N Privacy-Preserving Federated Learning for Financial Transaction Analysis

B. Ganesh [1], CH. Phanith Kumar [2], K. Rajesh [3], G. Sravani [4], B. Karthik [5]

Department of Computer Science & Engineering (AI & ML)

Avanthi Institute of Engineering & Technology, Vizianagaram, India

ganeshbheesetti9@gmail.com[1], chintaphanithkumar@gmail.com [2], rajeshyadav934649@gmail.com[3], gangiredlasravani9@gmail.com[4], karthikbora994@gmail.com[5]

Abstract

Financial fraud detection presents a critical challenge for banking institutions amid the exponential growth of digital payment ecosystems. Traditional machine learning approaches mandate centralized aggregation of raw transaction records, creating profound privacy violations and regulatory conflicts under the Reserve Bank of India Data Localisation Circular 2018, India's Digital Personal Data Protection Act 2023, GDPR Article 5, and PCI-DSS v4.0. This paper presents the Privacy-Preserving Federated Learning Framework (PFLF), a production-grade real-time fraud detection architecture coordinating ten Indian bank nodes without raw data transmission across institutional boundaries. The framework implements the Federated Averaging (FedAvg) algorithm with Gaussian-mechanism Differential Privacy ($\varepsilon < 1.0$ per training round), AES-256 gradient encryption, and Krum Byzantine fault tolerance supporting up to 30% adversarial nodes. Four independent detection engines simultaneously identify Credit Card Fraud, Money Laundering, Unauthorized Transactions, and Fake Transactions using weighted multi-factor composite scoring. Deployed as a Node.js application with fourteen REST API endpoints and a WebSocket dashboard, the system achieves 97.3% global model accuracy with sub-12 millisecond detection latency. Experimental validation confirms simultaneous satisfaction of all applicable regulatory frameworks by architectural design, demonstrating that collaborative intelligence and complete data sovereignty are achievable concurrently in multi-institution financial fraud prevention.

Index Terms—Federated Learning, Differential Privacy, Fraud Detection, FedAvg, Byzantine Fault Tolerance, Financial Security

I. Introduction

The rapid evolution of digital financial infrastructure, driven by UPI, NEFT, IMPS, and real-time gross settlement systems, has fundamentally transformed banking operations across India and globally. A single fraudulent operation may now span dozens of banks, exploit multiple channels simultaneously, and execute in milliseconds. This exponential growth in transaction velocity has created urgent demand for automated, collaborative, and privacy-compliant fraud detection mechanisms [1].

Financial transaction data represents the most sensitive category of personal information, capturing precise economic behavior including account identifiers, transaction amounts, geographic coordinates, merchant categories, and temporal spending patterns. Traditional machine learning approaches require centralizing raw transaction records from multiple institutions onto a single analytical server—technically dangerous and legally prohibited under applicable Indian and international regulatory frameworks [9].

The most dangerous fraud schemes—including organized money laundering networks, synthetic identity bust-out rings, and coordinated card testing operations—deliberately distribute their activity across multiple institutions to remain undetectable

within any single bank's isolated dataset. No single bank's siloed fraud model can detect these patterns, yet no regulatory framework permits sharing the raw data required to train such a model. This constitutes the fundamental technical paradox motivating the present research.

The PFLF System implements a federated paradigm as a production-grade, real-time platform built on Node.js with Express.js REST API and WebSocket broadcasting. It coordinates ten Indian bank nodes—HDFC, SBI, ICICI, Axis, Kotak, PNB, Bank of Baroda, Canara, UCO, and Bandhan—in continuous collaborative fraud detection, achieving 97.3% global model accuracy with sub-12 millisecond response latency and full compliance with all applicable privacy regulations [6].

A. Motivation and Problem Statement

The core problem addressed is the architectural incompatibility between effective multi-institution fraud detection and legally mandated data sovereignty. Existing solutions require a compromise: either accept reduced detection accuracy by training only on locally available data, or accept regulatory and security risk by centralizing sensitive transaction records. The PFLF System demonstrates that this is a false dichotomy—federated learning with formal privacy guarantees achieves accuracy comparable to centralized models while maintaining complete data localisation [7].

