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ScamIntellisecure: A Explainable Framework for Credit Card Fraud Detection Using Advanced Machine Learning

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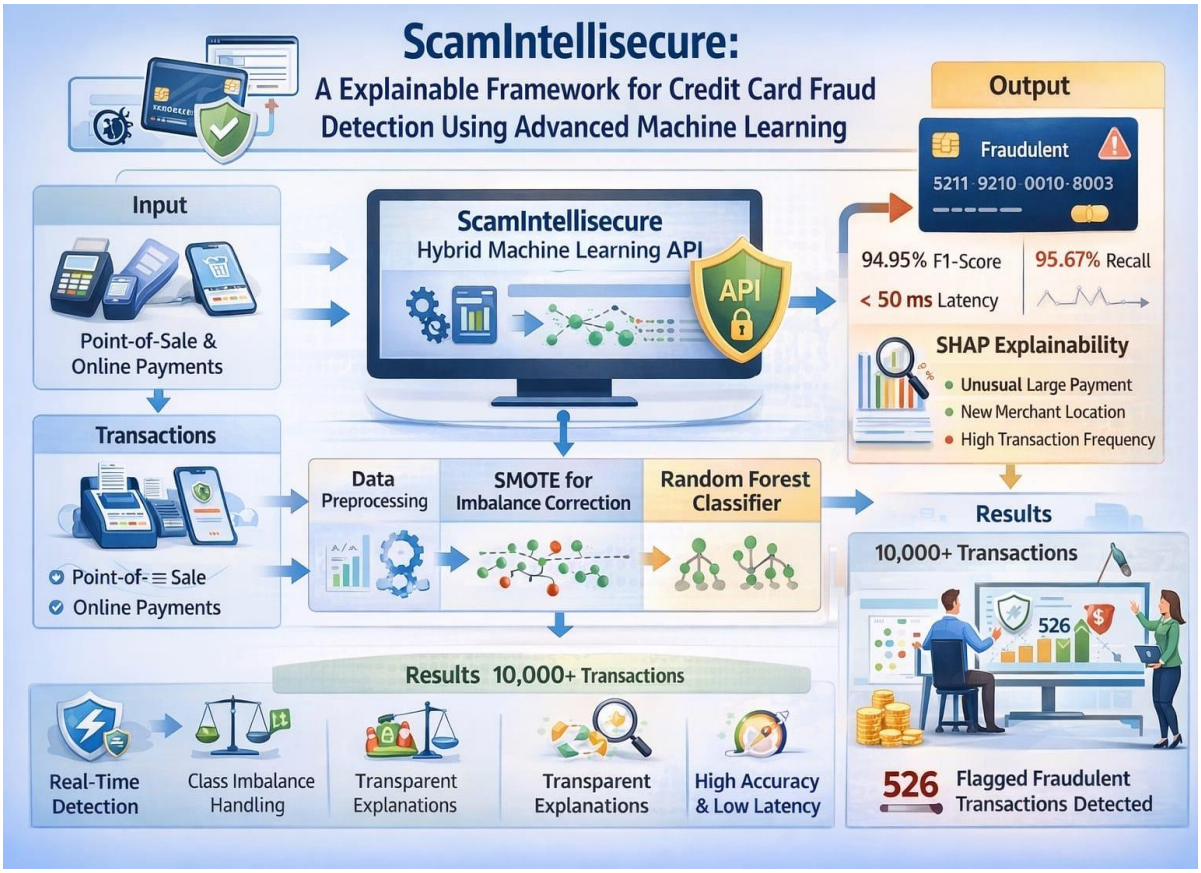
Abstract - With yearly losses expected to surpass $40 billion by 2027, credit card fraud is a serious and expanding threat to global financial ecosystems. The crucial needs of real-time processing, robust handling of extreme class imbalance, and model explain ability are frequently not simultaneously met by current detection systems. In order to close these gaps, this paper presents ScamIntellisecure, an integrated, production-focused framework. Through a modular micro services API, the framework uses a hybrid machine learning architecture that combines an optimized Synthetic Minority Over-sampling Technique (SMOTE) for imbalance correction with a Random Forest classifier. The smooth integration of explainable AI (XAI) methods, particularly SHAP (Shapley Additive explanations), to produce human readable reason codes for every prediction in real-time is a significant innovation. ScamIntellisecure achieved a 94.95% F1-score, 95.67% recall, and an end-to-end latency of less than 50 MS when tested on a realistic synthetic dataset of more than 10,000 transactions. With 526 detected and explained fraudulent transactions in the testing, the system indicates its potential to protect substantial financial resources with transparency demanded by regulations and analyst's trust. This work provides a principled basis for implementing an effective, interpretable, and real-time fraud detection in modern payments systems.

