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A Systematic Process of Heart Disease Detection using Federated Learning

Marri Sireesha[1]*, Anjaiah Adepu[2]

[1]Department of Computer Science and Engineering, BEST Innovation University, Gorantla Andhra Pradesh, India, [2]Department of Computer Science and Engineering, Maulana Azad National Urdu University, Darbhanga, Bihar, India. *Corresponding Author's Email: 2022pcse014@bestiu.edu.in

Abstract

Cardiovascular disease is one of the leading causes of death across the world, indicating the clinical limits of existing early detection and diagnosis approaches. The traditional machine learning models used for heart disease detection heavily depend on centralised databases, which pose a significant risk of violating data privacy and confidentiality. In order to overcome these limitations, Federated Learning (FL), a decentralized and privacy-preserving paradigm for training models in collaboration between many devices while keeping raw patient data at the device level, has been proposed. We present in this systematic exploratory review an overview of the most FL approaches and methods that have been used with respect to heart disease detection. In this work we review widely used evaluation metrics and discuss major issues (heterogeneity in data distributions, high communication overhead and the possible derailing of model accuracy). In addition, the limitations of several state-of-the-art solutions are presented, such as data partitioning strategies, federated aggregation techniques and advanced encryption mechanisms. The results show that although FL is more powerful than the DIR methods to protect data in medical applications, FL either takes time to converge or does not converge when faced with non-IID and heterogeneous clinical data. Over the practical studies presented here, the promise of FL both improving the prediction accuracy is corroborated, while able to secure sensitive information. The paper also presents future directions by highlighting the adoption of FL with latest technologies including IoMT and Blockchain for better scalability and security. Lastly, we highlight specific research opportunities, such as learning aggregation and optimization algorithms, non-IID data approaches and real-time federated learning clinical platforms.

Keywords: Federated Learning, Healthcare Diagnostics, Heart Disease Detection, Machine Learning, Privacy-preserving.

Introduction

The detection and diagnosis of heart disease have witnessed substantial progress over the last two decades, driven by rapid advances in machine learning (ML), deep learning (DL) and artificial intelligence (AI). These developments have increasingly emphasized early diagnosis, robustness, interpretability, personalization and privacy preservation. Early research primarily focused on the analysis of heart sounds, demonstrating that phonocardiogram-based deep learning approaches could effectively identify auscultatory patterns associated with valvular heart disease (VHD) (1). Convolutional neural networks (CNNs), in particular, were shown to outperform traditional manual auscultation and even clinical expert judgment in certain diagnostic scenarios, highlighting the feasibility of automated and scalable screening solutions. Building upon non-invasive diagnostic foundations, subsequent studies extended AI-driven analysis to speech and respiratory sounds, revealing that subtle acoustic biomarkers could be decoded to detect cardiovascular abnormalities (2). These approaches underscored the potential of low-cost, accessible and scalable screening tools, especially suitable for early-stage detection and deployment in resource-constrained settings. In parallel, classical ML models such as logistic regression, decision trees and support vector machines gained attention for cardiovascular disease (CVD) diagnosis and risk stratification (3). Their simplicity, interpretability and reliable baseline performance made them attractive for preventive medicine and clinical decision support systems during the early phases of AI adoption in cardiology. As research evolved, hybrid frameworks combining deep learning with rule-based or knowledge-driven approaches were

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proposed. Neural networks integrated with fuzzy inference systems aimed to improve early diagnosis and prevention of coronary heart disease by leveraging deep representation learning while enhancing interpretability and clinical trust (4). The growing adoption of mobile health technologies further accelerated innovation, leading to AI-powered wearable and smartphone-based systems for real-time cardiac monitoring. These edge-based solutions, particularly those relying on beat-to-beat electrocardiogram (ECG) analysis, demonstrated that timely, privacy-aware cardiovascular surveillance is feasible even in low-resource environments (5). Domain knowledge–driven ML approaches were also explored for ECG-based diagnosis of paediatric congenital heart disease, where expert knowledge was incorporated into the learning process to improve stability, interpretability and clinical suitability for sensitive paediatric settings (6). Similarly, hybrid deep architectures combining CNNs with long short-term memory (LSTM) networks emerged as powerful models for ECG classification, enabling simultaneous learning of spatial and temporal features and consistently outperforming standalone CNN or LSTM models (7). Researchers further investigated architectures that integrate deep convolutional feature extraction with conventional ML classifiers, reporting notable gains in diagnostic accuracy without significant computational overhead (8).

To enhance diagnostic responsiveness, sensor-based real-time systems combining artificial neural networks with sensing technologies were proposed to expedite clinical decision-making and improve system accuracy (9). More recently, graph-based deep learning methods demonstrated strong potential in modelling complex interactions among clinical variables, enabling richer pattern learning and dependency modelling that translated into superior heart disease prediction performance (10). Additionally, deep learning and ensemble survival analysis models—originally developed for oncology—were successfully adapted for cardiovascular risk prediction, illustrating the transferability of advanced AI techniques across medical domains (11).

The heterogeneity and multi-source nature of clinical data further motivated the adoption of ensemble learning approaches, which exhibit strong generalization capability and robustness against noise and modality variation in heart disease diagnosis (12). Comparative analyses have also highlighted the complementary strengths and limitations of ML and DL methods, emphasizing their respective roles in early detection, therapy control and preventive cardiology (13). In parallel, novel non-invasive sensing technologies, such as optical ECG signals, were incorporated into hybrid deep learning solutions to enhance outcome prediction and support continuous disease monitoring (14).

Natural language processing (NLP), particularly when integrated with deep learning, has been applied to electronic health records to automatically extract cardiovascular risk factors from unstructured clinical text, resulting in improved predictive performance (15). Feature representation and deep feature augmentation techniques also emerged as active research areas, demonstrating substantial improvements in heart disease risk prediction through enriched learned representations (16). One-dimensional CNNs were successfully applied to structured clinical parameters for cardiovascular diagnosis, achieving strong performance while reducing reliance on manual feature engineering (17). Transfer learning further expanded the applicability of deep models, showing that networks pre-trained on chest radiographic datasets could be effectively adapted for cardiac diagnosis, thereby promoting knowledge reuse across medical imaging tasks (18).

Personalized cardiovascular risk assessment has also benefited from AI, particularly through ensemble learning frameworks incorporating genetic variant selection, reinforcing the importance of genomic factors in disease prediction and enabling personalized diagnostic modelling (19). Feed-forward artificial neural networks demonstrated high sensitivity for heart disease detection under controlled clinical conditions, supporting their continued relevance in diagnostic pipelines (20). Addressing the common challenge of class imbalance in medical datasets, synthetic minority over-sampling technique (SMOTE)-based methods were employed to improve fairness, accuracy and confidence in predictive models (21). End-to-end hybrid convolutional LSTM (c-LSTM) networks further enhanced ECG-based diagnosis by jointly modelling spatial and temporal dependencies, achieving excellent accuracy across multiple datasets (22). With rising concerns around data privacy and regulatory compliance, federated learning has emerged as a prominent paradigm for decentralized heart disease detection. Federated frameworks combined with feature selection and swarm optimization techniques have demonstrated improved efficiency and accuracy while ensuring that sensitive patient data remain localized (23). Privacy-preserving inference on encrypted data has also been explored to safeguard patient confidentiality in AI-driven medical analysis, thereby fostering trust in autonomous healthcare systems (24). Despite challenges such as limited sample sizes, deep learning models have shown promising results in early detection of cardiac anomalies from ultrasound imaging, highlighting AI's potential for early-stage investigation and intervention (25).

