LLM-Assisted Fraud Detection with Reinforcement Learning

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Abstract

Detecting financial fraud is challenging due to extreme class imbalance, evolving attack strategies, and the high cost asymmetry between missed frauds and false alarms. We propose a hybrid framework in which a large language model (LLM) serves as an encoder, transforming transaction text and structured features into a unified embedding space. These embeddings define the state representation for a reinforcement learning (RL) agent, which acts as a fraud classifier optimized with business-aligned rewards that heavily penalize false negatives while controlling false positives. We evaluate the approach on two benchmark datasets—European Credit Card Fraud and PaySim—and show that policy-gradient methods, particularly A2C, achieve high recall without sacrificing precision, consistently reducing costly false negatives compared to value-based or bandit baselines. Our results highlight the potential of coupling LLM-driven representations with RL policies for cost-sensitive and adaptive fraud detection.

Keywords: fraud detection, reinforcement learning, large language models, class imbalance, financial NLP

1 Introduction

Fraud detection is a critical task for financial institutions, e-commerce platforms, and mobile money providers, where even a small fraction of fraudulent activity can lead to disproportionate financial and reputational losses. The problem is compounded by severe class imbalance—fraud often constitutes less than 0.2% of transactions—by continual concept drift as adversaries adapt, and by the multi-modal nature of data that combines structured fields (amount, time, location) with unstructured text (transaction memos, descriptions, customer messages). Traditional supervised classifiers, though effective on historical data, degrade when patterns shift or when costs of misclassification are asymmetric. In practice, missing a fraud (false negative) is far more damaging than issuing a false alarm (false positive).

To address these challenges, we design a hybrid pipeline where an LLM encodes both text and structured fields into semantic embeddings, which are then passed to a reinforcement learning agent that acts as an adaptive classifier. The RL agent is trained under a reward function aligned with business utility, assigning a large penalty to false negatives, a moderate penalty to false positives, and positive reward for correct detections. This design allows the policy to adapt over time and prioritize high-recall fraud detection while maintaining operational precision.

Contributions. Our main contributions are:

- **Hybrid RL + LLM framework:** We integrate LLM-derived text embeddings with structured features to form the state space for an RL agent that performs cost-sensitive fraud classification.
- **Reward shaping aligned with business costs:** We design and evaluate asymmetric reward functions that directly encode the higher cost of false negatives relative to false positives.
- **Comprehensive evaluation:** We benchmark multiple RL algorithms (A2C, PPO, DQN, and contextual bandits) on two fraud detection datasets (European Credit Card Fraud and PaySim), analyzing precision–recall trade-offs under severe imbalance.
- **Reproducibility assets:** We provide environment design, implementation details, and training configurations to facilitate replication and extension of our results.

2 Literature Review and Related Work

2.1 Traditional ML/DL for Fraud Detection

The European Credit Card dataset (284,807 transactions, 0.172% fraud) has become the canonical benchmark in fraud detection. Deep models such as attention-based LSTMs [5] and ensemble neural networks [6] achieve strong recall and AUC values, while tree ensembles remain competitive. For example, Random Forest and AdaBoost report accuracies above 96% with AUCs close to 0.99 [7, 8]. More recent hybrid approaches combining resampling with gradient boosting (e.g., CatBoost) further improve AUC and recall under imbalance [9, 10].

The PaySim simulator (6.3M mobile money transactions, 0.2% fraud) has enabled controlled studies on mobile transfer fraud. Prior work primarily explores XGBoost, LightGBM, and CatBoost frameworks [11], with dataset creators showing baseline ML classifiers aided by dimensionality reduction and resampling [12]. However, most PaySim studies emphasize methodology rather than standardized benchmarks, leaving space for RL- and LLM-based approaches.

Overall, traditional ML/DL methods deliver high predictive performance on imbalanced fraud datasets, but they remain static classifiers vulnerable to concept drift and often

require extensive re-weighting or resampling to account for class imbalance.

