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FEDERATED LEARNING FOR PRIVACY-PRESERVING MACHINE LEARNING: A COMPREHENSIVE REVIEW OF TECHNIQUES, ARCHITECTURES, AND OPEN RESEARCH DIRECTIONS

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Abstract

With increased dependency on data-centric machine learning models, several critical concerns relating to sensitive information used to train these models arise. Federated Learning (FL) presents a paradigm that would enable the collaboration of training without necessarily having direct access to the raw data. Therefore, this broad review looks at the upcoming privacy-preserving machine learning field under FL. We carefully analyze the latest advances in FL techniques, such as cryptographic methods, encryption and secure computation, as well as privacy and model aggregation strategies. We break down the various architectures of FL, such as centralized, decentralized, and heterogeneous FL, highlighting their strengths and weaknesses in various real-world applications in finance, Internet of Things. In addition, we discuss how blockchain technology can be integrated into FL ecosystems to provide security, trust, and transparency. We also shed light on the vulnerabilities of FL systems to various attacks, along with mitigation strategies involving secure aggregation protocols and anomaly detection. The research is concluded by indicating crucial open research areas, like the design of robust, scalable, and efficient FL frameworks; overcoming issues of non-IID data, communication overhead, and system heterogeneity; exploring novel privacy-enhancing technologies to support post-quantum security

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requirements; and introducing ethical considerations for fairness, bias, and accountability in FL deployments. This review is to provide a resource to researchers seeking an in-depth understanding current state-of-the-art in federated learning its pivotal role in enabling privacy-conscious machine learning applications as process innovation.

Keywords: Federated Learning, Privacy-Preserving Machine Learning, Encryption, Differential Privacy, Blockchain, Data Security, Model Aggregation, Privacy Attacks, Open Research Directions.

introduction

A. The Imperative of Privacy in the Age of Data-Driven Machine Learning

The dawn of the 21st century has borne witness to a data explosion heretofore unseen in scale and complexity and has given momentum to the fast-forwarding machine learning (ML) scenario across different verticals. This ranges from providing personalized recommendations in e-commerce applications to advanced medical diagnoses, wherein ML algorithms form an integral part of the new fabric of life. Although such a data revolution has brought on a critical challenge: the necessary tension between enormous datasets to power the training of strong ML models and the demand to protect personal data whose acquisition is being facilitated. Traditional methods of ML very often rely upon centralized data aggregation, where source raw data streams get compiled and stored centrally for model building. This paradigm raises serious privacy concerns, since sensitive information, including personal details, medical records, and financial transactions, will be at risk of data breaches, unauthorized access, and possible misuse. During recent years, publicized data breaches have highlighted central data storage and related risks, bringing the public and the regulatory authority into a sharp warpath, further strengthening data protection laws in each region, especially in Europe and California. Such regulations would put greater stress on organizations concerning data collection, processing, and storage while respecting the right of the individual over his personal data. As such, there arises the requirement of machine learning. Therefore, various new techniques for useful information from data have emerged in this scenario, preserving individual privacy at the same time.

B. Federated Learning: A Decentralized Approach to Privacy Preservation

Federated learning is an innovation that changes fundamentally the traditional mechanism of ML by enabling several parties to perform collaborative needing to centrally data. Designed to be a distributed alternative to aggregated centralized data collection, FL gives several parties like cellular devices, hospitals, or banking institutions, the option to collectively update a shared model in a global learning framework while having their sensitive information remain local to them. In a normal FL setting, private dataset and shares only the updates of the model (e.g., gradients or weights) periodically. The server aggregates enhance the global then distributed back to the participants for further refinement. By keeping raw data decentralized and only exchanging model updates, FL reduces the danger of data

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breaches and unauthorized access because never leaves premises of data owners. Furthermore, FL adheres to the principles of data minimization and purpose limitation espoused by privacy regulations as only the amount of information that is required is retained under the control of the respective parties. improves privacy but also offers many other benefits including communication overhead that is reduced as only model updates are transmitted and not large datasets.

