REVIEW OF "FEDERATED LEARNING APPLICATIONS, CHALLENGES AND FUTURE DIRECTIONS"

This review critically evaluates "Federated Learning: Applications, Challenges, and Future Directions" by Bharati et al. (2022), a comprehensive survey on the principles, architectures, and applications of federated learning (FL), with a focus on privacy-preserving mechanisms and healthcare use cases. The article's scientific value lies in its structured synthesis of foundational FL concepts. However, several critical gaps are identified, including the lack of discussion on emerging topics such as fairness, personalization, communication-efficient learning, and real-world deployment strategies. This review suggests specific improvements, including the incorporation of empirical algorithmic comparisons, real-world case studies (e.g., Google-SWIFT, Toyota, and Cambridge/NVIDIA collaborations), and recent advances in FL optimization. The report concludes that while Bharati et al.'s article remains a valuable introduction to FL, its future utility depends on addressing newer developments that reflect the rapidly evolving FL landscape. Overall, the work successfully highlights FL's potential as a transformative, privacy-conscious AI paradigm, but requires further refinement to maintain its relevance in ongoing applied research.

Keywords: *Federated Learning, Privacy-Preserving Machine Learning, Distributed Learning, FL Architectures, Collaborative AI, Data Privacy*

AMS 2020 classification:

Introduction

Federated learning (FL) is a decentralized approach to machine learning that enables multiple participants to collaboratively train models without sharing their raw data, thereby addressing significant concerns related to data privacy and security. Notably applicable in sectors like healthcare and finance, FL allows organizations to leverage sensitive information while complying with stringent regulatory frameworks.

1. Summary

The method has gained prominence due to its ability to enhance predictive model accuracy while preserving the confidentiality of individual data sources, making it particularly advantageous in environments where data sharing is restricted by law or ethical considerations(Syed Raza Abbas & Lee, 2023). Figure 1 shows the workflow how a FL-trained model progresses through a federated learning system's stages.

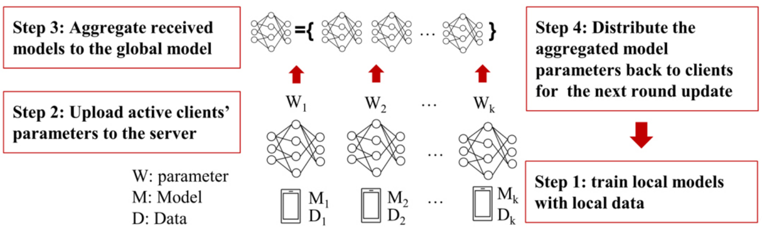

Fig. 1. FL system workflow

The integration of FL within healthcare systems, for instance, has transformed patient data handling and analysis. By utilizing Internet of Things (IoT) devices such as wearables and remote monitoring tools, healthcare providers can gather and analyze real-time health metrics without compromising patient privacy. Similarly, in financial services, FL facilitates applications such as fraud detection and credit scoring, allowing institutions to identify patterns across decentralized data while maintaining compliance with privacy regulations(Brodowicz, 2025). However, the implementation of FL is not without challenges; issues such as communication overhead, data heterogeneity, security vulnerabilities, and scalability concerns can hinder its effectiveness and broader adoption. Looking forward, ongoing research is focused on enhancing the privacy mechanisms and scalability of FL systems, with a particular emphasis on developing advanced communication protocols and lightweight models suitable for resource-constrained environments(Mohamed Rafik Aymene Berkani, 2025). As the landscape of federated learning continues to evolve, interdisciplinary collaboration among data scientists, healthcare professionals, regulatory bodies, and technology developers is crucial for addressing practical challenges and ensuring ethical deployment of FL technologies across various domains(Md Shahin Ali, 2024). Addressing these issues is vital for realizing the full potential of federated learning and for driving its future advancements in real-world applications(Weiming Zhuang, 2023).

