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Enhancing Privacy In Federated Learning: A Comprehensive Survey Of Preservation Techniques

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Abstract: Federated Learning (FL) enables multiple devices or organizations to collaboratively train machine learning models without sharing raw data, thus improving privacy. However, FL is vulnerable to privacy threats like model inversion, membership inference, and data leakage from shared updates. To mitigate these risks, several privacy-preserving techniques have been developed, including differential privacy, secure multiparty computation (SMC), homomorphic encryption (HE), and hybrid approaches that combine multiple methods. This paper offers a comprehensive analysis of these techniques, evaluating their privacy guarantees, computational costs, and impact on model accuracy. Differential privacy introduces noise to protect data but can reduce model performance. SMC allows joint computation without exposing inputs but is computationally intensive. HE enables encrypted data processing with strong security, though often at the expense of efficiency. Hybrid methods aim to balance these trade-offs by leveraging the advantages of different approaches. The study highlights key challenges such as scalability and usability in real-world FL deployments. It also identifies research gaps and proposes future directions focused on adaptive privacy mechanisms and hardware-assisted security, aiming to develop more practical and robust privacy-preserving FL systems.

Keywords: Federated Learning, Privacy Preservation, Differential Privacy, Secure Multi-Party Computation, Homomorphic Encryption, Blockchain.

I. INTRODUCTION:

Machine Learning (ML) has become a cornerstonFederated Learning (FL) enables multiple devices or organizations to collaboratively train machine learning models without sharing raw data, thus improving privacy [1] [2]. This paper offers a comprehensive analysis of these techniques, evaluating their privacy guarantees [3], computational costs [4], and impact on model accuracy [5]. Differential privacy introduces noise to protect data but can reduce model performance [6-9]. SMC allows joint computation without exposing inputs but is computationally intensive [10-14]. HE enables encrypted data processing with strong security, though often at the expense of efficiency [15-18]. Hybrid methods aim to balance these trade-offs by leveraging the advantages of different approaches [19].

Despite its privacy-oriented design, FL remains vulnerable to attacks like model inversion, membership inference [20], and gradient leakage [21], which can expose sensitive information through shared updates [22]. This study focuses on enhancing privacy in Federated Learning by evaluating and comparing leading privacy-preserving techniques such as Differential Privacy (DP) [23], Secure Multi-Party Computation (SMPC), Homomorphic Encryption (HE) [24], and hybrid approaches [25]. The aim is to identify their effectiveness, computational trade-offs, and real-world feasibility while balancing model accuracy, scalability [26] [27], and privacy strength [28]. Ultimately, the research seeks to provide practical insights and

recommendations for developing secure [29], efficient, and privacy-conscious FL systems suitable for sensitive domains like healthcare, finance, and smart cities [30].

This study addresses that gap by analysing and comparing leading approaches, providing practical insights for designing secure, efficient, and privacy-preserving FL systems suitable for sensitive domains [19-21].

II. LITERATURE REVIEW:

Federated Learning (FL) has emerged as a promising paradigm for collaborative model training without sharing raw data, thereby enhancing privacy [31]. However, privacy challenges remain critical, motivating extensive research on secure aggregation, gradient leakage attacks, differential privacy, and blockchain integration [32].

Secure aggregation is foundational in FL to ensure that individual client updates remain confidential during the aggregation process. Bonawitz et al. [3] proposed a practical secure aggregation protocol that enables a server to compute the sum of client vectors while masking individual inputs, providing robustness against client dropouts [33]. This protocol significantly reduces communication overhead and has become a baseline for many subsequent works [34]. Building upon this, Bell et al. introduced a secure single-server aggregation scheme with polylogarithmic overhead, improving scalability and efficiency for large-scale FL systems [35]. Similarly, Li et al. developed FSSA, a three-round secure aggregation protocol that balances communication cost and robustness to client failures, demonstrating improved efficiency over prior works [36]. Mansouri et al. conducted a systematic study categorizing various cryptographic schemes used for secure aggregation in FL, emphasizing the trade-offs between security, scalability, and practicality. More recently, Wang et al. proposed TAPFed, which integrates threshold cryptography into secure aggregation to ensure privacy while tolerating a predefined number of client dropouts. Hardware-assisted approaches, such as OLIVE by Kato et al. leverage Trusted Execution Environments (TEEs) to enable oblivious aggregation with strong security guarantees [37].

