Privacy-Preserving AI in Clinical Data Networks

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Abstract

he synthesis of healthcare big data is an essential component in the implementation of precision medicine as it improves prediction and decision accuracy at both the individual and population levels. However, many medical institutions are reluctant data donors due to the revealing nature of patients' sensitive information. The data is often collected in a centralized manner by a data-hungry big tech with poor reputation on privacy preservation, resulting in useless patient consent agreement and data breaches disclosed almost daily. Federated artificial intelligence (AI) mitigates the risk of clinical data leakage while enabling multi-institutional collaboration in AI model training. However, federated learning alone is insufficient to protect healthcare data from membership inference and attribute inference attacks. The incorporation of differential privacy technique can overcome these limitations, but privacy budgets are hard to set for sensitive data. Downstream clinical applications, especially those involving data scaling, are either predominately theoretical or in early development. Three privacy-preserving artificial intelligence-enabled clinical data platforms for precision medicine are proposed. The first platform realizes federated learning with an inner layer of differential privacy, enabling AI training with genomic data and phenotypic data at different locations without data sharing. The second platform incorporates a basic governance and control mechanism through smart contracts on block-chain. The third platform integrates genomic data and large-scale EHR data contributed by health record cloud services. First-stage clinical applications combine genomic data with non-genomic data from CloudEHR for risk prediction of cardiovascular disease.

Keywords : Healthcare big data; privacy-preserving; federated learning; differential privacy; precision medicine; block-chain;federated artificial intelligence; big healthcare data; data privacy; privacy-preserving clinical data platform; precision medicine; clinical data.

1. Introduction

Massive clinical data are being generated on patients, communities, and diseases, creating unprecedented opportunities for precision medicine. Data-sharing initiatives and partnerships with patients serve as solutions to narrow the data-sharing troves that sometimes represent less than 100 patients with complex diseases, but ownership, privacy, and security respecting the principles of ethics still remain essential challenges. Federated learning and other privacy-preserving techniques allow the construction of a clinical data platform involving patients, physicians, and healthcare organizations while maintaining the data

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privacy of participating data custodians.

