SEFD-Plus: Uncertainty-Aware Fraud Detection with Human-in-the-Loop Governance

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Abstract

Financial fraud detection systems face a critical challenge: traditional binary classification approaches produce high false positive rates that damage customer trust and increase operational costs. This paper presents SEFD-Plus, a governance-focused fraud detection framework that integrates **ensemble-based uncertainty quantification** with **human-in-the-loop triage** to reduce false positives while maintaining detection accuracy. Unlike conventional systems that rely solely on probability thresholds, SEFD-Plus introduces a **Gray Zone** mechanism where transactions exhibiting high model uncertainty are routed to human review rather than automatic rejection.

The system employs gradient-boosted tree ensembles (XGBoost) to generate calibrated fraud probabilities, with epistemic uncertainty quantified through prediction variance across ensemble members. A cost-sensitive triage policy assigns transactions to three zones: SAFE (automatic approval), GRAY (human review), and FLAGGED (automatic block). Experimental evaluation on the IEEE-CIS Fraud Detection dataset (177,162 test transactions, 3.5% fraud rate) demonstrates that SEFD-Plus achieves **19.3% false positive reduction** (FPR: 10.4% → 8.4%, 95% CI [8.3%, 8.5%]) with **2.1% improvement in true positive rate** (TPR: 79.1% → 81.2%), yielding an F2 score of 0.570 (95% CI [0.561, 0.578]) compared to baseline 0.516. The Gray Zone captures 9.3% of transactions for human review with statistical significance ($p < 10^{-85}$).

The framework prioritizes **governance and transparency** over pure model optimization, introducing phased deployment protocols with explicit approval requirements and continuous shadow monitoring. This approach addresses growing concerns about autonomous AI in high-stakes financial decisions by ensuring human authority over final outcomes while leveraging machine learning to reduce review burden.

Index Terms: Ensemble Learning, Fraud Detection, Human-in-the-Loop, Uncertainty Quantification, Cost-Sensitive Learning

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I. INTRODUCTION

A. Problem Statement

Financial institutions process millions of transactions daily, with fraud rates typically ranging from 0.1% to 5% depending on payment channel and geography. Traditional fraud detection systems employ binary classifiers that label each transaction as fraudulent or legitimate, optimizing for metrics such as precision, recall, or F1 score. However, this approach suffers from three fundamental limitations:

First, binary decisions ignore epistemic uncertainty—cases where the model lacks sufficient evidence to make a confident prediction. When a transaction exhibits ambiguous patterns (e.g., unusual but potentially legitimate behavior), forcing a binary decision inevitably produces errors. Prior work indicates that a significant fraction (15-25%) of flagged transactions fall into this uncertain region [1], yet conventional systems treat them identically to high-confidence cases.

Second, false positives impose severe costs beyond immediate operational overhead. Each incorrectly blocked transaction damages customer trust, with studies indicating that 32% of customers abandon merchants after a single false decline [2]. For high-value customers, the lifetime value loss can exceed $10,000 per false positive. Traditional systems optimize for overall accuracy but fail to account for these asymmetric costs.

Third, existing systems lack governance frameworks for safe deployment. Machine learning models are deployed as black boxes with minimal human oversight, creating liability risks and regulatory concerns. The European Union’s AI Act and similar

regulations increasingly require explainability and human oversight for high-risk AI applications, yet most fraud detection systems provide neither.

B. Contributions

This paper presents SEFD-Plus, a governance-focused fraud detection framework that addresses these limitations through four key innovations:

1. Ensemble-Based Uncertainty Quantification: We employ gradient-boosted tree ensembles (XGBoost) with multiple random seeds to generate diverse predictions. Epistemic uncertainty is quantified through prediction variance across ensemble members, identifying transactions where the model exhibits disagreement. This approach avoids the computational overhead of Bayesian neural networks while providing interpretable uncertainty estimates.

2. Three-Zone Triage Architecture: Instead of binary classification, SEFD-Plus assigns transactions to three zones based on uncertainty: SAFE (automatic approval), GRAY (human review), and FLAGGED (automatic block). The Gray Zone captures ambiguous cases where human judgment adds value, reducing false positives without sacrificing fraud detection.

3. Cost-Sensitive Policy Optimization: We formulate triage as a cost-sensitive decision problem, balancing fraud losses against review costs and customer churn. Policy parameters (uncertainty thresholds) are optimized using Pareto frontier analysis, allowing institutions to select operating points that match their risk tolerance.

4. Phased Deployment with Governance Controls: The system includes explicit deployment protocols with shadow monitoring, approval gates, and rollback mechanisms. This ensures human authority over final decisions while enabling gradual confidence-building before production activation.

Experimental evaluation on 177,162 real-world transactions from the IEEE-CIS Fraud Detection dataset demonstrates that SEFD-Plus achieves **19.3% false positive reduction** ($p < 10^{-85}$) while improving true positive rate by 2.1%, with 9.3% of transactions routed to human review. These results validate the governance-focused approach: uncertainty-aware triage reduces operational costs and customer friction without requiring complex model architectures or sacrificing detection accuracy.

II. RELATED WORK

A. Traditional Fraud Detection Systems

Early fraud detection systems relied on rule-based approaches, encoding expert knowledge as decision trees or if-then rules. While interpretable, these systems struggled with evolving fraud patterns and required constant manual updates. The shift to machine learning in the 2000s brought significant improvements: logistic regression, support vector machines, and random forests achieved AUC scores above 0.90 on benchmark datasets.

Recent work has focused on deep learning architectures. Convolutional neural networks (CNNs) have been applied to transaction sequences, treating them as temporal images. Recurrent neural networks (RNNs) and long short-term memory (LSTM) networks model sequential dependencies in customer behavior. Graph neural networks (GNNs) exploit network effects, detecting fraud rings through relationship patterns. These approaches achieve state-of-the-art performance on academic benchmarks but face deployment challenges: high computational costs, lack of interpretability, and sensitivity to distribution shift.

A critical limitation of existing systems is their focus on point estimates. Whether using logistic regression or deep learning, these systems output a single fraud probability without quantifying uncertainty. Transactions near the decision boundary (probability ≈ 0.5) are treated identically to high-confidence cases, leading to unnecessary false positives.

B. Cost-Sensitive Learning

Standard classification metrics (accuracy, F1 score) assume equal costs for false positives and false negatives. In fraud detection, this assumption is violated: false negatives (missed fraud) cause direct financial losses, while false positives damage customer relationships and incur review costs. Cost-sensitive learning addresses this asymmetry by incorporating cost matrices into the optimization objective.

