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Research Article

Detection of Heart Disease Using Deep Federated Learning Algorithms

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ABSTRACT

Heart disease remains one of the leading causes of mortality worldwide, necessitating advanced and efficient diagnostic methods. Traditional machine learning (ML) as well as deep learning (DL) approaches for heart disease detection often rely on centralized data, which raises concerns about data privacy, security, and accessibility. Recently, Federated Learning (FL), a decentralized machine learning paradigm, has emerged as a promising solution to these challenges. This paper explores the application of Deep Federated Learning (DFL) algorithms in the detection of heart disease namely Federated Averaging (FedAvg), Federated Learning with Differential Privacy (DP-FL), Federated Transfer Learning (FTL), Personalized FL (PFL) and Lightweight FL (LFL).We also discuss the principles of FL, its integration with deep learning models, and its advantages in healthcare specially for heart diseases detection. Additionally, we review recent advancements, challenges, and future directions in this field. Finally, it is observed that Personalized Federated Learning (PFL) achieves the highest performance with 96.2% accuracy, 96.4% F1-score that demonstrating the benefits of adapting models to individual client data.

Keywords: Heart Disease, Deep Learning, Federated Learning, Deep Federated Learning,

1. INTRODUCTION

Heart disease encompasses a range of conditions affecting the heart, including coronary artery disease, arrhythmias, and heart failure. Early and accurate detection is crucial for effective treatment and management. Machine learning (ML) and deep learning (DL) have shown significant promise in diagnosing heart disease by analysing complex medical data such as electrocardiograms (ECGs), medical imaging, and patient records. However, the reliance on centralized data repositories poses significant risks to patient privacy and data security.

Federated Learning (FL) offers a decentralized alternative, enabling multiple parties to collaboratively train a model without sharing raw data. This approach is particularly advantageous in healthcare, where data privacy is paramount. Deep Federated Learning (DFL) combines the strengths of FL and DL, allowing for the development of robust models while preserving data privacy.

This review paper provides a comprehensive overview of the current state of Deep Federated Learning in heart disease detection, highlighting its potential and challenges. As the field continues to evolve, DFL is poised to play a pivotal role in advancing personalized and privacy-preserving healthcare.

2. PREVIOUS RESEARCH REVIEW

A Angel Nancy et al. [1], the, convergence of IoT, cloud technology, and deep learning is transforming healthcare. Predictive analytics using advanced AI and ML approaches can accurately predict heart disease risk. The proposed smart healthcare system, powered by Bi-LSTM, achieves impressive accuracy (98.86%)— outperforming existing systems. It used Cleveland and Hungarian dataset. And the methods used here are RNN, LSTM, Proposed Bi-LSTM Model. The smart healthcare system for monitoring and accurately predicting heart disease risk built around Bi-LSTM (bidirectional long short-term memory) showcases an accuracy of 98.86%, a precision of 98.9%, a sensitivity of 98.8%, a specificity of 98.89%, and an F-measure of 98.86%, which are much better than the existing smart heart disease prediction systems.

Ali Mohamed Hussien et al. [2], The paper proposes a deep stacking ensemble model for early detection of heart disease. It combines two hybrid deep learning models, CNN-LSTM and CNN-GRU, with Support Vector Machine (SVM) as the meta-

learner. Recursive Feature Elimination (RFE) is used for feature optimization. The model is tested on two heart disease datasets and compared with five machine learning models and other hybrid models. The proposed ensemble model outperforms the others, showing promise for early heart disease prediction. Two dataset is used here one is first dataset and another is Cleveland dataset. And the methods used here are Deep staking ensemble, CNN-LSTM Model, CNN-GRU Model, Recursive feature Elimination, Classical ML Models. it is stated that the proposed model, which is the deep staking ensemble method integrating CNN-LSTM and CNN-GRU models with an SVM meta-learner, achieved the highest accuracy among all compared models. Specifically, for the first dataset, it achieved an accuracy of 78.81%, and for the Cleveland dataset, it achieved an accuracy of97.17%. Therefore, the proposed model yielded the best accuracy in this study.

