Federated Learning on Cloud Platforms: Privacy-Preserving AI for Distributed Data

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Abstract

Federated learning has also become a paradigm shift to making machine learning collaborative and not centralized around sensitive data. Federated learning solves the increasing privacy, regulatory compliance, and data sovereignty concerns by preventing the transfer of model training to centralized model training clients, like hospitals, financial institutions, and IoT devices. Cloud platforms are critical to the operationalization of this paradigm as it offers scalable orchestration, secure aggregation, and communication-efficient frameworks. The paper discusses how cloud-native federated learning systems decrease the amount of communication, enhance the model convergence, and provide more robust privacy guarantees without violating regulation of systems like GDPR and HIPAA. By applying federated learning to the medical diagnostic and financial fraud detection domains, the study shows that federated learning can be successful in providing a high level of model accuracy and strong privacy protection. The results indicate the significance of supporting federated learning by cloud-native infrastructure that will allow implementing privacy-safe AI solutions that can be widely adopted in regulated industries.

Keywords: Federated Learning, Cloud Platforms, Privacy-Preserving AI, Distributed Data, Secure Aggregation, GDPR, HIPAA, Healthcare AI, Financial Fraud Detection, Cloud-Native Architectures

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Introduction

The growing use of artificial intelligence (AI) in industries, including healthcare, finance, and the Internet of Things (IoT), has increased worries over data privacy, regulatory legal requirements,

and safe data management. Conventional machine learning paradigms are often built based on data aggregation in one location, and this approach can easily reveal vulnerable data to a considerable risk of breaches, abuse, and violation of laws like the General Data Protection Regulation (GDPR) and the Health Insurance Portability and Accountability Act (HIPAA). Such considerations have necessitated privacy-aware solutions that can balance the two goals of deriving value out of distributed data and provide individual privacy (Kurupathi and Maass, 2020; Li, Sharma and Mohanty, 2020).

Federated learning (FL) has emerged as a promising approach to address these challenges by enabling model training across distributed clients without transferring raw data to a central server. Instead, clients train local models on their respective datasets and only share model updates, such as gradients or weights, with a coordinating server for aggregation. This paradigm minimizes the exposure of sensitive information while leveraging the collective intelligence of distributed participants (Yang, Liu, Chen, & Tong, 2019). By design, federated learning enhances data sovereignty and aligns with privacy-first AI principles, making it increasingly relevant for organizations handling regulated or sensitive data (Kaissis, Makowski, Rückert, & Braren, 2020).

The role of cloud platforms in enabling federated learning is particularly significant. Cloud infrastructure provides the scalability, orchestration, and resource elasticity required to manage complex, large-scale federated training processes across heterogeneous clients (Patell, 2020; Meurisch, Bayrak, & Mühlhäuser, 2020). With the integration of advanced cloud-native services such as container orchestration through Kubernetes, serverless computing, and secure communication frameworks, federated learning can be operationalized more effectively in real-world applications. Moreover, the convergence of federated learning and cloud computing addresses challenges in model synchronization, communication efficiency, and heterogeneous system support, while providing avenues for incorporating advanced security mechanisms like secure multi-party computation and blockchain-based accountability (Kanagavelu et al., 2020; Awan, Li, Luo, & Liu, 2019).

Despite these advantages, federated learning introduces several technical and operational challenges. Non-independent and identically distributed (non-IID) data across participants often leads to slower convergence and biased model updates (Li, Meng, Wang, & Li, 2020). Furthermore, communication bottlenecks in large-scale distributed environments require efficient aggregation mechanisms to ensure scalability and responsiveness (Lu, Liao, Lio, & Hui, 2020). At the same time, balancing trade-offs between model accuracy, privacy guarantees, and resource efficiency remains a critical concern for widespread adoption (Nikolaidis & Refanidis, 2020; Zhou et al., 2019).