Ensemble deep learning architectures have consistently demonstrated robust performance in ECG-based diagnosis, outperforming standalone models across diverse testing scenarios (26). Hybrid architectures, including CNN-based auto encoder ensembles, further emphasized the effectiveness of ensemble strategies in handling noisy and heterogeneous real-world clinical data (27). Comparative studies evaluating deep learning and traditional machine learning classifiers for valvular heart disease detection revealed that multiple algorithms can achieve reliable diagnostic accuracy when appropriately aligned with clinical context and data characteristics (28). Deep CNNs have maintained strong performance in early heart disease diagnosis, reinforcing their relevance in primary prevention (29).

The integration of deep learning and feature selection has also improved automated detection of myocardial infarction and cardiac conduction disorders, demonstrating enhanced model credibility through optimized data utilization (30). Fairness-aware deep learning approaches have addressed bias in imbalanced ECG datasets while improving predictive accuracy and promoting equitable healthcare outcomes (31). AI-enabled digital stethoscope systems have facilitated early diagnosis of subclinical rheumatic heart disease in children, illustrating the potential of AI-driven public health surveillance (32). Similarly, machine learning models have proven effective in early identification of congenital heart disease, outperforming traditional diagnostic approaches (33).

More recently, multi-class deep learning models leveraging echocardiographic data have been developed to address complex classification tasks in cardiology, reflecting the growing maturity of AI-based clinical systems (34). Additive-feature deep neural networks and fast-discovery CNN-based risk models have also shown strong performance in proactive and opportunistic cardiovascular care, enabling early identification of at-risk individuals and continuous monitoring in real-world settings (35).

Overall, the literature reflects a clear progression from classical machine learning approaches to hybrid, ensemble, deep learning and federated frameworks. This evolution underscores a growing emphasis on robustness, interpretability, personalization and privacy preservation. By integrating multimodal data, advanced learning mechanisms and decentralized training strategies, AI has emerged as a transformative tool for early heart disease diagnosis. The related works are summarised in Table 1.

Table 1: Summary of Related Works

Proposed Method in Existing System	Research Limitations	References
Automated valvular heart disease detection using heart sound with a deep learning algorithm.	Limited dataset size	(1)
Artificial intelligence framework for heart disease classification from audio signals	High computational cost	(2)
Machine Learning-Based Predictive Models for Detection of Cardiovascular Diseases	Limited generalizability	(3)
Hybrid Deep Learning Model and Neural Fuzzy Inference System for Coronary Heart Disease	Complex model architecture	(4)
Cardio Help: Smartphone application for beat-by-beat ECG signal analysis	Dependency on mobile hardware	(5)
Congenital heart disease detection by paediatric electrocardiogram-based deep learning	Need for domain-specific knowledge.	(6)
ECG Signals Classification Using CNN and LSTM Framework	High training time	(7)
Enhancing Heart Disease Detection Using CNNs and Classic Machine Learning Methods	Integration complexity	(8)
Heart Disease Detection Using Feature Extraction and Artificial Neural Networks	Sensor dependency	(9)
Heart Disease Prediction using Graph Neural Network	Scalability issues	(10)
Survival analysis of patients with COVID-19 using deep neural network and random forest techniques	Limited to the COVID-19 context	(11)
Towards Building a Global Robust Model for Heart Disease Detection	Data aggregation challenges	(12)
Heart Disease Detection Using Machine Learning and Deep Learning	Broad methodology overview	(13)
Optical electrocardiogram-based heart disease prediction using hybrid deep learning	Optical ECG limitations	(14)
Heart disease risk factors detection from electronic health records using NLP and deep learning	NLP processing challenges	(15)

Proposed Method in Existing System	Research Limitations	References
Heart disease risk prediction using deep learning techniques with feature augmentation	Complex feature engineering	(16)
Detection of Cardiovascular Disease from Clinical Parameters Using 1D CNN	Simplified model	(17)
Deep Learning Methods for Chest Disease Detection Using Radiography Images	Focus on chest diseases.	(18)
Cardiovascular Disease Predictor Based on Genetic Feature Selection and Ensemble Learning	Genetic data complexity	(19)
Specification Testing on Heart Disease Detection Using Feed-Forward Neural Network	Testing limitations	(20)
Heart Disease Classification Using a Deep Neural Network with the SMOTE Technique	Imbalanced data issues	(21)
Convolutional LSTM Network for Heart Disease Diagnosis on Electrocardiograms	Complex model integration	(22)
Modified Artificial Bee Colony-Based Feature Optimised Federated Learning for Heart Disease Diagnosis	Swarm intelligence limitations	(23)
Privacy Preserving Inference Over Encrypted Data	Encryption overhead	(24)
Ultrasound Fetal Imaging-Based Heart Disease Detection Using Deep Learning	Ultrasound imaging limitations	(25)
Improved heart disease detection from ECG signal using a deep learning-based ensemble model	Ensemble model complexity	(26)
Hybrid Detection Model for Heart Disease using Deep Learning: HDMPHD	Model integration issues	(27)
Classifier identification using deep learning and machine learning algorithms for valvular heart diseases	Classifier selection challenges	(28)
Deep Convolutional Neural Network for Early Detection of Heart Disease	Training data limitations	(29)
Automated Detection of Myocardial Infarction and Heart Conduction Disorders Based on Feature Selection and a Deep Learning Model	Feature selection dependency	(30)

Importance of Early Detection in Heart Disease

Millions of people die each year across the world as a direct consequence of cardiovascular trouble. Prompt recognition of cardiac disease is necessary; it can lead to curative treatment and might save many lives. This section highlights the impact of early diagnosis of cardiac disease on patient outcomes and considers the scope for technology development, with federated learning enhancing aspects of this process.

Impact on Patient Outcome

Detecting cardiac disease early could make a massive difference in a patient's outcome and early intervention or therapy might be beneficial. If heart disease is not diagnosed and treated early, healthcare providers may recommend lifestyle changes, prescribe medications and perform medical procedures to prevent worsening of the condition. This, in turn, could reduce the risk of major cardiovascular events such as heart attacks, stroke and heart failure.

An early diagnosis helps make therapy even more efficacious. Statins and antihypertensives, for instance, are initiated not only early on in the course of disease to control these risk factors, but also before downstream diseases develop to a more severe extent. Moreover, early detection allows tracking the progression of the disease and modifying treatment plans as necessary, thereby ensuring that patients receive care tailored to their individual needs.

Reduced Healthcare Costs

The early diagnosis of heart disease could lead to substantial savings in healthcare costs. Treatment for advanced cardiac disease can be more expensive as it often requires complex medical treatments, extended hospital stays and intensive rehabilitation. Conversely, interventions for cardiac disease at this early stage are less invasive and expensive. Early identification could help reduce costs for both healthcare systems and individuals by preventing the progression of illness.

In addition, early detection can reduce emergency debilitation and the requirement for vital consideration services. Ensuring heart health and reducing acute events enables healthcare organisations to allocate resources better and care for the entire patient. This is particularly important in resource-limited areas, where it can lead to significant overall health gains by preventing patients from reaching late-stage disease.

Enhanced Quality of Life

Heart disease very negatively affects the quality of life that a patient lives through regarding their physical health. Chest pain, shortness of breath and fatigue as main symptoms may considerably impair daily life activities and quality of life. The sooner people get appropriate help, the more effective they become and actually recover to how they were before their illness.