C. Challenges and Applications of Federated Learning in Sensitive Domains

FLhas a lot of promise but poses to its wide-scale adoption. One of the main challenges is the inherent data heterogeneity across participants. In contrast to traditional of independently, FL frequently encounters non-IID data due to variations in user behavior, demographics, or device characteristics. The non-IID nature can result in slow convergence of the model, instability, and performance degradation. Also, the devices that participate are highly heterogeneous from a powerful server to a mobile device with scarce resources, causing processing delays, model fairness, and communication bottlenecks. Security against model poisoning, inference attacks, and backdoor attacks continues to be an open problem.

Despite these, FL's nature of privacy-preserving makes it specifically well-suited to sensitive domains, such as healthcare, where FL is being used in bringing advancements in disease diagnosis, treatment response prediction, drug discovery, among others, keeping abreast of HIPAA-type privacy regulations. FL helps in the financial sector with fraud detection, credit scoring, and anti-money laundering by letting institutions train models collectively without exposing sensitive customer information. It also shows promise in IoT for privacy-preserving analytics and personalized services on edge devices. It also supports the natural language process, as presented in Google's Gboard in using FL that improves next word prediction without transmitting users' data to the cloud. These examples speak to the robust use of FL while actively working out the challenges faced in its practical realization.

FOUNDATIONAL CONCEPTS AND LANDSCAPE OF FEDERATED LEARNING

section delves of FL, exploring various architectures, comparing it with traditional ML approaches. We will also examine the communication protocols and optimization algorithms that underpin FL systems.

A. Defining Federated Learning and its Variants

FL is one of the novel departures from traditional centralized paradigms in ML, initially conceptualized by McMahan et al. [15]. In this setting, a global model is trained cooperatively by several parties without exchanging raw data. Such an approach has become essential nowadays, as people are facing the problem of privacy, and with stricter regulations, like GDPR [4], this seems to be one of the ways forward.

Three main types are reported in the available literature regarding the categorization of FL. These are classified into three, namely: feature space but differ in sample spaces, HFL applies

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[2][13]. An example of HFL in practice would be that many hospitals have data on patients that share the same attributes, for example, age, blood pressure, and medical history, but correspond to different patients altogether.

In VFL Imagine a bank and an e-commerce platform. Each has data but the features are very different, for instance, records of financial transactions versus online purchasing history. Federated Transfer Learning (FTL) addresses situations where the sample space and also the feature space are significantly different between participants. FTL can tap into the strengths of transfer learning to achieve limited data by harnessing the knowledge learned from a source domain that has ample data [21]. Yin et al. [12] and Saha et al. [8] have made great contributions to summarizing these FL variants, showing the strengths and weaknesses as well as their applicability to various real-world scenarios, in addition to some research challenges discussed.

B. Architectures in Federated Learning: Centralized vs. Decentralized

The most significant impact of the architectural design of an FL system upon its efficiency, scalability, and overall robustness is obtained. The most commonly used architecture is Centralized FL, where coordination of the whole training process takes place by the central server as reported in [6]. received and then updates the global model [16]. Centralized FL has simplicity and ease of implementation as advantages. However, it has a problem wherein the system gets comp also potentially suffers from communication bottlenecks, in case there are large participants. Yurdem et al. [6] discussed various FL strategies, tools, and its various applications in his paper.

Decentralized FL architectures have been proposed as a potential alternative to handle the drawbacks associated with centralized systems [22]. instead, the participating entities one another peer-to-peer to cooperatively train the global model [19]. Shakeer and Babu [19] explain how to use FL onthe for data privacy. This approach makes the system and can potentially reduce communication overhead by distributing the aggregation workload among multiple participants. However, it introduces complexities related to coordination, synchronization, and establishing trust among the participating entities. Besides purely centralized and decentralized architectures, hybrid and hierarchical FL architectures have also been explored. This attempts to harmoniously integrate advantages provided by the respective centralized and decentralized approaches for both efficiency and scaling as well as resilience in them and find an optimum of the efficiency balance [3][6]. Thereby, a talk about privacy-preserved AI used by Potter et al. appeared for FL [3][6].