Applications of federated learning have demonstrated its potential in domains where privacy and collaboration are paramount. In healthcare, federated approaches allow hospitals to collaboratively train diagnostic models without exchanging patient records, advancing predictive accuracy while adhering to strict privacy standards (Kaissis et al., 2020). In financial services, federated learning facilitates joint fraud detection models among banks, enabling robust detection of illicit activity while maintaining institutional confidentiality (Li, Fan, Tse, & Lin, 2020). IoT ecosystems further benefit from federated learning by enabling edge devices to collaboratively train models, enhancing intelligence at the edge without overwhelming central infrastructure (Nagar, 2019).

This study builds on these foundations by examining how federated learning frameworks deployed on cloud platforms can deliver scalable, privacy-preserving AI solutions. By proposing optimized cloud-native architectures, the research aims to reduce communication overhead, improve model convergence, and strengthen privacy guarantees. Applications in healthcare diagnostics and financial fraud detection are explored to demonstrate the practical value of integrating federated learning with cloud platforms. Ultimately, this work highlights the transformative potential of cloud-enabled federated learning in reconciling the tension between data utility and privacy in the age of distributed intelligence.

Foundations of Federated Learning

Federated learning (FL) represents a paradigm shift in the design of machine learning systems by enabling model training across distributed datasets without requiring direct data sharing or centralization. Instead of aggregating raw data into a single repository, FL allows multiple clients such as hospitals, banks, and IoT devices to collaboratively train a shared global model while keeping sensitive data localized (Yang, Liu, Chen, & Tong, 2019). This approach addresses critical concerns of privacy, security, and regulatory compliance while ensuring that large-scale learning can leverage the diversity of distributed data sources.

At its core, the federated learning workflow consists of three fundamental steps: local training, model aggregation, and global model distribution. First, client devices or institutions independently train models using their local datasets. Next, the locally trained model parameters (e.g., weights and gradients) are securely transmitted to a centralized or cloud-based server for aggregation. Finally, the updated global model is redistributed to clients for iterative refinement until convergence is achieved (Kurupathi & Maass, 2020). This distributed methodology reduces the need for sensitive raw data to traverse networks, thereby minimizing exposure risks.

A key strength of FL lies in its integration with privacy-preserving technologies. Techniques such as secure multi-party computation (MPC), differential privacy (DP), and homomorphic encryption (HE) provide strong mathematical guarantees against data leakage (Kanagavelu et al.,

2020; Li, Sharma, & Mohanty, 2020). For instance, MPC enables collaborative computation on encrypted data, ensuring that intermediate results do not reveal sensitive information, while DP introduces calibrated noise to updates to prevent reconstruction of individual records. Such methods are particularly critical in healthcare and financial contexts, where regulations like GDPR and HIPAA mandate strict control of personal data (Kaissis, Makowski, Rückert, & Braren, 2020).

Another essential challenge in FL is dealing with non-independent and identically distributed (non-IID) data across clients. Unlike traditional centralized datasets, client data often varies in quantity, quality, and distribution, which can hinder model convergence and fairness (Li, H., Meng, Wang, & Li, 2020). To address this, hierarchical and knowledge-federation frameworks have been proposed, enabling clients with heterogeneous resources to contribute proportionally while maintaining privacy guarantees. Cloud platforms have further supported this by offering elastic scalability and communication-efficient aggregation strategies (Patell, 2020; Lu, Liao, Lio, & Hui, 2020).

The importance of federated learning extends beyond theoretical innovation, as real-world applications demonstrate its transformative impact. In medical imaging, FL has been shown to train high-quality diagnostic models across institutions without transferring patient records (Kaissis et al., 2020). Similarly, in financial systems, it supports fraud detection models across banks without compromising customer confidentiality (Nikolaidis & Refanidis, 2020). Moreover, blockchain-based FL frameworks have been introduced to ensure accountability and traceability in distributed training environments, further enhancing trust among participants (Awan, Li, Luo, & Liu, 2019; Nagar, 2019).