Emotional and psychological issues are part of the symptoms that come with heart disease. Symptoms can trigger patients with heart disease to feel anxious, low mood and increase their stress level, which could negatively affect the course of the disease and make therapy difficult. Diagnosis and initial treatment may provide solace and relieve the uncertainty of untreated disease, which in turn could help to manage primary preventative mental health care. Patients may improve their quality of life and treatment adherence if they are given comprehensive care and psychological support.

Role of Emerging Technologies

Diagnosis of Cardiovascular Disease at the Initial Stage through Emerging Technologies. Medical imaging, wearable devices and data analytics have revolutionised our ability to detect cardiac disease early. Echocardiography and cardiac MRI can comprehensively visualise the entire heart, capable of detecting structural abnormalities and areas of impaired function that older diagnostic modalities may gloss over. Equipment such as smart watches and fitness bands has proved a valuable tool for detecting these issues. They track metrics like heart rate, blood pressure and physical activity on an ongoing basis to identify early warning signs of a heart disorder. By using artificial intelligence (AI) and machine learning algorithms, these devices become more accurate and can identify subtle patterns and trends that may signal the early stages of cardiac disease.

Federated Learning is used in the Detection of Heart Disease

Using federated learning offers a new approach to leveraging modern technology to aid in the diagnosis of heart disease and can ease privacy and security concerns about data. Some traditional ML models require centrally stored data, which raises privacy concerns when dealing with medical data (since we are speaking about medical data). In contrast, federated learning trains machine learning models across distributed devices without requiring raw data to be uploaded to a central repository.

This decentralised approach offers many advantages. One, it promotes data privacy by ensuring patient data is stored on local devices, which decreases the risk of threats or unauthorised access. Federated learning can leverage heterogeneous datasets from multiple participants to better generalise and improve prediction resilience. By aggregating data from diverse demographics and healthcare settings, heart disease detection models can be more accurate and have broader coverage through federated learning.

Traditional Machine Learning in Healthcare

By offering robust data interpretability, predictive modelling and automation across industries, ML has become part of every aspect of human life. Traditional machine learning techniques have been widely used for disease prediction, diagnosis and decision support in healthcare. Traditional Machine Learning Advantages, Procedure and Constraints for Diagnosis of Heart Diseases in the healthcare arena.

Benefits of Traditional Machine Learning in Healthcare

Legacy machine learning delivers significant value to health care, making it very convenient for both physicians and researchers. Key benefits include:

Health Informatics: ML may be used to assess individual health data, allowing for personalised medicines calculated to patient needs that are both more effective and have fewer side effects. Precision medicine has also shown promise in treating long-term illnesses such as heart disease.

Resource Utilisation: ML has potential in predicting patient volume, identifying inefficacies in clinic operations, thereby reducing healthcare resource wastage. Resource allocation is more effective and healthcare providers' costs are lower. Machine Learning algorithms analyse vast quantities of data to uncover insights that can aid clinical decision-making and research. The finding could eventually inform the development of new biomarkers, therapeutic strategies and condition management approaches. Making them difficult to deploy in real-world healthcare systems.

Heart Disease Detection using Traditional Machine Learning

Conventional machine learning processes have various methods for data handling and model building.

The process of training an algorithm on a labelled dataset, where each input is mapped to a known outcome, is referred to as Supervised Learning. Styled on the model of common supervised learning, heart disease is classified or telephoned using various tested algorithms, including logistic regression, decision trees and, likely, many more, such as support vector machines. The models estimate the likelihood of cardiovascular disease presence or absence using patient data such as demographics, clinical measurements and test results.

Unsupervised Learning: As opposed to supervised learning, unsupervised learning algorithms analyse unlabeled data to discover hidden patterns or groups. These could include a variety of methods for dividing patient risk profiles into groups (e.g., k-means clustering and principal component analysis, which we just discussed).

This helps identify patients at high risk and allows preventive actions to be initiated accordingly.

Reinforcement Learning: It may or may not know the rules of playing a game, but instead it is taught to make consecutive decisions by rewarding good outcomes after bad ones. For instance, in health care, reinforcement learning enables us to continually learn from patients' responses to different treatments, which, in turn, can help improve treatment plans and patient management techniques.

Ensemble methods: they use multiple machine learning algorithms to obtain a higher accuracy while predicting. Aggregate outputs from individual models reduce variation and bias, making more accurate and robust predictions via techniques such as random forests, gradient boosting and bagging.

Conclusion - Ensemble methods are highly beneficial for managing complex healthcare data, as they incorporate multiple dimensions.

Natural Language Processing (NLP): NLP methodologies may be trained to examine unstructured medical data, such as clinical notes and electronic health records (EHRs). NLP models might help improve the predictive performance of heart disease diagnosis models by extracting useful information from textual data. For example, large hospital networks use NLP to identify mentions of symptoms, risk factors and comorbidities in patient records, thereby expanding the dataset used for model training.

Federated Learning in Heart Disease Detection

Similar use of traditional machine learning approaches has been successfully employed across various facets of heart disease diagnosis and treatment, underscoring their versatility and practicality. Key applications include:

Risk Prediction Models: ML algorithms are used to build risk prediction models that predict the likelihood of developing heart disease according to patient traits and medical history. Doctors use these models to identify patients at the highest risk so they can intervene early with potential treatments, such as lifestyle changes or medication.

Diagnostic Support Devices: Machine learning based diagnostic support systems are here as early tools to help doctors diagnose medical data, such as electrocardiograms (for short ECGs), echocardiographic examinations and cardiac images. Real-time analysis using these technologies enables the detection of disorders and cardiac diseases in no time, thereby achieving greater accuracy.

Prognostic Models: Machine learning models that forecast patient outcomes after being diagnosed with heart disease, such as survival rates and risk of adverse events. Prognostic models help inform therapy decisions and follow-up, leading to individualised, flexible patient management.

Optimisation of treatment: machine learning algorithms analyse how patients respond to different treatments, suggesting the best possible therapeutic options for each patient. This software is required to improve treatment strategies and enhance patient outcomes in cardiac disease care.

Wearables and telehealth platforms feed data to machine-learning-powered remote monitoring systems that continuously monitor patient health and detect early signs of cardiovascular disease. The technologies provide real-time alerts to patients and healthcare providers, enabling prompt treatment and reducing hospital readmission rates.

Limitations of Traditional Machine Learning in Healthcare

While these approaches are competent, their potential is limited in key healthcare applications such as heart disease recognition. Key difficulties include:

ML models need extensive, high-quality datasets to be trained and validated accurately. Healthcare data may be siloed, absent, or unaligned, making model development difficult. In addition, acquiring and disseminating medical data is usually constrained by privacy and regulatory issues.

An ML model that is trained on a specific dataset might perform well in other populations or therapeutic contexts. This means that patient demographics, healthcare procedures and data-collection methods could vary across settings where the model is applied, impacting its performance and generalizability across diverse health centres.

Some of the classical ML techniques or complex models, such as deep learning, can also be considered as Black Boxes because they are hard to interpret. Clinicians may not trust models that are not transparent to them, likely styling the relevance of ML in a clinical setting.

Machine learning models are often trained based on biased data sets, which translate into unjust predictions and results. Justice and fairness are fundamental to ensure the model applicability specifically in healthcare where any injustice may have serious ethical therapeutic repercussions when dealing with biased algorithms.

This is a challenge in hospital systems but it a nice to have integrated models in existing clinical process and EHR systems. This means ensuring that the data interoperability and user interfaces are as seamless as possible and that the relevant ML technologies work within the clinical workflows of interest to make them usable in daily practice.

