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A Review Paper on Federated Learning for Healthcare Data Privacy and Secure Disease Prediction Using Artificial Intelligence

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Abstract—Healthcare data is among the most sensitive and privacy-critical information in the digital era. Sharing patient data across hospitals and research institutions for AI model training raises serious concerns regarding data privacy, security, and regulatory compliance (GDPR, HIPAA). Federated Learning (FL) has emerged as a transformative approach that enables collaborative AI model training across distributed healthcare institutions without sharing raw patient data — only model updates (gradients) are exchanged. This review paper systematically analyzes existing literature on Federated Learning for healthcare data privacy and secure disease prediction published between 2017 and 2024. A total of 60+ research papers from IEEE, PubMed, Springer, ACM, and Google Scholar were systematically reviewed. Key FL frameworks including FedAvg, FedProx, SCAFFOLD, and personalized FL are examined alongside their application in disease prediction tasks such as cancer detection, diabetic prediction, cardiovascular disease diagnosis, and COVID-19 prognosis. Security mechanisms including differential privacy, secure multi-party computation, and homomorphic encryption applied within FL systems are analyzed. Key challenges including communication overhead, statistical heterogeneity (non-IID data), Byzantine attacks, and model poisoning are identified. The paper concludes with future research directions in personalized FL, blockchain-integrated FL, and explainable AI within federated healthcare systems.

Index Terms—*Federated Learning, Healthcare Privacy, Disease Prediction, Differential Privacy, FedAvg, Secure Aggregation, Non-IID Data, GDPR, HIPAA, Homomorphic Encryption, Byzantine Fault Tolerance.*

I. INTRODUCTION

The rapid digitization of healthcare has resulted in an unprecedented accumulation of patient data including electronic health records (EHRs), medical imaging, genomic sequences, and wearable sensor data. This data holds immense potential for training powerful AI models capable of early and accurate disease prediction, personalized treatment recommendation, and clinical decision support. However, patient data is inherently sensitive, legally protected under regulations such as GDPR (EU) and HIPAA (USA), and subject to strict institutional privacy policies that prohibit sharing across organizational boundaries.

Traditional centralized machine learning approaches require aggregating data from multiple sources into a single server for model training. In healthcare, this centralization is frequently infeasible due to patient consent requirements, data sovereignty laws, and institutional data governance

III. FL FRAMEWORKS AND ALGORITHMS

A. FedAvg — Federated Averaging

FedAvg [4] is the foundational FL algorithm. In each communication round, the server selects a subset of participating clients, distributes the current global model, each client trains locally for multiple epochs on its private data, and local model updates are sent back to the server for weighted averaging. FedAvg achieves strong convergence on IID data but suffers from degraded performance under non-IID data distributions, which is the norm in real-world healthcare settings.

B. FedProx — Proximal Optimization

FedProx [11] extends FedAvg by adding a proximal regularization term to each client's local objective function, penalizing local updates that deviate excessively from the global model. This significantly improves convergence stability under statistical heterogeneity and partial client participation. Studies on clinical datasets demonstrated 3-5% accuracy improvement over FedAvg under realistic non-IID

policies. These constraints severely limit the scale and diversity of training data available to AI models, resulting in models that are poorly generalized, biased toward the demographics of the single institution, and clinically unreliable when deployed in new settings.

Federated Learning (FL), introduced by McMahan et al. [4] in 2017, addresses this fundamental challenge by enabling multiple institutions to collaboratively train a shared AI model without exchanging raw patient data. Only local model updates are communicated to a central aggregation server, which combines them to produce an improved global model. This privacy-by-design paradigm has rapidly gained traction in the healthcare AI community as a practical solution for cross-institutional collaborative learning.

This review surveys the state-of-the-art research on Federated Learning for healthcare data privacy and disease prediction from 2017 to 2024. The primary contributions of this review are: (1) a comprehensive analysis of FL algorithms and frameworks applied in healthcare, (2) a systematic comparison of privacy-preserving mechanisms integrated with FL, (3) an evaluation of FL-based disease prediction systems across multiple clinical domains, (4) identification of key open challenges, and (5) a forward-looking analysis of future research directions.

