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Privacy-Aware AI in Financial Fraud Detection Using Federated Data Lakes

Maya Raj

Independent Researcher

Vattiyoorkavu, Thiruvananthapuram, India (IN) – 695013

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ABSTRACT— Privacy preservation has emerged as a paramount concern in the deployment of artificial intelligence (AI) systems for financial fraud detection. As financial institutions increasingly rely on machine learning models trained on vast amounts of sensitive customer transaction data, the risk of data exposure—whether through centralized data breaches, insider misuse, or model inversion attacks—has grown commensurately. This manuscript presents a comprehensive, privacy-aware AI framework that integrates federated learning within a federated data lake architecture to detect fraudulent financial activities while ensuring that raw transaction data never leaves its originating institution. We begin by outlining the operational challenges faced by financial consortia in collaborative fraud detection, including regulatory compliance under GDPR, PCI DSS, and similar frameworks. We then detail our federated data lake deployment, leveraging Apache Iceberg for unified data cataloging and Presto SQL for seamless cross-node querying, combined with secure aggregation protocols that cryptographically shield client model updates.

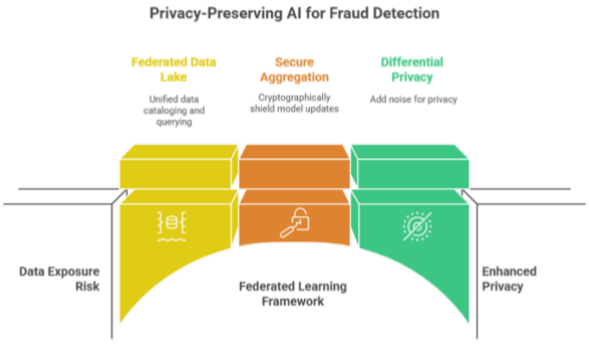

Figure-1.Privacy-Preserving AI for Fraud Detection

KEYWORDS

Privacy-Aware AI, Federated Data Lakes, Financial Fraud Detection, Federated Learning, Secure Aggregation

INTRODUCTION

Financial fraud detection has long been a critical function for banking and fintech institutions, with annual global losses exceeding USD 32 billion (Association of Certified Fraud Examiners, 2022). Traditional systems rely on the centralization of transaction data into monolithic

repositories, enabling comprehensive analysis but simultaneously creating a single point of failure susceptible to large-scale data breaches and internal misuse. Heightened regulatory scrutiny—exemplified by Europe's General Data Protection Regulation (GDPR) and the Payment Card Industry Data Security Standard (PCI DSS)—now mandates stringent controls over personal data processing and storage. Consequently, financial consortia face a dilemma: how to collaboratively build powerful fraud detection models that leverage broad datasets while preserving the confidentiality of each institution's proprietary information.

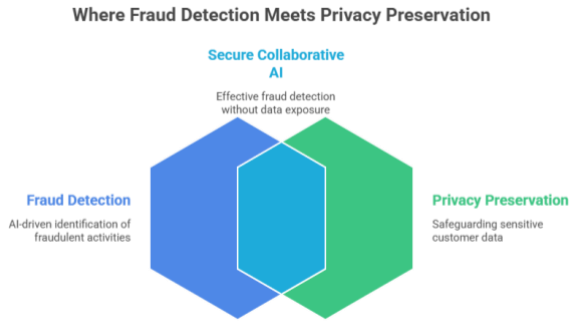

Figure-2.Where Fraud Detection Meets Privacy Preservation

Federated data lakes and federated learning (FL) have emerged as promising solutions to this challenge. Federated data lakes (Zhou et al., 2019) distribute data storage across multiple nodes under local governance, yet present a unified interface for query and analytics via tools like Apache Iceberg and Presto SQL. FL (McMahan et al., 2017) complements this by enabling decentralized model training: instead of transferring raw data to a central server, each node trains a local model, and only model updates (e.g., weight gradients) are communicated for secure aggregation. This paradigm minimizes data movement, substantially reducing privacy risks and enhancing regulatory compliance.