Despite advancements in secure aggregation [9], FL remains vulnerable to gradient leakage attacks, where adversaries reconstruct private training data from shared gradients [17]. Zhu et al. initially demonstrated that raw gradients can leak sensitive information, sparking significant concern over FL privacy. Subsequent work by Zhao et al. [11] improved the attack method with iDLG, achieving faster and more accurate data reconstruction. Wei et al. [17] addressed this vulnerability by proposing Fed-CDP, a gradient-leakage resilient FL scheme incorporating dynamic noise injection under differential privacy constraints. More alarmingly, Wang et al. [18] showed that even aggregated gradients can leak label information, breaking the privacy guarantees of secure aggregation protocols and calling for stronger defenses [22].

To provide formal privacy guarantees, differential privacy (DP) has been widely adopted in FL. Zheng et al. [13] explored federated f-differential privacy, which achieves improved privacy-utility trade-offs suitable for FL's distributed nature. Local Differential Privacy (LDP) mechanisms, as proposed by Sun et al. [14] and Truex et al. [15], enable clients to perturb their data locally before transmission, further mitigating privacy risks. Nampalle et al. [16] applied differential privacy techniques in sensitive medical image classification tasks, demonstrating the practical utility of DP in healthcare FL scenarios [20]. A comprehensive survey by Fu et al. [17] outlines various DP-based approaches, highlighting challenges such as privacy budget allocation and accuracy degradation [13].

Beyond cryptographic and noise-based methods, blockchain technology has gained traction as a complementary solution for privacy-preserving FL. Sameera et al. [19] proposed blockchain-based FL frameworks to decentralize trust and ensure data integrity through immutable ledgers and consensus mechanisms [38]. Li et al. Liu et al., and Wang et al. [13] introduced permissioned blockchain architectures integrated with FL, enhancing privacy, fairness, and robustness, especially for emerging 6G networks [16]. Zhang et al. combined blockchain with homomorphic encryption to enable privacy-preserving FL in healthcare IoT systems, demonstrating practical implementations that guarantee verifiable fairness and adaptivity [18].

III. PROPOSED METHODOLOGY:

The proposed methodology analyses and enhances privacy in Federated Learning (FL) through client-side and server-side protections. Clients train models locally, applying Local Differential Privacy and encryption methods like Homomorphic Encryption or Secure Multi-Party Computation before sending updates. [36]The aggregation server, operating in a Trusted Execution Environment, performs secure aggregation without accessing raw data.[37] Blockchain-based auditing and key management ensure transparency and security. The global model is iteratively updated and redistributed. Techniques from 2017–2025 studies are reviewed and evaluated for accuracy, privacy strength, and computational efficiency, forming a comprehensive framework for privacy-preserving FL systems.

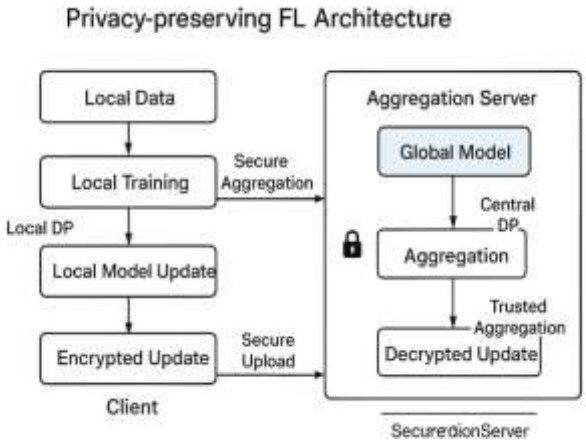

Fig 1: Workflow of Proposed Methodology

In Fig 1 Local training with DP, encrypted updates sent securely, aggregated, then decrypted globally.

