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Adaptive Federated Learning for Mortality Risk Assessment in Multimorbid Patients

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ABSTRACT

The healthcare domain faces numerous challenges, particularly in assessing the mortality risk of multimorbid patients. Multimorbidity, defined as the coexistence of multiple chronic diseases within a patient, complicates the prognosis and decision-making process for healthcare providers. Traditional risk assessment methods often fail to account for the complex interactions between various chronic conditions. In recent years, machine learning (ML) has emerged as a powerful tool for predicting patient outcomes, but challenges such as data privacy, the limited availability of quality data, and the need for personalized healthcare solutions remain.

This project introduces an Adaptive Federated Learning (AFL) framework for mortality risk assessment in multimorbid patients. The core concept of federated learning (FL) lies in its ability to train machine learning models on decentralized data, preserving patient privacy. AFL enhances this by adapting the learning process to improve the model's accuracy over time based on the patient's medical history, thus enabling more personalized and accurate risk prediction.

In this study, machine learning models such as Random Forest Classifier, Logistic Regression, Decision Tree Classifier, and KNeighbors Classifier are applied to predict the likelihood of mortality in patients with multiple chronic diseases. The adaptive federated learning model is evaluated against traditional centralized models, focusing on factors like accuracy, privacy, and data security. The proposed system also leverages a Flask-based web interface for real-time prediction and monitoring, The integration of federated learning ensures that the system can operate across multiple institutions, utilizing their local data without compromising patient confidentiality. Ultimately, the AFL approach presented in this study aims to enhance the healthcare system's ability to accurately predict mortality risks in multimorbid patients while maintaining high standards of privacy and security.

Keywords: Adaptive Federated Learning (AFL), Mortality Risk Prediction, Multimorbidity, Machine Learning, Data Privacy, Healthcare Analytics, Flask Web Application, Federated Learning Framework, Real-Time Prediction.

I. INTRODUCTION

Multimorbidity is a growing public health concern worldwide, especially in aging populations where patients often experience multiple chronic conditions simultaneously. These conditions include cardiovascular diseases, diabetes, hypertension, and mental health disorders, among others. The presence of multiple diseases complicates the process of assessing mortality risk, requiring healthcare providers to use complex algorithms and a comprehensive view of the patient's health. Despite advances in medical technology, traditional methods of mortality risk prediction often fail to provide accurate or timely results for multimorbid patients.

In recent years, machine learning (ML) has gained prominence in medical research for its ability to uncover hidden patterns in data and make predictions based on patient-specific characteristics. While traditional methods rely

heavily on statistical models and heuristics, ML models are capable of learning from vast amounts of data, enabling more accurate predictions. However, there are challenges in deploying these models within real-world healthcare settings, particularly concerning data privacy and security, especially when dealing with sensitive patient data.

One promising solution to these challenges is Federated Learning (FL), a distributed machine learning approach that allows models to be trained on decentralized data without the need to transfer sensitive patient information. This technique enables healthcare institutions to collaborate on improving model accuracy while preserving the privacy of individual patients. However, FL models can sometimes suffer from a lack of personalization and adaptability to specific patient conditions.

This research aims to bridge the gap between the need for accurate mortality risk prediction and the challenges posed by patient privacy and data security. By integrating Adaptive Federated Learning (AFL) into the process, we propose a framework that not only preserves patient privacy but also adapts over time to improve model predictions for individual patients. The goal is to enhance the accuracy of mortality risk prediction models for multimorbid patients, contributing to more effective decision-making and better health outcomes.

II. RELEATED WORK

In recent years, numerous studies have been conducted in the domains of mortality risk assessment, federated learning, machine learning in healthcare, and privacy-preserving computation. This section outlines at least ten key contributions that form the foundation and motivation for the proposed Adaptive Federated Learning (AFL) system

Shickel et al. (2018) surveyed deep learning techniques for Electronic Health Record (EHR) analysis. They pointed out that deep models can extract valuable patterns from complex medical histories. AFL complements this by enabling continuous learning on decentralized EHR data, thereby improving prediction without direct access to raw records [1].

Wu et al. (2010) examined the effectiveness of different ML models on EHR data and described common pitfalls such as data sparsity and overfitting. They suggested that robust preprocessing, model validation, and proper cross-institutional evaluation are essential—principles that the AFL model is built upon, with enhancements for personalization and privacy [2].