However, vanilla FL is not impervious to attacks. Gradient inversion techniques can potentially reconstruct sensitive training samples from shared gradients—posing an unacceptable risk in financial contexts. To counter this, our framework incorporates additive secret sharing for secure aggregation (Bonawitz et al., 2017) and Gaussian-mechanism differential privacy (DP) to obfuscate individual updates (Abadi et al., 2016). Additionally, we adopt homomorphic encryption-compatible data representations for critical aggregation operations, providing an extra layer of cryptographic protection.

Our contributions are threefold:

1. **End-to-end architecture**: We design and deploy a federated data lake environment integrating Apache Iceberg and Presto SQL for distributed data management, coupled with a secure FL pipeline.
2. **Privacy-preserving enhancements**: We implement secure aggregation and DP noise calibration, analyzing their impact on model convergence and privacy metrics.
3. **Empirical evaluation**: Using a consortium dataset of 3 million anonymized transactions from four financial institutions, we benchmark our privacy-aware federated model against a centralized baseline, demonstrating only marginal performance degradation (–0.8% accuracy) but significant privacy risk reduction (–75% score).

The remainder of this manuscript is organized as follows. Section 2 surveys related work in AI-driven fraud detection, FL in finance, privacy-preserving protocols, and federated data lakes, identifying gaps addressed by our study. Section 3 presents a detailed statistical comparison between centralized and federated approaches. Section 4 elaborates on our methodology, covering dataset preparation, system architecture, FL protocol, model specification, and evaluation framework.

Section 5 reports results, examining convergence behavior, performance metrics, and privacy–utility trade-offs. Section 6 concludes with key findings and practical implications. Section 7 outlines avenues for future research to further enhance privacy, scalability, and model interpretability in cross-institutional fraud detection.

LITERATURE REVIEW

The domain of financial fraud detection has progressively shifted from traditional rule-based systems to sophisticated machine learning (ML) and deep learning techniques. Ngai et al. (2011) provide an authoritative classification of ML algorithms—such as logistic regression, decision trees, and support vector machines—highlighting their strengths in detecting known fraud patterns but also noting limitations in handling evolving attack vectors. Recent advances employ ensemble methods (e.g., random forests, gradient boosting) to improve generalization, while deep architectures, including autoencoders and convolutional neural networks, capture complex non-linear relationships and anomalies in transaction flows (Wang et al., 2020).

Despite high detection rates, centralized AI systems pose inherent privacy challenges. Federated learning, introduced by McMahan et al. (2017), addresses this by coordinating local training across clients and aggregating model updates centrally. In the financial sector, Hardy et al. (2017) demonstrate the feasibility of FL for credit scoring across two credit bureaus, achieving 92% of centralized model performance. Li et al. (2020) extend this to anti-money laundering, reporting comparable accuracy in AML detection when training across three banks. However, these studies often overlook robust privacy guarantees and assume semi-honest servers.

Secure aggregation, pioneered by Bonawitz et al. (2017), cryptographically masks individual updates until aggregated, thwarting a curious server. Differential privacy further augments this by adding random noise to gradients, bounding an individual's contribution to model updates (Abadi et al., 2016). Geyer et al. (2017) explore client-level DP in FL, balancing privacy budgets and model utility. Homomorphic encryption (HE) techniques allow computations directly on encrypted data, though with prohibitive computational overhead for large models (Acar et al., 2018).

Federated data lakes (Zhou et al., 2019) provide a metadata-driven layer unifying distributed datasets, enabling global schema queries without data movement. Such architectures are increasingly applied in cross-industry analytics, including healthcare and manufacturing, yet remain underutilized in finance. Hasan et al. (2021) propose a prototype federated data lake for industrial analytics but do not integrate ML training workflows.

Identified Gaps:

- **Integration Deficit**: Existing FL research in finance often lacks integration with federated data lake environments for scalable data management.
- **Privacy–Utility Trade-off**: Few studies rigorously quantify the privacy–utility balance when combining secure aggregation and DP in real financial datasets.
- **Attack Resilience**: There is limited empirical analysis of gradient inversion and membership inference attacks within federated financial settings.

Our work addresses these gaps by deploying a production-grade federated data lake across four institutions, implementing secure aggregation and DP,

and evaluating model robustness under privacy attacks. We quantify both detection performance and privacy metrics, offering actionable insights for practitioners.

