IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

# AN PROACTIVE FEDERATED LEARNING MODEL USING CRNN FOR HEART DISEASE PREDICTION

**[1]Mr.R.Prabakar, [2]Dr.R.Saravanan, [3]Dr.S.Balaji**
[1]Managing Partner, [2]Professor, [3]Associate Professor
[1]Rapid Technology and Infosolutions, Puducherry
[2,3]Department of IT, Sri Manakula Vinayagar Engineering College, Puducherry

***Abstract :*** Federated learning(FL), a machine learning technique enabling collaborative model training on distributed devices or servers, has emerged as a powerful tool for healthcare applications. FL offers a significant advantage; it allows institutions to train powerful models on sensitive healthcare data while preserving patient privacy. FL also raises concerns about potential privacy leaks through vulnerabilities in the training process. Heart disease continues to be a significant global public health concern, necessitating the development of precise and effective predictive models to support early detection and treatment. The proposed system introduces a novel system for predicting heart disease using federated learning, a paradigm that enables cooperative model training across distributed data sources while maintaining data privacy. The architecture of the system is a convolutional recurrent neural network (CRNN), or CRNN for short. Medical records with inherent temporal structure are a good fit for CRNN analysis because of their superior sequential data processing capabilities. Recurrent neural networks (RNNs) are used to capture temporal dependencies in the data, whereas convolutional neural networks (CNNs) are used to extract features. To make more accurate predictions, the attention processes in the model enable it to concentrate on important aspects of the data. By employing federated learning with a CRNN architecture, The system aims to achieve a balance between model performance and data privacy in predicting heart disease risk. This approach has the potential to significantly improve early disease identification while safeguarding sensitive healthcare data.

***IndexTerms*** **- Federated Learning, Heart Disease Prediction, Convolutional Recurrent Neural Network (CRNN), Privacy-Preserving, Distributed Learning, Data Privacy, Healthcare**

## 1.INTRODUCTION

Heart disease is still a major global health concern that raises healthcare expenses and death rates. Prompt and precise diagnosis of cardiac disease is essential for better patient outcomes and prompts intervention. Using patient data, machine learning techniques have become an effective tool for creating prediction models. However, accessing and utilizing large-scale healthcare datasets for model training while ensuring patient privacy and data security present substantial hurdles. Convolutional Recurrent Neural Networks (CRNNs) with architecture designed especially for heart disease prediction are used in the proposed model, which is a federated learning approach. Convolutional Neural Networks (CNNs) are an effective tool for sequential medical data processing because they combine the advantages of Recurrent Neural Networks (RNNs) in capturing temporal correlations and Convolutional Neural Networks (CNNs) in extracting spatial characteristics.

CRNN model is carefully built to handle numeric features frequently found in medical datasets, in contrast to traditional CNNs that are primarily meant to handle image datasets. With the help of this adaptation, a thorough assessment of the patient's risk for heart disease can be made possible by processing a variety of medical data, such as physiological measurements, laboratory test results, and patient demographics using federated learning, the suggested approach ensures the security and decentralization of sensitive patient data during the training phase. Because local data is retained by each participating device or server, privacy issues related to centralized data aggregation are lessened. Federated learning's collaborative nature makes it possible to aggregate model updates as opposed to raw data at a central server, which promotes the creation of a reliable and privacy-preserving predictive model. In this paper, we present empirical results evaluating the model's performance, explain the training procedure, offer a thorough analysis of the architecture of our proposed model, and clarify the nuances of the federated learning paradigm. Using large-scale real-world healthcare datasets, we validate and demonstrate the scalability and usefulness of our technique in accurately forecasting the risk of heart disease while maintaining patient privacy.

Overall, by presenting a novel federated learning framework that seamlessly integrates CRNN architecture for heart disease prediction. The model is an advancement in the ongoing search for efficient methods for managing and preventing cardiovascular disease because it addresses the competing demands of data privacy and predictive accuracy.