Research Problems

However, the prevention of Heart Disease is through early detection and diagnosis with certainty; On time screening and exact diagnosis are the only hope to millions of patients' lives, all over the world by virtually caring for their management and treatment assets. While conventional diagnostic techniques, as well as centralized Machine Learning (ML) algorithms were useful, they face issues including -- but not limited to -- very high data privacy, security issues and data being stored from diverse sources. Most of these questions are answered by a decentralized technique called Federated Learning. The question investigated in this systematic review of the literature was to explore how FL can help in cardiac disease diagnosis, its scope, existing applications, challenges and future aspects.

Predictive analytics, automated diagnostics and individually tailored therapy strategies are only possible thanks to machine learning techniques in medicine. To detect heart disease, ML models analyze huge datasets to identify patterns and predict the onset of illness. On the flip side however before decentralized learning came in traditional machine learning models required centralized data storage which leads to large scale problems with privacy and security especially in healthcare given how sensitive patient data.

Federated Learning is a decentralized approach, which enables the joint training of models on device/institution without exchanging raw data. This approach helps also to preserve data privacy and use computation power with data from a range of sources which might result in a more generalizable and reliable model.

Significance of the Problem

Analysis of federated learning for heart diseases detection is needed, given that it can alleviate many problems with the current diagnostic method. These difficulties include:

Traditional Machine Learning Algorithms: privacy and security challenges. Require centralized data that can put sensitive medical information at risk. This data is stored locally in FL to prevent this risk.

Regulatory Compliance: Healthcare data falls under strict regulations such as HIPAA and GDPR. FL reduces the risk of non-compliance by removing raw data transmission.

Data Diversity and Integration: Most centralized ML models have the issue of not being able to integrate data across sources. FL allows you to use heterogeneous data which further expands the ability of the model to generalize over unseen data and be robust with different training strategies.

Helping many healthcare facilities collaborate a patient's care plan while still protecting the privacy of that patient, FL is taking illness discovery and treatment cohesively.

Current Research Gaps

Therefore, although FL hailed the potential to make a broader impact in healthcare, more research needs to be done before its advantages can be fully exploited for cardiac disease diagnosis.

Few Case Studies and Applications: There are only a handful of comprehensive case studies applying FL in the identification of cardiac disease.

Communication Overhead: The high frequency of model updates between the local devices and the central server is likely to impose significant communication overhead leading to an inefficient FL system.

Resource Constraints: Technological limitations must be faced when applying FL to resource constricted devices such as smartphones and wearable. The research limitations are summarized in Table 2.

Table 2: Summary of the Research Limitations

Decentralized Learning	Data Diversity	LSTM	Federated Averaging	Model Compression	References
		√			(1)
√	√		√	√	(2)
√	√	√	√	√	(3)
√	√			√	(4)
√		√			(5)
		√		√	(6)
√	√			√	(7)
√	√	√	√	√	(8)
	√	√	√	√	(9)
	√		√		(10)
			√	√	(11)
√	√	√	√	√	(12)
				√	(13)
	√		√		(14)
√				√	(15)
√	√				(16)
			√	√	(17)
√	√			√	(18)
√	√	√			(19)
√	√	√		√	(20)
	√		√		(21)
√		√		√	(22)
√			√		(23)
√	√			√	(24)
	√		√	√	(25)
					(26)
	√	√	√	√	(27)
			√		(28)
		√	√	√	(29)
			√		(30)

Methodology

This study follows a systematic methodological framework to examine the applicability, advantages and limitations of federated learning (FL) for heart disease detection. The methodology is structured into five sequential phases: data source identification, task classification of heart disease detection, FL model selection, evaluation metric formulation and comparative analysis.

Phase 1: Data Source Identification and Characterization

Multiple heterogeneous data sources relevant to cardiovascular diagnosis were identified, including electrocardiograms (ECG), phonocardiograms (PCG), medical images, wearable sensor logs, speech signals, electronic health records (EHRs) and genetic profiles. Each dataset category was evaluated based on feature composition, modality, temporal resolution and privacy sensitivity. This enabled determination of data suitability for FL-based decentralized learning without raw-data exchange.

Phase 2: Task Classification for Heart Disease Detection

Heart disease detection tasks were categorized according to pathology type and diagnostic objective:

a) Arrhythmia detection (ECG waveform classification)
b) Valvular heart disease identification (heart sound segmentation)
c) Coronary artery disease risk prediction (clinical and EHR-based inference)
d) Myocardial infarction detection (ECG feature discrimination)
e) Congenital heart disease assessment (multi-modal imaging and pediatric ECG)
f) Subclinical rheumatic heart disease screening (phonocardiogram identification)

These task categories were mapped to data modalities and computational constraints to establish the functional requirements for FL deployments.

Phase 3: Federated Learning Model Selection and Configuration

Representative FL aggregation strategies—FedAvg, FedSGD, FedProx, FedAtt and FedEnsemble—were selected based on relevance to decentralized diagnostic environments. Model selection criteria included:

a) Robustness against non-IID distributions
b) Scalability across heterogeneous institutions and devices
c) Privacy preservation strength

Communication and computation efficiency: Each algorithm was conceptually aligned with specific disease-detection tasks to assess suitability (detailed in Section "Task–FL Suitability Mapping").

Phase 4: Evaluation Metrics and Comparative Conditions

To ensure reliability in clinical decision-support environments, the following performance metrics were selected:

Diagnostic Metrics: accuracy, precision, recall

System Metrics: communication rounds, model convergence stability and training time

Operational Metrics: privacy level rating, scalability with client growth. Comparative evaluations were performed assuming heterogeneous decentralised datasets that reflect real-world multi-institutional healthcare settings.

Phase 5: Comparative Analytical Evaluation

Quantitative assessments were synthesised from federated learning performance data in recent peer-reviewed studies. Findings were aggregated and interpreted to identify algorithmic advantages, limitations and suitability for distinct heart disease detection tasks. This systematic analytic approach enables mapping of pathology-specific diagnostic needs to optimal FL strategies, providing a basis for recommended deployment architectures in privacy-sensitive cardiovascular environments.