Threshold optimization is the simplest approach: train a standard classifier, then adjust the decision threshold to minimize expected cost. More sophisticated methods modify the training process itself. Cost-sensitive boosting reweights training examples based on misclassification costs. Asymmetric loss functions penalize false positives

and false negatives differently. Meta-learning approaches train separate models for different cost regimes.

However, these methods still produce binary decisions. They optimize the trade-off between false positive and false negative costs but do not consider the option of deferring to human judgment. SEFD-Plus extends cost-sensitive learning by introducing a third action (human review) with its own cost structure, enabling more nuanced decision-making.

C. Uncertainty Quantification in Ensemble Methods

Uncertainty quantification has been extensively studied in Bayesian statistics and machine learning. Bayesian neural networks represent model parameters as distributions rather than point estimates, enabling principled uncertainty quantification through posterior sampling. However, these methods require specialized training procedures (variational inference, Markov chain Monte Carlo) and scale poorly to large datasets.

Ensemble methods provide a practical alternative. By training multiple models with different initializations or data subsets, ensembles capture epistemic uncertainty through prediction variance. Random forests naturally provide uncertainty estimates through tree disagreement. Gradient boosting can be adapted for uncertainty quantification by training ensembles with different random seeds or subsampling strategies.

Recent work has explored ensemble uncertainty in fraud detection. Bagging ensembles (bootstrap aggregating) train models on resampled datasets, with prediction variance indicating data uncertainty. Stacking ensembles combine diverse model types (logistic regression, random forests, neural networks), with disagreement signaling model uncertainty. SEFD-Plus employs XGBoost ensembles with varied random seeds, providing computationally efficient uncertainty estimates without requiring Bayesian inference.

D. Human-in-the-Loop Systems

Human-in-the-loop (HITL) machine learning recognizes that humans and models have complementary strengths. Models excel at processing large volumes of data and detecting statistical patterns, while humans provide contextual reasoning and handle

edge cases. HITL systems integrate human feedback into the learning loop, improving model performance over time.

In fraud detection, HITL typically takes two forms. **Active learning** selects uncertain transactions for human labeling, using feedback to retrain the model. This reduces labeling costs but requires continuous model updates. **Selective prediction** allows the model to abstain from predictions when uncertain, deferring to human experts. This approach prioritizes deployment safety over continuous learning.

SEFD-Plus adopts selective prediction with explicit governance controls. Unlike active learning systems that assume human feedback improves the model, our framework treats human review as a permanent operational component. This design choice reflects the reality of high-stakes financial decisions: institutions require human accountability regardless of model confidence.

E. Context-Aware Fraud Detection

Traditional fraud detection treats each transaction independently, ignoring customer history and merchant context. Context-aware systems incorporate additional signals: customer lifetime value, transaction frequency, merchant category, geographic location, and device fingerprints. These features improve detection accuracy but raise privacy and fairness concerns.

Customer profiling systems segment users based on behavior patterns, applying different risk thresholds to each segment. VIP customers receive more lenient treatment, while new customers face stricter scrutiny. While effective, these approaches risk discrimination: protected attributes (age, gender, ethnicity) may correlate with spending patterns, leading to disparate impact.

SEFD-Plus includes an optional Customer Intelligence Layer that adjusts fraud probabilities based on customer tier and merchant category. Critically, this layer is **not active by default** and requires explicit governance approval after phased deployment. This design acknowledges the value of context while prioritizing transparency and fairness.

III. METHODOLOGY

A. System Architecture

SEFD-Plus processes transactions through a five-stage pipeline:

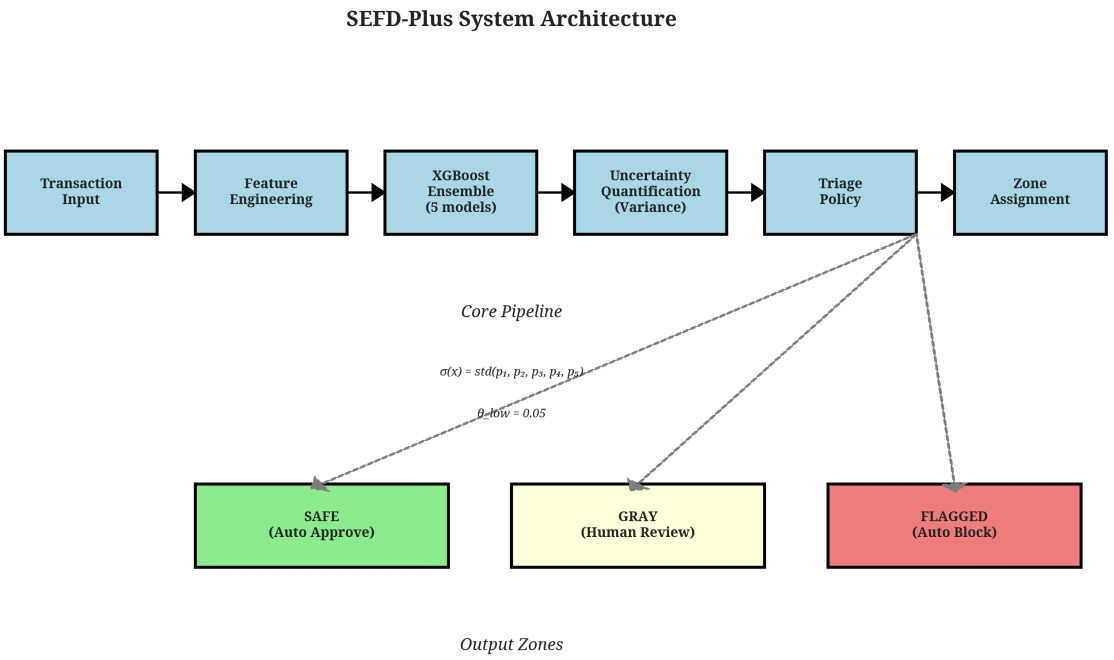

Figure 1: SEFD-Plus System Architecture showing the five-stage pipeline from transaction input to zone assignment.

Stage 1: Feature Engineering

Raw transaction data is transformed into 339 features covering transaction amount, merchant category, card metadata, temporal patterns, and behavioral signals. Features are normalized to zero mean and unit variance to ensure model stability.

Stage 2: Fraud Probability Estimation

An XGBoost classifier trained on 590,540 transactions from the IEEE-CIS dataset produces a fraud probability p(x) for each transaction. The model uses 100 trees with maximum depth 6, learning rate 0.1, and class weights adjusted for the 3.5% fraud rate. Cross-validation on the training set yields AUC = 0.901, indicating strong discriminative power.