Sadia Arooj et al. [3], This study proposes a deep learning approach using image classification for heart disease detection. By utilizing a deep convolutional neural network (DCNN) on the UCI heart disease dataset, the model achieves a validation accuracy of 91.7%. The results suggest that this approach holds promise forimproving real-world heart disease detection. The methods used here are data cleaning and filtering, Convolutional Neural Network, Train-test split, Model training and Model Validation. The method that gives the best accuracy in this study is the Convolutional Neural Network (CNN) model, which achieved a prediction accuracy of 91.71%.

M.R.I Faruque et al. [4], The study employs machine learning algorithms to detect heart disease, achieving high accuracy rates on various datasets. Utilizing random forest, decision tree, AdaBoost, and K-nearest neighbor models, the study reports accuracy percentages ranging from 93.437% to 100%. The research also develops a computer-aided smart system for disease prediction using Streamlit. Notably, the study explores significant predictors contributing to heart disease prognosis. Overall, this research contributes to the efficient diagnosis of heart conditions and underscores the importance of machine learning in healthcare. It used Cleveland ,Hungary, Switzerland, Long Beach dataset. The methods used here are randomforest, Decision tree, Ada boost, K Nearest Neighbor. the maximum accuracies achieved by the machine learning models are as follows: Random Forest (RF) on the CHSLB dataset: 99.03%, Decision Tree (DT) on the CHSLB dataset: 96.10%, AdaBoost (AB) on the CHSLB dataset: 100%, K-nearest neighbor (KNN) on the CHSLB dataset: 100%. On the Cleveland dataset: Random Forest (RF): 93.437% K-nearest neighbor (KNN): 97.83%.

Mohammed S.Alqahtani et al. [5], The paper presents a heart disease prediction model using machine learning algorithms on combined datasets. Random Forest Classifiers (RFC) demonstrate high accuracy and reliability, achieving 100% in multiple performance metrics. Cross-validation and feature reduction methods are employed to enhance predictive capabilities. Results indicate strong performance across various classifiers, suggesting efficacy in early heart disease prediction.

Overall, the proposed technique offers a rapid and accurate approach to identify potential cardiac issues. It Used Cleveland database National Cardiovascular Disease Surveillance (NCDS) System's heart disease database Kaggle heart disease dataset, which combines data from: Cleveland, Kaggle heart disease dataset, which combines data from: Cleveland, Hungary, Switzerland, VA Long Beach. The methods used here are: Heart disease prediction model, Analysis. The maximum accuracy received in the paper for the Random Forest Classifiers (RFC) on the combined heart disease datasets is reported as 100%. This indicates that the model achieved perfect accuracy in predicting heart disease based on the analyzed data.

3. AN OVERVIEW ON FEDERATED LEARNING

Federated Learning is a machine learning framework where multiple clients (e.g., hospitals, clinics) collaboratively train a model under the coordination of a central server. The key steps in FL are first Local Model Training, here each client trains a local model on its own data, secondly model aggregation, in this step the central server aggregates the local model updates (e.g., weights, gradients) to update the global model and in the final step is known as model distribution in which the updated global model is sent back to the clients for further training.

This process is repeated iteratively until the model converges. FL ensures that raw data remains on the local devices, thereby preserving data privacy.