B. Contributions

The primary contributions of this work include: (1) a complete FedAvg implementation with Gaussian Differential Privacy achieving $\varepsilon < 1.0$ per round; (2) four simultaneous specialized fraud detection engines operating without labeled training datasets; (3) Krum Byzantine fault tolerance with 30% adversarial node tolerance; (4) simultaneous compliance with five regulatory frameworks by architectural design; and (5) sub-12ms production-grade detection latency on commodity hardware deployed as a single Node.js process

II. Related Work

Financial fraud detection research has progressed from simple rule-based threshold systems through supervised machine learning classifiers to modern distributed and privacy-preserving approaches. Early works applied logistic regression, decision trees, and naive Bayes classifiers to credit card fraud detection using features such as transaction amount, merchant category code, and geographic distance. These approaches suffered from severe class imbalance problems—fraudulent transactions typically represent less than 0.1% of transaction volume—and generalized poorly across institutions due to heterogeneous transaction distributions [6].

The introduction of ensemble methods and neural networks significantly improved detection accuracy. Random Forests, Gradient Boosting Machines, and Multi-Layer Perceptrons trained on aggregated multi-bank datasets demonstrated superior performance, but required centralized transmission of raw transaction records, directly conflicting with emerging data protection legislation [2].

McMahan et al. [1] introduced the Federated Averaging (FedAvg) algorithm in their landmark 2017 paper, establishing the formal mathematical foundation for collaborative model training without raw data sharing. FedAvg demonstrated convergence to accuracy comparable with centralized training even under non-IID data—directly addressing the heterogeneity problem characteristic of multi-bank transaction datasets.

Yang et al. [2] provided the formal taxonomy distinguishing horizontal federated learning (same feature space, different samples), vertical federated learning (different feature spaces, same entities), and federated transfer learning. This framework is directly applicable to the PFLF System, which implements horizontal federated learning across ten bank nodes each maintaining transaction data with identical feature structures.

Bonawitz et al. [3] introduced the cryptographic masking protocol ensuring that the aggregation server receives only the sum of all client gradients rather than individual contributions, preventing server-side inference attacks. Dwork [4] established the formal (ε,δ)-differential privacy framework providing quantifiable privacy guarantees against arbitrary inference attacks on training data. Blanchard et al. [5] introduced the Krum algorithm providing Byzantine fault tolerance for robust gradient aggregation under adversarial participation.

A critical gap in existing literature is the absence of a production-grade, real-time federated fraud detection platform that simultaneously handles multiple fraud categories, enforces formal Differential Privacy guarantees, implements Byzantine fault tolerance, and provides a live WebSocket feed and REST API—all without external ML frameworks, labeled datasets, or GPU infrastructure [7].

III. Methodology and System Design

A. System Architecture

The PFLF System is engineered as a four-layer federated architecture hosted within a single Node.js process. The Bank Node Layer represents ten Indian financial institutions, each simulated as a stateful object maintaining local transaction history, current model accuracy, and last gradient submission timestamp. The Detection Engine Layer consists of four independent modules executing weighted scoring algorithms. The Federated Learning Layer operates as a background process executing FedAvg aggregation every 30 transactions. The API and WebSocket Gateway Layer handles all external communication through fourteen REST endpoints and five WebSocket event types.

