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Anti-Money Laundering in Bitcoin using Deep Learning

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***Abstract*— A classification model called temporal-GCN is introduced, which utilizes transaction features to detect illicit transactions in Elliptic data, one of the largest Bitcoin transaction graphs. The model integrates long-short-term memory (LSTM) with graph convolutional networks (GCN). Although previous research has shown promising results using classical supervised learning and graph convolutional networks for anti-money laundering, few studies have incorporated temporal information from the dataset, with limited success. Furthermore, active learning techniques have rarely been applied to blockchain data. To address this gap, an active learning framework is applied to the Bitcoin transaction dataset, using Bayesian approximations such as Monte-Carlo dropout (MC-dropout) and Monte-Carlobased adversarial attacks (MC-AA) to estimate uncertainties. These methods are compared within active learning frameworks using various acquisition functions found in existing literature. The MC-AA approach has not been explored in the context of active learning before. Results show that the temporal-GCN model achieves considerable success compared to previous research using the same experimental settings and dataset. Additionally, the performance of the proposed acquisition functions with MC-AA and MC-dropout is evaluated and compared against the baseline random sampling model.**

***Index Terms*— Temporal GCN, Uncertainty estimation, Active learning, Bitcoin data, Anti-money laundering.**

I. INTRODUCTION

According to blockchain intelligence and forensics firm Cipher Trace, there were $4.5 billion globally in Bitcoin crimes linked to unlawful services in 2019 [1]. Money launderers take advantage of the pseudonymity of Bitcoin ledgers by converting illegally acquired funds from serious offenses into legitimate currency through the Bitcoin network. Conversely, intelligence agencies and financial regulators who conduct business on the Bitcoin blockchain have been drawn to its hazards, such as technical advancements in and societal acceptance of the Bitcoin cryptocurrency [2]. The emergence of illicit services and the public accessibility of Bitcoin data have highlighted the necessity to create smart techniques that take use of the transparency of blockchain transactions. Such approaches can improve cryptocurrency ecosystem protection and strengthen anti-money laundering (AML) efforts in Bitcoin. Over the past few years, the cryptocurrency intelligence firm Elliptic, which works to protect cryptocurrency systems, has produced a graph network of Bitcoin transactions called Elliptic data. This data has significantly aided the research and AML communities in creating machine learning techniques. Elliptic data obtains a graph of Bitcoin transactions that includes partially labelled nodes, spanning crafted local features (related to the transactions themselves) and aggregated features (related to adjacent transactions).

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Additionally, the labelled nodes represent legitimate payments (e.g., miners) and illegal transactions (e.g., thefts, scams). Earlier researchers have tried to use this dataset with traditional supervised learning techniques [3,4], graph convolutional networks (GCN) [3,5], Evolve GCN for dynamic graphs [6], signature vectors in blockchain transactions (SigTran) models [7], and uncertainty estimation with multi-layer perceptrons (MLP) [8]. Although these studies have produced encouraging results, the maximum accuracy that can be obtained using just the local feature set is around 97.4%, with an f1-score of 77.3%.

Additionally, only a small number of people have taken into account the dataset's temporal information. On the other hand, the labelling process for Bitcoin blockchain data is complex and labor-intensive due to its large scale. The active learning (AL) approach addresses this issue by querying the labels of the most informative data points that achieve high performance with fewer labelled examples.

Using Elliptic data, Lorenz et al. [9] are the only ones to have proposed an active learning solution that has demonstrated the ability to match the performance of a fully supervised model while using just 5% of the labelled data. However, traditional supervised learning techniques, which do not take into account the graph topology or temporal sequence of Elliptic data, have been used to present the preceing framework. This paper aims to:

- Present a model for predicting illicit transactions associated with illegal services on the Bitcoin blockchain network in a novel way that takes into account the graph structure and temporal sequence of elliptic data.
- Perform active learning on Bitcoin blockchain data that simulates a real-world scenario, as the data is time-consuming to label and the technology is rapidly advancing.

