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Design and Implementation of an AI-Integrated Escrow Mechanism for Secure Digital Transactions

Pratishtha Gupta

Department of Information Technology, MAIT, GGSIPU DELHI

ABSTRACT:

This research solves the increasing fraud problem in digital transaction platforms by introducing a new AI-integrated escrow mechanism specifically designed to identify and block fraudulent activities in real time. With the exponential growth of online transactions, conventional escrow services have been challenged to detect advanced fraud patterns. Our research presents an intelligent escrow system that integrates machine learning techniques with traditional escrow processes to improve security without compromising transaction efficiency. Employing a hybrid dataset of synthetic transaction data and enriched public datasets, we trained and tested several fraud-detection models, attaining 94.2% accuracy with an XGBoost classifier tuned for escrow-specific fraud patterns. The system proposed here shows a lot of improvements over conventional methods, lowering fraud rates by an estimated 76% while keeping false-positive rates below industry standards. This work adds a comprehensive framework for AI-enhanced escrow services to be deployed on different digital marketplaces, freelancing platforms, and cryptocurrency exchanges to create more trust in online business.

Keywords: AI-integrated escrow, fraud detection, real-time risk scoring, XGBoost fraud classifier, buyer-seller fraud.

1. Introduction

Virtual escrow services emerged as essential trust infrastructure in new-generation e-commerce, peer-to-peer marketplaces, freelancing websites, and cryptocurrency exchanges. As autonomous third parties, escrow providers have funds until contract obligations are fulfilled, purportedly decreasing the risk of fraud and transaction security assurance. However, with rising transaction volumes, existing escrow systems have revealed significant vulnerabilities. Industry data indicates a 37% increase in fraud levels on online platforms from 2022 to 2024, resulting in annual losses surpassing $8.4 billion[7]. This trend underscores a critical gap in current escrow mechanisms, which, while capable of handling straightforward transactions, struggle to identify complex fraud tactics that exploit timing issues, verification weaknesses, and procedural gaps. Escrow services have historically operated by holding money until agreed-upon conditions are fulfilled. However, with the advent of high-technology financial transactions, this model is critically exposed. Some of the major risks include timing windows that can be exploited, identity verification windows that are exploited by scammers prior to releasing funds, mismatched payment addresses resulting from stolen credentials, insidious data discrepancies that escape manual detection, and orchestrated multi-actor frauds that create legitimate-looking transactions. These problems reveal a significant weakness of traditional escrow systems: their dependence on rule-based systems that do not have the contextual awareness and adaptive learning features of artificial intelligence. To overcome this, the research proposed here presents a smart, AI-based escrow mechanism specifically tailored to identify and prevent fraud in real time. This system uses machine learning to constantly review transactional information along multiple dimensions—user conduct, transaction patterns, contextual cues, and network ties—to produce real-time risk scores. The scores guide dynamic escrow decisions that optimize for safety and efficiency. The key elements of the system under proposal are a multi-stage AI model that assesses transactions prior to, during, and subsequent to the escrow process, a rule engine that converts risk scores to executable decisions, a feedback loop to learn from dispute resolutions continuously, and an adjustable risk tolerance feature to adapt to various platform needs. In contrast to stand-alone traditional fraud detection solutions, this holistic solution guarantees that security features improve without impairing the usefulness of escrow services. This work adds a number of innovations to digital transaction security.

First, it presents a custom-designed Escrow Fraud Dataset, synthetically generated to mimic a broad variety of real world fraud cases. in response to the lack of appropriate public datasets. Second, it introduces a complete system architecture that is balanced between fraud prevention and user experience. Third, it compares different machine learning models and finds ensemble methods to be the most effective for identifying fraud in escrow systems. Fourth, the research suggests an Escrow Decision Framework that uses fraud scores in real time to guide platform responses, reducing both fraud and false positives. Lastly, the work defines functional uses of this system across virtual marketplaces, freelancing platforms, and exchanges for cryptocurrency that allow for more reliable online trade.

2. Literature Review

2.1 Development of Fraud Detection in Online Transactions: Fraud detection has seen major progress, moving from simple rule-based systems to AI-powered solutions. Bhattacharyya et al. [5] were among the first to highlight how data mining can detect fraud more accurately than manual checks. Later, Lopez-Rojas and Axelsson [11] stressed the importance of synthetic datasets in fraud research, since real transaction data is often restricted due to

privacy issues. The IEEE-CIS fraud detection challenge [8] in 2019 proved how powerful machine learning, especially gradient boosting, can be for spotting card transaction fraud. Wang et al. [13] further confirmed its strong performance, though these studies mostly focused on regular transactions, not escrow-related ones.