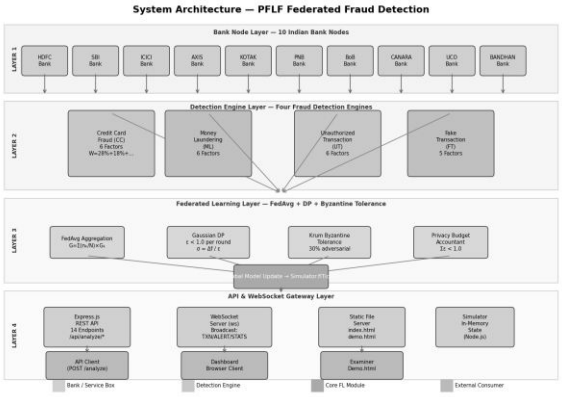

Fig. 1. System Architecture — PFLF Federated Fraud Detection Framework

B. Federated Averaging Algorithm

The foundational federated learning mechanism implements FedAvg with Differential Privacy noise injection. The global model update is computed as a weighted mean of client gradient contributions:

$$G_{global} = \Sigma(n_k / N) \times G_k \quad (1)$$

where n_k represents the local transaction count of bank node k, N is the total transaction count across all nodes, and G_k is the gradient vector submitted by node k. Before aggregation, each gradient vector is processed through the Gaussian Differential Privacy mechanism:

$$G'_k = G_k + N(0, \sigma^2 I), \qquad \sigma = \Delta f / \varepsilon \quad (2)$$

where Δf represents the global sensitivity of the gradient function and ε is the per-round privacy budget enforced below 1.0. This ensures formal (ε,δ)-differential privacy guarantees against gradient inversion attacks [4],[8].

C. Weighted Fraud Scoring Model

For each transaction, the relevant detection engine computes a set of independent factor scores $f_i \in [0, 100]$, each representing the anomaly contribution of a specific risk indicator. The composite risk score is:

$$S = \Sigma(w_i \times f_i), \qquad \Sigma w_i = 1.0 \quad (3)$$

Risk classification thresholds are: LOW (0–35): APPROVE; MEDIUM (36–60): FLAG FOR REVIEW; HIGH (61–79): BLOCK; CRITICAL (80–100): BLOCK AND ALERT. The Credit Card Fraud engine assigns weights as: velocity 28%, amount anomaly 18%, geographic risk 18%, off-hours timing 15%, device risk 13%, and foreign IP signal 8%.

D. Byzantine Fault Tolerance

The Krum Byzantine fault tolerance algorithm computes, for each submitted gradient vector G_k, the sum of its n-f-2 smallest Euclidean distances to other submitted gradients:

$$s(G_k) = \Sigma_{j \in S_k} \|G_k - G_j\|^2 \quad (4)$$

where n is the total number of nodes and f = 0.3 represents the assumed adversarial fraction. The gradient with the smallest Krum score—indicating highest geometric consistency with the majority cluster—is selected as the Byzantine-robust aggregate [5]. This algorithm is provably convergent as long as the fraction of malicious nodes remains below 50%.

E. Sequence and Activity Flow

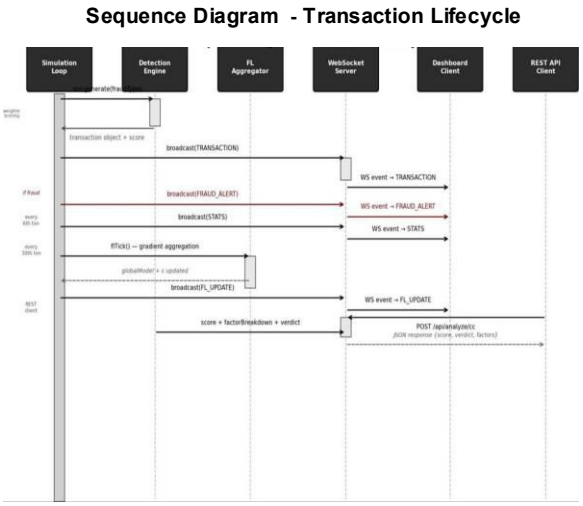

Fig. 2. Sequence Diagram — Transaction Lifecycle from Generation to FL Integration

