediction accuracy of the model within this diverse data environment but also notably diminishes the communication rounds required for Federated Learning (FL) training.

Key contributions of our research include:

Conducting comprehensive experiments utilizing baseline FL within the context of our dataset to establish the foundation for our study.

Proposing a novel Personalized Federated Learning (PFL) technique, POLA, which transforms the conventional global optimization problem of FL into individualized optimizations, thereby generating tailored models for each independent ICU center.

Empirically comparing POLA against baseline FL and two alternative PFL methods to showcase its dual benefits of enhancing model performance and reducing the communication overhead associated with FL.

Advantages

- The proposed scheme is a two-step and one-shot PFL, the overview of which is illustrated in the system. Two-step here refers to FL training and local adaptation, where FL training is to obtain a shared model with adequate global generalization experiment, and local adaptation is a subsequent step to generate high-performance personalized models for independent individuals.
- To simplify and automate it, a classical heuristic technique - Genetic Algorithm (GA) is introduced. GA is a classical and effective evolutionary algorithm that searches for the optimal solution through selection, crossover, and mutation. In this study, it can simultaneously provide a wide search space and optimal solutions for hyper parameters and model structures that need to be designed automatically.

IV.MODULES

- Data Collection and Preprocessing Module:

1.This module is responsible for collecting ICU patient data from multiple centers, ensuring data privacy and security.

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2. Preprocessing steps involve cleaning the data, handling missing values, and standardizing the format for compatibility with the learning algorithms.

➢ Federated Learning Framework Module:

1. This module establishes the framework for federated learning, enabling model training across distributed datasets while preserving data privacy.
2. It manages the communication between the central server and the local clients, coordinating model updates and aggregating gradients.

➢ Personalization Module:

1. This module implements algorithms for personalizing models to individual ICU centers.
2. Techniques like fine-tuning, meta-learning, or transfer learning may be employed to adapt the global model to each center's specific data distribution.

➢ Model Training and Evaluation Module:

1. Handles the training of machine learning models using federated learning techniques.
2. Evaluates model performance using metrics relevant to in-hospital mortality prediction, such as accuracy, precision, recall, and F1-score.
3. This module may also include techniques for cross-validation and hyperparameter tuning.

➢ Communication Optimization Module:

1. Focuses on optimizing communication between the central server and local clients to minimize bandwidth usage and reduce training time.
2. Techniques such as compression, quantization, and differential privacy may be employed to achieve efficient communication.

➢ Deployment and Integration Module:

1. Facilitates the deployment of trained models into production environments.
2. Ensures seamless integration with existing hospital systems and workflows for real-time prediction and decision support.

➢ Monitoring and Maintenance Module:

1. Monitors model performance over time, detecting drift and ensuring continued accuracy.
2. Provides mechanisms for retraining models periodically or in

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response to significant changes in data distribution.

➢ Privacy and Security Module:

1. Implements measures to safeguard patient data privacy throughout the federated learning process.
2. Adheres to regulations such as GDPR and HIPAA to ensure compliance with healthcare data protection standards

V.CONCLUSION

Our project focused on developing a personalized federated learning (PFL) system for in-hospital mortality prediction across multiple independent Intensive Care Units (ICUs). Through meticulous design and implementation of various modules, we addressed the challenges inherent in leveraging heterogeneous ICU datasets while safeguarding patient privacy and data security.

Our approach involved the collection and preprocessing of ICU patient data from diverse centers, followed by the deployment of a federated learning framework. This framework enabled collaborative model training across distributed datasets while respecting the privacy constraints of individual institutions. Leveraging advanced personalization techniques within the PFL framework, we tailored predictive models to the unique characteristics of each ICU center, enhancing prediction accuracy and generalization performance.

Throughout the project, we emphasized the importance of optimizing communication between the central server and local clients to minimize bandwidth usage and training time. We also prioritized the deployment and integration of trained models into real-world healthcare systems, ensuring seamless integration with existing workflows for timely prediction and decision support.

Our comprehensive evaluation demonstrated the effectiveness of the proposed PFL system in improving mortality prediction accuracy while reducing communication overhead. By adhering to stringent privacy and security measures, we ensured compliance with healthcare data protection standards, thereby fostering trust and reliability in our system.

In summary, our project represents a significant step towards personalized and collaborative healthcare analytics, leveraging federated learning techniques to empower healthcare providers with accurate and timely insights for

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improving patient outcomes across diverse ICU settings.

VI.FUTURE SCOPE

Moving forward, there are several promising avenues for enhancing the capabilities of the personalized federated learning (PFL) system in multi-center ICUs. Future research can delve into refining personalization techniques within the federated learning framework, exploring advanced transfer learning and ensemble methods to improve model adaptability across diverse datasets. Integrating real-time data streams from ICU monitoring systems can enable proactive interventions and enhance prediction accuracy, while mechanisms for continuous model monitoring and updating can ensure the system's resilience in evolving healthcare environments. Enhancing interoperability and collaboration between healthcare institutions, coupled with efforts to improve model explainability and address ethical and regulatory considerations, will be crucial for facilitating the adoption of federated learning systems in clinical practice. Additionally, conducting clinical validation studies and real-world deployments can provide empirical evidence of the system's effectiveness, paving the way for its widespread adoption and integration into routine healthcare workflows.

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