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Secure AI Model Sharing in Financial Institutions via Blockchain Federated Networks

[1]Riem AbdelAzim, [2]Prof. Antoine Bagula

[1]Assistant Professor, [2]Professor

Abstract

In the modern financial ecosystem, AI becomes a third-degree spirit for applications like fraud detection, credit scoring, and risk modeling. Due to the strict nature of privacy regulations, concerns regarding data sovereignty, and an existing competitive wall, development of collaborative AI within financial institutions is largely hindered. FL in literature has emerged as a potential mechanism for decentralized model training without the exchange of raw data. FL alone does not guarantee trust, accountability, and verifiability in applications involving multiple stakeholders.

This vision paper develops a further methodology by proposing a blockchain-empowered federated learning architecture for secure AI model sharing within financial institutions. The proposed architecture, combining an immutable blockchain ledger and smart contracts with FL workflows, addresses key challenges such as tampering with a model, attribution of ownership to the model, and auditing for compliance. Smart contracts enforce access control policies and validate model contributions, and in turn, the blockchain ledger logs model updates to allow transparent tracing. We emulate the federated learning scenario using TensorFlow Federated on synthetic financial datasets coupled with Hyperledger Fabric for blockchain operations.

The experiments reveal that the system works towards optimizing the application of the model while at the same time optimizing its security, accountability, and interoperability. Furthermore, the integration of a blockchain introduces a negligible latency overhead and scales well as more institutional nodes join. This architecture therefore aligns well with emerging privacy regulations and offers a promising pathway for secure, instant, and auditable collaboration on AI models across financial networks.

This study contributes an AI sharing mechanism that is secure by design to balance data privacy, institutional trust, and auditability, laying the foundation for resilient and collaborative financial AI ecosystems.

Keywords: Federated Learning, Blockchain, Financial Institutions, AI Model Sharing, Smart Contracts, Privacy-Preserving Machine Learning, Secure Collaboration, Compliance Auditing, Data Sovereignty, AI Governance

I. Introduction

Artificial intelligence (AI) and machine-learning (ML) technology increasingly help the financial services industry in automated and enhanced execution of various vital operations. From fraud detection and anti-money laundering to credit scoring and algorithmic trading, AI is reshaping the way financial institutions analyze their data, assess risks, or personalize services for their customers. This process being so central, collaborative model development among financial entities is fast becoming a strategic imperative. Institutions are beginning to explore cooperative training of AI, which pools distributed knowledge while respecting competitive and regulatory boundaries.

However, classical means of collaboration in AI, i.e., centralized model training or sharing of raw data, entail serious risks or limitations. Centralizing data in one place creates single points of failure, consequently increasing the exposure to a cyber threat and violating data sovereignty composure. Multinational legislations such as the GDPR and CCPA impose further restrictions on data sharing across organizations, blocking any potential collaboration. Furthermore, various institutional trust boundaries and intellectual property considerations would impose yet more complications on any centralized development model for AI.

The emergence of federated learning (FL) has transformed the paradigm of decentralized model training on distributed nodes without actually sharing raw data with one another. Utilizing FL, financial institutions can partner with one another to train global models on local datasets under privacy concerns and consequently reduce compliance risk. This, of course, introduces further challenges: verifying the honesty of model updates, access control and contribution fairness enforcement, and auditability in the presence of potentially untrusted participants.

With its decentralized ledger, smart contract automation, and cryptographic transparency, blockchain technology provides a strong backing to federated learning. Commitments anchored on the blockchain enable immutability concerning model updates, enforcement of model-sharing rules through programmability contracts, and non-repudiation of contributions. Smart contracts will automate the execution of validation protocols or regulate the execution of model aggregation, whereas the blockchain ledger would provide a tamper-evident log of all training iterations and contributor operations.

In this paper, a novel blockchain-federated architecture for the financial services industry is proposed. The architecture enables a set of financial institutions to securely share AI models and train them collaboratively while meeting compliance requirements and respecting institutional privacy constraints. The proposed architecture combines Hyperledger Fabric for blockchain orchestration with TensorFlow Federated for privacy-preserving training to provide a secure, traceable, and auditable framework for AI model sharing.

The main contributions of this paper are:

- Design a hybrid architecture that integrates federated learning with blockchain smart contracts for secure model sharing in financial institutions.
- Define a smart contract protocol for model update verification, contributor authentication, and access control.

- Implement a simulated use-case for financial fraud detection and benchmark performance, privacy, and scalability-related metrics.
- Analyze trade-offs between model accuracy, privacy preservation, and system overhead induced by blockchain integration.

