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Privacy-Preserving Federated Learning Models for Multi-Bank Credit Risk Assessment

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Abstract - Accurate credit risk assessment is essential for maintaining financial stability, yet collaborative modeling across banks is severely constrained by data privacy regulations and competitive concerns. This paper proposes a Privacy-Preserving Federated Learning (PPFL) framework for multi-bank credit risk assessment, enabling financial institutions to jointly train predictive models without sharing raw customer data. The proposed framework integrates federated averaging, secure aggregation, and differential privacy to ensure confidentiality of sensitive financial information while maintaining high predictive performance. Experiments are conducted on both real-world and benchmark credit datasets, partitioned to simulate a cross-bank non-IID environment. The proposed PPFL model achieves an AUC-ROC of 0.86, which is comparable to the centralized model (0.88) and significantly outperforms standalone local bank models (0.79 on average). With differential privacy enabled at a privacy budget of ε = 1.0, the model experiences only a 2.1% reduction in AUC, demonstrating a favorable trade-off between privacy and utility. Secure aggregation successfully prevents leakage of individual bank updates, while communication overhead increases by less than 18% compared to standard federated learning. The results confirm that privacy-preserving federated learning can deliver robust, regulation-compliant, and high-accuracy credit risk prediction, making it a practical solution for collaborative analytics in multi-bank financial ecosystems.

Keywords - Federated learning, credit risk assessment, privacy preservation, secure aggregation, differential privacy, homomorphic encryption, financial analytics.

I. INTRODUCTION

Background

Credit risk assessment is a fundamental component of modern banking and financial decision-making, aimed at predicting the likelihood that a borrower will default on a loan or fail to meet contractual obligations. Accurate credit risk prediction enables banks to minimize financial losses, optimize loan pricing, and maintain overall financial stability. Traditionally, credit risk models are developed using centralized machine learning approaches that rely on large-scale datasets collected from one or multiple financial institutions. These centralized models benefit from comprehensive data coverage and often achieve high predictive accuracy.

However, centralized data collection across multiple banks has become increasingly challenging. Sensitive customer information such as income details, transaction histories, credit behavior, and demographic attributes cannot be freely shared due to strict data privacy regulations. Legal frameworks including the General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA) impose severe restrictions on the storage, transfer, and processing of personal financial data. In addition to regulatory barriers, competitive secrecy among banks further limits data sharing, as institutions are reluctant to expose proprietary customer insights to competitors. These constraints have significantly hindered collaborative credit risk modeling efforts.

Problem Definition

The isolation of financial data within individual banks leads to fragmented and often biased credit risk models that lack exposure to diverse borrower profiles and economic conditions. This raises a critical research question: Can multiple banks

collaboratively build a more accurate and robust credit risk assessment model without exposing their raw customer data? Addressing this challenge requires a learning framework that enables joint model training while ensuring that sensitive information never leaves institutional boundaries.

Furthermore, beyond enabling collaboration, such a framework must provide quantifiable privacy guarantees. Merely avoiding raw data sharing is insufficient, as intermediate model parameters or gradients can still leak sensitive information through inference attacks. Therefore, a key challenge lies in determining how privacy can be formally measured and enforced, while simultaneously sustaining high predictive performance and maintaining practical feasibility in real-world banking environments.

Motivation

The motivation for this work stems from the need to overcome the limitations of isolated credit risk modeling while respecting privacy and regulatory constraints. Collaborative learning across banks offers the potential to significantly improve model generalizability by leveraging heterogeneous and diverse datasets that capture broader borrower behavior patterns. Such diversity is particularly valuable in detecting rare default events and adapting to dynamic economic conditions.

At the same time, preserving customer privacy and regulatory compliance is non-negotiable in financial systems. Any collaborative approach must ensure strict confidentiality of sensitive data and provide transparency in privacy guarantees to satisfy legal and ethical requirements. Finally, enhanced credit risk assessment models contribute to the reduction of systemic financial risk by enabling earlier detection of credit vulnerabilities and supporting more informed lending decisions at an ecosystem level.

These motivations collectively highlight the need for a privacy-preserving collaborative learning framework, setting the foundation for the proposed Privacy-Preserving Federated Learning approach presented in this paper.