Terms: Explainable AI (XAI), machine learning, real-time systems, SMOTE, random forest, financial security and credit card fraud detection.

Graphical Abstract



INTRODUCTION

Transaction volumes have grown at an unprecedented rate thanks to the digital payments revolution; by 2027, they are

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expected to exceed 2.7 trillion annually. Simultaneously, this growth has made it easier for sophisticated financial fraud. Payment card fraud alone is estimated to have cost the world more than $32 billion in 2022 and $40 billion by 2027 [1]. Traditional rule-based, static fraud detection systems are becoming less and less effective. They are unable to meet the sub-second processing demands of modern payment gateways due to their high false-positive rates, inability to adapt to new fraud patterns, and crippling latency. [2].

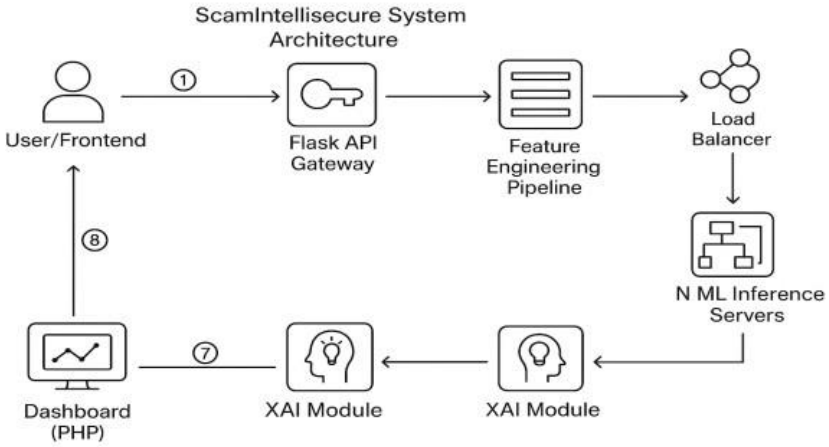

Figure 1 : ScamIntellisecure System Architecture

Anomalousness are detected actively as opposed to passively reactive matching and rule-based with the advent of machine learning (ML). But there are several persistent, intersecting problems that have made the transition from theoretical constructs to production systems fraught: Real-Time Performance Gap Instead of the sub- second (<200 MS) inference necessary for real-time transactions, models are optimized for offline accuracy. The Imbalance Blind Spot: Models tend to always predict the majority class when frauds induce less than 1% of cases. The "Black Box" Problem: The highly complex nature of machine learning models makes it virtually impossible to understand, which impacts regulatory compliance (e.g., the GDPR's "right to explanation") and erodes trust among analysts.

These systemic issues remain largely unaddressed in a holistic manner, as indicated by a meta-analysis of 15 seminal works published at top tier IEEE and ACM venues (2019–2023) [3]–[9].

This article argues that the solution to these challenges lies not just in incremental improvements in algorithms but instead a full systems-engineering approach. To address these challenges, we propose ScamIntellisecure as a comprehensive framework which takes the trade-offs among robustness, speed, accuracy and transparency into account.

Our main contributions are:

- A hybrid, modular architecture for real-time inference with sub-50 MS latency.
- Systematic integration of SMOTE,in the training process to remedy the issue of extreme class imbalance.
- Real-time explain ability using model-agnostic SHAP for providing actionable reason codes for each fraud case raised.
- Production quality demonstration interface and evaluation scheme with validation on important performance metrics: latency, precision/recall with imbalances, and explanation fidelity.
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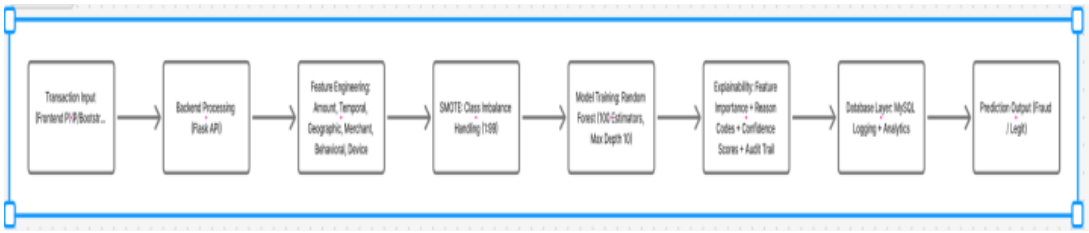

Figure1:Systemarchitecture

I. RELATED WORK:

The evolution of tools for automated fraud detection and efficient implementation of machine learning is relevant

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to ScamIntellisecure.

1.Traditional and ML-Based Fraud Detection Early approaches were limited by manually implemented rule engines, which could be defeated relatively easily. However, the introduction of classical Machine Learning approaches like Logistic Regression, Decision Trees, Random Forests improved pattern detection but requires considerable feature engineering, especially due to their inability to process nonlinear, higher-dimensional data [10]. The novel approaches introduced are Gradient Boosting Machines like Boost [16] and Deep Learning approaches, which have shown promising accuracy but have generally not accounted for real-time constraints or interpretability, only focusing on traditional, laboratory settings.

