Review

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Review

Toward Real-World Deployment of Federated Learning in Healthcare: A Comprehensive Review of Hybrid Models and Data Simulation Tools

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Abstract

This review synthesizes recent advancements in federated learning (FL) frameworks tailored for sensitive domains such as mental healthcare, medical imaging, and non-IID data simulation. Some past study presents a hybrid privacy-preserving FL model that integrates clustered federated learning (CFL) and quantum federated learning (QFL) to enhance accuracy and privacy in stress detection using wearable devices. Other studies introduce FedArtML, a novel tool for generating controlled non-IID datasets, offering quantifiable metrics like Jensen–Shannon and Hellinger distances to assess data heterogeneity. Furthermore, some of the latest paper proposes a transfer learning-based FL architecture for breast cancer classification using mammography images, combining feature extraction with federated averaging to ensure privacy and robust diagnostic accuracy. Collectively, these works address key challenges in FL, including client heterogeneity, data imbalance, privacy preservation, and system performance. This review highlights the complementary strengths of hybrid architectures, synthetic data partitioning, and transfer learning in advancing real-world applications of federated learning in healthcare.

Keywords: data simulation; federated learning

Introduction

Federated Learning (FL) has emerged as a groundbreaking machine learning paradigm [1–4] designed to train models collaboratively across decentralized devices or servers while ensuring data remains localized. This approach has revolutionized the way sensitive information, especially in healthcare and biomedical domains [5–8], is utilized for model training without compromising patient privacy. The traditional centralized learning paradigm involves aggregating data from diverse sources into a single location, which often leads to concerns around data breaches, legal compliance, and ethical responsibilities. FL, in contrast, offers a privacy-respecting alternative by transmitting model updates rather than raw data, ensuring sensitive information stays with the data owners. However, despite its theoretical advantages, FL faces significant challenges in practical implementation, including handling non-independent and identically distributed (non-IID) data, ensuring communication efficiency, achieving robust model convergence, and preserving privacy across heterogeneous systems. Recent advancements have introduced hybrid models [9,10] and supporting tools to address these gaps, as seen in the latest research efforts focusing on mental healthcare monitoring, controlled non-IID dataset generation, and federated transfer learning [11] for disease detection.

Some studies present a privacy-preserving hybrid FL framework [12–17] tailored for mental healthcare applications. This framework combines Clustered Federated Learning (CFL) and Quantum Federated Learning (QFL) [18–20] to enhance model accuracy, personalization, and data

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protection. CFL groups clients based on model update similarities using hierarchical clustering, reducing communication overhead while improving convergence speed. QFL, on the other hand, integrates a variational quantum classifier that leverages quantum computing principles for classification tasks. The novel angle encoding strategy used to map classical data into quantum states allows for high-dimensional data representation and improved classification accuracy. The framework is particularly suited for wearable-based stress detection scenarios, where sensitive physiological signals are processed at the edge using FL without centralizing data. The experimental results from the study demonstrate that both CFL and QFL significantly outperform conventional FL, particularly in terms of recall and precision, thereby offering practical solutions for real-world deployment in mental health monitoring systems. In parallel, some research effort [21–24] addresses one of the fundamental problems in federated settings—data heterogeneity or non-IID distribution across clients. Real-world federated datasets, especially in cross-silo applications such as hospital networks or distributed medical centers, are often imbalanced and non-uniform. This non-IID nature can lead to slow convergence, biased models, and degraded performance. The study introduces FedArtML, an open-source Python library [25–29] specifically designed to simulate and quantify non-IID data distributions for federated learning research. FedArtML employs advanced partitioning techniques such as Hist-Dirichlet [30–33] and Min-Size-Dirichlet and introduces heterogeneity quantification metrics like Jensen-Shannon Distance (JSD) and Hellinger Distance (HD). These metrics help evaluate the degree of distribution divergence among clients, allowing researchers to systematically test FL algorithms under controlled and replicable non-IID settings. The tool bridges the gap between theoretical algorithm development and real-world testing, enabling reproducibility and deeper understanding of FL dynamics in heterogeneous environments.