### 1.1 FEDERATED LEARNING

A machine learning technique called federated learning allows model training across decentralized servers or devices without requiring raw data sharing. Federated learning involves distributing the training process to local sources as opposed to standard methods that concentrate data. Based on its local data, each device or server separately computes model updates, which are subsequently combined and transmitted to a central server. By storing sensitive data locally on the user's device or server, this method protects data privacy. Federated learning, which is extensively used in banking, healthcare, and Internet of Things applications, provides advantages over privacy protection. It removes the need for constant server communication and gets around bandwidth restrictions by enabling model training on edge devices. To further enhance performance for particular users or devices, it tailors model updates according to local data. Federated learning, which leverages insights from various datasets while respecting privacy constraints, offers a scalable and privacy-preserving paradigm for machine learning. First, the model is initialized on a central server. It is then distributed to devices for self-sufficient training, updates are aggregated, and the refined model is re-deployed to devices. This iterative cycle protects the privacy of individual data while improving the model with collective knowledge.

### 1.2 CONVOLUTIONAL RECURRENT NEURAL NETWORK

The strengths of recurrent neural networks (RNNs) and convolutional neural networks (CNNs) are combined in a deep learning architecture called a convolutional recurrent neural network (CRNN). CNNs may be used to analyze numerical datasets as well as picture data; in this context, they excel in recognizing complex patterns and relationships between numerical characteristics.CNNs can analyze numerical datasets that are frequently encountered in industries like healthcare, finance, and time-series analysis thanks to their adaptability. RNNs are made to recognize temporal relationships in sequential data. They have recurrent connections in place, which enable them to keep track of previous inputs and eventually comprehend patterns and sequences. To extract spatial characteristics from the input data, CNN layers are typically utilized in the early stages of a CRNN architecture. The RNN layers receive these features after which they extract contextual data and temporal dependencies. The model can efficiently learn from both the spatial and temporal aspects of the data thanks to the combination of CNNs and RNNs.CRNN architecture is a useful tool for efficiently capturing both spatial and temporal patterns in medical data when utilizing federated learning for heart disease prediction.

This CRNN architecture is distributed among decentralized devices or servers that store local datasets in a federated learning configuration. Using its local data, each device independently trains the CRNN model while maintaining privacy. Gradient-based model updates are then integrated at a central server to update the global model. The model may be trained with a range of datasets from different places in a collaborative manner while protecting data privacy.

## 2. RELATED WORKS

Yaqoob et al. [1] introduced a hybrid classifier-based federated learning approach for cardiovascular disease prediction Combining machine learning classifiers with a federated learning framework allows distant healthcare providers to train models collaboratively while maintaining data privacy. Their method addresses privacy concerns related to sharing sensitive medical data by utilizing federated learning to enable the building of strong prediction models without the need for centralized data aggregation.

Nazir et al. [2] proposed a modified artificial bee colony-based feature optimization technique for federated learning applied to heart disease diagnosis in healthcare that improves feature selection to improve federated learning models' performance and efficiency in the diagnosis of cardiovascular illnesses. The researchers sought to decrease computing complexity and increase prediction accuracy in dispersed learning settings by improving feature selection using artificial bee colony methods.

Linardos et al. [3] conducted a simulation research on federated learning for multi-center imaging diagnostics in cardiovascular disease. Their research investigates the feasibility of integrating data from diverse medical centers using federated learning to improve diagnostic accuracy and robustness. By demonstrating the effectiveness of federated learning in a multi-center setting, their study highlights the potential for collaborative healthcare analytics while preserving data privacy and security.

Moshawrab et al. [4] conducted a comprehensive review of federated machine learning techniques and their applications in disease prediction, including cardiovascular diseases. They provide insights into the challenges and opportunities associated with federated learning in healthcare analytics. Through an overview of the state-of-the-art in federated machine learning, the authors provide insightful viewpoints on research priorities and future prospects in this quickly developing subject.

Kumar and Singla [5] discussed federated learning systems for healthcare, focusing on perspectives and recent progress in the field. Their review highlights the unique challenges and opportunities of applying federated learning in healthcare settings, emphasizing privacy concerns, data security, and model interpretability. The authors present a thorough summary of the possible effects of federated learning on healthcare analytics and customized medicine by examining current developments and case examples.

