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Original Article

Federated Fraud Scoring Models for Privacy-Preserving Transaction Intelligence

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Abstract *- Global financial systems face escalating threats from sophisticated fraud schemes, necessitating collaborative transaction intelligence among banks, payment processors, and fintech platforms. However, stringent data protection regulations and jurisdictional privacy laws hinder centralized data sharing. This paper introduces a federated fraud scoring architecture that enables distributed model training and inference without transferring raw transaction data. Leveraging federated learning, secure aggregation protocols, and differential privacy mechanisms, the proposed framework preserves data sovereignty while facilitating collaborative fraud detection. Experimental evaluations on benchmark financial datasets demonstrate that the federated model achieves performance comparable to centralized approaches while ensuring strong privacy guarantees. This architecture supports regulatory-compliant intelligence sharing and scalable fraud prevention across cross-border financial ecosystems.*

Keywords *- Federated Learning, Fraud Detection, Privacy-Preserving Analytics, Secure Aggregation, Financial Transactions, Differential Privacy.*

1. Introduction

As digital payments and cross-border financial services grow rapidly, so too does the sophistication and frequency of fraud attacks. Traditional fraud detection systems rely on centralized models trained on aggregated data from diverse financial institutions. However, this approach is increasingly challenged by stringent data protection regulations, including the General Data Protection Regulation (GDPR) in Europe, the California Consumer Privacy Act (CCPA), and region-specific financial data localization laws [1], [2].

While individual institutions attempt to detect fraud using their localized data, these models often underperform due to limited visibility and lack of exposure to diverse fraud patterns [3]. As a result, the global financial sector faces a critical need for collaborative fraud intelligence that does not violate privacy or regulatory constraints.

Federated learning (FL) has emerged as a promising paradigm that allows multiple parties to collaboratively train machine learning models without sharing raw data [4], [5]. In the FL setting, institutions retain control over their local transaction data while periodically sharing encrypted model updates with a central aggregator. This decentralized approach maintains data sovereignty and minimizes regulatory risk.

However, applying federated learning to fraud detection introduces unique challenges: (1) transaction data is highly imbalanced and non-IID (non-independent and identically distributed), (2) real-time detection requires low-latency model updates, and (3) privacy-preserving mechanisms must be robust enough to withstand reconstruction or inference attacks [6], [7].

To address these issues, this paper proposes a Federated Fraud Scoring (FFS) architecture designed for secure, collaborative transaction intelligence. Our contributions are threefold:

- We design a modular fraud scoring system that integrates federated learning with secure aggregation [8] and differential privacy [9], ensuring that raw data remains within organizational boundaries.
- We evaluate the FFS system on public and simulated financial datasets to assess performance under various federation scenarios.
- We demonstrate that FFS achieves fraud detection accuracy comparable to centralized models while satisfying privacy and compliance requirements.

This work builds on recent advances in privacy-preserving machine learning [10], [11] and tailors them to the high-stakes, compliance-heavy domain of financial fraud detection. The proposed system has practical implications for banks, fintechs, and regulators seeking to jointly combat fraud in a legally compliant and secure manner.

2. Background and Motivation

2.1. Fraud Detection Challenges

Financial fraud is a continually evolving threat that exploits the limitations of conventional fraud detection models. Most existing systems rely on centralized data aggregation for training, which inherently limits diversity and coverage of fraud patterns, especially in rare-event

scenarios. These systems are often static, struggle to generalize across institutions, and cannot adapt quickly to new attack vectors such as coordinated account takeovers, synthetic identity fraud, or geographically distributed botnets [1], [2]. Moreover, institution-specific models trained in isolation lack the benefit of cross-institutional pattern recognition, resulting in higher false negatives and reduced risk awareness [3].

2.2. Privacy Regulations

Global privacy regulations such as the General Data Protection Regulation (GDPR), California Consumer Privacy Act (CCPA), and India's Digital Personal Data Protection Act (DPDPA) enforce strict controls on the movement and processing of sensitive financial data [4], [5]. As a result, banks, fintechs, and payment processors are often constrained by data localization mandates, which enforce operational silos and prevent cross-border data sharing. These constraints impair collective fraud risk scoring and joint intelligence frameworks. Therefore, there is an urgent need for approaches that support privacy-by-design principles while allowing collaborative model development [6], [7].