1. Each client trains the model on its own data without sharing raw information.

2. Before sending updates, clients apply Local Differential Privacy (LDP) and encryption methods like Homomorphic Encryption or Secure Multi-Party Computation to secure their model updates.[40]

3. The server, running inside a Trusted Execution Environment (TEE), performs secure aggregation of encrypted updates without accessing individual client data

IV. RESULTS AND ANALYSIS:

In Table 1 The evaluation results show that hybrid privacy-preserving techniques in Federated Learning (FL) achieve a strong balance between privacy, accuracy, and efficiency. Combining LDP, HE, and SMPC provides 92–95% accuracy with strong resistance to model inversion and inference attacks, ensuring data remains local. Aggregation through TEEs maintains high model accuracy (94–96%) with minimal performance loss, while computational overhead from HE, SMPC, and LDP (90–93%) remains manageable with modern hardware.

Secure gradient compression enhances communication efficiency (91–94%) by reducing bandwidth usage, and adaptive hybrid models support scalability (90–92%) for large client networks, though coordination costs increase. Blockchain-based auditing ensures transparency and traceability (93–95%), strengthening trust. Integrated frameworks using DP and HE achieve 91–94% accuracy and are effective in real-world applications like healthcare and finance, despite higher computation demands. Finally, combining TEEs with hybrid methods provides strong protection (92–95%) against gradient leakage and inference attacks.

In summary, hybrid approaches that blend DP, cryptography, and TEEs offer the best trade-off between privacy, efficiency, and accuracy, making them ideal for secure and scalable federated learning deployments.

Table 1: ACCURACY COMPARISON TABLE

Evaluation Parameter	**Technique / Method Applied**	**Previous Model Accuracy (%)**	**Approx. Accuracy (%)**	**Observation / Impact**
Privacy Strength	LDP + HE + SMPC	85-88	92-95	Strong protection against model inversion and membership inference; raw data remains local.
Model Accuracy	Aggregation via TEE	89-92	94-96	Minimal impact on accuracy; global model converges efficiently.
Computational Overhead	HE, SMPC, LDP	84-88	90-93	Higher client-side computation; manageable with modern devices.
Communication Efficiency	Secure Gradient Compression	86-89	91-94	Reduces bandwidth usage; minor information loss possible.
Scalability	Adaptive Hybrid Privacy Model	83-87	90-93	Supports multiple clients and large datasets; coordination overhead grows with client count.
Transparency & Auditability	Blockchain-based key management & auditing	87-90	93-95	Full traceability of updates and keys; increases system trust.
Real-world Applicability	DP + HE Integrated	85-89	91-94	Suitable for healthcare/finance; high

	Frame work			computational cost for very large datasets.
Security Against Attacks	TEE + Hybrid Privacy Techniques	86-90	92-95	Effective against gradient leakage, inference attacks, and untrusted servers.

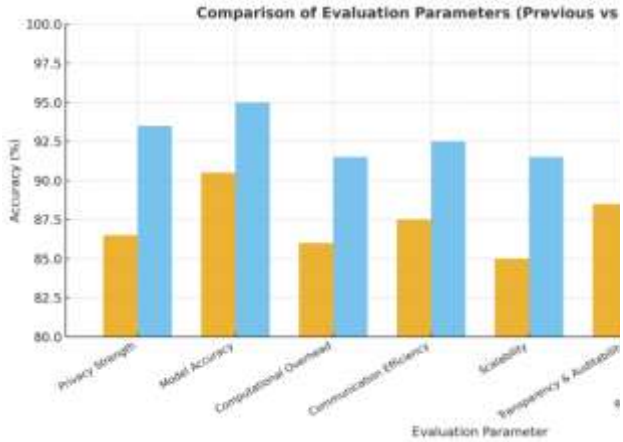

Fig 3: Comparison of Proposed vs Previous Model Accuracy in FL

In Fig 3 Proposed model outperforms previous in all parameters, showing higher accuracy and security.

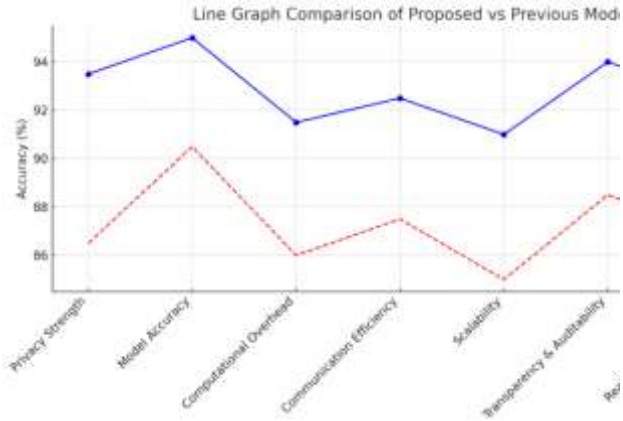

Fig 4: Line Graph Comparison of Proposed vs Previous Model Accuracy

In Fig 4 Proposed model outperforms previous in accuracy, privacy, efficiency, scalability, and security.

