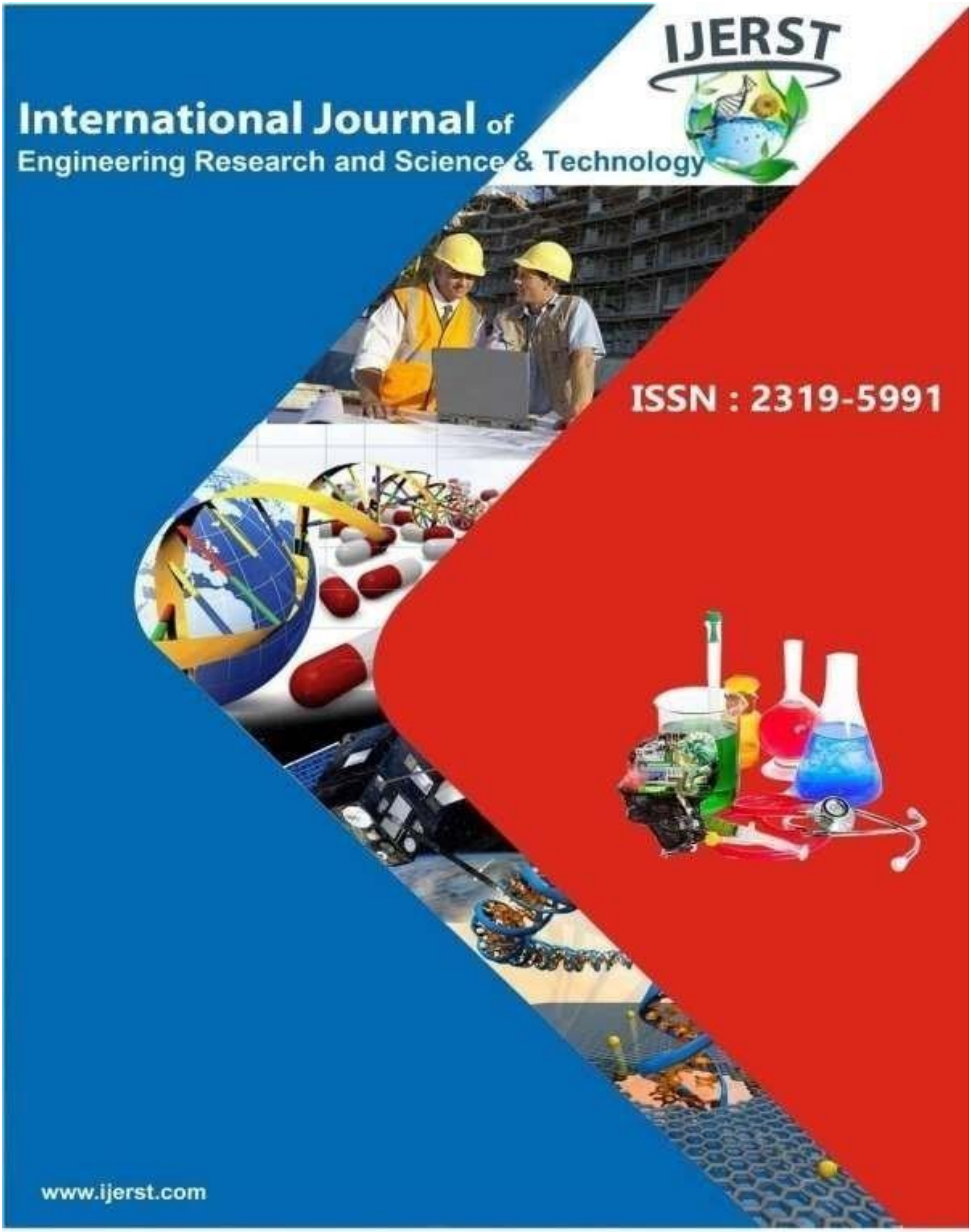

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International Journal of Engineering Research and Science & Technology
ISSN 2319-5991 www.ijerst.com
Vol. 19, Issue 3, 2023