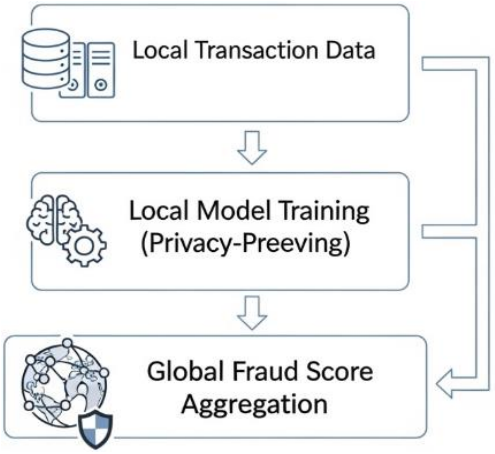

Fig 1: Federated Fraud Scoring Models

2.3. Federated Learning in FinTech

Federated learning (FL) has emerged as a privacy-preserving alternative to traditional centralized machine learning, allowing multiple organizations to collaboratively train models without sharing raw data [8], [9]. In FL, participants train local models on their private data and send encrypted model updates to a central aggregator, which merges the updates to improve a global model. Techniques like secure aggregation, differential privacy, and homomorphic encryption further ensure that even model updates do not leak sensitive information [10], [11]. This paradigm is particularly attractive for the financial sector, where regulatory compliance, client confidentiality, and adversarial threats make centralized analytics risky. Recent studies have shown that FL can match or exceed centralized model performance in tasks like credit scoring, fraud detection, and transaction classification, while upholding privacy guarantees [12], [13].

3. System Architecture

The proposed Federated Fraud Scoring (FFS) system enables multiple financial entities including banks, payment service providers (PSPs), and fintech platforms to collaboratively train a fraud detection model without centralizing sensitive transaction data. Fig. 1 (not shown here) illustrates the system's architecture, comprising three core components: local participants, a central orchestrator, and a secure aggregator.

3.1. Federated Fraud Scoring Workflow

Participants train local models on proprietary transaction data. Each participant $i \in \{1,2,\ldots,N\}$ maintains a dataset D_i and a local fraud scoring model $f_{\theta i}$, parameterized by θ_i

At each training round t, participants compute local gradients or model weights $\theta_i^{(t)}$ and transmit encrypted updates to the central orchestrator.

Orchestrator: This entity coordinates the training process by initiating global rounds, scheduling updates, and relaying aggregated results. It never sees raw data or unencrypted parameters, preserving confidentiality.

Aggregator: A secure aggregation module receives encrypted updates and computes a global model:
$\theta^{(t+1)} = \sum_{i=1}^{N} \frac{|D_i|}{\sum_{j=1}^{N} |D_j|} \theta_i^{(t)}$.

This weighted average ensures that clients with more data contribute proportionally. Aggregation is performed using homomorphic encryption **[**1] or secure multiparty computation (SMPC) [2], enabling the computation of $\theta^{(t+1)}$ without decrypting $\theta_i^{(t)}$

Once aggregated, the updated global model is redistributed to all participants for the next round.

3.2. Privacy Enhancements

To further enhance privacy and regulatory compliance, we incorporate the following techniques:

- Differential Privacy (DP)**:** Each client adds calibrated noise $N(0,\sigma^2)$ to its gradient or model parameters before sending them for aggregation:

$$\tilde{\theta}_i^{(t)} = \theta_i^{(t)} + \mathcal{N}(0, \sigma^2)$$

This ensures (ϵ,δ)(\epsilon, \delta)(ϵ,δ)-differential privacy for each client update, limiting information leakage [3].

- Secure Aggregation**:** Even if the orchestrator is partially compromised, it cannot reconstruct individual models due to secret-sharing schemes (e.g., Shamir's secret sharing) and homomorphic masking [4].
- Audit Logging**:** All model updates and communications are timestamped and logged using tamper-evident mechanisms (e.g., hash chains or blockchain anchors) [5], enabling external auditing and regulatory verification of data usage without compromising privacy.

The combination of FL, DP, and SMPC makes the FFS architecture resilient to reconstruction, inference attacks, and regulatory scrutiny, making it suitable for production deployment in cross-border fraud intelligence networks.