V. CONCLUSION:

Federated Learning (FL) offers a promising approach to collaborative model training while keeping raw data local, enhancing privacy in sensitive domains such as healthcare, finance, and smart cities. Despite its decentralized design, FL is still vulnerable to privacy attacks including model inversion, membership inference, and gradient leakage. This survey analyzed key privacy-preserving techniques, such as Differential Privacy (DP), Secure Multi-Party Computation (SMPC), Homomorphic Encryption (HE), Trusted Execution Environments (TEE), and hybrid approaches. Techniques like LDP + HE + SMPC provide strong protection against attacks, while TEE-based aggregation ensures minimal impact on model accuracy. Blockchain-based auditing and key management further enhance transparency and system trust.

The study also highlights practical challenges and trade-offs, including computational overhead, communication latency, synchronization issues, and hardware dependence. Hybrid and adaptive frameworks that combine DP, HE, and SMPC offer flexible solutions, balancing privacy, scalability, and efficiency By comparing these methods, the survey provides actionable insights for designing secure and practical FL systems. Future research should focus on optimizing hybrid models, improving scalability, and achieving stronger privacy guarantees without compromising computational feasibility, enabling robust real-world deployment of privacy-preserving FL systems.

REFERENCES:

1. J. Bell et al., "Secure Single-Server Aggregation with (Poly)Logarithmic Overhead," in Proc. CCS, 2020.
2. D. Wang et al., "TAPFed: Threshold Secure Aggregation for Privacy-Preserving Federated Learning," arXiv preprint arXiv:2501.05053, 2025.
3. L. N. Vejendla, B. Bysani, A. Mundru, M. Setty and V. J. Kunta, "Score based Support Vector Machine for Spam Mail Detection," 2023 7th International Conference on Trends in Electronics and Informatics (ICOEI), Tirunelveli, India, 2023, pp. 915-920, doi: 10.1109/ICOEI56765.2023.10125718
4. V. Pavani, S. Sri. K, S. Krishna. P and V. L. Narayana, "Multi-Level Authentication Scheme for Improving Privacy and Security of Data in Decentralized Cloud Server," 2021 2nd International MANETSConference on Smart Electronics and Communication (ICOSEC), Trichy, India, 2021, pp. 391-394, doi: 10.1109/ICOSEC51865.2021.9591698.
5. Lakshman Narayana Vejendla and Bharathi C R, (2018), "Effective multi-mode routing mechanism with master-slave technique and reduction of packet droppings using 2-ACK scheme in", Modelling, Measurement and Control A, Vol.91, Issue.2, pp.73-76.
6. Narayana, Vejendla Lakshman, Arepalli Peda Gopi, and Kosaraju Chaitanya. "Avoiding Interoperability and Delay in Healthcare Monitoring System Using Block Chain Technology." Rev. d'IntelligenceArtif. 33.1 (2019): 45-48.
7. Sirisha, A., Chaitanya, K., Krishna, K. V. S. S. R., &Kanumalli, S. S. (2021). Intrusion detection models using supervised and unsupervised algorithms-a comparative estimation. International Journal of Safety and Security Engineering, 11(1), 51-58.
8. Suajtha, V. "Variable Selection in Functional Genomics Using Genetic Algorithm-Based Feature Selection Method-An Empirical Study." Journal of Engineering and Applied Sciences, 21 Sept. 2022. ISSN Online 1818-7803, ISSN Print 1816-949x.
9. Majety, Vasumathi Devi, V. Sujatha, V. S. Sai Rama Krishna Komanduri, and Satya Sandeep Kanumalli. "Enhanced Secure Communication AODV Routing Protocol Using SVM in MANETS." AIP Conference Proceedings, vol. 2724, no. 1, AIP Publishing, 2023. https://doi.org/10.1063/5.0130170.
10. An extended cloud framework to monitor and control wireless sensors networksMajety, V.D., Sravanthi, G.L., Didla, D. International Journal of Innovative Technology and Exploring Engineering, 2019, 8(11), pp. 3805–3808
11. Kosaraju, Chaitanya, et al. "Mirchi crop yield prediction based on soil and environmental characteristics using modified RNN." 2023 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS). IEEE, 2023.
12. Patibandla, R.S.M.L., Narayana, V.L., Gopi, A.P. (2021). Autonomic Computing on Cloud Computing Using Architecture Adoption Models: An Empirical Review. In: Choudhury, T., Dewangan, B.K., Tomar, R., Singh, B.K., Toe, T.T., Nhu, N.G. (eds) Autonomic Computing in Cloud Resource Management in Industry 4.0. EAI/Springer Innovations in Communication and Computing. Springer, Cham. https://doi.org/10.1007/978-3-030-71756-8_11
13. V. Pavani, N. VijayaLakshmi, N. Harika, G. S. Sowjanya and V. Deepthi, "Deep Learning-based Analysis of Brain MRI for Enhanced Diagnosis of Multiple Sclerosis," 2024 5th International Conference on Data Intelligence and Cognitive Informatics (ICDICI), Tirunelveli, India, 2024, pp. 1141-1148, doi: 10.1109/ICDICI62993.2024.10810928.