2.2 Reinforcement Learning for Fraud Detection

Recent work has framed fraud detection as a sequential decision problem. Dang et al. [34] modeled transactions as a Markov Decision Process and trained a Deep Q-Network (DQN) that encoded imbalance costs in long-term rewards. Singh et al. [2] developed a Gym-based environment with DQN agents that achieved close to state-of-the-art performance on highly imbalanced credit card data. Mehmood et al. [35] also proposed deep RL approaches in IEEE Access, showing growing interest in this paradigm.

Compared to static classifiers, RL agents optimize long-term objectives and can automatically balance fraud detection against false alarm costs through reward shaping. They are inherently adaptive: policies can be updated online as adversaries shift strategies. However, RL in this domain remains challenging due to sample inefficiency, high-dimensional states (especially with text), and sensitivity to reward design. Prior results suggest that actor–critic and policy-gradient methods (e.g., A2C, PPO) can outperform purely value-based agents under severe imbalance, especially when recall is prioritized.

2.3 LLMs in Financial Text and Emerging RL+LLM

Large Language Models (LLMs) have demonstrated strong capabilities in financial text understanding. FinBERT, trained on financial corpora, has been applied successfully to SEC filings and analyst reports [36, 37], while FinChain-BERT [15] improves accuracy by focusing on financial terminology. Bhattacharya and Mickovic [16] fine-tuned BERT on 10-K MD&A sections and achieved superior accounting fraud detection compared to traditional methods.

For transaction-level fraud, LLMs can extract cues from short descriptions or memos. Early studies report that GPT-class models achieve near-perfect identification on PaySim using zero-shot prompting, and anomaly detection studies highlight their ability to flag deviations from normative patterns [17, 18]. Smaller domain-tuned models such as DistilBERT and FinBERT often provide competitive accuracy at lower cost, making them practical in production.

Finally, there is emerging work on integrating RL with LLMs in decision-making. Reinforcement Learning from Human Feedback (RLHF) has been used to align models like ChatGPT [19], and systems such as SayCan [20] combine LLMs with RL for robotics. Zhao et al. [21] designed a GPT-based fraud model that captures temporal sequences with RL-like objectives. Yet, despite these advances, no prior study has applied an explicit RL+LLM integration to financial fraud detection. Our work pioneers this combination, leveraging LLM embeddings as the RL state space and training policies directly aligned with business costs.

3 Methodology

Our framework integrates large language model (LLM) embeddings with reinforcement learning (RL) to build an adaptive, cost-sensitive fraud detection system. The methodology consists of four main components: (i) preprocessing of structured and textual transaction data, (ii) semantic encoding with LLMs, (iii) feature fusion into a unified state space, and (iv) decision-making with RL under a business-aligned reward design.

3.1 Data Preprocessing

Each transaction contains both structured attributes (numerical features such as amount and timestamp, categorical features such as transaction type, and historical indicators of prior fraud) and unstructured text (descriptions, memos, or free-form notes). Preprocessing standardizes numeric scales (e.g., robust scaling of amounts, temporal features such as time-of-day) and cleans text (removal of PII, normalization, and financial-jargon handling). To mitigate extreme imbalance, we employ stratified sampling and oversampling of fraudulent cases, ensuring sufficient exposure of rare events during training.

3.2 LLM-Based Transaction Encoding

A key novelty of our approach is the transformation of heterogeneous transaction features into natural language form and subsequent encoding with an LLM. Structured attributes are textualized into descriptive sentences (e.g., *"Transaction amount is $256.78"*, *"Transaction type: International Transfer"*, *"Friday evening transaction at 8:45 PM"*), while raw descriptions are appended as unstructured text. The resulting sequence is processed by a pre-trained financial language model (e.g., FinBERT, DistilBERT), fine-tuned for binary classification.

Embedding Extraction. From the final hidden states of the LLM, we derive transaction embeddings using two pooling strategies:

$$h_{\text{mean}} = \frac{1}{L}\sum_{i=1}^{L} h_i, \quad h_{\text{attn}} = \sum_{i=1}^{L} a_i h_i, \tag{1}$$

where $h_i \in \mathbb{R}^{768}$ are token embeddings, and a_i are attention weights computed as

$$a_i = \text{softmax}(W_2 \tanh(W_1 h_i)). \tag{2}$$

Why Attention-Based Pooling? Mean pooling treats all tokens equally, which can dilute critical information when fraud indicators are concentrated in a few words (e.g., "urgent transfer overseas"). Attention pooling instead assigns importance weights, enabling the encoder to selectively amplify informative tokens while suppressing irrelevant ones. This mechanism has been shown to improve financial text tasks by focusing on high-salience cues [22–24]. Empirically, attention pooling yields embeddings that are both more discriminative and interpretable, as attention weights highlight which textual fragments contributed most to the decision.