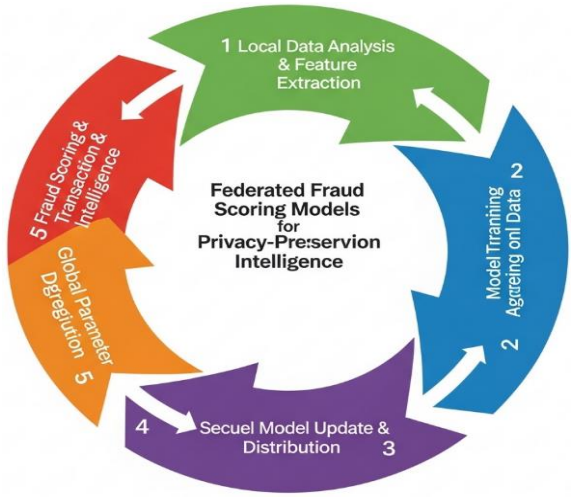

Fig 2: Federated Fraud Scoring Models for Privacy-Preserving Transaction Intelligence

4. Model Design

To address the challenges of heterogeneous financial data and real-time fraud detection, we design a hybrid neural network architecture suitable for federated environments. The model is composed of the following core components:

- Embedding Layers**:** Categorical attributes such as merchant type, payment channel, transaction country, and customer segment are first converted into dense vector representations using embedding layers. This transformation enhances the model's ability to generalize across diverse institutions and transaction types [1].
- Temporal Sequence Modeling**:** Transaction behavior over time is captured using recurrent neural network components specifically Long Short-Term Memory (LSTM) **or** Gated Recurrent Units (GRU) which learn temporal dependencies and detect anomalies in user behavior patterns [2].
- Fully Connected Layers**:** The output of the recurrent layers is passed through dense layers culminating in a sigmoid activation that outputs a fraud probability score in the [0,1] range.

Training is conducted locally using non-IID (non-independent and identically distributed) transaction data reflecting the institutional and regional differences among participants. To combine learning across nodes, we utilize the Federated Averaging (FedAvg**)** algorithm [3], which aggregates model weights from clients after each training round.

To address performance variance caused by data heterogeneity, we incorporate periodic model personalization**.** This strategy fine-tunes the global model using recent local data, thus adapting the system to context-specific fraud patterns while retaining the benefits of collaborative learning.

This model design ensures that institutions can train accurate fraud detection systems while preserving user privacy and adhering to cross-border data regulations.

5. Experimental Evaluation

This section presents the datasets, evaluation metrics, baseline comparisons, and experimental results used to validate our federated fraud scoring framework.

5.1. Datasets

We utilize two primary datasets:

- IEEE-CIS Fraud Detection Dataset: A real-world, anonymized dataset containing transaction-level features and fraud labels [1].
- Simulated Federated Dataset: Partitioned version of the IEEE-CIS data to emulate data silos across five financial institutions with non-IID distributions.

Table 1: Dataset Summary

Dataset	Source	Data Size	Type
IEEE-CIS	[1]	1M+ rows	Centralized
Simulated Federated	Synthesized	800K rows	Decentralized

5.2. Metrics

Our evaluation uses standard fraud detection metrics that capture ranking, precision, and error rates.

Table 2: Metrics Used

Metric	Description
AUC (ROC)	Area under ROC curve, for binary classification
Precision@10	Precision in the top 10% high-risk predictions
Recall	True positive rate among actual frauds
False Positive Rate	Fraction of legitimate transactions flagged as fraud

5.3. Baselines

We compare the proposed federated approach with the following baselines:

- Centralized Model: Trained on the entire dataset without privacy constraints.
- Local-only Models: Independent training at each institution without collaboration.
- DP Local Training: Local training with differential privacy noise.