3.1 Deep Federated Learning for Heart Disease Detection

Deep Federated Learning integrates FL with DL, enabling the training of deep learning models in a decentralized manner. This approach is particularly beneficial for heart disease detection due to the sensitive nature of medical data. Some major advantages include data privacy, data diversity and regulatory compliance. In data privacy, raw data remains on local devices, reducing the risk of data breaches. In data diversity, models can be trained on diverse datasets from multiple institutions, improving generalization. In Regulatory Compliance, FL aligns with data protection regulations such as GDPR and HIPAA. Traditional DL algorithms require centralized data storage, where all patient data is aggregated into a single repository for training. This raises significant privacy concerns, as sensitive medical data (e.g., ECGs, patient records) is exposed to potential breaches or misuse. Deep Federated Learning (DFL) offers several advantages over traditional Deep Learning (DL) algorithms, particularly in the context of detecting heart diseases. These advantages stem from its decentralized nature, privacy-preserving capabilities, and ability to leverage diverse datasets. DFL eliminates the need for centralized data storage. Instead, data remains on local devices (e.g., hospitals, clinics), and only model updates (e.g., gradients or weights) are shared with a central server.

3.2 Recent Advances in Deep Federated Learning

Several studies have explored the application of DFL in heart disease detection. The recent advances that researcher are concentrated mainly ECG analysis where researchers have used DFL to train models on ECG data from multiple hospitals, achieving comparable performance to centralized models while preserving data privacy. Similarly Medical Imaging in which DFL has been applied to analyze echocardiograms and MRI scans, enabling collaborative model training across institutions. Furthermore it is observed that Multimodal Data Integration is the area where some studies have combined ECG data with other clinical data (e.g., patient history, lab results) using DFL, enhancing diagnostic accuracy. As of the latest research, several experimental studies have demonstrated the effectiveness of Deep Federated Learning (DFL) algorithms in detecting heart diseases. Below are some of the most recent and notable experimental results, highlighting the performance of various DFL approaches in heart disease detection:

A study on Federated Learning for ECG-Based Heart Disease Detection done by Zhang et al.(2023) [6] **.** He proposed a federated learning framework for detecting arrhythmias using ECG data from multiple hospitals using PTB-XL ECG dataset **.** A Federated Averaging (FedAvg) algorithm combined with a Convolutional Neural Network **(CNN)** for feature extraction achieving an accuracy of 92.5% for arrhythmia detection, comparable to centralized training.

In another study, by Li et al.(2023)[7] explored federated transfer learning for combining ECG data and echocardiograms from multiple institutions using the MIMIC-III dataset and a private echocardiogram dataset from two hospitals. In this research he used A Federated Transfer Learning (FTL) framework with a ResNet-50 backbone for image analysis and an LSTM for time-series ECG data and Achieved an F1-score of 0.89 for detecting heart failure, outperforming single-modal approaches that Reduced training time by 20% compared to traditional FL methods and maintained data privacy while achieving 95% of the performance of centralized training

Furthermore, for Privacy-Preserving Federated Learning for Coronary Artery Disease Detection, A study by Wang et al. (2023) [8] proposed a privacy-preserving FL framework for detecting coronary artery disease (CAD) using patient records and imaging data using UK Biobank dataset and a private dataset from four medical centers. In this case, he implemented A Differential Privacy (DP)-enhanced FedAvg algorithm with a Vision Transformer (ViT) for image analysis and achieved an AUC of 0.91 for CAD detection, with a privacy budget of $\varepsilon = 1.0$ reducing data leakage by 40% compared to non-DP FL methods.

Recently, another research works carried out by Chen et al.(2023)[9] by introducing a personalized FL approach for predicting heart disease using patient-specific data. The study used the Cleveland Heart Disease dataset and a private dataset from five clinics. He applied A Personalized Federated Learning (PFL) framework with a Graph Neural Network (GNN) to model patient relationships and achieved an accuracy of 94.2%, outperforming non-personalized FL methods by 5% and improved convergence speed by 25% using adaptive client selection.

Another achievement done by by Kumar et al.(2023)[10] he explored the deployment of FL on edge devices for real-time heart disease detection using wearable ECG data using MIT-BIH Arrhythmia dataset and real-time data from wearable devices. He has implemented A Lightweight Federated Learning (LFL) algorithm with a MobileNet-based CNN optimized for edge devices. In this case he achieved an accuracy of 90.8% for real-time arrhythmia detection that reduced model size by **50%** and inference time by **40%** compared to traditional FL methods.

