A Multi-Feature Fusion Based Method for Detecting Illicit Bitcoin Transactions

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Abstract

Bitcoin's pseudo-anonymity facilitates illicit activities[1] such as money laundering, terrorist financing, and illegal goods trading, posing significant challenges to **blockchain regulation and digital forensics.**

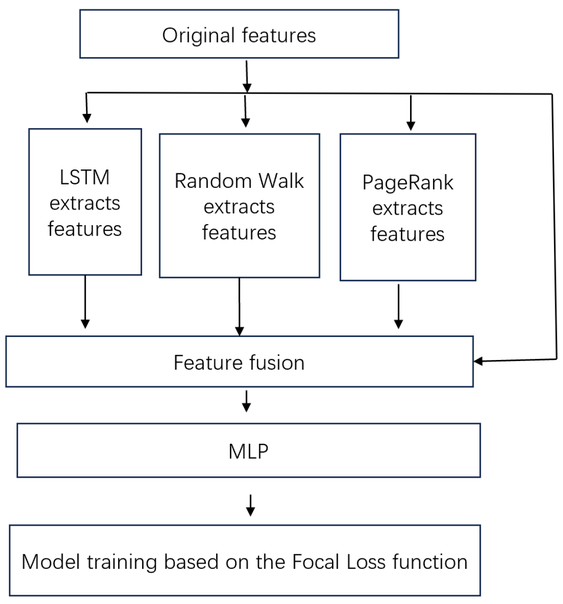
To address limitations in existing detection methods—particularly **insufficient feature representation and extreme class imbalance**—this work proposes **a multi-feature fusion framework for illegal Bitcoin transaction detection**.

The model integrates **traditional transaction attributes with temporal features extracted by LSTM**[2], **structural proximity features derived from Random Walks**[3], and **global importance indicators based on PageRank**[4], enabling a **comprehensive characterization of transaction behaviors**.

Experiments conducted on the Elliptic dataset[5] demonstrate that the proposed approach achieves **competitive performance under highly imbalanced conditions,** outperforming several mainstream graph-based and neural network baselines in terms of detection effectiveness.

The proposed framework provides practical support for **blockchain-based digital forensics and law enforcement investigations**, particularly in **prioritizing suspicious addresses, tracing illicit fund flows, and assisting investigators during early-stage case screening**. By improving detection performance under severe class imbalance, the approach helps **reduce manual analysis effor**t and **enhance investigative efficiency** in real-world cryptocurrency crime cases.

Methodology

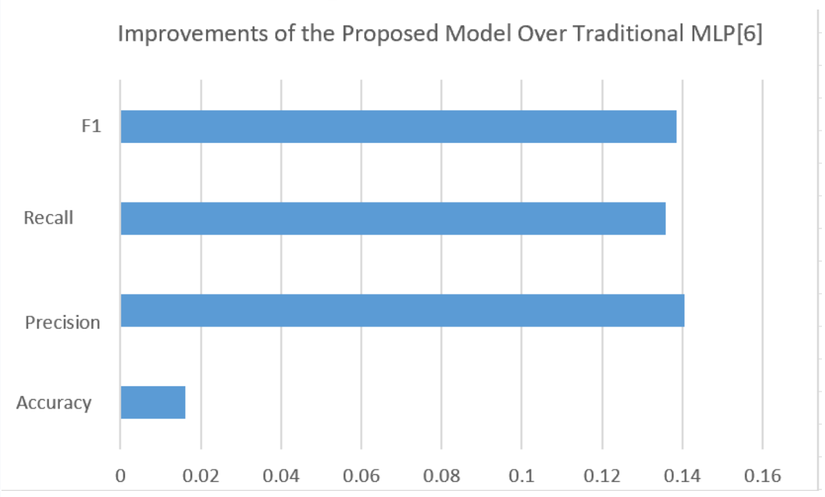


Experimental Settings

Dataset: Elliptic Bitcoin Dataset (4,545 illicit / 42,019 licit)
Data split: time-ordered, 34 train / 15 test snapshots (70/30)
Backbone: MLP (1 hidden layer, 100 units)
Training: 100 epochs, learning rate = 0.01
Framework: PyTorch
Metrics: Accuracy, Precision, Recall, F1-score

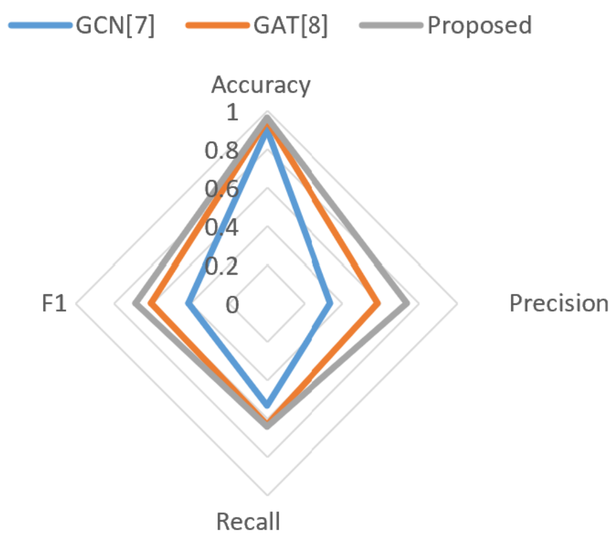
Experimental Results

1.Performance Comparison



2.Feature Combination Performance

3.Comparison with Mainstream Models



Conclusion

The proposed **multi-feature fusion** method, combining **LSTM**, **Random Walk**, and **PageRank** features, significantly enhances **illegal Bitcoin transaction detection**.

By incorporating **Focal Loss** to address **class imbalance**, the model demonstrates an exceptional ability to identify **illegal transactions** amidst the overwhelming majority of legal transactions.

Experimental validation shows that our method outperforms **traditional models** (MLP) and **graph-based models** (GCN, GAT), achieving the best overall performance in terms of accuracy, precision, recall, and F1 score.

Future Work

Further improvements can be made in **feature selection** and **model optimization** to enhance the detection accuracy in larger and more complex datasets.

The approach could be applied to other cryptocurrencies like **Ethereum** and **Tron**, expanding its applicability to **multi-cryptocurrency monitoring systems**.

Real-time monitoring systems can be developed using this approach to enable **proactive detection** of illicit transactions in Bitcoin and other digital currencies.

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