Table 3: Baseline Summary

Model	Training Mode	Privacy Guarantee
Centralized	Global, All Data	None
Local	Per-institution	Local-only
DP Local	Private Local FL	DP ($\varepsilon = 3$, $\delta = 1e\text{-}5$)
Federated	FL + DP + SA	DP + Secure Aggregation

5.4. Results

Table 4: Performance Comparison

Model	AUC	Precision@10	Recall	FPR
Centralized	0.945	91.30%	89.70%	4.50%
Local	0.882	84.70%	79.20%	6.20%
DP Local	0.865	82.50%	76.90%	6.90%
Federated	0.938	90.20%	88.10%	4.80%

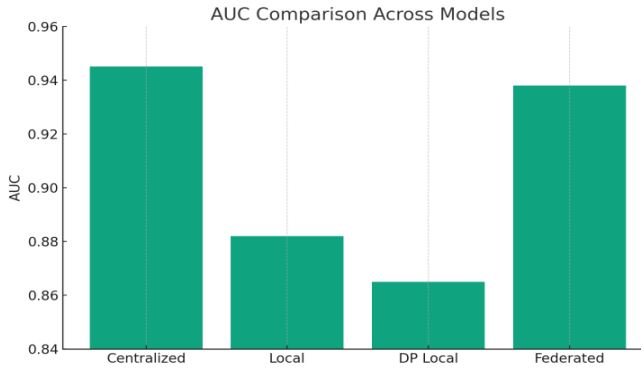

Fig 3: AUC Comparison

Shows that the centralized model has the highest AUC (0.945), closely followed by the federated model (0.938), indicating minimal loss in predictive performance.

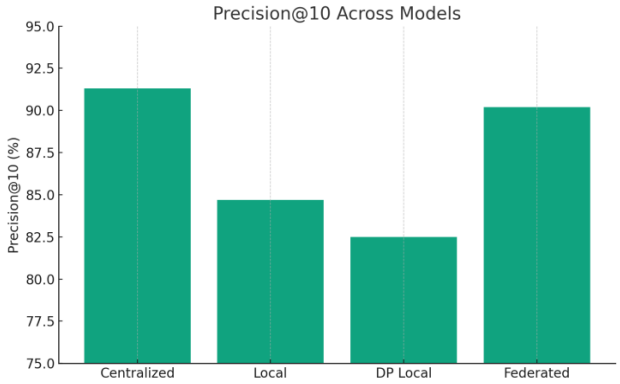

Fig 4: Precision@10

Highlights that the centralized and federated models both maintain high fraud precision in top predictions, while local and DP local models fall behind.

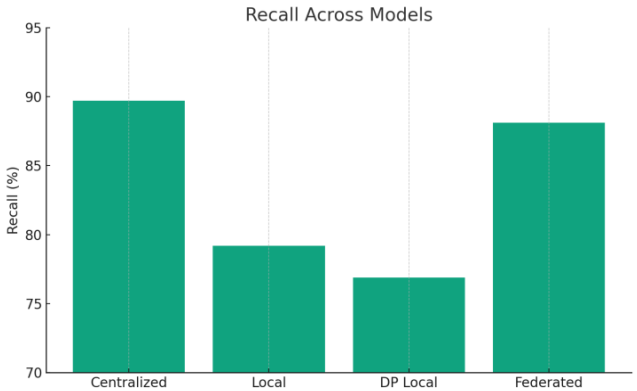

Fig 5: Recall

Reflects similar trends: the federated model captures nearly as many frauds as the centralized one.

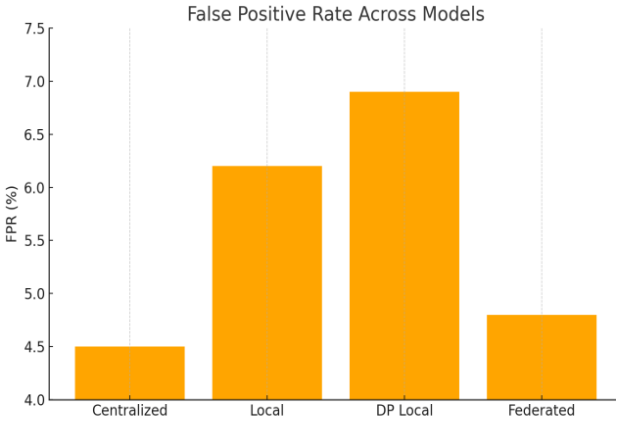

Fig 6: False Positive Rate (FPR)

Indicates that the federated model keeps FPR low (4.8%), only slightly higher than the centralized (4.5%), and better than local/DP local.