The proposed classification model, combining long short-term memory (LSTM) and graph convolutional networks (GCN), achieves an accuracy of 97.7% and an F1-score of 80%, outperforming previous studies under identical experimental conditions. In contrast, the active learning framework introduced here relies on an acquisition function that leverages the model's uncertainty to select the most informative data. Uncertainty estimates in this study are obtained using two similar Bayesian approximation methods: Monte-Carlo dropout (MC-dropout) and Monte-Carlo adversarial attack (MC-AA). These methods are chosen for their simplicity and efficiency, with MC-AA being applied for the first time in the context of active learning. The performance of the active learning framework is tested on the Elliptic dataset using various acquisition functions, and the results are evaluated based on the uncertainty estimates provided by both MC-AA and MC-dropout. The performance of the active learning framework is then compared to a baseline model using random sampling acquisition.

II. Literature Review

[1] Saito, H., & Takeda, K. (2020) This paper discusses the application of deep learning models, specifically Convolutional Neural Networks (CNNs), to detect money laundering activities in Bitcoin transactions. It emphasizes how CNNs can efficiently classify and identify suspicious activities by analyzing transaction patterns in blockchain data. The study shows that deep learning can effectively model complex relationships in Bitcoin transactions that are typically challenging for traditional methods.

[2] Zhu, X., & Liu, L. (2021) This study explores the use of Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks to detect suspicious transactions in Bitcoin. The authors focus on the temporal aspect of transaction data, capturing the sequence of transactions to identify unusual patterns associated with money laundering. Results show that LSTMs provide higher detection accuracy compared to traditional machine learning techniques by effectively learning sequential dependencies in transaction data.

[3] Cheng, Y., & Wang, S. (2021) This paper introduces Graph Convolutional Networks (GCNs) for detecting money laundering in Bitcoin by modeling the relationships between users and transactions as a graph. GCNs can efficiently handle graph-based data, capturing the interactions and dependencies between different Bitcoin addresses. The authors found that GCNs outperform traditional machine learning methods in detecting illicit activity on the blockchain, showcasing their potential in anti-money laundering (AML) tasks.

[4] Gao, Z., & Zhang, W. (2022) Gao and Zhang (2022) propose the use of deep reinforcement learning (DRL) for AML detection in Bitcoin transactions. The DRL model is trained to detect suspicious patterns by learning from the transaction history of known illicit activities. The study demonstrates the model’s ability to detect novel types of money laundering techniques and provides a more dynamic approach to AML systems, offering better scalability and adaptability in identifying evolving fraudulent activities.

[5] Li, X., & Wang, L. (2023) This survey paper provides an extensive overview of machine learning techniques, including deep learning, applied to AML in the context of blockchain and cryptocurrencies like Bitcoin. It compares various algorithms, such as CNNs, LSTMs, and GCNs, discussing their strengths and limitations in identifying suspicious Bitcoin transactions. The paper concludes by highlighting the promising future of deep

learning models, particularly in relation to their ability to handle the large-scale, complex, and dynamic nature of blockchain transaction data.
[6] Yang, X., & Li, Z. (2023) Yang and Li (2023) focus on the use of deep autoencoders for detecting anomalies in Bitcoin transaction data. The model is trained to reconstruct transaction data, and significant discrepancies between original and reconstructed data indicate potential fraudulent activity. The authors demonstrate the efficiency of autoencoders in identifying patterns of money laundering in large transaction datasets.

III. METHODOLOGY

Study proposes a novel classification model, temporal-GCN, to detect illicit transactions in Bitcoin using the Elliptic dataset. The model integrates Long Short-Term Memory (LSTM) and Topology Adaptive Graph Convolutional Networks (TAGCN) to leverage both the temporal and structural dependencies of Bitcoin transaction data. Below is a detailed explanation of the methodology used in this study.