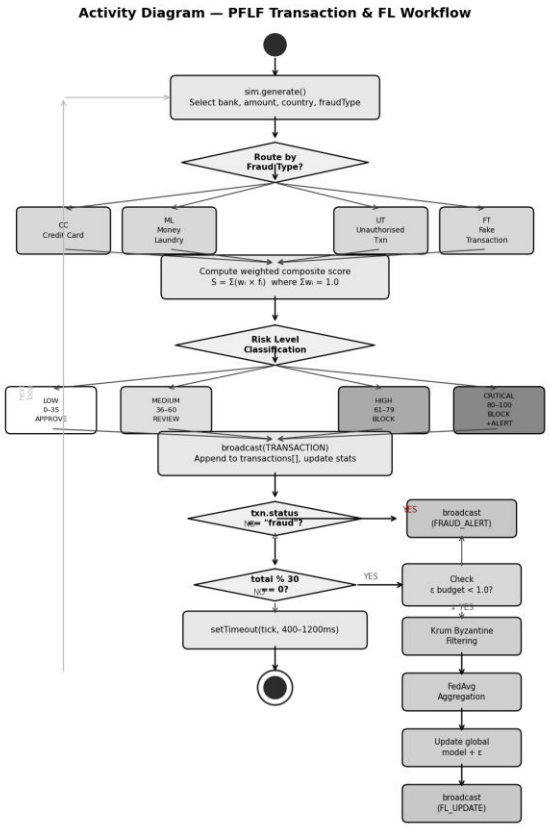

Fig. 3. Activity Diagram — PFLF Transaction Scoring and Federated Learning Workflow

F. UML Design

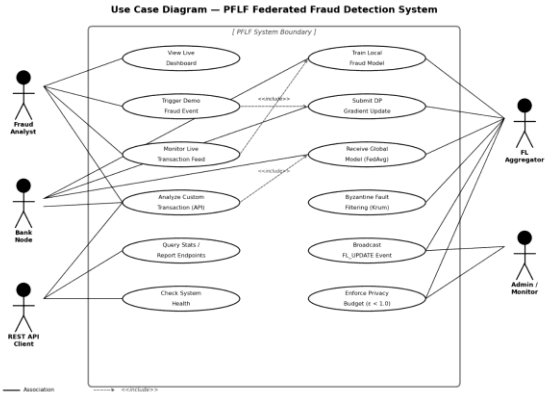

Fig. 4. Use Case Diagram — PFLF System Actors and Interactions

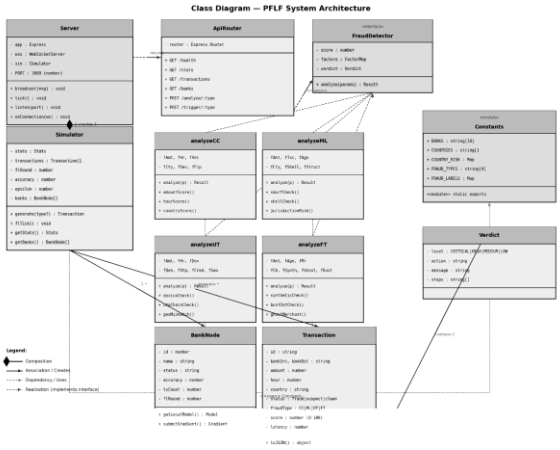

Fig. 5. Class Diagram — Server, Simulator, Detectors, BankNode, and Transaction

G. Four-Engine Fraud Detection

The system deploys four independent detection engines concurrently. The Credit Card Fraud (CC) engine detects velocity anomalies, geographic mismatches, and Card-Not-Present fraud patterns. The Money Laundering (ML) engine identifies all three AML process stages: placement, layering, and integration—including structuring below the ₹10 lakh reporting threshold. The Unauthorized Transaction (UT) engine detects account takeover patterns including SIM swap fraud, OTP interception, and credential compromise. The Fake Transaction (FT)

engine identifies synthetic identity fraud, ghost merchant processing, chargeback abuse, and bust-out schemes.