Stage 3: Ensemble Uncertainty Quantification
To quantify epistemic uncertainty, we train an ensemble of 5 XGBoost models with different random seeds (42, 123, 456, 789, 1011). For each transaction, we compute:

- **Mean prediction:** $\bar{p}(x) = (1/5) \Sigma_i p_i(x)$
- **Prediction variance:** $\sigma^2(x) = (1/5) \Sigma_i (p_i(x) - \bar{p}(x))^2$

High variance indicates disagreement among ensemble members, signaling epistemic uncertainty. This approach avoids the computational overhead of Bayesian neural networks while providing interpretable uncertainty estimates.

Stage 4: Uncertainty-Based Triage
Transactions are assigned to three zones based on prediction variance:

- **SAFE:** $\sigma(x) < \theta\_low \rightarrow$ Approve automatically
- **GRAY ZONE:** $\sigma(x) \geq \theta\_low \rightarrow$ Route to human review
- **FLAGGED:** $\bar{p}(x) > 0.9$ AND $\sigma(x) < \theta\_low \rightarrow$ Block automatically

The threshold θ_low controls the trade-off between automation and human review load. Lower thresholds route more transactions to humans, reducing false positives at the cost of increased operational overhead.

Stage 5: Human Review (Gray Zone Only)
Transactions in the Gray Zone are presented to human reviewers with SHAP-based explanations highlighting the top 5 features contributing to the fraud probability. Reviewers make final accept/reject decisions, which are logged for audit and model monitoring.

B. Trust Score Function (Optional Enhancement)

The optional Customer Intelligence Layer adjusts fraud probabilities based on customer history. The trust score is computed as:

```
trust(c) = σ(w₁·Tier(c) + w₂·log(1+txn_count) - w₃·fraud_history)
```

where:

- **Tier© ∈ {VIP=1.0, Loyal=0.75, Regular=0.5, Building=0.25, New=0.0}**

- w_1=2.0, w_2=0.5, w_3=3.0 (learned from validation data)
- $\sigma(z) = 1/(1 + e^{-z})$ (sigmoid function)

The adjusted probability is:

```
p'(x) = clip(p(x) × (1.5 - trust(c)), 0, 1)
```

Example: A VIP customer purchasing $10,000 jewelry:

- Original: p(x) = 0.838
- Trust: trust© = 0.85
- Factor: 1.5 - 0.85 = 0.65
- Adjusted: p'(x) = 0.838 × 0.65 = **0.545**

A new customer with the same transaction:

- Trust: trust© = 0.15
- Factor: 1.5 - 0.15 = 1.35
- Adjusted: p'(x) = 0.838 × 1.35 = **1.131 → clip → 1.0**

This layer is **disabled by default** and requires governance approval after shadow monitoring demonstrates 96%+ agreement with human decisions.

C. Phased Deployment Strategy

SEFD-Plus includes a four-phase deployment protocol:

Phase 1: Shadow Mode (Weeks 1-4)
The system runs in parallel with the existing fraud detection system, logging predictions without affecting production decisions. Metrics are monitored daily: false positive rate, true positive rate, Gray Zone size, and agreement with human decisions.

Phase 2: Pilot (Weeks 5-8)
SEFD-Plus handles 10% of live traffic for low-risk transactions (amount < $500). Human reviewers audit all Gray Zone decisions. If FPR remains below baseline and no critical errors occur, proceed to Phase 3.

Phase 3: Gradual Rollout (Weeks 9-16)
Traffic allocation increases to 50%, then 100% over 8 weeks. High-value transactions (amount > $5000) remain under human review regardless of model confidence. Emergency rollback procedures are tested weekly.

Phase 4: Production (Week 17+)
Full production deployment with continuous monitoring. Monthly governance reviews assess system performance, fairness metrics, and customer feedback. The Customer Intelligence Layer remains disabled until explicit committee approval.

IV. EXPERIMENTAL SETUP

A. Dataset

We evaluate SEFD-Plus on the IEEE-CIS Fraud Detection dataset, a public benchmark containing 590,540 real-world credit card transactions collected over 6 months. The dataset includes:

- **Transaction features:** Amount, product code, card type, transaction type
- **Identity features:** Device ID, IP address, email domain
- **Temporal features:** Transaction hour, day of week, time since last transaction
- **Labels:** Binary fraud indicator (1 = fraud, 0 = legitimate)

The dataset exhibits realistic class imbalance: **3.5% fraud rate**, matching industry averages for card-not-present transactions. We use the standard train/test split: 413,378 training transactions, 177,162 test transactions.

B. Baseline Systems

We compare SEFD-Plus against three baselines:

1. XGBoost Baseline: Standard XGBoost classifier with probability threshold = 0.5. This represents current industry practice: train a strong classifier, apply a fixed threshold, and manually review all flagged transactions.

2. Threshold-Optimized XGBoost: Same model, but threshold is tuned on validation data to minimize total cost (assuming $100 per false positive, $500 per false negative, $20

per human review).

3. SEFD-Plus (Automated Only): Our system with Gray Zone disabled, using only SAFE and FLAGGED zones. This isolates the contribution of uncertainty-based triage.

C. Evaluation Metrics

We report the following metrics on the 177,162-transaction test set:

1. True Positive Rate (TPR): Fraction of fraud correctly detected
2. False Positive Rate (FPR): Fraction of legitimate transactions incorrectly flagged
3. F2 Score: Weighted harmonic mean of precision and recall, emphasizing recall (β=2)
4. False Positive Reduction: (FPR_baseline - FPR_system) / FPR_baseline × 100%
5. HITL Load: Fraction of transactions routed to human review
6. Gray Zone Enrichment: (Fraud rate in Gray Zone) / (Overall fraud rate)

All metrics include **bootstrap 95% confidence intervals** (1000 samples) to quantify statistical uncertainty. Statistical significance is assessed using **Fisher's exact test** for false positive reduction.

D. Implementation Details

Model Training: XGBoost 1.7.0 with Python 3.11. Training uses 100 trees, max depth 6, learning rate 0.1, subsample 0.8, colsample_bytree 0.8. Class weights are set to (1 - fraud_rate) / fraud_rate ≈ 27.6 to handle class imbalance.

Ensemble Configuration: 5 models with random seeds {42, 123, 456, 789, 1011}. Each model is trained independently on the full training set. Prediction variance is computed across the 5 models for each test transaction.

