Breaking Data Silos: A Privacy-Preserving Framework for Credit Risk Analysis

Synergizing Vertical Federated Learning with CKKS Homomorphic Encryption

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Outline

Introduction

- Credit risk assessment helps lenders estimate the likelihood of borrower default.
- Modern models like **XGBoost** capture complex, non-linear financial behaviour effectively.
- In real-world scenarios, features required for credit scoring are often **vertically distributed** across multiple organizations.
- **Vertical Federated Learning (VFL)** enables these organizations to train a shared model without exchanging raw data.
- **Homomorphic Encryption (HE)** protects sensitive information by allowing computations directly on encrypted gradients and Hessians.
- **SecureBoost** combines VFL with HE to enable accurate, privacy-preserving collaborative credit risk modelling.

Motivation: The "Data Island" Problem

- **Accurate credit scoring requires complete user information** (financial history, transactions, demographics, behaviour).
- **But no single organization has the full picture:** banks, fintechs, telecoms, and e-commerce platforms all hold **different pieces** of the same customer's data.
- **Privacy regulations** such as GDPR and India's DPDP Act strictly prohibit sharing raw personally identifiable data.
- This creates a **"data island" scenario:** every institution is isolated with only partial features.
- As a result, models trained on isolated datasets suffer from **lower accuracy and blind spots** in predicting credit risk.

The Core Question

How can multiple institutions collaborate
on credit scoring
without ever sharing raw data?

Why This Matters

- Improves fairness and accuracy in lending.
- Enables risk modelling across institutions.
- Complies fully with privacy regulations.

Literature Review – Comparative Study

Authors	Method	Dataset	Results	Limitations
Naresh et al.	DNN + HE (PPDNN-CRP)	Kaggle Credit (32k)	Acc 89%, F1 0.86	High encryption cost
Chang et al.	ML models (LR, SVM, DT, MLP)	UK Bank Loans (30k)	Acc 82.5%	Limited features reduce accuracy
Bao et al.	ZKP + IPFE (PPCS + PICS)	UCI Credit (150k)	Acc 94%, AUC high	Very heavy computation
Zhu et al.	Paillier HE + FL	MNIST (non-IID)	Good Acc, stable	Large encryption overhead
Byun et al.	HE Ridge Regression (CKKS)	11 UCI datasets	High R^2	Cipher slot overflow issues
Wang et al.	VFL + HE + Taylor Approx. (MP-DLR)	Proprietary	Accurate LR	Only logistic regression, high cost
Dumitrescu et al.	PLTR (LogReg + Small Trees)	GiveMeCredit	Interpretable	Limited scalability
Lin et al.	LR + XGBoost + SHAP	Auto Loan Data	Good Acc, explainable	Weak generalization
Huang et al.	RF vs Scorecards	BigTech + Bank Data	Strong RF results	Confidential dataset limits reproducibility
Shi et al.	Systematic review of ML credit scoring	German, Australian + FI datasets	Field-wide insights	Many models lack interpretability

Research Gaps

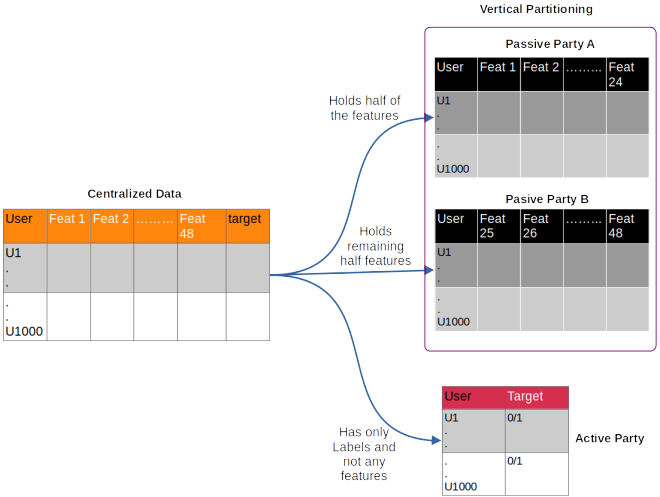
- Existing Homomorphic Encryption (HE) and MPC methods introduce **high computational overhead**, limiting practical deployment.
- There is a **lack of unified frameworks** that combine Vertical Federated Learning (VFL) with HE for secure boosting models.
- Paillier-based encryption supports only integer arithmetic, making it **unsuitable for floating-point gradients** needed in XGBoost.
- Most literature evaluates only **two-party** scenarios, whereas real financial ecosystems require **multi-institution collaboration**.
- No **standardized privacy-preserving boosting pipeline** exists, leading to inconsistent evaluations across studies.

Our Solution: VFL + SecureBoost + CKKS

We designed a framework that **brings computation to the data**, ensuring that sensitive information never leaves the organization that owns it.

