\*\*Abstract\*\*

This study proposes a hybrid framework integrating a \*\*Multi-Layer Perceptron (MLP)\*\* with a \*\*Graph Convolutional Network (GCN)\*\* for detecting illicit cryptocurrency transactions, combining deep feature learning with graph-structured relational analysis. The MLP generates low-dimensional embeddings from raw transaction data in the \*Elliptic Dataset\*, capturing nonlinear patterns, while the GCN leverages these embeddings to model topological relationships between transactions, enhancing detection of illicit activities.

\*\*Why MLP in the Hybrid Model Over Standalone GCN?\*\*

1. \*\*Nonlinear Feature Learning\*\*: Cryptocurrency transaction data exhibits complex nonlinear interactions (e.g., temporal sequences, address clustering). MLPs, with their deep architecture and activation functions (e.g., ReLU), excel at modeling these patterns, which standalone GCNs struggle to capture without robust feature preprocessing.

2. \*\*Dimensionality Reduction\*\*: The MLP compresses high-dimensional raw transaction data (166+ features) into a compact, lower-dimensional embedding space (32 features), reducing noise and redundancy. This allows the GCN to focus on propagating meaningful signals through the transaction graph.

3. \*\*Hierarchical Representation Learning\*\*: MLPs detect subtle fraud signatures (e.g., cyclic transactions, anomalous fee structures) through hierarchical feature abstraction, providing enriched inputs for the GCN’s graph-based analysis.

4. \*\*Class Imbalance Mitigation\*\*: MLP embeddings prioritize discriminative features for illicit transactions, countering dataset imbalance (1:10 illicit-to-licit ratio) and improving GCN’s ability to identify rare fraud patterns.

\*\*Results\*\*

The hybrid model achieves \*\*91.27% accuracy\*\*, \*\*83.30% precision\*\*, \*\*91.27% recall\*\*, and \*\*87.10% F1-score\*\*, outperforming standalone GCN and MLP baselines. Notably, recall matches accuracy (91.27%), indicating strong coverage of illicit transactions, while maintaining robust precision (83.30%)—a critical balance for minimizing false negatives in fraud detection.

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

- \*\*Feature-Graph Synergy\*\*: MLP embeddings enhance GCN’s ability to model transaction graphs by providing noise-reduced, semantically rich node features.

- \*\*Edge-Aware Training\*\*: The GCN propagates embeddings through the transaction graph, capturing money laundering chains and address clustering patterns missed by non-graph models.

- \*\*Stratified Sampling\*\*: Ensures representative inclusion of illicit transactions during training, addressing class imbalance.

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

The Elliptic Dataset’s graph structure encodes critical relational data (e.g., transaction flows between addresses). While standalone GCNs underperform on raw features due to noise and high dimensionality, the MLP’s embeddings enable the GCN to focus on graph topology, improving detection of illicit subgraphs (e.g., mixer services, darknet market transactions).

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

- \*\*Recall vs. Precision Trade-Off\*\*: The hybrid achieves \*\*91.27% recall\*\* (vs. 73.25% in GAT+MLP), critical for minimizing false negatives in high-stakes fraud detection, while maintaining \*\*83.30% precision\*\* (vs. 81.69% in GAT+MLP).

- \*\*F1-Score Superiority\*\*: The \*\*87.10% F1-score\*\* surpasses GAT+MLP (77.24%) and standalone DNN (80.91%), demonstrating balanced performance.

- \*\*Graph Topology Utilization\*\*: Unlike MLP+RF/LR hybrids, this model explicitly leverages transaction graph structure, capturing relational fraud patterns (e.g., multi-hop money laundering).

For implementation details, refer to the [Google Colab notebook](https://colab.research.google.com/drive/1rI-FwXLU1GlwQR40s9WCkPUv1CuOf9VA?usp=sharing).

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### \*\*Practical Implications\*\*

The hybrid’s high recall makes it ideal for initial fraud screening, where missing illicit transactions (false negatives) is costlier than manual review of false positives. Its graph-aware design is particularly suited for blockchain analytics platforms tracking transaction flows across decentralized networks.