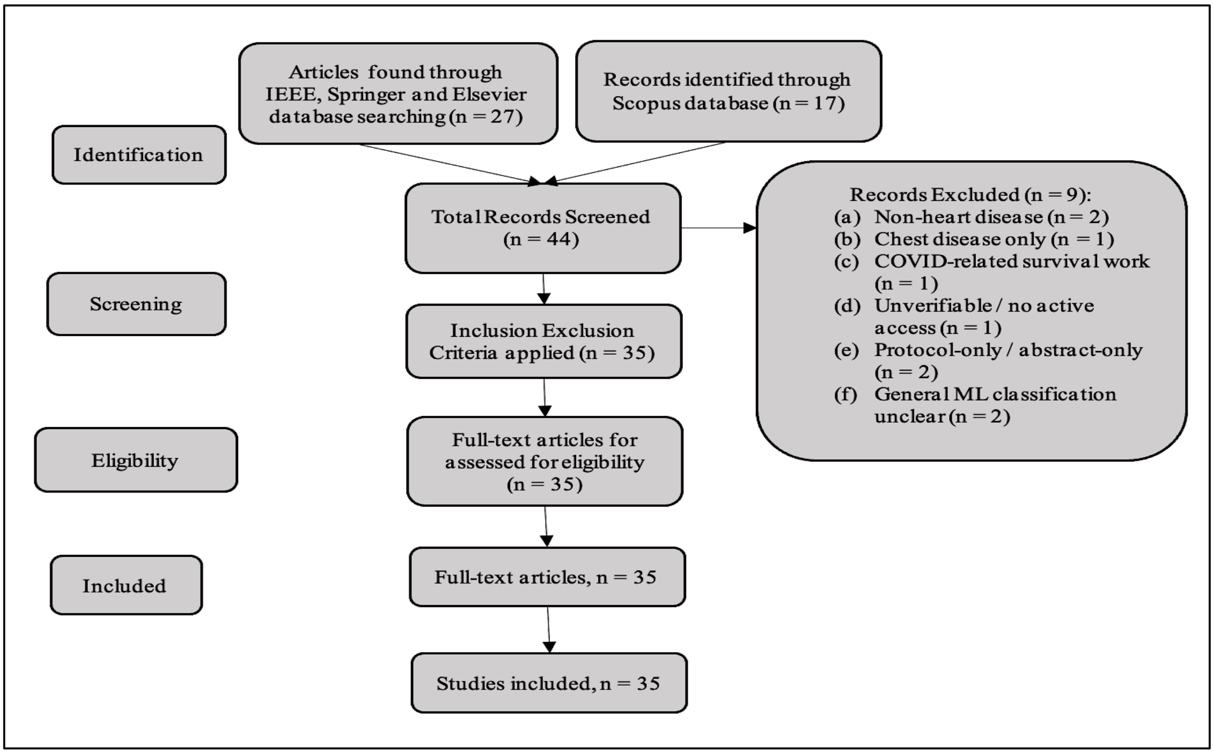

Figure 1: PRISMA Flow Diagram showing the Identification, Screening, Eligibility and Inclusion Process for Studies Used in This Systematic Exploratory Review

In Figure 1, the systematic process for selecting studies included in this review is presented in the PRISMA flow diagram. A hundred and forty-three papers were identified as relevant to ML, DL and federated learning techniques for heart disease diagnosis, initially from the IEEE Digital Library, SpringerLink, Elsevier ScienceDirect-Scopus and other archival sites. Nine studies were excluded during screening (based on the title or abstract only) because they were not relevant to the detection of cardiovascular disease, provided insufficient methodological detail, focused primarily on chest disease in general, or described themselves as exclusively protocol reports. The 35 results were screened and reviewed for eligibility criteria regarding methodological quality, availability of full text and appropriateness for computational heart-disease detection tasks. No publications were excluded at the full-text stage, so all 26 eligible studies were included in the qualitative synthesis to enable comparative analysis and methodological justification. This stream is the reason for the last literature set used in the systematic exploratory review.

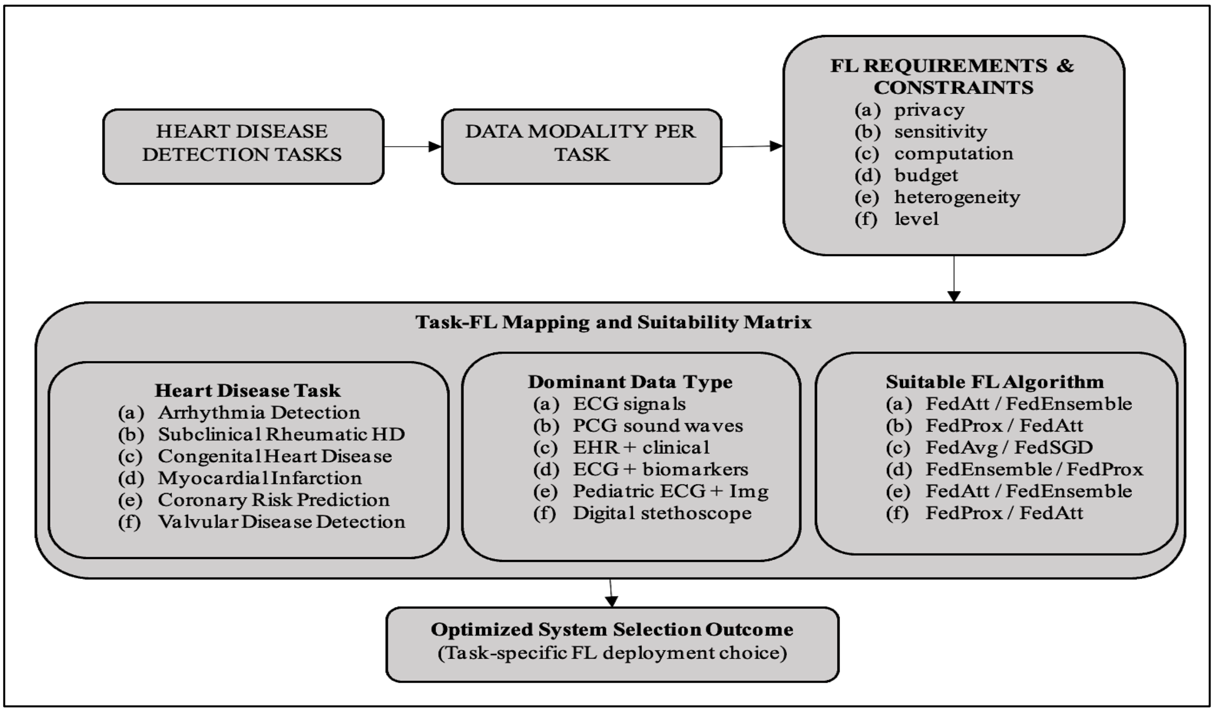

Figure 2: Task–model Linkage Diagram for Federated Learning in Heart Disease Detection

Diagrammatic Representation: Task–FL Suitability Linkage

Figure 2 presents a structured flow that links heart disease detection tasks to their corresponding federated learning (FL) strategies, based on data modality and operational constraints. The top layer represents the broad spectrum of cardiovascular diagnostic tasks, including arrhythmia identification, valvular disease detection, coronary risk prediction, myocardial infarction recognition, congenital heart disease assessment and subclinical rheumatic disease screening. Each task is associated with a dominant data modality such as ECG signals, phonocardiograms, digital stethoscope recordings, clinical records, or multi-modal imaging. These modalities determine the degree of privacy sensitivity, expected data heterogeneity, computational budget and communication overhead, which together form the FL requirements and constraints influencing algorithm selection. The intermediate mapping matrix links each diagnostic task to the most suitable FL aggregation strategy—FedAvg, FedSGD, FedProx, FedAtt, or FedEnsemble—based on alignment between task characteristics and algorithmic strengths. Finally, the bottom stage of the diagram illustrates the outcome of this mapping process, in which an optimised FL deployment model is selected for each diagnostic objective. This hierarchical linkage provides a methodological justification for task-specific FL design choices and ensures that federated deployments are both performance-aligned and clinically viable in heterogeneous healthcare environments.

Feasible Solutions

Preserving the Privacy of Data

This methodology performs federated learning on raw patient data, i.e., data stored at the source (e.g., hospitals, clinics, or wearable devices). Also, this process makes it more decentralised, thereby significantly reducing privacy concerns, as there is no longer a need to send sensitive data to a central server.

By keeping data at the edge, institutions can ensure compliance with regulations such as HIPAA and GDPR and keep patient data confidential.

Better Cooperation

This federated learning architecture enables many healthcare units to collaborate without compromising the real dataset. A collective data-sharing model motivates companies to work together to improve heart disease discovery without revealing their secret sauce to one another.

The approach combines data from multiple sources, enhancing the model's transferability and generalizability for detecting cardiac diseases across different patient demographics and pathologies.