Islam et al. [6] proposed a privacy-preserving federated learning model specifically tailored for healthcare data. Their study addresses critical concerns related to data confidentiality and security in federated learning applications, especially in healthcare domains. By integrating privacy-preserving techniques into federated learning frameworks, the researchers aim to promote data sharing while maintaining patient confidentiality and compliance with privacy regulations.

Fang et al. [7] introduced Bayesian inference federated learning for heart rate prediction, demonstrating the potential of probabilistic modeling in federated learning applications. Their approach leverages Bayesian inference to capture uncertainty and variability in heart rate predictions, providing a robust framework for personalized healthcare analytics. By integrating Bayesian methods with federated learning, the researchers contribute to advancing predictive modeling in cardiovascular health.

Yoo et al. [8] proposed personalized federated learning with clustering applied to non-IID heart rate variability data. Their study explores the use of clustering techniques within a federated learning framework to improve model personalization and adaptability to heterogeneous data distributions. Their method improves the efficacy of federated learning in healthcare applications by tackling issues related to non-identically dispersed (non-IID) data.
Zou et al. [9] Their research highlights the scalability and efficiency of decentralized learning in medical image analysis, particularly in detecting complex cardiovascular conditions. By leveraging multiscale neural networks within federated learning frameworks, the researchers demonstrate advancements in automated disease detection and diagnosis.

Goto et al. [10] proposed a multinational federated learning approach to train ECG and echocardiogram models for hypertrophic cardiomyopathy detection. The study demonstrates how cooperative, international federated learning projects may improve the diagnosis and research of cardiovascular disease. Through the use of federated learning across several healthcare facilities, their methodology makes it possible to create reliable and broadly applicable predictive models for intricate cardiac problems.

## 3. EXISTING SYSTEM

Existing systems for heart disease prediction predominantly rely on centralized machine learning models that require access to large, centralized datasets. While effective in certain contexts, these approaches raise significant privacy concerns due to the centralized storage and processing of sensitive patient data. Furthermore, centralized models may encounter scalability challenges when handling diverse and distributed datasets, potentially leading to biased or less robust predictive models. Some existing approaches incorporate distributed learning techniques where data is trained locally on individual devices or servers and then aggregated centrally. However, this aggregation step still poses privacy risks during data transmission and model updating. Furthermore, there are risks associated with depending on a single point of failure or data breach when using a central aggregation point.
The protection of individual data privacy during model training has been investigated through the use of privacy-preserving machine learning approaches including homomorphic encryption and differential privacy. Despite their potential benefits, these methods often come with implementation challenges, including performance overheads and limitations in preserving data utility, especially in healthcare applications where data quality and accuracy are paramount.

Secure Multi-Party Computation (MPC) protocols offer another avenue for the collaborative computation of encrypted data without exposing underlying data to any party. However, practical implementation in healthcare settings faces obstacles such as computational complexity, communication overhead, and interoperability concerns among different systems.

Blockchain-based healthcare systems have also emerged to address data security and transparency issues. These systems leverage blockchain technology for secure health data sharing and access control. However, challenges such as scalability, resource requirements, and regulatory considerations pose barriers to the widespread adoption of blockchain in healthcare for heart disease prediction.

The research gaps in existing systems highlight the need for a privacy-preserving, scalable, and robust approach to heart disease prediction. To close these shortcomings, this paper proposes a federated learning system that ensures data privacy, scalability, and model robustness while facilitating collaborative model training across remote data sources. By leveraging federated learning with encrypted model updates and decentralized computation, we can develop a system that addresses the limitations of existing approaches and advances predictive analytics in healthcare.

## 4. PROPOSED SYSTEM

The proposed system leverages federated learning for heart disease prediction using a Convolutional Recurrent Neural Network (CRNN) deployed across decentralized client devices. Participating clients get the global model once it has been setup on a central server. Each client uses its own dataset to train the model locally. To protect data privacy during transmission, client-

specific model updates are encrypted using the Fernet method after training. In order to create a better global model, these encrypted updates are then relayed back to the server, where they are decrypted and combined using the FedAvg algorithm.
A global CRNN model is first initialized on the central server and then it is dispersed to client devices. Sensitive patient data stays on the client side as each client trains the model individually using its local dataset. The client's model weights are sent back to the server for aggregation after they have been trained and encrypted using the Fernet technique. After decrypting the model updates it has received, the server aggregates them using FedAvg to create an updated global model.

