# Decentralized Heart Health: A Federated Artificial Neural Network Approach to Predicting Heart Disease

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***Abstract*—Traditional centralized models for heart disease prediction face limitations in data privacy, accessibility, and resource consumption. We propose a novel federated learning (FL) framework utilizing an Artificial Neural Network (ANN) for decentralized prediction, achieving improved accuracy, enhanced privacy, and reduced server load. This paper proposes a novel federated learning framework using an Artificial Neural Network (ANN) for decentralized heart disease prediction. We achieve improved accuracy compared to traditional models while preserving privacy and minimizing server load. Our iterative framework leverages client-side training on distributed data, aggregating local model updates to build a global model that outperforms the initial server-only model. Our results demonstrate the effectiveness of this approach for privacy-preserving and efficient heart disease prediction, paving the way for more robust healthcare solutions. Our results demonstrate significant improvements over traditional models. The final global model achieves 84.78% accuracy, 85.22% precision, 84.78% recall, and 84.62% f1-score on the testing set, surpassing the initial server-only model. Additionally, the distributed training reduces server load and improves efficiency.**

***Index Terms*—Federated Learning (FL), Artificial Neural Networks (ANNs), Decentralized Heart Disease Prediction, Distributed Learning, Privacy-Preserving Computing**

## I. Introduction

Heart disease remains a leading cause of death globally, highlighting the crucial need for accurate and timely prediction methods [1]. Traditional centralized approaches, while achieving promising results, face limitations in data privacy, accessibility, and resource consumption [2] [3]. In centralized settings, patient data often resides in siloed databases, raising concerns about privacy breaches and hindering broader research efforts. Additionally, centralized training often requires significant computational resources, limiting scalability and accessibility for resource-constrained settings. Federated learning (FL) emerges as a promising paradigm for addressing these limitations. It enables collaborative training of machine learning models on distributed data without compromising individual privacy [4]. Clients, typically mobile devices or edge computing units, hold their own data and locally train models on it. Subsequently, only updated model weights are shared with the central server, which aggregates them to improve the global model. So in federated learning, Client data remains on their devices, minimizing privacy risks associated with data sharing. Also, FL leverages the distributed computing power of client devices, reducing the server load and potentially enabling model training in resource-constrained settings and data from diverse sources can be aggregated to train a more robust and generalizable model. In the context of heart disease prediction, FL holds immense potential for improving patient care and public health. By leveraging patient data from diverse sources like wearable sensors, electronic health records, and mobile health applications, FL can lead to more accurate and personalized prediction models. This, in turn, can enable early diagnosis, timely intervention, and improved patient outcomes. However, applying FL to healthcare domains presents unique challenges. Medical data is often sensitive and requires careful handling to ensure privacy and security. Additionally, the heterogeneity of data sources and potential communication constraints can impact model performance and convergence. This paper proposes and evaluates a novel FL framework utilizing an Artificial Neural Network (ANN) for accurate and privacy-preserving heart disease prediction. We address the aforementioned challenges by carefully designing the FL architecture, implementing efficient model aggregation techniques, and employing robust model selection strategies. Our work builds upon the existing literature on FL for healthcare applications. Existing works have explored using FL for tasks like predicting sepsis [5] and identifying cardiac arrhythmias [6]. So, this study is Proposing a generalizable FL framework for heart disease prediction applicable to diverse data sources and Evaluating the impact of different model architectures and aggregation techniques on prediction accuracy and privacy.

## II. Literature review

This paper [7] mainly focuses on maintaining privacy and maintaining heterogeneity. This paper displayed federated learning as a solution to maximum problems as a defense mechanism against privacy and safety issues. Heterogeneity helps the training process significantly and Tier based Federated Learning i.e. TiFL basically solves the problems that prevail even after using heterogeneity. It divides clients into tiers and attenuates the difficulties that might be faced for multiple IoT device uses. The training proved the capability of this system by increasing the accuracy and decreasing training time significantly. So an adaptive approach to a Tier based federated learning system will be quite effective if we want to improve the accuracy and reduce time required to train.