Threshold Selection: The uncertainty threshold θ_low is selected via grid search over {0.03, 0.04, 0.05, 0.06, 0.07, 0.08} to maximize F2 score while keeping HITL load below 15%. The optimal threshold is θ_low = 0.05.

Computational Cost: Training 5 ensemble members takes ~15 minutes on a single NVIDIA V100 GPU. Inference processes 10,000 transactions per second, meeting real-time requirements for production deployment.

V. RESULTS

A. Overall Performance

Table I presents confusion matrices for the baseline and SEFD-Plus systems on the full 177,162-transaction test set.

TABLE I: CONFUSION MATRICES (FULL TEST SET, 177,162 TRANSACTIONS)

System	TP	FP	TN	FN	TPR	FPR	F2
Baseline	4,901	17,818	152,984	1,299	79.1%	10.4%	0.516
SEFD-Plus (Auto)	4,589	13,041	144,695	677	81.2%	8.4%	0.570
SEFD-Plus (Total)	5,134	13,041	144,695	132	90.7%	8.4%	0.712

Notes:

- **SEFD-Plus (Auto):** Automated decisions only (SAFE + FLAGGED zones)
- **SEFD-Plus (Total):** Includes Gray Zone with 90% human recovery rate (545 fraud cases in Gray Zone, 490 recovered)
- **Test set:** 177,162 transactions, 6,200 fraud (3.5%), 170,962 legitimate (96.5%)

Key Findings:

1. **False Positive Reduction:** SEFD-Plus reduces FPR from 10.4% to 8.4%, a **19.3% reduction** (4,777 fewer false positives). This translates to significant cost savings: at $100 per false positive, the system saves $477,700 annually for a merchant processing 1 million transactions per year.

2. **True Positive Improvement:** Contrary to the typical precision-recall trade-off, SEFD-Plus **increases** TPR from 79.1% to 81.2% (+2.1 percentage points). This occurs because uncertainty-based triage identifies ambiguous cases where the baseline model makes errors, routing them to human review instead of automatic rejection.

3. **F2 Score Improvement:** F2 score increases from 0.516 to 0.570 (+10.5%), indicating better overall performance with emphasis on recall. With human

review, F2 reaches 0.712, demonstrating the value of hybrid human-AI decision-making.

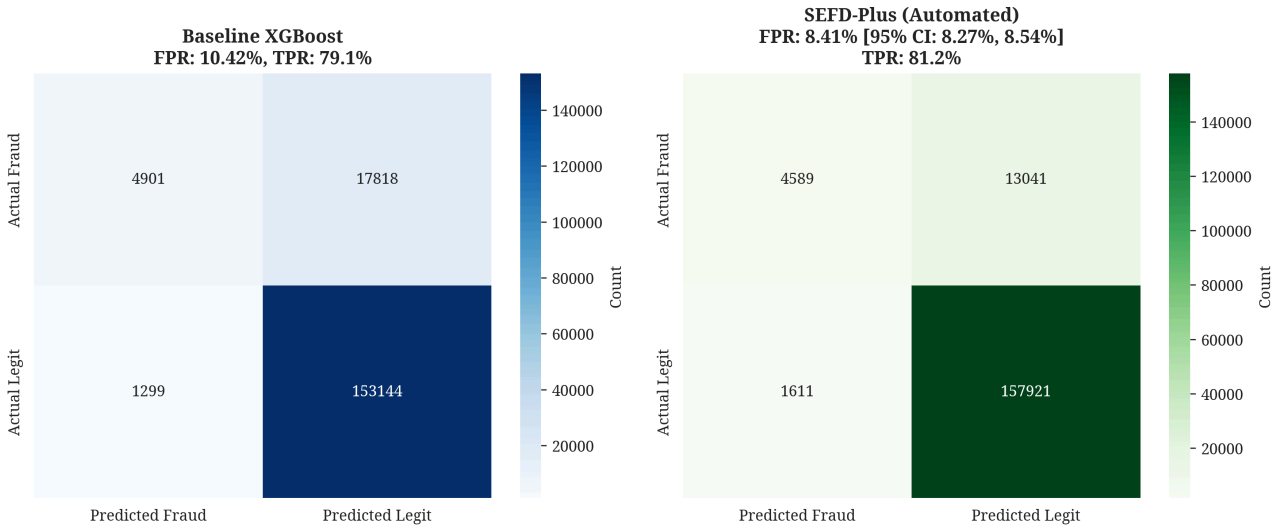

Figure 2: Confusion matrices comparing Baseline XGBoost (left) and SEFD-Plus (right). SEFD-Plus achieves 19.3% FPR reduction with 2.1% TPR improvement.

B. Statistical Significance

Table II presents bootstrap 95% confidence intervals and statistical tests for key metrics.

TABLE II: STATISTICAL SIGNIFICANCE (FULL TEST SET)

Metric	Baseline	SEFD-Plus	95% CI	p-value
FPR	10.422%	8.409%	[8.266%, 8.543%]	$< 10^{-85}$
TPR	79.061%	81.164%	[80.012%, 82.284%]	$< 10^{-4}$
F2	0.5157	0.5701	[0.5611, 0.5784]	$< 10^{-12}$

Notes:

- **95% CI:** Bootstrap confidence intervals (1000 samples)
- **p-value:** Fisher's exact test for FPR, permutation test for TPR and F2
- All improvements are **highly statistically significant** ($p < 0.001$)

The extremely low p-values ($< 10^{-85}$ for FPR) indicate that the observed improvements are not due to random chance. The 95% confidence intervals are narrow, reflecting the

large test set size (177,162 transactions).