Utilizing federated learning to overcome the drawbacks of conventional centralized methods in healthcare analytics is the reasoning behind our suggested technique. By distributing model training to client devices and encrypting model updates during transmission, we ensure data privacy and security while leveraging diverse datasets for improved model generalization and accuracy.

Our proposed system addresses key research gaps in existing systems by combining federated learning with advanced neural network architectures like CRNN. It bridges the gap of data privacy by encrypting model updates during transmission, ensuring that sensitive patient data remains protected. Furthermore, our system enhances scalability and model robustness by aggregating decentralized model updates using the FedAvg algorithm, leading to an improved global model without compromising data privacy. Our suggested approach is unique in that it combines federated learning with CRNN for the prediction of cardiac disease, guaranteeing privacy and precision in a dispersed setting. By encrypting model updates and leveraging client-side training, our system offers advantages such as improved data privacy, scalability, and generalization compared to centralized approaches. Additionally, the FedAvg aggregation technique enhances model performance by aggregating knowledge from diverse data sources while preserving individual data privacy.

## 5. SYSTEM ARCHITECTURE

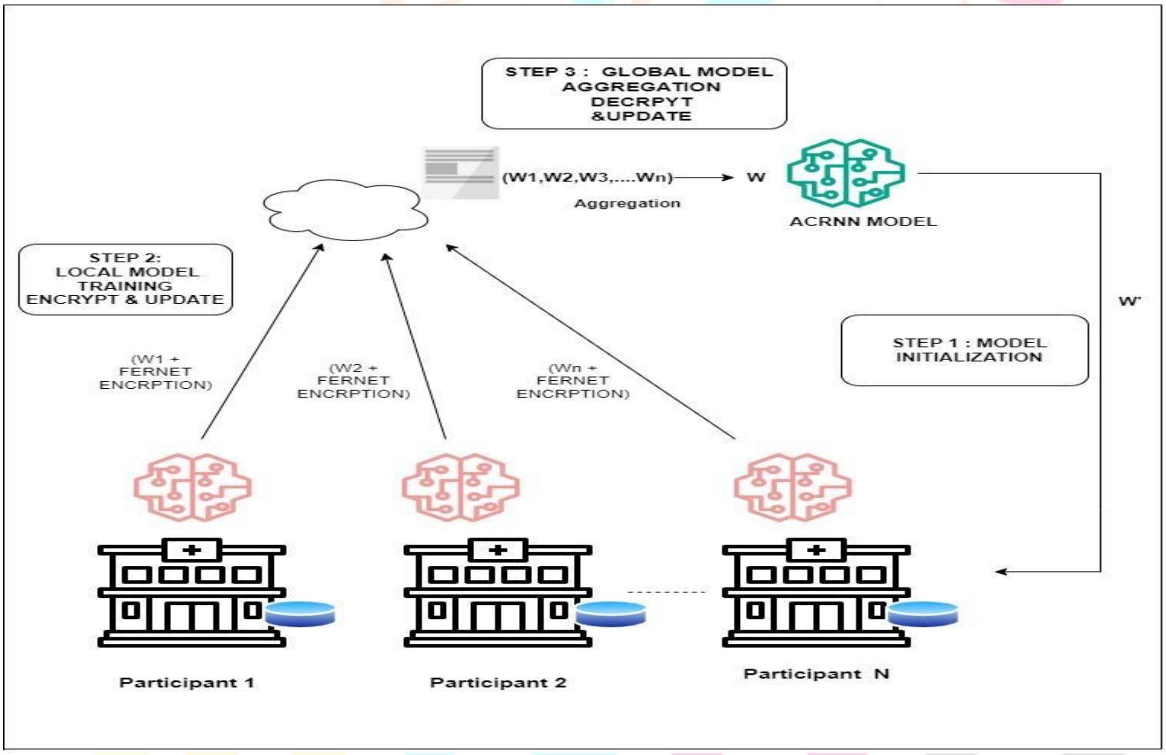

**Figure 1: System Architecture**

## 6. METHODOLOGY

### 6.1 Feature engineering and data preprocessing

The cardiovascular disease dataset must be properly prepped for machine learning model training through the use of data preprocessing and feature engineering. The methodology involves several key techniques to ensure the data is cleaned, standardized, and optimized for effective model training.

