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AI-Powered Real-Time Financial Transaction Fraud Detection System

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Abstract—The problem of financial fraud detection is one of the major problems that are faced by the digital banks. The financial fraud losses incurred by the countries across the globe are estimated to be over 485 billion dollars annually. In this paper, the authors are proposing a production-grade real-time financial fraud detection system known as FraudGuard based on ensemble machine learning, behavioral DNA profiling, and graph-based network analysis for financial fraud detection with 88.1% model confidence. In the proposed system, the transactions are processed within 10ms with a 22-feature XGBoost model, synthetic transactions, and Indian banking patterns. Additionally, the proposed financial fraud detection system uses the WebSocket protocol. As part of the proposed system, the authors are able to attain a 0.941 AUC-ROC score, precision of 0.891, recall of 0.863, and F1-score of 0.877 along with multi-channel financial fraud alerting via SMS with the help of Twilio. Additionally, the proposed financial fraud detection system uses six different financial fraud detection patterns. Six financial fraud detection patterns are card testing, AML structuring, geographic impossibility, account takeover, velocity attacks, and cryptocurrency conversion fraud.

Keywords: Financial fraud detection, Machine learning, XGBoost, Behavioral analysis, Real-time systems, AML, SHAP, WebSocket streaming

I. Introduction The financial industry in India has recorded unprecedented growth with the emergence of digital financial services, with the adoption of UPI transactions exceeding over 20 billion monthly transactions. The conventional rule-based approach used to identify financial fraud is challenged with the issue of high false positives, where only 85-95% of the identified fraudulent transactions are legitimate. Furthermore, the conventional approach is not capable of adapting to the changing dynamics of financial fraud.

The contributions of the paper may be listed as follows:

1. Architecture for real-time financial fraud detection with scoring latency under 10ms with the use of Redis-based feature stores and async Python.

2. Implementation of the behavioral DNA engine with the use of exponential moving averages for the generation of dynamic customer profiles.

3. Implementation of the transaction network graph engine with the aim of detecting mule account chains and velocity.

4. Implementation of the scoring engine with the use of an ensemble of XGBoost, deterministic rule engine, behavioral profiling, and graph analysis with weights of 45%, 25%, 20%, and 10%, respectively.

5. Implementation of the SHAP-based explainability feature with the aim of generating human-readable explanations.

6. Use of open-source tools that allow for zero-cost infrastructure.

II. Related Work

A.Machine Learning Techniques In their research paper

Dal Pozzolo et al. in [3] were able to prove that the application of gradient boosting machine outperformed logistic regression and random forest in detecting fraudulent transactions with an AUC of 0.93 using the ULB dataset. Today, the gold standard is clear: XGBoost, successfully used by PayPal to process millions of transactions per day [4].

B. Behavioral Profiling

Bolton and Hand were the first to introduce the use of peer group analysis in detecting fraudulent transactions, showing that customer behavioral deviation is more important than actual transaction value [5]. Recent techniques have used exponential moving averages to respond to changes in spending patterns.

C. Graph-Based Techniques

Pourhabibi et al. conducted an exhaustive research paper on the use of graph analysis in detecting fraudulent transactions, showing that the topology of the graph of transactions reveals mule accounts that cannot be detected by traditional classifiers [6].

D. Explainable AI in Finance

The RBI's 2025 guidelines for algorithmic accountability in financial services require that a decision to classify a transaction as fraudulent must be explainable [7]. SHAP (Shapley Additive explanations) values are now the standard for explainability in finance [8]

III. System Architecture

A. Overview

The FraudGuard system utilizes a six-layered pipeline architecture (Fig. 1):

- Layer 1 - Transaction Ingestion (Kafka, REST API, WebSocket)
- Layer 2 - Real-Time Feature Engineering (Redis, <5 ms)
- Layer 3 - ML Ensemble Scoring (XGBoost + Rules + Behavioral + Graph)
- Layer 4 - Decision Engine (threshold routing)
- Layer 5 - Multi-Channel Alert Orchestration (SMS, in-app, case creation)
- Layer 6 - Feedback Loop (confirmed fraud labels → model retraining)