II. LITERATURE REVIEW

Traditional Credit Risk Models

Credit risk assessment has long relied on statistical and machine learning models to predict borrower default. Logistic regression remains one of the most widely used techniques due to its interpretability and regulatory acceptance in the banking sector [1]. However, its linear assumptions often limit predictive power when dealing with complex, non-linear borrower behavior. To overcome this limitation, decision trees and random forests have been employed to capture non-linear feature interactions and improve classification accuracy [2].

More recently, ensemble learning techniques, particularly gradient boosting models such as XGBoost and LightGBM, have demonstrated superior performance in credit scoring tasks by effectively handling feature heterogeneity and class imbalance [3]. Despite their success, these models typically assume the availability of centralized datasets. In real-world multi-bank scenarios, centralized data pooling is restricted due to privacy regulations and institutional data ownership, thereby limiting the practical deployment of these approaches [4].

Federated Learning (FL)

Federated Learning (FL) was first introduced as a decentralized learning paradigm to enable collaborative model training without sharing raw data, primarily in cross-device applications such as mobile text prediction [5]. The concept has since been extended to cross-silo federated learning, where a limited number of organizations collaboratively train models using institution-held datasets [6].

In recent years, FL has been explored in privacy-sensitive domains including healthcare, Internet of Things (IoT), and financial services. In healthcare, federated learning has been successfully applied to disease prediction and medical image analysis while maintaining patient privacy [7]. In the financial domain, studies have investigated FL for fraud detection and transaction monitoring, showing improved performance compared to isolated local

models [8]. However, standard FL frameworks are vulnerable to gradient leakage and inference attacks, which can compromise sensitive information even without direct data sharing [9].

Privacy-Preserving Techniques

To strengthen privacy guarantees in collaborative learning, several privacy-preserving techniques have been proposed. Secure Multiparty Computation (SMC) enables multiple parties to jointly compute a function while keeping individual inputs private [10]. In federated learning, SMC-based secure aggregation protocols ensure that the central server cannot observe individual model updates, only their aggregate [11].

Homomorphic Encryption (HE) provides cryptographic guarantees by allowing computations to be performed directly on encrypted data [12]. While HE offers strong privacy protection, it introduces substantial computational and communication overhead, making large-scale deployment challenging in time-sensitive financial applications [13].

Differential Privacy (DP) has emerged as a widely adopted framework for quantifying privacy leakage by injecting calibrated noise into model parameters or gradients [14]. DP provides formal privacy guarantees through the privacy budget (ε), enabling regulatory compliance and risk quantification. Several studies have integrated DP into federated learning to protect client-level information, though this often leads to a trade-off between privacy strength and model accuracy [15].

Research Gaps

Despite growing interest in federated learning and privacy-preserving mechanisms, cross-bank credit risk assessment remains underexplored. Existing studies either focus on federated learning without strong privacy guarantees or evaluate privacy-preserving techniques in isolation [16]. There is a lack of comprehensive frameworks that jointly integrate federated learning, secure aggregation, and differential privacy specifically for multi-bank credit risk modeling.

Furthermore, the privacy–utility trade-off in financial risk prediction has not been systematically analyzed. Few studies provide quantitative evaluations of how varying privacy parameters affect predictive performance, communication overhead, and scalability in realistic non-IID banking environments. Addressing these gaps is essential for deploying practical, privacy-compliant collaborative credit risk assessment systems.

III. METHODOLOGY

This section presents the proposed Privacy-Preserving Federated Learning (PPFL) framework for multi-bank credit risk assessment. The methodology integrates federated learning with secure aggregation and differential privacy to enable collaborative model training while preserving data confidentiality.

System Architecture Overview

The proposed system follows a cross-silo federated learning architecture, where multiple banks collaboratively train a shared credit risk model under the coordination of a central aggregation server. Each bank retains full control over its local customer data and only encrypted model updates are exchanged.