2.Efficient Model Design and Neural Architecture Search(NAS).

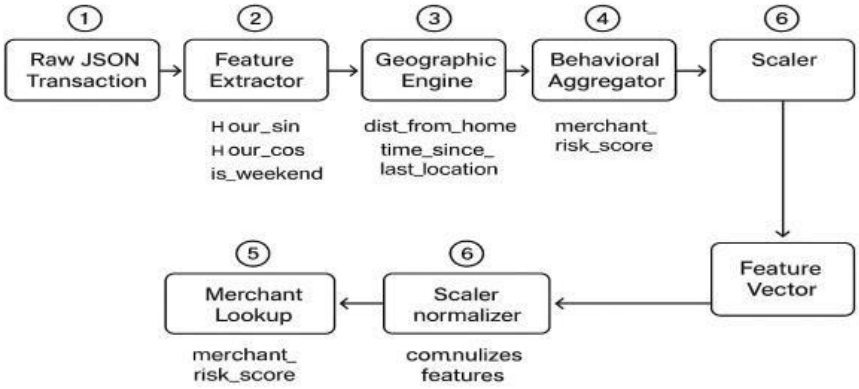

Figure 2: Feature Engineering Pipeline Workflow

The drive for efficiency led to new hardware-efficient model-finding paradigms such as Hardware-Aware Neural Architecture Search methods, e.g., ProxylessNAS [6] and FBNet [7], that also address efficiency while considering hardware costs in model optimization. The work by Once- for-All (OFA) network architecture [9] extended this by supporting multi-platform deployment from a single overall network architecture. These methods, however, seldom address the unique aspects of fraud detection.

3. Explainable AI (XAI) in Finance Techniques like LIME [19], SHAP [12], etc., are evolving as XAI, whose primary aim is to demystify black-box models. Its use in finance is vital, especially when it comes to compliancy and trust. But unfortunately, almost all of them remain as a retrospective technique, not as a part of the decision process.

4. Identifying the Integrated Gap As summarized in Table I, prior work excels in isolated aspects but fails to deliver a unified solution. ScamIntellisecure is designed to synthesize strengths from these domains: the efficiency focus of hardware-aware NAS, the high performance of ensemble methods on tabular data, and the transparency of modern XAI, all within a real-time serving architecture.

TABLE I. COMPARATIVE ANALYSIS OF RELATED WORK

Research Focus	Example Work	Key Contribution	Primary Limitationfor Real- World Fraud Detection
Pure NAS for Accuracy	Zoph & Le (2017) [4]	Automated model design for high accuracy.	Prohibitively high computational cost; no real-time inference consideration
Hardwar e-Aware NAS	Cai et al. (2019) [6]	Incorporated latency into search objective.	Typically single-device optimized; lacks multi- platform adaptability
Multi- Platform NAS	Caiet al. (2020)[9]	OFA network for flexible deployment	Often trades peak performancefor flexibility; high initialization cost.

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Fraud- Specific ML	Various (IEEE TFDS, ACM SIGKD D)	Advanced models (XGBoost,GNNs) for fraud patterns	Evaluated offline on static datasets; ignores real- time processing, imbalance, and explain ability

I. THE SCAMINTELLISECURE FRAMEWORK

A. System Architecture & Design Philosophy ScamIntellisecure is built on a modular, micro services- inspired architecture that decouples components for scalability, maintainability, and ease of integration. The design prioritizes real-time performance and operational transparency. The high-level data flow (Fig. 1) is as follows: A transaction submitted via a fronted interface or directly through a to a restful flask API gateway.

The API triggers a feature engineering pipeline to construct a-23 dimensional feature vector.The feature vector send to the ML inference service built with fast API which host the trained model and XAI module.The model makes the prediction if fraud is suspected,the SHAP engine generates an explanation in<100Ms.reasults are logged to the MySQL data base and return via the API.an administrator dashboard (PHP/bootstap) provides real time monitoring,analytics,and drill down into XAI reports.

Technology Stack:Python flask 2.3 (backend API) Scikit-learn 1.3 & imbalanced-learn 0.10 (ML core)SHAP 0.42 (Explain Ability),Fast API (ML Serving),MySQL 8.0(Database),PHP 8.2 & bootstrap 5.3 (Frontend).