II. BACKGROUND AND RELATED WORK

A. Traditional Centralized Healthcare AI

Before the advent of Federated Learning, healthcare AI models were trained on centralized datasets collected from single institutions or federated data repositories with explicit data sharing agreements. Landmark studies such as Google's diabetic retinopathy detection [6] and Stanford's CheXNet for chest X-ray diagnosis [7] demonstrated the exceptional diagnostic capability of deep learning models trained on large centralized datasets. However, these systems required pooling hundreds of thousands of images into a single data center — a process ethically and legally prohibited in most multi-institutional healthcare settings.

B. Emergence of Federated Learning

McMahan et al. [4] introduced the concept of Federated Learning in 2017 with the FedAvg algorithm, which aggregates locally computed gradient updates using weighted averaging. FedAvg demonstrated that high-quality models could be trained across 100-1000 clients with communication rounds an order of magnitude fewer than naive gradient averaging. This conditions.

C. SCAFFOLD — Variance Reduction

SCAFFOLD [12] addresses client drift — the phenomenon where local updates diverge from the global optimum due to heterogeneous local data distributions. SCAFFOLD introduces control variates that correct the direction of local gradient updates, demonstrating up to 40% reduction in communication rounds compared to FedAvg in healthcare applications with highly heterogeneous EHR data.

D. Personalized Federated Learning

Standard FL trains a single global model that may not perform optimally for any individual institution due to data heterogeneity. Personalized FL approaches such as per-FedAvg [13] and pFedMe allow each client to maintain a personalized local model adapted to its specific patient population, while still benefiting from collaborative training — particularly important given how disease prevalence and equipment vary across institutions.

IV. COMPARISON OF FL ALGORITHMS

The comparison in Table I reveals that while FedAvg remains the most widely used FL algorithm due to its simplicity and communication efficiency, it underperforms on non-IID healthcare data. Algorithms incorporating proximal regularization, variance reduction, or personalization strategies consistently outperform FedAvg on realistic multi-institutional healthcare datasets, involving a trade-off between privacy, communication efficiency, and accuracy.

foundational work sparked an explosion of FL research, with healthcare emerging as the most critical application domain due to the inherent sensitivity of medical data.

C. Privacy-Enhancing Technologies in FL

The basic FL framework provides privacy through data localization — raw data never leaves the client institution. However, research has shown that model gradients can leak sensitive information through gradient inversion attacks [8]. This motivated the integration of formal privacy-preserving mechanisms including Differential Privacy (DP), which adds calibrated noise to gradients; Secure Multi-Party Computation (SMPC), which enables joint computation without revealing individual inputs; and Homomorphic Encryption (HE), which enables computation on encrypted model parameters.

TABLE I — Comparison of Key Federated Learning Algorithms in Healthcare

Algorithm	Year	Key Innovation	Non-IID Perf.	Comm. Efficiency	Healthcare Application
FedAvg [4]	2017	Weighted gradient averaging	Moderate	High	EHR, imaging
FedProx [11]	2018	Proximal regularization	Good	High	Clinical EHR
SCAFFOLD [12]	2020	Control variates	Excellent	Moderate	Multi-hospital EHR
per-FedAvg [13]	2020	MAML-based personalization	Excellent	Moderate	Personalized diagnosis
FedMA [14]	2020	Layer-wise matching	Good	Moderate	Medical imaging
DP-FedAvg [9]	2018	Differential privacy	Moderate	High	Privacy-sensitive EHR
HE-FL [10]	2019	Homomorphic encryption	Moderate	Low	Sensitive genomics
FedBN [15]	2021	Local batch normalization	Excellent	High	Multi-site imaging

V. FL FOR DISEASE PREDICTION

A. Cancer Detection

Federated Learning has been extensively applied to cancer detection from medical imaging across multiple cancer types. Sheller et al. [16] demonstrated FL-based brain tumor segmentation across 10 institutions achieving performance within 1% of centralized training — a landmark demonstration of FL's feasibility in healthcare. Subsequent studies applied FL to breast cancer histopathology classification, lung cancer CT screening, and prostate cancer MRI grading, consistently approaching centralized model performance while eliminating raw data sharing.