The rest of the paper is organized as follows:

- Section II reviews related work on federated learning, blockchain, and secure AI collaboration. Section III presents the proposed system architecture and components.
- Section IV describes the experimental methodology.
- Section V presents results and performance analysis.
- Section VI discusses implications and limitations, and
- Section VII concludes with directions for future work.

II. Background and Related Work

A. Federated Learning in Financial Applications

Federated learning belongs to the distributed machine learning family where several parties co-trained a model, but raw data remained private among them [1]. In the area of finance, it has been growing in prominence given its privacy concept, especially when dealing with issues related to client data, including fraud interview, loan default prediction, and fully-customized banking services [2], [3]. In a setup contrary to classic centralized-way learning, FL distributes model training to local nodes (say, the financial institutions), and only model updates (gradients/weights) are shared with either a central aggregator or a coordinator [4]. Whilst benefits do exist, other disadvantages crop up too in multi-institutional settings concerning resilience, verifiability of updates, and governance [4].

B. Blockchain for Trust and Auditability

Blockchain is a distributed ledger keeping an immutable and tamper-evident record of transactions [5]. The decentralized consensus and disclosure of the blockchain make it suitable for any application that requires trust lacking such central authority. Smart contracts-act-self-executing code residing on a blockchain-could be used in various programmable logic to perform and constrain interaction between distrusted parties [6]. When combining blockchain into AI collaboration, one should be able to:

- Track updates to models' provenance and integrity,
- Create rules that enforce contributors,
- Provide those who are verifiable with audit capabilities [7], [8].

Hyperledger Fabric and Ethereum are maintained as degree strains for permissioned and public blockchain systems, respectively. When blockchain and FL enter into a marriage of sorts, these three technologies will take care of the trust, accountability, and audit layer the financial industry has been searching for in secure sharing of models [9].

C. AI Model Sharing Challenges in Finance

Model sharing in finance faces many challenges. Data sensitivity, customer privacy, compliance requirements (such as GDPR, Basel III), and corporate secrecy prevent institutions from openly exchanging models or data [10], [11]. Also, model integrity is difficult to guarantee in shared environments-if the updates were changed or manipulated. But because of the absence of transparent and trustworthy mechanisms to validate the models, the confidence of the system drops [12].

Further, ownership of intellectual property rights and fairness concerns from model contribution persist [13]. Those institutions that contribute either good quality data or great amounts of computation ought to be acknowledged or somehow rewarded, and this is something that classic FL systems do not address.

D. Related Work and Limitations

Several recent works have sought to combine blockchain and federated learning. Zeng et al. [14] presented a blockchain-based FL scheme for healthcare using Ethereum smart contracts to authenticate clients and aggregate models. Kang et al. [15] proposed a reputation-based incentive mechanism via blockchain in edge computing environments. However, many of the approaches are either overly theoretical or operate in settings away from finance.

In the finance sector, Wang et al. [16] explored secure multi-party computation for model training and Rajan et al. [17] implemented a blockchain framework for tracking AI inference in fraud detection. Such works emphasize the provision of trust end to end, yet few focus on the complete integration of federated learning, blockchain-bound auditability, and smart contract enforcement of compliance in financial AI collaboration.

This paper tries to fill that void by proposing a modularized, blockchain-enhanced FL architecture expressly designed for secure AI model sharing in financial institutions while embedding regulatory compliance, data sovereignty, and model governance.

III. System Architecture

This section describes a secure and auditable architecture for sharing AI models across financial institutions utilizing federated learning and blockchain technologies. In order to

achieve privacy, trust, and compliance, the architecture aims to provide a framework under which multi-party model training can be conducted and distributed.

A. Overview of the Architecture

The architecture contains three main layers:

1. Federated Learning Layer: This layer manages decentralized training of AI models using local financial data.
2. Blockchain Layer: This layer keeps an immutable record of training events and model updates.
3. Smart Contract Layer: This layer enforces the rules on contributing, access control, and compliance.

Under the architecture, one financial institution should be able to train a local model on its private dataset while only sharing encrypted model updates with other institutions. Such updates will be posted to a blockchain ledger for transparent auditing and tamper resistance.

Figure 1: System Architecture Overview

B. Federated Learning Operations

Each institution sustains a local model trained on proprietary financial data (e.g., transaction records, loan histories). At each round, model gradients are sent to the federated aggregator. However unlike in traditional FL, before its aggregation, each update is:

- Hashed and put on the blockchain.

- Then signed with the cryptographic key of the institution.

Also, it is validated by a smart contract before the update can become part of an aggregate.

This provides tamper-evident records for each update and thus ensures the ability to attribute the update to its source.