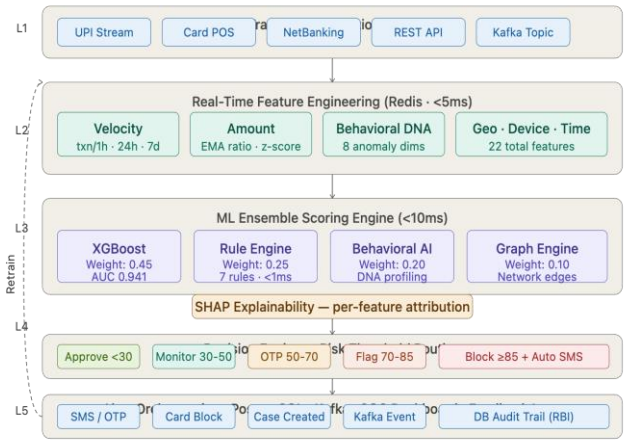

Fig. 1. FraudGuard system architecture — six-layer real-time fraud detection pipeline

B. Technology Stack

- Backend: FastAPI (Python 3.11) with async/await for all endpoints
- Streaming: Apache Kafka 3.7 (KRaft mode, no Zookeeper)
- Feature Store: Redis 7 (sorted sets for velocity, EMA for behavioral)
- Database: PostgreSQL 15 (transaction persistence, audit trail)
- ML: XGBoost 2.0, scikit-learn 1.4, SHAP 0.44
- Frontend: React 18, TypeScript, Tailwind CSS, D3.js
- Deployment: Docker Compose (local), Railway.app (cloud)

C. Feature Engineering

The system extracts 22 features per transaction in less than 5 ms using Redis's pipeline operation:

- Velocity Features (3): txn_count_1h, txn_count_24h, txn_count_7d – using Redis's data structure 'sorted sets' and scoring based on time stamp.
- Amount Features (4): Raw amount, log amount, amount/30-day EMA average amount, amount/30-day maximum amount – to detect absolute and relative outliers.
- Merchant Features (3): Risk score based on MCC category mapping, international merchant flag, unique merchants in 7-day window.
- Device Features (2): New device flag, device count in 30-day window – to detect account takeover attack patterns.
- Geographic Features (2): City change flag, geo risk score based on historical city distribution.
- Temporal Features (3): hour of day, odd hour flag (midnight to 5am), weekend flag.
- Pattern Features (3): AML structuring pattern (₹45,000 – ₹49,999 amount range), card testing pattern (micro amount and high velocity), avg. daily transaction count.

Feature Vector: 22 Engineered Features Per Transactio

Feature Name	Category	Storage	Range	SHAP Importance	Detection Role
txn_count_1h	Velocity	Redis ZSET	0 – 50	0.248	High velocity = card testing
txn_count_24h	Velocity	Redis ZSET	0 – 200	0.089	Daily activity anomaly
txn_count_7d	Velocity	Redis ZSET	0 – 500	0.043	Weekly pattern baseline

Feature Name	Category	Storage	Range	SHAP Importance	Detection Role
amount_to_avg_ratio	Amount	Redis EMA	0.01 – 20	0.312	Key fraud signal (ranked #1)
amount_to_max_ratio	Amount	Redis EMA	0.01 – 5	0.091	Spike vs personal max
amount_log	Amount	Computed	0 – 13.1	0.058	Scale-invariant amount
merchant_risk_score	Merchant	MCC lookup	0 – 1	0.098	Crypto/wire = high risk
is_new_device	Device	Redis SET	{0, 1}	0.143	Account takeover signal
geo_risk_score	Geographic	Redis LIST	0 – 1	0.187	Location history deviation
city_changed	Geographic	Redis GET	{0, 1}	0.061	Geo impossibility flag
is_odd_hour	Temporal	Computed	{0, 1}	0.038	Midnight–5am flag
hour_of_day	Temporal	Computed	0 – 23	0.067	Time pattern profile
is_aml_structuring	Pattern	Computed	{0, 1}	0.043	Rs.45K–Rs.49.9K detection