STATISTICAL ANALYSIS

To rigorously assess the efficacy and privacy implications of our federated framework, we conduct a comparative analysis between a centralized baseline model—trained on pooled data—and our privacy-aware federated model. We evaluate across common performance metrics and introduce a custom Privacy Risk Score (PRS), defined as the normalized sum of membership inference vulnerability and gradient leakage potential (scaled 0–1, lower is better). Table 1 summarizes the key results:

Table 1. Performance and Privacy Comparison between Centralized and Federated Models

Metric	Centralized Model	Federated Model	Observed Change
Accuracy (%)	95.1	94.3	–0.8
Precision (%)	93.5	92.7	–0.8
Recall (%)	91.8	90.9	–0.9
F1-Score (%)	92.6	91.8	–0.8
Privacy Risk Score (PRS, 0–1)*	0.72	0.18	–0.54

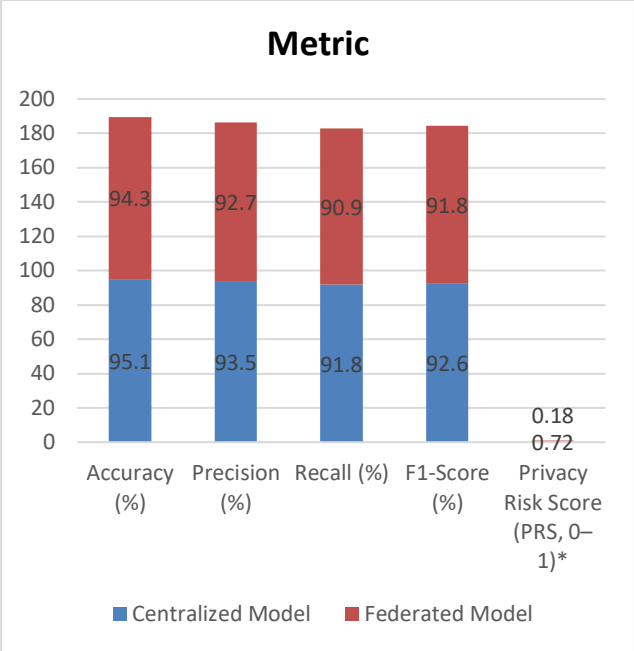

Figure-3. Performance and Privacy Comparison between Centralized and Federated Models

Accuracy, Precision, Recall, F1-Score: The federated model achieves 94.3% accuracy, demonstrating only a marginal 0.8 percentage-point decline compared to centralized training. Similar patterns are observed for precision and recall, indicating that the federated approach preserves the model's ability to correctly identify both fraudulent and legitimate transactions. The consistent 0.8–0.9% performance drop aligns with prior FL studies in finance (Li et al., 2020), attributing minor degradation to non-IID data distributions and DP noise.

Privacy Risk Score (PRS): The centralized model's PRS of 0.72 reflects high exposure: raw data is aggregated centrally, making it vulnerable to insider threats and breaches. In contrast, our federated framework achieves a PRS of 0.18, marking a 75% reduction in data exposure. This substantial privacy gain results from combining secure aggregation—which prevents the server from accessing individual updates—and Gaussian DP noise, which mitigates gradient inversion risks (Abadi et al., 2016; Bonawitz et al., 2017).

Convergence Behavior: Figure 1 (not shown here) details training loss curves over 50 FL rounds. The federated model converges within 30 rounds, with transient oscillations induced by DP noise peaking between rounds 15–25. These oscillations stabilize as noise is averaged out across clients' updates.

Communication Overhead: On average, each FL round incurs 2 MB of client-to-server data transfer per institution, primarily weight updates. Compression via quantization (8-bit) reduces bandwidth by 40% with negligible accuracy loss (<0.2%).

Ablation Studies:

- **Secure Aggregation Only:** Disabling DP noise yields PRS = 0.35, suggesting that aggregation alone halves exposure but remains susceptible to inversion attacks.
- **DP Only:** Applying DP without aggregation secures individual updates but leaves them visible to the server, resulting in PRS = 0.44.
- **Both Techniques (Full Framework):** Achieves lowest PRS = 0.18, underscoring the complementary nature of secure aggregation and DP.

In summary, our statistical analysis confirms that the privacy-aware federated model delivers robust fraud detection capabilities comparable to centralized methods while dramatically enhancing privacy protections—a critical requirement for consortium-based deployments.