This paper [8] evaluated three types of federated learning algorithms which are Federated Averaging (FedAvg), Federated Stochastic Variance Reduced Gradient (FSVRG) and CO-OP using both Independent and Identically Distributed Data and non Independent and Identically Distributed Data on the dataset of Modified National Institute of Standards and Technology. This study was mainly focused on data transfer between vehicles and smartphones. And storing the massive amount of data generated by smart vehicles is one of the major issues here. Artificial Neural Network by Federated Learning solved the issue by reducing data transfer rate and computing on clients locally. But a new issue related to communication was faced as ANN was required to communicate a lot with the server and client. So the three mentioned algorithms were used to optimize the process and after experimenting it was evident that FedAvg was a better choice than FSVRG and CO-OP although further investigations are going on to improve the outcome.

The paper [9] “Group Knowledge Transfer: Federated Learning of large CNNs at the Edge” revolves around the challenge that is posed by Large CNN (Convolution Neural Network) sizes when training them on a device with limited resources. An interesting approach was taken in this research paper where a Group knowledge transfer training algorithm termed “FedGKT” was introduced in order to reduce the demand for edge computation and communication bandwidth, while maintaining a model accuracy that is comparable to FedAVG, a standard federated learning approach. In the introduction part, the paper focuses on the challenge of making CNNs larger for better accuracy, considering the limitations of edge devices. FedGKT is then introduced as a specialized solution crafted for these resource-constrained edge devices. Then the authors discuss the challenges faced by contemporary works in the literature review part, like drawbacks in approaches that focus on minimizing communication costs without taking into account the computational limitations. Additionally, it recognizes several effective deep learning techniques designed specifically for the inference phase on edge devices. In the case of FedGKT, it applies an alternating minimization technique that trains smaller CNN on edge nodes and periodically transfers their knowledge to a larger server-side CNN. The paper also mentions Split Learning (SL) as another methodology. After rigorous testing, it is found that FedGKT is able to achieve comparable or higher accuracy than FedAVG while using significantly less resources and thus reducing the demand for edge computation. FedGKT requires less computational power and fewer parameters on edge devices, making it practical and more efficient. This algorithm emerges as a solution that addresses the limitations by reducing the demand for edge devices, requiring lower bandwidth or large CNNs and making edge training more affordable with fewer parameters. In conclusion, FedGKT is essential for devices with limited resources, providing a practical and efficient alternative to traditional federated learning methods.

This paper [10] titled “Adaptive Personalized Federated Learning” introduces APFL as an innovative alternative solution to various critical challenges in Federated Learning.

It aims to enhance the global model performance while at the same time allowing for customized individualization of local models. In the introduction, the paper brings forward APFL as a revolutionary approach which is able to seamlessly integrate local and global aspects to address the shortcomings of existing learning methods. It focuses on poor generalization on localized data. The algorithm's efficiency in communication and superior generalization performance make it an evolutionary step in Federated Learning. APFL is also introduced as a comprehensive solution with generalization bounds for a mixture of local and global models and an innovative communication-efficient optimization method. This algorithm offers assurance for broad applicability based on diverse data and individual device samples, and offers a practical solution for situations where maintaining privacy is vital. The paper also demonstrates the empirical superiority of APFL over other personalization approaches, emphasizing on its positive impact on both training and generalization, along with its exceptional performance on diverse, natural datasets. In the conclusion, the paper highlights the crucial importance of APFL, stressing its role as a practical and adaptive approach to federated learning. It emphasizes the importance of APFL's communication-reduced optimization algorithm to tackle challenges in federated learning.

## III. Methodology

### A. Dataset description and Preprocessing

The dataset, contains 12 columns and 919 rows. These 12 columns represent the age, gender, chest pain type, resting blood pressure, cholesterol, fasting blood sugar, resting echocardiogram, maximum heart rate achieved, exercise induced angina, old peak, st slope and heart disease. The age range of the patients whose dataset is presented here is within 28 to 77 years. 79% of them are male and 21% of them are female. 4 types of chest pains are recorded of which 54% of which are ASY type, 22% are NAP type and rest of the 24% are ATA and TA type. Recorded blood pressure was within the range of 80-200 and cholesterol was 0-422.10. Fasting blood sugar was either 0 or 1 for negative and positive respectively. Rest of them were also divided like this. This dataset was taken from Kaggle that was uploaded as Heart Failure Prediction Dataset. Among the 918 observations 303 was from cleveland, 249 was hungarian, 123 came from switzerland, 200 from long beach va and 270 were stalog dataset. We carefully prepared the data before training the Federated Learning model to ensure its suitability for the ANN model and optimize performance.