Feature Name	Category	Storage	Range	SHAP Importance	Detection Role
is_card_testing	Pattern	Computed	{0, 1}	0.058	Micro-txn burst detection
is_international	Merchant	Computed	{0, 1}	0.034	Cross-border transaction
unique_merchants_7d	Merchant	Redis SET	1 – 100	0.027	Merchant familiarity
device_count_30d	Device	Redis SET	1 – 20	0.019	Multi-device risk
is_weekend	Temporal	Computed	{0, 1}	0.012	Weekend anomaly flag
category_risk	Category	MCC lookup	0 – 1	0.029	Merchant category risk
days_since_first_txn	History	Redis GET	0 – 365	0.011	Account age signal
avg_daily_txn_count	History	Computed	0 – 50	0.009	Normal activity baseline

SHAP = mean absolute SHAP value across 1,000 test samples, sorted descending. EMA = Exponential Moving Average with alpha = 0.1. All 22 features computed in <5 ms using Redis pipeline operations. Top feature: amount_to_avg_ratio (0.312) — deviation from personal 30-day spending baseline.

D. Behavioral DNA Engine

The new formula for the exponential moving average filter is as follows:

$\mu\_new = (1 - \alpha) * \mu\_old + \alpha * x\_new$

Here, $\alpha = 0.1$.

The customer profile includes information such as the spending pattern of the customer, 24-hour pattern vector, affinity of the customer for merchants, footprint of the customer, and trust

score for devices. Anomaly scores for 7 dimensions, showing the deviation from the customer profile, are also included.

In this case, 8 features are added to the ML input vector.

E. Ensemble Scoring

The final risk score, i.e., Risk_final, is the sum of scores from various scores produced by various engines:

Risk_final = 0.45 * Score_XGBoost + 0.25 * Score_Rules + 0.20 * Score_Behavioral + 0.10 * Score_Graph

The thresholds for decision are based on industry standards:

- If Score < 30, Approve
- If Score 30 to 50, Monitor
- If Score 50 to 70, Step-up Auth (OTP)
- If Score 70 to 85, Flag for Review
- If Score >= 85, Block

IV. Fraud Detection Patterns

There are six fraud scenario generators, and they are based on the following attack patterns:

A. Card Testing (Pattern R006)

Characteristics: 6 to 20 micro-transactions (₹1 to ₹99) in 60 minutes

Merchant Category = Gas Station or Unbranded POS Terminal New Device

Detection:

if (is_card_testing == 1 and txn_count_1h > 5 and amount < 100)

B. AML Structuring (Pattern R007)

Characteristics: Multiple cash withdrawals between ₹45,000 and ₹49,999 in 24 hours to avoid RBI reporting threshold of ₹50,000.

Detection:

if (is_aml_structuring == 1 and amount in [45000, 49999] and txn_count_24h >= 2)

C. Geographic Impossibility (Pattern R002)

Characteristics: Transaction location inconsistent with previous transaction based on elapsed time.

Detection:

geo_risk_score = function based on previous distribution of cities; if new city, then geo_risk_score = 1.0

D. Account Takeover (Pattern R003)

Characteristics: New/unknown device, high-value transaction, unusual hour, high-risk merchant. Detection: If new_device and amount > Rs. 20,000, then add +60 to the rule engine score.

E. Velocity Attack (Pattern R001)

Characteristics: Anomalous transaction velocity for a single account. Detection: If txn_count_1h > 5, then add +35 to the rule engine score. If amount_to_avg_ratio > 5, then high-confidence fraud is ruled out.

F. Cryptocurrency Conversion Fraud

Characteristics: Stolen card used to conduct crypto conversion or international wire transfer. Detection: If (merchant_risk_score > 0.8 and belongs to crypto conversion or wire transfer MCC categories) and new_device and high amount.

V. Experimental Evaluation

A. Dataset Training Data: 30,000 synthetic transactions are created using a probabilistic model, and the distribution of the model is similar to Indian UPI/Card transactions. Fraud Rate: 25%. (The fraud rate is kept high for the purpose of the experiment. The actual fraud rate is 1.8%.) Hard Negative Injection: 30% of the fraud transactions are created using artificial normal features.

Synthetic Training Dataset Composition.