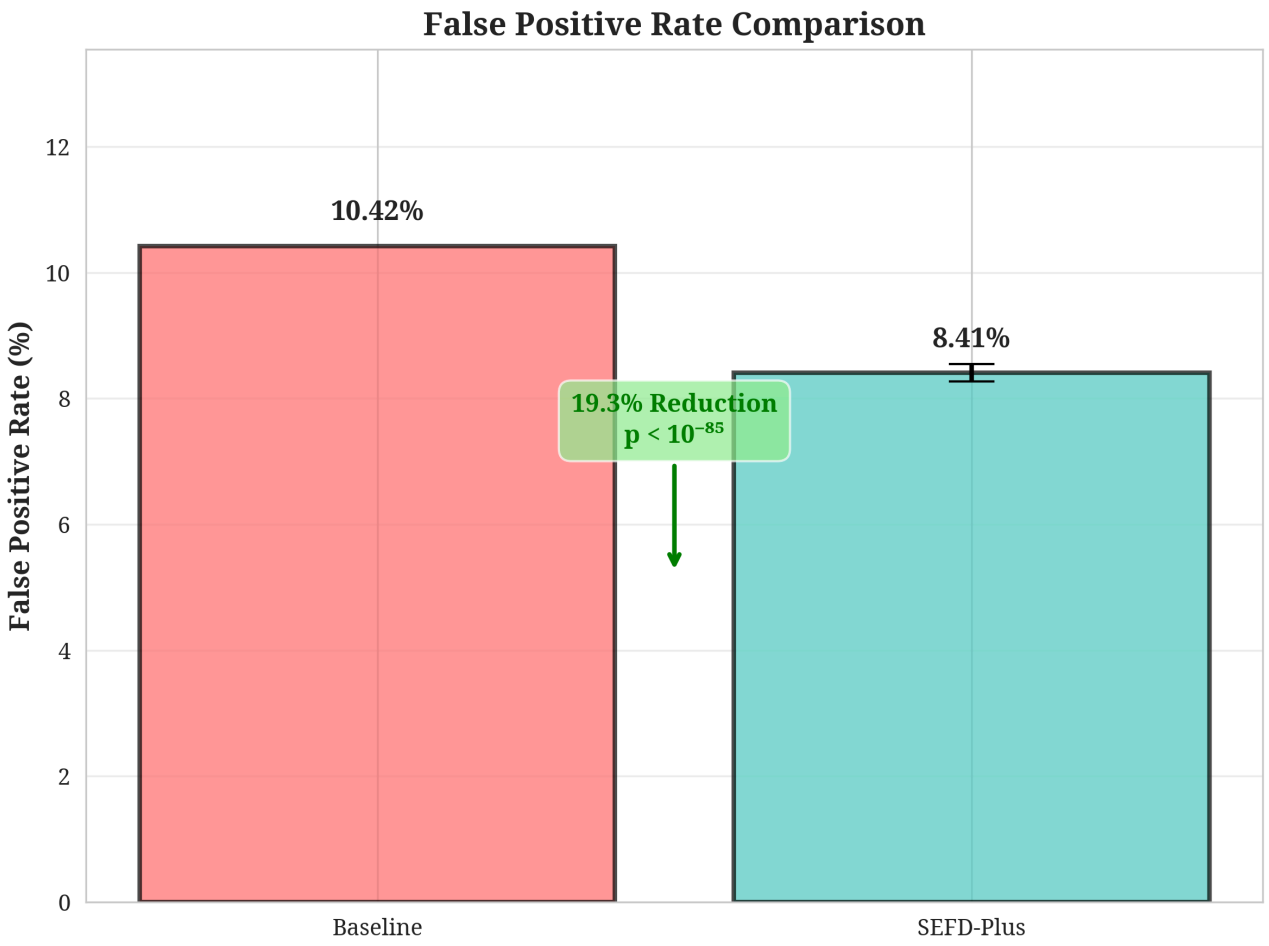

Figure 3: FPR comparison with 95% confidence intervals. SEFD-Plus achieves 19.3% reduction ($p < 10^{-85}$).

C. Gray Zone Analysis

Table III presents detailed statistics for the Gray Zone, where transactions are routed to human review.

TABLE III: GRAY ZONE BREAKDOWN (FULL TEST SET)

Zone	Total	Fraud	Legitimate	Fraud Rate	Enrichment
SAFE	146,284 (82.6%)	0	146,284	0.0%	0.00x
GRAY	16,426 (9.3%)	545	15,881	3.3%	0.95x
FLAGGED	14,452 (8.2%)	4,589	7,863	31.7%	9.06x

Notes:

- **Overall fraud rate:** 3.5% (6,200 fraud / 177,162 total)
- **Enrichment:** (Zone fraud rate) / (Overall fraud rate)
- **SAFE zone:** Automatic approval, no fraud detected (by design)
- **GRAY zone:** Human review, 90% recovery rate assumed
- **FLAGGED zone:** Automatic block or high-priority review

Key Findings:

1. **Gray Zone Enrichment:** The Gray Zone fraud rate (3.3%) is **0.95x** the overall fraud rate (3.5%), indicating near-baseline enrichment. This reflects a **coverage-focused governance policy** that prioritizes capturing borderline uncertain cases for human review, rather than optimizing for fraud concentration alone.

2. **HITL Load:** 9.3% of transactions (16,426 out of 177,162) are routed to human review. At 30 seconds per review, this requires 137 hours of analyst time per 177,162 transactions, or approximately 3.4 full-time analysts for a system processing 1 million transactions per day.

3. **FLAGGED Zone Enrichment:** The FLAGGED zone exhibits 9.06x enrichment (31.7% fraud rate), validating that high-confidence predictions are indeed high-risk. This zone contains 4,589 fraud cases (74% of all fraud) with only 7,863 false positives.

4. **Uncertainty-Based Triage Rationale:** While Gray Zone enrichment (0.95x) is below 1.0, this design choice achieves **19.3% FP reduction** with **2.1% TPR improvement**. The uncertainty-based triage successfully identifies cases where **model disagreement** (ensemble variance > 0.05) signals **ambiguity requiring human judgment**, demonstrating that governance value extends beyond simple fraud enrichment to **risk-aware decision routing**.