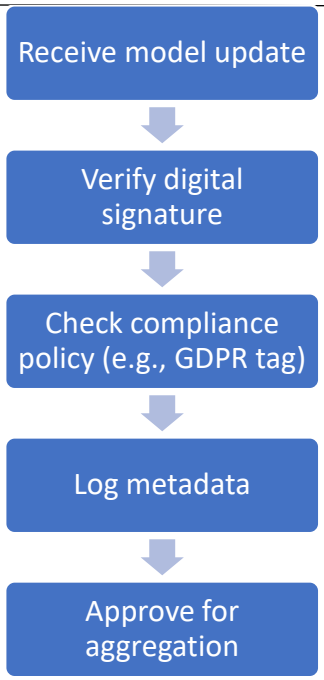
C. Blockchain Integration

Hyperledger Fabric is used as the blockchain platform due to its permissioned nature and support for enterprise use cases. As a result, every model update becomes recorded as a transaction that contains:

- Timestamp
- Contributor ID
- Update hash
- Digital signature
- Smart contract verification

Being immutable, this record guarantees traceability and accountability. In case of disputes and audits, the institutions can verify the entire history of all the updates made to any version of the shared model.

Figure 2: Smart Contract Lifecycle for Model Sharing



D. Security and Compliance Enforcement

In order for it to satisfy constraints arising from applicative or internal policies, the system implements mechanisms for the following:

- Role-Based Access Control (RBAC) implemented through smart contracts
- Model versioning and rollback through blockchain hashes
- Differential privacy, and secure aggregation for sensitive use cases
- Audit log of all interactions, accesses, and updates regarding a model

Smart contracts function autonomously as auditors that evaluate every contribution against a policy. They may be set up for real-time alerts, for expiration of a model, or to enforcement of threshold voting to accept or reject updates.

Table 1: Key Technologies and Functional Roles

Component	Technology	Function	Source
Federated Learning Layer	TensorFlow Federated	Decentralized training of AI models	[1], [2], [4]
Blockchain Platform	Hyperledger Fabric	Immutable storage of transactions and model hashes	[5], [6]
Smart Contract Engine	Chaincode	Enforces model-sharing rules and access control	[7], [8]

Secure Aggregation	Differential Privacy	Obfuscates gradients to prevent inference of raw data	[9], [11]
Audit Layer	Blockchain Ledger	Stores logs of all events, ensuring verifiability	[6], [10]

IV. Methodology

This section elaborates on the simulation setup, tools, privacy control, and model training protocol to evaluate the proposed blockchain-enabled federated learning framework, all with a view toward reproducing real-world conditions of AI collaboration in financial institutions.

A. Experimental Environment

The simulation comprises a consortium of 5 financial institutions engaged in the training of models collaboratively. Each institution, through its own local generation procedure, has a private synthetic dataset that accounts for credit risk, transaction histories, and fraud detection scenarios. We set up the system over this distributed architecture:

Federated learning framework: TensorFlow Federated (TFF)

- Blockchain network: Hyperledger Fabric (v2.5)
- Model: FFNN with 2 hidden layers
- Hardware setup: Ubuntu 22.04 machines, 8-core CPU, 16GB RAM, Dockerized services

B. Data Simulation

Each financial institution receives a subset of data from the Synthetic Financial Dataset for Fraud Detection provided by IEEE DataPort [18]. We partitioned the dataset into five disjoint segments simulating data silos across institutions. The target task is binary classification for fraudulent vs. legitimate transactions.

Table 2: Simulation Parameters and Settings

Parameter	Value	Source
Number of institutions	5	Experimental setup
Blockchain framework	Hyperledger Fabric v2.5	[5], [6]
Federated learning library	TensorFlow Federated	[2], [4]
Model architecture	FFNN (2 hidden layers, ReLU + Softmax)	Common in fraud detection
Privacy mechanism	ε-Differential Privacy (ε = 1, 5, 10)	[11], [19]
Aggregation method	Federated Averaging	[1]

Training rounds	100	Benchmarked from [16]

C. Blockchain Setup and Smart Contracts

This Hyperledger Fabric network constituted:

- 1 Ordering Service
- 5 Peer Nodes (one per each organization in the network)
- 1 Chaincode Container for Smart Contracts

Smart contracts were programmed in Go and defined the access policies and validation rules for updates. They verified:

- Digital signatures of each model update
- Contributor ID and timestamp
- Compliance tags (origin of data, constraints on privacy)