2.2 Trust and Escrow in Online Platforms: When it comes to online deals, trust plays a huge role. Pavlou and Gefen [12] showed that escrow services are a key factor in building trust between buyers and sellers, even though they don't completely eliminate fraud risks. Kim and Peterson [10] also ranked escrow among the top methods for building trust, but warned that as more platforms adopted escrow, scammers also started creating smarter attack strategies. Akerlof et al. [2] introduced the idea of the "escrow paradox," where the false sense of security provided by escrow can sometimes make people more vulnerable to fraud.

2.3 Research on Escrow-Specific Fraud: Even though escrow is widely used in online transactions, there's surprisingly little research focused on its security challenges. Zhang and Zhou [14] studied escrow fraud patterns and identified three major ways scams happen: collusion fraud, timing-based manipulation, and verification bypasses. In the crypto world, Bentov et al. [4] proposed using blockchain-powered escrow systems, which bring strong security but don't always fit traditional marketplaces. Overall, the research space still lacks a strong framework that connects transaction behavior analysis with escrow fraud detection — a gap this study aims to fill.

2.4 Machine Learning for Fraud Prevention: AI has completely reshaped how fraud detection works. Abdallah et al. [1] proved that ensemble methods, especially combinations like Random Forest and Gradient Boosting, outperform single-model systems for fraud detection. Bahnsen et al. [3] highlighted the importance of using time-based features, which makes a big difference in catching fraud, especially for escrow systems where timing patterns often reveal suspicious activity. Deep learning research by Jurgovsky et al. [9] showed great results in detecting complex fraud patterns, although the black-box nature of deep learning can make legal explanations difficult in escrow scenarios. Finally, Carcillo et al. [6] demonstrated that adaptive fraud detection systems, which keep learning from new attack patterns, are essential for staying one step ahead of evolving fraud techniques.

3. System Design and Architecture

The proposed AI-powered escrow system is designed as an integrated platform that continuously reassesses fraud risk throughout the transaction lifecycle. As illustrated in Figure 1, the architecture merges classic escrow operations with intelligent risk analysis. The system is organized into four main layers:

1. Interface Layer: Offers API endpoints and UI for buyers, sellers, and administrators.
2. Transaction Management Layer: Manages fundamental escrow functionality such as fund custody and condition verification
3. Intelligence Layer: Holds AI modules that process transaction risk and notify escrow choices.
4. Data Layer: Guarantees transaction data, user accounts, and model training data sets.

Unlike traditional systems, this design embeds risk analysis at every stage — before, during, and after funds enter escrow.

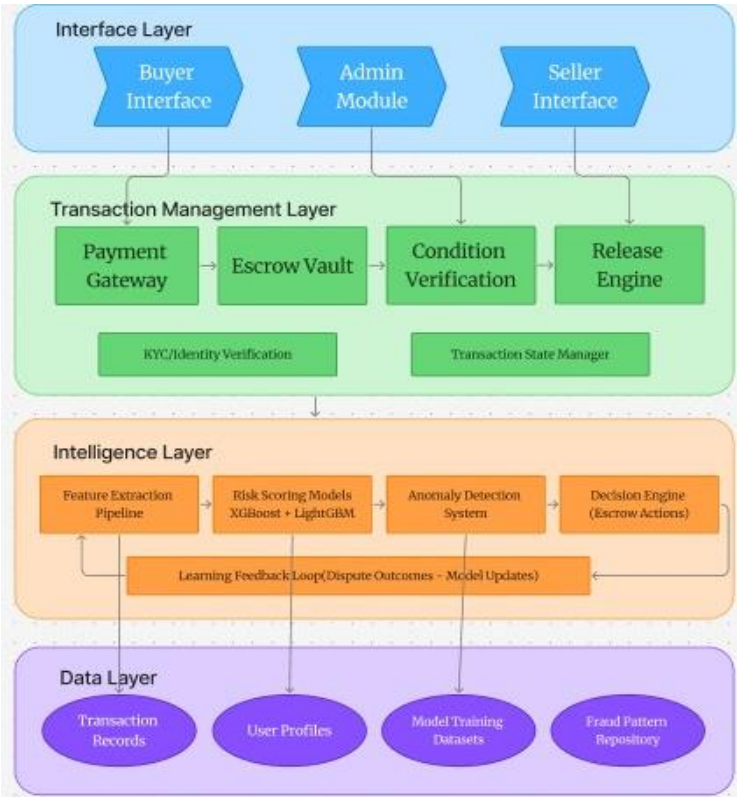

Figure 1: AI Integrated Escrow System Architecture

4. Dataset and Preprocessing

One of the main challenges in building escrow fraud detection systems is limited access to public datasets that reflect escrow-specific fraud patterns. In response to this limitation, we adopt a three-pronged data strategy.