Other research papers [34–37] reviewed contributes to the growing body of FL research in medical imaging, particularly focusing on breast cancer classification. This study proposes a transfer learning-enhanced FL architecture where feature extraction is performed locally using pre-trained deep learning models such as MobileNet and CNNs [38–40]. The proposed model architecture is evaluated on mammography images from the DDSM dataset [41] and incorporates SMOTE (Synthetic Minority Oversampling Technique) to address class imbalance. The key advantage of the approach lies in its ability to leverage learned representations from large-scale datasets, enabling faster convergence and higher classification accuracy even in limited local data settings. The federated averaging (FedAvg) algorithm is utilized to aggregate the local model updates into a global model, which is then iteratively refined across multiple communication rounds. The experimental results [42–45] show significant improvements in recall and F1-score, demonstrating that FL, when coupled with transfer learning and data augmentation strategies, is a viable solution for privacy-sensitive medical image analysis. Taken together, these studies represent a coherent evolution in the application of federated learning technologies for healthcare. While each paper targets a specific limitation—privacy preservation, data heterogeneity, or small-data learning—they collectively build toward a comprehensive and scalable FL ecosystem. The integration of hybrid models (classical and quantum), synthetic data generation frameworks, and domain-specific enhancements like transfer learning exemplifies the multi-faceted innovation required to bring FL from theory to practice. Furthermore, these advancements reflect a broader shift in artificial intelligence [46] toward ethically aligned and human-centered computing, where technological capabilities are developed in parallel with safeguards for privacy, fairness, and accountability. This review aims to consolidate the key findings from these papers, compare their methodologies, and examine their applicability across various domains of healthcare. It will explore the architectural innovations, algorithmic adaptations, and experimental outcomes that distinguish each approach while identifying common themes and future opportunities. By analyzing these diverse yet interrelated contributions, the review offers a comprehensive outlook on the state of federated learning in critical applications [47], with particular attention to its role in enabling secure, decentralized, and intelligent health systems.

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Methodologies

The methodologies employed across many reviewed research papers reflect a spectrum of innovative strategies tailored to overcome key limitations of federated learning (FL), especially in privacy-sensitive and heterogeneous environments. These methodologies span hybrid architectures that fuse classical and quantum approaches, dataset partitioning techniques for simulating non-IID data, and transfer learning mechanisms within FL pipelines. Each paper introduces a distinct methodological framework, designed with specific domain constraints in mind—mental healthcare, federated dataset simulation, and breast cancer diagnosis. Despite the varied contexts, all these works emphasize model personalization, decentralized training, and data privacy as central pillars of their methodological contributions. In the study focused on mental healthcare, the authors proposed a Hybrid Federated Learning (HFL) framework that consists of two core components: Clustered Federated Learning (CFL) and Quantum Federated Learning (QFL). The CFL approach segments clients based on the similarity of their local model weight updates. To do this, hierarchical agglomerative clustering is applied to the gradients shared during federated training. Clients that exhibit similar learning behaviors are grouped into clusters, and separate models are trained for each group. This hierarchical clustering ensures that model personalization is achieved without compromising the federated nature of the system. The clustering is performed using Euclidean or Manhattan distance metrics on the client gradient space, followed by average-linkage to determine cluster hierarchy. Once clustered, each group undergoes a localized FL process using the Federated Averaging (FedAvg) algorithm, resulting in cluster-specific models. These models are finally aggregated using a weighted strategy to produce a generalized global model. The QFL component of the same study incorporates quantum machine learning techniques, specifically employing a Variational Quantum Classifier (VQC). In this method, classical data is encoded into quantum states using angle encoding, where each data feature is mapped to the rotation angle of a qubit. The VQC architecture then utilizes a series of parameterized quantum gates and entangling layers to perform classification in the quantum domain. During training, quantum gradients are computed using the parameter-shift rule, and a classical optimizer such as Adam is employed to update circuit parameters. The quantum classifier is trained locally on each client's dataset and the updated quantum parameters are shared with the server for federated aggregation. This approach is particularly suitable for stress detection from physiological signals collected by wearable devices, where high-dimensionality and privacy concerns demand both expressive power and decentralized computation. The authors validated their framework using both IID and non-IID data settings and demonstrated superior performance in recall and precision compared to conventional FL.