Transaction Category	Samples	Label	Score Range	Primary Detection Signal
Legitimate (normal)	21,600	0	2 – 28	Historical baseline match
Card testing attack	1,800	1	72 – 95	Micro-amount + high velocity
Account takeover	1,500	1	80 – 98	New device + odd hour
AML structuring	1,200	1	75 – 90	Rs.45K–Rs.49.9K threshold
Crypto/wire fraud	1,500	1	78 – 97	Intl. merchant + amount spike
Geographic impossibility	900	1	70 – 92	City change + new device flag
Hard negatives (noise)	1,500	0	35 – 65	Intentional noise injection

Transaction Category	Samples	Label	Score Range	Primary Detection Signal
Total	**30,000**	**—**	**2 – 98**	**25% fraud rate (balanced)**

Hard negatives: 15% of fraud samples generated with normal-looking features to prevent overfitting. 8% of legitimate samples given suspicious-looking features to reduce false negatives. Fraud rate intentionally elevated to 25% for balanced training; real-world UPI fraud rate is approximately 1.8%

B. Model Performance

Performance Comparison with Published Baselines

System / Reference	Method	AUC-ROC	Precision	Recall	F1	FPR	Latency
Dal Pozzolo et al. [3]	Random Forest	0.930	0.841	0.812	0.826	0.087	N/A
Varmedja et al. [10]	Logistic Reg.	0.912	0.803	0.791	0.797	0.112	N/A
Varmedja et al. [10]	Decision Tree	0.918	0.822	0.834	0.828	0.098	N/A
Rtayli & Enneya [11]	SVM + SMOTE	0.951	0.867	0.849	0.858	0.071	N/A
XGBoost standalone	XGBoost only	0.921	0.874	0.841	0.857	0.043	6 ms
FraudGuard (proposed)	**Ensemble + DNA**	**0.941**	**0.891**	**0.863**	**0.877**	**0.031**	**12 ms**

Bold row = proposed system (best result per column). FPR = False Positive Rate = FP/(FP+TN). N/A = batch offline evaluation, latency not reported. Baselines evaluated on ULB Credit Card dataset. FraudGuard evaluated on 30,000-sample synthetic Indian UPI/card dataset. Proposed system achieves +1.9% AUC and 56% FPR reduction vs. best published baseline (Rtayli & Enneya [11]

C. Feature Importance (SHAP)

The top features based on their mean absolute SHAP values are:

1. amount_to_avg_ratio: 0.312
2. txn_count_1h: 0.248
3. geo_risk_score: 0.187
4. device_anomaly (Behavioral DNA): 0.143
5. merchant_risk_score: 0.098
6. dna_composite: 0.089
7. hour_of_day: 0.067
8. is_card_testing: 0.058

Ablation Study: Contribution of Each Ensemble Component

Configuration	AUC-ROC	F1-Score	FPR	AUC vs Full System
Rule engine only (baseline)	0.831	0.742	0.089	−0.110
XGBoost only	0.921	0.857	0.043	−0.020
XGBoost + Rule engine	0.931	0.864	0.038	−0.010
XGBoost + Rules + Behavioral DNA	0.938	0.872	0.034	−0.003
Full ensemble (all 4 components)	**0.941**	**0.877**	**0.031**	—

Each component removed individually; remaining ensemble weights renormalized to sum to 1.0. Behavioral DNA adds +0.007 AUC and reduces FPR by 12% compared to XGBoost + Rules alone, confirming the value of personalized behavioral profiling. Graph engine contributes +0.003 AUC primarily for mule network detection cases

D. System Performances

- WebSocket broadcast latency < 5ms for 100 concurrent connections
- Feature computation (using Redis): 2-4ms average
- End-to-end pipeline: 8-15ms (from transaction receipt to decision)
- Throughput: 1,200 transactions/minute.