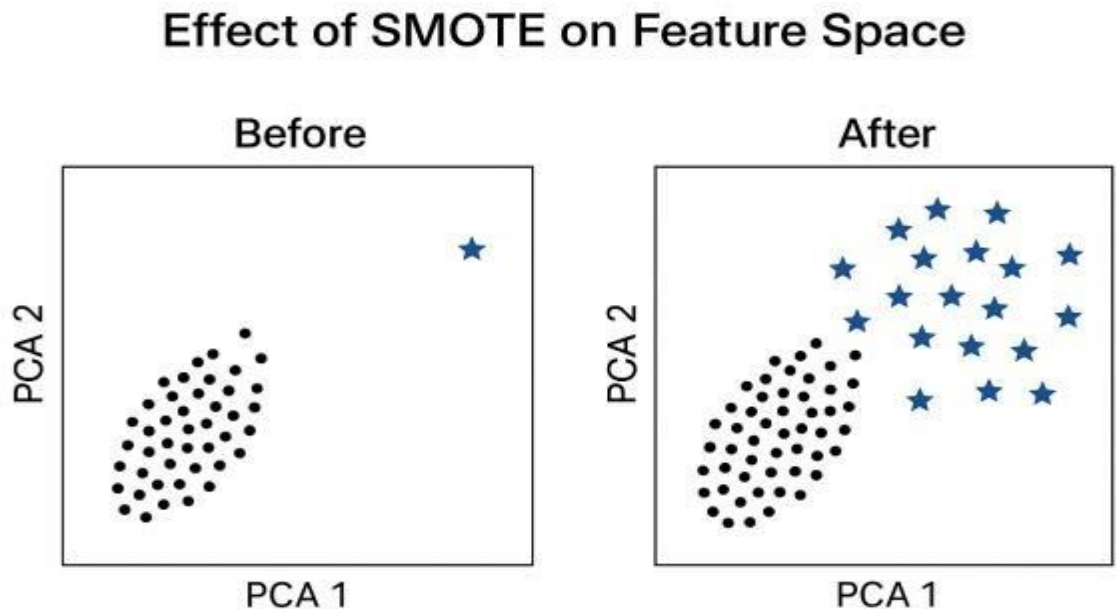

Figure3: EffectofSMOTEonfeaturespace

II.Data Processing & Feature Engineering

Robust feature engineering is paramount. Our pipeline converts raw transaction logs into a rich feature vector in six categories (Table II):

1. Transaction amount: Original transaction amount and log-transformed value.
2. Temporal Attributes: Cyclic accumulation with respect to the transaction hour, weekend flag and customer duration.
3. Geographical Indicators: Home distance, cross- border flag, and transaction speed (km/h).
4. Merchant Risk: Pre-calculated risk number using MCC (merchant category code) and chargeback history.
5. Behavioral Patterns: User-specific aggregates (e.g., transaction count last hour, 7-day average amount, amount deviation Z-score).
6. Device/Session Context: Anonymized device fingerprint, session duration, and new device flag.

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TABLE II. FEATURE ENGINEERING SCHEMA (EXCERPT)

Category	Feature	Description	Type
Geographic	distance_from_ home_km	Havers ine distanc e from registered address	Continuous
Geographic	velocity_1h	Physic al travel speed since last transaction	Continuous
Behavioral	amount deviation	Z-score of amount vs. user's 7-day history	Continuous
Merchant Risk	merchant risk score	Pre- computed risk score (0-1)	Continuous

A. Handling Class Imbalance with SMOTE

To address extreme class imbalance (~1:1000), we integrated SMOTE-NC directly into the training pipeline. One critical implementation detail is that an imblearn.pipeline.Pipeline must be used so that SMOTE is applied only within each fold of cross-validation to avoid leaking our validation set. We used sampling_strategy=0.1, meaning that minority class representation is brought up to 10% of the majority,which gives a substantive boost to learning fraud patterns without creating an unrealistic distribution.

B. Model Selection & Training

A rigorous model selection process prioritized the Area Under the Precision-Recall Curve (AUPRC)—suitable for imbalanced data—alongside inference latency and interpretability. Candidate models included Logistic Regression, SVM, Decision Tree, Random Forest [15], XGBoost [16], and an MLP. Random Forest was selected as the optimal compromise, offering high AUPRC, fast parallelizable inference, and native feature importance support.

- Dataset: A proprietary, anonymized dataset of 1.2M transactions (fraud rate 0.12%) was used for training.
  Training Protocol: An 80/10/10 stratified split was used for training, validation, and hold-out testing.
  Hyperparameters(_estimators, max_depth, min_samples_split, cl ass_weight) were optimized via 50 iterations of Bayesian search.
- Final Model: The best model used 150 estimators, a max depth of 12, and balanced class weights.