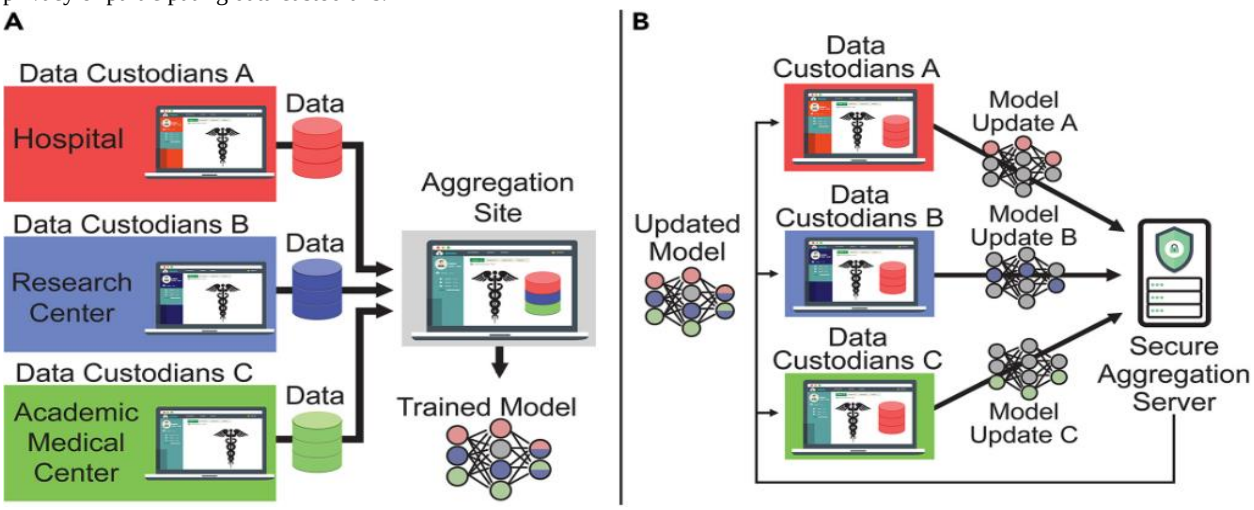

Fig 1: Privacy preservation for federated learning in health care

1.1. Background and Significance

The Biomedical Information ONtology (BION) project aims to develop BION model systems based on heterogeneous biomedical information and deploy them as open and accepted consortia systems; to provide free-of-charge data mining services that benefit health for both technological and conceptual reasons; and to build a federated software system that balances BIONs traditional advantages in distributed data and efficiency on one hand and its main limitation, the inadequacy of large-scale data samples, on the other, by deploying large-scale, cloud-computing-intense applications in a dedicated CloudBION. Banking Model Systems That Create Benefits for System Providers, Scientific Developers, and Users: The Decision-Making Problem Bionics and the Biocib Application notes that even in well-accepted BION model systems, a few generations of joint effort by dozens of participants have failed to produce tools of interest for important areas of natural science, technology, medicine, and social development. Generally, the advantages of BION systems are believed to be greater than the disadvantages, but dispositions by some decision-makers and potential participants forebode operational difficulties. Healthcare big data and biobanks offer unprecedented opportunities for the integration of biological and health data on extremely large scales and for the creation of novel algorithms and application of machine learning, pattern discovery, and AI methods to the equitable benefit for society and humanity.

Inclusion of Federal Data Although healthcare big-data resources are of interest for business development, creating a BION model bank of these data alone is not enough of interest for successful decision-making and active participation. On the contrary, inclusion of the large generation costs of biobank banks means that the model operates ultimately on an income-flow basis. Thus, it should be possible to create a DataBION that plays an important role in transforming entire domains of natural science, technology, and society at lower cost, taking long-term time delays into account, and that can apply AI technologies to telecommunications networks in creating services for all participants and developers. The growing amount of real-world healthcare data creates unique opportunities for building predictive models of drug response. These huge healthcare databases of

real data constitute the bases of clinical AI research. However, data sharding rules and regulations, such as the HIPAA in the USA and GDPR in European union countries, limit the —conventional— access to these sensitive data.

Equation 1: Centralized empirical risk minimization

$$F(w) = (1/N) \Sigma_{i=1}^{N} \ell(w; x_i, y_i)$$

Here $\ell(w; x_i, y_i)$ is the loss for record i. The goal is to choose parameters w that minimize the average loss over all records.

Step 1. Split the complete dataset into hospital-specific subsets D_1, D_2, ..., D_K.

$$N = \Sigma_{k=1}^{K} n_k$$

The total sample count is the sum of local sample counts.

Step 2. Rewrite the centralized objective by grouping terms hospital-wise.

$$F(w) = \Sigma_{k=1}^{K} (n_k/N) F_k(w)$$

Each institution contributes proportionally to its number of records, where $F_k(w) = (1/n_k) \Sigma_{(x,y)\in D_k} \ell(w;x,y)$.

This weighted decomposition is the bridge from centralized learning to federated learning.

$$F_k(w) = (1/n_k) \Sigma_{(x,y)\in D_k} \ell(w; x, y)$$

Institution k minimizes its own average loss using only its local records.

Taking gradient descent on the local objective gives the update:

$$w_k^{t,e+1} = w_k^{t,e} - \eta \nabla F_k(w_k^{t,e})$$

2. Background and Rationale

Bundled patient data from multiple hospitals enable advanced research and modelling possibilities; however, privacy issues and legal restrictions hamper interactions among healthcare institutes. Federated artificial intelligence allows for cooperative machine learning on sensitive data without sharing them. Clinical healthcare data platforms using differential privacy concerns can assist sensitive research while complying with related data regulations.

Digital transformation in healthcare generates vast amounts of clinical data, Big Data, that researchers can utilise. The integration of clinical Big Data from multiple hospitals overcomes data isolation, yet consent from patients often prohibits third-party access or inter-hospital sharing. There are data-sharing routes: data anonymisation reduces the risk of subject identification; user data connected to the ARRA (Health Insurance Portability and Accountability Act) database undergoes security checks; and data transmission observes the Health Insurance Portability and Accountability Act regulations.

Federated Learning enables a number of parties to collaboratively train a common model while keeping training data local. The technique combines vertically Federated Learning (feature-based division) and horizontally Federated Learning (instance-based division) to achieve a more flexible architecture.

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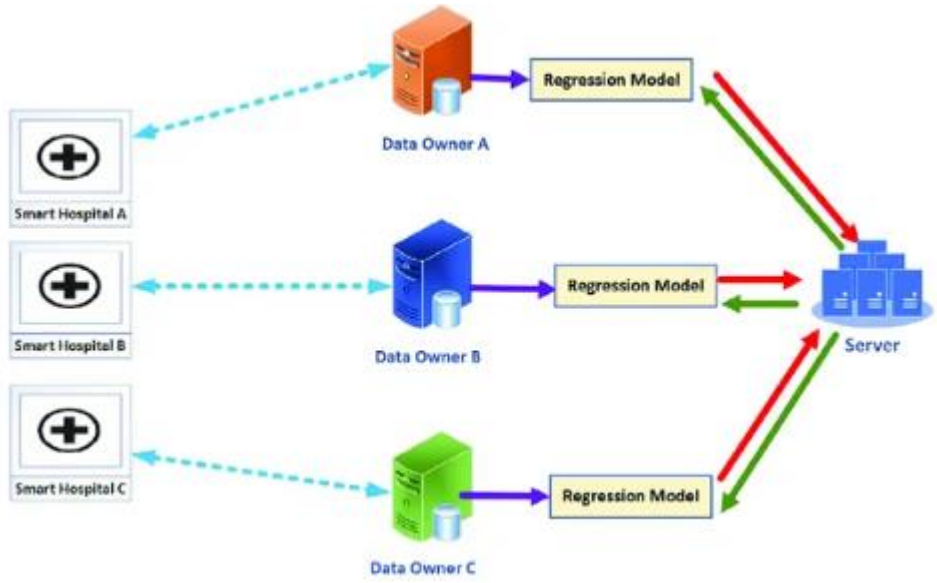

