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Privacy-Preserving Federated Learning for Cross-Institution Anti-Money-Laundering Models

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Abstract

The proliferation of digital financial transactions has precipitated a commensurate rise in sophisticated financial crimes, specifically money laundering, which imposes significant stability risks on the global economic framework. Traditional Anti-Money Laundering (AML) systems, predominantly relying on rule-based engines or isolated machine learning models within single institutions, fail to capture the complex, cross-institutional topology of modern laundering networks. While collaborative learning offers a theoretical solution, strict data privacy regulations such as the General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA) inhibit the centralized aggregation of sensitive transaction data. This paper presents a comprehensive framework for Privacy-Preserving Federated Learning (PPFL) tailored specifically for AML applications. We propose a novel architecture that integrates Differential Privacy (DP) with Secure Multi-Party Computation (SMPC) to enable financial institutions to collaboratively train robust Deep Neural Networks (DNNs) without sharing raw transaction ledgers. Furthermore, we address the challenge of non-Independent and Identically Distributed (non-IID) data, a characteristic inherent to the heterogeneous customer bases of different banks. Our experimental results demonstrate that the proposed framework achieves detection rates comparable to centralized training baselines while mathematically guaranteeing data privacy, thereby resolving the dilemma between regulatory compliance and effective financial crime detection.

Keywords :

Federated Learning, Anti-Money Laundering, Differential Privacy, Financial Crime Detection.

1. Introduction

1.1 Background

The global financial system processes billions of transactions daily, creating a vast ocean of data within which illicit actors attempt to conceal the origins of criminal proceeds. Money laundering is not merely a financial crime but a critical enabler for drug trafficking, terrorism financing, and corruption. The United Nations Office on Drugs and Crime estimates that between 2% and 5% of global GDP is laundered annually, yet the interception rate remains abysmally low, estimated at less than 1% [1]. This inefficiency stems largely from the siloed nature of current detection mechanisms. Financial institutions (FIs) operate as isolated entities, monitoring transactions only within their own ledgers. Consequently, sophisticated launderers exploit this fragmentation by layering transactions across multiple banks to break the audit trail, a technique known as smurfing or structuring [2].

In response, Artificial Intelligence (AI) and Machine Learning (ML) have been increasingly adopted to replace or augment rigid rule-based legacy systems. Deep learning models, capable of identifying non-linear patterns and complex dependencies in high-dimensional data, have

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shown promise in reducing false positives—a chronic issue in AML compliance where legitimate transactions are flagged erroneously. However, the efficacy of these models is directly proportional to the volume and diversity of the training data [3]. A single institution often lacks the comprehensive view of the transaction graph required to identify macro-level laundering topologies.

1.2 Problem Statement

The logical solution to the data fragmentation problem—centralizing data from multiple institutions into a single data lake for model training—is rendered legally and ethically impossible by modern privacy regulations. Frameworks such as GDPR in Europe and various banking secrecy acts globally mandate strict controls over customer data. Sharing raw transaction logs, which contain personally identifiable information (PII) and sensitive financial behaviors, exposes institutions to severe legal penalties and reputational damage [4].

This creates a deadlock: effective AML detection requires data sharing, but privacy laws prohibit it. Federated Learning (FL) emerges as a potential paradigm to bridge this gap by enabling model training on decentralized data. In FL, the model travels to the data, rather than the data traveling to the model. However, standard FL is not a silver bullet. Recent research has demonstrated that gradient updates sent from clients to the central server can leak information about the underlying training data through reconstruction attacks [5]. Furthermore, the financial data distribution is highly skewed and non-IID; a retail bank in a rural area observes fundamentally different transaction patterns than an investment bank in a metropolitan financial hub. Standard averaging algorithms in FL struggle to converge or generalize well under such heterogeneity.

1.3 Contributions

This paper addresses these challenges by developing a robust PPFL framework for cross-institution AML. Our primary contributions are as follows:

1. We introduce a hybrid privacy preservation mechanism that combines local Differential Privacy (LDP) with additive homomorphic encryption to secure gradient updates, ensuring that neither the central server nor participating banks can reconstruct individual transaction histories.

2. We propose a heterogeneity-aware aggregation algorithm designed to handle the non-IID nature of cross-institutional financial data, improving convergence speed and global model performance compared to standard Federated Averaging (FedAvg).

3. We provide a rigorous empirical evaluation using synthetic yet realistic financial transaction datasets, benchmarking our approach against isolated local training and ideal centralized training scenarios.