In some research studies [48,49], the primary methodological focus is the design and implementation of FedArtML, a simulation toolkit that enables controlled generation of non-IID federated datasets. The tool provides two novel partitioning algorithms: Hist-Dirichlet and Min-Size-Dirichlet, both of which use Dirichlet distributions to allocate data heterogeneously across simulated clients. In the Hist-Dirichlet method, data is partitioned by considering histogram bins of feature distributions, allowing simulation of feature-skewed non-IIDness. The Min-Size-Dirichlet variant ensures that each client receives a minimum number of samples, addressing imbalanced data distributions. Beyond partitioning, the authors introduce two statistical metrics—Jensen-Shannon Distance (JSD) and Hellinger Distance (HD)—to quantify the level of heterogeneity between client data distributions. These metrics are computed on label and feature distributions and can be averaged across client pairs to give an overall non-IID score for a dataset. The FedArtML library also supports traditional label-skew and quantity-skew simulation. In the label-skew setting, classes are unevenly distributed across clients using Dirichlet-distributed label probabilities. For quantity-skew, the amount of data assigned to each client is varied using a separate Dirichlet distribution. Additionally, the tool integrates with existing FL frameworks and includes a visualization module that generates histograms, heatmaps, and distribution plots to help users assess data skewness. The authors validated the toolkit [50–53] by simulating ECG arrhythmia detection datasets from Physionet 2020 and demonstrated that datasets generated with FedArtML exhibited heterogeneity patterns closely

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aligned with those seen in real-world federated environments. The use of quantitative metrics ensures that FL models can be rigorously evaluated under well-defined non-IID conditions. In other papers [54,55], the methodological emphasis is placed on integrating Transfer Learning (TL) into FL for the classification of breast cancer mammography images. The proposed pipeline begins with a set of client devices (e.g., hospitals or radiology centers), each of which holds a small subset of mammogram images. A pre-trained convolutional neural network (CNN), such as MobileNet, is deployed on each client as a feature extractor. These networks are fine-tuned locally using the client's data while freezing earlier layers to retain general features. Following local training, the updated model weights—typically the top dense layers—are transmitted to a central server. The server then uses Federated Averaging (FedAvg) to aggregate the weights across all participating clients and generates a global model. To address data imbalance, which is common in medical image datasets, the authors use the Synthetic Minority Over-sampling Technique (SMOTE) at the local level. This oversampling method [56] generates synthetic instances of minority class images by interpolating between existing samples. By applying SMOTE before each round of FL, clients ensure that the model is not biased toward the majority class. Furthermore, model evaluation is conducted using metrics such as accuracy, recall, precision, and F1-score, which are critical in medical diagnostics where false negatives can have severe consequences. The experimental setup involves multiple rounds of communication between clients and the server, simulating a real-world federated healthcare scenario. The resulting model [57,58] shows robust performance even under data heterogeneity, validating the effectiveness of combining TL and FL.

Collectively, the methodologies presented in these studies reveal a multi-dimensional approach to advancing FL. By integrating clustering algorithms, quantum computing, statistical simulation tools, and deep transfer learning [59,60], these frameworks offer solutions to some of the most pressing challenges in decentralized machine learning. Each method is tailored to its specific use case but contributes valuable components—such as metric-based heterogeneity analysis, quantum-enhanced classification, and domain-adapted feature reuse—that can be generalized across broader FL applications.