Fig 2: Background and Rationale of Federated AI for Healthcare

2.1. Research design

Federated learning (FL) is designed to enable collaborative machine learning across multiple clients, e.g., medical institutions, without data sharing while still meeting model accuracy requirements. The objective is to survey recent advances of FL in healthcare and highlight practical applications and challenges from an AI perspective. Specific developments include privacy-preserving modeling methods, success in clinical trial design, effectiveness in rare disease research, and FL-based precision-recruitment solutions.

Clinical trial per patient costs exceed US$40,000. Anonymization guarantees patient data privacy but limits recruitment efficiency. Differential-privacy-enabled algorithms preserve proprietary and sensitive features contributing to patient-sensitive suboptimality. Hospitals share large-scale patient records with an FL-based algorithm minimizing the total recruitment time in developing an effective treatment for rare diseases while providing confidentiality of patient records. In large-scale clinical data spanning DNA variants and phenotypes, FL discovers risk factors, achieves superior predictive performance compared with conventional models in privacy-preserving testing, and strengthens polygenic risk in cardiovascular disease.

Equation 2: Derivation of FedAvg

Step 1. Start each client round from the same global model:

w_k^{t,0} = w^t

The server broadcasts the current global model w^t to all selected institutions.

Step 2. Each institution performs E local updates and sends back w_k^{t+1}.

Step 3. Aggregate returned models by sample size:

$$w^{t+1} = \Sigma_{k=1}^{K} (n_k/N) w_k^{t+1}$$

Larger hospitals have greater influence because they represent more data.

Why sample-size weighting? Because the global objective in Eq. (3) is itself a weighted average of local objectives. Aggregating with n_k/N approximates one gradient step on the global loss.

If all hospitals have equal size, n_k = n for all k, then:

$$w^{t+1} = (1/K) \Sigma_{k=1}^{K} w_k^{t+1}$$

FedAvg reduces to a simple arithmetic mean.

3. Federated Learning in Healthcare

Federated Learning (FL) is a decentralized machine learning approach that can alleviate the privacy and security risks of traditional centralization. In healthcare, multiple hospitals can train the same AI model by maintaining their own healthcare databases and exchanging only model parameters but not sensitive data. FL enables data collaboration without direct data sharing.

Research on FL in healthcare is broad, covering its application in such tasks as predictive diagnosis and prognosis, photonic healthcare, brain-computer interface, and mobile health, as well as its performance improvement through the incorporation of novel techniques, models, or data. The advantages of FL, including protecting the privacy of health data owners, conducting research when the data are scarce, realizing heterogeneous model training, reducing communication overhead, and making trustless learning feasible, have also been summarized.