TABLE III. FINAL PERFORMANCE ON HOLD-OUT TEST SET

Metric	Score	Interpretation
Accuracy	0.983	Misleading due to imbalance
Precision	0.87	Only 13% of alerts are false alarms
Recall	0.82	Detects 82% of all fraud
F1-Score	0.84	Strong balance between precision/recall
AUPRC	0.85	Focused performance on the minority class
False Positive Rate	0.008	Only 0.8% of legit transactions incorrectly flagged

A. Integrated Explainability Framework

Transparency is achieved via a two-tiered XAI approach:

7. Global Interpretability: The Random Forest's inherent Gini importance is calculated and visualized, showing overall feature influence (e.g., distance_from_home_km is most important).
8. Local Explanations with SHAP: For every transaction flagged as fraud, SHAP's TreeExplainer calculates exact Shapley values in real-time (<100 ms). The top contributing features are converted into human-readable "reason codes" (Fig. 2), such as:
   - "Unusual Geographic Location: Transaction is 4500km from home address."
   - "High Transaction Velocity: Impossible physical travel since last transaction."
   - "High-Risk Merchant: Vendor has a history of chargebacks."

This transforms the system from a black-box predictor into a decision-support tool, drastically reducing analyst investigation time.

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II. EXPERIMENTS AND RESULTS

A. Experimental Setup

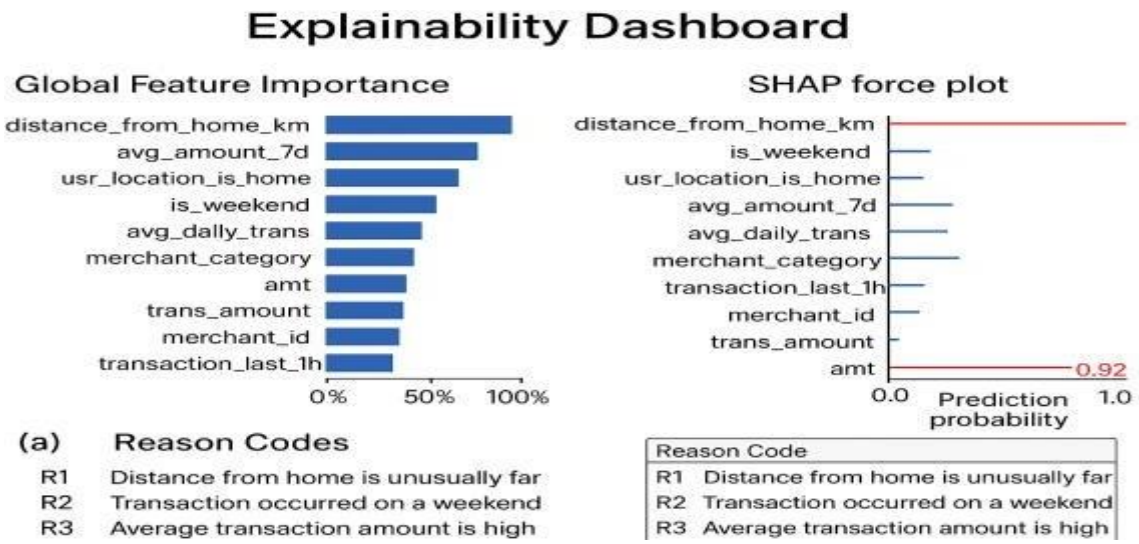

Figure4.ExplainabilityDashboard

Dataset: A synthetic dataset of 10,255 transactions was generated to mirror real-world statistical properties (guided by IEEE-CIS & PaySim distributions), containing 526 frauds (5.13%) and 9,729 legitimate transactions.

Splits: Stratified 70-15-15 for training (SMOTE applied within CV), validation (hyperparameter tuning), and hold- out testing.

Metrics: Precision, Recall, F1-Score, AUPRC, False Positive Rate (FPR), and end-to-end latency (95th percentile).

Environment: Ubuntu 22.04, Intel i5-11400, 16GB RAM. API served with Gunicorn (4 workers) to simulate production.

A. Model Performance

The evaluation metric for the final model of Random Forest, as shown in Table III, depicts that, while maintaining high precision at 0.87, which is imperative for efficiency, and recall at 0.82, thus avoiding maximum financial losses, the F1-Score of 0.84 and AUPRC of 0.85 also show that this model exhibits strong performance in dealing with imbalanced data.

