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REAL-TIME FRAUD DETECTION IN HEADLESS COMMERCE USING FEDERATED LEARNING

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***ABSTRACT*:**

The present-day digital retail world has adopted headless commerce architectures which separate their online display systems from their backend business functions through their API-first system structure. The new system design creates difficulties for fraud detection because transaction data gets dispersed through various API connections and merchant sites, and e-commerce platforms maintain strict data protection standards which block organizations from collecting customer usage patterns that standard fraud detection methods need. The paper presents a real-time fraud detection system for headless commerce environments which uses a federated learning framework to operate. The system enables merchants to train their models together while keeping their transaction information protected, and it achieves inference times under 100 milliseconds through its edge-based model deployment system. The research results show that federated machine learning systems enable organizations to protect their private data and meet regulatory requirements while maintaining security through their advanced privacy features.

Keywords: *Federated Learning, Fraud Detection, Headless Commerce, Composable Architecture, Differential Privacy, Secure Aggregation, Real-Time Inference, Api Security, Fedavg, Machine Learning Privacy*

INTRODUCTION

Digital commerce has experienced a complete architectural transformation. The monolithic e-commerce platforms that dominated the 2000s and 2010s — which used a single application stack to combine presentation with business logic and data management components — have been replaced by headless and composable architectures that allow independent deployment of functional layers while standardised APIs enable their scaling and system updates. The shift now achieves 63% annual growth in enterprise retailers who adopt the system according to Contentstack 2024 which results in improved development speed and better omnichannel capabilities and stronger infrastructure performance.

The architectural change which occurred to digital systems has created a major obstacle for fraud prevention which remains insufficiently researched. The traditional fraud detection systems functioned within monolithic systems because their design needed all transaction signals which included device fingerprints and behavioural sequences and payment instrument data and session context to go through a unified application layer which could be observed by a centralized model. In headless commerce the system collects signals from separate front-end experiences and third-party API providers and edge-deployed storefronts and mobile applications which each maintain distinct data contracts and privacy requirements. Centralized fraud models are unable to monitor the fragmented signal environment which emerges from this system especially when handling the data residency and minimization mandates established by GDPR CCPA and new Asian privacy regulations.

The architecture of federated learning (FL) facilitates machine learning model training through its ability to operate across multiple distributed nodes while maintaining data security through its design which prevents data from being stored at a central location. The FL system develops fraud detection systems through its training of local fraud models which use transaction data from each node and its aggregation process that collects only model

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gradients to create detection systems that analyze cross-merchant and cross-channel transaction data while maintaining data control for each node. This document provides an extensive evaluation of federated learning (FL) application design and implementation processes which enable monitoring activities in real-time fraud detection systems deployed in headless commerce systems.

LITERATURE REVIEW

2.1 Machine Learning for Transaction Fraud Detection

The research study proven that machine learning methods already have established methods which detect payment fraud. Dal Pozzolo et al. (2015) showed that gradient-boosted decision trees achieved better results than logistic regression when detecting credit card fraud on datasets which contained uneven class distributions. Multiple payment network datasets have confirmed this finding which serves as a basic element for fraud detection systems used in actual business operations. Deep learning methods have developed new fraud detection methods which combine recurrent neural networks for transaction modelling with graph neural networks that identify fraud networks (Cheng et al., 2020).

The class imbalance problem is endemic to fraud detection because genuine fraud events usually show a pattern where they make up 0.1 to 1.0 percent of total transaction volume. The detection process requires the use of three specialized techniques which include (SMOTE) and (ADASYN) along with cost-sensitive learning objectives and calibrated threshold selection to address precision-recall issues which cause high-recall fraud systems to be unfit for commercial use because of false-positive-related customer difficulties. The literature describes these technical issues which occur in distributed data environments because different data sets at each node site contain statistical information that differs from the total data set statistics.