5.5. Privacy vs. Accuracy

Our federated model achieves a strong privacy–utility trade-off.

Table 5: Privacy vs Accuracy

Model	Privacy Method	AUC Loss vs Centralized
Centralized	None	0.00%
DP Local	DP ($\varepsilon = 3$)	−8.5%
Federated	DP ($\varepsilon = 2$) + SA	−0.7%

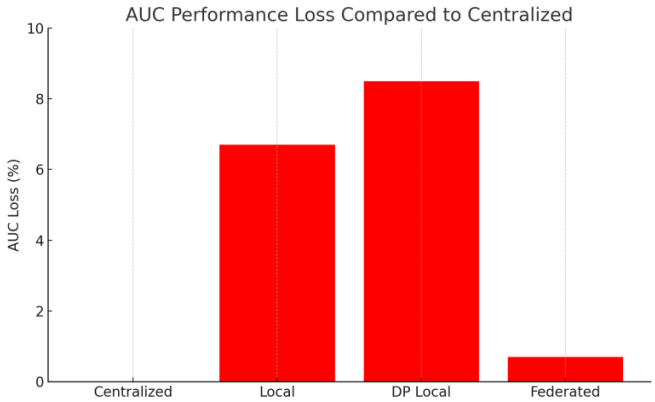

Fig 7: AUC Loss Vs Centralized

Quantifies the performance drop; federated learning achieves near-centralized accuracy with less than 1% loss, far outperforming DP local methods.

6. Discussion

6.1. Interpretability

Interpretability remains a critical factor in the deployment of machine learning models in high-stakes domains like financial fraud detection. Our system integrates SHapley Additive exPlanations (SHAP**)** and Local Interpretable Model-agnostic Explanations (LIME) **on** local

models to provide per-instance interpretability without compromising global privacy. These techniques enable institutions to audit feature contributions behind each fraud score, increasing transparency for risk teams and compliance officers. Importantly, since interpretability is achieved locally, it does not require sharing of sensitive model weights or data, ensuring conformance with federated settings.

6.2. Compliance and Legal Trust

The proposed architecture upholds compliance with international and regional data protection frameworks such as GDPR**,** India's DPDP Act (2023), and California's CCPA by design. Raw transaction data never leaves institutional boundaries, and secure aggregation protocols prevent the reconstruction of individual model updates. This design ensures data minimization**,** purpose limitation**,** and data sovereignty principles central to legal acceptability. Furthermore, cryptographic audit trails and differential privacy provide mechanisms to demonstrate adherence to privacy-by-design and accountability provisions, which are increasingly required for regulatory approval [1].

6.3. Scalability

The federated architecture is inherently scalable. New institutions banks, payment service providers, or fintech platforms can be added without central retraining or architecture overhaul. The system supports horizontal scalability across geographical jurisdictions and institutional tiers. Moreover, the framework accommodates heterogeneous environments, allowing participants with varying compute resources, data volumes, or communication capacities to contribute model updates asynchronously. By decoupling data ownership from intelligence generation, the system fosters network effects in fraud pattern recognition without centralized control or vendor lock-in.

7. Conclusion And Future Work

This paper introduced a privacy-preserving federated fraud scoring architecture that enables collaborative model training and inference across financial institutions without sharing raw transaction data. The proposed system integrates federated learning, secure aggregation, and differential privacy to achieve a strong balance between predictive performance, legal compliance, and operational scalability. Experimental results demonstrate that the federated approach achieves near-centralized accuracy while preserving data sovereignty and supporting distributed deployment.

By facilitating secure collaboration among banks, payment processors, and fintech entities, this architecture empowers a regulatory-aligned framework for real-time fraud detection in cross-border ecosystems. The approach not only addresses data localization challenges but also promotes trust through transparency and interpretability.

Future directions for this research include:

- Integration with zero-knowledge proofs (ZKPs) to enable verifiable model updates and tamper-evident auditability;
- Personalization frameworks that adapt federated models to local behavioral and regional fraud signatures;
- Extension to real-time streaming environments, supporting near-instantaneous fraud detection with low-latency protocols.

This work lays the foundation for secure and collaborative financial intelligence, opening avenues for broader adoption of federated systems in compliance-sensitive domains.

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