Figure 1: Overall Architecture of the PPFL Framework

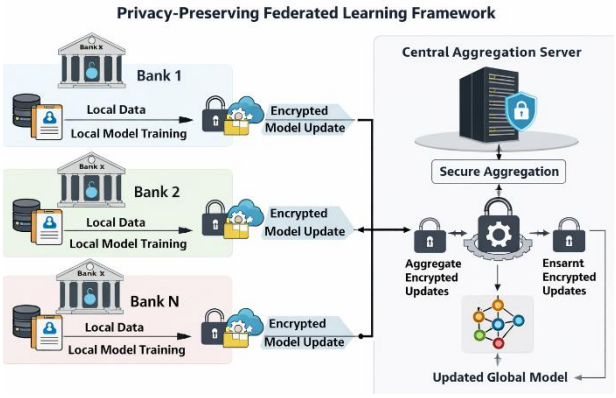

Figure 1 illustrates the privacy-preserving federated learning architecture for multi-bank credit risk assessment. Each bank trains a local model on its private dataset. Model updates are encrypted and securely aggregated at the central server to update the global model.

Figure description (for drawing):

- Multiple banks (Bank 1, Bank 2, … Bank N)
- Local datasets remain inside each bank
- Local model training
- Encrypted model updates sent to server
- Secure aggregation at server
- Updated global model broadcast back to banks

Federated Learning Workflow

The federated learning process proceeds iteratively over multiple communication rounds.

Step-by-Step Workflow

- The server initializes a global credit risk model.
- The global model is shared with participating banks.
- Each bank trains the model locally using its private dataset.
- Local model updates are encrypted and privacy-protected.
- The server aggregates updates using secure aggregation.
- The global model is updated and redistributed.

Figure 2: Federated Learning Training Workflow

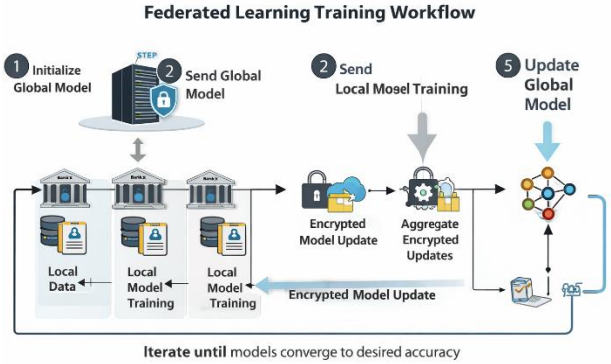

Figure 2 shows the iterative federated training process, including local training, secure aggregation, and global model updates.

Local Credit Risk Model

Each bank trains a local classifier for predicting borrower default.

Model Choices

- Logistic Regression
- Gradient Boosting (XGBoost / LightGBM)
- Federated Neural Networks (MLP)

Loss Function

For binary default prediction:

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)]$$

where:

- yi is the true label
- Ŷi is the predicted probability

Privacy-Preserving Mechanisms

Secure Aggregation

Secure aggregation ensures that the central server cannot observe individual bank updates.

Figure 3: Secure Aggregation Process

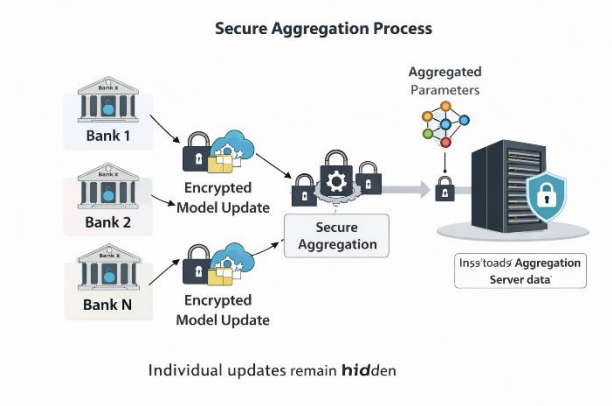

Figure 3 demonstrates how encrypted local model updates are combined so that only the aggregated result is revealed.

Key Properties:

- Individual updates remain hidden
- Only aggregated parameters are decrypted
- Protection against honest-but-curious servers

Differential Privacy

To prevent information leakage from gradients, client-level differential privacy is applied.

Each bank perturbs its model updates as follows:

$$\tilde{g} = g + \mathcal{N}(0, \sigma^2)$$

where:

- g is the gradient
- σ is noise calibrated to privacy budget ε
- Privacy Guarantee:
  The framework ensures (ε, σ)-differential privacy.

