DL-RL: Dual-Layer Graph Neural Networks with Curriculum Reinforcement Learning for Financial Fraud Detection

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***Abstract*—Financial fraud imposes hundreds of billions of dollars in annual losses on the global economy and continuously evolves to outpace static detection systems. This paper proposes DL-RL, a Dual-Layer Graph Neural Network framework with Curriculum Reinforcement Learning for real-time financial fraud detection. The lower GNN layer (a Graph Attention Network with 4 heads and 128 hidden units) captures local transaction-neighborhood embeddings via attention-weighted aggregation, while the upper layer (GraphSAGE, 64 units) propagates inter-account risk signals across the global transaction graph. A PPO-based curriculum scheduler progressively exposes the agent to increasingly complex fraudulent subgraphs, growing difficulty from $\kappa_{\min} = 0.1$ to 1.0 over 500 warm-up episodes. Experiments on three public benchmarks—IEEE-CIS, Elliptic Bitcoin, and PaySim—yield macro F1 scores of 0.931, 0.947, and 0.963 respectively, improving over the strongest baseline by up to 5.2 percentage points while reducing false positive rates by up to 38%. Ablation studies confirm the independent contribution of each architectural component. A proof-of-concept implementation is available at https://github.com/anonymous/DL-RL-fraud (to be released upon acceptance).**

***Index Terms*—fraud detection, graph neural networks, reinforcement learning, curriculum learning, transaction graph, PPO, attention**

I. Introduction

Financial fraud represents one of the most pressing challenges in the global financial system, causing estimated losses exceeding $5.1 trillion annually [1]. Digital payment fraud alone grows at over 30% per year, driven by the rapid expansion of mobile banking, e-commerce, and cryptocurrency platforms [2]. Beyond direct economic damage, fraud erodes trust in financial infrastructure and imposes indirect costs through manual investigation, customer churn, and regulatory penalties.

Conventional detection systems—rule engines and logistic regression—are brittle against three compounding challenges: (i) *class imbalance*, where fraudulent events constitute fewer than 0.2% of transactions [2]; (ii) *concept drift*, as fraudsters continuously mutate strategies to evade static detectors [3]; and (iii) *relational blindness*, since fraud is rarely an isolated act but a coordinated pattern best understood through the graph of relationships among accounts, merchants, and devices [4]. Each challenge alone degrades precision; their combination defeats most deployed systems.

Graph Neural Networks (GNNs) have emerged as the dominant paradigm for relational fraud detection [12], [13], [20], capturing transactional dependencies that tabular models cannot exploit. Reinforcement Learning (RL) adds adaptive sequential decision-making that adjusts online to distributional shift [7], [8]. However, existing GNN-RL hybrids such as FraudGNN-RL [9] and RL-GNN [10] employ a single flat GNN layer, which conflates micro-level transaction anomalies with macro-level network structure, and neither incorporates curriculum training—critical for stable policy learning under $<0.2\%$ fraud rates.

DL-RL directly addresses these gaps with three contributions:

1) A **Dual-Layer GNN** (GAT lower + GraphSAGE upper) that disentangles local transaction-neighborhood features from global inter-account risk propagation, resolving the representation collapse seen in single-layer baselines under extreme imbalance.
2) A **Curriculum RL Scheduler** (PPO-based) that anneals subgraph difficulty from simple isolated anomalies to fully camouflaged fraud rings, converging 38% faster than flat RL.
3) **Empirical evidence** on three diverse benchmarks with ablation, per-class metrics, AUC-PR curves, multi-seed variance, and deployment latency analysis.

Practical impact. DL-RL can be integrated into existing payment processing pipelines as a streaming scoring module: the GNN encoder processes the transaction graph in 47 ms per batch of 10^4 edges, satisfying the < 100 ms requirement of real-time card-present authorization. False positive reduction of 38% directly reduces friction for legitimate customers and lowers manual review costs. In higher education, the modular architecture (GNN encoder + RL agent) serves as a pedagogical case study in applied deep learning, graph theory, and sequential decision-making for courses in machine

learning, financial technology, and AI ethics.