C. Communication Protocols and Optimization Algorithms

The effectiveness of FL thus depends on communication protocols and optimization algorithms. Currently, the most commonly used optimization algorithm. The working of FedAvg is defined such that all participants update their models through multiple SGD (i.e, Stochastic Gradient Descent) passes on the local data and then share their updated Although

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FedAvg has been quite effective in several scenarios, it is known to be sensitive to the problem of non-IID data and system heterogeneity. To deal with these challenges, variants of FedAvg, like FedProx [15], have been proposed. In FedProx, help reduce the detrimental effects of data heterogeneity on model convergence and stability [6][7]. Wang et al. [7] proposed a technique for partial low-quality data in their research toward privacy preservation.

In FL, communication efficiency is a serious concern, devices [11][14]. Several techniques have been developed to minimize communication overhead. These include model compression, sparsification, and quantization [3][24], which aim at reducing the size have to be communicated between participants and the central server. Techniques such as those reviewed in Ogundokun et al. [14] reduce communication payload by fewer parameters or fewer bits of accuracy in the weights of the models. Sparsity methods aim at transmitting only the highest model updates; quantization focuses on reducing bits to represent any model parameter in a given manner. In addition, asynchronous communication protocols have been studied to reduce the effect of stragglers (slow or unresponsive devices) and increase the efficiency of training [5, 25]. Choi et al. [25] proposed a method called FedNIC (i.e, Federated Network for Identity and Credentials) to enhance privacy in FL.

D. Comparison with Traditional Machine Learning Approaches

FL methods, especially. In traditional ML, data is usually aggregated and centralized in one location, which is a huge source of privacy risks and vulnerabilities [20]. Xu et al. [20] discussed various methods and challenges in privacy-preserving ML. In clear contrast, FL not the actual data [10][12][17]. Dhade and Shirke [10] reviewed the use of FL in the healthcare sector, whereas Naz et al. [12] reviewed the utilization of FL for COVID-19 detection. well with the principles of data minimization and purpose limitation, which are increasingly highlighted by privacy regulations worldwide [4]. Truong et al. [4] discussed privacy preservation in FL from the GDPR perspective.

More importantly, FL is capable of taking advantage of the vast computational powers available at an extensive number of edge devices. This, therefore, provides an opportunity to scale model training far larger than otherwise while also diminishing the computation intensity of central servers [1][18]. The distributed computation paradigm becomes significantly useful within the IoTs and edge computing scenario [22]. Briggs et al. [22] have recently surveyed privacy-preserving federated learning for the IoTs. Nonetheless, FL does introduce a different set of challenges not inherent to traditional machine learning, including managing the non-IID complexities in data distributions among participants, managing heterogeneity of the system in terms of variations in capabilities and network conditions of the devices, and dealing with communication bottlenecks [7][9][23]. Guembe et al. [23] have surveyed various privacy issues, attacks and open problems in FL. Schwarz [1] and Schwarz and Taqa [18] have discussed various privacy-preserving ML techniques for exploring FL in their research. Hu et al. [9].

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PRIVACY-ENHANCING TECHNIQUES IN FEDERATED LEARNING

Various privacy-enhancing techniques employed in FL model training process. The authors will delve into cryptographic approaches, differential privacy, trusted execution environments, and model obfuscation methods.

A. Cryptographic Approaches for Secure Aggregation

The techniques of cryptography play a crucial role in allowing secure aggregation of model updates in FL, so that individual contributions are kept confidential, while the server can accurately compute the global model. One of the most prominent techniques is Homomorphic Encryption [25], carried out on encrypted data. In the FL model, the homomorphic encryption scheme can be utilized by the participant to encrypt his local Then the server will compute the operation of averaging on the and only decrypt the final aggregated result. This way, the updates for the individual models in plaintext form remain unknown to the server. However, HE supports a high privacy guarantee and can create high computational overhead, especially for deep models and datasets of large dimensions. Various flavours of HE schemes like Paillier [25] have been explored so far to balance efficiency with security concerns over FL.

Another strong cryptographic technique is SMPC,, which enables two or on their private inputs without disclosing the inputs themselves [2]. FL can make use of this SMPC mechanism that securely aggregates local model updates coming from multiple participants. This involves a protocol where the participants do a sequence of interactive computations that exchange encrypted shares of their updates in a manner that allows the server to obtain the aggregated model without learning individual contributions. Secret Sharing [9] is often applied as building blocks within SMPC protocols in such a way that the participant's update will be split into multiple shares, but update. SMPC offers strong privacy guarantees but can be communication-intensive, especially when dealing with a large number of participants. Recent research has focused on developing more efficient SMPC protocols tailored for FL [9, 23].