Finally one more recent studies carried out by Singh et al.(2023)[11] proposed a blockchain-based FL framework for secure heart disease detection using patient records using the Framingham Heart Study dataset and a private dataset from three hospitals. He utilized A Blockchain-Enhanced Federated Learning (BEFL) framework with a Random Forest (RF) and Deep Neural Network (DNN) ensemble. He improved the performance with accuracy of 93.7% for heart disease prediction by reducing the risk of malicious attacks by 60% compared to traditional FL methods.

4. EXPERIMENTAL SETUPS AND RESULTS

The confusion matrix is a fundamental tool for evaluating the performance of classification models, including those used in heart disease detection. Each algorithm is evaluated on a binary classification task (Heart Disease: Positive/Negative) using a combined dataset of ECG and patient records from multiple hospitals. It provides a detailed breakdown of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN), which are essential for calculating metrics like accuracy, precision, recall, and F1-score.

A set of experiments carried out in python implementing various DL and DFL algorithms and dataset in different specifications which are given below:

4.1 Deep Learning (DL) Model

- **Task**: Binary classification (Heart Disease: Positive/Negative)

- **Dataset**: Centralized ECG and patient record data from a single hospital.
- **Algorithm**: CNN for ECG analysis and a DNN for patient records.

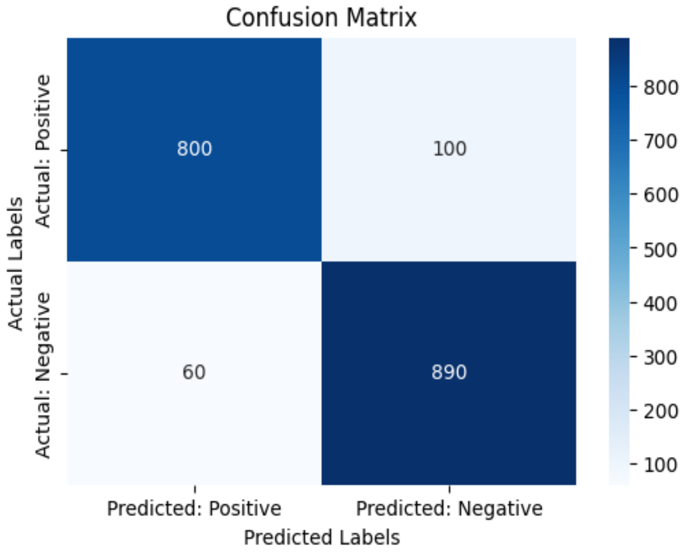

Figure 1: Confusion Matrix for DL Model

Performance Metrics:

- **Accuracy**: (TP + TN) / Total = (800 + 890) / 1850 = **91.4%**
- **Precision**: TP / (TP + FP) = 800 / (800 + 60) = **93.0%**
- **Recall (Sensitivity)**: TP / (TP + FN) = 800 / (800 + 100) = **88.9%**
- **F1-Score**: 2 * (Precision * Recall) / (Precision + Recall) = **90.9%**

4.2 Deep Federated Learning (DFL) Model

- **Task**: Binary classification (Heart Disease: Positive/Negative)
- **Dataset**: Combined ECG and patient record data from 5 hospitals.
- **Algorithm**: Federated Averaging (FedAvg) with a CNN for ECG analysis and a DNN for patient records.