B. Diabetic Disease Prediction

Diabetes prediction from EHR data is a well-studied FL application. Brisimi et al. [19] applied FL to predict diabetes hospitalization risk across

VII. PRIVACY AND SECURITY IN FL

A. Differential Privacy

Differential Privacy (DP) [9] provides a mathematically rigorous privacy guarantee by adding calibrated noise to gradient updates before transmission. The privacy budget (epsilon) controls the trade-off between privacy strength and model utility. DP-SGD is the most widely used DP mechanism in FL, implemented in TensorFlow Privacy and Meta's Opacus libraries.

B. Secure Multi-Party Computation

SMPC [8] enables multiple parties to jointly compute model aggregation without revealing individual inputs. Google's SecAgg protocol uses secret sharing to implement secure aggregation with logarithmic communication overhead, making it practical for large-scale FL deployments.

multiple hospitals, demonstrating that federated models outperform locally trained models and approach centralized performance, improving AUC-ROC by 8-12% compared to single-institution models.

C. Cardiovascular Disease Prediction

Liu et al. [20] proposed a federated deep learning model for heart failure prediction across 6 hospitals, achieving an AUC of 0.87 compared to 0.82 for single-hospital models, with superior generalizability when tested on data from unseen hospitals.

D. COVID-19 and Pandemic Response

The NVIDIA FLARE platform was used to train federated COVID-19 chest CT diagnosis models across 20 hospitals in 5 countries, achieving diagnostic accuracy of 94.3% — exceeding single-institution models by 6.3% [21], validating FL's large-scale practical feasibility.

VI. COMPARATIVE ANALYSIS

The comparative analysis in Table II reveals that FL consistently achieves near-centralized model performance across diverse healthcare prediction tasks. Most early FL healthcare studies did not incorporate formal privacy-preserving mechanisms beyond data localization, with differential privacy and secure aggregation adoption increasing only in more recent works (2020-2024). Non-IID data heterogeneity remains the most significant technical challenge, and communication overhead with encryption remains prohibitively high for real-time clinical applications.

C. Homomorphic Encryption

Homomorphic Encryption (HE) allows arithmetic operations directly on encrypted data. While HE provides the strongest privacy guarantees, its computational overhead is currently 100-1000x greater than plaintext operations, limiting practical applicability to small models or partial encryption of sensitive layers [10].

D. Byzantine Fault Tolerance

FL systems are vulnerable to Byzantine attacks where malicious clients submit poisoned updates. Defense mechanisms including Krum aggregation [25], coordinate-wise median, and FLTrust have been proposed to identify and exclude malicious updates — critical in healthcare where poisoning could cause systematic misdiagnosis.

VIII. DATASETS IN FEDERATED HEALTHCARE AI

Table III summarizes key publicly available and credentialed datasets used in federated healthcare research, spanning brain tumor MRI, ICU electronic health records, chest X-rays, dermoscopy images, population-scale biobanks, and cardiac ECG signals.

TABLE II — Comparative Analysis of Federated Learning Studies in Healthcare

Author & Year	Disease/Domain	FL Algorithm	Dataset	Privacy Mechanism	Key Result
McMahan et al. [4] (2017)	General ML	FedAvg	MNIST, CIFAR	None	FL feasibility proven
Sheller et al. [16] (2019)	Brain tumor	FedAvg	BraTS (10 sites)	None	Within 1% of central
Brisimi et al. [19] (2018)	Diabetes	Federated SVM	EHR (6 hospitals)	None	AUC +8-12% vs local
Liu et al. [20] (2021)	Heart failure	Federated DL	EHR (6 hospitals)	DP	AUC 0.87 vs 0.82
NVIDIA FLARE [21] (2022)	COVID-19 CT	FedAvg variant	CT (20 sites, 5 countries)	Secure agg.	94.3% accuracy
Yang et al. [22] (2019)	General health	FedProx	EHR data	SMPC	Privacy-preserved FL
Rieke et al. [23] (2020)	Multi-disease	FedBN	Multi-site imaging	DP	Non-IID robust FL

Author & Year	Disease/Domain	FL Algorithm	Dataset	Privacy Mechanism	Key Result
Dayan et al. [24] (2021)	COVID-19	Swarm Learning	Chest X-ray (20 sites)	Blockchain	AUC 0.92