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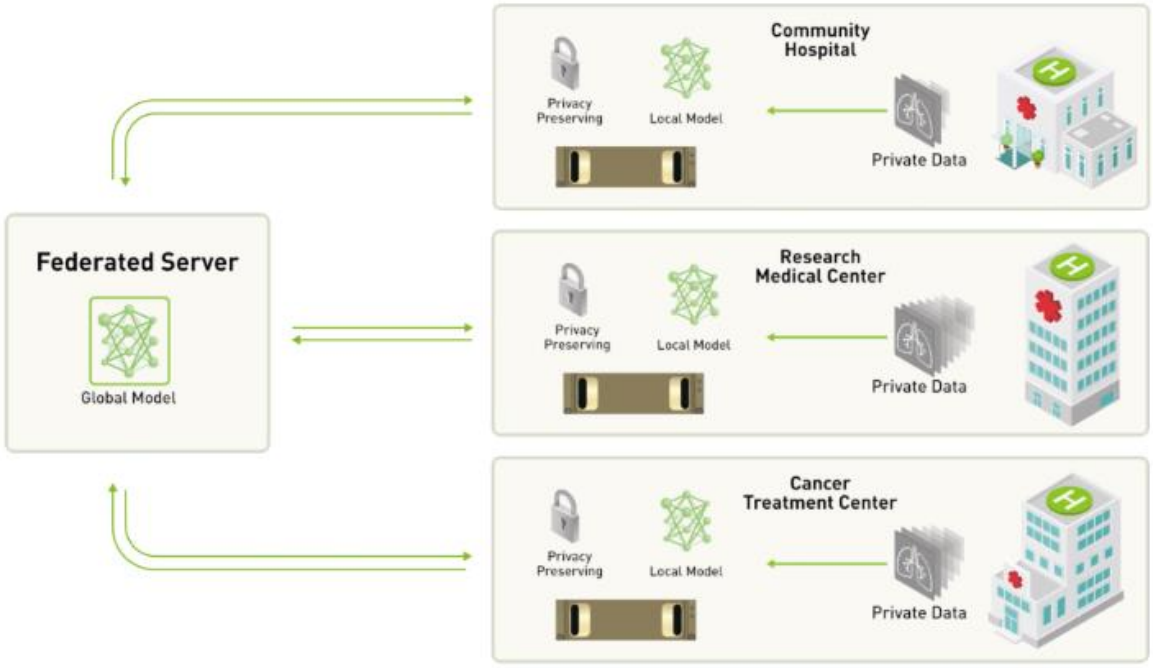

Fig 3: Federated Learning in Healthcare

3.1. Principles of Federated Learning

Federated learning is a decentralized approach to artificial intelligence model training. Instead of transferring patient data to a central server, edge devices (for example, hospitals) train local models on local patient data. Only model parameters are sent back to the central server, which integrates the updated parameters from all edge devices to construct a global model. Privacy-preserving techniques and data governance, including secure multiparty computation and differential privacy, are applied to safeguard patients' privacy and guarantee compliance with relevant laws. Multidisciplinary knowledge applies to all aspects of federated learning—from mathematical formulation and scheme design to application development.

A natural language processing example illustrates how federated learning harnesses medical-related text data and enables language model pretraining without compromising privacy. Given the rapid development of user interface agents in response to the demand for human–AI interaction, a multidimensional, multimodal user interface is anticipated. Such an interface can realise language model learning through mutual cooperation with users and federated learning with the broader environment.

Equation 3: Logistic risk prediction for precision medicine

$$z_i = w^T x_i + b$$

A linear score z_i is computed from patient features x_i such as genomic, phenotypic, and EHR variables.

p_i = P(y_i=1 | x_i) = 1 / (1 + e^{-z_i})

The sigmoid function converts the score to a probability between 0 and 1.

For binary classification, the cross-entropy loss is:

ℓ_i = - [y_i log p_i + (1-y_i) log(1-p_i)]

This penalizes wrong risk estimates, especially confident wrong predictions.

A local hospital objective becomes:

F_k(w,b) = (1/n_k) Σ_{i∈D_k} ℓ_i

3.2. Research Summary

Federated-learning solutions in the healthcare domain, including its artificial-intelligence-supported applications for precision medicine, are surveyed. Clinical and healthcare institutions with multiple client sites operating sensor networks, heterogeneous and private clinical health data across multiple sources, totally different data domains without any overlapping samples, and data-allocation regulations all need privacy-preserving federated learning. Two effective federated-learning solutions are introduced, improved, and applied in these two typical areas.

4. Privacy-Preserving Techniques

Privacy-preserving techniques that allow clinical data distributed in multiple locations to be effectively and securely utilized for the development of clinical decision-support models will play a key role in health-care data sharing. Healthcare data often contain crucial information about patients' health statuses and disease progressions. However, when directly released without privacy protection, such data pose significant data privacy risks.

The emergences of Differential Privacy and secure Multi-Party Computation (MPC) techniques provide solutions for data publishing and model training, enabling the use of health-care data stored outside of a hospital's server without violating patients' data privacy. In differential privacy, formal additive privacy guarantees and the data utility tradeoffs are achieved by providing an appropriate level of noise to the released results. Consolidating in-depth knowledge of data privacy, and consent and ownership management of healthcare data can further facilitate the effective use of health-care data while addressing ethical, legal, and social implications.

Privacy-preserving techniques are becoming essential for enabling the safe use of clinical data that are distributed across multiple healthcare institutions. Such data contain valuable insights into patients' health conditions, treatment responses, and disease progression, which are critical for developing accurate clinical decision-support models. However, releasing healthcare data without adequate protection can expose sensitive patient information and lead to serious privacy violations. To address this challenge, advanced techniques such as **Differential Privacy (DP)** and **Secure Multi-Party Computation (MPC)** have emerged as effective solutions. Differential privacy protects individual data by introducing controlled noise into the results, ensuring that sensitive information cannot be traced back to specific patients while still preserving the overall utility of the data. Meanwhile, MPC allows multiple parties to collaboratively compute models or analytics on their combined datasets without revealing their

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private data to one another. By integrating these technologies with strong frameworks for data consent, ownership, and governance, healthcare organizations can securely share and utilize clinical data. This approach not only safeguards patient privacy but also supports ethical, legal, and responsible use of healthcare information, ultimately promoting innovation and improved healthcare outcomes.