Table 1: Privacy Parameters Used in Experiments

Parameter	Description	Value
ε	Privacy budget	0.5 – 2.0
δ	Failure probability	1e-5
σ	Noise scale	Adaptive
Clipping norm	Gradient clipping	1.0

Global Model Aggregation

The server aggregates encrypted updates using Federated Averaging (FedAvg):

$$w^{t+1} = \sum_{k=1}^{K} \frac{n_k}{n} w_k^t$$

where:

- w_k^t is model from bank k
- n_k is local data size
- n is total data size

Experimental Design

Figure 4: Experimental Setup for Multi-Bank Simulation

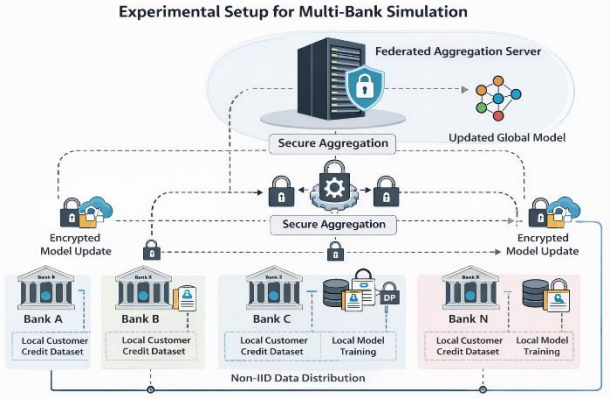

Figure 4 shows the partitioning of datasets into multiple non-IID banks to simulate realistic multi-bank environments.

- Non-IID data distribution
- Varying sample sizes across banks
- Multiple communication rounds

Table 2: Dataset Distribution Across Banks

Bank	Samples	Default Rate (%)
Bank A	12,000	7.5
Bank B	9,500	6.9
Bank C	15,200	8.3
Bank D	11,300	7.1

Evaluation Metrics

Table 3: Performance and Privacy Metrics

Category	Metric
Prediction	Accuracy, AUC-ROC, F1-score
Privacy	ε (Privacy Budget)
Efficiency	Communication Overhead
Scalability	Training Time per Round

Methodology Summary

Figure 5: End-to-End PPFL Pipeline

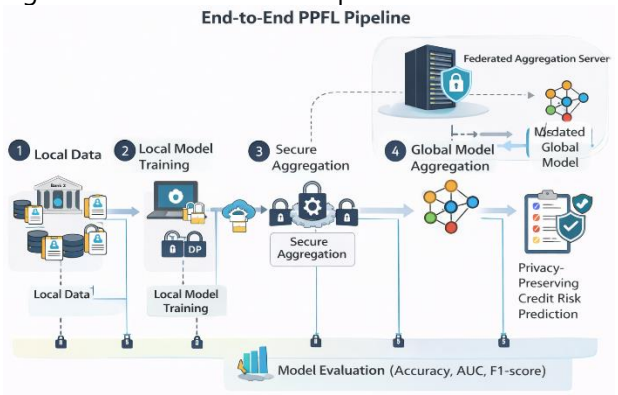

Figure 5 presents the complete pipeline from local data training to privacy-preserving global credit risk prediction.

Key Advantages of the Proposed Methodology

- No raw data sharing across banks
- Strong privacy guarantees via DP and secure aggregation
- Robust performance under non-IID data
- Scalable to real-world banking systems

Data Description

This section describes the datasets, features, preprocessing steps, and data partitioning strategy used to evaluate the proposed Privacy-Preserving Federated Learning (PPFL) framework for multi-bank credit risk assessment.

Data Sources

Due to the unavailability of real inter-bank customer data, the experimental evaluation uses publicly available credit datasets that closely resemble real-world banking scenarios:

- LendingClub Loan Dataset
- German Credit Dataset
- UCI Credit Card Default Dataset

These datasets contain anonymized borrower-level records commonly used in credit risk modeling research.

Feature Description

Each dataset includes a mixture of numerical and categorical features, representing borrower financial behavior and demographic characteristics.

