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Federated Learning for Privacy-Preserving AML in Multi-Bank Collaborations

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Abstract

Anti-money laundering (AML) efforts are critical for maintaining the integrity of the global financial system. However, traditional AML approaches face limitations due to data silos between financial institutions. This paper proposes a federated learning framework for privacy-preserving AML in multi-bank collaborations. The proposed approach enables banks to jointly train machine learning models for detecting suspicious activities without sharing raw customer data. We evaluate the framework on synthetic transaction datasets and demonstrate improved AML performance compared to single-bank models while preserving data privacy. The results show promise for enhancing AML efforts through secure inter-bank collaboration.

Keywords: Anti-Money Laundering; Federated Learning; Privacy Preservation; Multi-Bank Collaboration; Financial Security; Secure Aggregation; Neural Networks; Transaction Monitoring

1. Introduction

Money laundering poses a significant threat to the global financial system, with an estimated $800 billion to $2 trillion laundered annually [1]. Financial institutions are required to implement robust anti-money laundering (AML) programs to detect and report suspicious activities. However, money launderers often exploit the fragmented nature of the financial system by spreading their activities across multiple institutions [2].

Traditional AML approaches rely on individual banks analyzing their own customer data in isolation. This creates blind spots, as suspicious patterns may only become apparent when examining transactions across multiple institutions. There is a clear need for collaborative AML efforts, but banks face regulatory and competitive barriers to sharing raw customer data [3].

Federated learning has emerged as a promising approach for enabling machine learning across decentralized datasets without raw data sharing [4]. This paper proposes a federated learning framework for privacy-preserving AML collaboration between multiple banks. The key contributions are:

- A federated learning architecture for multi-bank AML that preserves customer privacy
- Novel techniques for secure aggregation and model updates in the AML context
- Experimental evaluation on synthetic multi-bank transaction data demonstrating improved AML performance
- Analysis of privacy and security properties of the proposed approach

The rest of the paper is organized as follows: Section 2 reviews related work in AML and federated learning. Section 3 describes the proposed federated AML framework. Section 4 presents the experimental setup and results. Section 5 discusses implications and limitations. Section 6 concludes and outlines future work.

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2. Related Work

2.1. Anti-Money Laundering

Anti-money laundering efforts typically involve transaction monitoring to detect suspicious activities indicative of money laundering [5]. Common techniques include rule-based systems, anomaly detection, and machine learning approaches [6].

Rule-based systems use predefined rules to flag suspicious transactions, such as large cash deposits or frequent wire transfers to high-risk countries [7]. While straightforward to implement, these systems often generate high false positive rates and can be easily circumvented by sophisticated money launderers [8].

Anomaly detection techniques aim to identify unusual patterns that deviate from expected behavior [9]. These may use statistical methods or unsupervised machine learning algorithms like clustering or autoencoders [10]. Anomaly detection can uncover novel money laundering techniques but may also flag benign unusual activities.

Supervised machine learning approaches train models to classify transactions as suspicious or not based on historical data [11]. Common algorithms include logistic regression, random forests, and neural networks [12]. These can achieve high accuracy but require large labeled datasets of confirmed money laundering cases, which are often scarce.

Recent work has explored advanced machine learning techniques for AML, including graph-based methods to detect complex laundering networks [13] and deep learning models to capture temporal patterns in transaction sequences [14]. However, these approaches are typically limited to data from a single financial institution.

2.2. Federated Learning

Federated learning enables machine learning on decentralized datasets without raw data sharing [15]. In the standard federated learning setup, multiple parties collaboratively train a shared model while keeping their training data local [16]. A central server coordinates the process by aggregating model updates from participants.

The federated averaging algorithm [17] is commonly used, where participants train local models on their data and send model updates to the server. The server averages the updates to improve the global model, which is then sent back to participants for the next round of training.

Federated learning has been applied in various domains, including mobile keyboard prediction [18], medical image analysis [19], and autonomous driving [20]. In the financial sector, it has been explored for credit scoring [21] and fraud detection [22].