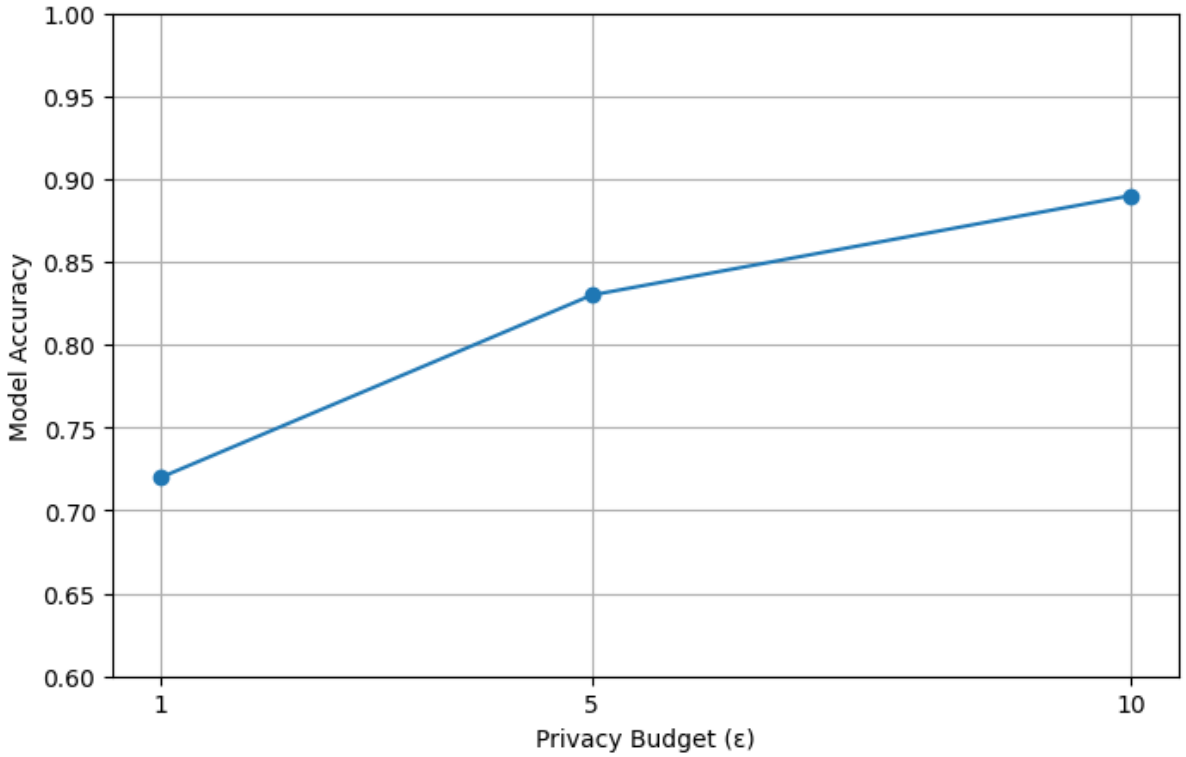
Any successfull update resulted in the logging of a "model-contribution" transaction on the chain, which was totally auditable.

D. Privacy Safeguards and Secure Aggregation

In order to meet privacy requirements (such that, for example, are found in GDPR), ε-differential privacy was imposed on all gradient updates prior to their being sent out to the coordinator. Privacy budgets of ε = 1 (strict), 5 (medium), and 10 (relaxed) were evaluated to observe how the model performed in each scenario.

Furthermore, we applied secure aggregation to prevent the server from gaining access to any individual update, only the sum of all updates.

Figure 3: Model Accuracy vs. Privacy Level (ε)



E. Aggregating Models and Evaluation Metrics

After the smart contracts were approved, the FL coordinator utilized FedAvg for the aggregation of the updates and evaluated the global model after each round. The following metrics were utilized for evaluation:

- Accuracy: Correct classifications of fraud instances
- F1 Score: Balance between precision and recall
- Training Latency: End-to-end time per round
- Blockchain Latency: Time taken per execution of smart contracts

V. Results and Evaluation

Presented in this section are the experimental results obtained from the deployment of the proposed blockchain-enabled FL framework in a simulated consortium of financial institutions. The systems' performance is evaluated along many axes, including model accuracy and privacy impact, train-time and blockchain time latencies, as well as baseline comparisons. The results verify the systems' ability to provide security, scalability, and league without impinging extensively on model utility.