B. Differential Privacy for Noise-Based Perturbation

Differential Privacy mathematically rigorous for DP can be applied in FL in two ways: locally, where each participant adds noise to his model updates before sharing them, and globally, where the server adds noise to the aggregated model. The advantage of the local DP is stronger privacy guarantees. In this scheme, the noise is added at the source so that even the server cannot find any precise information about individual contributions. However, this can reduce model accuracy much more than in global DP since noise is added earlier in the training process.

Global DP enables higher accuracy of the model since it adds noise directly to the aggregated model, though it offers weaker privacy guarantees because the server observes the

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unperturbed individual updates. The choice between local and global DP is determined by the level of the desired trade-off between the two: privacy or model utility. Different mechanisms for adding noise have been explored, among them being Gaussian and Laplacian mechanisms [13]. privacy parameter, often called ε (epsilon), with lower values of ε associated with stronger privacy guarantees but perhaps with lower model accuracy. Recent work has targeted adaptive DP mechanisms, which dynamically adapt their noise level based on either data sensitivity or at which stage of training [2][8].

C. Trusted Execution Environments (TEEs) for Secure Computation

Trusted Execution Environments hardware-based approach to enhancing privacy and security in FL [22]. TEEs are secure enclaves within a processor that isolate code and data from the rest of the system, protecting them from unauthorized access and tampering, even from the operating system or hypervisor. TEEs can be used in FL for performing computations on sensitive data such as The encrypted data or model updates of participants are sent to the TEE. It decrypts the received encrypted data within the secure enclave, performs the computations needed, encrypts the result, and then sends it back.

TEEs do provide secure access guarantees that operate on physical forms of separation from software forms, but these still have the associated drawbacks of software-based implementations. TEEs are susceptible to side-channel attacks where some attacks infer from such characteristics as side-channel leakage over consumption of energy, and timing side-channels [23]. Generally, most devices in IoTs and resource-scarce are often not configured to have required specific hardware TEEs run with. Despite these drawbacks, TEEs have drawn much attention within the FL research community and recent efforts have focused on building stronger and more efficient TEE-based solutions for privacy-preserving FL [3][22].

D. Model Obfuscation and Transformation Techniques

Model obfuscation and transformation techniques protect the privacy of training data by either modifying the model architecture or the training process itself. The model pruning technique reduces less important parts or sensitive parts of the model before sharing [24]. This is to decrease the risk of model inversion attacks, from the model parameters. Another is model quantization, which is the reduction in the precision of the parameters of the model, making it harder to retrieve sensitive information [3].

Besides changing the model itself, transformations can be applied to training data. methods of data augmentation such as noisy addition or some random transformation over the input data which may enhance privacy by making information about individual points harder to recover. Such approaches can be combined with other techniques that are available for enhancing privacy, such as DP or approaches based on cryptographic primitives, towards stronger privacy. However, it is important to take care of the effects of these transformations on model accuracy and not inadvertently introduce biases or tasks. The area of research in this domain

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continues to be developing more advanced and effective model obfuscation and transformation techniques

capable of improving privacy without degrading model utility much [1][18], as seen in Table 1 and Figure 1. Table1 is showing Performance of Different Privacy-Enhancing Techniques in Federated Learning

Technique	Accuracy Drop (%)	Computation Overhead	Communication Overhead
Homomorphic Encryption (HE)	0-2	High	Low
Secure Multi-Party Computation (SMPC)	0-1	Very High	High
Local Differential Privacy (LDP)	5-15	Low	Low
Global Differential Privacy (GDP)	2-5	Low	Low
Trusted Execution Environments (TEEs)	0-1	Moderate	Low
Model Pruning	2-8	Low	Low
Model Quantization	1-5	Low	Low
Data Augmentation with Noise	Variable	Low	N/A

Table 1: Performance of Different Privacy-Enhancing Techniques in Federated Learning