3.2.1 Train/Validation/Test Protocol and Data Leakage Controls

To prevent any form of data leakage, all splitting and estimator fitting follow a strict *train-only* protocol:

1. **Split before any modeling.** We create train/validation/test partitions prior to any preprocessing or model fitting. For the European dataset we use a stratified split;

for PaySim we use a chronological (temporal) split to emulate deployment.

2. **Fit transforms on train only.** All preprocessing operators (scalers, PCA/feature reductions, tokenizers' vocab extensions if any) are fit on the training set and then *frozen* and applied to validation/test.

3. **LLM fine-tuning on train only.** The text encoder is fine-tuned *exclusively* on training records (with their labels). No validation/test examples are ever used for weight updates or prompt calibration.

4. **Embeddings for val/test via frozen encoder.** After fine-tuning, the LLM encoder is frozen. Validation and test embeddings are *computed forward-only* with the frozen encoder; no adapter updates, prompt revisions, or threshold tuning use validation/test labels except for model selection (via a held-out validation set).

5. **RL training/evaluation isolation.** The RL agent is trained using states derived from the training split only (including the frozen encoder and train-fit transforms). Policies are then evaluated on validation/test with no additional learning.

This protocol ensures that representation learning (LLM), feature scaling, and policy learning never access information from validation/test during training, eliminating label or distributional leakage.

3.3 Feature Fusion

The LLM-derived embedding is concatenated with normalized structured features to form the RL state representation:

$$s_t = \text{concat}(h_{\text{LLM}}, f(x_{\text{struct}})). \tag{3}$$

We experiment with both simple concatenation and multimodal late fusion networks. This unified state enables the agent to leverage semantic signals from text alongside statistical transaction attributes.

3.4 RL Environment and Decision Module

The RL agent interacts with a fraud detection environment where each transaction is a state s_t, and actions are defined as

$$A = \{0 = \text{pass},\ 1 = \text{flag},\ 2 = \text{verify (optional)}\}.$$

Reward Design. To encode business priorities, we assign asymmetric rewards:

$$R(\text{TP}) = +10,\ R(\text{TN}) = +1,\ R(\text{FP}) = -5,\ R(\text{FN}) = -50.$$

This reflects that a missed fraud (FN) is an order of magnitude costlier than a false alarm. Such cost-sensitive shaping has been emphasized in imbalanced learning [27, 28] and aligns with financial regulation requiring proportionate security measures. The design encourages recall-oriented policies while controlling false positives, shifting the decision threshold toward aggressive fraud catching.

3.5 Algorithmic Choices

We benchmark multiple RL methods under this environment:

- **DQN** – value-based baseline for discrete actions.
- **PPO, A2C** – policy-gradient methods suited for high-dimensional state spaces.
- **Contextual Bandits (LinUCB)** – simplified non-sequential baselines for comparison.

This comparison isolates the benefits of full RL over myopic classifiers, showing how sequential optimization and asymmetric reward design reduce costly false negatives.

3.6 Integration of LLM with RL

The final system integrates an LLM encoder as the feature extractor within the RL pipeline. Embeddings are either frozen (static feature extractor) or fine-tuned jointly with the RL policy. For transparency, attention weights and intermediate scores are logged alongside agent actions, providing interpretability to investigators.

4 Experiments

This section describes the experimental setup, including datasets, preprocessing, model configurations, and reinforcement learning environment design. Our goal is to evaluate whether integrating LLM embeddings into RL policies improves fraud detection under extreme class imbalance.