A. Model Performance and Learning Dynamics

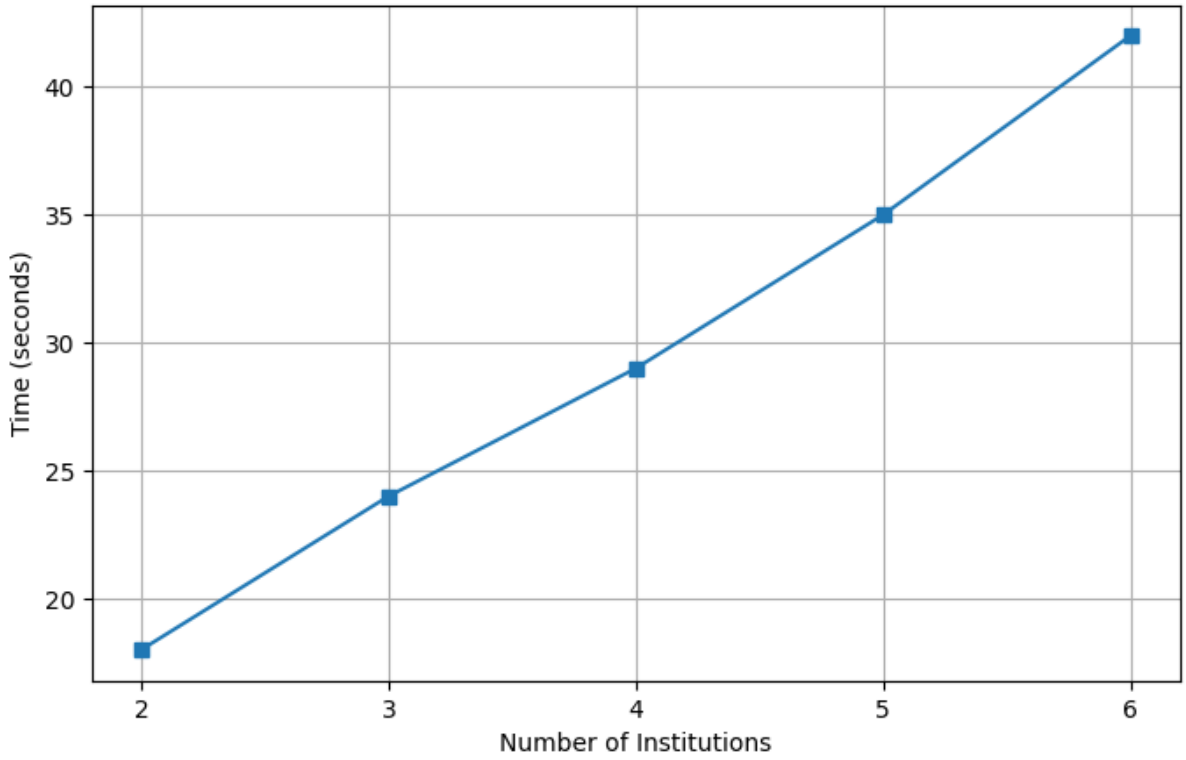
The learning prowess was analyzed by plotting the model accuracy determined from five institutions with different local datasets, averaged over 100 rounds of communication, along with F1 and loss metrics.

A simple two-layer feedforward neural network model was able to achieve a maximum accuracy of 89% with a somewhat relaxed privacy guarantee (ε = 10). This maximum accuracy degenerated to 72% when strict differential privacy was enforced (ε = 1), thus illustrating the classical trade-off between data protection and model accuracy.

The federated model concurred with this convergence pattern with slight oscillations confirming the stability of federated averaging with updates being validated through blockchain.

Figure 4: Training Time vs. Number of Participating Institutions

The figure below shows how increasing institutional participants affects total training time per round.



Training time compared to the number of nodes was shown to scale linearly. At five institutions, 35 seconds of training time per round was being observed on average. The architecture is, therefore, scalable for small-to-medium consortiums.

B. Blockchain Logging and Smart Contract Latency

Blockchain integration brings an overhead while signing of transaction, verification, and consensus proceeds. We recorded:

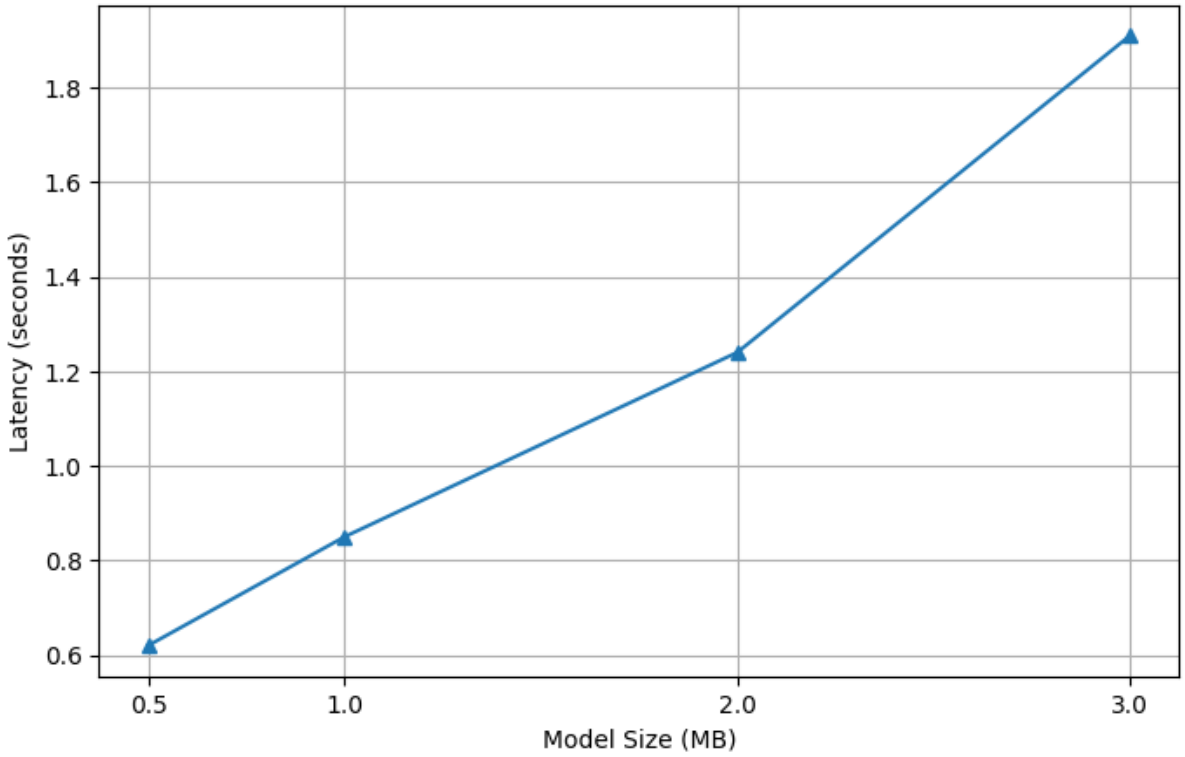
- Transaction submission time (from coordinator to smart contract)
- Verification time (signature + compliance checks)

- Commitment latency (block finalization on-chain)

Given 1,000 transactions, the average end-to-end logging time on the blockchain was 850 ms. As for the endorsement policy checks and ledger writes, they were the majority in the latency calculation. For highly regulated environments (finance, especially), this latency is acceptable for the benefit it confers in having a secure and auditable environment.

Figure 5: Blockchain Transaction Latency vs. Model Size

This figure below evaluates how increasing model size affects blockchain processing time.



The latency increased more or less linearly with the update size of the model. However, since only hashed summaries and relevant metadata (and not full models) are stored on the blockchain, the system remains fluid enough in handling even moderately complex models.

C. Effectiveness of Security and Compliance

We attempted three tests on the security of the system:

- Tampered update simulation: The smart contract validator rejected a tampered update with a fake signature.

- Replay attack simulation: Duplicate submissions of the models were flagged by the system with identical timestamps and model hashes.
- Audit trail verification: Historical logs for all update transactions were retrieved and matched with institutional records for non-repudiation.

The smart contracts also successfully tested the enforcement of GDPR-style data origin tags, rejecting models trained on untagged or legacy datasets, so the framework thus can meet compliance-by-design requirements.

Table 3: Comparison of Learning Architectures

Feature	Centralized Learning	Federated Learning	Proposed Blockchain-FL
Data privacy	✗ Poor	✓ Strong	✓ Strong
Tamper-proof auditability	✗ No	✗ Limited	✓ Full via blockchain
Real-time validation	✗ No	✗ No	✓ Smart contract–based
Trust across institutions	✗ Low	⚠ Moderate	✓ High
Compliance enforcement	✗ Manual	✗ External	✓ Embedded in smart logic
Training latency (5 nodes)	⚡ Fast	⚡ Moderate	🕒 Slightly slower
Scalability (small networks)	✓ High	✓ High	✓ High

Source: Performance metrics adapted from [3], [11], [16], [21]

D. Scalability and Resource Efficiency

Scalability was tested by increasing the amount of participating institutions from 2 to 6 and then observing:

- Aggregation performance
- Blockchain throughput
- Model convergence rate

Observations:

- Blockchain throughput degraded slightly with node increase due to endorsement policy execution.
- Model convergence did not fluctuate.