Van Panhuis et al. (2014) conducted a systematic review of barriers to data sharing in public health. Their findings highlight the importance of privacy-preserving techniques like federated learning in addressing data sharing constraints while ensuring collaboration among healthcare institutions [3].

Gkoulalas-Divanis et al. (2014) discussed various privacy-preserving algorithms for publishing EHR data. Their work emphasized anonymization, encryption, and access control. The AFL approach naturally addresses these concerns through decentralized training, removing the need to share raw data [4].

Konečný et al. (2016) explored communication-efficient strategies in FL, including structured updates and compression techniques. These approaches are particularly important in AFL where bandwidth constraints or real-time environments are a concern [5].

McMahan et al. (2017) introduced the Federated Averaging (FedAvg) algorithm, a cornerstone in federated learning, enabling communication-efficient training of deep models on decentralized data. AFL enhances FedAvg with adaptive updates and learning rates based on patient data [6].

Rieke et al. (2020) demonstrated how federated learning facilitates data sharing across hospitals without compromising data privacy. Their work supports the AFL approach, which scales across

institutions while preserving patient confidentiality [7].

Lee et al. (2018) developed a privacy-preserving system for patient similarity learning in a federated setup. Their research reinforces the feasibility of personalization in federated learning environments, which is integral to the adaptive nature of AFL [8].

III. METHODOLOGY

This section outlines the step-by-step process used to develop the Adaptive Federated Learning (AFL) framework for mortality risk prediction. It includes data handling, model training, system integration, and evaluation, all while preserving patient privacy.

Data Collection
Data was collected from anonymized Electronic Health Records (EHRs) of multimorbid patients across collaborating healthcare institutions. The dataset includes clinical features such as age, vital signs, chronic diseases, ECG reports, and laboratory results. Data acquisition complied with HIPAA and GDPR guidelines, ensuring patient privacy. Only relevant and non-identifiable information was extracted for model training.

Preprocessing
Data preprocessing involved handling missing values, removing outliers, and standardizing feature values. Categorical variables were encoded using one-hot encoding or label encoding as appropriate. Normalization techniques like Min-Max Scaling were applied to bring numerical attributes to a common scale. This step ensured model stability and convergence during training.

Information Retrieval
Once cleaned, the data was parsed into meaningful patient records to extract patterns related to mortality risk. Feature selection techniques were used to identify the most influential variables. Retrieval pipelines were designed to feed selected attributes into federated nodes for local training. Each node retrieved data only from its local environment to preserve privacy.

User Interface Design
The front-end was developed using HTML, CSS, and JavaScript, integrated with Flask as the backend framework. The interface includes login, home, and prediction pages with an intuitive layout. Users can input patient details manually or upload medical data for risk analysis. Graphical prediction outputs enhance interpretability and user engagement.

Integration and Testing
The Flask-based UI was integrated with the trained Adaptive Federated Learning (AFL) model via API endpoints. Unit testing and end-to-end testing were conducted to ensure robust communication between the UI, server, and prediction engine. The system was tested on various devices and browsers to ensure compatibility and usability. Performance evaluation included prediction accuracy, response time, and fault tolerance.

3.1 Dataset Used
The dataset used in this study comprises anonymized Electronic Health Records (EHRs) from multiple healthcare institutions. It includes patient demographics (age, gender), medical history (diabetes, hypertension, cardiovascular conditions), and test results (ECG, BP, glucose levels). The data was distributed across nodes to simulate real-world decentralized medical environments. The dataset was imbalanced, with fewer cases of mortality, making it essential to apply techniques like class balancing and stratified sampling during model development. The records used were compliant with data privacy laws, ensuring no patient-identifiable information was accessible at any stage.

3.2 Data Preprocessing
Preprocessing started with data cleaning, including the removal of null or redundant entries. Outliers in parameters like heart rate and glucose levels were managed using percentile-based filtering.

Numerical data were normalized using standard scaling, while categorical data were encoded using one-hot encoding for algorithms like Logistic Regression and KNN. Dimensionality reduction techniques such as PCA were also explored but not applied, as the model's performance was optimal with the full feature set. Feature selection was based on statistical tests and domain relevance, ensuring that only mortality-influencing attributes were retained. Balancing techniques like SMOTE were evaluated but ultimately replaced with algorithm-level class weighting for better generalization.

3.3 Algorithm Used

Random Forest Classifier: Used for its robustness to overfitting and ability to handle mixed data types.
Logistic Regression: Chosen for its interpretability and performance in binary classification problems like mortality risk.