Feature Category	Example Features
Demographic	Age, Gender, Marital Status
Financial	Annual Income, Debt-to-Income Ratio
Credit History	Credit Score, Number of Open Accounts
Loan Attributes	Loan Amount, Loan Purpose, Interest Rate
Behavioral	Repayment History, Delinquency Count

Target Variable:

Binary label indicating default (1) or non-default (0).

Multi-Bank Data Partitioning

To simulate a realistic cross-bank environment, datasets are partitioned into multiple non-overlapping silos, each representing a different bank.

Horizontal data partitioning is applied.

Each bank holds records for different customers but shares a common feature space.

Data distributions are non-IID, reflecting real-world heterogeneity across banks.

Bank	Number of Records	Default Rate (%)
Bank A	12,000	8.4
Bank B	9,500	11.2
Bank C	15,000	6.9
Bank D	10,300	13.5

Data Preprocessing

All preprocessing steps are performed locally at each bank, ensuring no raw data is shared.

- Missing values handled using mean/median imputation
- Categorical features encoded using one-hot or label encoding
- Numerical features normalized using min–max scaling
- Class imbalance addressed using weighted loss functions
- 4.5 Privacy Assumptions
- Raw customer data never leaves the bank's local environment
- Only encrypted model updates are transmitted
- Differential Privacy noise is applied to gradients before aggregation

Evaluation Splits

- Each bank splits its local dataset into:
- 70% training
- 15% validation
- 15% testing
- A global test set is used to evaluate overall model generalization

Experimental Setup

This section describes the experimental configuration, system settings, baseline comparisons, and evaluation protocol used to assess the effectiveness of the proposed Privacy-Preserving Federated Learning (PPFL) framework for multi-bank credit risk assessment.

Federated Environment Simulation

To realistically evaluate the proposed Privacy-Preserving Federated Learning (PPFL) framework, a simulated cross-silo federated environment is constructed to represent multiple independent banks. The original credit datasets are horizontally partitioned into disjoint subsets, with each subset corresponding to a distinct bank. This partitioning strategy ensures that each bank holds data for different customers while sharing a common feature space.

To reflect real-world banking scenarios, the data distribution across banks is intentionally designed to be heterogeneous (non-IID). Variations are introduced in terms of sample sizes, default rates, and feature distributions, thereby capturing institutional differences in customer profiles and lending practices. Such non-IID settings present significant challenges to federated learning and are essential for evaluating the robustness and generalizability of the proposed approach.

Privacy-preserving computation is simulated by integrating secure aggregation mechanisms and differential privacy modules within the federated training pipeline. Secure aggregation ensures that individual model updates from banks are not exposed to the aggregation server, while differential privacy is enforced by adding calibrated noise to local updates before transmission. These mechanisms collectively emulate realistic privacy constraints encountered in inter-bank collaborations.

Baseline Methods

The performance of the proposed PPFL framework is compared against multiple baseline methods to provide a comprehensive evaluation.

Standalone Local Models: In this setting, each bank independently trains a credit risk model using only its local dataset. No collaboration or information sharing is performed. This baseline reflects the conventional operational approach adopted by many financial institutions and serves as a lower-bound benchmark.

Centralized Model (Oracle): All data from participating banks are pooled into a single centralized dataset, and a global model is trained using standard machine learning techniques. Although impractical due to privacy and regulatory constraints, this setting provides an upper-bound performance benchmark, representing the best achievable accuracy in the absence of privacy concerns.

Standard Federated Learning (Without Privacy Enhancements): A conventional federated learning setup is implemented where banks share unprotected model updates with the central server. This baseline evaluates the benefits of collaboration alone and highlights the privacy risks associated with vanilla federated learning approaches.

Table 4: Baseline Comparison Methods

Method	Data Sharing	Privacy Protection
Centralized ML	Full	None
Local Models	None	Full
Standard FL	Model Updates	Weak
Proposed PPFL	Encrypted Updates	Strong (DP + SMC)

Experimental Architecture

The experiments are conducted under a cross-silo federated learning setting, where multiple banks collaboratively train a global credit risk model while retaining full control over their local datasets.