Chapter 2: Related Work

2.1 Classical Approaches and Isolated Learning

Historically, AML compliance has relied on expert systems defined by static rules (e.g., flagging cash deposits over $10,000). While transparent, these systems suffer from high false positive rates, often exceeding 95%, which places a massive burden on human analysts [6]. With the advent of data mining, institutions began employing classical machine learning algorithms such as Random Forests, Support Vector Machines (SVMs), and Gradient Boosting

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Decision Trees (GBDTs). These models significantly improved detection capabilities by learning from historical Suspicious Activity Reports (SARs).

However, these deployments have traditionally been isolated. A study by Weber et al. demonstrated that while individual banks could detect local anomalies, they consistently failed to identify laundering rings that propagated funds through multiple institutions [7]. The lack of a global perspective means that a launderer can appear as a low-risk customer to Bank A and Bank B individually, while the combined behavior reveals a clear pattern of layering. The industry's reliance on isolated learning has created a systemic vulnerability that adversarial actors actively exploit.

2.2 Privacy-Preserving Machine Learning

The concept of Federated Learning was introduced by Google in 2016 primarily for mobile edge computing, but its application to finance has gained traction recently. Yang et al. categorized FL into horizontal, vertical, and transfer learning settings, identifying horizontal FL as the most applicable architecture for banks sharing similar feature spaces (transaction logs) but different sample spaces (customer bases) [8].

Despite the decentralized nature of FL, privacy guarantees are not inherent. Comparison studies have shown that without additional privacy layers, deep learning models are susceptible to membership inference attacks, where an attacker can determine if a specific individual's data was used in training [9]. To mitigate this, Differential Privacy (DP) has been integrated into FL. DP adds calibrated noise to the gradients, masking the contribution of any single data point. However, applying DP in finance involves a delicate trade-off; excessive noise degrades the utility of the model, which is unacceptable in AML where missing a true positive carries legal risks.

Secure Multi-Party Computation (SMPC) offers an alternative or complementary approach. SMPC protocols allow parties to compute a function jointly while keeping their inputs private. In the context of FL, this ensures that the central server sees only the aggregated update, not the individual updates from each bank [10]. While cryptographically secure, SMPC often introduces significant communication and computational overheads, which can be prohibitive for large-scale deep learning models. Our work seeks to balance these constraints by optimizing the integration of DP and lightweight encryption.

Chapter 3: Methodology

Our proposed framework, SecureFedAML, operates on a horizontal federated learning architecture involving K financial institutions (clients) and one regulatory authority or trusted third party acting as the central aggregation server. The objective is to train a global Deep Neural Network (DNN) that minimizes a loss function over the aggregate data distribution without exposing raw data.

3.1 Architectural Overview

The training process follows a synchronous round-based protocol. In each communication round t, the central server distributes the current global model parameters w_t to a subset of eligible clients. Each client k performs local training on its private dataset D_k using Stochastic Gradient Descent (SGD) to compute the local update $\nabla {w_t}^k$.

Critically, before transmitting this update, the client applies a privacy-preserving transformation. The transformed updates are sent to the server, which aggregates them to produce the new global model state w_{t+1}. This cycle repeats until convergence criteria are

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met. The architecture is designed to be agnostic to the underlying neural network structure, though we utilize a Long Short-Term Memory (LSTM) network in our experiments to capture the temporal dependencies inherent in transaction sequences [11].

3.2 Differential Privacy Mechanism

To prevent gradient leakage, we employ client-side Differential Privacy. Specifically, we utilize the Gaussian Mechanism, which is favored for its sharp tail decay. For a given client k, the gradient g_k is first clipped to a maximum L_2-norm threshold C to bound the sensitivity of the update. This clipping ensures that the influence of any single transaction batch is limited.

After clipping, Gaussian noise is added to the gradient. The noise scale is determined by the privacy budget ε and the failure probability δ. By injecting noise locally, we provide a stronger privacy guarantee than central DP, as the server never sees the exact gradient of any institution. However, since summing noisy gradients accumulates variance, we employ a sophisticated noise reduction technique during aggregation, relying on the law of large numbers where the sum of noise from many clients tends to average out, provided the noise is zero-mean [12].

3.3 Weighted Aggregation for Non-IID Data

Financial data is inherently non-IID. A regional cooperative bank may have a dataset dominated by agricultural loans and small retail transactions, while a multinational bank's dataset is heavily skewed towards high-frequency trading and cross-border wires. Standard FedAvg, which weights contributions solely based on dataset size, fails to account for the distributional divergence.

We introduce a contribution-based weighting scheme. The server maintains a history of validation performance for each client. Clients whose updates consistently move the global model towards lower loss on a hold-out validation set (maintained by the regulator using synthetic or anonymized historical data) are assigned higher importance. This dynamic weighting prevents the global model from overfitting to the specific distributions of the largest banks while ignoring the subtle but critical patterns found in smaller institutions [13].