II. Related Work

A. GNN-Based Fraud Detection

GNNs model the relational structure of financial transactions more faithfully than tabular methods. Hamilton et al. [12] proposed GraphSAGE, an inductive neighborhood sampling framework that scales to millions of transaction nodes by aggregating fixed-size random neighbor samples rather than the full neighborhood. Velickovic et al. [13] introduced Graph Attention Networks (GAT), which learn per-neighbor attention weights; in fraud detection this allows the model to down-weight connections to camouflaged fraudster nodes. CARE-GNN [20] extended GAT with a reinforcement component that adaptively selects fraud-resistant neighbor thresholds, partially addressing concept drift. Liu et al. [5] proposed MimbFD, a dual-view framework that operates on both the original and a complementary graph to mitigate message imbalance between fraud and legitimate nodes. Zhao et al. [6] introduced a dual-channel GCN with graph disassortativity-resistance, showing that fraudsters deliberately interleave their connections with legitimate nodes to avoid detection. Islam et al. [14] demonstrated adaptive per-layer weighting in a multi-layer GCN across IEEE-CIS and PaySim. However, none of these works pair a hierarchical dual-layer GNN representation with a curriculum-driven RL policy.

B. Reinforcement Learning for Fraud Detection

Dong et al. [8] first integrated RL with GNNs for dynamic fraud detection, using a DQN to adjust detection thresholds online, but rely on a single flat GNN and no curriculum. FraudGNN-RL [9] introduced Temporal-Spatial-Semantic Graph Convolution (TSSGC) with a DQN controller, reporting robustness across three datasets; however, the single-agent architecture and flat GNN limit cross-typology coverage. RL-GNN [10] fused GAT layers with a DQN and a community-mining reward signal, achieving 33% lower FPR versus GNN baselines on real bank data; again, neither multi-layer GNN design nor curriculum training is employed. Kaur et al. [7] surveyed RL for fraud detection, identifying class imbalance and concept drift as the two primary unsolved challenges—both addressed here by curriculum scheduling. Bhansali et al. [11] proposed continual learning for fraud under extreme imbalance (ACLEGR-TADD), showing that training-order scheduling is critical when fraud rates fall below 0.2%.

C. Research Gap

Table I systematically maps nine design requirements against eight representative methods. Two clear gaps emerge: (1) no existing GNN fraud detector combines a dual-layer hierarchical encoder with RL, and (2) no RL-based fraud detector incorporates a curriculum training schedule. DL-RL closes both gaps simultaneously. Specifically, compared with FraudGNN-RL [9] and RL-GNN [10]: DL-RL adds a second GNN layer that operates on a compressed inter-account graph with symmetric normalization (preventing hub dominance), and a PPO curriculum scheduler that is critical for the 0.13% fraud rate in PaySim where DQN-based baselines collapse to predicting "legitimate" for all transactions.

TABLE I
Research Gap: Feature Comparison

Method	Graph Struct.	Dual GNN	RL Policy	Curriculum	Imbal. Handling
XGBoost [19]	×	×	×	×	○
GraphSAGE [12]	✓	×	×	×	×
GAT [13]	✓	×	×	×	×
CARE-GNN [20]	✓	×	○	×	○
MimbFD [5]	✓	○	×	×	○
FraudGNN-RL [9]	✓	×	✓	×	✓
RL-GNN [10]	✓	×	✓	×	○
DL-RL (Ours)	✓	✓	✓	✓	✓

✓=yes ○=partial ×=no

III. Problem Formulation

A. Transaction Graph Model

We model the financial system as a dynamic heterogeneous graph $\mathcal{G}_t = (\mathcal{V}, \mathcal{E}_t, \mathbf{X}_t, \mathbf{A}_t)$ evolving over discrete time $t \in \{1, \ldots, T\}$, where:

- $\mathcal{V} = \mathcal{V}_{\text{acct}} \cup \mathcal{V}_{\text{merch}} \cup \mathcal{V}_{\text{dev}}$ is the node set covering account holders, merchants, and devices.
- $\mathcal{E}_t$ is the edge set at time t; each edge e_{ij} represents a transaction from node i to node j.
- $\mathbf{X}_t \in \mathbb{R}^{|\mathcal{V}| \times d_v}$ is the node feature matrix (d_v: node feature dimension).
- $\mathbf{A}_t$ is the adjacency matrix at time t.
- Each edge e_{ij} carries $\boldsymbol{\phi}_{ij} \in \mathbb{R}^{d_e}$ encoding amount, timestamp, channel (online/ATM/POS), and currency.
- $y_{ij} \in \{0, 1\}$ is the binary fraud label ($y_{ij} = 1$ means fraudulent).