Overall, federated learning provides a robust foundation for privacy-preserving artificial intelligence by combining distributed computing principles with advanced cryptographic and statistical privacy techniques. Its alignment with cloud-native architectures and regulatory compliance makes it a cornerstone for deploying AI systems in sensitive and highly regulated domains (Li, Fan, Tse, & Lin, 2020; Meurisch, Bayrak, & Mühlhäuser, 2020; Zhou, Wang, Guo, Gong, & Zheng, 2019; Malikireddy & Algubelli, 2017).

Cloud Platforms as Enablers of Federated Learning

Cloud platforms have become the central infrastructure for deploying federated learning (FL), providing the scalability, orchestration, and security mechanisms required to support collaborative AI across distributed environments. Federated learning relies on multiple clients such as hospitals, banks, or IoT networks locally training models on private data, while only sharing model parameters or gradients with a central coordinator. Cloud services, particularly those offered by providers such as AWS, Azure, and Google Cloud, deliver the computational

resources, networking layers, and privacy-preserving services necessary to manage these distributed training processes effectively (Patell, 2020; Li et al., 2020).

A core advantage of using cloud platforms is their ability to handle the orchestration challenges inherent in FL. Through container orchestration tools such as Kubernetes and serverless functions, cloud providers facilitate elastic resource allocation, fault-tolerance, and low-latency coordination between distributed clients (Yang et al., 2019). Additionally, cloud-based integration of privacy-preserving technologies such as differential privacy, secure multi-party computation (Kanagavelu et al., 2020), and homomorphic encryption ensures that sensitive data remains local while maintaining compliance with regulations like GDPR and HIPAA (Kaissis et al., 2020; Kurupathi & Maass, 2020).

Another enabler is the deployment of communication-efficient protocols in cloud environments. Federated learning often struggles with communication overhead caused by large model updates and non-IID data distributions. Cloud platforms mitigate this challenge through compression techniques, adaptive update mechanisms, and asynchronous aggregation strategies (Lu et al., 2020; Nikolaidis & Refanidis, 2020). By leveraging geographically distributed data centers, they also reduce latency between clients and aggregators, which improves convergence speed and system reliability.

Cloud platforms also enhance the security and accountability of FL ecosystems. Blockchain-based privacy-preserving frameworks (Nagar, 2019; Awan et al., 2019) and hybrid decentralization models (Meurisch et al., 2020) have been integrated into cloud-native federated architectures to ensure data provenance, verifiability, and trust between participants. This is particularly critical in cross-institutional collaborations where entities may not fully trust a central aggregator.

The table below highlights how major cloud platforms support federated learning through their services and architectures.

Table 1: Cloud Platform Capabilities for Federated Learning

Cloud Platform	Federated Learning Enablers	Privacy-Preserving Techniques	Use Cases
AWS	SageMaker distributed training, Kubernetes on EKS, edge-cloud synergy	Differential privacy, secure parameter aggregation	Healthcare imaging (HIPAA-compliant), fraud detection in financial services

Microsoft Azure	Azure ML pipelines, container orchestration, secure enclaves (Confidential Computing)	Multi-party computation, encryption-in-use	Cross-hospital diagnostic AI, distributed IoT analytics
Google Cloud (GCP)	TensorFlow Federated integration, Anthos for hybrid orchestration	Secure aggregation APIs, asynchronous updates	Collaborative recommender systems, mobile/edge device personalization
Hybrid/Custom Architectures	Kubernetes-based multi-cloud deployments, blockchain integration	Differential data sharing (Nagar, 2019), blockchain accountability	Decentralized AI across multi-institutional collaborations

By leveraging these capabilities, cloud platforms act as the backbone for operationalizing federated learning at scale. They not only provide the computational and networking layers but also embed regulatory compliance and advanced cryptographic methods, thereby addressing the dual challenges of efficiency and privacy (Li et al., 2020; Zhou et al., 2019). As a result, federated learning is no longer confined to theoretical or small-scale applications; it is increasingly being deployed in real-world environments where data sensitivity and distributed ownership are paramount.