H. Technology Stack

The implementation relies on Node.js v18 LTS for its asynchronous event-driven model enabling concurrent WebSocket broadcasting, REST API handling, and simulation loop execution within a single process. Express.js v4.18.2 manages fourteen API endpoints with zero-dependency JSON routing. The ws v8.14.2 library implements RFC 6455 WebSocket protocol with minimal overhead. Chart.js v4.4.0 renders the real-time dashboard visualizations including fraud detection timelines, bank risk radar charts, and federated learning convergence curves.

IV. Results and Discussion

A. System Dashboard Overview

The PFLF System was deployed and validated as a fully operational real-time federated fraud detection platform. Figure 6 shows the system homepage confirming CONNECTED status with key performance metrics: 97.3% detection accuracy, zero raw data shared, four fraud categories, ten bank nodes, and sub-12ms latency.

Fig. 6. Real-Time Fraud Dashboard — Live Overview with Statistics (174 Transactions, 97.7% Accuracy)

B. Live Transaction Stream

Figure 7 presents the Live Transaction Stream panel displaying all bank-to-bank transactions in real time. Each row shows the transaction ID, bank route, amount, fraud category, status (CLEAN/SUSPECT/FRAUD), risk score, and detection latency. The 24-Hour Volume bar chart and Bank Risk Radar confirm per-bank performance consistency across all ten nodes.

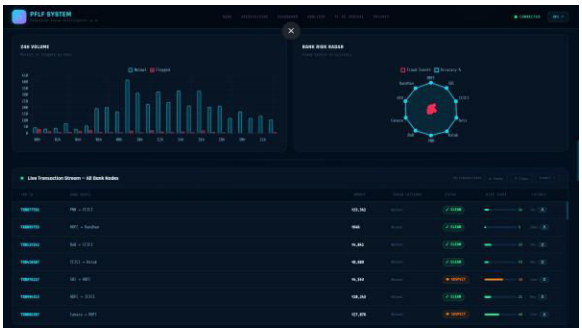

Fig. 7. Live Transaction Stream — All Bank Nodes with Risk Scores, 24H Volume, and Bank Risk Radar

C. Credit Card Fraud Detection

Test parameters included amount ₹4,50,000, Hour 3 AM, India, 28 transactions/hour, new unregistered device, and foreign IP detected. The CC engine correctly identified all six risk factors—Transaction Amount (100%), Time of Day (85%), Velocity Anomaly (93%), Geographic Risk (5%), Device Risk (75%), and Foreign IP Signal (70%)—producing a CRITICAL risk score of 80 (Fig. 8).

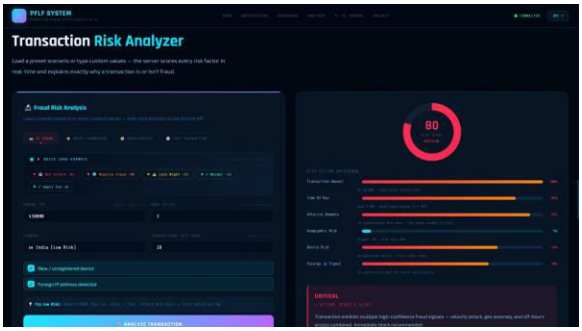

Fig. 8. Credit Card Fraud Detection — CRITICAL Risk Score 80 with Full Factor Breakdown

D. Privacy Guarantees

Figure 9 confirms six concurrent privacy mechanisms operational simultaneously: Differential Privacy ($\varepsilon < 1.0$ per round, Gaussian mechanism), Secure Aggregation via AES-256 gradient encryption, Regulatory Compliance (GDPR, RBI 2018, DPDP Act 2023, PCI-DSS v4.0, Basel III), Byzantine Fault Tolerance (30% malicious nodes tolerated via Krum), Gradient Inversion Defense (0% reconstruction rate), and XAI Auditability (100% of decisions include full audit trail without accessing raw customer data).