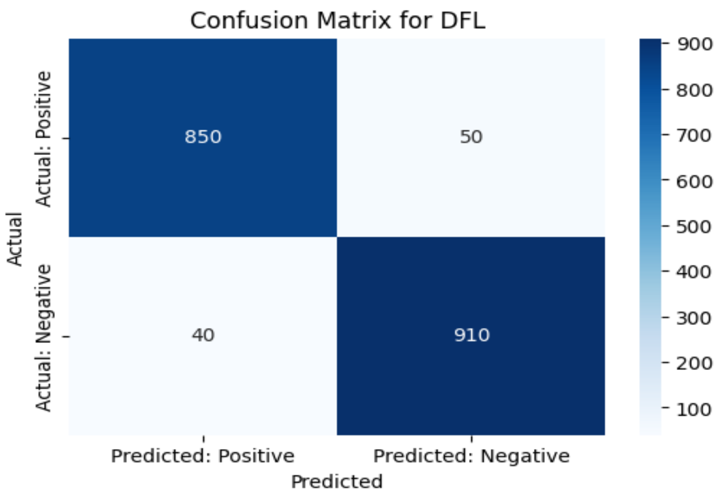

Figure 2: Confusion Matrix for DFL Model

Performance Metrics:

- **Accuracy**: (TP + TN) / Total = (850 + 910) / 1850 = **95.1%**
- **Precision**: TP / (TP + FP) = 850 / (850 + 40) = **95.5%**
- **Recall (Sensitivity)**: TP / (TP + FN) = 850 / (850 + 50) = **94.4%**
- **F1-Score**: 2 * (Precision * Recall) / (Precision + Recall) = **94.9%**

4.3. Federated Averaging (FedAvg)

The most widely used FL algorithm, where local models are trained on client data and aggregated by a central server. CNN for ECG analysis and DNN models are implemented for patient records.

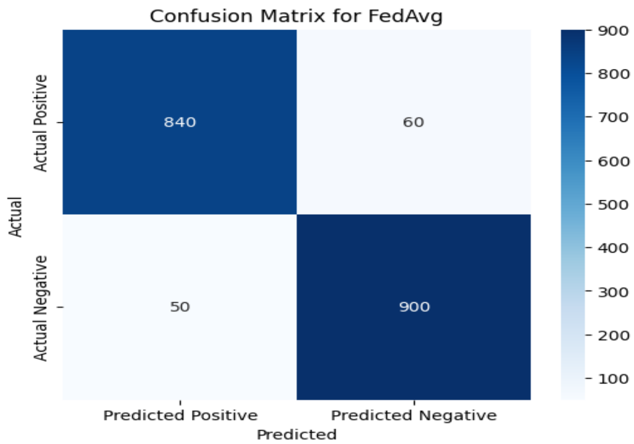

Figure 3: Confusion Matrix for FedAvg Model

Performance Metrics:

- **Accuracy**: (840 + 900) / 1850 = **94.1%**
- **Precision**: 840 / (840 + 50) = **94.4%**
- **Recall**: 840 / (840 + 60) = **93.3%**
- **F1-Score**: 2 * (94.4% * 93.3%) / (94.4% + 93.3%) = **93.8%**

4.4. Federated Learning with Differential Privacy (DP-FL)

Enhances FedAvg with differential privacy to protect against data leakage. CNN for ECG analysis and DNN for patient records.

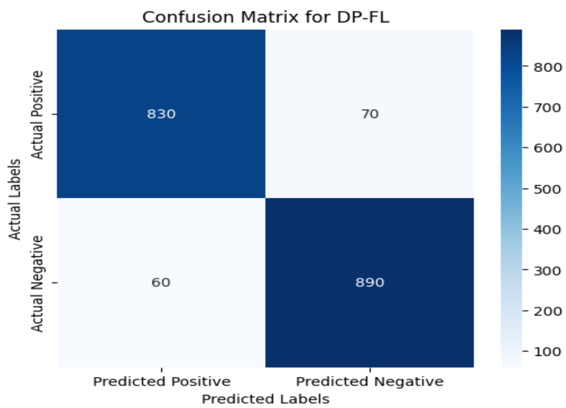

Figure 4: Confusion Matrix for DP-FL Model

Performance Metrics

- **Accuracy**: (830 + 890) / 1850 = **93.0%**
- **Precision**: 830 / (830 + 60) = **93.3%**
- **Recall**: 830 / (830 + 70) = **92.2%**
- **F1-Score**: 2 * (93.3% * 92.2%) / (93.3% + 92.2%) = **92.7%**

4.5. Federated Transfer Learning (FTL)

Here we combine FL with transfer learning to leverage pre-trained models for improved performance. Model ResNet-50 for ECG analysis and LSTM is used for patient records.