Architectural Considerations

Designing federated learning (FL) architectures on cloud platforms requires balancing scalability, efficiency, and privacy preservation. Unlike centralized learning, federated learning relies on orchestrating distributed clients such as hospitals, banks, and IoT devices—while ensuring secure communication and compliance with privacy regulations. Cloud-native infrastructures provide the elasticity and orchestration capabilities necessary for deploying FL at scale, but architectural decisions must address three critical aspects: communication efficiency, model convergence, and privacy guarantees.

1. Communication Efficiency

Communication bottlenecks remain one of the most significant challenges in federated learning. Since updates must be frequently exchanged between clients and servers, the architecture must reduce communication overhead. Techniques such as asynchronous aggregation (Lu et al., 2020), compression, and selective update sharing can optimize bandwidth usage. Leveraging

container orchestration (e.g., Kubernetes) enables elastic scaling and resource allocation across clients.

2. Model Convergence

Data heterogeneity across clients (non-IID distributions) can hinder convergence. Cloud-native architectures can incorporate hierarchical models where local models are trained at the edge and aggregated in the cloud to ensure faster convergence and robustness (Li et al., 2020; Yang et al., 2019). Techniques such as knowledge federation further improve stability in heterogeneous data environments (Li, Meng, Wang, & Li, 2020).

3. Privacy and Security Guarantees

Ensuring privacy preservation requires integrating secure multiparty computation (Kanagavelu et al., 2020), differential privacy (Nagar, 2019), and blockchain-based accountability mechanisms (Awan et al., 2019). Cloud-enabled architectures can integrate trusted execution environments (TEEs) and privacy-preserving AI services (Meurisch et al., 2020) to enhance data confidentiality. These approaches are especially critical in healthcare and financial applications, where regulatory alignment with GDPR and HIPAA is mandatory (Kaissis et al., 2020).

4. Architectural Trade-Offs

Each architectural strategy introduces trade-offs between scalability, communication cost, convergence speed, and privacy preservation. Table 1 below summarizes these considerations by comparing representative architectural approaches.

Table 2: Architectural Trade-Offs in Cloud-Native Federated Learning

Architectural Strategy	**Advantages**	**Challenges**	**Key References**
Centralized Aggregation	Simple orchestration, supported by major cloud providers	Single point of failure, higher communication overhead	Yang et al., 2019; Li et al., 2020
Hierarchical/Hybrid FL	Improves convergence with edge-cloud cooperation, scalable across IoT	More complex orchestration, edge reliability concerns	Li et al., 2020; Li, Meng, Wang, & Li, 2020

Asynchronous FL	Reduces idle time, improves communication efficiency	Risk of stale updates, requires robust synchronization mechanisms	Lu et al., 2020
Blockchain-Enabled FL	Provides transparency, auditability, and accountability	High computational cost, integration complexity	Nagar, 2019; Awan et al., 2019
Secure Multi-Party Computation	Strong cryptographic privacy guarantees	High computational overhead, limited scalability	Kanagavelu et al., 2020
Differential Privacy Integration	Ensures individual-level confidentiality, compliance with GDPR/HIPAA	May reduce model accuracy if noise is too strong	Li, Sharma, & Mohanty, 2020; Kaissis et al., 2020
Decentralized Architectures	No central server, resilience against single-point failures	Complex trust management, higher synchronization requirements	Meurisch et al., 2020; Nikolaidis & Refanidis, 2020

5. Towards Cloud-Native Federated Architectures

Cloud platforms such as AWS, Azure, and GCP increasingly integrate federated learning into their machine learning stacks, enabling secure aggregation, elastic scaling, and automated orchestration. Leveraging these platforms allows for the deployment of hybrid architectures that combine edge computing, cloud aggregation, and advanced privacy-preserving mechanisms. Such designs are not only technically feasible but also align with the regulatory and security requirements of sensitive domains like healthcare and finance (Patell, 2020; Kurupathi & Maass, 2020).