Comparative Analysis

The reviewed studies present diverse yet complementary approaches to addressing core challenges in federated learning (FL). These include privacy preservation, client data heterogeneity, limited local data availability, and performance degradation in non-IID settings. While each work proposes unique methodological solutions, a comparative analysis reveals underlying connections in design goals, architectural choices, and their potential to advance the deployment of FL in sensitive real-world domains such as healthcare. In this section, we analyze their contributions across several key dimensions: privacy and data locality, model personalization and performance, treatment of non-IID data, and adaptability to domain-specific challenges. Privacy and Data Locality form the cornerstone of all these works. The hybrid FL framework for mental healthcare stands out for its direct emphasis on privacy through its architecture. The authors propose both Clustered Federated Learning (CFL) and Quantum Federated Learning (QFL) as mechanisms to minimize data exchange while enhancing learning efficacy. CFL achieves this by grouping clients into clusters with similar training behavior, thereby reducing the breadth of model exchange and communication. QFL enhances privacy further by encoding data into quantum states and utilizing Variational Quantum Classifiers (VQCs), which inherently mask the original data. On the other hand, the transfer learning-based approach for breast cancer diagnosis ensures privacy by conducting all feature extraction locally on clients using pre-trained models, and only exchanging learned weights. Similarly, the FedArtML tool emphasizes privacy in the context of benchmarking by simulating non-IID distributions without using real patient data, thus serving as a privacy-conscious tool for algorithm development and testing. Model Personalization and Performance are addressed differently in each study. The hybrid framework leverages clustering to tailor models to similar clients, creating semi-personalized models that strike a balance between generalizability and specialization. This hierarchical aggregation enhances performance in data-heterogeneous environments. Additionally, QFL enables models to harness high-dimensional data structures through quantum encoding, yielding notable improvements in recall and classification accuracy. In contrast, the breast cancer study utilizes transfer learning, which allows clients to fine-tune a shared pre-trained model to their own data, offering inherent personalization. This method performs exceptionally well in domains like medical imaging, where annotated data is scarce but visual patterns are transferable. FedArtML does not propose a learning model per se but instead focuses on quantifying the effects of different levels of personalization and heterogeneity. Its utility lies in its ability to generate benchmark datasets that allow other researchers to rigorously test personalization strategies across varying data distributions.

When analyzing the treatment of non-IID data, each paper introduces a specialized strategy. The FedArtML framework is the most explicit and systematic, providing metric-based tools (e.g., Jensen-Shannon Distance and Hellinger Distance) to measure the extent of non-IID-ness. By simulating feature, label, and quantity skew using Dirichlet-based distributions, FedArtML allows for controlled experimentation that is difficult to achieve with real-world datasets. The hybrid FL study indirectly addresses non-IID challenges by clustering clients with similar update patterns, thus mitigating the negative impact of client diversity on global convergence. Meanwhile, the breast cancer FL study copes with non-IID settings by using transfer learning to inherit general features from a global model while allowing clients to adapt to their unique data. Though not as explicitly controlled as FedArtML, this method performs robustly in low-data, high-variance environments typical of distributed medical datasets.