2. Scientific Value

Bharati et al. present a comprehensive survey of federated learning (FL) systems, with a particular focus on healthcare applications(Bharati, Mondal, Podder, & Prasath, 2022). The paper clearly defines FL as a distributed learning paradigm where a central server aggregates updates from multiple clients while keeping training data localized. It systematically reviews FL frameworks, architectures, and classes (horizontal, vertical, and transfer FL), as well as privacy-enhancing techniques (secure multi-party computation, homomorphic encryption, differential privacy, etc.) and applications ranging from wireless communications to medical diagnosis(Bharati et al., 2022). This breadth makes the article a valuable introduction for newcomers to FL, especially in applied health contexts. Moreover, its 35-page length and structured presentation with figures contribute to its clarity. The article was published in International Journal of Hybrid Intelligent Systems (vol. 18, no. 1–2, 2022)(Bharati et al., 2022), ensuring it underwent peer review. Its official citation details and DOI (10.3233/HIS-220006) are documented on arXiv(Bharati et al., 2022). In terms of reception and impact, this work has been cited within the research community. According to Google Scholar, it has over 100 citations as of 2025 (Scholar, 2025), indicating that subsequent surveys and studies reference it. For example, a recent survey on FL in healthcare and disease prediction explicitly lists Bharati et al. as a key reference(Moshawrab, 2023). The citation count reflects the article's relevance as a go-to summary of FL concepts. While the article itself does not report new empirical results, its scholarly value lies in synthesizing diverse FL developments up to mid-2022. Industry interest in FL has also surged (e.g., collaborative projects by Google, NVIDIA, Toyota, etc.), underscoring the timeliness of the survey's publication. In summary, Bharati et al.'s paper provides an accessible, well-organized overview of FL, contributing a useful literature synthesis that has been embraced by academia and signals the importance of privacy-preserving AI in practice.

3. Gaps

Despite its thoroughness, the article has some notable omissions. In particular, it does not address certain emerging aspects that have become important in FL research. For instance, concerns about fairness in federated learning are not discussed. Contemporary literature highlights group fairness and bias issues in FL, showing that naïvely aggregated models can underperform on underrepresented groups. Recent surveys explicitly classify fairness as a key FL research direction(Huang, 2023), but Bharati et al. make no mention of fairness frameworks or metrics. Similarly, personalization – tailoring models to individual client data – is another active area not covered. The authors do not explore personalized FL techniques (e.g. multi-task learning, meta-learning approaches) that improve per-client performance in heterogeneous environments. The paper also provides only a general acknowledgment of communication costs and does not delve into optimization strategies. For example, Konečný et al. (2016) showed that uplink communication overhead can be reduced by two orders of magnitude using techniques like structured (low-rank) and quantized updates(Konečný, 2016). Such quantitative results on communication-efficient protocols are absent from Bharati et al., even though communication efficiency is listed as a challenge in the abstract. In short, recent technical advancements in compression and learning stability (e.g. FedProx) are omitted. Finally, the article's focus on conceptual overview means it lacks concrete real-world deployment details. It surveys applications conceptually (in healthcare, IoT, etc.) but does not include case studies of actual FL implementations. These gaps suggest that, while the paper is a solid introductory review, it does not cover the latest advances in personalization, fairness, or system optimization that have gained prominence after its writing(Huang, 2023)(Konečný, 2016).

4. Potential Improvements

To strengthen the article, several additions could be made. First, comparative technical evaluations of FL algorithms would add rigor. For example, Konečný et al. demonstrated concrete benefits of communication reduction strategies by experiments on neural networks(Konečný, 2016). Including such empirical comparisons (e.g. FedAvg vs. compressed-update FL) would help illustrate trade-offs between methods. Real-world implementation examples would also enhance the paper. The authors could describe proof-of-concept projects and pilot studies to ground their discussion. Notably, Toyota Motor Corporation has collaborated on an FL pilot for electric vehicle battery range estimation, finding that personalized FL models not only improved prediction accuracy but also required an order of magnitude less communication and computation than centralized learning(Toyota & TensorOpera, 2024). Similarly, Google Cloud and SWIFT are partnering on a federated anti-fraud project for cross-border payments; they plan a multi-institution sandbox involving 12 banks to prototype FL-based fraud detection(Cloud & SWIFT, 2025). These commercial case studies would illustrate FL's industrial impact. In healthcare, recent large-scale studies could be highlighted. Pati et al. (2023) conducted a global FL study across 71 sites (over 6 continents) to improve glioblastoma tumor boundary detection; their federated model achieved 33% better delineation than a model trained on public data(Pati, 2023). Likewise, a Cambridge University–NVIDIA collaboration (the EXAM study) used FL on data from 10,000 COVID-19 patients worldwide to predict oxygen needs; this effort validated that FL can produce robust global models without compromising patient privacy(Cambridge, 2021). Incorporating these examples would emphasize FL's success in practice. Finally, citing other foundational FL surveys (e.g. FedAvg and FedProx) and benchmark studies would provide context. For instance, FedAvg's significance was established early in FL research, and FedProx addresses client heterogeneity. By comparing such algorithms and their evaluated performance, the authors could offer a more nuanced, quantitative perspective. Overall, adding discussions of these comparative studies, real deployments, and commercial projects - Toyota EVs(Toyota & TensorOpera, 2024), Google-SWIFT finance(Cloud & SWIFT, 2025), Cambridge/NVIDIA healthcare(Cambridge, 2021) would greatly enrich the article and bridge it to ongoing applied work.