Applications and Case Insights

Federated learning (FL) has matured into a pivotal methodology for privacy-preserving machine learning, particularly when sensitive data cannot be centralized due to ethical, regulatory, or technical constraints (Kurupathi & Maass, 2020; Li, Sharma, & Mohanty, 2020). The following case insights highlight real-world applications across healthcare, finance, and IoT, where cloud-native federated learning architectures enable secure and collaborative intelligence.

1. Healthcare Diagnostics

The healthcare sector is a prime domain for FL, as medical data are often siloed across hospitals and bound by strict regulations such as HIPAA. By training models locally and aggregating them through secure multi-party computation, hospitals can collaborate on diagnostic models without exposing patient records (Kaissis et al., 2020; Kanagavelu et al., 2020). FL has been particularly effective in radiology and medical imaging tasks, where pooling diverse data sources enhances accuracy while safeguarding privacy. Cloud platforms enable orchestration of cross-hospital learning pipelines, reducing both communication latency and deployment complexity.

Table 3: Applications of FL in Healthcare Diagnostics

Use Case	**FL Benefits**	**Example Application**	**Supporting Study**
Radiology (CT/MRI scans)	Privacy-preserving collaborative AI	Cancer and tumor detection	Kaissis et al. (2020)
Genomics and precision care	Data decentralization	Personalized treatment recommendations	Nikolaidis & Refanidis (2020)
Electronic health records	Improved model convergence	Predictive risk modeling	Li, L., Fan, Tse, & Lin (2020)

2. Financial Fraud Detection

In finance, institutions are traditionally reluctant to share raw transaction data due to confidentiality concerns and competitive interests. Federated learning allows banks and payment networks to co-train fraud detection models across distributed datasets while preserving client privacy (Yang, Liu, Chen, & Tong, 2019; Meurisch, Bayrak, & Mühlhäuser, 2020). Cloud-based FL platforms integrate secure aggregation protocols that mitigate risks of data leakage, improving fraud detection accuracy through richer collaborative datasets.

Table 4: FL in Financial Fraud Detection

Use Case	Challenge	FL Contribution	Reference
Credit card fraud	Sensitive client transaction data	Collective training without sharing	Yang et al. (2019)
Cross-bank money laundering	Inter-institutional privacy barriers	Secure model updates via FL	Li et al. (2020)
Real-time fraud analytics	High-volume, distributed transactions	Cloud-enabled scalable orchestration	Meurisch et al. (2020)

3. IoT and Edge Ecosystems

The proliferation of IoT devices ranging from smartphones to industrial sensors generates large amounts of sensitive, distributed data. Traditional centralized training is both inefficient and insecure in these contexts. FL enables on-device model training with periodic updates to the cloud, ensuring both bandwidth efficiency and privacy (Lu, Liao, Lio, & Hui, 2020; Malikireddy & Algubelli, 2017). This approach is particularly powerful for applications such as smart cities, predictive maintenance, and personalized mobile services.

Table 5: FL in IoT Applications

IoT Application	Benefit of FL	Cloud Integration Role	Reference
Smart cities	Localized privacy-preserving training	Edge-cloud orchestration	Zhou et al. (2019)
Predictive maintenance	Reduced communication overhead	Federated updates across devices	Lu et al. (2020)
Personalized mobile services	Confidentiality of user-generated data	On-device training with secure sync	Nagar (2019)