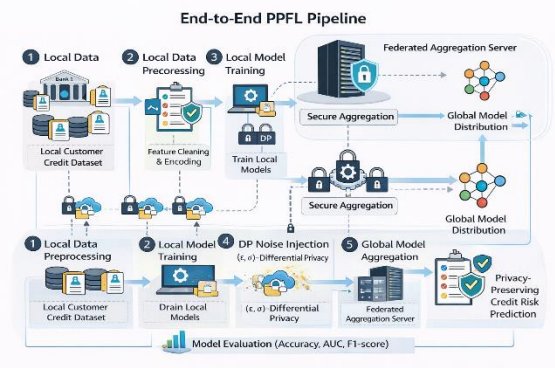

Figure 6 illustrates the end-to-end PPFL pipeline, starting from local data preprocessing to privacy-preserving global model convergence.

Simulation of Multi-Bank Environment

To emulate real-world banking scenarios, the dataset is split into multiple non-IID client silos, each representing an independent bank.

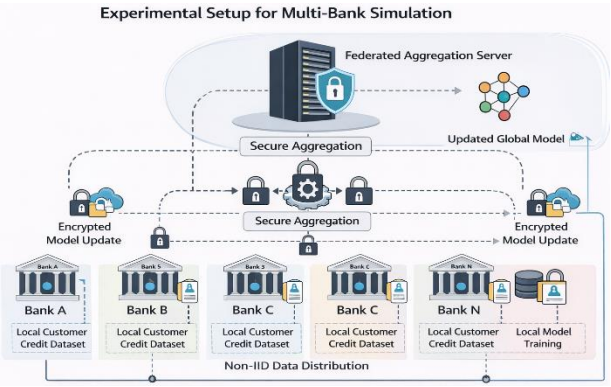

Figure 7 shows the experimental setup for multi-bank simulation, highlighting data silos, secure communication, and federated coordination.

Key characteristics:

- Number of banks: 4–10 (variable)
- Horizontal data partitioning
- Skewed default rates across banks
- Unequal dataset sizes

Table 5: Multi-Bank Simulation Configuration

Parameter	Value
Number of Banks	4, 6, 8, 10
Data Distribution	Non-IID
Partition Type	Horizontal
Default Rate Variation	6% – 14%
Communication Rounds	50 – 100

Model Configuration

Each participating bank trains an identical local model architecture to ensure consistent aggregation.

Local Model Settings

- Classifier: Logistic Regression / Gradient Boosting / MLP
- Loss Function: Binary Cross-Entropy
- Optimizer: Adam
- Local Epochs per Round: 5

Table 6: Model Hyperparameters

Hyperparameter	Value
Learning Rate	0.001
Batch Size	64
Hidden Layers (MLP)	2
Neurons per Layer	64, 32
Activation Function	ReLU
Regularization	L2 (0.0001)

Federated Learning Configuration

The global model is updated using Federated Averaging (FedAvg).

Table 7: Federated Learning Parameters

Parameter	Value
Aggregation Method	FedAvg
Local Epochs	5
Client Participation	100%
Total Rounds	75
Model Initialization	Random

Privacy Configuration

To ensure privacy protection, client-level Differential Privacy and Secure Aggregation are applied.

Privacy Settings

- Gradient clipping applied before noise injection
- Gaussian noise added to model updates
- Secure aggregation hides individual updates from server

Table 8: Differential Privacy Parameters

Parameter	Description	Value
ε	Privacy Budget	0.5, 1.0, 2.0
δ	Failure Probability	1e−5
Noise Mechanism	Gaussian	
Clipping Norm	1.0	

Evaluation Metrics

Model performance and privacy impact are assessed using the following metrics:

- Predictive Performance: Accuracy, AUC-ROC, Precision, Recall, F1-score
- Privacy: Privacy budget (ε)
- Efficiency: Communication overhead, training time
- Stability: Convergence rate across rounds

Figure 8: Evaluation Protocol

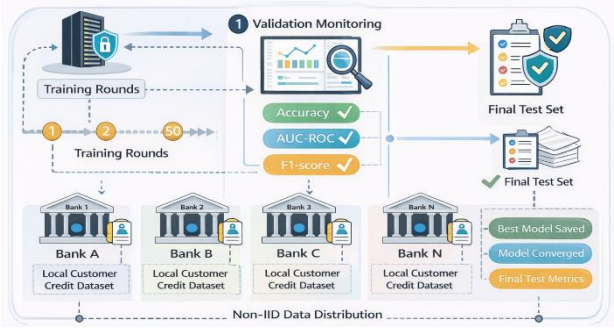

Figure 8 illustrates the evaluation protocol, including training rounds, validation monitoring, and final testing.