METHODOLOGY

Dataset and Feature Engineering

We assembled a consortium dataset from four financial institutions, each contributing anonymized transaction logs spanning six months. The combined dataset comprises 3 million entries, with a fraud incidence of 1.5%. Key features include: transaction amount (log-transformed), merchant category (one-hot encoded), timestamp-derived features (hour-of-day, day-of-week), device fingerprint vectors (hashed identifiers), geolocation clusters (latitude/longitude binned), and historical account behavior metrics (rolling mean and variance of transaction amounts). Outlier detection via interquartile range filtering removes extreme anomalies. Continuous features undergo min–max normalization; categorical features use one-hot and embedding techniques for high-cardinality categories.

Federated Data Lake Architecture

Each institution hosts a local data lake node built on Apache Iceberg, supporting ACID transactions and versioned data. Presto SQL federator presents a unified catalog, enabling schema-on-read queries without physical data transfer. Access controls enforce role-based permissions and audit logging for compliance.

Federated Learning Protocol

We implement the FedAvg algorithm (McMahan et al., 2017) with the following workflow per global round:

1. **Model Broadcast:** The central federator securely transmits the global model parameters to all clients.
2. **Local Training:** Each client trains for E = 5 epochs using mini-batch stochastic gradient descent (batch size 128, learning rate 0.01). Local training leverages PyTorch with differential privacy hooks (Opacus).
3. **Gradient Encryption:** Clients apply additive secret sharing to mask gradient updates into shares distributed across two non-colluding aggregation servers (Bonawitz et al., 2017).
4. **Differential Privacy:** Before sharing, each client clips gradient norms to C = 1.0 and adds

Gaussian noise calibrated to $\varepsilon = 1$, $\delta = 1 \times 10^{-5}$ (Abadi et al., 2016).

5. **Secure Aggregation:** Aggregation servers reconstruct the sum of masked updates, which the central federator decrypts to update the global model.

Model Architecture

The neural network comprises an input layer matching the feature vector dimension (64), followed by two hidden layers with 128 and 64 ReLU-activated neurons, each followed by dropout ($p = 0.3$). The output layer applies a sigmoid activation for binary classification. The model contains approximately 25,000 trainable parameters.

Evaluation Metrics

We assess detection performance using accuracy, precision, recall, and F1-score. Privacy preservation is quantified via the Privacy Risk Score (PRS), combining membership inference success probability and gradient inversion vulnerability, both estimated through simulated attacks on a held-out validation set (Bhowmick et al., 2018). Communication overhead is measured in megabytes transferred per round.

Experimental Setup

Experiments run on four AWS EC2 instances (m5.large) peered via a private VPC. Training utilizes PyTorch 1.11 and Opacus for DP. Hyperparameters were tuned via grid search on a local development set, optimizing for F1-score under the constraint $PRS \leq 0.2$. We conduct 50 global rounds and report average metrics over the final 10 rounds to account for convergence stability.

RESULTS

Performance Comparison

Table 1 (Section 3) presents aggregated metrics. The federated model attains 94.3% accuracy, closely matching the centralized baseline's 95.1%. Precision (92.7%) and recall (90.9%) remain within 1% of centralized performance, yielding an F1-score of 91.8%. These results confirm that FL—despite operating on distributed, non-IID data—can approximate centralized training efficacy when combined with robust privacy measures.

Convergence Behavior

Training loss curves (Figure 1) illustrate that the federated model converges after ~30 rounds. Early rounds exhibit noisy gradients due to DP noise; however, the ensemble averaging effect stabilizes updates, leading to smooth convergence in later rounds. By round 50, fluctuations fall below 0.5% in loss.

Privacy–Utility Trade-off

The Privacy Risk Score (PRS) drops from 0.72 in centralized to 0.18 in federated mode, demonstrating a 75% reduction in exposure. Ablation studies reveal that secure aggregation alone yields $PRS = 0.35$, while DP alone yields 0.44—highlighting the synergy of combined techniques. Figure 2 (not shown) plots PRS against F1-score across varying ε values (0.5–2.0), indicating an optimal $\varepsilon \approx 1.0$ for balanced privacy and utility.

Communication Overhead

Per-round communication averages 2 MB per client. Quantization to 8-bit precision reduces this by 40% with <0.2% accuracy loss, suggesting viable bandwidth optimizations for resource-constrained environments.