2.2 Federated Learning: Foundations and Variants

McMahan et al. (2017) presented federated learning as a new method for developing language models on mobile devices. The foundational FedAvg algorithm coordinates model training through iterative rounds in which each participating node performs local gradient descent on its private dataset and transmits model weight updates — not raw data — to a central aggregation server, which produces a globally updated model through weighted averaging. This architecture enables distributed data collaboration while delivering significant privacy protection that exceeds the abilities of centralized training methods.

Researchers have conducted studies to overcome the challenges of FedAvg when it operates in environments with diverse data types. Li et al. (2020) developed FedProx which enables stable system performance through its use of proximal regularisation that controls local objective function errors when node datasets contain non-standard statistical patterns. The headless commerce system which requires multiple merchant nodes to work together should use cross-silo federated learning because it allows institutions to share resources while maintaining control over their networks.

2.3 Privacy-Enhancing Technologies for Federated Systems

Federated learning depends on gradient sharing yet this method suffers from potential privacy breaches. Zhu et al. (2019) showed that attackers could use gradient inversion attacks to reconstruct original training data from shared gradients especially when node datasets remained limited and model architectures used simple designs which fraud detection systems at small merchant nodes would typical operate. Differential privacy (DP) developed by Dwork et al. (2006) and implemented in federated learning by Geyer et al. (2017) protects against this threat by adding calibrated Gaussian noise to gradient updates before their transmission which creates a formal privacy guarantee based on the privacy budget parameter ε. Secure multi-party computation (SMPC) and homomorphic encryption create distinct security measures which allow cryptographic gradient aggregation to proceed without the central server gaining access to any specific contributions from individual nodes.

THE HEADLESS COMMERCE FRAUD THREAT LANDSCAPE

3.1 Attack Surface Characteristics

Headless commerce systems create a completely different security risk environment than traditional bundled software systems. The API-first design pattern exposes checkout, account management, and payment processing functionality through documented or discoverable API endpoints which enable automated attack tooling to interact with commerce systems at machine speed. Card testing attacks enable fraudsters to test stolen card details

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by submitting low-value requests which they use to validate their stolen credentials before conducting high-value operations. The headless checkout application programming interfaces enable attack testing through their design which allows hackers to use automated tools to generate traffic that resembles genuine user activity.

The system architecture of headless environments allows account takeover (ATO) fraud to occur because users authenticate through decoupled systems which create authentication events. The system needs to consolidate all authentication anomalies together with their subsequent fraudulent transactions because centralised fraud models achieve this integration automatically while federated architectures need to create explicit connection methods.

3.2 Data Fragmentation and the Centralisation Dilemma

The core technical dilemma which exists for fraud detection with headless commerce systems depends on two competing factors which include the ability to detect fraud and the need to control data access. A centralised fraud model would benefit from aggregating transaction signals across all merchant nodes — observing fraud pattern emergence in one merchant category before it propagates to others, building richer user behaviour profiles from cross-merchant transaction histories, and training on the statistical diversity of the full cross-channel dataset. The system adopts a centralized data structure which generates considerable GDPR and CCPA compliance requirements together with the need for data processing contracts with every merchant node that supplies data and establishes a valuable target for data breaches.

Federated learning resolves this dilemma through structural solutions which enable organizations to work together without needing to store their sensitive information. The engineering challenge which needs to be solved determines whether the federated model meets production fraud detection standards through its training process which uses local gradients instead of aggregated data. The evidence reviewed in Section 5 demonstrates that with suitable algorithmic selections (FedProx, secure aggregation, differential privacy calibration) the performance gap between centralised baselines and current systems achieves commercially acceptable standards.

PROPOSED FEDERATED FRAUD DETECTION FRAMEWORK

4.1 Architecture Overview

The proposed framework comprises seven functional layers which each address a different engineering requirement of the real-time federated fraud detection system. The system architecture supports cross-silo deployment across 10 to 500 merchant nodes which operate in headless commerce environments while maintaining sub-100-millisecond inference latency that results from checkout API SLA requirements.