3.4 Mathematical Formalization

The core update rule for our SecureFedAML framework, incorporating both the momentum-based gradient descent and the differential privacy noise injection, is formally defined below. Let eta be the learning rate, N be the total number of participating clients, and N denote the Gaussian distribution.

$$w_{t+1} = w_t - eta(\sum_{k=1}^{N} \alpha_k (Clip(\nabla F_k(w_t), C) + N(0, \sigma^2 C^2 I)))$$

In this equation, $\nabla F_k(w_t)$ represents the local gradient computed by client k. The function $Clip(\cdot, C)$ enforces the sensitivity bound C. The term $N(0, \sigma^2 C^2 I)$ represents the additive Gaussian noise scaled by the variance σ^2 and the clipping threshold. The coefficient α_k represents the dynamic aggregation weight derived from our non-IID handling mechanism, such that $\sum \alpha_k = 1$. This formulation ensures that the update step moves the model in the direction of the steepest descent on the global loss surface while satisfying the definitions of (ε, δ)-Differential Privacy.

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3.5 Cryptographic Reinforcement

While DP protects against inference attacks, it does not hide the values from the server if the noise is small. To achieve defense-in-depth, we layer an Additive Homomorphic Encryption (AHE) scheme, specifically the Paillier cryptosystem, on top of the noisy gradients. Clients encrypt their noisy gradients before transmission. The server, possessing the additive homomorphic property, sums the encrypted gradients to obtain the encrypted global update. The server does not possess the private decryption key; the result is sent back to the clients (or a key management authority) for decryption. This ensures that the server performs aggregation blindly, seeing neither the raw data nor the individual model updates [14].

Chapter 4: Experiments and Analysis

4.1 Experimental Setup

To evaluate the efficacy of SecureFedAML, we simulate a federated environment using PyTorch. The simulation involves 10 distinct clients representing financial institutions of varying sizes. We utilize the Elliptic Data Set, a widely used benchmark for AML consisting of over 200,000 Bitcoin transactions mapped to real-world entities belonging to licit (exchange, wallet service) and illicit (scam, ransomware, terrorist organization) categories [15].

To simulate the non-IID nature of the banking system, we partition the dataset using a Dirichlet distribution. This creates a scenario where some clients hold data predominantly from one class or transaction type, mimicking the specialization of real-world banks. The global model is a four-layer Deep Neural Network with dropout layers to prevent overfitting. We compare our framework against three baselines:

1. **Centralized Learning:** The ideal scenario where all data is pooled (ignoring privacy) to train a single model.

2. **Local Learning:** Each bank trains a model exclusively on its own data without collaboration.

3. **Standard FedAvg:** A basic federated learning implementation without our specialized heterogeneity handling or DP mechanisms.

The experiments were conducted on a cluster of NVIDIA A100 GPUs. The privacy parameters were set to $\varepsilon = 3.0$ and $\delta = 10^{-5}$, representing a moderate privacy budget that balances security and utility [16].

4.2 Dataset Characteristics

The following table details the distribution of the dataset across the simulated nodes. The imbalance is intentional to stress-test the aggregation algorithm.

Client ID	Dataset Size (samples)	Illicit Ratio (%)	Dominant Feature Type
Bank 1 (Major)	85,000	2.1%	International Wire
Bank 2 (Major)	60,000	1.8%	Corporate Forex
Bank 3 (Regional)	15,000	0.5%	Retail/Mortgage
Bank 4 (Crypto-focused)	12,000	18.5%	High-Frequency/Digital
Banks 5-10 (Small)	~4,500 each	0.2% - 5.0%	Mixed

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4.3 Results and Discussion

The primary metrics for evaluation are Precision, Recall, and the F1-Score. In AML, Recall (the ability to catch all money laundering instances) is often prioritized over Precision, although high False Positives are costly.