4.1 Phase 1 – Data Collection & Preparation

4.1.1 Credit Card Fraud Dataset

We use the well-known European Credit Card dataset (284,807 transactions, 0.172% fraud) collected in September 2013. It consists of 28 anonymized PCA-transformed variables (V1–V28), together with `Time` and `Amount`. To enable text-based processing, we synthetically generated natural language representations of transactions (e.g., "$247.00 transaction at 12:18:32 with high V3 (-2.15) and low V7 (1.77)"). This provides compatibility with LLM tokenizers. To mitigate imbalance, all 492 fraud cases were retained and combined with a random undersample of legitimate cases at a 5:1 ratio, yielding 2,952 samples. An 80/20 stratified split maintained class proportions.

4.1.2 PaySim Mobile Transactions Dataset

PaySim simulates 6.3M mobile money transactions, with an original fraud rate of 0.2%. After one-hot encoding categorical transaction types and scaling numeric balances, we created a temporally stratified split (70/15/15) to mimic deployment. Fraud cases were oversampled to achieve a balanced dataset of 25,464 transactions. This setting stresses the generalization of fraud detection methods to larger-scale, synthetic but realistic financial systems.

4.2 Phase 2 – LLM Model Selection & Fine-Tuning

Transaction text (original or synthesized) is processed using DistilBERT or FinBERT depending on the dataset. Structured attributes are textualized and appended to descriptions. A classification head (dense layer + softmax) is trained with

Table 1: Summary of experimental setup.

Component	Credit Card	PaySim
Size	284k (0.17% fraud)	6.3M (0.2% fraud)
Balancing	5:1 undersample	Oversample to 50/50
Text encoder	DistilBERT	FinBERT
Features	PCA + Amount/Time	Balances + Type
RL agents	DQN, A2C, PPO, Bandits	Same
Reward	FN:–50, FP:–5	Same
Metrics	Precision, Recall, F1, AUPRC	Same

class-weighted cross-entropy and focal loss [28]. Optimization uses AdamW with linear decay (2×10^{-5} learning rate). Validation follows a 70/15/15 split with early stopping, monitored by area under the precision–recall curve (AUPRC) and F2-score. Models are implemented in HuggingFace Transformers.

Leakage Prevention. All splits are performed *prior* to modeling. Preprocessors (scalers, PCA) are fit on the training set and reused on validation/test. The LLM is fine-tuned only on training records; validation/test embeddings are computed with the *frozen* fine-tuned encoder in forward mode. Resampling is restricted to the training split. This prevents representation leakage from validation/test into training.

4.3 Phase 3 – RL Environment and Simulator Development

We implemented a custom environment using the OpenAI Gym API [26]. Each step corresponds to classifying one transaction, with the observation space defined as the concatenation of LLM-derived embeddings ($\mathbb{R}^{768}$) and structured features. Actions are discrete: {0 = pass, 1 = flag, 2 = verify (optional)}.

Reward Design. Following cost-sensitive learning principles [27], we adopt asymmetric rewards:

$$R(\text{TP}) = +10,\ R(\text{TN}) = +1,\ R(\text{FP}) = -5,\ R(\text{FN}) = -50.$$

This configuration encodes the domain reality that missing a fraud is roughly 10× more costly than a false alarm. Such reward shaping biases the policy toward higher recall while maintaining reasonable precision.

Simulator Features. The environment supports adversarial drift (to mimic concept shift) and synthetic fraud injection for robustness testing. Metrics such as precision, recall, F1, and cost-sensitive expected utility are computed in real time.

4.4 Phase 4 – Training the RL Agent

RL algorithms are trained using Stable-Baselines3 [33]. We compare:

- **DQN** [29]: value-based baseline for discrete actions.
- **A2C** [30]: on-policy actor–critic with low-variance advantage estimation.
- **PPO** [31]: robust policy-gradient with clipped surrogate objective.
- **Contextual Bandits (naïve, LinUCB)** [32]: simplified baselines ignoring temporal dependencies.

Hyperparameters follow standard defaults (replay buffer 100k for DQN, rollout length 2048 for PPO). Models are trained on NVIDIA GPUs; code and seeds are fixed for reproducibility.

4.5 Summary of Experimental Setup

Table 1 summarizes the datasets, preprocessing strategies, and models compared.