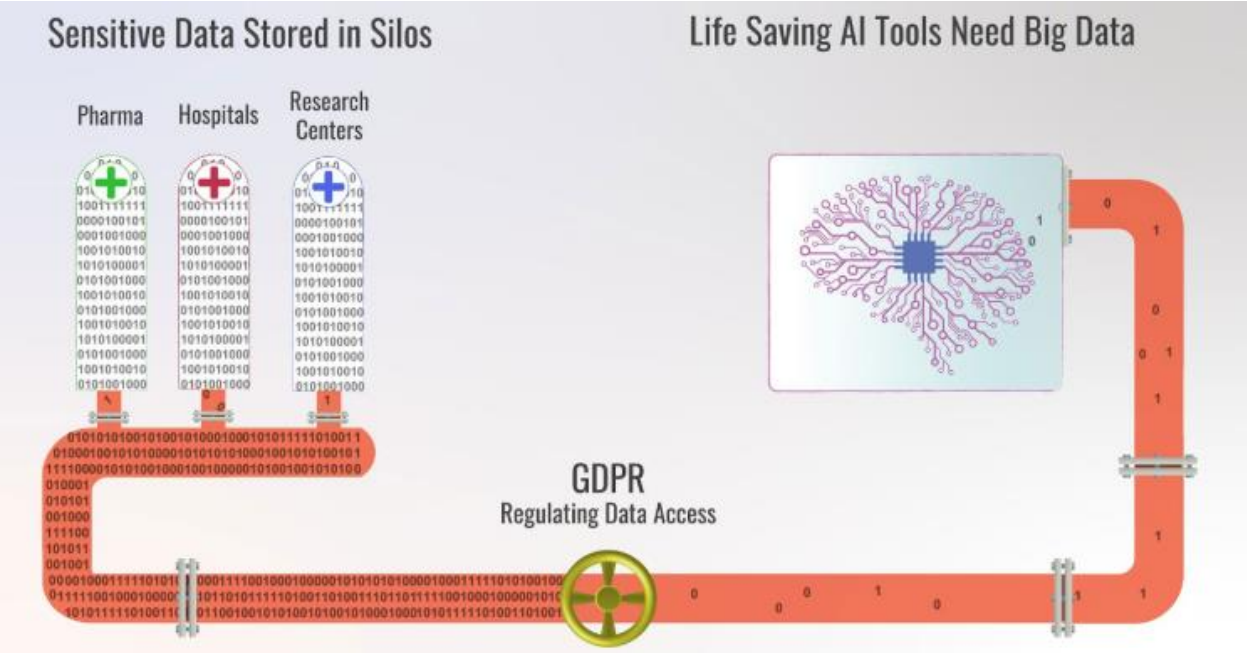

Fig 4: Privacy-preserving machine learning to protect health data

4.1. Differential Privacy in Healthcare Data

Differential privacy allows a data custodian to develop a machine learning algorithm on collected sensitive data without revealing individual identity. An output from a machine learning algorithm is said to be differentially private if two neighbouring datasets, one containing additional record than the other, produce similar outputs. In text detection, differential privacy can ensure that the detection accuracy is above 0.90 while preserving the privacy of training images. Using a 1550-head-big dataset, differentially private federated deep learning model for text detection maintains a better equilibrium between the learning accuracy of the model and the difficulties in a process associated with differential privacy. Using a differentially private smart visual incentive-backed mobile edge computing framework in the Internet of Things can promotes social behaviour towards energy conservation.

Research on breast cancer survival has been conducted with fairer predictions through a differential privacy approach for distributed random forest learning using multiple sensitive attributes. The research demonstrates that the differential privacy procedure is fundamentally important for protecting the shared data under distributed-trained machine learning applications, and the artificial neural network has contributed to lowering privacy breaches during privacy prescription while achieving above-par

prediction accuracy. A differentially private federated convolutional neural network has also been designed for facial recognition but does not perform as well as a non-private one on clean facial images.

Equation 4: Differential privacy: formal derivation

M(D) is (ε,δ)-DP if P[M(D)∈S] ≤ e^ε P[M(D')∈S] + δ

Datasets D and D' are neighbors if they differ by one patient's record. The output distribution must remain nearly unchanged when one record is added or removed.