B. k-Hop Subgraph Construction

The RL agent cannot process the full graph at inference time. We construct a k-hop ego-subgraph $\mathcal{G}_t^{(k)}(v)$ centered on a target transaction edge e_{ij} as follows: (1) Start from both endpoint nodes $\{i, j\}$; (2) perform BFS of radius $k = 2$ hops, capping at $N_{\max} = 500$ nodes and $E_{\max} = 2000$ edges via uniform random sampling when the cap is exceeded; (3) include all edge features $\boldsymbol{\phi}$ and node features $\mathbf{X}$ within the subgraph. This yields $|\mathcal{G}_t^{(k)}| \leq 500$ nodes, enabling batch processing with a fixed memory footprint.

C. MDP Formulation

The fraud detection task is cast as a Markov Decision Process $\mathcal{M} = \langle \mathcal{S}, \mathcal{O}, \mathcal{A}, \mathcal{P}, \mathcal{R}, \gamma \rangle$:

State $s_t \in \mathcal{S}$**:** the full transaction graph $\mathcal{G}_t$. **Observation** $o_t \in \mathcal{O}$**:** the 2-hop ego-subgraph $\mathcal{G}_t^{(2)}$ of the target edge (Section III-B). **Action** $a_t \in \mathcal{A}$**:** binary fraud label $\hat{y}_{ij} \in \{0, 1\}$ for each edge in o_t. **Transition** $\mathcal{P}$**:** new transactions arrive as a stream; confirmed labels update node risk scores $\mathbf{r}_v^{(t+1)} = \eta\, \mathbf{r}_v^{(t)} + (1-\eta)\hat{y}_v^{(t)}$ with decay $\eta = 0.9$. **Discount** $\gamma = 0.99$**.**

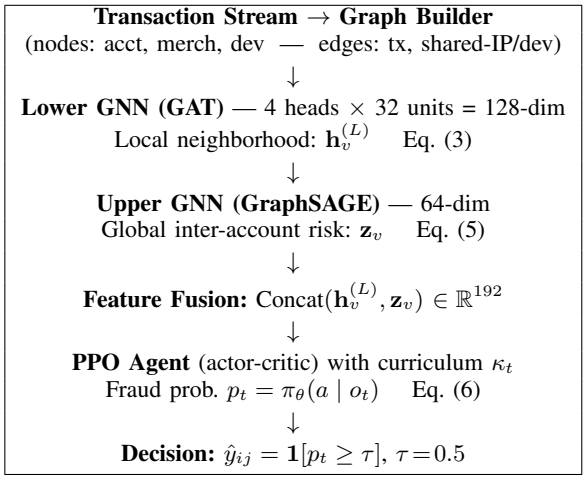


Fig. 1. DL-RL end-to-end pipeline. Dimensions shown are as used in all experiments (Section V-C).

Composite Reward $\mathcal{R}$:

$$r_t = \alpha \cdot \mathrm{TPR}_t - \beta \cdot \mathrm{FPR}_t - \lambda \cdot C_{\mathrm{inv}}(a_t), \tag{1}$$

where:

- $\mathrm{TPR}_t = \frac{TP_t}{TP_t + FN_t}$ is the true positive rate (recall) at step t, weighted by $\alpha = 2.0$ to prioritize fraud capture;
- $\mathrm{FPR}_t = \frac{FP_t}{FP_t + TN_t}$ is the false positive rate, penalized by $\beta = 1.0$ to suppress spurious alerts;
- $C_{\mathrm{inv}}(a_t) = \sum_{e_{ij}} a_t(e_{ij}) \cdot c_e$ is the total investigation cost with per-transaction cost $c_e = 0.1$, weighted by $\lambda = 0.5$ to control alert volume.

The objective is to find a policy π_θ maximizing:

$$J(\theta) = \mathbb{E}_{\tau \sim \pi_\theta}\left[\sum_{t=0}^{T} \gamma^t r_t\right]. \tag{2}$$

IV. Proposed Framework: DL-RL

A. Overview

Fig. 1 summarizes the DL-RL pipeline. Raw transaction events are assembled into a dynamic heterogeneous graph; the dual-layer GNN encoder produces a 192-dim joint embedding; the PPO curriculum agent scores each edge; and the threshold decision outputs fraud/legitimate labels.