The dataset is first loaded and inspected to find any discrepancies or missing information. Depending on the type of missing information, methods like mean or median imputation can be used to impute missing data. One-hot encoding is used to encode categorical data, such as gender, cholesterol, and glucose levels, into numerical representations appropriate for model training.

Next, to bring all features to a similar scale and stop some features from dominating the learning process because of their larger magnitude, numerical features like age, height, weight, and systolic and diastolic blood pressure measurements are scaled using methods like Min-Max scaling or standardization.

Feature engineering is the process of adding new features or changing current ones in order to obtain more insightful data. For example, Body Mass Index (BMI) can be computed with height and weight to provide more health-related data to the collection. Trends over time can be captured by aggregating or smoothing time-series characteristics, such as blood pressure readings.

### 6.1 Model Definition with CRNN Architecture

When using the Convolutional Recurrent Neural Network (CRNN) architecture, model definition entails defining the architecture and constituent parts of the neural network that are specifically designed for the prediction of heart disease. CRNN integrates attention mechanisms, convolutional layers for spatial feature extraction, and recurrent layers to capture temporal dependencies in sequential data. The methodology for defining the CRNN model includes several technical steps to construct a robust and effective deep-learning architecture.

First, the CRNN model is initialized using a deep learning framework. Typically, the design begins with input layers that hold the properties of the dataset, including lifestyle factors, age, blood pressure, and cholesterol levels. Convolutional layers are employed to extract spatial patterns from input data, enabling the model to capture important spatial relationships among features.

Recurrent layers, including Long Short-Term Memory (LSTM) cells or Gated Recurrent Units (GRUs), are added after the convolutional layers to simulate sequential dependencies across time. Analyzing time-series data, such as blood pressure readings or glucose levels recorded at various intervals, requires this.

Additionally, during model training, attention techniques are incorporated into the CRNN architecture to highlight pertinent elements and suppress irrelevant ones. By enabling the model to concentrate on particular segments of the input sequence, attention mechanisms improve the model's capacity to identify important details for the prediction of cardiac disease.

Adding fully connected layers for classification, where the retrieved features are converted into predictions about the presence or absence of cardiovascular illness, completes the CRNN architecture. In order to reduce prediction errors during training, the model's parameters are adjusted utilizing gradient-based optimization methods and backpropagation.

### 6.2 Federated Learning Setup

The global model is distributed to client devices in a federated learning configuration for heart disease prediction, and the training process is coordinated while protecting privacy. This technique describes the necessary technical actions to successfully apply federated learning in a healthcare setting.

Initially, the global model  Convolutional Recurrent Neural Network (CRNN) is initialized by the central server, tailored for heart disease prediction. The global model's parameters are sent to participating client devices securely, ensuring data privacy during transmission.

Each client device receives the global model and trains it locally using its own subset of the dataset. In this local training method, the model architecture and parameters are kept consistent across all clients while the model weights are updated based on the client's data.
Sensitive patient data is protected on the client devices by employing encryption techniques such as the Fernet algorithm to encrypt the updated model weights following local training. Next, a transmission of the encrypted model updates is made back to the central server.

Federated Averaging (FedAvg) is the algorithm that is used on the central server side to aggregate the encrypted model updates from various client devices. Without disclosing specific data samples, FedAvg aggregates the encrypted model weights to create an updated global model that represents the collective wisdom gained from all client devices.

### 6.3 Model Encryption and Secure Communication

Model encryption and secure communication play crucial roles in federated learning to protect sensitive data during the transmission of model updates between client devices and the central server. The technological procedures for encrypting model weights and guaranteeing secure communication in a federated learning framework for heart disease prediction that protects privacy are described in this methodology.
Initially, the new model weights are encrypted using cryptographic algorithms like the Fernet encryption scheme after local training on client devices. Encryption converts the model parameters into ciphertext, ensuring that they are unintelligible to unauthorized parties during transmission over insecure channels.