PERSONALIZED FEDERATED LEARNING FOR IN-HOSPITAL

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ABSTRACT

When dealing with privately dispersed data, such as in healthcare settings where numerous independently owned institutions are present, federated learning (FL) offers a potential answer. Nevertheless, institutions may be discouraged from engaging in training and FL's performance may be negatively affected due to the data's intrinsic imbalance and non-IID (non-identically distributed) characteristics. Keeping the original non-IID and imbalanced distribution, this research examines these difficulties using real-world multi-center intensive care unit electronic health record data. In order to address these concerns, the research first investigates why baseline FL does not perform well in these settings. Then, it introduces a personalised FL (PFL) method named POLA. POLA is a two-step FL approach that is customised for each participant and is aimed to generate high-performance personalised models. Testing POLA in comparison to two other PFL approaches shows that it can improve prediction accuracy and decrease communication rounds. It also shows promise for use in comparable cross-silo FL settings. Due to its scalability and adaptability, it might find use in many other fields outside 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

International Journal of Engineering Research and Science & Technology
ISSN 2319-5991 www.ijerst.com
Vol. 19, Issue 3, 2023

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,

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ISSN 2319-5991 www.ijerst.com

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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,

ISSN 2319-5991 www.ijerst.com

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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.

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

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ISSN 2319-5991 www.ijerst.com

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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 response to significant changes in data distribution.

- Privacy and Security Module:

International Journal of Engineering Research and Science & Technology
ISSN 2319-5991 www.ijerst.com
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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

In order to anticipate hospital mortality rates across different ICUs, our study focused on creating a personalised federated learning (PFL) system. We overcame the difficulties of using diverse intensive care unit datasets in a secure way by carefully designing and implementing a number of modules that protect patients' privacy.

Prior to implementing a federated learning framework, our method included gathering and cleaning intensive care unit patient data from several facilities. Collaborative model training across dispersed datasets was made possible by this approach, which also respected the privacy restrictions of different institutions. To improve prediction accuracy and generalisation performance, we used sophisticated personalisation methods inside the PFL framework to modify predictive models according to the specifics of each intensive care unit.

In order to keep training time and bandwidth consumption to a minimum, we stressed the need of optimising communication between the central server and local clients throughout the project. For real-time prediction and decision assistance, we also made it a priority to deploy and integrate trained models into healthcare systems in the real world, making sure they worked seamlessly with current procedures.

We found that the suggested PFL approach improved mortality prediction accuracy and reduced communication overhead in our thorough assessment. Our system's trustworthiness and compliance with healthcare data protection regulations were fostered by our rigorous privacy and security procedures.

In conclusion, our initiative is a major advancement in the field of personalised and collaborative healthcare analytics. By using federated learning approaches, we want to give healthcare practitioners with up-to-date and accurate insights that might improve patient outcomes in various intensive care units.

VI. FUTURE SCOPE

The personalised federated learning (PFL) system in multi-center intensive care units has a lot of potential for future improvement. Improving model

International Journal of Engineering Research and Science & Technology

ISSN 2319-5991 www.ijerst.com

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flexibility across varied datasets may be explored via future research by examining advanced transfer learning and ensemble approaches, as well as by enhancing personalisation strategies within the federated learning framework. Proactive interventions and improved prediction accuracy may be achieved by integrating real-time data streams from intensive care unit monitoring systems, and the system's resilience in changing healthcare settings can be assured by implementing mechanisms for ongoing model monitoring and update. Efforts to increase model explainability, address ethical and legal constraints, and enhance interoperability and cooperation amongst healthcare institutions are vital for supporting the deployment of federated learning systems in clinical practice. The system's efficacy may be shown by clinical validation studies and real-world deployments, which can lead to its broad acceptance and incorporation into regular healthcare processes.

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