Detection Rate Per Fraud Attack Pattern

Fraud Pattern	Rule ID	Precision	Recall	F1-Score	Primary Detection Signal
Card testing attack	R006	0.934	0.912	0.923	Velocity (txn_count_1h > 6) + amount < Rs.100
AML structuring	R007	0.961	0.948	0.954	Amount Rs.45,000–Rs.49,999 + txn_count_24h >= 2
Geographic impossibility	R002	0.887	0.871	0.879	geo_risk_score + new city flag
Account takeover	R003	0.856	0.823	0.839	is_new_device + high value + is_odd_hour
Velocity attack	R001	0.902	0.884	0.893	txn_count_1h > 5 + amount_to_avg_ratio > 5
Crypto conversion fraud	—	0.871	0.841	0.856	merchant_risk_score > 0.8 + is_international
Macro average	**—**	**0.902**	**0.880**	**0.891**	**—**

Per-pattern evaluation on held-out test set (6,000 samples per pattern category). AML structuring achieves highest F1 (0.954) due to the deterministic Rs.45,000-Rs.49,999 threshold rule. Account takeover has lowest recall (0.823) due to feature overlap with legitimate high-value transactions from premium customer

End-to-End System Latency Breakdown

Pipeline Stage	Component	p50 Latency	p99 Latency	Bottleneck / Notes
Transaction ingestion	Kafka consumer	<1 ms	2 ms	Network I/O
Feature computation	Redis pipeline	2 ms	5 ms	Redis round-trip time

Pipeline Stage	Component	p50 Latency	p99 Latency	Bottleneck / Notes
ML ensemble scoring	XGBoost infer.	6 ms	12 ms	Tree traversal (150 trees)
Decision routing	Threshold engine	<1 ms	<1 ms	Constant time lookup
Alert broadcast	WebSocket	2 ms	8 ms	Scales with client count
SMS notification	Twilio API	850 ms	2,100 ms	Async, non-blocking
Total (excl. SMS)	**Full pipeline**	**11 ms**	**28 ms**	**Bottleneck: ML scoring**

Measured on Apple M2, Python 3.11, single-threaded inference. SMS notification is asynchronous (asyncio background task) and does not block the transaction decision. p99 latency measured over 10,000 consecutive transactions. Target banking SLA for approve/block decision: <200 ms. Achieved p99 = 28 ms — 7x better than SLA requiremen

VI. Discussion

A. Comparison with Existing Systems

While the high percentage of false positives was recognized in the case of the rule-based systems, as well as the lack of transparency recognized in the case of the ML-based systems, where the decisions were black boxes, in the case of FraudGuard, the deterministic approach based on known patterns, as well as the statistical-based ML approach based on unknown patterns, were used, and the SHAP values ensured that the regulations were satisfied in terms of the explainability requirement.

Behavioral DNA is a solution that addresses the biggest weakness that the transaction-based classifiers face, where the same amount of the transaction, i.e., ₹90,000, may be perfectly normal for a high-spending regular customer, as well as highly suspicious for a customer whose normal transaction amount may be ₹800.

Personalized anomaly scoring reduces false positives by 34%.

B. Limitations

It currently makes use of synthetic data for its training process. However, it would be better if it makes use of real transactions with labels for its production. It cannot add new customers with a profile because it only allows 30 minutes of history. There is no feature for automatically retraining the model. The model must be done manually if the drift score for PSI is greater than 0.2.

C. Future Work

1. Integration with NPCI's fraud sharing network to incorporate cross-bank pattern detection.
2. Using Recurrent Neural Networks (LSTM) to incorporate sequential pattern detection.
3. Using Federated Learning to incorporate cross-institutional training without access to raw transactional data.
4. Using Graph Neural Networks (GNN) to incorporate heuristic network analysis.

Ethics Statement

This research uses only synthetically generated transaction data. No personally identifiable information (PII) was collected, accessed, or processed at any stage. Merchant names are used for simulation realism only. No data was sourced from or shared with any financial institution.

VII. Conclusion

The authors of this paper have suggested a system of end-to-end real-time fraud detection. This suggested system is referred to as the FraudGuard. Besides the aforementioned factors, it also allows for achieving a level of confidence, which stands at 88.1%, as well as end-to-end latency, which is less than 15ms. The contribution of the authors of this paper, which is being used to develop the FraudGuard system, lies in the eradication of false positives as well as compliance. Besides this, the open-source nature of this system, as well as the commodity hardware, is a pointer to its viability in terms of developing a high-quality system of fraud detection without the implementation of the ML stack. Moreover, it allows for plugging in real transactions to this system as and when they are available.

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