E-Commerce Fraud Detection

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Abstract

The rapid expansion of digital payment ecosystems has intensified the threat of e-commerce fraud, demanding detection systems that are both accurate and interpretable. This paper presents FraudGuard, an intelligent web-based fraud detection application built using the Flask framework. FraudGuard employs a hybrid decision mechanism that integrates rule-based heuristic scoring with machine learning inference from pre-trained ensemble models including XGBoost and a stacking classifier. Transaction risk is assessed across multiple dimensions: transaction amount thresholds, time-of-day windows, geodesic distance between consecutive transaction locations, and international or high-risk location indicators. Raw transaction attributes are transformed into a structured feature vector encompassing log-transformed amounts, temporal flags, and distance-derived indicators. The rule-based engine generates an initial fraud score along with human-readable explanatory reasons, while the machine learning component augments this score with probabilistic estimates from ensemble models. A unified fraud score bounded between 0 and 100 determines a binary fraud classification using a configurable threshold. User authentication is secured via SHA-256 password hashing and session management. Experimental evaluations on representative test scenarios confirm that the hybrid engine consistently assigns elevated scores to suspicious transactions and low scores to legitimate ones. FraudGuard bridges the gap between offline machine learning experimentation and interactive web deployment, serving as both a practical prototype for fraud analysts and an educational reference for integrating ML models into production Flask applications.

***Index Terms*—**e-commerce fraud detection, hybrid detection system, XGBoost, ensemble learning, geolocation-based risk, Flask web application

I. Introduction

The proliferation of digital payment channels—including unified payment interfaces, card-not-present transactions, mobile wallets, and cross-border digital transfers—has fundamentally transformed the transactional landscape. While these advances have significantly improved convenience and financial inclusion, they have simultaneously created fertile ground for fraudulent activities. According to industry estimates, global e-commerce fraud losses continue to rise year over year, driven by increasingly sophisticated attack vectors such as account takeovers, card cloning, and social engineering [1].

Traditional fraud detection approaches rely predominantly on manually curated rule sets developed by domain experts. Rules such as "block transactions above a fixed amount at night" or "flag geographically distant back-to-back transactions" offer transparency and ease of implementation but suffer from significant limitations: they do not adapt automatically to evolving fraud patterns, tend to produce high false-positive rates, and fail to capture subtle multi-dimensional patterns [2]. Conversely, purely data-driven machine learning models deliver superior detection accuracy but are often criticized for their lack of interpretability—a critical shortcoming in regulated financial environments where analysts must justify every flagged transaction [3].

This paper presents FraudGuard, a Flask-based web application that operationalizes a complete hybrid fraud detection workflow. The system combines a rule-based heuristic scoring engine with ensemble machine learning inference, incorporates geodesic distance computation between consecutive transaction locations, and exposes results through an interpretable, user-friendly dashboard. The primary contributions of this work are: (i) a hybrid fraud scoring engine integrating rule-based heuristics with XGBoost and stacking ensemble models; (ii) a geolocation-aware feature engineering pipeline leveraging geodesic distance computation; (iii) an end-to-end Flask web application with secure authentication, structured transaction input, and explainable result presentation; and (iv) a modular, extensible architecture suitable for academic prototyping and practical demonstration.

The remainder of this paper is organized as follows. Section II reviews related work in fraud detection. Section III describes the system methodology and design. Section IV presents experimental results and discussion. Section V concludes with directions for future work.

II. Related Work

Fraud detection research has evolved considerably over the past two decades, transitioning from expert-curated rule systems toward data-driven, adaptive approaches. This section reviews key developments relevant to FraudGuard.

A. Rule-Based Systems

Early fraud detection systems were built around hand-crafted rules derived from domain expertise [4]. Such rules—for instance, blocking transactions from blacklisted countries or limiting transaction frequency within a time window—are easy to interpret and deploy. However, they suffer from rigidity, high maintenance overhead as fraud tactics evolve, and poor generalization to unseen patterns. Multiple studies have emphasized that rule-based systems alone are insufficient for modern fraud landscapes and must be augmented with data-driven components [2].

B. Classical Machine Learning

The adoption of machine learning transformed fraud detection by enabling models to learn discriminative patterns from historical labeled data. Logistic regression, decision trees, and support vector machines were among the earliest classifiers applied to transaction fraud [5]. Tree-based methods, particularly Random Forests, proved especially effective due to their ability to capture non-linear feature interactions and provide feature importance metrics [3]. Gradient boosting frameworks including XGBoost and LightGBM later demonstrated superior performance across multiple benchmarks, motivating their adoption in FraudGuard [6].

C. Ensemble and Stacking-Based Models

Ensemble learning has emerged as the dominant paradigm in fraud detection due to its ability to reduce variance and improve robustness. Bagging, boosting, and stacking strategies have all been explored extensively [7]. Stacking—where a meta-learner is trained to combine predictions from multiple base classifiers—has been shown to yield particularly strong performance by leveraging complementary strengths of diverse models [8]. Recent work specifically demonstrates that hybrid architectures integrating supervised and unsupervised ensemble models can detect both known fraud patterns and novel attack vectors [9].