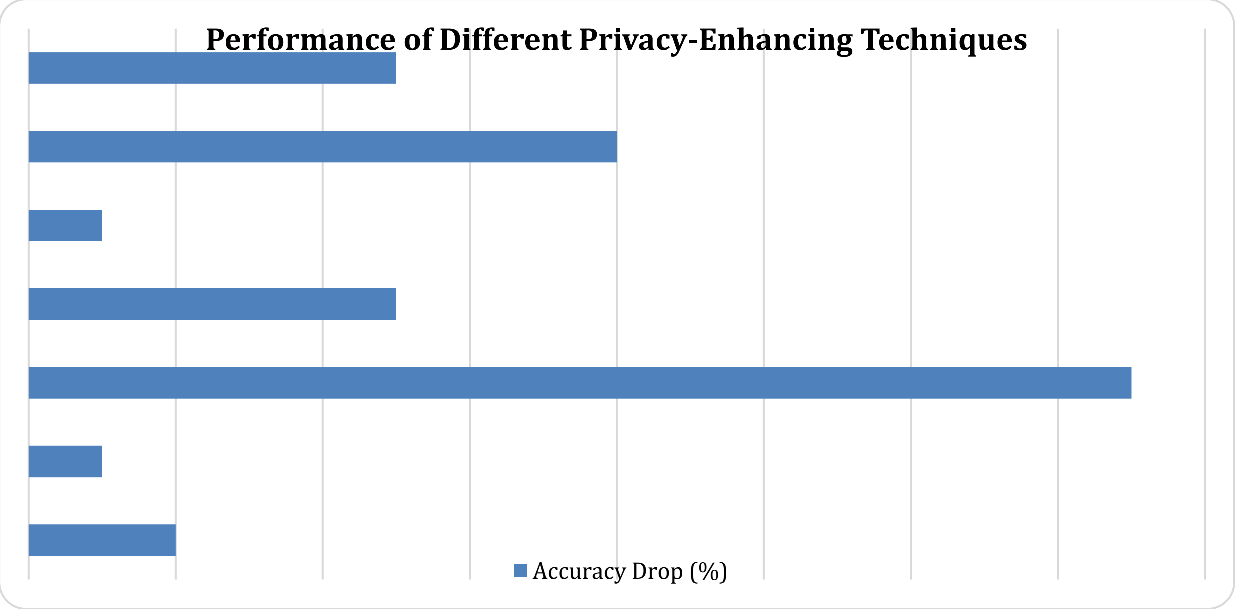

Fig 1.Performance of Different Privacy-Enhancing Techniques in Federated Learning

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EMERGING TRENDS AND APPLICATIONS OF FEDERATED LEARNING

This section explores the emerging trends and cutting-edge applications of FLacross various domains. The authors focus on two key areas: the integration of blockchain for enhanced security and trust, and the transformative potential of FL in sensitive sectors like healthcare and finance.

A. Blockchain-Based Federated Learning for Enhanced Security and Trust

Integration of blockchain technology with FL has emerged as a very promising trend in bridging the security and trust problems in a decentralized learning system [19][21]. Indeed, blockchain technology, on its own, possesses intrinsic properties such as immutability, transparency, and decentralization, which can boost the integrity and auditability of the FL process. In a FL-based blockchain framework, model updates and other pertinent data, including participant identities and timestamps of model update events, are stored in the distributed ledger. This results in an immutable record of model training, preventing malicious actors from manipulating the model or disclaiming their involvement. Furthermore, blockchain allows for the secure and transparent aggregation of model updates by smart contracts that are self-executing agreements that automatically enforce the rules of the aggregation process [19].

Furthermore, blockchain can enable decentralized reputation systems for the participants in the FL network [21]. The blockchain can maintain the record of the participants' contributions in the training process and thereby will be able to evaluate and record the behavior of the participants in a transparent, auditable manner. This will allow good behavior to be promoted and problematic or non-contributive participants to be identified. Although the integration of blockchain with FL affords many benefits, it raises scalability issues and computational overhead when maintaining the blockchain. Current work in research is aimed at developing FL blockchain-based frameworks that are more scalable and efficient to deal with the challenges [19, 21].