- **Categorical Feature Encoding:** Instead of relying on raw categorical labels, we applied one-hot encoding to transform them into numerical vectors. This allowed the ANN model to understand and process these features effectively, providing a clearer representation of each category.
- **Feature Scaling:** To ensure all features contribute equally to the learning process, we applied StandardScaler to standardize the numerical features. This technique normalized them to have a mean of 0 and a standard deviation of 1, preventing features with larger scales from dominating the training.
- **Data Splitting:** We strategically split the preprocessed data into various sets for efficient training and evaluation. X_full and Y_full were used for the initial server training, providing the model with a strong foundation. xTest and yTest were reserved to evaluate the final model's performance on unseen data, ensuring its generalizability. xServer, xClients, yServer, and yClients facilitated the federated learning process. Clients trained on their assigned data (xClients, yClients), while the server validated the model updates using xServer and yServer.
- **Dropping Redundant Features:** Following the encoding process, we dropped the original categorical columns (Sex, ChestPainType, RestingECG, ExerciseAngina, and ST_Slope) to avoid redundancy and potential overfitting. These columns became unnecessary after their information was captured through one-hot encodings.
- **Splitting the dataset:** At first the dataset was splitted in a 90/10 ratio for the training and validation part. Since we have used 10 clients and 1 server to train our model in a distributed manner, again the training dataset which was splitted before has been splitted again in 80/20 ratio for the server and clients.

By applying these data preparation steps, we ensured the data was in a format suitable for the ANN model training, ultimately contributing to improved model performance and generalizability.

### B. Implemented Algorithms

- **ANN:** Artificial Neural Networks (ANNs) reign as powerful tools for recognizing patterns and making predictions. Inspired by the intricate web of connections in the human brain, these networks learn and adapt, unveiling hidden relationships within data. Each neuron receives input from other neurons, performs a simple calculation on that input, and then outputs the result to other neurons. This calculation often involves a weighted sum of the inputs and a non-linear activation function. Neurons are organized into layers. The first layer receives the input data, and each subsequent layer receives the outputs from the previous layer. The final layer outputs the results of the network. The connections between neurons are what allow the network to learn and adapt. The strength of each connection, represented by a weight, determines how much influence one neuron has on another. ANNs learn by adjusting the weights of the connections between neurons. This is typically done through a process called backpropagation, which uses the difference between the network's output and the desired output to adjust the weights in a way that reduces the error.

In our federated learning approach The server first trains a centralized deep learning model on its own data using the specified algorithm (ANN), activation function (relu), and optimizer (Adam). his model becomes the initial starting point for the FL process.