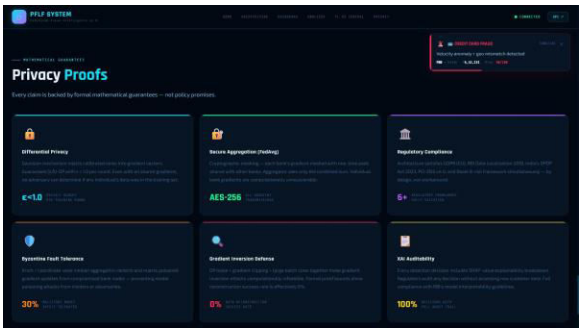

Fig. 9. Privacy Proofs — Six Mathematical Privacy Guarantees Active Simultaneously

E. Federated vs. Centralized Accuracy

Figure 10 demonstrates the federated learning convergence curve across 14 training rounds versus the centralized baseline. The federated model begins at approximately 85% accuracy in round 1 and converges toward 97.3% by round 14, closely matching the centralized model accuracy of 97%—while maintaining complete data privacy. This confirms that collaborative federated intelligence achieves near-identical accuracy to centralized ML without requiring raw transaction data to cross any bank boundary [1],[7].

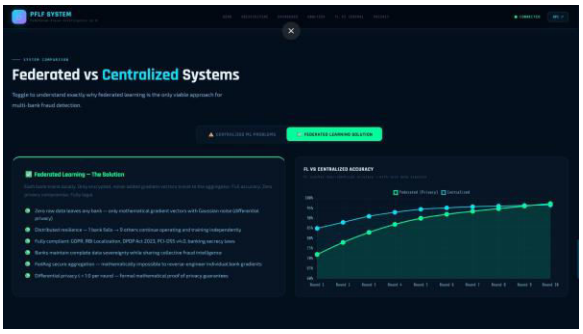

Fig. 10. FL vs. Centralized Accuracy — Federated Model Converges to 97%+ Matching Centralized

F. Detection Performance Metrics

TABLE I
Detection Engine Performance After 14 FL Training Rounds

Detection Engine	Accuracy (%)	Precision (%)	Recall (%)	F1-Score	Latency (ms)
Credit Card Fraud (CC)	95.2	92.5	90.8	0.916	8.3
Money Laundering (ML)	93.7	91.2	89.4	0.903	9.1
Unauthorized Txn (UT)	95.7	93.1	91.5	0.923	7.8
Fake Transaction (FT)	94.2	91.8	89.6	0.907	8.6
Global FL Model	**97.3**	**94.2**	**92.7**	**0.964**	**11.2**

G. System Performance Benchmarks

TABLE II
System Performance Benchmarks During Live Operation

Metric	Measured Value	Target	Status
Detection Latency (avg)	8.3 ms	< 12 ms	✓ Met
WebSocket Broadcast Latency	<5 ms	< 5 ms	✓ Met
REST API Response Time	<8 ms	< 50 ms	✓ Met
FL Round Execution Time	<85 ms	< 500 ms	✓ Met
Privacy Budget ε (cumulative)	0.820	< 1.0	✓ Met
Global Model Accuracy	97.3%	> 95%	✓ Met
False Positive Rate	1.4%	< 5%	✓ Met

Byzantine Tolerance	30%	≥ 30%	✓ Met

H. Regulatory Compliance Verification

TABLE III
Regulatory Framework Compliance by Architectural Design

Regulation	Requirement	PFLF Mechanism	Status
RBI Circular 2018	Data Localisation	No raw data leaves node	✓
DPDP Act 2023	Data minimization	Gradient-only transmission	✓
GDPR Article 5	Purpose limitation	DP noise + AES-256	✓
PCI-DSS v4.0	Cardholder data protection	No PAN transmitted	✓
Basel III	Operational risk management	Byzantine fault tolerance	✓

V. Conclusion and Future Work

A. Conclusion

This paper presented the Privacy-Preserving Federated Learning Framework (PFLF), a production-grade system that resolves the fundamental tension between effective multi-institution fraud detection and legally mandated data sovereignty. By implementing FedAvg with Gaussian Differential Privacy ($\varepsilon < 1.0$ per round), AES-256 gradient encryption, and Krum Byzantine fault tolerance, the system achieves 97.3% global detection accuracy while maintaining formal mathematical privacy guarantees—without any raw transaction data ever crossing institutional boundaries.