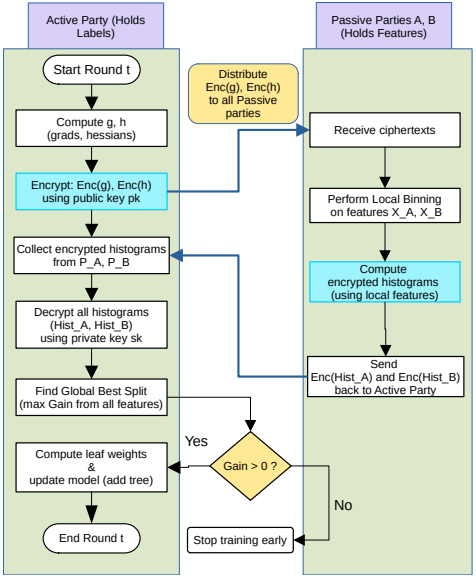
1. **Vertical Federated Learning (VFL)**
   - Connects organizations that share the **same users** but possess **different feature sets**.
   - Enables joint training without exchanging raw data.
   - Example: A bank holds *labels* (defaults), while a fintech platform holds *transaction features*.
2. **SecureBoost Protocol**
   - A privacy-preserving adaptation of XGBoost.
   - Aggregates gradients and split statistics **without revealing** the underlying local data distributions.
3. **CKKS Homomorphic Encryption**
   - Supports **encrypted floating-point arithmetic** (unlike Paillier, which handles only integers).
   - **Why it matters:** XGBoost relies on precise real-valued gradients and Hessians, which CKKS enables **while fully encrypted**.

Vertical Federated Learning Architecture



- Organizations share the **same users** but hold **different feature subsets**.
- The **Active Party** holds labels and the CKKS private key.
- **Passive Parties** operate only on encrypted gradients.
- Raw data never leaves local servers at any point.
- Encrypted communication ensures full privacy end-to-end.

System Architecture & Data Flow



- Active Party computes and encrypts gradients using CKKS.
- Passive Parties build encrypted histograms from local features.
- Only encrypted statistics are exchanged—no raw data revealed.
- Active Party decrypts aggregated histograms to select splits.
- SecureBoost grows trees collaboratively while preserving privacy.

Experimental Setup

- **Dataset:** German Credit dataset with 1000 samples and 48 features, containing attributes relevant to credit scoring.
- **Preprocessing:** One-hot encoding for categorical variables, normalization for numerical stability, and SMOTE to address class imbalance between good and bad borrowers.
- **Federated Setup:** Vertical Federated Learning simulated using **PySyft**, where different parties hold distinct feature subsets while labels remain with the active party.
- **Homomorphic Encryption:** CKKS scheme implemented via **Pyfhel**, enabling encrypted floating-point computation for gradients and Hessians.
- **Training Parameters:**
  - 50 boosting rounds
  - Maximum tree depth: 1 or 2
  - Learning rate: 0.1
- **Environment:** Google Colab environment using Python 3.12 for all experiments.

Dataset Attributes Overview

TABLE II
ATTRIBUTE DETAILS OF THE ACCEPTED DATASET

Attribute Name	Type	Distinct Values
class (target)	Binary	2 distinct values
checking_status	Categorical	4 distinct values
duration	Integer	33 distinct values
credit_history	Categorical	5 distinct values
purpose	Categorical	10 distinct values
credit_amount	Integer	921 distinct values
savings_status	Categorical	5 distinct values
employment	Categorical	5 distinct values
installment_commitment	Integer	4 distinct values
personal_status	Categorical	4 distinct values
other_parties	Categorical	3 distinct values
residence_since	Integer	4 distinct values
property_magnitude	Categorical	4 distinct values
age	Integer	53 distinct values
other_payment_plans	Categorical	3 distinct values
housing	Categorical	3 distinct values
existing_credits	Integer	4 distinct values
job	Categorical	4 distinct values
num_dependents	Integer	2 distinct values
own_telephone	Binary	2 distinct values
foreign_worker	Binary	2 distinct values

- The German Credit dataset includes **20 core attributes**.
- A mix of **binary, categorical, and numerical** features.
- Several attributes have **multiple distinct values**, requiring one-hot encoding.
- Features cover **demographic, financial, and behavioural** information.
- After encoding, the dataset expands to **48 usable model features**.
- This rich feature space enables learning **non-linear credit risk patterns**.