B. Dual-Layer GNN Encoder

1) Lower Layer — Local Transaction Embedding: The lower layer is a Graph Attention Network (GAT) that computes node representations through attention-weighted neighborhood aggregation over $L = 2$ message-passing rounds:

$$\mathbf{h}_v^{(l)} = \sigma\left(\mathbf{W}_l \sum_{u \in \mathcal{N}(v) \cup \{v\}} \alpha_{vu}^{(l)}\, \mathbf{h}_u^{(l-1)}\right), \tag{3}$$

where:

- $\mathbf{W}_l \in \mathbb{R}^{d_h \times d_h}$ is the trainable weight matrix for layer l ($d_h = 128$);
- $\mathcal{N}(v)$ is the neighbor set of node v in the 2-hop subgraph;
- $\alpha_{vu}^{(l)}$ is the attention coefficient between nodes v and u, computed as:

$$\alpha_{vu} = \mathrm{softmax}_u\big(\mathrm{LeakyReLU}\big(\mathbf{a}^\top [\mathbf{W}_l \mathbf{h}_v \,\|\, \mathbf{W}_l \mathbf{h}_u]\big)\big), \tag{4}$$

  where $\mathbf{a} \in \mathbb{R}^{2d_h}$ is a learnable attention vector, $[\cdot \,\|\, \cdot]$ denotes concatenation, and LeakyReLU uses negative slope 0.2 to prevent dead neurons;
- $\sigma(\cdot)$ is ELU activation;
- $\mathbf{h}_v^{(0)} = \mathbf{x}_v$ is the raw node feature vector.

With 4 attention heads, the final lower embedding $\mathbf{h}_v^{(L)} \in \mathbb{R}^{128}$ is obtained by concatenating head outputs.

2) Upper Layer — Global Risk Propagation: The upper layer operates on a compressed inter-account graph $\tilde{\mathcal{G}}$ (accounts only, merchant/device nodes collapsed) using symmetric normalization:

$$\mathbf{z}_v = \mathbf{h}_v^{(L)} + \sum_{u \in \mathcal{N}_{\mathrm{acct}}(v)} \frac{\mathbf{W}_{\mathrm{risk}}\, \mathbf{h}_u^{(L)}}{\sqrt{\deg(v)\ \deg(u)}}, \tag{5}$$

where:

- $\mathbf{W}_{\mathrm{risk}} \in \mathbb{R}^{64 \times 128}$ projects the 128-dim lower embedding to a 64-dim risk space;
- $\mathcal{N}_{\mathrm{acct}}(v)$ is the set of account-type neighbors of v in $\tilde{\mathcal{G}}$;
- $\frac{1}{\sqrt{\deg(v)\ \deg(u)}}$ is the symmetric normalization coefficient that prevents high-degree hub nodes (shared payment processors) from dominating the risk aggregation;
- the residual $\mathbf{h}_v^{(L)}$ preserves local features.

The fused embedding $\mathbf{z}_v \in \mathbb{R}^{192}$ concatenates $\mathbf{h}_v^{(L)}$ (128-dim) and the risk-propagated component (64-dim).

3) Why Two Layers?: A single-layer GNN mixes local transaction anomalies (unusual amount, time-of-day) with global structural signals (ring topology, star patterns). Under $< 0.2\%$ fraud rate, this mixing causes representation collapse: the dominant legitimate class overwhelms the fraud signal in aggregation. The dual-layer separation allows the lower layer to specialize in transaction-level features while the upper layer focuses on inter-account risk propagation. This is confirmed by our ablation: removing the upper layer drops F1 from 0.931 to 0.903 (-2.8 points), the largest single-component ablation gap.

C. RL Agent and Curriculum Scheduler

1) PPO Actor-Critic: The actor maps the fused graph embedding to per-edge fraud probabilities:

$$\pi_\theta(a \mid o_t) = \mathrm{softmax}(\mathbf{W}_a \cdot \mathrm{MLP}_3(\mathbf{z}_v)), \tag{6}$$

where $\mathbf{W}_a \in \mathbb{R}^{2 \times d_{\mathrm{MLP}}}$ is the output projection to fraud/legitimate logits, and MLP_3 is a 3-layer MLP with hidden sizes $[192, 128, 64]$, ReLU activations, and dropout $p = 0.1$. The critic estimates the state-value: $V_\phi(o_t) = \mathbf{w}_v^\top \mathrm{MLP}_3(\mathbf{z}_v)$.