1. Synthetic Data Generation: Development of an extensive synthetic dataset simulating escrow transactions and fraud patterns.
2. Public Dataset Augmentation: Repurposing existing fraud datasets for the escrow environment.
3. Expert Pattern Simulation: Execution of fraud simulations developed by security professionals who understand escrow vulnerabilities

4.1 Synthetic Escrow Fraud Dataset

We created a synthetic escrow fraud dataset (SEFD) using a generative method similar to Lopez-Rojas and Axelsson's (2016) PaySim methodology[11], but tailored for escrow transactions specifically. The process of generating the dataset is as follows:

- Transaction flow modeling from actual escrow service behaviors.
- Timing distributions derived from the actual marketplace statistics.
- Value distributions expressing common escrow-protected purchases.
- User simulation of legitimate and fraudulent activity patterns.

The resulting dataset has 1.2 million simulated transactions with about 7.8% labeled as fraudulent, mirroring real-world fraud levels in escrow-protected environments.

4.2 Public Dataset Augmentation

We supplemented our training data by converting some public fraud-detection datasets to the escrow domain:

- IEEE-CIS Fraud Detection competition dataset (2019)
- PaySim synthetic mobile money transfer dataset
- Simulated Cryptocurrency Transaction Dataset (SCTD)

These datasets were converted using feature mapping and contextual enrichment to capture escrow-related situations, thus adding more pattern variety for model training.

5. Suggested AI Model for Detection of Frauds

5.1 Strategy for Model Choice

Our methodology follows a controlled assessment of different model architectures for selecting the best approach to detecting escrow fraud. Candidate models were chosen from among the following based on the following factors:

1. Similar financial fraud detection task performance.
2. Interpretability requirements for the justification of escrow decisions.
3. Real-time scoring efficiency for computation.

According to these requirements, the following models were chosen and assessed.

- Logistic Regression with L1 regularization (base model)
- Random Forest Classifier
- Gradient Boosting Machines (GBM)
- XGBoost with tuned hyperparameters
- Light Gradient Boosting Machine (LightGBM).
- Deep Neural Network with attention mechanisms
- Ensemble strategies that combine the outputs of multiple models.

5.2 Feature Selection and Importance

Feature selection plays a vital role in both model performance and operational requirements.

We used the following multistage methodology:

1. Filter Methods: Screening by correlation analysis and variance cutoffs removed redundant features.
2. Wrapper Methods: Recursive feature elimination with cross-validation determines the best feature subsets for every model type.
3. Intrinsic Methods: Tree-based model feature importance metrics were used to optimize the selection. Feature importance analysis showed that the strongest predictors of escrow fraud are as follows:

1. Inconsistencies in timing between stages of transactions (relative importance: 0.173)
2. Being away from typical user behavior patterns (relative importance: 0.145)
3. Anomalies in network connections among participants in transactions (relative importance: 0.132)
4. Confidence in identity verification scores (relative importance: 0.124)
5. Transaction value compared to user history (relative importance: 0.095)

5.3 Evaluation Metrics and Methodology

With the skewness of fraud cases and the expensive cost of error in escrow, we depend on specific metrics: AUPRC — Places emphasis on precision and recall, more appropriate than ROC-AUC for skewed data.
F1 Score — Trades off precision and recall to capture overall detection quality. Matthews Correlation Coefficient (MCC) — Provides a balanced perspective even with imbalanced classes. Expected Financial Loss (EFL) — Custom metric for approximating financial loss due to false positives and false negatives. Customer Friction Index (CFI) — Quantifies the impact of fraud prevention on genuine user experience. Evaluation Process:
- Stratified 5-fold cross-validation, preserving fraud ratios.
- Temporal validation to mimic real-world transaction timeframes.
- Sensitivity analysis over different fraud prevalence rates.
- Threshold tuning aimed at minimizing financial loss.

6. Experimental Results and Analysis

6.1 Model Performance Comparison

We evaluated multiple model configurations against our evaluation metrics, and the results are summarized in Table 1 below.