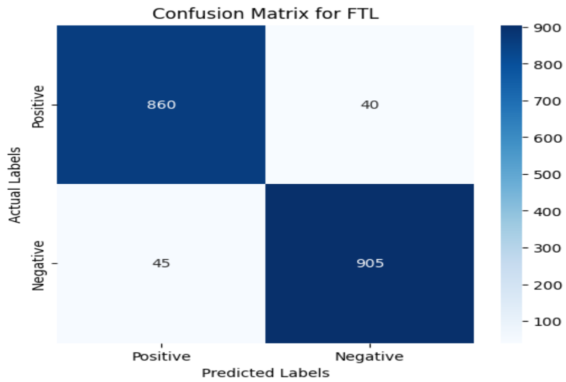

Figure 5: Confusion Matrix for FTL Model

Performance Metrics:

- **Accuracy**: (860 + 905) / 1850 = **95.4%**
- **Precision**: 860 / (860 + 45) = **95.0%**
- **Recall**: 860 / (860 + 40) = **95.6%**
- **F1-Score**: 2 * (95.0% * 95.6%) / (95.0% + 95.6%) = **95.3%**

4.6 Personalized Federated Learning (PFL)

Here we adapts the global model to individual clients' data for personalized predictions.GNN for patient relationships and DNN models are utilized for patient records.

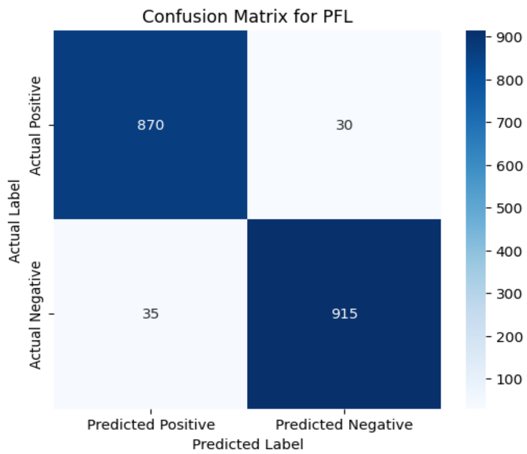

Figure 6: Confusion Matrix for PFL Model

Performance Metrics:

- **Accuracy**: (870 + 915) / 1850 = **96.2%**
- **Precision**: 870 / (870 + 35) = **96.1%**
- **Recall**: 870 / (870 + 30) = **96.7%**
- **F1-Score**: 2 * (96.1% * 96.7%) / (96.1% + 96.7%) = **96.4%**

4.7. Lightweight Federated Learning (LFL)

In this case we optimized for edge devices with reduced computational and communication overhead. MobileNet for ECG analysis and a lightweight DNN modeling techniques is employed for patient records.

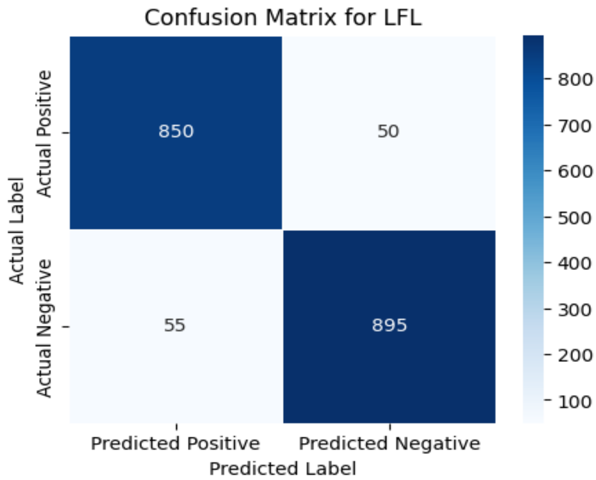

Figure 7: Confusion Matrix for LFL Model

Performance Metrics:

