1 Related Work: Dataset-Specific Performance Analysis

1.1 European Credit Card Dataset (Kaggle/IEEE-CIS) Studies

The European credit card fraud dataset (284,807 transactions, 0.172% fraud rate) serves as the primary benchmark in fraud detection research. Multiple studies have evaluated ML/DL approaches on this exact dataset, providing direct performance comparisons.

1.1.1 Deep Learning Approaches

Qayoom et al. (2024) [1] achieved **97.10% accuracy** using Deep Q-Network with 30-transaction history analysis on the European dataset. Their DQN approach utilized Z-score calculations over previous transactions with reward-based learning.

Benchaji et al. (2021) [2] implemented attention mechanism with LSTM recurrent networks on the same European dataset, achieving: - **96.72% accuracy** - **98.85% precision** - **91.91% recall**

Esenogho et al. (2022) [3] compared multiple algorithms on the European dataset, with LSTM ensemble achieving **89% AUC**. Their study included SVM, MLP, Decision Trees, AdaBoost, and LSTM variants.

1.1.2 Tree-Based Methods Performance

Randhawa et al. (2018) [4] evaluated 12 different algorithms on the European dataset: - **AdaBoost with majority voting**: Perfect 1.0 MCC score on financial institution subset - **Random Forest**: 96% accuracy with 98.9% AUC - Stability verified with 30% noise injection: 0.942 MCC score

Tanouz et al. (2021) [5] applied multiple ML algorithms on the same Kaggle European dataset: - **Random Forest**: **96.77% accuracy** (highest among traditional methods) - Logistic Regression, Naive Bayes, Decision Trees also evaluated with lower performance

1.1.3 Hybrid and Ensemble Methods

Alfaiz & Fati (2022) [6] implemented a two-stage approach on the European dataset: - Stage 1: 9 ML algorithms with stratified K-fold cross-validation - Stage 2: 19 re-sampling techniques with top 3 algorithms - **Best result**: AllKNN-CatBoost with **97.94% AUC**, **95.91% recall**, **87.40% F1-score**

Khalid et al. (2024) [7] tested various algorithms on the European dataset: - **Proposed Method 1**: 93.68% accuracy - **Proposed Method 2**: 94.73% accuracy - Compared against SVM, KNN, Random Forest, Logistic Regression

1.1.4 European Dataset Performance Summary

Table 1: European Dataset Performance Summary

Method	Accuracy	AUC/F1	Precision	Recall	Reference
DQN (Qayoom)	97.10%	-	-	-	[1]
AllKNN-CatBoost	-	97.94% AUC	-	95.91%	[6]
LSTM + Attention	96.72%	-	98.85%	91.91%	[2]
Random Forest	96-96.77%	98.9% AUC	-	-	[4,5]
AdaBoost Ensemble	-	1.0 MCC	-	-	[4]
LSTM Ensemble	-	89% AUC	-	-	[3]

1.2 PaySim Mobile Money Dataset Studies

The PaySim dataset (6.3M transactions, 0.2% fraud rate) provides synthetic mobile money transaction simulation for fraud detection research.

1.2.1 XGBoost-Based Frameworks

Zhou et al. (2022) [8] developed an XGBoost-based framework specifically for PaySim dataset: - XGBoost with under-sampling: Superior performance for class imbalance handling - XGBOD (XGBoost Outlier Detection): Effective for mobile payment fraud patterns - Focus on financial consequences of detection systems rather than pure accuracy

Multiple GitHub implementations [9,10,11] demonstrate various approaches on PaySim: - XGBoost vs LightGBM vs CatBoost comparisons on PaySim synthetic data - 24 million financial records across 5 transaction types (CASH-IN, CASH-OUT, DEBIT, PAYMENT, TRANSFER) - 30-day simulation period (744 hours) replicating typical user behaviors

1.2.2 Traditional ML Performance on PaySim

Lopez Rojas & Axelsson (2016) [12] - Original PaySim creators evaluated basic ML approaches: - Dataset comprises 594,643 transactions over 180 simulated days - Multiple dimensionality reduction techniques (PCA, UMAP, t-SNE) applied - SMOTE technique used for class imbalance handling

Performance gaps identified: Most studies on PaySim focus on methodology rather than reporting specific accuracy metrics, creating a research gap that our RL approach addresses.

1.3 Cross-Dataset Comparative Analysis

1.3.1 Performance Gaps Across Datasets

European Credit Card: Well-established benchmarks with multiple 95–97% accuracy results.
PaySim: Our A2C model achieved near-perfect results with **99.92% accuracy, 100% precision, and 99.7% recall**, establishing a new benchmark for this dataset.
SEC Filings: Excluded in this analysis due to limited standardized results and high variability across studies.

1.3.2 Methodological Limitations in Existing Work

Single-Dataset Focus: Most studies optimize for one specific dataset without cross-domain validation.
Evaluation Metric Inconsistency: Different studies emphasize different metrics (accuracy vs. AUC vs. F1-score vs. MCC).
Class Imbalance Handling: Varied approaches (SMOTE, under-sampling, cost-sensitive learning) make comparison difficult.

1.3.3 Positioning of Our Research

Our research demonstrates competitive and, in the case of PaySim, state-of-the-art performance with the A2C model. By achieving nearly perfect classification results on a widely used synthetic dataset, we highlight the advantages of reinforcement learning in handling extreme imbalance. Furthermore, validating across multiple datasets ensures stronger generalizability than existing studies focused on single domains.

1.4 Performance Context for Our RL Approach

1.4.1 Competitive Positioning

Our RL results demonstrate competitive performance across multiple datasets:

European Credit Card Dataset: - Our A2C (99.92%) exceeds current best results (97.94% AUC, 97.10% DQN accuracy) - Our PPO (96.95%) matches Random Forest performance tier - Our DQN (89.13%) provides sequential learning advantages despite lower accuracy

PaySim Dataset: - Our results address a significant research gap as most PaySim studies lack detailed performance reporting - Cross-domain validation demonstrates generalizability lacking in existing work

1.4.2 Novel Contributions Beyond Performance

Multi-Dataset Validation: Unlike existing studies focusing on single datasets, our approach validates across three distinct fraud domains
Sequential Decision Making: Addresses fundamental limitation of static classification approaches prevalent in literature
Text Integration: SEC filings analysis through LLM processing represents novel approach not present in existing comparative studies

The literature review reveals that while individual datasets have established benchmarks, no existing work provides the comprehensive cross-domain validation and sequential decision-making capabilities demonstrated by our RL approach.

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