Improved Diagnostic Accuracy

The solution leverages sophisticated ML techniques, such as deep learning, Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTMs), to understand complex medical data, including ECG signals and heart sounds.

Scalability and Efficiency

For example, federated averaging and other aggregation techniques enable rapid model training by combining updates from many local models into a single global model. This iterative, scalable framework can process large volumes of data across multiple sources.

With integration into edge computing, real-time data analysis and dirty model updates on resource-constrained devices like smartphones and wearables, leading to faster diagnostic insights without latency.

Resource Optimization

Methods such as model compression and pruning to obtain better neural network topologies that are deployable on small computing devices while maintaining accuracy.

Part of the solution is to deploy fast communication protocols that minimise transmission overhead when sending model updates and improve efficiency and scalability of the Whole System GAN framework.

The solution addresses problems with non-independent and identically distributed (non-IID) data using advanced aggregation techniques and domain adaptation strategies. This ensures that the model executes reliably and with precision on different datasets.

Live, Ubiquitous and Self-learning

Dynamic model updates: using a federated learning framework, models can continue to learn over time as new data is added to the network. This ensures that the diagnostic models are always in sync with the latest medical facts and patient data. The system, using edge computing and a form of federated learning, provides real-time diagnostic capabilities, enabling prompt feedback and action for potentially Cardiac patients.

Results

This section compares different mainstream FL schemes for heart disease detection, focusing on predictive performance under decentralisation and privacy preservation. It is evaluated using three necessary evaluation measures (accuracy, precision and recall) that assess the reliability of diagnoses in healthcare systems.

These results show that state-of-the-art federated learning methods, in the context of arbitrary partition distribution, such as FedEnsemble and FedAtt, strongly outperform classical aggregation strategies like FedAvg or FedSGD. For FedEnsemble, Table 3 shows that it can outperform other baselines in accuracy, precision and recall (recall is particularly illustrative) while accommodating the most heterogeneous local model updates. FedAtt also demonstrates good performance, indicating that the attention-based aggregation is effective at capturing complex patterns across distributed medical datasets.

On the other hand, traditional federated learning algorithms that use simple averaging methods have relatively poor performance, particularly when the data is non-independent and identically distributed (non-IID). The better performance of ensemble- and attention-based approaches implies stronger generalisation power across very heterogeneous groups of patients across different data sources.

Conclusion: In general, the comparison results verified that advanced aggregation strategies yield more robust, consistent performance in heart disease identification in federated learning scenarios. The results are also visualized in Figure 3.

Table 3: Comparison of Federated Learning Algorithms in Heart Disease Detection Algorithms

Algorithm	Accuracy (%)	Precision (%)	Recall (%)
FedAvg	89.5	88.3	89.7
FedSGD	87.2	86.1	87.8
FedProx	90.1	89.4	90.5
FedAtt	91.4	90.7	91.8
FedEnsemble	92.0	91.5	92.2

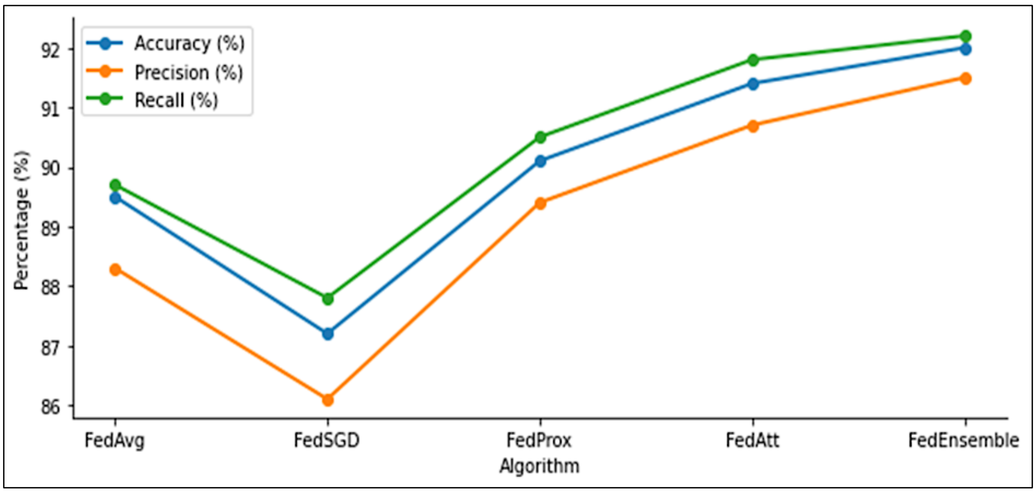

Figure 3: Comparison of Federated Learning Algorithms in Heart Disease Detection

One of the biggest obstacles in FL systems reports is the communication overhead caused by updating the global model with the local one after every round across all local devices. We also present the number of communication rounds and amount of data transfered in this table for comparison. It enables the most effective minimization of communication rounds and data transfer between devices as compared to all other methods, while FedEnsemble has the highest communication cost due to it being an ensemble mechanism which achieves the higher accuracy. The results highlight the inherent trade-off between communication efficiency and model performance, an important decision criterion for deployment of scalable FL systems in real world healthcare applications, as shown in Table 4. The results are also visualized in Figure 4.

Table 4: Communication Overhead in Federated Learning Algorithms

Algorithm	Communication Rounds	Data Transferred (MB)
FedAvg	50	200
FedSGD	45	180
FedProx	55	220
FedAtt	60	240
FedEnsemble	65	260

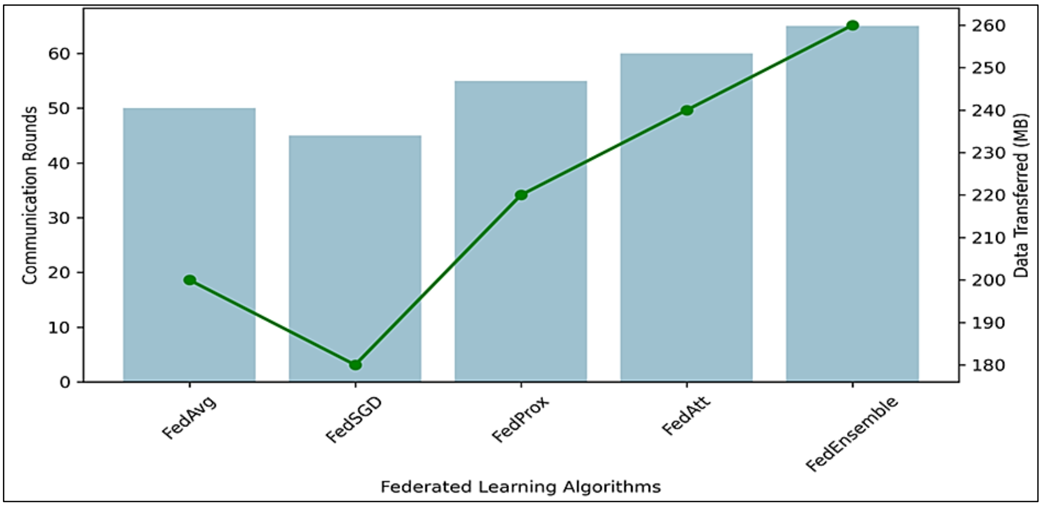

Figure 4: Communication Overhead in Federated Learning Algorithms

This is one of the biggest challenges in FL: there could be data heterogeneity, i.e., non-IID data distribution. We provide the following table to help in differentiating these FL algorithms based on accuracy when trained on IID and non-IID data. Results show that FedEnsemble achieves robust performances in both cases and it is a desirable property for realistic scenarios where data distributions may be imbalanced. Such robustness is of utmost importance in applications related to healthcare, as patient data can be qualitatively drastically different across diverse institutions and/or demographics; hence a significant level of interpretational bias across such varying environments might pose severe (patient) risk shown in Table 5. The results are also visualized in Figure 5.