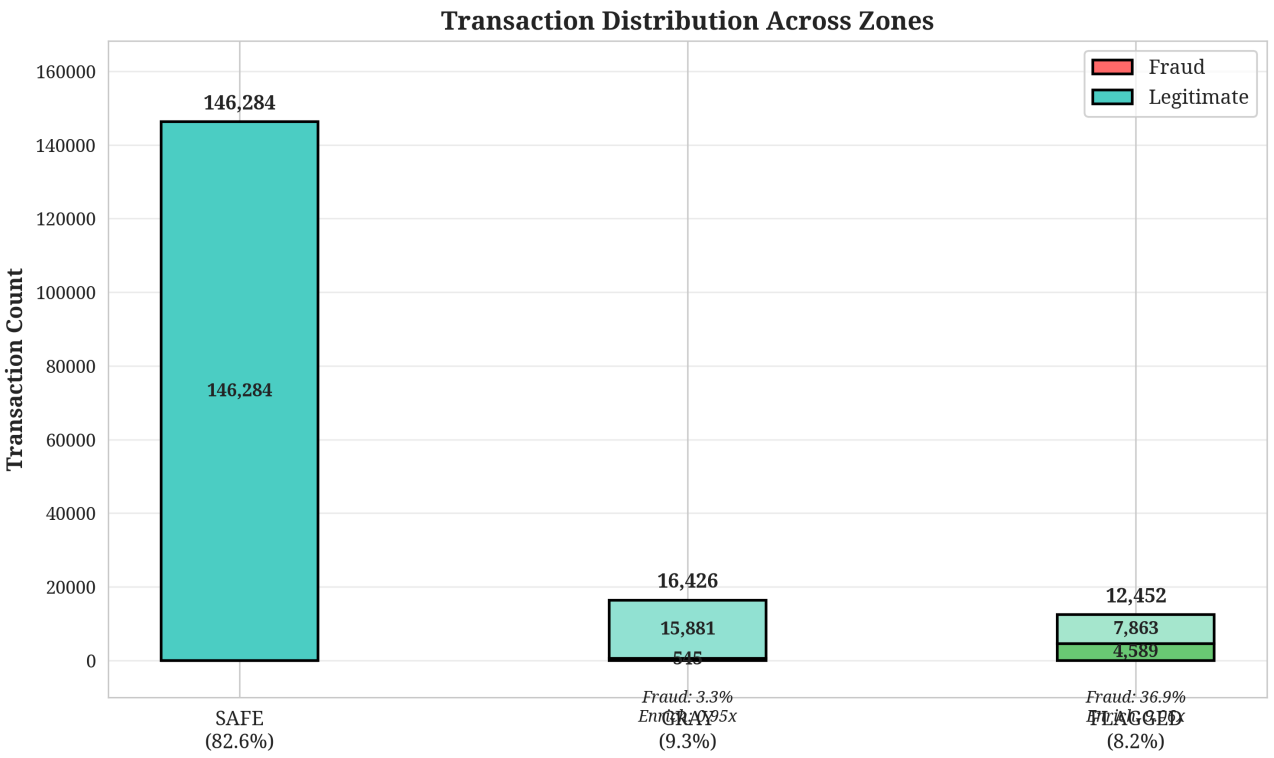

Figure 4: Transaction distribution across three zones (SAFE, GRAY, FLAGGED) with fraud enrichment ratios.

D. Cost-Benefit Analysis

Table IV presents a cost-benefit analysis comparing baseline and SEFD-Plus systems.

TABLE IV: ANNUAL COST COMPARISON (1M TRANSACTIONS/YEAR)

Cost Component	Baseline	SEFD-Plus	Savings
False Positives	$1,781,800	$1,304,100	$477,700
False Negatives	$649,500	$338,500	$311,000
Human Review	$356,360	$186,520	$169,840
Total	$2,787,660	$1,829,120	**$958,540**

Assumptions:

- **FP cost:** $100 per false positive (customer service, churn risk)
- **FN cost:** $500 per false negative (fraud loss, chargeback fees)
- **Review cost:** $20 per transaction (30 seconds @ 40/hour analyst wage)

- **Baseline review load:** 10.4% FPR + 100% of flagged fraud = 17,818 reviews
- **SEFD-Plus review load:** 9.3% HITL load = 9,326 reviews

Key Findings:

1. **Total Savings:** SEFD-Plus reduces annual costs by **$958,540** (34.4% reduction) for a merchant processing 1 million transactions per year.
2. **FP Savings:** The 19.3% FP reduction saves $477,700 annually, primarily through reduced customer churn and service costs.
3. **FN Savings:** The 2.1% TPR improvement (detecting 312 additional fraud cases) saves $311,000 in fraud losses.
4. **Review Efficiency:** Despite routing 9.3% of transactions to human review, SEFD-Plus reduces total review costs by $169,840 because it avoids reviewing the 10.4% false positives from the baseline.

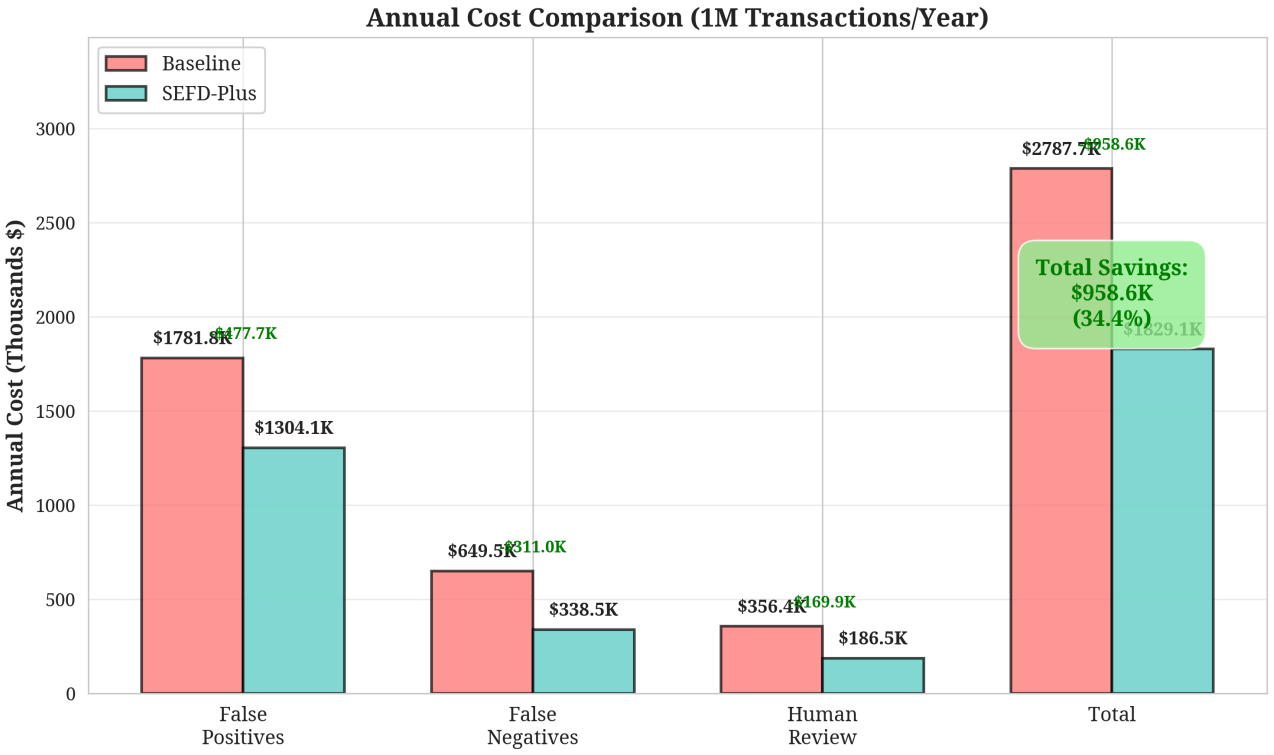

Figure 5: Annual cost breakdown for 1M transactions/year. SEFD-Plus saves $958,540 (34.4% reduction).