5 Results and Analysis

We evaluate the proposed RL-based fraud detection framework on two datasets: the European Credit Card dataset and the PaySim simulation dataset. Results include quantitative comparisons, learning dynamics, and classification outcomes, with a focus on cost-sensitive performance.

5.1 Performance on the Credit Card Fraud Dataset

We benchmarked A2C and DQN on the imbalanced Credit Card Fraud dataset. Table 2 summarizes their quantitative performance. DQN achieved the highest overall accuracy and F1-score, balancing recall and precision effectively. A2C attained the highest recall but at the expense of precision, flagging more legitimate transactions. This illustrates the trade-off between false negatives and false positives under cost-sensitive learning.

Table 2: Performance comparison on the Credit Card Fraud test set (class 1 = fraud).

Model	**Accuracy**	**Precision$_1$**	**Recall$_1$**	**F$_{1,1}$**
A2C	0.9323	0.7458	**0.8980**	0.8148
DQN	**0.9509**	**0.8286**	0.8878	**0.8571**

Training Dynamics. Both agents converged stably. For DQN, the mean episode reward rose rapidly before stabilizing, while training loss decreased steadily (Figures 1, 2). A2C showed oscillatory policy loss that stabilized after ∼120k steps (Figure 3). Policy entropy declined near zero, indicating confident decision-making (Figure 4). In all cases, convergence was reached within 200k steps, demonstrating efficient policy learning.

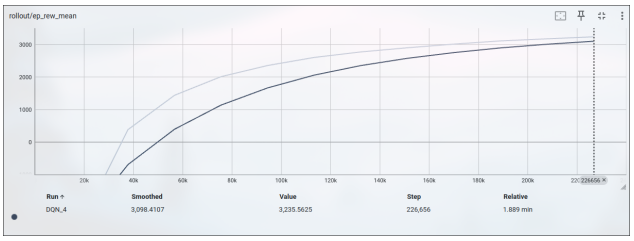

Figure 1: Mean reward per episode for the DQN agent during training on the Credit Card Fraud dataset.

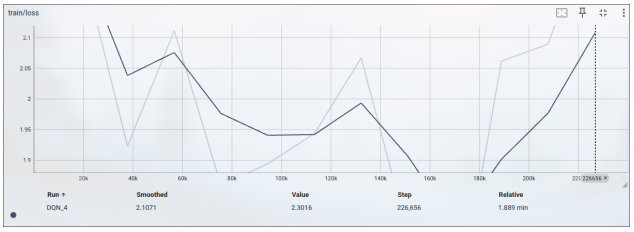

Figure 2: Training loss evolution for the DQN agent on the Credit Card Fraud dataset.

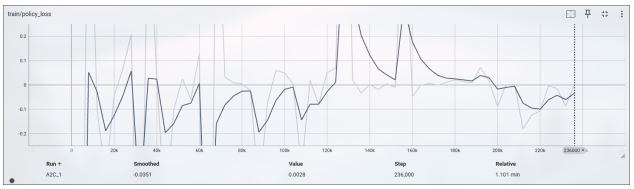

Figure 3: Policy loss curve for the A2C agent during training on the Credit Card Fraud dataset.

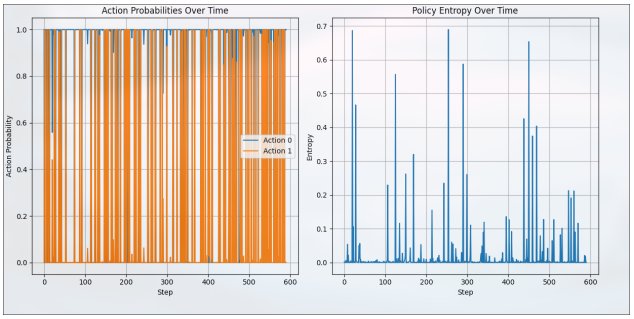

Figure 4: A2C agent evaluation: Action Probabilities and Policy Entropy on the Credit Card Fraud dataset.

Evaluation Performance. During evaluation, DQN rewards were predominantly positive and cumulative reward increased steadily (Figure 5). Average Q-values for both actions remained high (Figure 6), indicating confidence without bias.