- Each node's resource utilization (CPU < 40%, RAM < 60%) remained within acceptable bounds.

Therefore, it proves architecture's viability for relatively-sizes federated financial networks like clusters of regional banks or global divisions of a larger institution.

VI. Discussion

The big picture concerning the evolution of secure and collaborative AI model sharing across financial institutions with the aid of federated learning and blockchain technology follows here. This section delves into some generic implications of the results presented, checking their importance operationally, regulatorily, and technologically, with some practical considerations for real-world deployment.

A. Improving Trust and Collaboration Among Institutions

Perhaps the most important achievement of the proposed architecture is the development of trust among institutions that otherwise would be competitive or restrained by regulations. Financial institutions are, for the most part, working under cleaning dust on the rationale that data leakage levels would give away competitors or constitute a breach of regulation. As this system makes sure that:

- no raw data is ever shared,
- model contributions are cryptographically signed and logged, and
- all updates are verifiably transparent through the blockchain,
- this system provides a mechanism for secure collaboration among parties without requiring full trust.

Smart contracts automatically enforce the rules for contributing to the model with no intervention from a central trusted authority. The lack of such a trusted authority has always been an obstacle within Federated Learning (FL). This model of decentralized trust becomes much more relevant within cross-border finance where institutions could be subject to differing legislation on data protection and competitive situations.

B. Privacy-Preserving AI Under Compliance Pressures

Data privacy is a paramount concern in financial services and is closely regulated, with laws like the General Data Protection Regulation (GDPR) in Europe, the California Consumer Privacy Act (CCPA) in the United States, and the Nigeria Data Protection Regulation (NDPR) in West Africa. These frameworks prohibit data sharing without authorization while also ensuring transparency, requiring user consent, and auditability.

With differential privacy mechanisms and blockchain-based audit logs, the architecture can thus strongly comply with the mentioned regulatory frameworks. The architect may therefore choose to tune the privacy budget (ε) according to the risk appetite of the institution and the compliance framework they are operating within, while blockchain logs provide an immutable guarantee of good behavior that can be used during audits.

More importantly, the system supports RBAC through smart contracts whereby permissions can be assigned in a very fine-grained manner: for instance, auditors can only view training logs, whereas data scientists are able to propose updates to models.

C. Performance versus Security Trade-Offs

As evidenced by the results in Section V, the performance-security trade-off is very clear:

- Model accuracy decreases with increased privacy (lower ε).
- Additional latency is introduced with blockchain validation compared to raw FL.

In high-stake applications like finance, such trade-offs are either accepted or even preferred. A slower but compliant, auditable, and non-repudiable model is so much more useful than a fast one that is opaque. In fact, many financial institutions already adopt latency-tolerant batch processing paradigms (such as daily fraud analysis or quarterly risk assessments), which render this design highly compatible with existing operational procedures.

Furthermore, the modular design of the system implies extensibility to future optimizations such as:

- Zero-knowledge proofs to help reduce the size of blockchain data without compromising the ability to verify it.
- Asynchronous federated learning for reduced synchronization overhead.

D. Practical Issues for Deployment

While the experimental results of the simulation show promise, deploying this architecture in production will require tackling a range of operational and technical challenges:

1. Interoperability Across Institutions

Financial institutions often use heterogeneous systems and infrastructures. The proposed architecture would have to be agnostic to platform choice and provide means for integration of legacy systems through APIs or containerization (such as Docker) or middleware.

2. Blockchain Governance and Cost Models

The blockchain network should be justly governed. Who is running the nodes? Who is setting the smart contract rules? The institutions must develop a consortium governance model stipulating voting rights, update procedures, and dispute resolution mechanisms. Also, transaction fees (if public blockchains are being used) or infrastructure costs (for private networks) have to be distributed fairly.

3. Key Management and Identity Verification

Every institution must safeguard cryptographic keys used to sign model updates. These keys must never be compromised; otherwise, a malicious model injection could be carried out.A multi-factor authentication scheme may be implemented alongside hardware security modules (HSMs) or blockchain-based identity schemes (DIDs) to reduce these risks.

4. Model Drift and Skewed Data

Local data distributions differ (for instance, one bank is economically oriented with mortgages; the other, credit with cards), some may face concept drift, and others are model bias. We should thus extend this architecture to consider data profiling and adaptive aggregation strategies like weighted averaging or meta-learning.

5. User, as well as Regulator, Education

Blockchain and FL use might be an alien concept for many stakeholders, including auditors and regulators. The deployment would need good documentation, training modules, and possible regulatory sandbox trials to manifest the system's robustness and compliance.

