\*\*Abstract\*\*

This study presents a hybrid framework combining a \*\*Multi-Layer Perceptron (MLP)\*\* with \*\*Random Forest (RF)\*\* for detecting illicit cryptocurrency transactions, leveraging the strengths of deep feature learning and ensemble-based classification. The MLP generates low-dimensional embeddings from raw transaction data in the \*Elliptic Dataset\*, capturing complex nonlinear patterns, while the Random Forest classifier utilizes these embeddings to improve detection performance. The hybrid model is evaluated on two feature sets: \*\*transaction-only (TX)\*\* and \*\*transaction + aggregated (TX+AGG)\*\* features, demonstrating its versatility and robustness across different data representations.

\*\*Why MLP in the Hybrid Model?\*\*

1. \*\*Nonlinear Feature Learning\*\*: Cryptocurrency transaction data often exhibits complex, nonlinear relationships (e.g., temporal patterns, address clustering, and transaction flow dynamics). MLPs, with their deep architecture and activation functions (e.g., ReLU), excel at modeling these intricate patterns, which simpler models like Random Forest alone cannot capture effectively.

2. \*\*Dimensionality Reduction\*\*: The MLP compresses the high-dimensional raw transaction data (166+ features) into a compact, lower-dimensional embedding space (32 features). This reduces noise, eliminates redundancy, and focuses on the most discriminative features, improving the downstream classifier's performance.

3. \*\*Hierarchical Representation Learning\*\*: MLPs learn hierarchical representations of data, enabling them to detect subtle fraud signatures (e.g., cyclic transactions, sudden fee spikes, or unusual transaction velocities) that are often missed by traditional models.

4. \*\*Adaptability to Imbalanced Data\*\*: The MLP’s ability to learn robust representations helps mitigate the challenges of class imbalance (common in fraud detection) by focusing on the most relevant features for distinguishing illicit transactions.

\*\*Results\*\*

- \*\*With TX+AGG Features\*\*: The hybrid model achieves \*\*97.63% accuracy\*\*, \*\*93.88% precision\*\*, \*\*80.97% recall\*\*, and \*\*86.95% F1-score\*\*.

- \*\*With TX Features Only\*\*: The hybrid model achieves \*\*97.86% accuracy\*\*, \*\*95.98% precision\*\*, \*\*81.52% recall\*\*, and \*\*88.16% F1-score\*\*.

Notably, precision surpasses standalone Random Forest and MLP baselines by \*\*5–10%\*\*, highlighting its effectiveness in minimizing false positives—a critical metric for financial institutions.

### \*\*Key Innovations\*\*

- \*\*Dimensionality Reduction\*\*: The MLP compresses high-dimensional transactional features into 32 interpretable embeddings, preserving discriminative patterns while eliminating redundancy.

- \*\*Class Imbalance Mitigation\*\*: Stratified sampling during train-test splits ensures representative inclusion of rare illicit transactions (1:10 class ratio).

- \*\*Hybrid Synergy\*\*: MLP’s nonlinear embeddings empower Random Forest to model complex relationships without sacrificing interpretability and ensemble-based robustness.

### \*\*Why This Hybrid on the Elliptic Dataset?\*\*

The Elliptic Dataset’s transaction graph structure contains intricate temporal and topological patterns (e.g., money laundering chains). While Random Forest alone struggles with high-dimensional data and nonlinearities, the MLP’s embeddings provide a rich, compact representation of these patterns, enabling the hybrid model to achieve state-of-the-art precision for crypto fraud detection.

This framework balances performance and practicality, achieving high precision and computational efficiency while remaining scalable across evolving transaction networks.

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### \*\*Comparative Advantage Over Previous Models\*\*

While the earlier \*\*DT + MLP\*\* and \*\*LR + MLP\*\* hybrids prioritized interpretability and computational efficiency, \*\*RF + MLP\*\* excels in precision and robustness. The 95.98% precision (with TX features) and 93.88% precision (with TX+AGG features) significantly reduce false positives, critical for minimizing operational costs in fraud investigation teams. The marginal trade-off in recall (81.52% vs. 86.14% in LR+MLP) is offset by the model’s ability to handle high-dimensional data and nonlinear relationships more effectively.

For implementation details, refer to the [Google Colab notebook](https://colab.research.google.com/drive/1V3EtyJBQh69FUGzrJEgcGP1W639I6zPI?usp=sharing).