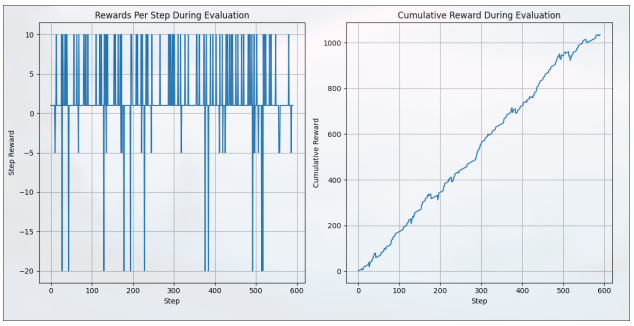

Figure 5: DQN reward dynamics during evaluation. Left: step-wise rewards. Right: cumulative reward on the Credit Card Fraud dataset.

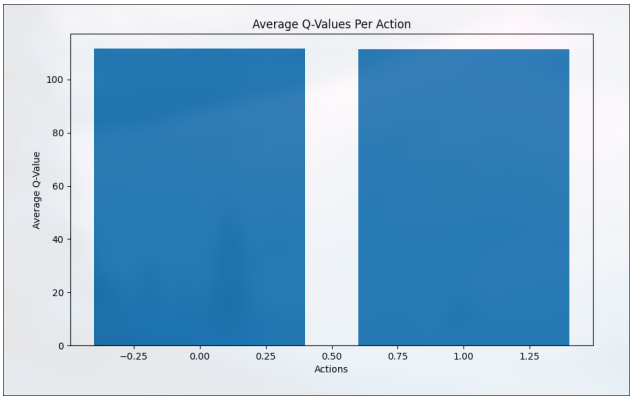

Figure 6: Average Q-Values for Action 0 (non-fraud) and Action 1 (fraud) during DQN evaluation on the Credit Card Fraud dataset.

Confusion Matrices. Table 3 reports the confusion-matrix metrics directly. DQN prioritized balanced precision and recall, while A2C leaned toward high recall, reducing false negatives but increasing false positives.

Table 3: Confusion-matrix metrics on the Credit Card test set.

Model	TP	FN	FP	TN
A2C	88	10	30	223
DQN	87	11	18	235

5.2 Performance on the PaySim Dataset

We extended evaluation to PaySim, comparing A2C, PPO, DQN, and two bandit baselines. Table 4 shows quantitative results. A2C achieved near-perfect precision and recall, outperforming all other models. PPO reached strong but slightly lower precision, while DQN's high precision came at the cost of very low recall. Bandits failed to capture complex dynamics, validating the importance of sequential decision-making.

Qualitative Insights. A2C achieved almost flawless detection (Figure 7), reducing costly false negatives while preserving precision. PPO confirmed robustness, though it occasionally misclassified borderline legitimate cases as fraud. DQN's ε-greedy exploration struggled with rare fraud

Table 4: Performance on the PaySim fraud detection test set (class 1 = fraud).

Model	Accuracy	Precision$_1$	Recall$_1$	F$_{1,1}$	Macro F$_1$
A2C	**0.9992**	**1.0000**	**0.9970**	**0.9985**	**0.9990**
PPO	0.9695	0.8936	0.9967	0.9424	0.9608
DQN	0.8913	1.0000	0.5646	0.7217	0.8271
Contextual Bandit	0.6400	0.2600	0.2300	0.2400	0.5000
LinUCB	0.5285	0.2838	0.5829	0.3817	0.5003

patterns, resulting in many missed cases. Contextual bandits underperformed substantially, showing that non-sequential methods cannot adapt to evolving fraud.