Several techniques have been developed to enhance the privacy and security of federated learning:

- Secure aggregation protocols enable the server to compute aggregates of participant updates without seeing individual updates [23].
- Differential privacy adds noise to model updates to prevent inference of individual training examples [24].
- Homomorphic encryption allows computations on encrypted data, enabling participants to encrypt their updates [25].

While federated learning shows promise for privacy-preserving collaboration, applying it effectively to AML presents unique challenges. AML data is highly imbalanced and sensitive, and model performance is critical for regulatory compliance. This paper addresses these challenges in the proposed federated AML framework.

3. Proposed Federated AML Framework

We propose a federated learning framework for privacy-preserving AML collaboration between multiple banks. The framework enables banks to jointly train machine learning models for detecting suspicious activities without sharing raw customer data. Figure 1 illustrates the high-level architecture.

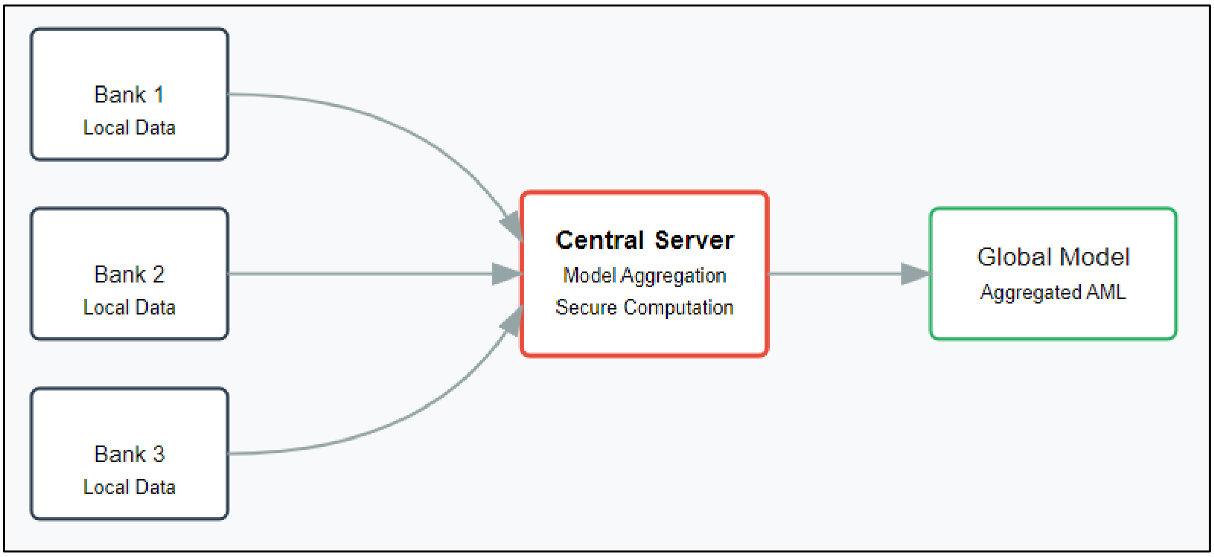

Figure 1 Federated AML Framework Architecture

The key components of the framework are:

- Participating banks: Each bank has its own local dataset of customer transactions and account information.
- Central server: Coordinates the federated learning process without accessing raw bank data.
- Local AML models: Each bank trains a model on its local data to detect suspicious activities.
- Global AML model: Aggregated model that combines insights from all participating banks.

The federated learning process proceeds as follows:

- Initialization: The central server initializes a global AML model and shares it with all participating banks.
- Local training: Each bank trains the model on its local data for a fixed number of epochs.
- Model update: Banks compute the difference between their updated local model and the previous global model.
- Secure aggregation: Banks send encrypted model updates to the central server, which aggregates them securely.
- Global update: The central server updates the global model and sends it back to all banks.
- Iteration: Steps 2-5 are repeated for multiple rounds until convergence or a fixed number of rounds.