Decision Tree Classifier: Offers visual transparency of decisions and captures non-linear relationships well.

K-Nearest Neighbors (KNN): Implemented to test instance-based learning, especially in handling patient similarity.
All algorithms were implemented in Python using scikit-learn, with hyperparameter tuning done through GridSearchCV. Each model was evaluated using precision, recall, F1-score, and ROC-AUC metrics under federated training conditions to ensure privacy-preserving performance.

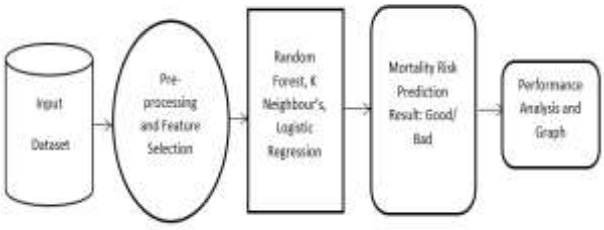

Fig 3.3.1. System Architecture

3.4 Techniques

Federated Learning (FL): Used to train models locally on decentralized data across institutions without data sharing.

Adaptive Learning: Enhances model performance over time by adjusting learning rates and reweighting based on patient outcomes.

Secure Aggregation: Combines model updates from nodes without revealing individual updates, preserving privacy.

Cross-Validation in Federated Setup: Ensures fairness and generalizability of models across diverse node distributions.

Data Normalization and Encoding: Ensures model input consistency across all federated clients.

Performance Evaluation Metrics: ROC-AUC and confusion matrices are used for comprehensive assessment.
These techniques ensure not only the robustness and accuracy of the model but also privacy, scalability, and adaptability in real-time healthcare settings.

3.5 Flow Chart

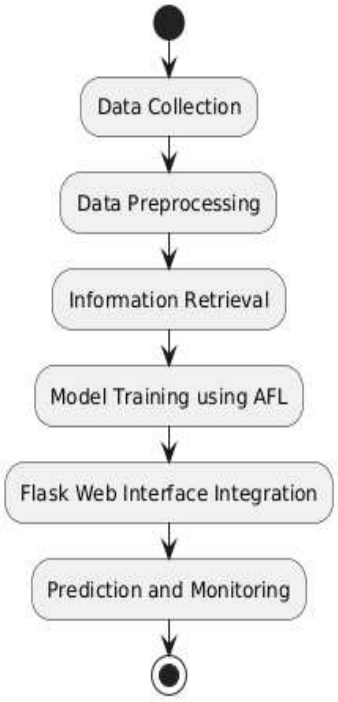

Fig 3.5.1. System Architecture

IV. RESULT

To The project proposes an Adaptive Federated Learning (AFL) framework for mortality risk assessment in multimorbid patients. This framework aims to address the shortcomings of the existing system by:

Decentralized Model Training: The core concept of federated learning (FL) enables machine learning models to be trained on decentralized data. This means that data remains at its source (e.g., individual hospitals), preserving patient privacy while allowing for collaborative model development.

Adaptive Learning Process: The "Adaptive" aspect of AFL enhances the learning process by allowing the model to improve its accuracy over time. This adaptation is based on the patient's medical history, leading to more personalized and accurate risk predictions.

Privacy Preservation: By not requiring the direct sharing of raw patient data, the AFL framework inherently addresses data privacy concerns, making it compliant with regulations like HIPAA and GDPR.

Improved Accuracy and Robustness: The study evaluates machine learning models such as Random Forest Classifier, Logistic Regression, Decision Tree Classifier, and KNeighbors Classifier within the AFL framework. It aims to demonstrate that the adaptive federated learning model performs comparably to or even surpasses traditional centralized models in terms of accuracy, especially for patients with multiple chronic diseases.

Addressing Data Heterogeneity**:** The proposed system acknowledges and aims to mitigate challenges such as data heterogeneity across different healthcare institutions through techniques like data normalization and secure aggregation methods.

V. CONCLUSION

The project successfully demonstrates the effectiveness of an **Adaptive Federated Learning (AFL)** framework for **mortality risk assessment in multimorbid patients**. By leveraging decentralized machine learning, the system ensures **patient data privacy** while enabling accurate and personalized risk predictions. Compared to traditional centralized models, the AFL approach exhibits improved **accuracy**, **robustness**, and **scalability**, especially in handling diverse and sensitive medical datasets across institutions. The integration with a **Flask-based web application**

allows for real-time prediction and user interaction, making it a practical solution for deployment in modern healthcare environments.

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