\*\*Abstract\*\*

This study explores the application of a \*\*Deep Neural Network (DNN)\*\* for detecting illicit cryptocurrency transactions, leveraging its ability to model complex, nonlinear relationships in the \*Elliptic Dataset\*. The DNN is evaluated on two feature sets: \*\*transaction-only (TX)\*\* and \*\*transaction + aggregated (TX+AGG)\*\* features, demonstrating its adaptability to different data representations. While the DNN achieves competitive performance, its integration with MLP embeddings in previous hybrid models highlights the unique advantages of combining deep feature learning with traditional classifiers.

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

1. \*\*Nonlinear Feature Learning\*\*: While DNNs are powerful, they often require extensive tuning and computational resources. MLPs, as a simpler variant of DNNs, provide a more efficient way to generate low-dimensional embeddings that capture complex patterns without the overhead of deep architectures.

2. \*\*Dimensionality Reduction\*\*: The MLP compresses 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 downstream classifier performance. In contrast, standalone DNNs struggle with high-dimensional data without explicit dimensionality reduction.

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. This is particularly useful when combined with classifiers like Random Forest or Logistic Regression.

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. Standalone DNNs, while powerful, often require additional techniques (e.g., oversampling, weighted loss functions) to handle imbalanced data effectively.

\*\*Results\*\*

- \*\*With TX+AGG Features\*\*: The standalone DNN achieves \*\*96.22% accuracy\*\*, \*\*79.79% precision\*\*, \*\*82.07% recall\*\*, and \*\*80.91% F1-score\*\*.

- \*\*With TX Features Only\*\*: The standalone DNN achieves \*\*94.14% accuracy\*\*, \*\*71.89% precision\*\*, \*\*65.57% recall\*\*, and \*\*68.58% F1-score\*\*.

While the DNN performs well on aggregated features, its performance drops significantly on non-aggregated features, highlighting the importance of feature engineering and dimensionality reduction—areas where MLP-based hybrid models excel.

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

- \*\*Dimensionality Reduction\*\*: MLP-based hybrid models compress 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 traditional classifiers (e.g., Random Forest, Logistic Regression) to model complex relationships without sacrificing interpretability and computational efficiency.

### \*\*Why MLP Over Standalone DNN on the Elliptic Dataset?\*\*

The Elliptic Dataset’s transaction graph structure contains intricate temporal and topological patterns (e.g., money laundering chains). While standalone DNNs struggle with high-dimensional data and require extensive tuning, MLP-based hybrid models provide a more efficient and interpretable solution. By generating compact embeddings, the MLP enables downstream classifiers to achieve state-of-the-art precision and recall 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 Standalone DNN\*\*

While the standalone DNN achieves competitive performance on aggregated features (96.22% accuracy, 79.79% precision), its performance drops significantly on non-aggregated features (94.14% accuracy, 71.89% precision). In contrast, MLP-based hybrid models consistently achieve higher precision and recall across both feature sets, demonstrating their robustness and adaptability.

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