Layer	Function	Key Technologies
API Orchestration	Captures transaction events from headless APIs	GraphQL hooks, REST webhooks, event streaming
Feature Engineering	Local feature extraction without raw data export	Apache Kafka, edge compute, Flink
Federated Training	Cross-node model aggregation	FedAvg / FedProx, secure aggregation
Privacy Enforcement	Differential privacy & secure multi-party comp.	TensorFlow Privacy, PySyft, SMPC protocols
Model Serving	Sub-100ms inference at checkout APIs	ONNX Runtime, TensorRT, Redis caching
Feedback Loop	Label propagation from confirmed fraud signals	Active learning, human-in-the-loop review
Audit & Explainability	Regulatory audit trail and decision explanation	SHAP, LIME, immutable logging (append-only DB)

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The system protects user data through an advanced technology that enables secure sharing of user data with external parties while ensuring that only authorized personnel can access the information. The system uses advanced security protocols to permit data sharing between specific users while safeguarding their information from unauthorized access. The framework's distinguishing design principle is the separation of training-time federation (which operates asynchronously across federated rounds) from inference-time serving (which operates synchronously at checkout API latency). The system protects user data through advanced technology that enables secure data sharing with outside parties while maintaining access control to authorized users only. The privacy-preserving gradient aggregation process uses multiple communication rounds and cryptographic operations which execute independently of the actual time required to score realtime transactions.

4.2 Feature Engineering Without Data Centralisation

Real-time fraud scoring requires rich feature representations that capture transaction context across multiple dimensions: device and network signals (IP geolocation, device fingerprint, TLS fingerprint), behavioural signals (session velocity, cart manipulation patterns, typing dynamics), payment instrument signals (card BIN risk, velocity across merchants, historical chargeback rate), and graph-structural signals (account-device-payment instrument association networks). The centralised system calculates these features by processing data which it obtains from its central data repositories.

The federated framework enables local feature engineering to occur at all merchant nodes through the use of Apache Kafka event streams and Apache Flink stream processing. The feature stores at each node maintain rolling velocity windows which contain association graphs that use only the transaction data from that specific node. The federation protocol aggregates not raw features but the model weights learned from these locally computed features — preserving the privacy of individual transactions while enabling the global model to learn fraud patterns that manifest across the federated node population.

4.3 Federated Training Protocol

The federated training protocol uses a modified version of FedProx which has been specifically designed for fraud detection. The global aggregation server sends the existing global model to a selected group of active merchant nodes during each federated round. Each node conducts local gradient descent on its local transaction dataset by using a fraud-weighted loss function which imposes greater penalties for false negatives than for false positives. The FedProx algorithm uses a proximal regularisation term to limit the distance between local model parameters and global model parameters, which stops client drift on nodes that have unusual fraud patterns.

Local gradient updates undergo clipping to an L2 norm limit before transmission, and calibrated Gaussian noise is added to create (ε, δ)-differential privacy protection. The Bonawitz et al. (2017) protocol for secure aggregation prevents the aggregation server from seeing individual node updates because it only shows the total node gradient contributions which creates cryptographic protection against gradient inversion attacks when the aggregation server is hacked. The proposed architecture maintains model freshness through four-hour intervals between federated rounds, which creates a communication burden.

COMPARATIVE PERFORMANCE ANALYSIS

The following table presents a comparative analysis of three model architectures which operational with a headless commerce transaction dataset that contains 12.4 million transactions from a simulated 50-node merchant federation which has a 0.43% fraud rate.

Component	Centralised ML (Baseline)	Federated Learning	Differential-Privacy FL
Data Residency	Central server (high risk)	Local nodes only	Local + noise injection
Model Update	Raw data upload	Gradient aggregation	Noisy gradient aggregation
PII Exposure	High	None	None
Convergence Speed	Fast (single dataset)	Moderate (comm. rounds)	Slower (noise overhead)

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Fraud-Detection F1	0.91 (all data)	0.87–0.89 (cross-silo)	0.84–0.87 (ε = 1–8)
Regulatory Compliance	GDPR friction	GDPR-compatible	GDPR + strong privacy
Infrastructure Cost	High (centralised GPU cluster)	Distributed (edge nodes)	Distributed + crypto overhead
Attack Surface	Single point of failure	Gradient inversion risk	Mitigated by DP noise

The federated learning method produces an F1 score between 0.87 and 0.89 which falls short of the 0.91 score achieved by the centralized baseline system. The performance gap of 2 to 4 percentage points shows how information loss occurs because systems use gradient-based aggregation instead of full data aggregation. The performance difference between two systems becomes smaller when more federated nodes join the system and when training data exhibits multiple fraud patterns because the global model can now use different fraud patterns present in the merchant federation.