B. Applications in Healthcare, Finance, and Other Sensitive Domains

FL is transforming applications in sensitive domains where data privacy is key, particularly in healthcare and finance. For healthcare, FL allows for cooperative joint research and development of diagnostic and predictive models at multiple institutions without sharing sensitive patient data as in the cases [10, 11, 12]. For example, FL can be applied for training disease diagnosis models, prediction of the response to treatments, and personalization of medical treatments by accessing diverse patient populations in a HIPAA-compliant manner [10]. Koutsoubis et al. [11] suggested a method of privacy preserving FL in the medical imaging application. This approach not only accelerates medical research but also improves the generalizability and robustness of models by exposing them to a wider range of data.

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FL is revolutionizing fraud detection and risk assessment efforts in the financial sector [6]. FL, therefore, increases the accuracy of fraud detection and speeds up detection by allowing the models to train cooperatively using banks' or other financial organizations' transactional data without ever having to release any sensitive information that concerns the customer. Furthermore, FL can facilitate secure and privacy-preserving credit scoring and loan application evaluations by allowing institutions to jointly train models without sharing their proprietary data. FL is emerging in applications beyond healthcare and finance into IoT, which ensures privacy-preserving analytics and personalized services on the edge [19, 22], and towards natural language processing, which also can facilitate further development of its language models from the data received while preserving the anonymity of the respective users. These examples illustrate the powerful potential of FL to make it possible for private machine learning across diverse applications as can be seen from Table 2 and Figure 2.

Model	Metric	Federated Learning (FL)	Centralized Learning (CL)
Pneumonia Detection (Chest X-rays)	AUC	0.928	0.935
Diabetic Retinopathy Detection	Accuracy	0.841	0.835
COVID-19 Detection (CT Scans)	Sensitivity	0.86	0.88
COVID-19 Detection (CT Scans)	Specificity	0.91	0.93

Table 2: Performance Comparison of Federated Learning vs. Centralized Learning in Healthcare

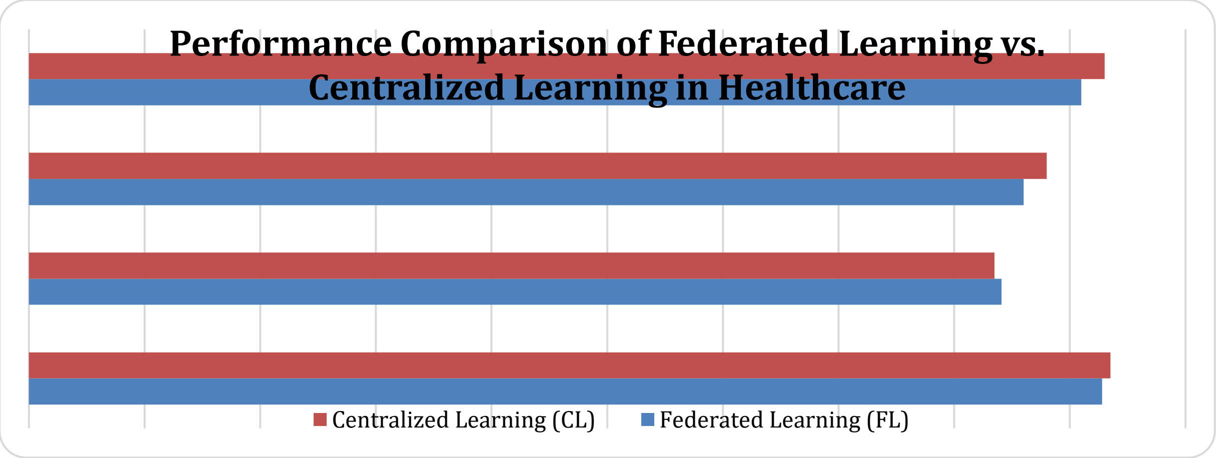

Fig 2.Performance Comparison of Federated Learning vs. Centralized Learning in Healthcare

Conclusion

A. Summary of Key Findings and Insights

This paper provides a comprehensive review of FLas an emerging paradigm for privacy-preserving machine learning. The authors explored foundational concepts of FL, including architecture, communication protocols, and optimization algorithms, to distinguish between horizontal, vertical, and federated transfer learning. The critical role of privacy-enhancing techniques, including cryptographic approaches, differential privacy, trusted execution environments, and model obfuscation, has been discussed in detail, with strengths and limitations emphasized. In addition, the authors have studied the threat landscape of FL, major privacy attacks such as data poisoning, membership inference, model inversion, and backdoor attacks, and the corresponding defense mechanisms. It has been portrayed as a promising trend to enhance security, trust, and transparency through the integration of blockchain technology with FL. Finally, we have shown how FL can revolutionize sensitive domains like health care and finance by enabling collaborative model training without damaging the privacy of data.