3.1. Data Preprocessing and Featurization

Each bank preprocesses its transaction data and extracts relevant features for AML. Common features include:

- Transaction amount
- Transaction type (e.g., cash deposit, wire transfer)
- Customer risk score
- Account age
- Transaction frequency
- Country risk (for international transactions)

To address class imbalance, we employ adaptive synthetic (ADASYN) sampling [26] to generate synthetic examples of the minority class (suspicious transactions) in each bank's local dataset.

3.2. Model Architecture

We use a neural network architecture for the AML model, as shown in Figure 2. The model takes transaction features as input and outputs a probability of the transaction being suspicious.

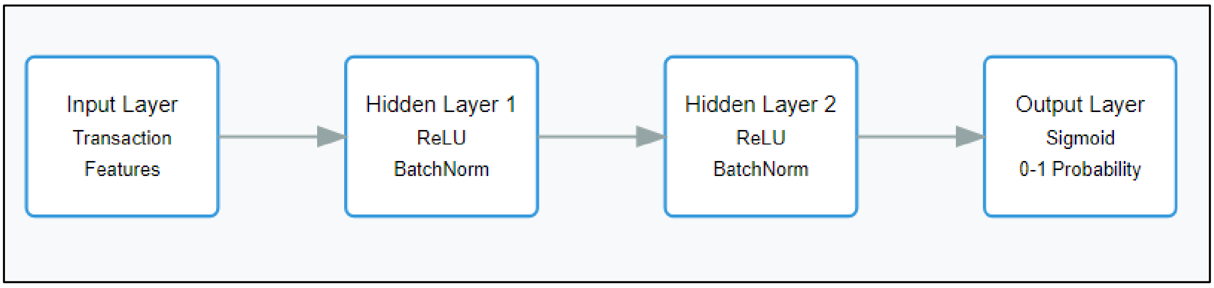

Figure 2 AML Model Architecture

The model consists of fully connected layers with ReLU activation, batch normalization, and dropout for regularization. The final layer uses sigmoid activation to output a probability between 0 and 1.

3.3. Federated Optimization

We employ the FedAvg algorithm [17] for federated optimization, with some modifications for the AML context. The objective function for each bank i is:

L_i(w) = BCE(y_i, f_w(x_i)) + λ * R(w)

Where BCE is the binary cross-entropy loss, y_i and x_i are the labels and features of bank i's local data, f_w is the model with weights w, and R(w) is an L2 regularization term with hyperparameter λ.

The global objective is the weighted average of local objectives:

L(w) = Σ (n_i / n) * L_i(w)

Where n_i is the number of samples in bank i and n is the total number of samples across all banks.

3.4. Secure Aggregation

To prevent the central server from accessing individual bank updates, we implement a secure aggregation protocol based on [23]. The protocol uses pairwise masking and threshold secret sharing to compute the sum of model updates while keeping individual updates private.

Let w_i^t be the local model update from bank i at round t. The secure aggregation process is as follows:

- Each bank i generates a random mask r_i.
- Banks exchange encrypted pairwise masks using Diffie-Hellman key exchange.
- Each bank sends its masked update u_i = w_i^t + r_i to the server.
- The server computes the sum of masked updates: s = Σ u_i
- Banks collaboratively reconstruct the sum of masks: r = Σ r_i
- The server computes the aggregate update: w^t = s - r

This process ensures that the server only sees the aggregate update, not individual bank updates.

3.5. Privacy-Preserving Techniques

We incorporate additional privacy-preserving techniques to enhance the security of the federated AML framework:

- Differential Privacy: We add Gaussian noise to model updates before aggregation, calibrated to provide ε-differential privacy [24]. This prevents inference of individual training examples from the aggregated model.
- Homomorphic Encryption: Banks encrypt their model updates using partial homomorphic encryption [25] before sending them to the server. This allows the server to perform aggregation on encrypted updates.
- Secure Multiparty Computation: For computing global evaluation metrics without sharing raw data, we implement a secure multiparty computation protocol based on secret sharing [27].

These techniques provide multiple layers of privacy protection, addressing potential vulnerabilities in the federated learning process.