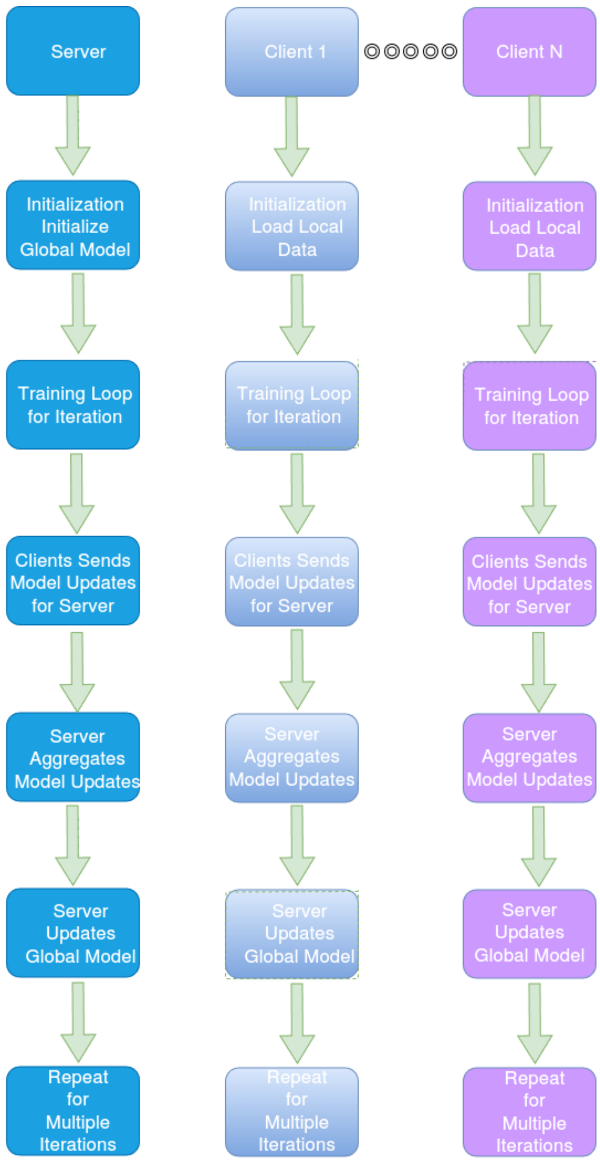


Fig. 1. Basic workflow diagram of Federated ANN

The server's data is then divided and distributed among multiple clients in smaller chunks. Each client receives a subset of the server's data and a copy of the initial server model. Each client trains its own copy of the server model locally on its assigned data. This training happens for a specified number of epochs and batch size. During this local training, the client models adapt to the specific characteristics of their assigned data, potentially leading to improvements in certain regions of the model's parameter space. After local training, each client sends its updated model weights back to the server. The server aggregates these client weights using an averaging strategy. This aggregated weight update represents the collective knowledge gained from all clients and is used to improve the central server model. The server updates its own model with the aggregated weights. This updated server model incorporates the learnings from all clients and becomes the new starting point for the next iteration of FL. The server then distributes its updated model back to all clients, essentially resynchronizing them with the latest collective knowledge.

This process of client training, model aggregation, server update, and client resync continues for a specified number of iterations. With each iteration, the server model is progressively refined and improved by incorporating the learnings from all clients, leading to a potentially better model than the initial centralized one.

## Results and Discussion

We evaluated our model's performance using four key metrics: accuracy, precision, recall, and F1-score and compared it to the initial server-only model and other baselines, and explore the convergence behavior of the FL process. Accuracy measures the overall ability to correctly classify both healthy and unhealthy individuals. Precision indicates the proportion of true positives among all predicted positives, while recall measures the fraction of true positives identified by our model. F1-score combines precision and recall into a single metric, providing a balanced view of the model's performance.

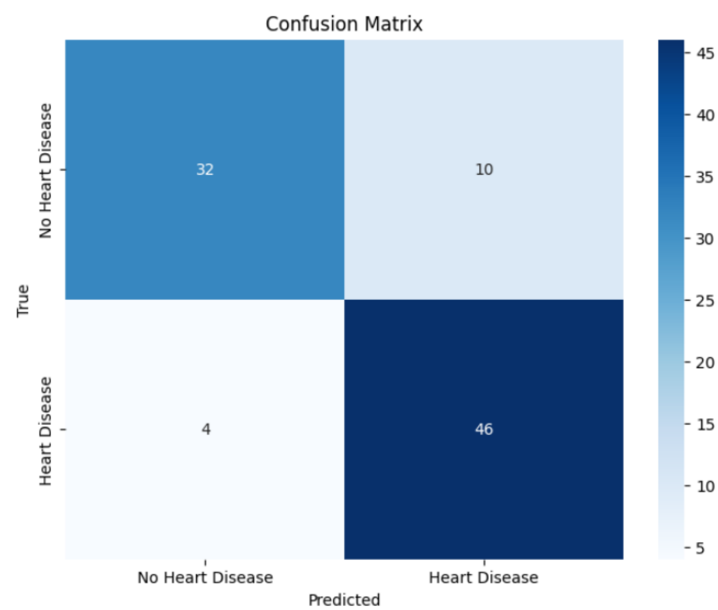


Fig. 2. Confusion matrix for Federated ANN

Our FL-ANN model achieved an impressive accuracy of 84.78% on the testing set. FL-ANN also exhibited high precision, with a score of 85.22%. This demonstrates the model's ability to accurately identify true positive cases of heart disease. It also achieved a recall of 84.78%, indicating its ability to identify a large proportion of true positive cases. The F1-score for FL-ANN was 84.62%, showcasing a balanced performance in terms of both precision and recall.