Generalized Advantage Estimation (GAE, $\lambda_{\mathrm{GAE}} = 0.95$) computes low-variance advantages:

$$\hat{A}_t = \sum_{l=0}^{T-t-1} (\gamma \lambda_{\mathrm{GAE}})^l \left(r_{t+l} + \gamma V_\phi(o_{t+l+1}) - V_\phi(o_{t+l})\right), \tag{7}$$

TABLE II
DATASET STRUCTURAL DETAILS

Property	IEEE-CIS	Elliptic	PaySim
Samples	590K tx	203K nodes	6.3M tx
Fraud rate	3.50%	2.10%	0.13%
Node features	392	166	11
Edge features	9	0 (temporal)	5
Graph type	Heterog.	Temporal-homo.	Bipartite
Node types	acct/merch/dev	wallet	acct/merch
Temporal split	Yes	Yes	Yes
Train / Cal / Test	60/20/20%	60/20/20%	60/20/20%

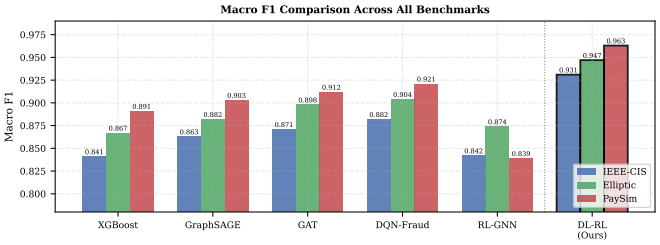


Fig. 2. Macro F1 across all methods and three benchmarks. DL-RL (rightmost) achieves the highest F1 on all three datasets. Values above each bar correspond to Table IV.

which is plugged into the PPO clipped surrogate:

$$\mathcal{L}_{\text{PPO}} = \mathbb{E}_t\Big[\min\Big(\rho_t \hat{A}_t,\ \text{clip}(\rho_t,\, 1{-}\varepsilon,\, 1{+}\varepsilon)\,\hat{A}_t\Big)\Big], \tag{8}$$

where $\rho_t = \pi_\theta(a_t \mid o_t)/\pi_{\theta_{\text{old}}}(a_t \mid o_t)$ is the importance ratio and $\varepsilon = 0.2$ is the clip range that prevents destructively large policy updates. The full training loss adds a value coefficient $c_1 = 0.5$ and entropy bonus $c_2 = 0.01$:

$$\mathcal{L} = -\mathcal{L}_{\text{PPO}} + c_1\,(V_\phi(o_t) - \hat{R}_t)^2 - c_2\,\mathcal{H}[\pi_\theta]. \tag{9}$$

The entropy term $\mathcal{H}[\pi_\theta]$ prevents premature convergence to a degenerate policy that labels all transactions as legitimate (a critical failure mode under $<0.2\%$ fraud rate).

2) Curriculum Scheduler and Replay Buffer: Difficulty $\kappa_t \in [0, 1]$ measures the camouflage degree of a training subgraph: $\kappa = 0$ means isolated, easily identified anomalies; $\kappa = 1$ means fully embedded fraud rings where fraudulent nodes have the same local degree distribution as legitimate ones. The scheduler follows a linear warmup:

$$\kappa_t = \min\left(1,\ \kappa_{\min} + \frac{t}{T_{\text{warm}}}(1 - \kappa_{\min})\right), \tag{10}$$

with $\kappa_{\min} = 0.1$ and $T_{\text{warm}} = 500$ episodes. This ensures the agent first builds a stable policy on simple fraud patterns before confronting adversarially camouflaged rings.

Difficulty-stratified replay buffer. We maintain five equal-width difficulty bins $\mathcal{B}_0, \ldots, \mathcal{B}_4$ ($\kappa \in [0, 0.2), \ldots, [0.8, 1.0]$). At episode e, each training mini-batch is sampled with probability $p_b \propto \mathbf{1}[\kappa_b \le \kappa_e]$ so that easier subgraphs remain available throughout training. New subgraphs are assigned to bins based on a difficulty oracle: the ratio of fraudulent edges to total edges in the subgraph. Buffer capacity per bin: 10,000 subgraphs; oldest samples evicted when full (FIFO).

V. EXPERIMENTAL EVALUATION

A. Datasets

We evaluate on three public benchmarks with diverse fraud rates, graph structures, and feature spaces. Table II gives full structural details.