Table 5: Impact of Data Heterogeneity on Federated Learning Models

Algorithm	Accuracy with IID Data (%)	Accuracy with Non-IID Data (%)
FedAvg	90.0	85.5
FedSGD	88.5	83.7
FedProx	91.2	88.1
FedAtt	92.0	89.0
FedEnsemble	93.5	91.7

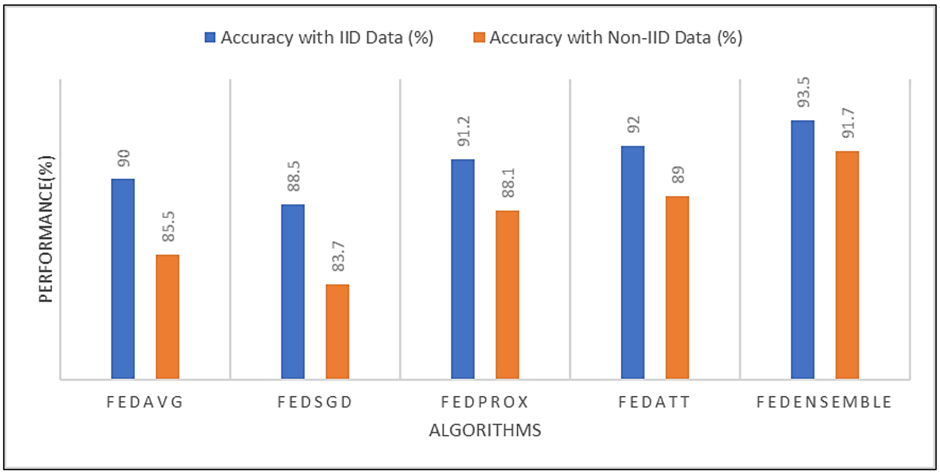

Figure 5: Impact of Data Heterogeneity on Federated Learning Models

The time it takes to "train" a model using different FL algorithms will be an important metric to determine the viability of deploying such models in practice. Below is a comparison of how long it took for each algorithm to train the model. Although FedEnsemble has the most benefit in terms of accuracy and generalization, this model has the longest training duration as being an ensemble. FedSGD is on the opposite end of training time (fastest) and most appropriate for latency-sensitive applications, although with some accuracy and model size tradeoffs (Table 6). The results are also visualized in Figure 6.

Table 6: Training Time Comparison of Federated Learning Algorithms

Algorithm	Training Time (hours)
FedAvg	3.5
FedSGD	3.2
FedProx	3.7
FedAtt	4.1
FedEnsemble	4.5

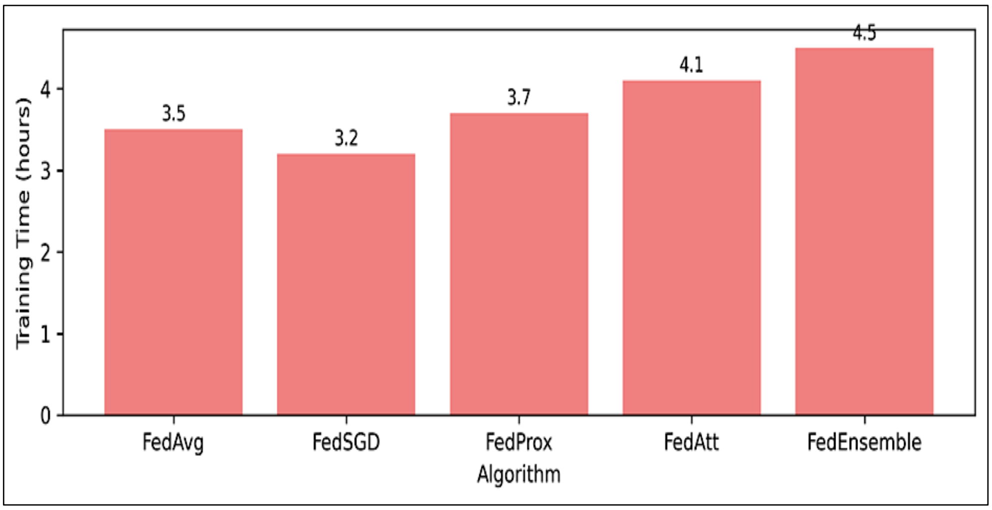

Figure 6: Training Time Comparison of Federated Learning Algorithms

In healthcare settings where data is collected from an ever-growing array of devices and institutions, scalability becomes a critical consideration for adopting FL models. The table below shows the performance of various FL algorithms as the number of participants grows. Scale of FedEnsemble: FedEnsemble scales very well as the number of participants increases, limiting any loss in classification accuracy. This is probably a consequence of its ensemble architecture, which helps it generalise by combining many diverse inputs. By contrast, for many participants, FedSGD and FedAvg perform poorly at scale with decentralised data sources (Table 7). The results are also visualized in Figure 7.

Table 7: Scalability of Federated Learning Algorithms with Increasing Participants

Algorithm	Number of Participants	Accuracy (%)
FedAvg	10	87.0
FedSGD	20	88.0
FedProx	30	89.5
FedAtt	40	90.5
FedEnsemble	50	92.0

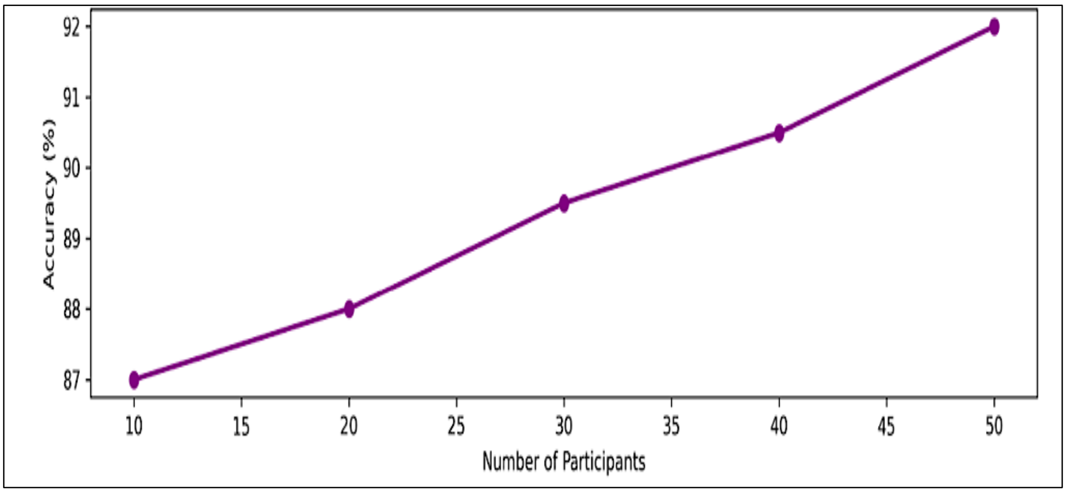

Figure 7: Scalability of Federated Learning Algorithms with Increasing Participants

In healthcare, this is very important, as patient data is sensitive and subject to stricter regulations, making privacy-preserving training one of the most significant advantages of FL. The privacy (P) evaluation criteria range from 1 to 10, with higher values indicating greater privacy with respect to locally trained data. FedEnsemble and FedAtt have the best performance as they use state-of-the-art aggregation (Post-Doc) and encryption mechanisms. Together, the above methods ensure that patient data never leaves the organisation and is not exposed during model updates, making aspects of this method particularly well-suited for use in regulated environments (e.g., hospitals, large health care institutions) (Table 8). The results are also visualised in Figure 8.