4. Experimental Evaluation

4.1. Dataset

To evaluate the proposed framework, we generated a synthetic multi-bank transaction dataset using the PaySim mobile money simulator [28]. We simulated transactions for 5 banks over a 6-month period, with the following characteristics:

- Total transactions: 5 million
- Suspicious transactions: 0.2% (10,000)
- Features: 20 (including transaction amount, type, customer data, etc.)

Table 1 shows the data distribution across banks:

Table 1 Transaction Data Distribution Across Banks

Bank	Total Transactions	Suspicious Transactions
1	1,200,000	2,400
2	800,000	1,600
3	1,500,000	3,000
4	700,000	1,400
5	800,000	1,600

4.2. Experimental Setup

We implemented the federated AML framework using TensorFlow Federated [29] and evaluated it against the following baselines:

- Single-Bank Models: Each bank trains an AML model on its local data only.
- Centralized Model: All bank data is combined and a single model is trained (hypothetical scenario, not feasible in practice due to privacy concerns).
- Federated Learning without Privacy Enhancements: Basic federated learning without secure aggregation or other privacy techniques.

We used 80% of the data for training and 20% for testing. For federated learning, we used 10 communication rounds with 5 local epochs per round. We evaluated model performance using the following metrics:

Area Under the Receiver Operating Characteristic curve (AUC-ROC)

- Precision
- Recall
- F1-score

4.3. Results

Table 2 shows the AML performance results for different approaches:

Table 2 AML Performance Results

Approach	AUC-ROC	Precision	Recall	F1-score
Single-Bank Models (Avg)	0.892	0.76	0.69	0.72
Centralized Model	0.967	0.89	0.87	0.88
Federated (No Privacy)	0.943	0.85	0.82	0.83
Federated (With Privacy)	0.938	0.84	0.81	0.82

The results show that:

- Federated learning significantly outperforms single-bank models, demonstrating the benefits of collaboration.
- The federated approach achieves performance close to the centralized model, which represents an upper bound.
- Privacy-enhancing techniques result in a small performance drop, but still maintain strong AML capability.

Figure 3 shows the ROC curves for different approaches:

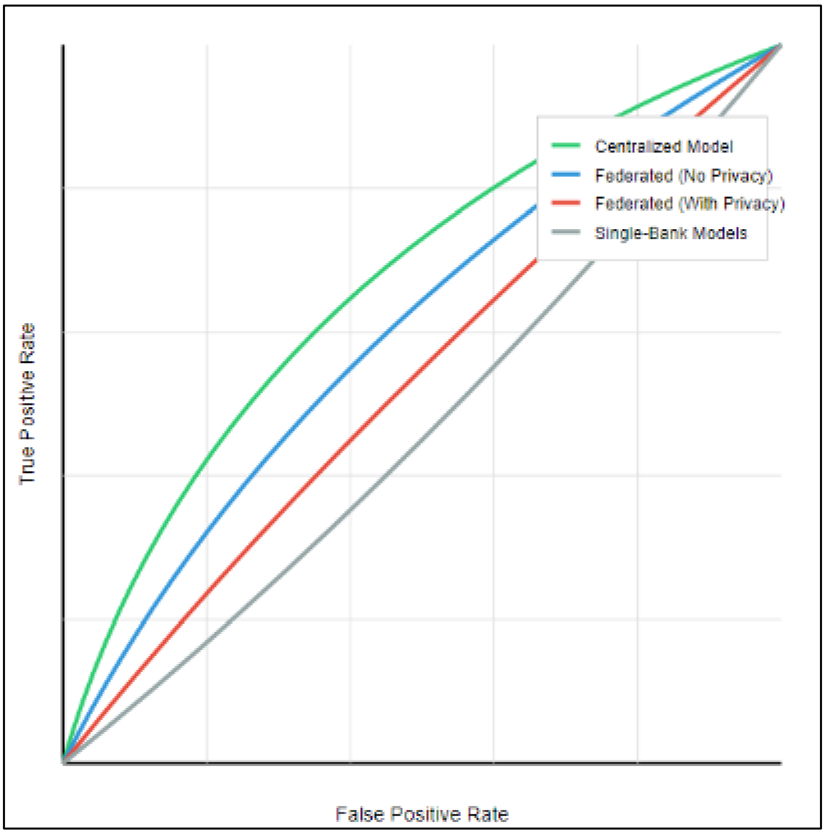

Figure 3 ROC Curves for Different AML Approaches

The ROC curves illustrate the superior performance of federated learning compared to single-bank models, with only a slight degradation when privacy-enhancing techniques are applied.