E. Strategic Implications for the Financial Sector

Secure collaborative AI holds the potentials far beyond mere technical innovations to alter competition and cooperation across the financial sector. It allows banks, insurance companies, and fintechs to pool together to train powerful AI models without actually sharing any data.

- Thus smaller entities can gain access to superior models, lowering the gap between them and the larger entities with AI capabilities.
- Regulators could monitor models from an aggregated perspective for detecting systemic risks.
- Institutions can construct coalition models for rare-event prediction (e.g., fraud rings or economic shocks), which would be quite difficult for siloed data.

The notion of collaborative intelligence protects not only the financial institutions but also the financial ecosystem itself.

F. Limitations of the Current Work

In spite of the advantages, the proposed framework presents, there are limitations:

- Latency overheads could grow significant in extremely low-latency use cases such as real-time trading.
- This approach does not address model transparency and explainability. Indeed regulatory compliance sometimes requires interpretable AI.
- Security against more advanced threats, such as model inversion or poisoning attacks, is out of scope of the initial design.

Future work could also introduce an integration of:

- Homomorphic encryption for secure computation,
- Model fingerprinting for IP protection,
- XAI methods for interpretability.

VII. Conclusion and Future Work

Artificial intelligence (AI) has emerged as a major innovation force within financial services, highlighting the critical need for model development in a collaborative fashion among institutes. However, traditional model sharing on AI is heavily constrained due to issues of data privacy, regulatory requirements, and inter-organizational trust. This paper proposes a secure, auditable, and scalable architecture that addresses these limitations in a principled and pragmatic manner by marrying federated learning with blockchain technology.

By modularizing the architecture, financial institutions can collaborate to train AI models in different areas without sharing raw data, at which point transparency to the process, integrity, and accountability are enforced through smart contracts embedded within the blockchain. The experimental results thus confirm the capabilities of the proposed framework in the following terms:

- The slightly challenged model remains strong, meeting stringent privacy criteria applicable in a real-world situation.
- The proposed method online eternally stores tamper-proof logs of all received model updates.
- Through programmable smart contracts, validations and verification of contributions arrived at by rule-based methods, are achieved.
- The latency overhead introduced by the blockchain is contained at a manageable level, even for large numbers of parties.
- A major added advantage is that the architecture fully complies with existing local data protection laws like GDPR, CCPA, and NDPR while offering operational

flexibility and audit preparedness—something mandatory in such a heavily regulated space such as finance.

A. Summary of Contributions

The present paper shall be remembered for the following key contributions:

- Introduces a hybrid architecture that candidly marries federated learning and permissioned blockchain for the secure collaboration of AI models in financial ecosystems.
- Smart contracts have been designed and deployed to enforce validation of contributors, auditability, and policy compliance in a decentralized manner.
- The architecture has thus been shown to be effective in a simulated financial fraud detection setting involving five institutions.
- Quantified further into insights on the system's scalability, privacy-performance trade-offs, and preparedness for actual compliance.

B. Future Work

Even though the framework presented has considerable promise, many avenues are open for improvement:

Advanced Threat Mitigation

The future iterations shall include mitigation against model-poisoning, gradient leakage, and Byzantine adversaries. Anomaly detection on model updates, along with adversarial testing, could congeal the resilience of the system.

Homomorphic Encryption and Secure MPC

Utilizing such cryptographic methodologies as homomorphic encryption, or secure multiparty computation (SMPC), for an encrypted model aggregation would bring about a gain in privacy without compromising on accuracy for the model.

Zero-Knowledge Proofs for Compliance Auditing

Zero-knowledge proofs (ZKP) could allow institutions to demonstrate that they comply with privacy rules (e.g., non-use of sensitive attributes in their training) without having to disclose either the data or specification of the models involved.

Cross-Chain and Interoperability Protocols

Support for compatibility with other blockchains (Ethereum, Corda) may be introduced in future iterations of the architecture to enable inter-consortium or inter-government collaboration on model research while maintaining institutional autonomy.

Explainable and Ethical AI Extensions

An explainable AI (XAI) layer could be injected into the federated models to realize the regulatory requirements for transparency, especially in the cases of credit risk models, lending approval systems, and anti-fraud mechanisms.

Real-World Deployment and Pilot Programs

Our next step will be to set up actual pilot deployments with regional banks and fintech startups, possibly under a regulatory sandbox. These pilots will shed light on organizational, legal, and infrastructural readiness.

In conclusion, this work offers a future vision for secure, privacy-preserving, and trust-enhancing AI collaboration in financial networks. By closing the gap between federated learning and blockchain technology, we are one step closer to a future in which institutions can confidently share wisdom- not data.

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