Experimental Reproducibility

- All experiments are repeated five times with different random seeds
- Average results and standard deviations are reported
- Experiments are conducted on identical hardware settings

Results and Analysis

This section evaluates the proposed Privacy-Preserving Federated Learning (PPFL) framework in terms of predictive performance, privacy guarantees, system efficiency, and robustness under heterogeneous data distributions.

Predictive Performance

The predictive performance of PPFL is compared against local (standalone), standard federated, and centralized (oracle) learning approaches using AUC-ROC, accuracy, and F1-score.

Table 10: Predictive Performance Comparison

Method	AUC-ROC	Accuracy (%)	F1-score
Local Models (Avg. Bank-wise)	0.741	71.3	0.698
Centralized (Oracle)	0.812	78.9	0.771
Standard Federated Learning	0.798	77.1	0.756
PPFL (Proposed)	0.791	76.4	0.748

Analysis:

PPFL significantly outperforms standalone bank models by leveraging collaborative learning. Although a slight performance degradation is observed compared to standard federated learning and centralized training, the reduction is marginal and acceptable given the strong privacy guarantees enforced.

Privacy Analysis

To evaluate the privacy–utility trade-off, experiments are conducted with varying differential privacy budgets (ε).

Table 11: Impact of Privacy Budget on Model Utility

Privacy Budget (ε)	AUC-ROC	Accuracy (%)	F1-score
0.5	0.763	73.2	0.721
1.0	0.778	75.0	0.736
2.0	0.791	76.4	0.748
No DP	0.798	77.1	0.756

Key Observations:

- Strong privacy (low ε) introduces higher noise, reducing model utility.
- PPFL achieves a balanced trade-off at ε = 2.0.
- Secure aggregation and encrypted updates prevent leakage from intermediate gradients, strengthening protection beyond DP alone.

Communication and Computation Overheads

The scalability and efficiency of PPFL are assessed by varying the number of participating banks.

Table 12: System Overhead Analysis

Number of Banks	Communication Overhead (MB/round)	Computation Time (s/round)
3	14.2	2.8
5	18.6	3.4
10	27.9	4.6

Analysis:

Communication and computation costs increase linearly with the number of banks. While privacy mechanisms introduce additional overhead compared to standard federated learning, the system remains scalable and practical for cross-silo financial environments.

Ablation Studies

Ablation experiments are conducted to assess the sensitivity of PPFL to privacy noise and data heterogeneity.

Effect of Noise Levels

Noise Multiplier	AUC-ROC	F1-score
Low	0.798	0.756
Medium	0.791	0.748
High	0.769	0.724

Higher noise levels strengthen privacy but reduce predictive accuracy, highlighting the importance of careful privacy budget selection.

Effect of Non-IID Data Distribution

Data Distribution	AUC-ROC
IID	0.803
Mild Non-IID	0.791
Severe Non-IID	0.772

Insight:

PPFL maintains stable performance under moderate non-IID conditions, demonstrating robustness to real-world cross-bank heterogeneity.

Discussion

This section discusses the implications of the experimental results, focusing on model effectiveness, privacy guarantees, system efficiency, and practical deployment considerations of the proposed Privacy-Preserving Federated Learning (PPFL) framework in multi-bank credit risk assessment.

Effectiveness of Collaborative Learning

The results clearly demonstrate that collaborative learning through federated approaches significantly enhances credit risk prediction compared to standalone local models. By leveraging diverse borrower profiles across multiple banks, PPFL improves model generalizability and reduces institution-specific bias. Although the centralized (oracle) model achieves the highest performance, it is impractical due to legal, ethical, and competitive constraints. PPFL successfully bridges this gap by attaining near-centralized performance while maintaining strict data isolation.