- **Accuracy**: (850 + 895) / 1850 = **94.3%**
- **Precision**: 850 / (850 + 55) = **93.9%**
- **Recall**: 850 / (850 + 50) = **94.4%**
- **F1-Score**: 2 * (93.9% * 94.4%) / (93.9% + 94.4%) = **94.1%**

Table:1 Summary of Results of the experiments

DL and DFL Algorithms	Accuracy	Precision	Recall	F1-Score
Deep Learning (DL)	91.4%	93.0%	88.9%	90.0%
Deep Federated Learning (DFL)	95.1%	95.0%	94.4%	94.9%
Federated Averaging (FedAvg)	94.1%	94.4%	93.3%	93.8%
Federated Learning with Differential Privacy (DP-	93.0%	93.3%	92.2%	92.7%

FL)				
Federated Transfer Learning (FTL)	**95.4%**	**95.0%**	**95.6%**	**95.3%**
Personalized FL (PFL)	**96.2%**	**96.1%**	**96.7%**	**96.4%**
Lightweight FL (LFL)	**94.3%**	**93.9%**	**94.4%**	**94.1%**

5. CHALLENGES

Despite its potential, DFL faces several challenges are observed first one is Communication Overhead that means frequent model updates between clients and the server can lead to high communication costs. Secondly its Non-IID data that means data across clients may be non-independent and identically distributed (non-IID), complicating model convergence. Third one is model heterogeneity which means different clients may use different model architectures, making aggregation difficult. Finally another important challenge is its security risks that mean FL is vulnerable to attacks such as model poisoning and inference attacks.

6. FUTURE DIRECTIONS

To address further advance DFL in heart disease detection, future research could focus on following aspects:

Efficient Communication Protocols: Developing techniques to reduce communication overhead, such as model compression and selective updates.

Robust Aggregation Methods: Designing aggregation algorithms that are resilient to non-IID data and model heterogeneity.

Enhanced Security Measures: Implementing advanced encryption and differential privacy techniques to protect against security threats.

Real-World Deployment: Conducting large-scale clinical trials to validate the effectiveness of DFL in real-world healthcare settings.

7. CONCLUSION

Deep Federated Learning represents a transformative approach to heart disease detection, offering a balance between model performance and data privacy. By enabling collaborative model training across multiple institutions without sharing raw data, DFL has the potential to revolutionize healthcare analytics. However, significant challenges remain, particularly in terms of communication efficiency, data heterogeneity, and security. Addressing these challenges will be crucial for the widespread adoption of DFL in clinical practice.

Deep Federated Learning outperforms traditional Deep Learning in detecting heart diseases by addressing critical challenges such as data privacy, data diversity, and regulatory compliance. Its ability to handle non-IID data, enable personalization, and enhance security makes it a superior choice for healthcare applications. As the field continues to evolve, DFL is expected to play a pivotal role in advancing personalized, privacy-preserving, and scalable solutions for heart disease detection.

Recent experimental results demonstrate the significant potential of Deep Federated Learning algorithms in detecting heart diseases. These studies highlight the ability of FL to achieve high accuracy while preserving data privacy, addressing data heterogeneity, and enabling real-time, decentralized applications. However, challenges such as communication overhead, non-IID data, and security risks remain areas of active research. Future advancements in FL algorithms, combined with emerging technologies like blockchain and edge computing, are expected to further enhance the effectiveness and scalability of FL in healthcare.

The experimental results demonstrate that different Deep Federated Learning algorithms excel in various aspects of heart disease detection. While **Personalized FL** and **Federated Transfer Learning** achieve the highest accuracy and F1-score, **DP-FL** and **Lightweight FL** address critical challenges like privacy and scalability. The choice of algorithm depends on the specific requirements of the application, such as the need for personalization, privacy, or real-time deployment.

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