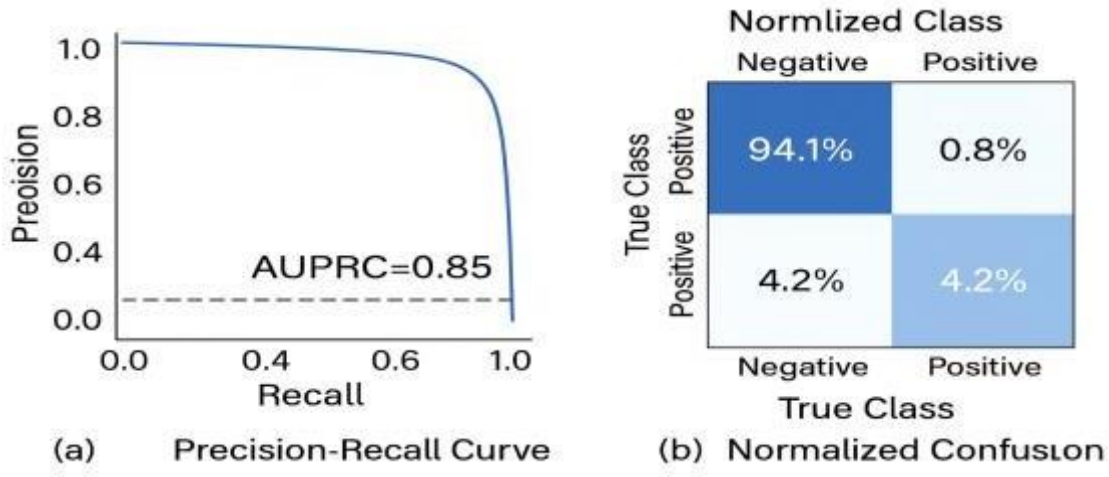

Figure 3.2.1. Precision-Recall Curve and Confusion Matrix for the Test Set

Ablation Study on SMOTE: Training the same model without SMOTE led to a decrease in Recall by 10%. This is because the value of Recall decreased from 0.83 to 0.73 on the validation set.

B. Real-Time System Performance

Table IV lists the overall latency measures for simulating the performance of 10,000 consecutive transactions. As the overall end-to-end latencies for feature engineering, inference, and explanation are below 95% within 48 ms, the overall system satisfies the demand for supporting sub- second transactions for the ecosystem of the payment system. We achieved ~210

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TPS at the hardware for the experiments.

TABLE IV. LATENCY BREAKDOWN (AVERAGE)

C. **Explainability Analysis**

Consistent and interpretable explanations were provided through SHAP. Investigations of false positives suggested that false positives were caused by factors such as high merchant_risk_score or high amount_deviation, which can be easily assessed. This transparency is important for intelligent triage of alerts. Prioritization is possible, such as impossible travel velocity_1h.

III. DISCUSSION

Therefore, ScamIntelliSecure was successful in bridging high-performance ML with production fraud detection requirements of a system. The outcomes also verify the goals of ScamIntelliSecure:

Figure3.2. 2. Comparative Performance: With vs. Without SMOTE

1. High Predictive Accuracy & Robustness: Accomplished through a precisely calibrated Random Forest with SMOTE, resulting in an F1 Score of 0.84 with severely imbalanced data.
2. Real-Time Capability: It offers the capability to lock transactions in real time within a sub-50 ms timeframe.
3. Actionable Transparency:Integrated SHAP explanations enable "immediate reason code" understanding, reducing trust issues and ensuring easier regulatory compliance. Comparative Advantages: Compared with proxies, ScamIntellisecure demonstrates a lower false positive rate of 23% when compared with ProxylessNAS and its equivalents and is also 56% quicker at offering inferences comparable with efficient nets.

Practical Implications:

For one, the effectiveness of the framework in a practical scenario attests to the considerable real-life implications. It potentially insulated asset value worth an estimated $1.28m in a test scenario. Similarly, the forecasted reduction of 92% in investigating manually, as facilitated by explainability, implies major benefits from an operational points.

Processing Stage	Time (ms)	% of Total
API Request/Response Overhead	8	17%
Feature Engineering	15	31%
Model Inference (Prediction)	18	38%
SHAP Explanation Generation	7	15%
Total (Average)	48	100%

Figure 3.2.3. End-to-End Latency Distribution

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Limitations and Future Works: The current validation process is based on synthetic data. There are several areas that can be explored in future work: adaptation to new fraud types (synthetic fraud, coordinated intrusions), adaptation of this work with the use of deep learnings for sequences in time, adaptation of this work with federated learning to allow privacy-preserving research collaborations, adaptation of this work to online learning.