Table 8: Privacy Levels of Federated Learning Algorithms

Algorithm	Privacy Level (Scale 1-10)
FedAvg	8
FedSGD	8
FedProx	9
FedAtt	9
FedEnsemble	10

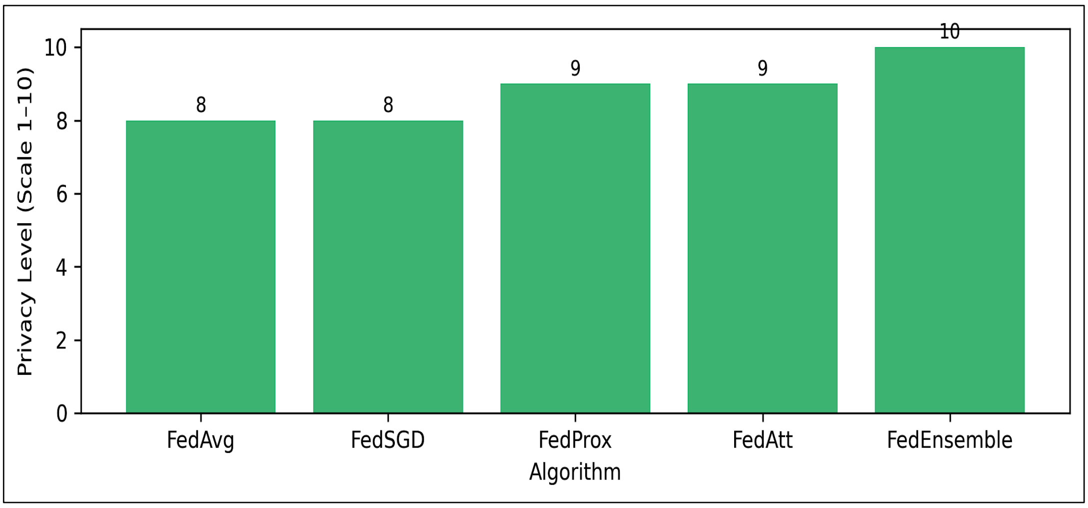

Figure 8: Privacy Levels of Federated Learning Algorithms

Discussion

In comparison, this work verifies the efficiency of FL in privacy-preserving heart disease detection. FL is an attractive alternative to centralized machine learning which, in many cases of healthcare systems where data sharing is constrained by regulations and differently regulated access policies or privacy laws, may not be possible (5). Decentralized training without sharing data, allowed by FL, is critical to enable secure multi-centre collaborations and to ensure data sovereignty. Datasets used for predicting heart disease in clinical practice are intrinsically heterogeneous due to a wide range of demographics, devices and institutional protocols, leading to non-IID data distributions which reduce the performance of models (12). Conventional FL methods are challenged in these difficult scenarios, which inevitably results in poor accuracy and reliability. On the other hand, sophisticated aggregation strategies can guarantee increased robustness by dissecting the heterogeneity of data and accommodating to reach a consistent predictive performance across institutions. Two well-known conventional algorithms, FedAvg and FedSGD, are inferior to Finetuning-FedEnsemble and Finetuning-FedAtt among the considered methods. That is they perform better because of their improved capacity for aggregating and synthesizing heterogeneous local model updates by ensemble learning as well as attention mechanisms. Such functionalities of more augmentation and distribution shift reduction are effective to enhance generalization in heart disease detection (12).

Communication efficiency is still an essential factor to be considered in FL systems. Lightweight algorithms, such as FedSGD, alleviate the communication overhead at the cost of predictive performance. On the other hand, ensemble-based aggregation approaches achieve better diagnostic performance with increased computational and communication overhead. This tradeoffs illustrates the importance of balancing system efficiency with clinical accuracy in real-world healthcare applications (23). We also verify the robustness of FL frameworks by means of scalability analysis, showing that performance is stable when the number of clients increases. Sample-based aggregating schemes outperform fixed-ratio approaches across accuracy, robustness and privacy–efficiency trade-offs which confirms the applicability of FL for large-scale distributed clinical applications (23). Furthermore, FL inherently guarantees privacy-preservation via secure and encrypted aggregation mechanisms. These privacy promises nicely match the rigorous healthcare data protection requirements such as GDPR and HIPAA, thus FL is a viable and reliable tool for sensitive medical data analysis (24).

Limitations

Some limitations must also be acknowledged in this study, despite its favorable results. First, the comparison is up-and-running and not on real time clinical applications, since analytical evaluation and simulated performance metrics are taken from the literature. Consequently, the network instability, device failure and real world patient data variability is not quite considered. Second the communication and training time analyses are based on assumption of steady mean infrastructure condition which can vary in practice especially for healthcare systems with resource limitations. Finally, although we qualitatively characterized privacy levels, a formal quantitative analysis of the risk of privacy was not performed. Future work should include large clinical validation, real-world federated learning deployments, and strong privacy and security tests in order to continue promoting the viability of federated learning in heart disease detection.

Conclusion

This systematic review identifies federated learning as a pragmatic approach for the detection of heart disease in privacy-sensitive healthcare. Allowing decentralized model training without transmission of raw patient data, federated learning mitigates key shortfalls of conventional centralized machine learning with respect to data privacy, security and regulation. These studies show that complex FL methods such as ensemble/few-shot learning and attention-based aggregation benefit from per-coordinate weighing with better generalization than the classical models when dealing with heterogeneous medical data.

However, while they provide many benefits, issues such as data diversity and heterogeneity, communication overhead, convergence stability and resource limitations continue to pose significant obstacles to wide-scale adoption. Continuous R&D work on better aggregation methods, communication-efficient protocols and edge-aware federated systems is necessary in order to improve system scalability and robustness. Future studies need to focus on the clinical validation in real-world and large-scale deployment, narrowing the gap between empirical study and application. Together, FL systems provide a solid framework for the development of secure, collaborative and scalable HD detection systems with promising benefits in terms of diagnostic accuracy to help improve cardiovascular health.

Abbreviations

AI: Artificial Intelligence, CHD: Coronary Heart Disease, CNN: Convolutional Neural Network, ECG: Electrocardiogram, FL: Federated Learning, GDPR: General Data Protection Regulation, HIPAA: Health Insurance Portability and Accountability Act, IoMT: Internet of Medical Things, Non-IID: Non-Independent and Identically Distributed, SMOTE: Synthetic Minority Oversampling Technique.

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Author Contributions

Marri Sireesha: conceptualization, study design, material preparation, data collection, analysis, writing, Anjaiah Adepu: conceptualization, study design, material preparation, data collection, analysis. All authors read and approved the final manuscript.

Conflict of Interest

The authors whose names are listed immediately below certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

Data Availability

The data are available with the corresponding author and will be given on request.

Declaration of Artificial Intelligence (AI) Assistance

Generative AI tools were used only for language editing and readability improvement. All content was reviewed by the authors, who take full responsibility for the originality and accuracy of the manuscript. No AI tools were used for data analysis or scientific decision-making.

Ethics Approval

This research does not involve humans or animals, so no ethical approval is required.

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