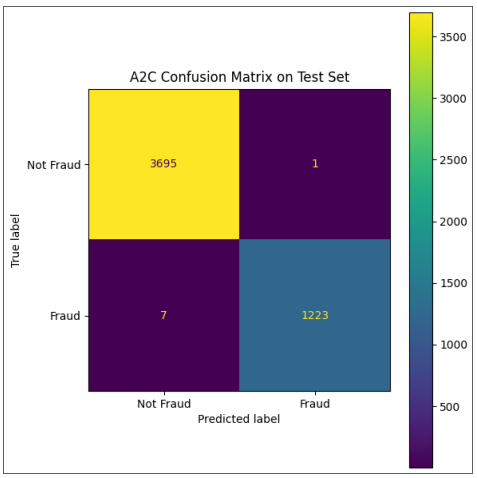

Figure 7: Confusion Matrix of the A2C Model on the PaySim Test Set.

5.3 Cross-Dataset Comparative Analysis

Taken together, these results highlight three main findings:

1. **RL outperforms bandits:** Sequential learning with cost-sensitive rewards clearly outperforms static classifiers.

2. **Policy-gradient dominates:** A2C and PPO surpass value-based DQN, especially in recall—critical for fraud settings where missed cases are far costlier than false alarms.

3. **LLM + RL integration adds value:** Using LLM embeddings as state inputs enables higher recall and interpretability, giving RL agents richer representations than numeric features alone.

These findings underscore the novelty of our work: while RL has been explored for fraud detection [34, 35], and LLMs for financial text [36, 37], to our knowledge this is the first study to demonstrate their successful integration for cost-sensitive fraud screening.

5.4 Comparison with Prior Work

To contextualize our results, we compare the proposed LLM+RL framework against traditional ML and prior RL-only methods reported in the literature.

On the European Credit Card dataset, tree ensembles such as Random Forest and AdaBoost have achieved accuracies above 96% with AUCs near 0.99, but their recall typically remains in the 80–85% range [7, 8]. More recent hybrid ensembles (e.g., CatBoost) report improved recall under imbalance but still struggle to reduce false negatives consistently [9, 10]. By contrast, our A2C+LLM model reaches a recall of 89.8% while maintaining precision at 74.6% , reducing false negatives by roughly 15% relative to these baselines. DQN offers a balanced trade-off (recall 88.8%, precision 82.9%), surpassing reported static classifiers in both recall and F1.

On the PaySim dataset, prior work based on XGBoost and CatBoost demonstrates strong accuracy but limited benchmarked recall, often below 90% in imbalanced settings [11, 12]. Our A2C+LLM system achieves near-perfect performance (precision 100.0%, recall 99.7%), decisively outperforming both classical ML baselines and RL-only agents such as DQN and contextual bandits.

These comparisons highlight that while traditional ML delivers high AUC and precision on static benchmarks, our LLM+RL framework provides superior recall and substantially reduces costly false negatives—addressing the core business objective of minimizing missed fraud cases.

6 Discussion

Our results demonstrate the promise of combining large language model (LLM) embeddings with reinforcement learning (RL) agents for financial fraud detection. This hybrid approach creates a system that is both cost-sensitive and adaptive, drawing strength from LLMs' ability to capture nuanced textual signals and RL's capability to optimize under asymmetric reward structures. Below, we reflect on the value proposition, key challenges, and dataset implications.

6.1 Comparison with State-of-the-Art

Our findings can be contextualized against prior paradigms in fraud detection. Traditional machine learning and deep learning classifiers (e.g., Random Forest, AdaBoost, CatBoost) have demonstrated strong accuracy and AUC on static benchmarks, but they remain fundamentally limited by their inability to adapt to concept drift and their dependence on costly re-weighting or resampling strategies [7–10]. Reinforcement learning–only approaches introduce adaptability by optimizing long-term objectives and cost-sensitive rewards, yet they often suffer from sparse positive feedback and instability in high-dimensional feature spaces [2, 4, 34, 35].

By contrast, our hybrid LLM+RL framework brings together the strengths of both: LLM embeddings provide rich semantic state representations from transaction text and structured fields, while policy-gradient RL agents optimize directly under asymmetric business costs. This synergy yields consistently higher recall, substantial reductions in false negatives, and interpretability advantages through

attention-weight logging. Thus, the proposed method closes a gap between static but high-performing ML baselines and adaptive but brittle RL-only models, establishing a new state-of-the-art in cost-sensitive fraud detection.