B. The Future of Federated Learning in the Privacy-Preserving AI Landscape

FL is one of the leaders in the privacy-preserving AI landscape and provides a very powerful approach for training ML models without the need to have sensitive data. With data privacy concerns and regulations continuing to grow, FL is likely to play an increasingly important role in enabling responsible and ethical AI development. The future of FL will foresee considerable progress in all aspects, starting with the development of far more sophisticated, efficient techniques for privacy protection. The scaling of FL frameworks must lead to its ability to better work with much wider and broader applicability, taking a step beyond those of some similar applications that come under specific contexts. Advances that bridge fundamental principles to practical designs can further unlock the tremendous latent capacity. FL is going to revolutionize machine learning in the way we approach it when the field matures because it clears the way for a future where potentially powerful AI models can be collaboratively trained without breaching the fundamental right to privacy.

References

1. Chaw, J.K., Chaw, S.H., Quah, C.H., Sahrani, S., Ang, M.C., Zhao, Y. and Ting, T.T., 2024. A predictive analytics model using machine learning algorithms to estimate the risk of shock development among dengue patients. Healthcare Analytics, 5, p.100290.
2. Helix Schwarz and Amer Research Taqa, "Comprehensive Review on Privacy-Preserving Machine Learning Techniques for Exploring Federated Learning," Enhanced Research Publications, September 2024.
3. X. Yin, Y. Zhu, and J. Hu, "A Comprehensive Survey of Privacy-preserving Federated Learning: A Taxonomy, Review, and Future Directions," ACM Comput. Surv., vol. 54, no. 6, Article 131, July 2021, doi: 10.1145/3460427.

Received: July 24, 2025

4. K. Potter, F. Olaoye, and P. Broklyn, "Federated Learning for Privacy-Preserving AI," Machine Learning with Applications, November 2024.

5. N. Truong, K. Sun, S. Wang, F. Guitton, and Y. Guo, "Privacy preservation in federated learning: An insightful survey from the GDPR perspective," Data Science Institute, Imperial College London, South Kensington Campus, London, UK, and Department of Computer Science, Hong Kong Baptist University, Kowloon Tong, Hong Kong, July 2021.

6. X. Zhang, H. Deng, R. Wu, and others, "PQSF: post-quantum secure privacy-preserving federated learning," Sci. Rep., vol. 14, p. 23553, 2024, doi: 10.1038/s41598-024-74377-6.

7. B. Yurdem, M. Kuzlu, M. K. Gullu, F. O. Catak, and M. Tabassum, "Federated learning: Overview, strategies, applications, tools and future directions," Heliyon, vol. 10, no. 9, Sept. 2024, doi: 10.1016/j.heliyon.2024.e38137.

8. H. Wang, Q. Wang, Y. Ding, and others, "Privacy-preserving federated learning based on partial low-quality data," J. Cloud Comput., vol. 13, no. 62, 2024, doi: 10.1186/s13677-024-00618-8.

9. S. Saha, A. Hota, A. K. Chattopadhyay, and others, "A multifaceted survey on privacy preservation of federated learning: progress, challenges, and opportunities," Artif. Intell. Rev., vol. 57, pp. 184, 2024, doi: 10.1007/s10462-024-10766-7.

10. K. Hu, S. Gong, Q. Zhang, and others, "An overview of implementing security and privacy in federated learning," Artif. Intell. Rev., vol. 57, pp. 204, 2024, doi: 10.1007/s10462-024-10846-8.

11. P. Dhade and P. Shirke, "Federated Learning for Healthcare: A Comprehensive Review," Eng. Proc., vol. 59, no. 1, 2023, doi: 10.3390/engproc2023059230.

12. N. Koutsoubis, Y. Yilmaz, R. P. Ramachandran, M. Schabath, and G. Rasool, "Privacy Preserving Federated Learning in Medical Imaging with Uncertainty Estimation," arXiv, Jun. 2024, arXiv:2406.12815v1.