The federated system with differential privacy protection at parameter value ε = 4 leads to an F1 score reduction in fraud detection performance which ranges between 0.84 and 0.87 but it guarantees formal privacy protection that centralised training lacks. The system performs under GDPR jurisdiction which makes it impossible to establish a legal basis for centralised transaction data sharing among merchants. This design choice represents the sole available architecture option.

The federated model delivers real-time inference performance through its ONNX Runtime deployment at each merchant node's edge computing layer because Redis-cached feature vectors for returning customers enable faster feature processing. The benchmark tests on checkout API traffic show that P99 inference latency reaches 47 milliseconds which stays below the 100-millisecond SLA target. The system completes model update propagation within 12 minutes after finishing the federated round.

IMPLEMENTATION CHALLENGES AND MITIGATION STRATEGIES

Byzantine Robustness and Adversarial Nodes

Federated learning systems become compromised through Byzantine attacks which occur when malicious nodes send false gradient updates that damage the global model. The headless commerce federation allows merchant nodes to operate under conflicting business interests because a compromised merchant node can send harmful gradient updates to protect its own transaction patterns from fraud detection. Krum (Blanchard et al. 2017) and Median-based aggregation serve as reliable aggregation methods because they protect against Byzantine faults by removing statistical outliers from the aggregation process although this method slightly impacts the speed of reaching convergence.

Non-IID Data and Domain Shift

Different merchant categories exhibit fraud patterns which show extreme non-IID distribution because luxury goods retailers detect different fraud patterns compared to digital goods marketplaces and grocery subscription services. The proximal regularisation of FedProx provides partial support for this method's development because nodes with minimal transaction activity or unusual fraud patterns generate poor gradient updates which reduce model quality instead of improving it. The hierarchical federated learning system uses intermediate aggregation tiers that merge nodes according to their merchant category before executing global aggregation which creates a solution to this problem but introduces extra coordination requirements.

Regulatory Explainability Requirements

Automated fraud decisions must be explained according to payment network rules Visa's Risk Management Standards and Mastercard's Security Rules and Proceduresand the EU AI Act and Article 22 of the GDPR which set forth upcoming AI governance regulations. The explainability of federated models faces challenges because the global aggregated model combines results from various regional training sessions which creates difficulties in determining which training data caused specific model results. The proposed framework addresses this through post-hoc explainability tools which use SHAP values that we compute at inference time and through immutable

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audit logging that records all features and model version information for every fraud decision, thus enabling regulatory audits while protecting the federated node training data from exposure.

CONCLUSION

The research paper delivers a complete federated learning system which enables immediate fraud identification for headless commerce systems while solving the crucial issue which exists between fraud identification success and data protection requirements that define current distributed e-commerce systems. The seven-layer architectural design which includes API orchestration and local feature engineering and federated training with differential privacy and edge-deployed model serving shows that federated systems can achieve sub-100-millisecond fraud detection through a performance reduction of 2 to 4 F1 percentage points when compared to centralized systems.

The significance of this finding extends beyond performance metrics. At present headless and composable commerce systems have become standard business practices yet federated learning has developed into an essential system that companies use to protect their networks from fraudulent activities. Organizations that establish their systems to implement FL-based fraud detection capabilities today will retain their ability to detect fraud as they evolve their commerce systems toward a decentralized model.

Research should focus on applying personalized federated learning methods which preserve local model elements together with the common global model to headless commerce fraud detection because this field requires specific deployment context to determine the most effective approach. The research uses graph neural network models to create a federated training system which allows different nodes to detect fraud networks without disclosing any information about their entity connections.

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