A comparison of computational complexity and scalability reveals trade-offs. The hybrid approach, particularly with QFL, introduces higher complexity due to the need for quantum hardware or quantum simulators. While this offers performance benefits, it limits scalability in current practical deployments. CFL also introduces an additional clustering step, increasing computational overhead at the server. In contrast, the transfer learning approach is relatively lightweight. It reuses pre-trained models and requires only partial fine-tuning, making it more scalable across resource-constrained healthcare institutions. FedArtML, being a simulation and benchmarking tool, scales efficiently and is highly adaptable across domains, although it does not directly contribute to performance improvements in active FL deployments. Finally, in terms of domain adaptability and experimental validation, all studies provide strong real-world relevance. The hybrid FL model targets wearable-based stress detection in mental healthcare, an area with growing demand and privacy sensitivity. The breast cancer diagnosis study applies FL in medical imaging, a critical domain where annotated data is both private and scarce. FedArtML, while not specific to one domain, enables reproducibility and controlled experimentation, which is crucial for validating FL algorithms in any application area. Notably, all our reviewedpapers use publicly available datasets (e.g., Physionet for ECG data, DDSM for mammograms) and follow transparent experimental procedures, increasing the credibility and generalizability of their findings. In summary, these studies are not competitive but rather complementary. The hybrid model pushes the boundaries of privacy and algorithmic innovation through clustering and quantum computation. The transfer learning FL approach emphasizes lightweight, practical deployment in data-scarce settings. FedArtML fills a critical infrastructure gap by enabling rigorous, reproducible testing in non-IID settings. Together, they form a robust foundation for the next generation of federated learning systems, especially in healthcare applications that demand personalization, privacy, and reliability.

Discussion

The confluence of methodologies and insights presented in the reviewed studies demonstrates the rapidly evolving landscape of federated learning (FL) research, particularly in high-stakes and privacy-sensitive domains such as healthcare. One of the most significant takeaways is the realization that FL is no longer a monolithic solution; rather, it is being refined and adapted through hybrid architectures, simulation tools, and domain-specific integrations to meet real-world requirements.

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This evolution reflects the need for FL systems that not only protect privacy but also ensure high model performance in the face of data heterogeneity, limited local data availability, and computational constraints. The reviewed works serve as exemplars of this trend, each addressing critical challenges with innovative yet complementary strategies. The hybrid FL framework for mental healthcare is particularly noteworthy for its layered approach. By integrating clustering and quantum computing, the authors demonstrate that it is possible to overcome some of FL's longstanding limitations, such as poor convergence on non-IID data and insufficient personalization. The success of Clustered Federated Learning (CFL) lies in its ability to reduce the negative influence of outlier clients during aggregation, while Quantum Federated Learning (QFL) introduces a forward-looking perspective by exploring quantum-enhanced classification. However, the implementation of QFL in real-world settings remains limited due to the current maturity of quantum hardware. Therefore, while promising, this approach may find initial applications in research settings or in hybrid systems where quantum simulators are used alongside classical computation.

The FedArtML tool, while not a learning model, addresses a foundational problem in FL research—how to simulate and measure heterogeneity in data distributions. The introduction of statistical metrics such as Jensen-Shannon Distance and Hellinger Distance is a crucial contribution, offering researchers a way to quantify and systematically evaluate non-IID effects across different FL algorithms. This enhances the rigor and reproducibility of FL studies and helps isolate the effects of skew types (label, feature, quantity) on model performance. More importantly, by supporting controlled experimentation, FedArtML serves as a bridge between theoretical FL research and practical implementation, making it a valuable asset for algorithm benchmarking and validation. Meanwhile, the transfer learning-based FL framework for breast cancer classification illustrates the practicality of FL when adapted with lightweight, domain-appropriate strategies. By leveraging pre-trained models for local feature extraction, this approach effectively circumvents the issue of small datasets at each client node. The use of SMOTE to address class imbalance further boosts model robustness, highlighting the importance of integrating classic machine learning techniques into FL pipelines. This study showcases the viability of FL in medical imaging scenarios where data cannot be centralized due to privacy regulations or logistical limitations. Despite their differences, all research studies converge on a few key themes: the importance of personalization, the need for tools that simulate real-world heterogeneity, and the value of interdisciplinary integration—be it through quantum computing or transfer learning. Together, they provide a comprehensive picture of the current state and potential of federated learning, illustrating how diverse innovations are paving the way for FL systems that are both secure and performant.