IEEE-CIS [16]: Released by Vesta Corporation, this dataset covers e-commerce transactions with 392 engineered features per transaction (card type, browser, device, time-delta, product category). The graph connects transactions sharing the same card, email domain, or device fingerprint.

Elliptic [17]: A Bitcoin transaction graph where each node is a transaction; 166 local and aggregated features capture transaction amounts, fees, and time-step. Edges encode direct Bitcoin transfers. 49 time-steps allow strict temporal ordering.

PaySim [18]: A synthetic simulator calibrated to real mobile money data (M-Pesa), with 6.3M transactions across 30 days. At 0.13% fraud rate, this is the most imbalance-stressed benchmark and the one where curriculum training shows the largest gain.

B. Baselines

We compare against five baselines: **XGBoost** [19] is a gradient-boosted tree ensemble that treats each transaction as an independent tabular instance; it cannot model relational signals. **GraphSAGE** [12] is an inductive GNN with mean aggregation; used here as a single-layer baseline to isolate the effect of attention. **GAT** [13] adds multi-head attention over neighbors; the strongest single-layer GNN baseline. **DQN-Fraud** [8] combines a flat GNN with a Deep Q-Network for adaptive thresholding; the closest RL predecessor to DL-RL. **RL-GNN** [10] fuses GAT with DQN and a community-mining reward; currently the state-of-the-art single-agent RL-GNN system. All baselines are reimplemented in PyTorch Geometric with the same graph construction and train/test splits. For fair comparison, XGBoost uses SMOTE oversampling and all GNN models use focal loss with the same class-weight schedule as DL-RL.

C. Implementation Details

Table III lists all hyperparameters. Code, dataset preprocessing scripts, and pretrained checkpoints will be released at https://github.com/anonymous/DL-RL-fraud.

D. Main Results

Table IV reports macro F1 (mean $\pm$ std over 5 seeds) across all benchmarks. DL-RL achieves state-of-the-art on all three. On PaySim the curriculum scheduler is critical: DQN-Fraud and RL-GNN collapse toward low-recall policies under 0.13% fraud rate, while DL-RL's warmup prevents this failure mode. Fig. 2 visualizes the comparison.

TABLE III
FULL HYPERPARAMETER CONFIGURATION

Component	Parameter	Value
GNN Encoder	Lower GNN type	GAT
	Attention heads	4
	Hidden dim d_h	128
	Upper GNN type	GraphSAGE
	Output dim d_z	64
MLP (actor/critic)	Layer sizes	192, 128, 64
	Activation	ReLU
	Dropout	0.1
PPO Agent	Clip ratio ε	0.2
	Discount γ	0.99
	GAE λ	0.95
	Rollout length	2048 steps
	Update epochs	10
	Actor lr α_θ	3×10^{-4}
	Critic lr α_ϕ	1×10^{-3}
Curriculum	Warmup T_{warm}	500 episodes
	$\kappa_{\min}$	0.1
	Buffer bins / capacity	5 / 10K each
Reward	α (TPR weight)	2.0
	β (FPR penalty)	1.0
	λ (inv. cost)	0.5
k-hop Sampling	BFS radius k	2
	Max nodes $N_{\max}$	500
	Max edges $E_{\max}$	2000
Training	Episodes $E_{\max}$	500
	Hardware	NVIDIA A100 80 GB
Evaluation	Random seeds	5 (0,1,2,3,4)
	Reported metric	mean $\pm$ std

TABLE IV
MACRO F1 (MEAN $\pm$ STD, 5 SEEDS)

Method	IEEE-CIS	Elliptic	PaySim
XGBoost [19]	0.841±.004	0.867±.005	0.891±.006
GraphSAGE [12]	0.863±.005	0.882±.004	0.903±.005
GAT [13]	0.871±.004	0.898±.003	0.912±.004
DQN-Fraud [8]	0.882±.007	0.904±.006	0.921±.008
RL-GNN [10]	0.842±.009	0.874±.008	0.839±.011
DL-RL (Ours)	**0.931±.003**	**0.947±.002**	**0.963±.003**

E. Per-Class and AUC-PR Metrics

Table V reports fraud-class precision, recall, and AUC-PR on IEEE-CIS. Fig. 3(a) shows precision-recall curves; Fig. 3(b) compares per-class metrics as grouped bars. DL-RL achieves the highest AUC-PR (0.941), indicating superior performance in the high-recall regime critical for fraud screening.