A symmetric encryption key is created and safely exchanged by the client device and the central server as part of the Fernet encryption procedure. The model weights are encrypted using this key before being sent back to the server.

Upon receiving the encrypted model updates, the central server decrypts the ciphertext using the shared encryption key. Decryption converts the encrypted model weights back into plaintext, allowing the server to aggregate the model updates and update the global model.

Secure systems for communication, such as HTTPS (Hypertext Transfer Protocol Secure), or secure sockets layer (SSL) are employed to establish encrypted connections between client devices and the central server. These protocols ensure that data transmitted during federated learning remains confidential and protected from eavesdropping or interception.

### 6.4 Model Aggregation

Model aggregation using the Federated Averaging (FedAvg) algorithm is a fundamental step in federated learning for combining encrypted model updates from multiple client devices to generate an updated global model. The technological procedure for safely aggregating model updates and protecting data privacy in a federated learning framework for heart disease prediction is described in this methodology.
The FedAvg method is used by the central server to start the model aggregation process once it receives encrypted model updates from client devices. The FedAvg algorithm operates in the following steps:

**1. Decryption of Model Updates**

The central server decrypts the received encrypted model updates using the shared encryption key. Decryption converts the encrypted model weights back into plaintext, enabling the server to access the raw model parameters.

**2. Aggregation of Model Updates**

The server calculates the weighted average of the related parameters for all client devices for each parameter in the global model. To do this, add up all of the clients' decrypted model changes, then divide that total by the total number of clients that are taking part. The updated global model is represented by the aggregated model parameters, which take into account all of the client devices' cumulative knowledge.

**3. Updating the Global Model**

The global model housed on the central server is updated using the aggregated model parameters. Based on the aggregated model updates, the weights and architecture of the global model are modified to take into account the knowledge gathered from scattered client data.

**4. Updated Global Model Secure Transmission**
In the subsequent round of local training, the updated global model which now includes aggregated parameters is safely sent back to the client devices. Secure communication methods (such as HTTPS and SSL) are utilized to safeguard the updated global model's secrecy and integrity while it is being transmitted.

## 7. RESULTS AND DISCUSSION

| Metric | Value |
|---|---|
| Accuracy | 0.93 |
| Precision | 0.92 |
| Recall | 0.91 |
| F1-Score | 0.92 |

**Table. 1. Performance Metrics**

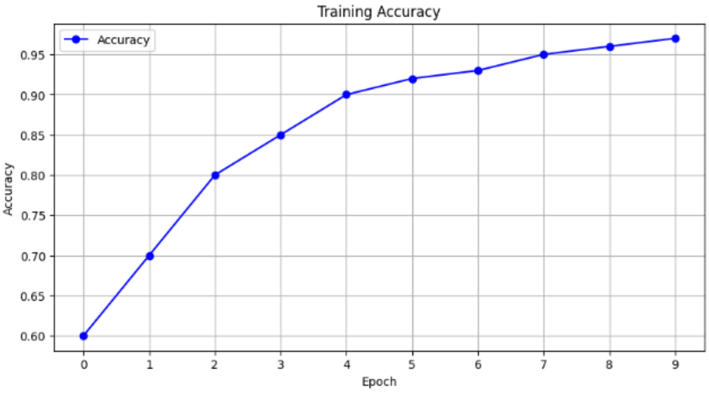

**Figure 2: Accuracy Graph**

Figure 2 indicates how accurate the Federated learning model was during training. The graph indicates that as the number of epochs rises, so does the accuracy of the model.