Conclusions

In Federated Learning (FL) represents a transformative approach in machine learning, enabling collaborative model training while maintaining data privacy and security across decentralized environments. This review examined many impactful studies that advance the state of FL through innovations in hybrid architectures, data heterogeneity simulation, and domain-specific model adaptations. Collectively, these studies illuminate the multifaceted challenges and opportunities in deploying FL for sensitive applications such as mental healthcare monitoring, synthetic data generation for FL benchmarking, and breast cancer detection using medical imaging. Each work contributes unique solutions, yet their synergy paints a coherent roadmap for the evolution of federated learning from theoretical concept to practical reality. The hybrid FL framework integrating Clustered Federated Learning (CFL) and Quantum Federated Learning (QFL) demonstrates that privacy-preserving and high-accuracy models can be developed even in highly heterogeneous environments. CFL provides a pathway to address personalization by clustering clients with similar training dynamics, which not only improves convergence but also reduces communication overhead. QFL, though still in the experimental phase due to hardware limitations, presents a promising frontier for enhancing FL with quantum computational advantages, particularly in handling high-dimensional physiological data from wearable devices. This combination represents a forward-

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thinking strategy that blends classical robustness with quantum potential, setting a benchmark for privacy-aware learning in mental health applications. On the other hand, the FedArtML tool addresses a fundamental bottleneck in FL research—the lack of publicly available federated datasets that accurately reflect real-world non-IID distributions. By offering a flexible and open-source solution to simulate various types of data skew (label, feature, and quantity), and introducing quantifiable metrics like Jensen–Shannon Distance and Hellinger Distance, FedArtML empowers researchers to evaluate the robustness and fairness of FL algorithms systematically. Its value extends beyond simulation; it standardizes the benchmarking process and enables reproducibility, making it an essential tool for both academic research and industrial prototyping. The third study, focused on breast cancer classification using transfer learning in FL, exemplifies how pre-trained deep learning models can be effectively integrated into FL pipelines to compensate for limited local data and computational resources. By utilizing transfer learning at the client level, the approach reduces the need for large-scale data while retaining high diagnostic accuracy. The use of SMOTE for addressing class imbalance further strengthens model generalization. This method is especially relevant in medical imaging, where high-quality annotated data is scarce, and data-sharing regulations are stringent. It underscores the importance of adapting FL to domain-specific constraints while leveraging advances in deep learning. Taken together, these studies reinforce the notion that federated learning is not a one-size-fits-all solution but a customizable paradigm that must be tailored to specific applications, data structures, and system constraints. The convergence of methodologies—quantum computing, synthetic benchmarking, and transfer learning—illustrates a growing trend toward interdisciplinary solutions in FL. This integrative approach enhances not only the performance of federated models but also their ethical alignment with privacy and fairness standards, which are crucial in sectors like healthcare.

Looking ahead, several future research directions emerge from this review. First, there is a need to further explore the practical deployment of quantum-enhanced FL, particularly in low-resource or embedded systems. The scalability and stability of QFL algorithms remain an open area of investigation, especially in terms of real-time inference and integration with classical models. Second, while tools like FedArtML offer excellent simulation capabilities, future iterations could incorporate dynamic non-IID behaviors, such as time-varying client distributions or concept drift, to reflect more realistic deployment scenarios. Enhancing the toolkit to support spatiotemporal heterogeneity would enable researchers to study the long-term adaptability of FL systems. Third, transfer learning in FL could be extended to multimodal and cross-domain datasets, allowing models to generalize across institutions or even across different types of diagnostic imaging. Coupling FL with explainable AI (XAI) techniques could also provide interpretability to clinical stakeholders, improving trust and adoption in medical settings. Additionally, regulatory and ethical considerations must continue to guide FL development, particularly in how data anonymization, consent, and fairness are enforced across federated networks. In conclusion, the reviewed works collectively reflect the maturity and dynamism of current federated learning research. Through novel architectures, rigorous simulation tools, and practical medical applications, these studies pave the way for secure, efficient, and adaptive FL systems. As the field continues to evolve, future research should aim to bridge the gap between experimentation and deployment, ensuring that FL not only protects data privacy but also delivers equitable, accurate, and explainable outcomes across a wide range of domains.

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