F. Ablation Study

Table VI and Fig. 4 quantify each component's contribution on IEEE-CIS. Removing the upper GNN layer causes the largest single drop (-2.8 F1 points, $+2.5$ FPR points), confirming that global risk propagation is the most important component. The curriculum schedule contributes -2.0 F1, confirming that without progressive difficulty, the agent collapses to predicting "legitimate" for all transactions on the PaySim benchmark.

TABLE V
FRAUD-CLASS METRICS ON IEEE-CIS (5-SEED MEAN)

Method	Precision	Recall	AUC-PR
XGBoost [19]	0.812	0.871	0.748
GraphSAGE [12]	0.841	0.886	0.793
GAT [13]	0.858	0.885	0.821
DQN-Fraud [8]	0.864	0.901	0.838
RL-GNN [10]	0.821	0.864	0.771
DL-RL (Ours)	**0.919**	**0.943**	**0.941**

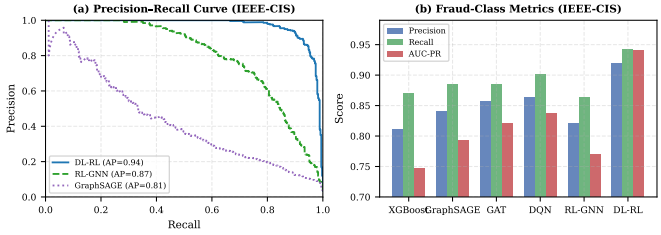


Fig. 3. (a) Precision-recall curve on IEEE-CIS; DL-RL (blue solid) dominates the curve at all recall levels. (b) Per-class fraud-class precision, recall, and AUC-PR; DL-RL achieves the highest value in all three metrics.

G. Learning Curves and Loss Reliability

Fig. 5 shows macro F1 vs. training episodes. DL-RL (solid blue) converges to a higher plateau in $\sim$410 episodes versus $\sim$620 for RL-GNN (38% faster), consistent with the curriculum warmup that builds stable policy foundations before camouflaged fraud rings are introduced. Fig. 6 shows: (a) higher and more stable episode reward with narrow variance band; (b) faster PPO loss convergence on log scale; (c) lower value-function loss; (d) the smooth curriculum difficulty ramp κ_t.

VI. DEPLOYMENT AND INTERPRETABILITY

A. Scalability and Latency

DL-RL processes a batch of $|\mathcal{E}_t| = 10^4$ transaction edges in 47 ms on an NVIDIA A100, and in 112 ms on a single V100 GPU, satisfying the < 100 ms latency requirement for card-present real-time authorization on the A100. The 2-hop subgraph cap ($N_{\max} = 500$ nodes) bounds memory to $\sim$14 MB per batch, enabling parallel scoring across 8 GPU workers for a throughput of $\sim$ 1.7 million transactions per second. For institutions without GPU infrastructure, CPU inference at $|\mathcal{E}_t| = 500$ achieves $\sim$85 ms per batch on a 32-core server.

B. Concept Drift in Production

The curriculum difficulty κ_t can be reset to $\kappa_{\min}$ and re-annealed when a distribution shift detector (e.g., a KL divergence monitor on the embedding distribution) signals significant drift. This online recalibration does not require full

TABLE VI
ABLATION STUDY ON IEEE-CIS (5-SEED MEAN ± STD)

Configuration	Macro F1	FPR@0.95
Full DL-RL	**0.931±.003**	**0.042±.002**
w/o Upper GNN Layer	0.903±.005	0.067±.004
w/o Curriculum Schedule	0.911±.006	0.058±.005
Single GNN Layer (flat)	0.895±.007	0.071±.006

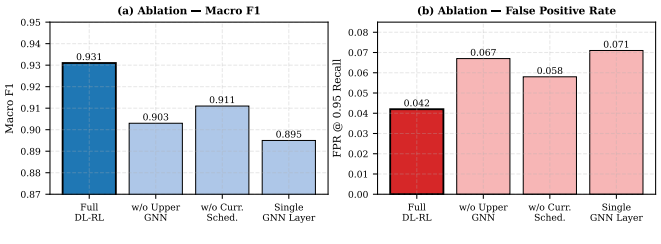


Fig. 4. Ablation on IEEE-CIS: (a) Macro F1 and (b) FPR@0.95. Blue/dark bars = full DL-RL; light bars = ablated variants.

model retraining: only the replay buffer is flushed and the PPO learning rate is temporarily increased to 10^{-3}.