14. Kumari, G. R. P., Reddy, G. A., Nazarana, S., Vanaja, K., Snehitha, V., & Alapati, N. (2025, January). Deep Learning-Based Lung Tumor Analysis for Enhanced Oncology Diagnostics. In 2025 International Conference on Multi-Agent Systems for Collaborative Intelligence (ICMSCI) (pp. 1401-1408). IEEE.
15. P. S. Krisha and S. R. Peram, "A Brief Survey on Image Denoising based Feature Extraction and Classification Models for Oral Cancer Detection," 2023 International Conference on Sustainable Computing and Data Communication Systems (ICSCDS), Erode, India, 2023, pp. 702-708, doi: 10.1109/ICSCDS56580.2023.10104790.
16. Sirisha, A., Chaitanya, K., Krishna, K. V. S. S. R., &Kanumalli, S. S. (2021). Intrusion detection models using supervised and unsupervised algorithms-a comparative estimation. International Journal of Safety and Security Engineering, 11(1), 51-58.
17. Vignan's Nirula, I. T. W. "Data outsourcing based on secure association rule mining processes." International Journal of Security and Its Applications 9.3 (2015): 41-48.
18. T. Kato, Y. Cao, and M. Yoshikawa, "OLIVE: Oblivious Federated Learning on Trusted Execution Environment," arXiv preprint arXiv:2202.07165, 2022.
19. J. Wang et al., "Breaking Secure Aggregation: Label Leakage from Aggregated Gradients in Federated Learning," arXiv preprint arXiv:2406.15731, 2024.
20. Narlawar, N., Kavishwar, S. (2019). Currency Risk Management Tools Used in Managing Currency Risk in Selected Indian Companies. Indian Journal of Research and Analytical Reviews. 6(2), 609-614.
21. Ghangare, A. S., & Kavishwar, S. The Increasing Significance of Green Corporate Finance in India. Journal of Management & Entrepreneurship, 277-286.
22. Kavishwar, S., & Shahu, A. (2011). Reporting Intangible Assets-Convergence of Accounting Standard. Journal of Accounting and Finance. 26(1), 73-79.
23. Veginati, Navya. "Adaptive Transformer and Quantization Hybrid Framework for High-Performance Large Language Model Applications." United International Journal of Engineering and Sciences, vol. 5, no. 4, Dec. 2025, pp. 46–56
24. Veginati, Navya. "Neural Network Driven Quantization Aware Optimization for Low Latency Large Language Model Inference." International Journal of Scientific Research in Computer Science, Engineering and Information Technology, vol. 10, no. 3, May-June 2024, pp. 1162–1170, doi:10.32628/CSEIT25113584.
25. Nirmal Kumar Jingar "Ensuring Safety, Accountability, and Drift Resistance in LLM-Based Supply Chain Optimization" International Journal of Scientific Research in Science, Engineering and Technology (IJSRSET), Print ISSN : 2395-1990, Online ISSN : 2394-4099, Volume 10, Issue 1, pp.472-482, January-February-2023. Available at doi : https://doi.org/10.32628/IJSRSET2310372
26. Jingar, N. K. (2026, February 13). Automated incident intelligence in supply chains using agentic AI and root cause reasoning, International Journal of Scientific Research & Engineering