5. Conclusion

In conclusion, Bharati et al. deliver a thorough review of federated learning as understood in 2022, particularly valuable for its clear exposition of privacy mechanisms and FL categories. The article successfully compiles the state of the art at that time, making it a useful resource. However, as federated learning continues to advance, future relevance will depend on updates in personalization and fairness. The paper's core message—that FL enables collaborative model training without sharing raw data—remains important. This significance is underscored by real-world initiatives: for example, Google and SWIFT's joint work on FL-powered fraud detection(Cloud & SWIFT, 2025) and Cambridge/NVIDIA's EXAM project for COVID-19 prediction(Cambridge, 2021) demonstrate FL's transformative impact across industries. My takeaway is that while the article accurately captures the privacy-centric promise of FL, the field is rapidly evolving. Federated learning addresses critical needs in applied AI by allowing organizations to pool data under privacy constraints, and thus it continues to be a pivotal paradigm. As Dr. Mona Flores of NVIDIA noted, FL "allows researchers to collaborate" on global AI problems and will "advance AI not just for healthcare but across all industries" by yielding robust models without sacrificing privacy(Cambridge, 2021). This underscores why federated learning is a significant and growing topic in applied machine learning.

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РЕФЕРУВАННЯ СТАТТІ "ФЕДЕРАТИВНЕ НАВЧАННЯ: ЗАСТОСУВАННЯ, ВИКЛИКИ ТА МАЙБУТНІЙ НАПРЯМОК"

У цьому огляді критично оцінюється стаття «Федеративне навчання: застосування, виклики та майбутні напрямки» Бхараті та ін. (2022), комплексне дослідження принципів, архітектур та застосувань федеративного навчання (ФН) з акцентом на механізми збереження конфіденційності та випадки використання в охороні здоров'я. Наукова цінність статті полягає в її структурованому синтезі фундаментальних концепцій ФН. Однак виявлено кілька критичних прогалин, зокрема відсутність обговорення нових тем, таких як справедливість, персоналізація, комунікаційно-ефективне навчання та стратегії розгортання в реальному світі. У цьому огляді пропонуються конкретні вдосконалення, включаючи додавання емпіричних алгоритмічних порівнянь, тематичних досліджень з реального світу (наприклад, співпраця Google-SWIFT, Toyota та Cambridge/NVIDIA) та останніх досягнень в оптимізації ФН. У звіті робиться висновок, що хоча стаття Бхараті та ін. залишається цінним вступом до ФН, її майбутня корисність залежить від врахування новіших розробок, які відображають швидкозмінний ландшафт ФН. Загалом, робота успішно підкреслює потенціал ФН як трансформаційної парадигми штучного інтелекту, що свідомо ставиться до конфіденційності, але потребує подальшого вдосконалення, щоб зберегти свою актуальність у сучасних прикладних дослідженнях.

Ключові слова: ***федеративне навчання (FL), машинне навчання із збереженням конфіденційності, розподілене навчання, архітектури FL, колаборативний штучний інтелект, конфіденційність даних***

Автори заявляють про відсутність конфлікту інтересів. Спонсори не брали участі в розробленні дослідження (у зборі, аналізі чи інтерпретації даних, якщо це мало місце), у написанні рукопису та в рішенні про публікацію результатів.

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