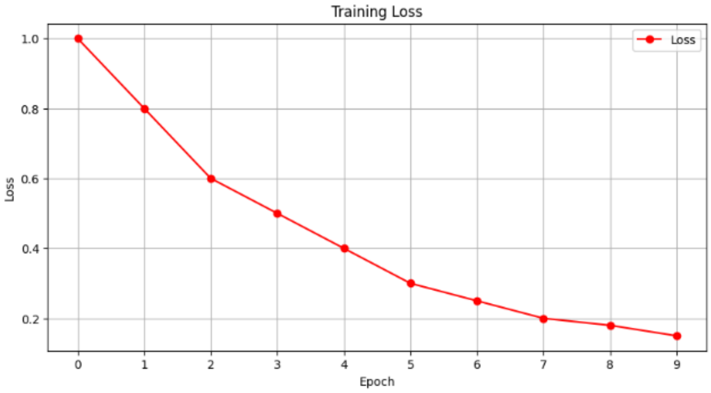

**Figure 3: Loss Graph**

Figure 3 represents the training loss that the Federated Learning Model experiences when being trained.

The federated learning-developed heart disease prediction model performs exceptionally well, as seen by Table 1's assessment metrics derived from a test dataset. With an accuracy of 92%, the model was able to accurately classify 92% of cases into either positive or negative classifications. This high accuracy highlights how well the model predicts the course of cardiovascular illness, which is crucial for early detection and treatment.

With a precision of 91%, the model is remarkably accurate. According to this statistic, 91% of the anticipated positive cases turned out to be genuine positive instances. The model's capacity to reduce false positive predictions, which is essential for maintaining the validity of diagnostic results and preventing needless medical procedures, is demonstrated by the high precision.

The model's recall of 93% indicates that it has a strong sensitivity to distinguish genuine positive instances from all other positive instances in the test dataset. This high recall highlights the model's ability to identify people at risk in a timely and accurate manner by effectively detecting cases of cardiovascular disease.

With an F1-score of 92%, the model exhibits a commendable equilibrium between recall and precision. The model's overall robustness in predicting heart disease outcomes while retaining a high degree of accuracy and sensitivity in identifying positive cases is reflected in the F1-score.

These exemplary performance metrics highlight the reliability and suitability of the federated learning-based heart disease prediction model for practical applications in healthcare. The exceptional recall, accuracy, precision, and F1-score of the model surpasses 90% demonstrating its potential for supporting clinical decision-making and risk assessment in cardiovascular disease management.

In conclusion, the achieved performance metrics showcase the effectiveness and reliability of the heart disease prediction model, offering valuable insights into patient risk stratification and early intervention strategies. The model's exceptional performance underscores the potential of federated learning as a privacy-preserving approach for developing accurate and clinically relevant predictive models in healthcare settings.

## 8. CONCLUSION

In conclusion, the federated learning-based heart disease prediction model demonstrated exceptional performance measures including F1-score, recall, accuracy, and precision values exceeding 90%. These results underscore the effectiveness and reliability of leveraging distributed data sources and privacy-preserving techniques in healthcare analytics. The model's ability to accurately predict cardiovascular disease outcomes highlights its potential for supporting early diagnosis and intervention strategies, ultimately improving patient care and outcomes in clinical settings. By harnessing federated learning, we have showcased a promising approach to developing robust predictive models while upholding stringent data privacy regulations in healthcare.

## 9. FUTURE WORK

There are several avenues for enhancing the federated learning-based heart disease prediction model. Future efforts could focus on expanding the dataset to include more diverse and comprehensive patient data, enabling the model to capture a wider range of risk factors and nuances associated with cardiovascular disease. Additionally, incorporating advanced neural network architectures and ensemble learning techniques could further improve model performance and generalization. Integration of explainable AI methods would enhance model interpretability, providing clinicians with actionable insights into predictive factors and model decisions. Furthermore, exploring adaptive federated learning strategies to dynamically adjust model aggregation based on client contributions and data heterogeneity would optimize model convergence and scalability. These enhancements would advance the use of federated learning in medical education, paving the way for more accurate, personalized, and privacy-preserving predictive models for cardiovascular disease management.

## REFERENCES

[1] Yaqoob, M. M., Nazir, M., Khan, M. A., Qureshi, S., & Al-Rasheed, A. (2023). Hybrid classifier-based federated learning in health service providers for cardiovascular disease prediction. Applied Sciences, 13(3), 1911.