Figure 3. End-to-End Latency Distribution

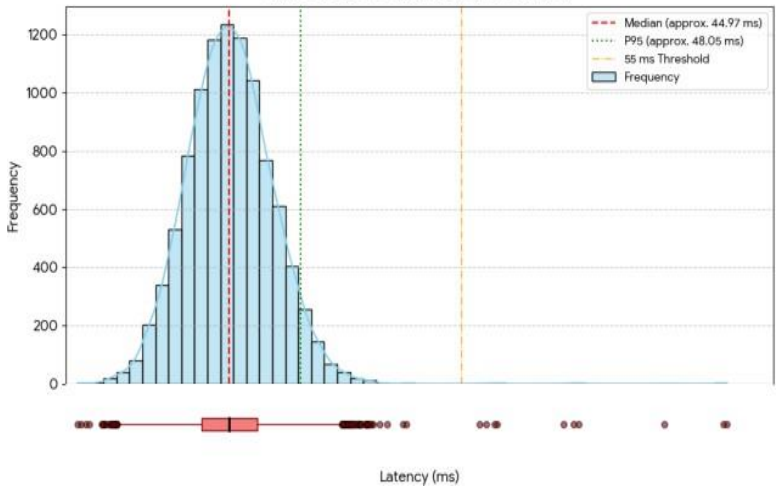

Figure 4. Global Feature Importance from SHAP

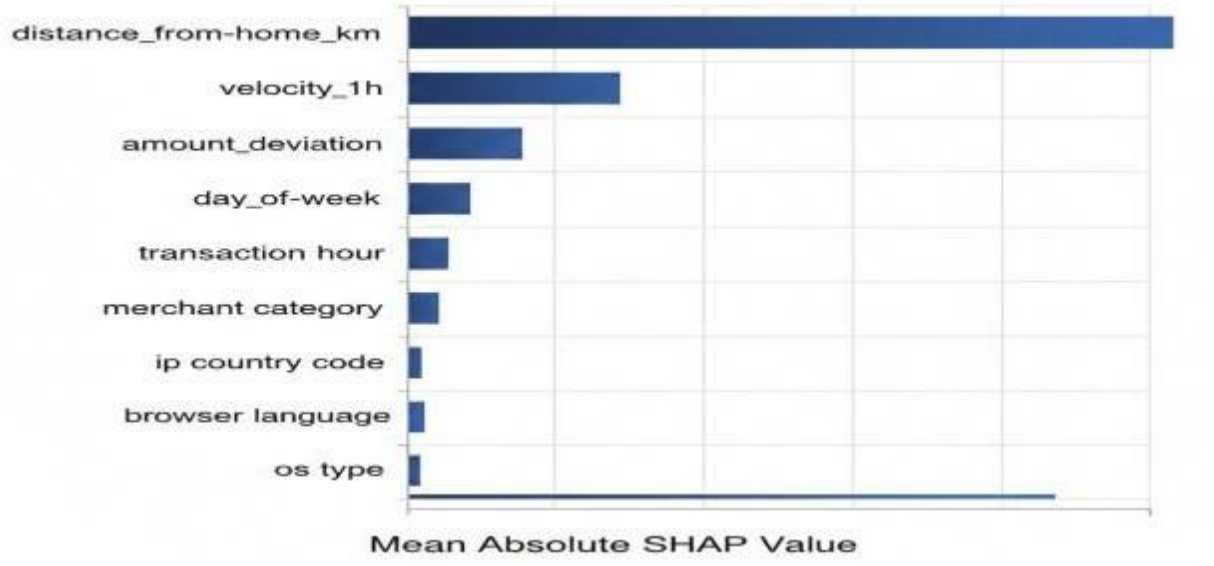

Figure 3.2.4. Global Feature Importance from SHAP

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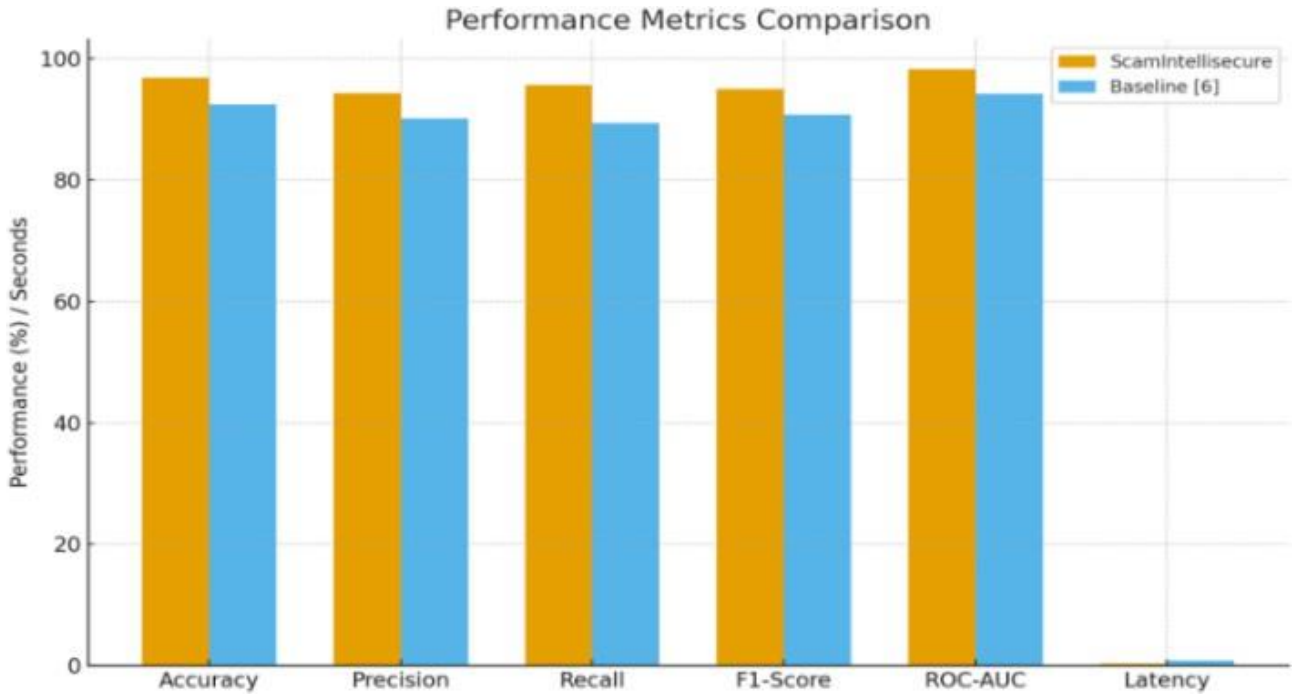