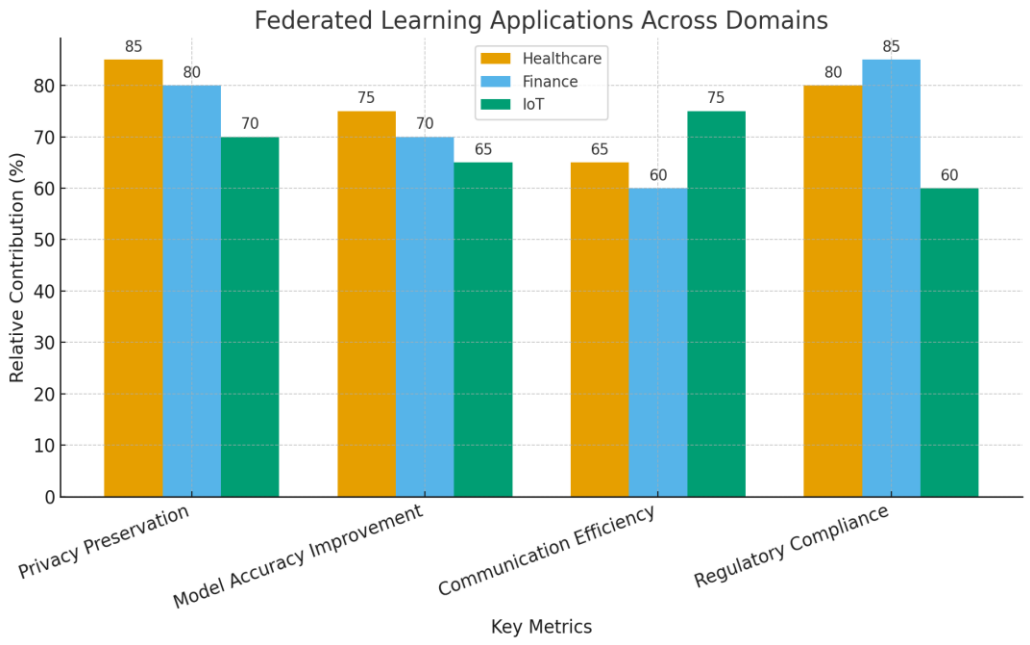

Fig 1: The clustered bar chart showing Federated Learning applications across domains, comparing key metrics in Healthcare, Finance, and IoT.

The cross-domain analysis reveals that federated learning enables significant advancements in privacy-preserving collaboration, improved accuracy from diverse datasets, and scalable cloud-native orchestration. In healthcare, it facilitates compliance with strict data protection laws while enhancing diagnostic accuracy; in finance, it overcomes inter-institutional data silos to strengthen fraud detection; and in IoT, it ensures secure and efficient analytics at the edge. These insights affirm the potential of federated learning to reshape privacy-preserving AI services in regulated and data-sensitive industries (Li et al., 2020; Patell, 2020).

Challenges and Research Directions

Despite the promise of federated learning (FL) on cloud platforms, several challenges must be addressed for large-scale, privacy-preserving deployment across critical domains such as healthcare, finance, and IoT ecosystems.

1. Data Heterogeneity and Non-IID Distributions

One of the foremost challenges in FL is the presence of heterogeneous, non-independent and identically distributed (non-IID) data across clients, which can lead to poor model convergence and degraded accuracy (Kurupathi & Maass, 2020; Li, Sharma, & Mohanty, 2020). Variations in

feature space, label distributions, and device capabilities create significant optimization hurdles, demanding adaptive aggregation mechanisms and personalized federated models.

2. Communication Overhead and System Scalability

Federated learning frameworks often face excessive communication costs due to frequent model parameter exchanges between clients and cloud servers. This becomes critical when scaling across thousands of devices or institutions (Lu, Liao, Lio, & Hui, 2020). Research into compression techniques, asynchronous updates, and edge-cloud synergies can alleviate latency and bandwidth bottlenecks while maintaining learning efficiency (Yang, Liu, Chen, & Tong, 2019).

3. Privacy and Security Threats

Although FL prevents direct data centralization, it remains vulnerable to inference attacks, gradient leakage, and model inversion attacks, where adversaries can reconstruct sensitive information from shared updates (Kaissis, Makowski, Rückert, & Braren, 2020). Enhanced mechanisms such as secure multi-party computation, differential privacy, and homomorphic encryption provide promising defenses (Kanagavelu et al., 2020; Nikolaidis & Refanidis, 2020). Blockchain-based accountability frameworks have also been proposed to ensure integrity and transparency of federated systems (Awan, Li, Luo, & Liu, 2019; Nagar, 2019).