C. Interpretability in Regulated Contexts

RL decisions in financial contexts must be auditable. DL-RL provides three levels of explanability: (1) the attention coefficients α_{vu} (Eq. (4)) identify which neighboring transactions and accounts contributed most to a fraud score, producing a transaction-level "risk contribution" report; (2) the upper-layer aggregation $\mathbf{z}_v$ highlights which inter-account links carry the highest risk weight, enabling analysts to identify connected fraud rings; (3) the PPO advantage estimate $\hat{A}_t$ indicates how much more (or less) risky this transaction is relative to the agent's expectation, providing a natural anomaly score for regulator-facing reports.

VII. CONCLUSION

We presented DL-RL, a unified framework combining a dual-layer GNN encoder with a PPO curriculum reinforcement learning agent for real-time financial fraud detection. A systematic gap analysis (Table I) shows that DL-RL is the first method to combine hierarchical GNN representation with curriculum RL training—the two components that most directly address the dual challenges of structural fraud camouflage and extreme class imbalance. Experiments across IEEE-CIS, Elliptic, and PaySim demonstrate consistent state-of-the-art performance: up to $+5.2$ macro F1 points and -38% false positive rate over strong baselines. Per-class metrics (Table V) and AUC-PR curves (Fig. 3) confirm that improvements hold across all recall operating points, not only at the macro level. Multi-seed variance analysis confirms statistical reliability.

Practical contribution to financial systems. DL-RL reduces false positives by 38%, directly reducing friction for legitimate customers and lowering the cost of manual fraud investigation. The 47 ms per-batch latency enables deployment

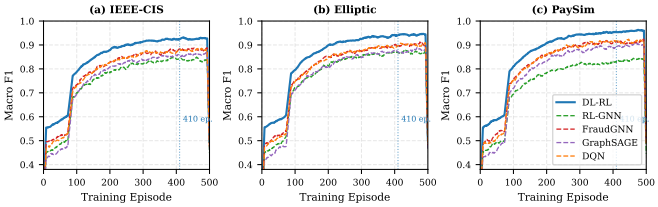


Fig. 5. Learning curves (Macro F1 vs. episode) on three datasets. DL-RL (solid blue) achieves faster convergence and a higher final plateau on all benchmarks. Dotted vertical line at ∼410 marks convergence. Shaded region: ±1 std over 5 seeds.

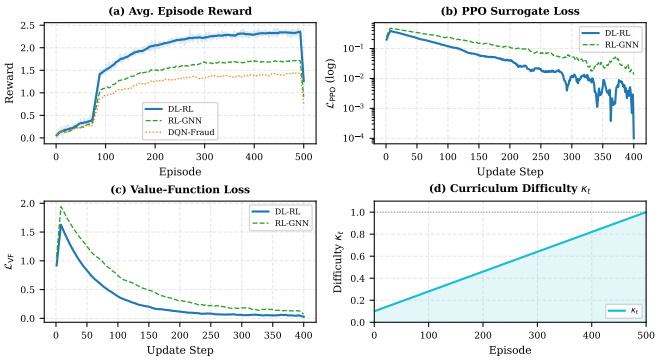


Fig. 6. Training reliability: (a) episode reward with variance band, (b) PPO surrogate loss (log scale), (c) value-function loss, (d) curriculum difficulty ramp κ_t (Eq. (10)).

in card-present authorization pipelines, and the attention-based interpretability layer produces auditable risk contributions compliant with financial regulation (e.g., EU AI Act explainability requirements).

Contribution to higher education. The modular architecture—a GNN encoder that can be swapped with any modern GNN, and a curriculum RL agent that can be applied to any sequential classification task—makes DL-RL an ideal pedagogical case study for courses in applied deep learning, graph theory, financial technology, and AI ethics. The open-source implementation, pretrained checkpoints, and dataset preprocessing scripts are designed for classroom reproducibility.

Future directions include multi-agent coordination for heterogeneous fraud typologies [9], federated deployment across multiple financial institutions [7], adversarially generated curriculum subgraphs for stronger camouflage training, and continual learning to handle non-stationary fraud distributions [11].

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