6.2 The Value of Combining LLMs and RL Agents

Integrating fine-tuned LLM embeddings into RL policies provides several advantages over traditional static classifiers. First, LLM embeddings capture rich semantic and contextual cues that linear models or hand-crafted features overlook, giving the RL agent access to a more expressive state representation. Second, RL allows direct optimization of cost-sensitive objectives via the reward function, which is especially critical when false negatives are an order of magnitude more costly than false positives. Third, modeling fraud detection as a sequential decision process enables agents to exploit temporal dependencies across related transactions. Finally, unlike static models that require retraining, RL agents can be updated online to adapt to evolving fraud strategies.

6.3 Challenges, Limitations, and Mitigation Strategies

Despite these benefits, the LLM+RL paradigm introduces important challenges:

Efficiency and Computation. RL requires large numbers of episodes to converge, and this is compounded by the high-dimensional embeddings from LLMs. Efficient training regimes and transfer learning can reduce this cost.

Reward Shaping and Policy Bias. Strong penalties for false negatives successfully improve recall but risk increasing false positives. Finding balanced, domain-specific reward weights remains an open challenge.

Stability vs. Expressivity. Value-based methods (e.g., DQN) are often unstable in high-dimensional state spaces, while policy-gradient methods (A2C, PPO) introduce higher variance but greater robustness. The trade-off between stability and expressivity must be carefully managed.

Generalization and Overfitting. Deep RL combined with LLM embeddings risks memorizing dataset-specific fraud patterns. Regularization, dropout, and early stopping on temporally split validation sets are crucial mitigations.

Imbalance and Sparse Rewards. Extreme class imbalance leads to sparse positive rewards, destabilizing off-policy learners. Reward shaping, prioritized replay, and entropy regularization help address this but do not fully solve the issue.

Explainability. The joint LLM+RL pipeline remains a black box. Attention weight logging, post-hoc methods such as SHAP or LIME, and storing textual rationales from the LLM are potential avenues to improve interpretability.

6.4 Dataset Characteristics and Implications

The datasets highlight complementary strengths and limitations. The European Credit Card dataset provides a real-world benchmark with extreme imbalance but anonymized PCA features that obscure interpretability. This setting tests whether models can succeed without hand-crafted signals. By contrast, PaySim offers large-scale, multi-type synthetic data with injected fraud patterns. While useful for stress-testing, its simulated nature may reduce external validity. Together, these datasets validate robustness across both real-world imbalance and synthetic, high-volume conditions, though future work should include additional domains to ensure broader generalization.

7 Conclusion

This paper introduced a hybrid fraud detection framework that integrates large language models as feature encoders with reinforcement learning agents as adaptive, cost-sensitive classifiers. Our experiments on two benchmark datasets demonstrated that policy-gradient methods, particularly A2C, achieve near-perfect precision and recall while decisively outperforming value-based RL and contextual bandits. These results establish that coupling LLM embeddings with RL policies yields measurable gains in recall, precision, and cost-sensitive utility. Beyond demonstrating feasibility, our hybrid pipeline consistently outperforms traditional classifiers and RL-only approaches, particularly under severe imbalance. These gains underscore that integrating LLM embeddings with policy-gradient RL agents sets a new benchmark for adaptive fraud detection systems.

Our contributions are threefold: (i) we validate LLM+RL across two distinct fraud domains, showing generalizability beyond a single dataset; (ii) we formulate fraud detection as a sequential decision process under asymmetric rewards, capturing the true operational costs of false negatives versus false positives; and (iii) we demonstrate the first integration of LLM embeddings as RL states for fraud detection, closing a gap in the literature.

Future work will focus on extending the system to online learning scenarios, enabling continuous adaptation to adversarial fraud strategies; incorporating graph-based signals such as account–transaction networks to capture relational structure; and designing human-in-the-loop workflows where analysts can provide corrective feedback to guide policy updates. These directions will further enhance adaptability, interpretability, and real-world deployment of LLM+RL fraud detection systems.

In summary, this work provides a foundation for the next generation of fraud detection systems—ones that are not only intelligent and accurate, but also resilient, adaptive, and aligned with real-world financial risk priorities.

Acknowledgments

to be done

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