TABLE III — Key Datasets Used in Federated Learning Healthcare Studies

Dataset	Disease Domain	Data Type	Size	Access	FL Usage
BraTS [16]	Brain tumor	MRI	1,251 cases (multi-site)	Public	Brain tumor FL
MIMIC-III [26]	General ICU	EHR	~40,000 ICU stays	Credentialed	Mortality/readmission FL
eICU [27]	ICU disease	EHR	200,000+ ICU stays	Credentialed	Multi-center FL
ChestX-ray14 [7]	Lung diseases	X-Ray	112,120 images	Public	Federated chest AI
ISIC Skin Cancer	Skin cancer	Dermoscopy	~33,000 images	Public	Federated skin AI
UK Biobank	Multi-disease	EHR + imaging	500,000 participants	Credentialed	Population FL
COVID-19 CT [21]	COVID-19	CT Scan	Multi-site global	Restricted	Federated COVID-19
PhysioNet (ECG)	Cardiac disease	ECG signals	100,000+ recordings	Public	Federated CVD

IX. KEY CHALLENGES

A. Statistical Heterogeneity (Non-IID Data)

The most significant technical challenge in healthcare FL is statistical data heterogeneity — different hospitals serve different patient populations with varying disease prevalence, demographics, imaging equipment, and clinical protocols, degrading global model convergence. Addressing non-IID data through personalization and robust aggregation remains an active research area.

B. Communication Overhead

FL requires repeated communication of model parameters across multiple rounds. For large models such as ResNet-50 or BERT, each round transfers hundreds of megabytes, creating significant bandwidth requirements for hospitals with limited network infrastructure. Model compression and federated distillation are actively researched to reduce this overhead.

C. Regulatory and Institutional Barriers

Despite FL's privacy-preserving design, healthcare institutions face complex regulatory and contractual barriers to FL participation regarding liability, model ownership, and institution-specific data governance. Regulatory frameworks specifically addressing federated AI in healthcare are largely absent and urgently needed.

D. Model Fairness and Bias

FL models may perpetuate demographic biases present in local datasets. If certain hospitals

X. FUTURE RESEARCH DIRECTIONS

A. Blockchain-Integrated FL

Integrating blockchain with FL offers decentralized, tamper-proof model aggregation without a trusted central server. Swarm Learning [24] has demonstrated promising results in multi-site disease prediction. Future research should improve blockchain throughput and reduce transaction latency for real-time clinical FL.

B. Personalized and Adaptive FL

Future FL systems should move beyond one-size-fits-all global models toward dynamically personalized models adapted to each institution's patient population. Meta-learning, mixture-of-experts, and hierarchical FL frameworks represent promising personalization strategies.

C. Explainable Federated AI (XFL)

Clinical deployment of FL-trained models requires transparent, interpretable explanations. Federated variants of Grad-CAM, SHAP, and LIME that generate explanations without centralizing patient data remain largely unexplored and represent a high-priority research direction.

D. FL for Multi-Modal Healthcare Data

Real-world disease prediction benefits from integrating imaging, EHR, genomics, and wearable sensor data. Federated multi-modal learning frameworks that handle diverse data types across institutions with differing data availability represent a critical frontier for practical deployment.

predominantly serve specific demographic groups, the globally aggregated model may exhibit systematic performance disparities — an emerging and critical research direction for healthcare FL.

E. Gradient Leakage and Inference Attacks

Model gradients exchanged in FL can inadvertently leak sensitive patient information through gradient inversion and membership inference attacks. While DP and secure aggregation mitigate these risks, residual privacy leakage under realistic threat models remains incompletely characterized.

XI. CONCLUSION

This review has systematically examined the rapidly evolving landscape of Federated Learning for healthcare data privacy and secure disease prediction, analyzing 60+ studies published between 2017 and 2024. The review covered foundational FL algorithms, privacy-preserving mechanisms, disease-specific applications, benchmark datasets, and comparative analysis of existing research.

The evidence demonstrates that FL is a mature and clinically validated approach for privacy-preserving healthcare AI, consistently achieving near-centralized performance across cancer detection, diabetic prediction, cardiovascular diagnosis, and COVID-19 prognosis — while eliminating raw patient data sharing. Despite progress, challenges in non-IID heterogeneity, communication efficiency, regulatory compliance, fairness, and gradient leakage remain. Future research in blockchain-integrated FL, personalization, explainable AI, and multi-modal FL will be pivotal for translating FL-based healthcare AI into routine clinical practice.

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