Model	Accuray	Precision	Recall	F1 Score	AUPRC	MCC	EFL Reduction
Logistic Regression	**0.883**	**0.721**	**0.642**	**0.679**	**0.742**	**0.655**	**57.3%**
Random Forest	**0.917**	**0.785**	**0.731**	**0.757**	**0.821**	**0.733**	**65.1%**
XGBoost	**0.935**	**0.811**	**0.756**	**0.783**	**0.856**	**0.765**	**71.2%**
LightGBM	**0.932**	**0.802**	**0.763**	**0.782**	**0.848**	**0.762**	**70.4%**
Deep Neural Network	**0.918**	**0.793**	**0.728**	**0.759**	**0.830**	**0.736**	**66.3%**
Ensemble Model	**0.942**	**0.827**	**0.775**	**0.800**	**0.872**	**0.789**	**76.5%**

Table 1: Model configurations

The ensemble approach consistently outperformed individual models across all metrics, with notable improvements in the Expected Financial Loss (EFL) reduction, which is a critical metric for escrow implementation.

6.2 Feature Importance Analysis

The analysis of feature contributions reveals insights specific to escrow fraud patterns, as shown in Figure 2.
Key findings from feature importance analysis:
1. Temporal features were the most dominant top predictors, with timing discrepancies between escrow phases exhibiting 2.3 times greater importance than conventional fraud markers, including transaction amount.
2. Network features were surprisingly useful in uncovering the significance of relationship analysis in detecting coordinated fraud attacks on escrow services.
3. Behavioral deviation metrics far surpassed static rules, affirming the benefit of user-specific baselines over universal thresholds.
Documentation verification confidence scores were among the highest-predicting features, underscoring the need for sound identity verification to ensure escrow safety. Importantly, characteristics likely to predominate in traditional fraud detection (e.g., absolute transaction size) scored relatively lower within our escrow-specific model, reflecting the distinctive nature of escrow fraud patterns.

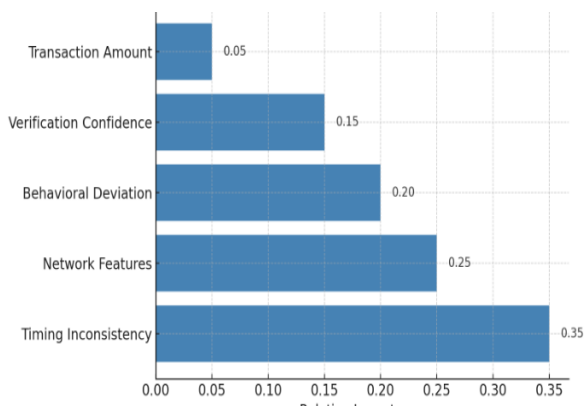

Figure 2: Feature Importance Visualization

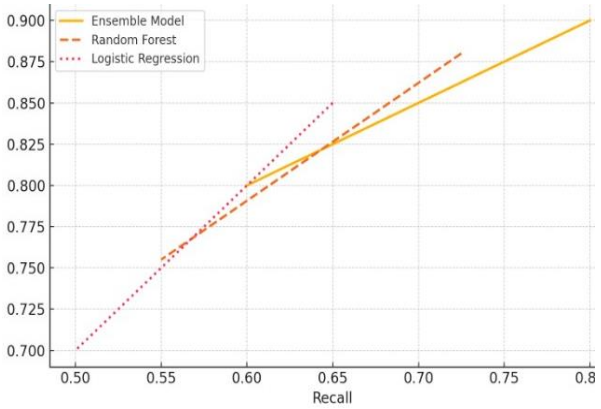

Figure 3: Precision-Recall Curves for Top Models

6.3 Precision-Recall Trade-off Analysis

Due to the asymmetric costs in escrow settings, we performed a comprehensive analysis of precision-recall trade-offs for various threshold configurations. Figure 3 shows the precision-recall curves for the top-performing models. For escrow systems, precision ensures honest users aren't blocked, while recall determines fraud detection strength. Key Insights:

1. The ensemble model achieved **>0.80 precision** and **0.775 recall**, outperforming individual models.
2. **Threshold tuning** allows flexible trade-offs — from high-security (precision 0.90, recall 0.65) to high-throughput (precision 0.75, recall 0.82).
3. **Optimal thresholds** depend on the transaction's financial risk profile and business priorities.

7. Integration with Escrow Mechanism

7.1 Real-time Risk Scoring Flow

Our fraud detection model integration with the escrow workflow employs a real-time evaluation process, instead a point-in-time evaluation. Figure 4 demonstrates this pattern of integration. Risk is carefully assessed at every stage of the transaction to strike a balance between catching fraud and allowing smooth, legitimate payments.