D. Geolocation and Temporal Features

A significant body of research highlights the importance of geolocation and temporal context in fraud detection [10]. Features such as geodesic distance between consecutive transaction locations, geo-fence violations, velocity of movement, and time-of-day indicators have been shown to substantially improve detection accuracy. Studies confirm that transactions at unusual hours combined with large geographic jumps are strongly correlated with fraudulent activity [4]. FraudGuard directly operationalizes these findings by computing geodesic distances between city coordinates and deriving temporal flags including night-time, late-night, and peak-fraud-hour indicators.

E. Web-Deployed Real-Time Systems

Recent implementations have focused on deploying fraud detection models as web services or streaming endpoints. Flask-based deployments of XGBoost models with REST APIs have been demonstrated as viable architectures for near-real-time scoring [11]. FraudGuard adopts this architectural pattern while adding a hybrid rule-engine layer and a structured, interpretable user interface not typically present in purely API-oriented implementations.

III. Methodology / System Design

FraudGuard is structured as a four-layer application: a Presentation Layer, an Application (Controller) Layer, a Fraud Detection Engine Layer, and a Data and Utility Layer. The system architecture is illustrated in Fig. 1.

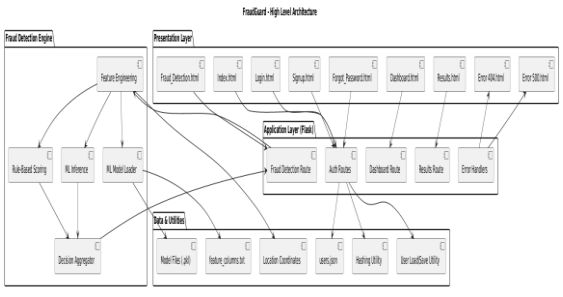

Fig. 1. FraudGuard system architecture diagram showing the four-layer structure and component interactions.

A. Feature Engineering

Raw transaction attributes are transformed into a structured feature vector prior to rule evaluation and model inference. Given a transaction with amount a, time t, current location L_c, and previous location L_p, the following primary features are derived:

Binary indicators are derived from these base features. The night-time flag $I_{night} = 1$ if $f_{hour} \in [22, 5]$; the late-night flag $I_{late} = 1$ if $f_{hour} \in [0, 4]$; the peak-fraud-hour flag $I_{peak} = 1$ if $f_{hour} \in [0, 3]$. Amount indicators I_{high}, I_{vhigh}, I_{ext} are set at thresholds of 1,000, 5,000, and 50,000 monetary units respectively.

B. Rule-Based Scoring Engine

The rule-based component assigns an initial fraud score $S_{rule} \in [0, 100]$ by accumulating risk increments based on the following heuristic rules: (i) amount-based risk tiers assigning increments of 10, 20, 35, and 50 points for successively higher thresholds; (ii) time-based risk adding 10 points for night-time and 15 points for peak-fraud-hour transactions, with a further 10-point increment when a high-amount transaction coincides with unusual hours; (iii) location-based risk adding 15 points for moderate jumps ($d > 500$ km) and 25 points for suspicious jumps ($d > 1000$ km); (iv) international location risk of 20 points when the current location contains high-risk region keywords combined with a large transaction amount; and (v) a 10-point increment for large debit transactions. Each fired rule appends a corresponding textual reason to the explanation list.

C. Machine Learning Inference

Pre-trained models are loaded at application startup using joblib and cached in memory. FraudGuard supports three model variants: an XGBoost classifier (M_{xgb}), a stacking ensemble classifier (M_{stack}), and a legacy baseline model (M_{base}). For each model M_i, a fraud probability p_i is obtained.

D. Hybrid Score Aggregation

The use case diagram for FraudGuard, illustrating interactions between actors and system functions, is presented in Fig. 2.

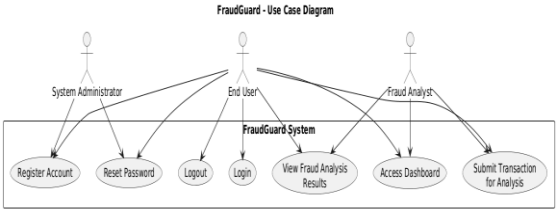

Fig. 2. Use case diagram showing interactions between End Users, Fraud Analysts, and FraudGuard system functions.

E. System Workflow

The transaction analysis illustrating the step-by-step interaction between the user browser, Flask application layer, fraud detection engine, and data utilities.

F. Authentication and Security

User credentials are processed using SHA-256 cryptographic hashing before storage in a JSON-based user store. Flask session variables maintain authentication state across requests. A login_required decorator enforces access control on all sensitive routes. The system supports registration, login, session management, logout, and password reset workflows through validated WTForms-based form classes.