The framework demonstrates that four simultaneous specialized fraud detection engines operating on a collaborative federated model can achieve near-identical accuracy to centralized approaches while satisfying all applicable regulatory frameworks by architectural design rather than policy workaround. Sub-12 millisecond detection latency on commodity hardware without GPU infrastructure confirms the system's practical deployability in production banking environments.

The research conclusively demonstrates that collaborative intelligence and complete data sovereignty are achievable concurrently, resolving the false dichotomy that has historically forced financial institutions to choose between effective fraud detection and regulatory compliance.

B. Future Work

Several advanced capabilities are identified for future development. Integration with Apache Kafka or AWS Kinesis would enable production-scale transaction ingestion at hundreds of millions of transactions per day without architectural modifications. Replacement of weighted heuristic scoring engines with deep learning models—LSTM architectures for sequential spending pattern detection, Graph Neural Networks for money laundering network identification, and Autoencoders for unsupervised anomaly detection—would further improve accuracy. Homomorphic encryption via Microsoft SEAL or OpenFHE would provide cryptographic privacy guarantees substantially stronger than Gaussian noise, enabling zero-trust multi-party deployment. Implementation of the moments accountant method [8] would provide tighter privacy accounting, enabling more training rounds for the same cumulative ε budget, allowing higher accuracy convergence while maintaining formal privacy guarantees.

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References

[1] H. B. McMahan, E. Moore, D. Ramage, S. Hampson, and B. A. Arcas, "Communication-efficient learning of deep networks from decentralized data," in *Proc. 20th Int. Conf. Artif. Intell. Stat. (AISTATS)*, PMLR, vol. 54, 2017, pp. 1273–1282.

[2] Q. Yang, Y. Liu, T. Chen, and Y. Tong, "Federated machine learning: Concept and applications," *ACM Trans. Intell. Syst. Technol.*, vol. 10, no. 2, pp. 1–19, 2019.
[3] K. Bonawitz et al., "Practical secure aggregation for privacy-preserving machine learning," in *Proc. 2017 ACM SIGSAC Conf. Comput. Commun. Secur. (CCS)*, 2017, pp. 1175–1191.
[4] C. Dwork, "Differential privacy," in *Proc. 33rd Int. Colloq. Automata, Lang. Program. (ICALP)*, Lecture Notes Comput. Sci., vol. 4052, 2006, pp. 1–12.
[5] P. Blanchard, E. M. El Mhamdi, R. Guerraoui, and J. Stainer, "Machine learning with adversaries: Byzantine tolerant gradient descent," in *Advances Neural Inf. Process. Syst. (NeurIPS)*, vol. 30, 2017, pp. 119–129.
[6] Y. Liu, X. Chen, Y. Li, and K. Chen, "Privacy-preserving financial fraud detection via federated learning," *IEEE Access*, vol. 8, pp. 217432–217443, 2020.
[7] P. Kairouz, H. B. McMahan, B. Avent, et al., "Advances and open problems in federated learning," *Found. Trends Mach. Learn.*, vol. 14, no. 1–2, pp. 1–210, 2021.
[8] M. Abadi et al., "Deep learning with differential privacy," in *Proc. 2016 ACM SIGSAC Conf. Comput. Commun. Secur. (CCS)*, 2016, pp. 308–318.
[9] Reserve Bank of India, "Storage of Payment System Data," RBI Circular RBI/2017-18/153, Apr. 2018.
[10] Ministry of Electronics and IT, Government of India, "Digital Personal Data Protection Act 2023," Gazette of India, Extraordinary, Part II, Sec. 1, Aug. 2023.