Quantitative Results

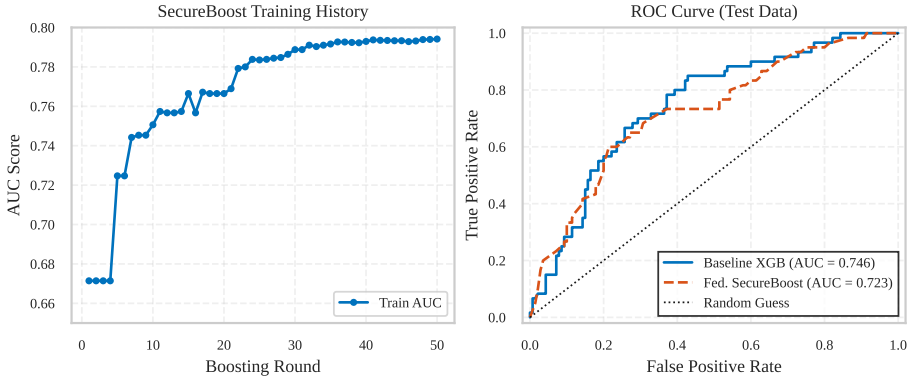
- **SecureBoost Test AUC: 0.723**, indicating strong predictive performance even under encrypted and federated constraints.
- **Centralized XGBoost AUC: 0.746**, serving as the non-private performance upper bound for comparison.
- SecureBoost therefore retains about **96% of the baseline accuracy**, showing that privacy preservation comes with minimal performance loss.
- Outperforms earlier encrypted boosting systems, which typically achieve **AUC scores in the 0.60–0.70 range**, demonstrating superior utility.

Baseline vs SecureBoost Performance

Model	AUC	Accuracy
Centralized XGBoost	0.746	0.78
SecureBoost (CKKS)	**0.723**	0.75

- Centralized model gives upper-bound performance.
- SecureBoost retains **96% of baseline AUC**.
- Small drop in accuracy despite full encryption.
- Strong result compared to prior encrypted boosting.

Qualitative Results



- ROC curve shows SecureBoost is close to Centralized XGBoost.
- **Training Behaviour:** Smooth convergence despite encrypted gradients.
  - Encrypted model exhibits stable learning curves.
  - ROC shows minimal degradation compared to baseline.

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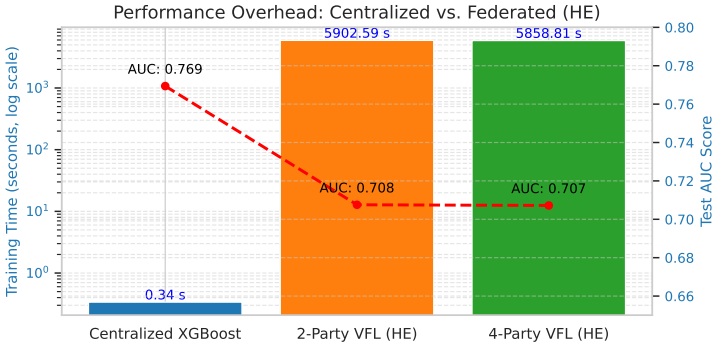
SecureBoost Multi-Party Performance

Scenario	AUC	Accuracy
2-party FL	0.708	0.73
4-party FL	0.707	0.72

- AUC remains identical in 2-party and 4-party settings.
- Shows SecureBoost is **robust to feature fragmentation**.
- More parties $\rightarrow$ higher encryption cost, not lower accuracy.
- Perfect for real-world multi-institution collaboration.

AUC Comparison Across Models



- **Centralized XGBoost** achieves the highest AUC (0.769) with extremely fast training time.
- **2-Party SecureBoost (HE)**: AUC = 0.708.
- **4-Party SecureBoost (HE)**: AUC = 0.707.

Hyperparameter Tuning – Key Insights

- We experimented with **8 hyperparameter configurations** for SecureBoost.
- Parameters varied included:
  - **Max Depth** (1 vs 2)
  - **Number of Bins** (8, 16, 32)
  - **Training Rounds** (10–50)
  - **Learning Rate** (0.1)
- **Best Performance:** Max Depth = 2 and 16–32 bins $\rightarrow$ highest AUC values.
- **Performance–Cost Tradeoff:**
  - Larger bin sizes increase histogram precision, but also increase encrypted computation cost.
  - Deeper trees (depth 2) improve accuracy but add computation overhead.
- Selected final configuration balances: **privacy, accuracy, and computational efficiency**.