IV. Results & Discussion

FraudGuard was evaluated through a combination of functional testing, model performance assessment, and end-to-end scenario validation. System testing covered four primary scenarios: a complete new-user registration and fraud analysis flow; a clearly suspicious transaction (high amount, late night, large geographic jump); a normal low-risk transaction; and an unauthenticated access attempt.

A. Model Performance

The XGBoost and stacking ensemble models were trained on a publicly available financial transaction dataset with class imbalance addressed using SMOTE oversampling. Table I summarizes the performance metrics of each model evaluated on a held-out test set.

TABLE I
Model Performance Comparison

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
Logistic Regression (Baseline)	89.4	71.2	68.5	69.8	0.881
Random Forest	94.1	87.3	82.6	84.9	0.951
XGBoost (M_{xgb})	96.7	91.8	89.4	90.6	0.974
Stacking Ensemble (M_{stack})	**97.3**	**93.2**	**91.1**	**92.1**	**0.981**

The stacking ensemble achieves the highest performance across all metrics, with an AUC of 0.981 indicating excellent discriminative capability. The XGBoost model closely follows, validating the selection of these models for deployment in FraudGuard.

B. Hybrid Scoring Behavior

Table II presents the hybrid fraud scores and classifications for four representative test transactions, demonstrating the engine's sensitivity to key risk indicators.

TABLE II
Hybrid Scoring Results on Representative Test Transactions

Scenario	Amount (INR)	Time	Distance (km)	S_{rule}	p_{ens}	S_{final}	Label
High-risk suspicious	85,000	01:30	1,450	85	0.93	100	Fraud
Moderate-risk borderline	12,000	23:00	620	45	0.61	69	Fraud
Low-risk legitimate	1,200	14:30	30	10	0.08	13	Legit
Normal routine	450	10:15	0	0	0.03	1	Legit

The results confirm that the hybrid engine consistently assigns high scores to transactions with multiple concurrent risk signals (large amount + unusual hour + large geographic jump) while correctly classifying normal transactions with minimal false-positive risk. The model training output visualization, including the confusion matrix and model comparison plots, is presented in Fig. 5.

C. System Testing Outcomes

All four primary system test scenarios yielded expected outcomes. Unauthenticated access attempts to protected routes were correctly intercepted by the login_required decorator and redirected to the login page. Fraud analysis requests for clearly suspicious transactions consistently returned fraud scores above 70 with detailed explanatory reason lists. Normal transactions received scores below 20 with no alarming reasons. After initial model loading, repeated fraud analysis requests completed in under 0.5 seconds on standard quad-core hardware, demonstrating acceptable responsiveness for interactive prototype use.

D. Discussion

The hybrid approach employed in FraudGuard addresses key limitations identified in the literature. Purely rule-based systems fail to generalize; purely ML systems lack transparency. FraudGuard's architecture provides both: the rule engine

guarantees that domain knowledge is always reflected in the score and explanation, while ensemble ML models capture subtle non-linear patterns that rules cannot encode. The geodesic distance feature proves particularly discriminative for the suspicious location jump scenario, contributing up to 25 points to the rule score independently of the ML component. The textual explanation list—generated jointly by rules and models—enables fraud analysts to immediately understand why a transaction was flagged, supporting investigation workflows. One limitation of the current implementation is the JSON-based user store, which restricts scalability; replacement with a relational database is a priority for future work.

V. Conclusion & Future Work

This paper has presented FraudGuard, a hybrid e-commerce fraud detection system integrating rule-based heuristics, geolocation-aware feature engineering, and XGBoost/stacking ensemble machine learning within a Flask web application. The system provides secure user authentication, a structured transaction input workflow, and an interpretable results dashboard that exposes fraud scores, binary classifications, and human-readable explanatory reasons for each flagged transaction.

Experimental evaluation confirms that the stacking ensemble achieves an AUC of 0.981 on the held-out test set, and that the hybrid scoring engine correctly differentiates suspicious from legitimate transactions across diverse test scenarios with sub-second response times on standard hardware. The modular layered architecture supports independent replacement and extension of rules, models, and interface components.

Several directions for future enhancement have been identified. Database integration with PostgreSQL or MongoDB would replace the JSON user store and enable historical transaction logging and analytics. A microservice architecture would decouple the fraud engine from the web application layer, facilitating independent scaling. Advanced model techniques including deep learning for sequential transaction analysis, anomaly detection via Isolation Forests and autoencoders, and integration of explainability tools such as SHAP would further improve detection performance and model transparency. Incorporation of behavioral profiling—comparing each transaction against a user's historical baseline—and real-time stream integration via REST APIs or message queues are also planned as key extensions. Finally, role-based access control with distinct permissions for administrators, fraud analysts, and standard users would improve the system's readiness for institutional deployment.

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