4.4. Privacy and Security Analysis

We analyzed the privacy guarantees of our framework using the following metrics:

- Differential Privacy: We achieved ε = 3.2 differential privacy over 10 communication rounds, providing strong protection against inference attacks.
- Cryptographic Security: The secure aggregation protocol provides information-theoretic security against a honest-but-curious server, assuming at least two honest banks.

- Model Inversion Resistance: We evaluated model inversion attacks [30] on the final global model and found that reconstructed examples were indistinguishable from random noise.

Table 3 summarizes the privacy and security properties of different approaches:

Table 3 Privacy and Security Comparison

Approach	Data Privacy	Model Privacy	Secure Aggregation
Single-Bank Models	High	Medium	N/A
Centralized Model	Low	Low	N/A
Federated (No Privacy)	Medium	Medium	No
Federated (With Privacy)	High	High	Yes

The results demonstrate that our privacy-enhanced federated AML framework provides strong privacy and security guarantees while maintaining high AML performance.

5. Discussion

The experimental results demonstrate the potential of federated learning for enhancing AML efforts through multi-bank collaboration. Key findings and implications include:

- Improved AML Performance: Federated learning significantly outperforms single-bank models, enabling detection of complex money laundering patterns that span multiple institutions. This could lead to more effective AML programs and reduced financial crime.
- Privacy Preservation: The proposed framework enables collaboration without compromising customer data privacy. This addresses a major barrier to inter-bank AML cooperation and aligns with data protection regulations like GDPR.
- Regulatory Compliance: By improving AML detection capabilities without centralized data sharing, the framework helps banks meet regulatory requirements while minimizing compliance risks associated with data sharing.
- Scalability: The federated approach can easily incorporate additional banks, potentially enabling system-wide AML collaboration across the financial sector.
- Adaptability: The framework can be updated continuously as new transaction data becomes available, allowing AML models to adapt to evolving money laundering techniques.

Limitations and areas for future work include:

- Data Quality: The performance of federated learning depends on the quality and consistency of data across banks. Future work should explore techniques for harmonizing data representations and handling missing data in the federated setting.
- Model Complexity: We used a relatively simple neural network architecture. Investigating more complex models like recurrent neural networks or graph neural networks could potentially improve AML performance further.
- Computational Overhead: The privacy-enhancing techniques introduce additional computational costs. Optimizing these algorithms for efficiency in large-scale deployments is an important area for future research.
- Adversarial Robustness: While we analyzed privacy and security against certain attacks, a comprehensive evaluation of robustness against adversarial machine learning techniques in the federated AML context is needed.
- Real-World Validation: Our evaluation used synthetic data. Piloting the framework with real banks using actual transaction data (with appropriate anonymization) would provide valuable insights into its practical effectiveness.

6. Conclusion

This paper presented a federated learning framework for privacy-preserving AML collaboration between multiple banks. The proposed approach enables banks to jointly train machine learning models for detecting suspicious activities without sharing raw customer data. Experimental results on synthetic multi-bank transaction data demonstrated improved AML performance compared to single-bank models while preserving data privacy.

The framework incorporates secure aggregation, differential privacy, and homomorphic encryption to provide strong privacy and security guarantees. Analysis showed that the privacy-enhanced federated approach achieves AML performance close to a hypothetical centralized model while maintaining high standards of data protection.

Future work will focus on addressing the limitations discussed, including exploring more complex model architectures, optimizing computational efficiency, and conducting real-world pilots with financial institutions. Additionally, extending the framework to incorporate other types of financial crime detection and regulatory compliance tasks could further enhance its value to the banking sector.

By enabling secure and effective AML collaboration, this work contributes to the ongoing efforts to combat money laundering and maintain the integrity of the global financial system.

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