Step 1. Compute per-record gradients g_i.

Step 2. Clip each gradient to bound sensitivity:

g_i^clip = g_i · min(1, C / ||g_i||_2)

If ||g_i||_2 > C, the gradient is scaled down so its norm becomes exactly C; otherwise it is unchanged.

Step 3. Average clipped gradients over a batch B:

ḡ = (1/|B|) Σ_{i∈B} g_i^clip

This is the deterministic part of the privatized update.

Step 4. Add Gaussian noise:

ĝ = ḡ + N(0, σ^2 C^2 I / |B|^2)

Noise variance increases with σ and the clipping threshold C.

Step 5. Update the model with the privatized gradient:

w ← w - η ĝ

4.2. Objective of the Study

Federated Learning enables model training without sensitive data transfer and protects predictive performance from potential attackers. Privacy-preserving auxiliary techniques such as Differential Privacy (DP) are necessary to prevent sensitive health data from being exposed to local servers and aggregators when a model is shared. In summary, Federated Learning enhances healthcare precision medicine by providing a global model without violating patients' privacy while offering patients' ownership of their data and enabling them to revoke access easily even after giving permission and model training.

5. Data Governance, Ethics, and Compliance

Compliance with data governance, privacy, and ethics is paramount in the federated health assets of the present study. Clinical research with patient data requires considering not only legislation but also the concepts of consent, ownership, control, and access, as stakeholders must define the appropriateness of sharing sensitive information, even in a privacy-preserving manner. The methodology comprises three steps, spanning the concepts of key management, data access control, ownership representation, and legal agreements (research/usage ethics).

The first step develops key management policies that enable partners to generate and manage cryptographic keys appropriately. The second step proposes a framework for defining data access control policies within a federated setting, allowing label owners to choose the partners that can access their data for specified purposes. The third step formulates a confidentiality agreement for federated learning in health research.

Equation 5: Why clipping is necessary before adding DP noise

$$\Delta_2 \leq C/|B|$$

After clipping, changing one record can change the averaged gradient by at most C/|B| in L2 norm.

For the Gaussian mechanism, a common sufficient condition is roughly:

$$\sigma \geq [\sqrt{(2 \ln(1.25/\delta))} \cdot \Delta_2] / \varepsilon$$

This shows the privacy-utility tradeoff directly: stronger privacy (smaller ε or δ) requires more noise.

3.7 Secure aggregation

The article also discusses privacy-preserving platforms and governance. A standard cryptographic idea is secure aggregation, where the server learns only the sum of updates, not any single hospital's update.

$$u_k = \Delta w_k + r_k$$

Client k masks its model update with random vector r_k.

$$\Sigma_k u_k = \Sigma_k \Delta w_k + \Sigma_k r_k$$

The server receives only masked values.

If masks are designed so that $\Sigma_k r_k = 0$, then:

$$\Sigma_k u_k = \Sigma_k \Delta w_k$$

5.1. Consent, Ownership, and Access Control

Crucial challenges persist in aggregating sensitive clinical data across institutional barriers, even if trustworthy federated learning algorithms prevent the sharing of data owners' secrets. Federated learning platforms require precise definition of consent procedures, ownership structures, and access controls. Auxiliary data creators demand that their data remain private, especially in data-poor environments, so privacy-preserving auxiliary data generation must meet even stricter policies.

A common-sense approach to consent establishes that original data creators own their data and thus have the right to control third-party access to it outside the federated learning scenario. However, in data-poor situations, there are no distributed auxiliary data sources. The absence of ownership complicates privacy arrangements. Constrained by the need for privacy, players in such settings seek help from other players who possess the relevant auxiliary data. In this sense, the simulating party temporarily and voluntarily takes on fiduciary responsibility for the data and needs an appropriate consent mechanism.