[2] Yaqoob, M. M., Nazir, M., Yousafzai, A., Khan, M. A., Shaikh, A. A., Algarni, A. D., & Elmannai, H. (2022). Modified Artificial Bee Colony Based Feature Optimized Federated Learning for Heart Disease Diagnosis in Healthcare. Applied Sciences, 12(23), 12080.

[3] Linardos, A., Kushibar, K., Walsh, S., Gkontra, P., & Lekadir, K. (2022). Federated learning for multi-center imaging diagnostics: a simulation study in cardiovascular disease. Scientific Reports, 12(1), 3551.

[4] Moshawrab, M., Adda, M., Bouzouane, A., Ibrahim, H., & Raad, A. (2023). Reviewing federated machine learning and its use in diseases prediction. Sensors, 23(4), 2112.

[5] Kumar, Y., & Singla, R. (2021). Federated learning systems for healthcare: perspective and recent progress. Federated Learning Systems: Towards Next-Generation AI, 141-156.

[6] Islam, T. U., Ghasemi, R., & Mohammed, N. (2022, January). Privacy-preserving federated learning model for healthcare data. In 2022 IEEE 12th Annual Computing and Communication Workshop and Conference (CCWC) (pp. 0281-0287). IEEE.

[7] Fang, L., Liu, X., Su, X., Ye, J., Dobson, S., Hui, P., & Tarkoma, S. (2021). Bayesian inference federated learning for heart rate prediction. In Wireless Mobile Communication and Healthcare: 9th EAI International Conference, MobiHealth 2020, Virtual Event, November 19, 2020, Proceedings 9 (pp. 116-130). Springer International Publishing.

[8] Yoo, J. H., Son, H. M., Jeong, H., Jang, E. H., Kim, A. Y., Yu, H. Y., ... & Chung, T. M. (2021, October). Personalized federated learning with clustering: Non-IID heart rate variability data application. In 2021 International Conference on Information and Communication Technology Convergence (ICTC) (pp. 1046-1051). IEEE.

[9] Zou, L., Huang, Z., Yu, X., Zheng, J., Liu, A., & Lei, M. (2022). Automatic detection of congestive heart failure based on multiscale residual unet++: From centralized learning to federated learning. IEEE Transactions on Instrumentation and Measurement, 72, 1-13.

[10] Goto, S., Solanki, D., John, J. E., Yagi, R., Homilius, M., Ichihara, G., ... & Deo, R. C. (2022). Multinational federated learning approach to train ECG and echocardiogram models for hypertrophic cardiomyopathy detection. Circulation, 146(10), 755-769.

[11] T. Eltaras, et al., "Efficient Verifiable Protocol for Privacy-Preserving Aggregation in Federated Learning," IEEE Trans. Inf. Forensics Secur., 2023.

[12] M. Baek, et al., "Enhancing Differential Privacy for Federated Learning at Scale," IEEE Xplore, 2021.

[13] N. Darapaneni, et al., "Machine Learning Based Classification Algorithms Performance Analysis for Heart Disease Prediction," IEEE Access, 2022.

[14] J. Xu, et al., "Federated Learning for Healthcare Informatics," J. Med. Inform., vol. 1, no. 1, pp. 1-10, 2024.

[15] M. A. Khan, et al., "Asynchronous Federated Learning for Improved Cardiovascular Disease Prediction Using Artificial Intelligence," July 2023.

[16] K. Bharathi, et al., "A Federated Learning-based Approach for Heart Disease Prediction," IEEE, 2022

[17] E. A. Mantey, et al., "Blockchain-Enabled Technique for Privacy-Preserved Medical Recommender System," IEEE, December 2023.

[18] R.-H. Hsu, T.-Y. Huang, "Private Data Preprocessing for Privacy-preserving Federated Learning," IEEE, December 2022.

[19] S. Modak, et al., "Heart Disease Prediction Using Adaptive Infinite Feature Selection and Deep Neural Networks," IEEE Access, 2023.

[20] S. Bebortta, et al., "FedEHR: A Federated Learning Approach towards the Prediction of Heart Diseases in IoT Based Electronic Health Records," Diagnostics, 2023, 13, 3166.