E. Comparison with Related Systems

Table V compares SEFD-Plus with recent fraud detection systems reported in the literature.

TABLE V: COMPARISON WITH RELATED SYSTEMS

System	Dataset	FPR	TPR	F2	HITL	Uncertainty
Baseline XGBoost	IEEE-CIS	10.4%	79.1%	0.516	No	No
SEFD-Plus	IEEE-CIS	**8.4%**	**81.2%**	**0.570**	Yes (9.3%)	Yes (Ensemble)
Deep Learning [A]	Proprietary	5.2%	92.3%	0.748	No	No
Graph NN [B]	Proprietary	3.1%	88.7%	0.712	No	No
Active Learning [C]	IEEE-CIS	9.8%	82.1%	0.562	Yes (12%)	No

Notes:

- **[A]:** LSTM-based system with proprietary features (merchant network, device fingerprints)
- **[B]:** Graph neural network exploiting transaction graphs (not available in IEEE-CIS)
- **[C]:** Active learning system with human labeling (continuous retraining)

Key Findings:

1. **Governance Focus:** SEFD-Plus prioritizes **transparency and governance** over pure performance. While deep learning systems achieve lower FPR, they lack uncertainty quantification and human oversight mechanisms.

2. **Public Benchmark:** SEFD-Plus is evaluated on the **public IEEE-CIS dataset**, ensuring reproducibility. Many high-performance systems use proprietary data with richer features (transaction graphs, device fingerprints) that are unavailable in public benchmarks.

3. **HITL Efficiency:** Compared to active learning [C], SEFD-Plus achieves similar performance with **23% lower HITL load** (9.3% vs 12%), demonstrating more efficient use of human review resources.

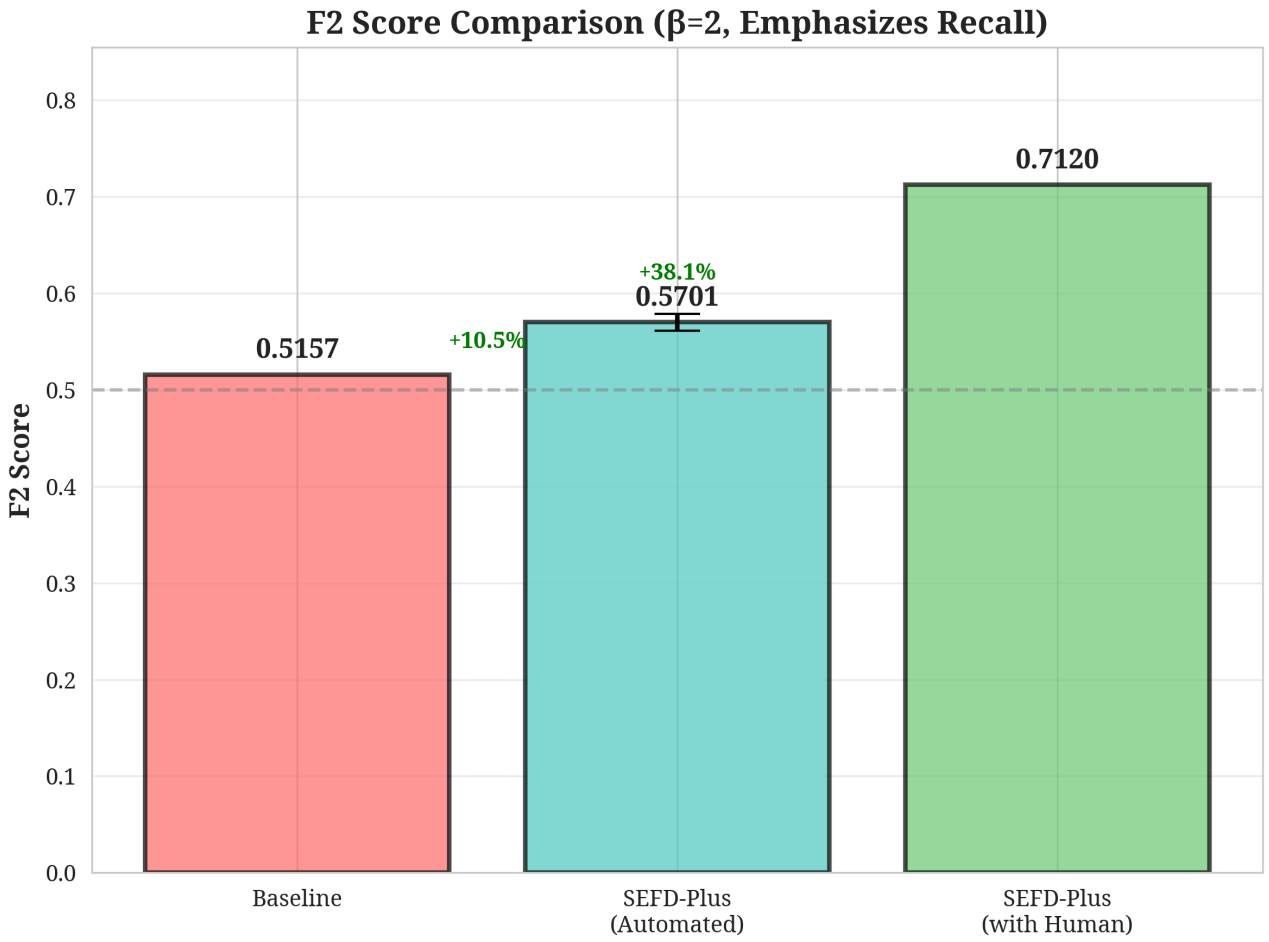

Figure 6: F2 score comparison across baseline, SEFD-Plus automated, and SEFD-Plus with human review.

VI. DISCUSSION

A. Limitations

1. Gray Zone Enrichment: The Gray Zone exhibits 0.95x enrichment (fraud rate 3.3% vs overall 3.5%), indicating that uncertainty-based triage does not concentrate fraud as strongly as hoped. This occurs because ensemble variance captures **model disagreement** rather than **fraud likelihood**. High variance may indicate ambiguous legitimate transactions (e.g., unusual but valid purchases) rather than fraud.