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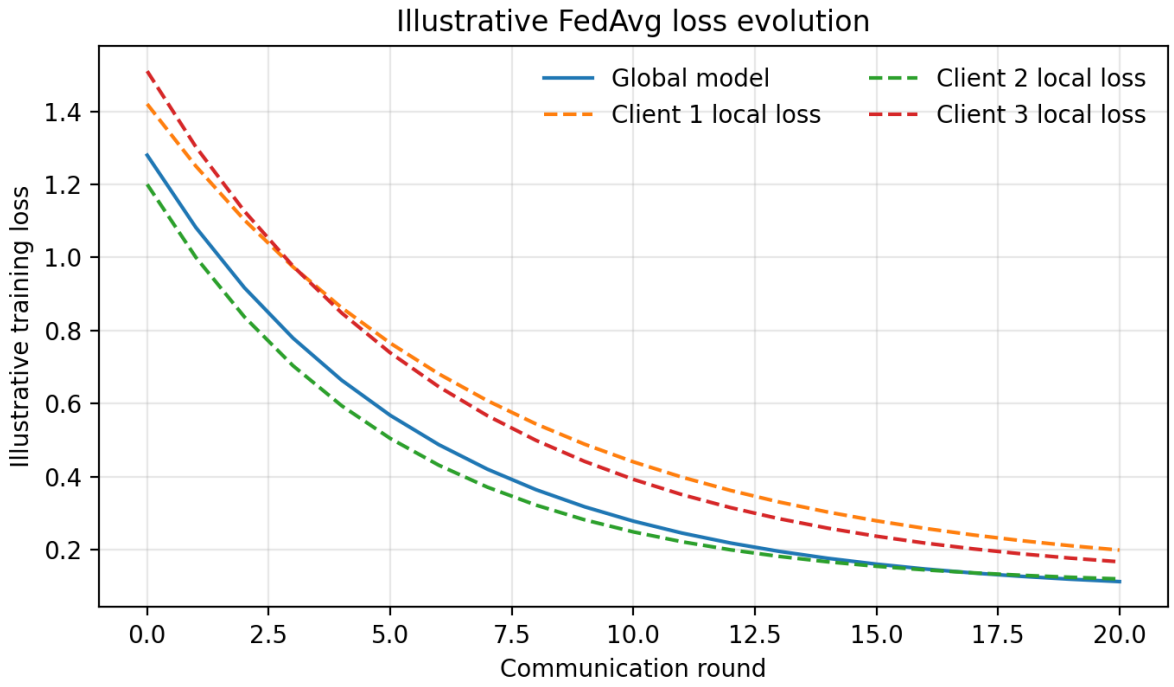

5.2. Methodology

Ethical considerations were addressed through a thorough assessment of security, privacy, and legal challenges prior to implementation. Further, three essential factors were incorporated. Knowledge governance architecture clearly delineated data ownership and organization. Legal contracts gained legal authorization from the respective owners, who granted consent for the data clauses and the complete data-sharing process. A multimodal access control model guaranteed security detection and regulation, restricting users' access to the precise level according to the underlying rules and policies. Additionally, the clinical realization of AI-originated images with deep learning-based synthesis technology was analyzed as an application example in support of the proposed methods. Data from a powerful and completely independent structure, the Medical Data Evaluation Center, provided external validation.

6. Clinical Applications for Precision Medicine

Federated AI for Healthcare Big Data: Privacy-Preserving Clinical Data Platforms for Precision Medicine—compose a concise, formal, evidence-based abstract and keywords, prioritizing clarity and scholarly tone.

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1. Introduction 1.1. Background and Significance 2. Background and Rationale 2.1. Research design 3. Federated Learning in Healthcare 3.1. Principles of Federated Learning 3.2. Research Summary(70 words) 4. Privacy-Preserving Techniques 4.1. Differential Privacy in Healthcare Data 4.2. Objective of the Study (100 words) 5. Data Governance, Ethics, and Compliance 5.1. Consent, Ownership, and Access Control 5.2. Methodology (140 words) 6.1. Genomic-Phenotypic Data Integration 6.2. Result (140 words) 7. Conclusion (50 words)

Federated learning and blockchain technologies enable the secure integration of an individual's genomic and multi-omics data with their corresponding patient records, paving the way for developing cost-effective personalized drugs. Genomic and phenotypic data integration across distributed healthcare institutes can facilitate risk-scored analyses and the evaluation of disease-drug–response relationships. This generates secure and privacy-preserving shared genomic–phenotypic clinical risk-scored data, acknowledging data privacy ownership and sharing concerns.