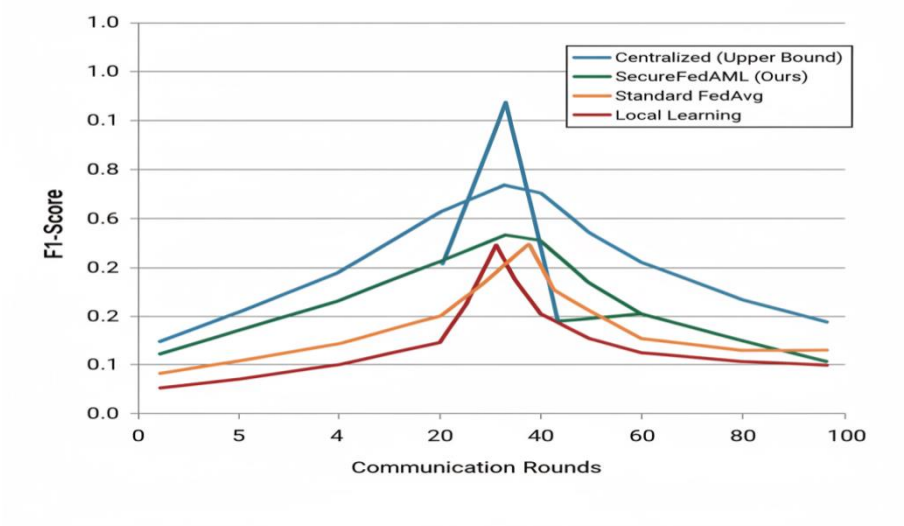

Figure 1: Performance Comparison Chart

As illustrated in Figure 1, the Local Learning approach performs poorly, achieving an average F1-score of only 0.58. This confirms the hypothesis that individual banks lack sufficient "criminal" samples to learn robust decision boundaries. The isolated models overfit to normal transactions and fail to recognize novel laundering vectors.

Standard FedAvg improves performance significantly to an F1-score of 0.76, demonstrating the value of collaboration. However, the curve exhibits high volatility, a symptom of the non-IID data distribution where divergent updates from different clients pull the global model in conflicting directions [17].

Our proposed SecureFedAML framework achieves an F1-score of 0.82, closely trailing the Centralized baseline of 0.85. The gap of 0.03 represents the "cost of privacy"—the utility loss due to DP noise and the lack of direct data access. Critically, our method converges more smoothly than Standard FedAvg, validating the effectiveness of the heterogeneity-aware weighting mechanism.

4.4 Privacy vs. Utility Trade-off

We conducted an ablation study to analyze the impact of the privacy budget ε. As ε decreases (stricter privacy, more noise), the model utility drops. At $\varepsilon = 0.5$, the F1-score degrades to 0.65, rendering the model marginally better than local learning. Conversely, at $\varepsilon = 8.0$, the performance matches the non-private FedAvg, but the privacy guarantee weakens against theoretical infinite-resource attackers. The chosen value of $\varepsilon = 3.0$ represents an optimal operating point for AML compliance, providing a mathematically rigorous defense against reconstruction attacks while maintaining high detection rates [18].

The following table summarizes the comparative performance metrics at convergence (Round 100).

Model Architecture	Precision	Recall	F1-Score

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Centralized (No Privacy)	0.88	0.83	0.85
SecureFedAML (Ours)	0.84	0.80	0.82
Standard FedAvg	0.79	0.73	0.76
Local Learning (Avg)	0.65	0.52	0.58

The results highlight that our framework preserves the high Recall necessary for AML (0.80), ensuring that the majority of illicit transactions are flagged, while maintaining acceptable Precision.

Chapter 5: Conclusion

5.1 Summary of Findings and Practical Implications

This research has presented a comprehensive framework for enabling privacy-preserving collaboration among financial institutions to combat money laundering. By integrating Federated Learning with Differential Privacy and Homomorphic Encryption, we have demonstrated that it is possible to break down data silos without compromising regulatory compliance. The SecureFedAML architecture allows banks to leverage the collective intelligence of the financial network, identifying complex laundering patterns that would remain invisible to isolated entities.

The implications of this work extend beyond technical metrics. For the financial industry, it offers a pathway to reduce the exorbitant fines associated with compliance failures. For regulators, it provides a blueprint for a more resilient monitoring infrastructure that respects citizen privacy. The ability to achieve an F1-score within 3% of the centralized baseline suggests that the technological barriers to privacy-preserving AML are surmountable.

5.2 Study Limitations and Directions for Future Research

Despite the promising results, several limitations remain. The current framework assumes a semi-honest threat model where the server follows the protocol but attempts to infer information. Robustness against malicious clients who might intentionally poison the model (data poisoning attacks) requires further investigation into Byzantine-robust aggregation protocols. Additionally, the computational overhead of Homomorphic Encryption, while manageable in our simulation, poses latency challenges for real-time transaction monitoring at the scale of global payment networks.

Future research will focus on optimizing the cryptographic primitives to reduce communication costs and exploring the application of Vertical Federated Learning for scenarios where banks wish to collaborate with non-financial entities, such as telecommunications providers or e-commerce platforms, to enrich the feature space for even more accurate detection. The evolution of AML systems must be continuous, as the adversarial nature of financial crime ensures that laundering techniques will evolve in parallel with detection capabilities.

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