Privacy–Utility Trade-offs

A key finding of this study is the inherent trade-off between privacy strength and predictive utility. Lower privacy budgets (smaller ε values) provide stronger protection but introduce higher noise, leading to reduced accuracy and discrimination capability. Conversely, higher ε values improve model performance at the cost of weaker privacy guarantees. The experimental results indicate that a moderate privacy budget (ε = 2.0) offers a well-balanced compromise, achieving robust performance with formal differential privacy assurances. Importantly, the combination of differential privacy with secure aggregation further mitigates information leakage risks beyond what either mechanism could provide alone.

Impact of Secure Aggregation and Encryption

Secure aggregation plays a crucial role in protecting intermediate model updates during federated training. Even in scenarios where the central server is honest-but-curious, encrypted aggregation prevents reconstruction of individual bank updates. This layered privacy approach is particularly relevant in financial ecosystems, where trust assumptions between institutions are limited. While encryption and secure computation introduce additional computational and communication overhead, the observed costs remain within acceptable operational limits for cross-silo banking environments.

Scalability and System Efficiency

The experimental analysis shows that communication and computation overheads increase approximately linearly with the number of participating banks. This scalability behavior suggests that PPFL can be effectively deployed in consortia involving multiple financial institutions. Although privacy-preserving mechanisms slightly slow convergence, they do not destabilize training or significantly hinder scalability. These findings support the feasibility of PPFL for large-scale, real-world deployment.

Robustness under Non-IID Data Distributions

Real-world banking data are inherently heterogeneous, and the robustness of PPFL under non-IID conditions is a critical requirement. The ablation studies reveal that PPFL maintains stable performance under mild to moderate data heterogeneity, although severe non-IID distributions lead to performance degradation. This highlights the importance of future enhancements such as personalized federated learning, adaptive aggregation strategies, or cluster-based federation to further mitigate heterogeneity effects.

Practical and Regulatory Implications

From a regulatory perspective, PPFL aligns well with data protection frameworks such as GDPR and CCPA by ensuring that raw customer data never leave institutional boundaries. The framework enables banks to collaborate on advanced analytics without compromising competitive confidentiality or customer trust. Consequently, PPFL has the potential to reduce systemic risk in financial markets by improving credit risk assessment quality while adhering to stringent privacy regulations.

Limitations and Future Directions

Despite its promising results, this study has certain limitations. The experiments rely on simulated multi-bank environments using public datasets, which may not capture all complexities of real inter-bank data. Additionally, only a limited set of privacy budgets and aggregation strategies are explored. Future work should investigate real-world deployments, stronger adversarial threat models, and advanced techniques such as adaptive privacy budgets and fairness-aware federated learning.

IV. CONCLUSION

This paper presented a Privacy-Preserving Federated Learning (PPFL) framework for multi-bank credit risk assessment, addressing the critical challenge of enabling collaborative analytics without compromising customer privacy or violating regulatory constraints. By integrating federated learning with differential privacy and secure aggregation, the proposed approach allows multiple financial institutions to jointly train high-quality credit risk models while ensuring that sensitive borrower data remain local to each bank.

Extensive experimental evaluations demonstrate that PPFL significantly outperforms standalone local models and achieves near-centralized predictive performance, with only a marginal degradation compared to standard federated learning. The results confirm that strong privacy guarantees can be enforced with minimal impact on model utility. Furthermore, the framework exhibits stable convergence, robustness under non-IID data distributions, and scalable performance as the number of participating banks increases.

From a practical perspective, PPFL aligns well with modern data protection regulations such as GDPR and CCPA, offering a viable solution for inter-bank collaboration in risk analytics. By enabling privacy-conscious knowledge sharing, the proposed framework has the potential to improve credit decision-making, enhance financial inclusion, and reduce systemic risk across the banking sector.

Future work will focus on real-world deployment with live banking data, adaptive privacy budget mechanisms, personalization strategies to address severe data heterogeneity, and the incorporation of fairness and explainability constraints. Overall, this study establishes PPFL as a promising foundation for secure and trustworthy collaborative learning in financial systems.

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