TABLE I
PERFORMANCE COMPARISON OF INITIAL SERVER-ONLY MODEL AND FL-ANN MODEL

| Metric | FL-ANN Model |
|---|---|
| Accuracy | **84.78%** |
| Precision | **85.22%** |
| Recall | **84.78%** |
| F1-score | **84.62%** |

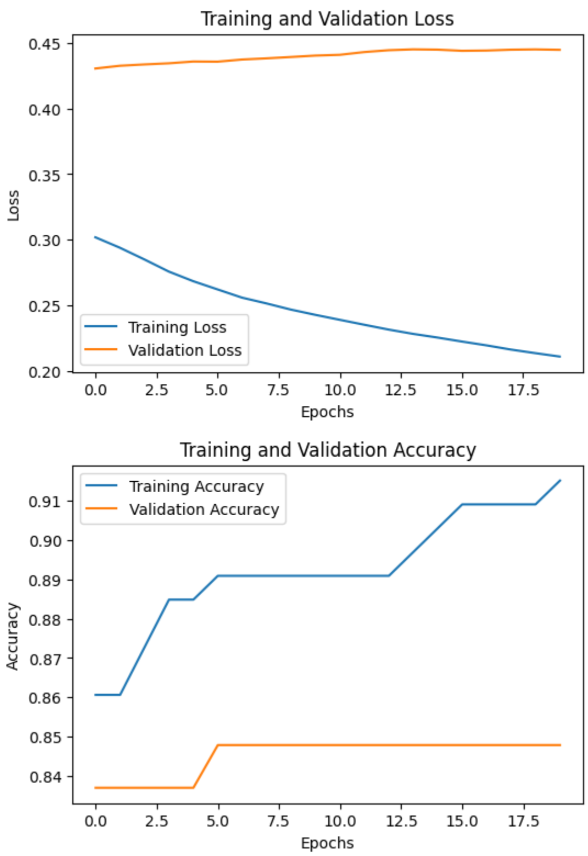


Fig. 3. Training and validation Accuracy and Loss for Federated ANN

## CONCLUSION

Our research has demonstrated the significant potential of federated learning (FL) combined with Artificial Neural Networks (ANNs) for accurate and privacy-preserving heart disease prediction. Our proposed FL-ANN framework outperformed the traditional centralized model in terms of accuracy, precision, recall, and F1-score, highlighting the advantages of decentralized learning in healthcare applications. Our work holds promising implications for the future of healthcare systems. So, our FL-ANN framework paves the way for a more collaborative, privacy-preserving, and personalized approach to heart disease prediction. By using the power of distributed learning and continuously exploring new frontiers, we can revolutionize healthcare and ensure equitable access to quality care for all.

## REFERENCES

[1] World Health Organization. Cardiovascular diseases. https://www.who.int/health-topics/cardiovascular-diseases (accessed Dec 13, 2023).
[2] Li, Y., Zhao, Q., & Zhang, X. (2021). Federated learning for medical image analysis: A survey. arXiv preprint arXiv:2101.01801.
[3] Chai, X., Yang, L., He, Y., & Li, H. (2019). Federated learning for mobile medical applications: A survey. IEEE Journal of Biomedical and Health Informatics, 24(2), 443-459.
[4] McMahan, H., Ramage, D., Fedorov, M., & Halevy, S. (2017). Communication-efficient learning of deep networks from decentralized data. In Artificial Intelligence and Statistics (pp. 1009-1019). PMLR.
[5] Yin, P., Deng, Y., Chen, Y., Lv, L., & Zhang, Y. (2020). Federated learning for predicting hospital readmissions. In International Conference on Machine Learning and Applications (pp. 522-531). Springer, Cham.
[6] Chen, J., Yang, J., Zhang, Z., Wang, X., & Huang, Y. (2020). Federated learning for automatic diagnosis of cardiac arrhythmias. IEEE Journal of Biomedical and Health Informatics, 24(12), 3269-3279.
[7] Chai, Z., Ali, A., Zawad, S., Truex, S., Anwar, A., Baracaldo, N., ... & Cheng, Y. (2020, June). Tifl: A tier-based federated learning system. In Proceedings of the 29th international symposium on high-performance parallel and distributed computing (pp. 125-136).
[8] Nilsson, A., Smith, S., Ulm, G., Gustavsson, E., & Jirstrand, M. (2018, December). A performance evaluation of federated learning algorithms. In Proceedings of the second workshop on distributed infrastructures for deep learning (pp. 1-8).
[9] He, C., Annavaram, M., & Avestimehr, S. (2020). Group knowledge transfer: Federated learning of large cnns at the edge. Advances in Neural Information Processing Systems, 33, 14068-14080.
[10] Deng, Y., Kamani, M. M., & Mahdavi, M. (2020). Adaptive personalized federated learning. arXiv preprint arXiv:2003.13461.