4. Regulatory and Compliance Integration

Meeting the stringent requirements of GDPR, HIPAA, and sector-specific compliance frameworks presents ongoing difficulties. Current research emphasizes the design of cloud-native FL frameworks that inherently align with regulatory standards while minimizing operational friction (Meurisch, Bayrak, & Mühlhäuser, 2020; Patell, 2020). Achieving auditability and explainability in federated systems remains an important direction for trustworthy AI deployment.

5. Emerging Architectures and Frameworks

Novel paradigms such as hierarchical knowledge federation (Li, Meng, Wang, & Li, 2020) and privacy-preserving recommender systems (Zhou et al., 2019) demonstrate opportunities to broaden FL applications. Integrating blockchain, trusted execution environments, and hybrid edge-cloud frameworks may further reinforce privacy guarantees and scalability (Malikireddy & Algubelli, 2017). Moreover, advancements in asynchronous and decentralized learning mechanisms are expected to reduce reliance on central cloud servers, creating more resilient and efficient infrastructures (Li, Fan, Tse, & Lin, 2020).

Research Directions

Future research must focus on bridging the gap between theoretical privacy guarantees and real-world performance. This includes developing adaptive algorithms for non-IID data, lightweight cryptographic techniques to balance efficiency and privacy, and architectures that unify secure aggregation with cloud-native orchestration. Additionally, domain-specific frameworks tailored to healthcare diagnostics, financial fraud detection, and IoT-driven analytics will be critical for advancing practical adoption. Ultimately, federated learning research should aim to create scalable, secure, and regulation-aware AI systems that harness the full potential of cloud-enabled distributed intelligence.

Conclusion

Federated learning on cloud platforms has demonstrated strong potential in reconciling the need for advanced AI capabilities with stringent data privacy requirements. By enabling collaborative model training across distributed nodes without requiring raw data centralization, federated learning directly addresses concerns raised by regulations such as GDPR and HIPAA, while simultaneously fostering innovation in domains such as healthcare, finance, and IoT ecosystems (Kurupathi & Maass, 2020; Kaissis et al., 2020). Federated learning deployed using cloud-native infrastructures is more scalable, less costly in terms of communication, and allows heterogeneous clients to coordinate effectively, which makes it a feasible solution to real-world applications (Patell, 2020; Li, L. et al., 2020).

Despite these, there are still some issues of making sure that privacy is robustly preserved and that there is convergence in non-IID data distributions. Secure aggregation, differential privacy, and multi-party computation approaches have demonstrated the ability to increase confidentiality and accountability in federated settings, but there are still tradeoffs between efficiency, accuracy, and security (Li, Z. et al., 2020; Kanagavelu et al., 2020; Nikolaidis and Refanidis, 2020). More so, it has suggested knowledge federation and blockchain-based systems to expand privacy protection and create confidence in decentralized AI systems as a future of increasingly reliable and transparent collaborative intelligence (Li, H. et al., 2020; Awan et al., 2019; Nagar, 2019).

Its use in medical imaging, financial fraud detection, and social recommender systems is another indication of the applicability of federated learning to sensitive areas (Kaissis et al., 2020; Zhou et al., 2019). The combination of edge-cloud computing and asynchronous processes show great potential in scaffolding federated learning to dynamic settings that have latency and resource constraints (Lu et al., 2020; Meurisch et al., 2020). These developments, as a whole, confirm that federated learning, paired with a powerful cloud setup, can form the basis of the future privacy-conscious AI in the distributed data setting.

In the future, further investigation should aim to maximize trade-offs between privacy, efficiency, and accuracy and mitigate the problems with model interpretability, fairness and compliance in cross-jurisdictional applications. As a source of robust, reliable, and effective AI applications in any industry, federated learning on cloud platforms can be used as the backbone by balancing technological progress with regulatory and ethical concerns (Yang et al., 2019; Malikireddy and Algubelli, 2017).

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