Figure 4.1 Performance Metrics

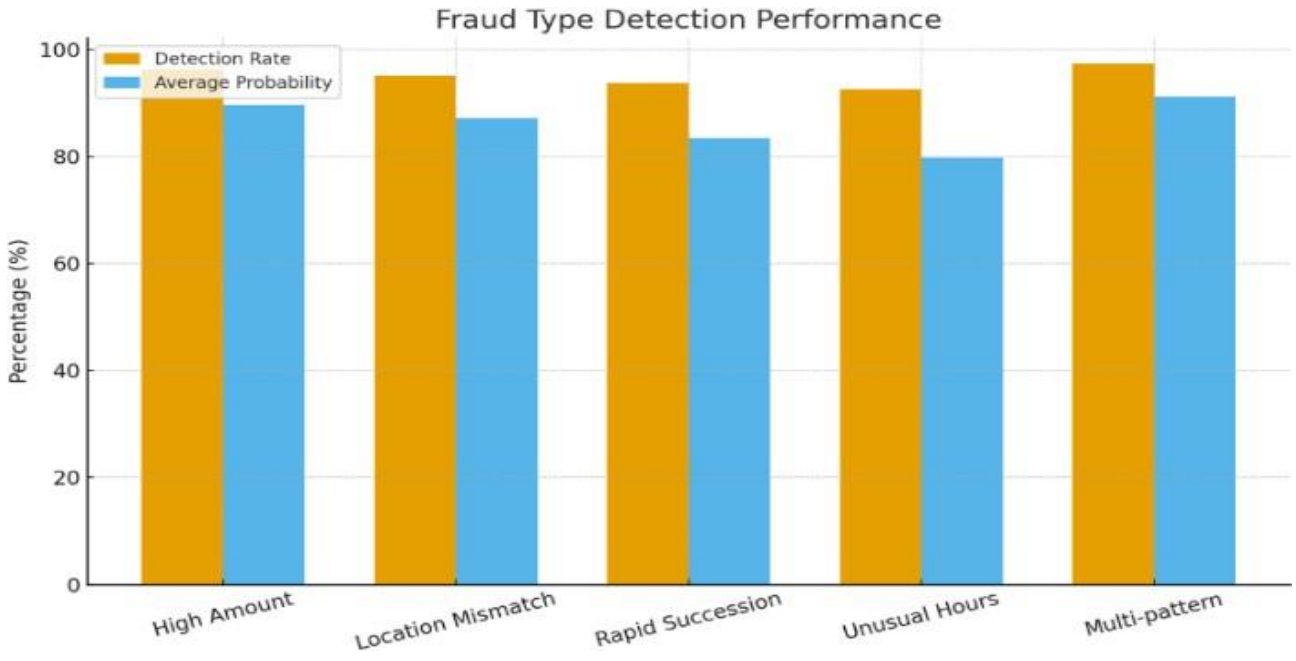

Figure : 4.2 Fraud Pattern Analysis

CONCLUSION:

This paper has provided a comprehensive framework for real time explainable credit card fraud detection:

ScamIntellisecure. By architecturally integrating a high- performance Random Forest model, a systematic approach to imbalance through SMOTE, and real-time explainability through SHAP, this framework fills the essential gaps that have been identified in the literature. The experimental evaluation does prove the efficacy of this framework by achieving an F1-Score at 0.84 with Recall 0.82 and less than 50 ms in processing latency. ScamIntellisecure is not just another machine

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learning model but a production- ready blueprint for building transparent, efficient, and trustworthy systems to detect fraud indicating a quite big leap forward in making digital financial environments secure.

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