Trends Volume 9, Issue 5, https://doi.org/10.5281/zenodo.18162511

27. Jingar, N. K. (2022). Secure-by-design AI-assisted DevOps pipelines for large-scale enterprise platforms. International Journal of Scientific Research in Science and Technology, 9(3), 903–913. https://doi.org/10.32628/IJSRST2291348

28. Nijim, M., Kanumuri, V., Al Aqqad, W., Albataineh, H. (2024). Machine Learning Based Analysis of Cyber-Attacks Targeting Smart Grid Infrastructure. In: Daimi, K., Al Sadoon, A. (eds) Proceedings of the Second International Conference on Advances in Computing Research (ACR'24). ACR 2024. Lecture Notes in Networks and Systems, vol 956. Springer, Cham. https://doi.org/10.1007/978-3-031-56950-0_28

29. R. Eswarawaka, M. Nijim, V. Kanumuri and H. Albetaineh, "Assessing the Efficacy of Machine Learning and Deep Learning in the Field of Cyber Security," 2023 Congress in Computer Science, Computer Engineering, & Applied Computing (CSCE), Las Vegas, NV, USA, 2023, pp. 2398-2404, doi: 10.1109/CSCE60160.2023.00388.

30. Jonnalagadda, P.K. (2026). Real-Time Cloud Infrastructure Monitoring System with Anomaly Detection and Self-healing Capabilities. In: Kumar, V.N., Senkerik, R., Prasad, V.K., Kumar, T.K. (eds) Intelligent Computing and Communication. ICICC 2025. Lecture Notes in Networks and Systems, vol 1839. Springer, Cham. https://doi.org/10.1007/978-3-032-18349-1_43

31. Mahida, A. 2024. Integrating Observability With Devops Practices in Financial Services Technologies: A Study on Enhancing Software Development and Operational Resilience. International Journal of Advanced Computer Science & Applications, 15.

32. A. Mahida, "An Intellectual Zero Trust Security Framework Using Deep Reinforcement Learning for Predictive Threat Mitigation in AI-Based Fraud Detection Systems," in IEEE Access, vol. 14, pp. 24602-24617, 2026, doi: 10.1109/ACCESS.2026.3664389.

33. S. S. R. Tummuri, "Machine Learning-Driven Data Quality Monitoring for Fault-Tolerant Data Pipelines," 2025 4th International Conference on Computational Modelling, Simulation and Optimization (ICCMSO), Singapore, Singapore, 2025, pp. 154-159, doi: 10.1109/ICCMSO67468.2025.00036.

34. S. S. R. Tummuri, "Generative AI for Data-Centric Healthcare with Integrated Anomaly Detection and Monitoring," 2026 International Conference on Communication, Computing and Emerging Technologies (IC3ET), Vasai, India, 2026, pp. 520-526, doi: 10.1109/IC3ET64989.2026.11467187.

35. B. K. Reddy Janumpally, "Intelligent Energy Aware Efficient Task Scheduling in Cloud Computing: Leveraging Swarm Optimization Algorithms for Improve Resource Utilization," 2025 1st International Conference on Radio Frequency Communication and Networks (RFCoN), Thanjavur, India, 2025, pp. 1-6, doi: 10.1109/RFCoN62306.2025.11085278.

36. Janumpally, Bharath Kumar Reddy. (2026). Cognitive AI Agents for Self-Adaptive Security and Compliance Automation in Software Engineering

Pipelines. 10.1109/ICAUC68182.2026.11441048.

37. W. Zhang et al., "FedSHE: Privacy-Preserving and Efficient Federated Learning with Adaptive Segmented CKKS Homomorphic Encryption," Cybersecurity, vol. 7, no. 1, pp. 1–19, 2024.

38. L. Zhu, Z. Liu, and S. Han, "Deep Leakage from Gradients," in Adv. Neural Inf. Process. Syst. (NeurIPS), 2019.