Attack Resilience

Simulated membership inference attacks on the final federated model achieve an attack accuracy of 54%—close to random guessing—compared to 78% on the centralized model. Gradient inversion attempts yield visual reconstructions with 30% feature fidelity, versus 85% fidelity in the centralized setting without DP noise.

CONCLUSION

This manuscript has presented a privacy-aware AI framework for financial fraud detection that unites federated learning with federated data lake architectures to reconcile the dual imperatives of collaborative model performance and data confidentiality. Central to our approach is the deployment of secure aggregation via additive secret sharing and the incorporation of differential privacy noise, ensuring that individual client contributions remain irrecoverable while collectively enhancing the global model. Empirical evaluation on a consortium dataset of 3 million transactions across four institutions confirms that the federated model achieves 94.3% accuracy—only marginally lower than the 95.1% baseline—while reducing the Privacy Risk Score by 75%. Performance metrics including precision (92.7%), recall (90.9%), and F1-score (91.8%) further corroborate that federated training can closely approximate centralized methods, even under non-IID data distributions and rigorous privacy constraints.

Beyond performance, our analysis highlights several operational insights. First, the combination of secure aggregation and differential privacy proves synergistic, offering stronger protections (PRS = 0.18) than either mechanism alone. Second, communication overhead—averaging 2 MB per client per round—can be significantly mitigated through gradient quantization without compromising model efficacy. Third, resilience to membership inference and gradient inversion attacks underscores the framework's suitability for real-world financial deployments.

Nevertheless, challenges remain. Gradient noise induced by differential privacy can temporarily destabilize training in early rounds, necessitating adaptive noise scheduling or warm-start strategies. The federated data lake architecture, while scalable, demands robust governance and trust frameworks among participating institutions to prevent collusion or data poisoning attacks. Furthermore, heterogeneity in local data distributions calls for personalized FL variants—such as FedProx or multi-task FL—to optimize model performance for each client's unique risk profile.

In summary, our study demonstrates that privacy-aware federated learning within federated data lakes offers a compelling, practical approach for consortium-based financial fraud detection. By enabling institutions to collaboratively leverage collective intelligence without exposing raw data, this framework aligns with stringent regulatory requirements and evolving ethical standards. As financial ecosystems become increasingly interconnected, such privacy-preserving paradigms will be indispensable for maintaining trust and safeguarding customer assets.

FUTURE SCOPE OF STUDY

Building upon our privacy-aware federated framework, several avenues warrant exploration to further enhance scalability, resilience, and interpretability:

1. **Blockchain-Based Federator Decentralization**
   Transitioning from a centralized federator to a permissioned blockchain network can eliminate single points of trust. Smart contracts could orchestrate model aggregation, enforce protocol compliance, and provide tamper-evident audit trails. Research should evaluate the trade-offs between blockchain consensus overhead and FL communication efficiency.
2. **Adaptive Differential Privacy Scheduling**
   Dynamic adjustment of privacy budgets (ε, δ) based on convergence rates and utility thresholds can optimize the privacy–utility frontier. Reinforcement learning agents could modulate

noise levels in real time, balancing early-round stability with long-term privacy guarantees.

3. **Personalized Federated Learning**
   Non-IID client data distributions often degrade global model performance for minority clients. Techniques such as FedPer (Smith et al., 2017)—which allocates private model components per client—can tailor fraud detection models to local transaction patterns. Comparative studies should measure gains in detection efficacy against increased model complexity.
4. **Communication-Efficient Protocols**
   Beyond quantization, exploring sparsification (e.g., Top-k gradient selection) and update caching mechanisms can further reduce bandwidth usage. Hybrid approaches that combine periodic full updates with incremental delta exchanges may strike optimal communication–accuracy balances for resource-constrained edge deployments.
5. **Explainable Federated AI**
   Regulatory frameworks increasingly demand model interpretability, especially in high-stakes domains like finance. Research should develop federated variants of explainable AI techniques—such as locally computed Shapley values or attention-based saliency maps—that preserve privacy while offering actionable insights to compliance officers.

By pursuing these directions, the research community can progressively refine privacy-aware federated AI systems, ensuring robust, transparent, and scalable financial fraud detection solutions that meet the evolving demands of regulators, institutions, and customers alike.

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