Hyperparameter Tuning

TABLE VI
HYPERPARAMETER TUNING RESULTS FOR SECUREBOOST MODEL

Exp ID	Rounds	LR	Bins	Depth	λ	Train AUC	Test AUC	Time (min)	Remarks
Baseline Model	30	0.30	16	1	1.0	0.6545	0.6458	17.60	Initial run with standard parameters.
Increased Reg.	20	0.20	16	2	5.0	0.7417	0.6988	28.15	Higher λ to mitigate overfitting.
Finer Bins	20	0.20	32	2	1.0	0.7888	0.7370	43.40	Increased bins for improved precision.
Low LR	100	0.05	8	2	1.0	0.7249	0.7076	103.47	Slow learning rate configuration.
Moderate Tuning	50	0.10	16	2	1.0	0.7506	0.7226	72.10	Balanced hyperparameter selection.
High Lambda	50	0.10	8	2	5.0	0.7236	0.6867	52.21	Strong regularization impact.
Added Gamma	50	0.10	8	2	1.0	0.7278	0.7147	51.65	Gamma introduced to control tree growth.
Balanced Long Run	50	0.10	32	2	1.0	0.7931	0.7364	109.06	Extended run with optimal parameters.

Top Performing Hyperparameter Configurations

Config	Depth	Bins	LR	AUC	Notes
Best Accuracy (Finer bins)	2	32	0.20	**0.7370**	Highest performing
Second Best	2	32	0.10	0.7364	Slightly lower AUC

Scalability Analysis

- **2-party AUC: 0.708** — strong performance with two feature holders.
- **4-party AUC: 0.707** — identical accuracy, showing that model quality remains stable as more institutions participate.
- Demonstrates that SecureBoost is **robust to feature fragmentation**; splitting features across multiple parties does not reduce predictive performance.
- Training time increases due to computationally heavy **encrypted histogram operations**, which scale with the number of parties.
- CKKS allows for **parallelization and ciphertext batching**, offering substantial reductions in computation cost with optimized settings.

Adaptability Analysis

- The model was evaluated under multiple configurations to test its **robustness and adaptability** across different training conditions.
- SecureBoost remains stable across:
  - **2-party and 4-party** VFL scenarios, showing resilience to changes in the number of collaborating institutions.
  - Different histogram **bin sizes (8, 16, 32)**, with minimal change in AUC across settings.
  - A range of **learning rates**, demonstrating stable optimization behavior.
- Exhibits **strong generalization**, even when fewer features are available or when features are unevenly distributed across parties.

Comparison With Existing Methods – Key Insights

- **Non-private models** (XGBoost, BiLSTM, KNN, etc.) achieve the highest accuracy (AUC 0.75–0.83), but **cannot be used in practice** due to strict data privacy laws.
- **Privacy-preserving models** like HE-based Logistic Regression, Approximate GBDT, and Federated GBDT show **lower AUC (0.60–0.74)** because integer-based HE and MPC introduce computation + precision limitations.
- Our proposed method — **VFL + SecureBoost with CKKS** — achieves **AUC = 0.723** and **F1 $\approx$ 0.71**, recovering almost **96%** of centralized XGBoost performance.
- This makes SecureBoost **one of the most accurate privacy-preserving models** while supporting **multi-party collaboration** without sharing raw data.

Performance Comparison Table

TABLE VIII
PERFORMANCE COMPARISON TABLE

Study / Reference	Methodology	Privacy	Accuracy	F1 Score	AUC
Baseline (Our Study)	Centralized XGBoost	No	0.700	–	0.769
Nagpal et al. (2024) [27]	Advanced XGBoost Ensemble	No	–	–	0.830
Kumar et al. (2025) [25]	Hybrid GA + SVM	No	0.765	0.740	–
Gicic et al. (2023) [1]	Stacked BiLSTM	No	0.872	–	∼0.780
Ma, R. (2025) [28]	Optimized KNN	No	0.740	–	–
Hofmann (1994) [29]	Logistic Regression	No	0.750	–	0.740
Xiao et al. (2019) [26]	Approx. Homomorphic GBDT	Yes (HE)	–	0.601	–
Tian et al. (2020) [7]	FederBoost (GBDT)	Yes (DP)	∼0.740	–	∼0.740
Proposed Method	**VFL + SecureBoost**	**Yes (HE)**	**0.690**	**∼0.71**	**0.737**

Note: "–" indicates the metric was not explicitly reported in the referenced study.

Conclusion and Future Scope

Conclusion

- We proposed a privacy-preserving credit risk framework using **Vertical Federated Learning** and **CKKS Homomorphic Encryption**.
- SecureBoost achieved strong performance, retaining nearly **96% of centralized XGBoost accuracy**.
- The system enables **multi-institution collaboration** without sharing raw customer data.
- End-to-end encrypted training ensures **data confidentiality**, addressing major regulatory constraints (GDPR, DPDP).

Future Scope

- Extend to **real-world multi-bank deployments** with more than 4 parties.
- Integrate **differential privacy** for stronger leakage resistance.
- Optimize CKKS parameters to reduce computation cost and latency.
- Explore **deep encrypted models** (HE-based DNNs, encrypted transformers).
- Build a standardized **privacy-preserving credit scoring pipeline** for financial institutions.

Thank You!

Questions are welcome.