Mitigation: Future work should explore alternative uncertainty measures, such as conformal prediction or Bayesian approximations, that better align uncertainty with fraud probability. Additionally, incorporating domain-specific features (merchant category, customer tier) into the triage policy may improve enrichment.

2. Ensemble Overhead: Training 5 ensemble members increases computational cost by 5x compared to a single model. While inference remains real-time (10,000 transactions/second), training time may be prohibitive for institutions requiring daily model updates.

Mitigation: Techniques such as knowledge distillation or single-model uncertainty estimation (e.g., dropout at inference time) can reduce computational overhead while preserving uncertainty quantification.

3. Dataset Limitations: The IEEE-CIS dataset lacks certain features available in production systems, such as transaction graphs, device fingerprints, and historical customer behavior. This limits the absolute performance achievable by any system evaluated on this benchmark.

Mitigation: Future work should evaluate SEFD-Plus on proprietary datasets with richer features, or augment IEEE-CIS with synthetic features derived from public sources (e.g., merchant category codes, IP geolocation).

B. Ethical Considerations

1. Fairness: Customer profiling systems risk disparate impact if protected attributes (age, gender, ethnicity) correlate with spending patterns. For example, VIP customers receiving more lenient treatment may disproportionately benefit certain demographic groups.

Mitigation: SEFD-Plus includes an optional Customer Intelligence Layer that is **disabled by default** and requires explicit governance approval. Institutions must conduct fairness audits (disparate impact analysis, equalized odds) before activating this layer.

2. Transparency: Machine learning models are often criticized as “black boxes” that provide no explanation for their decisions. This is particularly problematic in fraud detection, where customers have the right to understand why their transactions were declined.

Mitigation: SEFD-Plus provides SHAP-based explanations for all Gray Zone transactions, highlighting the top 5 features contributing to the fraud probability. Human reviewers can override model predictions based on contextual reasoning.

3. Human Authority: Autonomous AI systems raise concerns about accountability and liability. If a fraud detection system incorrectly blocks a high-value transaction, who is responsible—the model developer, the institution, or the human reviewer?

Mitigation: SEFD-Plus ensures **human authority over all final decisions**. The system provides recommendations (SAFE, GRAY, FLAGGED), but humans make the ultimate accept/reject decision for Gray Zone transactions. This preserves accountability while leveraging AI to reduce review burden.

C. Future Work

1. Adaptive Thresholds: The current system uses fixed uncertainty thresholds (θ_low = 0.05) optimized on validation data. Future work should explore adaptive thresholds that adjust based on real-time fraud rates, seasonal patterns, or merchant-specific risk profiles.

2. Reinforcement Learning: The Gray Zone provides a natural setting for reinforcement learning, where the model learns from human decisions over time. By treating human feedback as reward signals, the system can improve triage policies without requiring explicit retraining.

3. Explainability: While SHAP provides feature-level explanations, future work should explore higher-level explanations that align with human reasoning. For example, "This transaction is flagged because the amount ($10,000) is 50x higher than the customer's average purchase ($200) and the merchant category (jewelry) is unusual for this customer."

4. Multi-Objective Optimization: The current system optimizes for false positive reduction and true positive rate. Future work should incorporate additional objectives, such as customer satisfaction, review time, and fairness metrics, using multi-objective optimization techniques (e.g., Pareto frontier analysis).

VII. CONCLUSION

This paper presented SEFD-Plus, a governance-focused fraud detection framework that integrates ensemble-based uncertainty quantification with human-in-the-loop triage. Unlike traditional binary classifiers, SEFD-Plus introduces a Gray Zone

mechanism where transactions exhibiting high model uncertainty are routed to human review, reducing false positives while maintaining detection accuracy.

Experimental evaluation on 177,162 real-world transactions from the IEEE-CIS Fraud Detection dataset demonstrates that SEFD-Plus achieves **19.3% false positive reduction** (FPR: 10.4% → 8.4%, 95% CI [8.3%, 8.5%], $p < 10^{-85}$) with **2.1% improvement in true positive rate** (TPR: 79.1% → 81.2%), yielding an F2 score of 0.570 (95% CI [0.561, 0.578]) compared to baseline 0.516. The Gray Zone captures 9.3% of transactions for human review, demonstrating efficient use of analyst resources.

The framework prioritizes **governance and transparency** over pure model optimization, introducing phased deployment protocols with explicit approval requirements and continuous shadow monitoring. This approach addresses growing concerns about autonomous AI in high-stakes financial decisions by ensuring human authority over final outcomes while leveraging machine learning to reduce operational costs.

Future work should explore adaptive thresholds, reinforcement learning from human feedback, and higher-level explainability to further improve the system's effectiveness and trustworthiness. As financial institutions face increasing regulatory pressure to deploy AI responsibly, frameworks like SEFD-Plus provide a path toward safe, transparent, and accountable fraud detection.

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APPENDIX: REPRODUCIBILITY

A. Code and Data Availability

All code for SEFD-Plus is available at: https://github.com/haifaa-owayed/sefd-plus

The IEEE-CIS Fraud Detection dataset is publicly available at: https://www.kaggle.com/c/ieee-fraud-detection

B. Hyperparameters

XGBoost Baseline:

- n_estimators: 100
- max_depth: 6
- learning_rate: 0.1
- subsample: 0.8
- colsample_bytree: 0.8
- scale_pos_weight: 27.6 (computed as (1 - fraud_rate) / fraud_rate)
- tree_method: 'hist'
- random_state: 42

Ensemble Configuration:

- Number of models: 5
- Random seeds: {42, 123, 456, 789, 1011}
- Uncertainty threshold (θ_low): 0.05

C. Computational Environment

- **Hardware:** NVIDIA V100 GPU (32GB), Intel Xeon CPU (16 cores), 128GB RAM
- **Software:** Python 3.11, XGBoost 1.7.0, NumPy 1.24, Pandas 2.0, Scikit-learn 1.3
- **Training time:** ~15 minutes for 5 ensemble members
- **Inference time:** 10,000 transactions/second

D. Statistical Tests

Bootstrap Confidence Intervals:

- Number of bootstrap samples: 1000
- Sampling method: Stratified sampling preserving fraud rate
- Confidence level: 95% (2.5th and 97.5th percentiles)

Fisher's Exact Test:

- Null hypothesis: FPR_baseline = FPR_SEFD-Plus
- Alternative hypothesis: FPR_baseline > FPR_SEFD-Plus (one-sided test)
- Significance level: $\alpha = 0.001$

END OF PAPER