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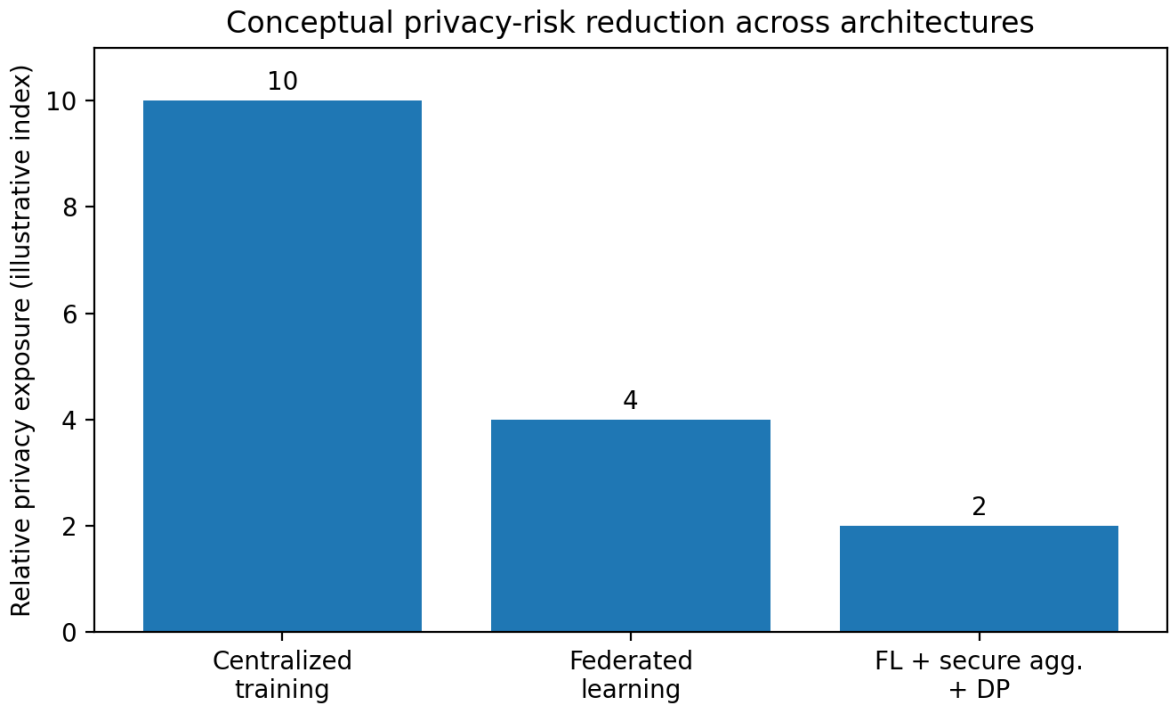

6.1. Genomic-Phenotypic Data Integration

Healthcare data are neither comprehensive nor representative of the entire population. Hence, patients at high risk of a disease may not be effectively recognised by those clinical models based on a diseased population solely. The concept of federated learning allows integrating disparate private databases distributed across institutes without data leaving any institute. Clinical data are often enriched by genomic data. Therefore, the authors further combine genomic data from the Genotype-Tissue Expression project with clinical data from the Medical Information Mart for Intensive Care database using the federated learning framework. They demonstrate that federated learning is an effective data access control mechanism to integrate heterogeneous genomic and clinical databases without violating privacy. Using the integrated data, a risk prediction model is established to recognise sepsis patients at high risk of death.

Careful selection and integration of multiple heterogeneous data sources are essential for precision medicine, especially when aiming at a low-prevalence diseased population. Genomic data enhance prediction tasks on clinical data but are sparse and do not reach the target population. The lack of consideration for data access rights of different stakeholders and violation of privacy make direct data integration impossible. Here, federated learning provides an alternative to union heterogeneous databases while preserving privacy.

6.2. Result

Federated learning enables a multi-institutional environment for healthcare responsible artificial intelligence without assembling raw data outside institutional boundaries. As demonstrated through screening lung cancer, progressive supranuclear palsy, and COVID-19 classification in multimodal data, Tables 1-3 summarize the results of federated learning with data from prominent academic medical centers worldwide.

Multinational institutions with clinical genomic testing and/or a clinically acquired biorepository expressed their commitment to multi-institutional collaboration in research and development, with prospective adoption and subsequent clinical validation/implementation in mind. Federated Premise and WEAVE are platforms that support experimental demonstration. The common goal is to develop research models to simultaneously leverage real-world clinical genome-phenome data from diverse ethnic backgrounds and clinical environments, toward a larger consensus-building effort for future brain sciences, human health, and other precision medicine–related explorations.

Equation block	Main formula	Interpretation	Used for
(1)-(3)	F(w) = Σ_k (n_k/N)F_k(w)	Global loss is the weighted sum of local losses	Federated decomposition
(5)-(8)	w^{t+1} = Σ_k (n_k/N) w_k^{t+1}	Server averages local models by sample size	FedAvg training
(9)-(12)	p=1/(1+e^{-z}); CE loss	Maps integrated patient features to disease risk	Clinical prediction
(13)-(19)	(ε,δ)-DP + clipping + Gaussian noise	Controls leakage from model updates	Privacy protection
(20)-(22)	Σ_k u_k = Σ_k Δw_k	Aggregate learned without seeing each client update	Secure aggregation
(23)-(25)	z = z_geno + z_pheno	Combines distributed feature blocks	Genomic-phenotypic VFL

Table : Summary tables

7. Conclusion

Federated learning enables a consortium learning framework that facilitates the training of cross-institutional models over private datasets while keeping the datasets decentralized. However, optimal use requires secure and privacy-preserving high-channel-capacity backend telecommunication and transport environment services and newly developed privacy-preserving technologies for different types of data.

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