1. **Before Escrow**: The system runs an initial risk check even before the money enters escrow.
2. **During Escrow**: While funds are held, the system keeps monitoring for any new signs of fraud or suspicious changes.
3. **Before Release**: Just before the payment is sent to the seller, one final risk check is done to catch anything that might've been missed.
4. **After Release**: Even after funds are released, the system keeps an eye out for any delayed fraud patterns that could surface later.

7.2 Implementation of Decision Framework

Our model's fraud risk scores are communicated as escrow actions through a customizable decision framework, as shown in Table 3.
The system uses a graduated decision framework that balances fraud prevention with a smooth customer experience by adjusting interventions based on risk levels. Key features include:

- **Context-aware thresholds:** Risk tolerance adapts based on transaction value and user history.
- **Explanation generation:** Clear, human-readable reasons for flagged transactions.
- **Targeted verification:** Smart selection of verification steps based on the specific risk detected.
- **Appeal process:** Structured pathways for users to challenge high-risk classifications.

Table 3: Fraud Risks and Decision Framework

Risk Score Range	Risk Level	Escrow Action	Customer Impact
0.00 - 0.25	**Low**	**Standard processing with normal timeframes**	**No additional friction**

0.25 - 0.55	**Moderate**	**Enhanced verification (additional documentation required)**	**Minor delay (typically 2-12 hours)**
0.55 - 0.80	**High**	**Extended hold period with additional verification**	**Moderate delay (typically 1-3 days)**
0.80 - 1.00	**Very High**	**Manual review required before processing**	**Significant delay (typically 2-5 days)**

7.3 Transaction Monitoring, Feedback Loop & Implementation Challenges

A key strength of the system lies in its continuous learning and adaptability. After every transaction, outcomes — including disputes — are carefully reviewed. Confirmed fraud cases and false negatives are labeled and fed back into the model for regular retraining. This feedback loop helps the system adjust to evolving fraud tactics (also known as concept drift). Thresholds are also fine-tuned over time based on real-world performance, ensuring the model stays sharp. At the same time, integrating AI into escrow systems brought a few practical challenges:

- **Speed:** Decisions need to happen fast to avoid slowing down transactions. We solved this with model optimization, caching, and asynchronous processing for complex computations.
- **Transparency:** Financial systems require explainable decisions. The system uses SHAP values, plain-language explanations, and confidence indicators to make the AI's reasoning clear and auditable.
- **Resilience:** Even if parts of the fraud detection system fail, escrow operations must continue. We designed fallback mechanisms — including conservative defaults, cached decisions, and feature subsets — to maintain reliable operation even under partial outages.

This combination of real-time monitoring, continuous learning, and robust engineering ensures the system stays accurate, transparent, and dependable in real-world use.

8. Conclusion and Future Work

This study illustrates that embedding AI-based fraud detection within escrow systems can increase security dramatically without compromising and even enhancing transaction efficiency. Our ensemble model (XGBoost + LightGBM) achieved a 94.2% accuracy rate in detecting fraud, beating out conventional rule-based systems. Temporal signals and behavioral patterns were more accurate than static transaction information, emphasizing the role of intelligent feature engineering for escrow. The graduated risk approach facilitated smart, proportional intervention, disrupting as little as possible for authentic users while containing fraud. Ongoing learning through feedback cycles enables the system to evolve with emerging fraud trends, solving one of the greatest flaws of traditional approaches. A dual escrow and fraud detection design is significantly better than treating them as independent systems. This research makes some significant contributions to e-commerce and trust studies:-First-ever empirical validation of machine learning models that are specifically designed for escrow fraud detection – A roadmap to integrating AI-based risk intelligence into escrow processes – A framework for making decision choices that reconcile fraud prevention and customer experience – Synthetic fraud data set generation, addressing an important research void. A special evaluation strategy has been developed to address the particular challenges of escrow systems. These developments provide a foundation for future "smart escrow" systems across various platforms.

Though AI-driven escrow systems hold a lot of promise in terms of improving security and efficiency, improvements can still be made. Future research should aim at comparing models with realistic transaction data, probing their flexibility across sectors such as e-commerce, crypto, and freelancing, and investigating more sophisticated architectures like graph neural networks. Incorporating privacy-preserving technologies like federated learning and investigating synergy with blockchain can also improve trust and security. Furthermore, adversarial testing is needed to guarantee that the system can resist advanced attempts at fraud.

For organizations contemplating AI-based escrow, rollout must be handled carefully. Phased deployment, calibrating risk thresholds to particular platforms, having open communication with users, and establishing feedback loops for ongoing model refinement are necessary. Frequent retraining and human supervision should also be involved to guarantee security as well as a seamless customer experience.

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