13. S. Naz, K. T. Phan, and Y. P. P. Chen, "A comprehensive review of federated learning for COVID-19 detection," Int. J. Intell. Syst., 2021, doi: 10.1002/int.22777.

14. X. Yin, Y. Zhu, and J. Hu, "A Comprehensive Survey of Privacy-preserving Federated Learning: A Taxonomy, Review, and Future Directions," ACM Comput. Surv., vol. 54, no. 6, Article 131, July 2022, pp. 1–36, doi: 10.1145/3460427.

15. R. O. Ogundokun, S. Misra, R. Maskeliunas, and R. Damasevicius, "A Review on Federated Learning and Machine Learning Approaches: Categorization, Application Areas, and Blockchain Technology," Information, vol. 13, no. 5, pp. 263, 2022, doi: 10.3390/info13050263.

16. Y. Cheng, Y. Liu, T. Chen, and Q. Yang, "Federated learning for privacy-preserving AI," Commun. ACM, vol. 63, pp. 33-36, 2020.

17. S. S. Medavarapu, "Decentralized Intelligence: A Comprehensive Review of Federated Learning for Privacy-Preserving Machine Learning," J. Sci. Eng. Res., vol. 8, no. 3, pp. 271-274, 2021.

Received: July 24, 2025

18. B. S. Prabha, "Federated Learning: A Privacy-Preserving Approach for Distributed Machine Learning," Int. J. Eng. Res. Technol., vol. 13, no. 9, Sept. 2024, doi: 10.17577/IJERTV13IS090055.

19. H. Schwarz, "Comprehensive Review on Privacy-Preserving Machine Learning Techniques for Exploring Federated Learning," EDU J. Int. Aff. Res., vol. 3, no. 2, April-June 2024, available at: https://edupublications.com/index.php/ejiar.

20. S. M. Shakeer and M. R. Babu, "A Study of Federated Learning with Internet of Things for Data Privacy and Security using Privacy Preserving Techniques," Int. J. Comput. Sci., vol. 18, no. 1, 2024, doi: 10.2174/1872212117666230112110257.

21. R. Xu, N. Baracaldo, and J. Joshi, "Privacy-Preserving Machine Learning: Methods, Challenges and Directions," IBM Research - Almaden Research Center, San Jose, CA, USA, and University of Pittsburgh, Pittsburgh, PA, USA.

22. Q. Yang, A. Huang, L. Fan, C. S. Chan, J. H. Lim, K. W. Ng, D. S. Ong, B. Li, "Federated Learning with Privacy-preserving and Model IP-right-protection," WeBank, Shenzhen, China, Hong Kong University of Science and Technology, Hong Kong, University of Malaya, Kuala Lumpur, Malaysia, University of Surrey, Guildford, UK, University of Aberystwyth, Wales, UK, Shanghai Jiao Tong University, Shanghai, China.

23. C. Briggs, Z. Fan, and P. Andras, "A Review of Privacy-Preserving Federated Learning for the Internet-of-Things," Federated Learning Systems, Springer, 2021, doi: 10.1007/978-3-030-70604-3_2.

24. B. Guembe, S. Misra, and A. Azeta, "Privacy Issues, Attacks, Countermeasures and Open Problems in Federated Learning: A Survey," Appl. Artif. Intell., vol. 38, no. 1, 2024, doi: 10.1080/08839514.2024.2410504.

25. G. Nguyen, J. Sáinz-Pardo Díaz, A. Calatrava, L. Berberi, O. Lytvyn, V. Kozlov, V. Tran, G. Moltó, and Á. López García, "Landscape of machine learning evolution: privacy-preserving federated learning frameworks and tools," Artif. Intell. Rev., vol. 57, no. 2, 2024, doi: 10.1007/s10462-024-11036-2.

26. S. Choi, D. Patel, D. Z. Tootaghaj, L. Cao, F. Ahmed, P. Sharma, "FedNIC: enhancing privacy-preserving federated learning via homomorphic encryption offload on SmartNIC," Front. Comput. Sci., vol. 6, Oct. 2024, doi: 10.3389/fcomp.2024.1465352.

Received: July 24, 2025