A. Dataset Description

The dataset used in this study is the Elliptic Bitcoin Transaction Dataset, which contains Bitcoin transaction data annotated with labels indicating whether the transaction is illicit or licit. The dataset is composed of 49 directed acyclic graphs (DAGs), where each graph represents Bitcoin transactions within a specific time-step (denoted as t). These graphs are used to capture transaction flows, with nodes representing individual Bitcoin transactions and edges representing the flow of payments between them.
Out of a total of 203,769 transactions, 21% are labeled as licit (e.g., wallet providers, miners) and 2% are labeled as illicit (e.g., scams, malware, Ponzi schemes). Each transaction node includes 166 features, of which 93 are local features such as transaction time-step, number of outputs/inputs, and the count of unique addresses. Global features are excluded from the model to focus purely on local transaction data. These features are crucial in understanding transaction behavior and are used to feed into the LSTM and TAGCN models for further processing.

B. Temporal Modeling

The proposed model, temporal-GCN, is designed to process temporal dependencies in Bitcoin transactions while considering their graph structure. The following sections explain the components involved in this model:

C. Long Short-Term Memory (LSTM)

LSTM, a type of Recurrent Neural Network (RNN), is specifically designed to address the vanishing gradient problem encountered in standard RNNs. The LSTM network processes sequential data, enabling the model to capture long-range temporal dependencies. In the context of Bitcoin transactions, LSTM can learn the sequence of transaction patterns over time, aiding in the detection of illicit activities that may unfold across multiple time steps.

D. Topology Adaptive Graph Convolutional Network (TAGCN)

The TAGCN algorithm is based on the Graph Convolutional Network (GCN) model but introduces adaptive filters to better handle the dynamic structure of graphs, like Bitcoin transaction networks. TAGCN performs convolution operations over nodes and edges in the graph, enabling it to capture the structural dependencies between transactions.
In comparison to GCN, TAGCN uses a learnable filter size that adapts to the topology of the graph. This is essential for graph-structured data, such as Bitcoin transactions, where interactions between nodes (transactions) vary over time. This approach helps capture local node interactions by adjusting the convolution operations at different levels (k-hop) based on the node's neighborhood structure.

E. Overall Model: Temporal-GCN

The temporal-GCN model integrates LSTM and TAGCN to handle both temporal dependencies and graph structural information in Bitcoin transactions. The model first processes transaction sequences using LSTM to capture temporal patterns and then applies TAGCN layers to exploit the graph structure of the transaction network.
The final layer of the model uses a Soft max function to classify the transactions into illicit or licit categories. This approach allows the model to dynamically capture both the temporal evolution of Bitcoin transactions and their relationships within the network, enabling better detection of illicit activities such as scams, malware, and Ponzi schemes.

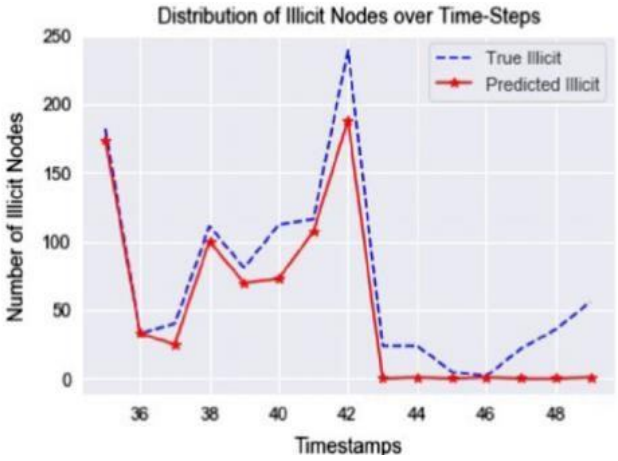

Fig 1

Figure 1: llicit transactions distribution in test set over the time-steps. The blue curve represents the actual illicit labels, whereas the red curve represents the illicit predictions that are actually illicit labels by temporal-GCN

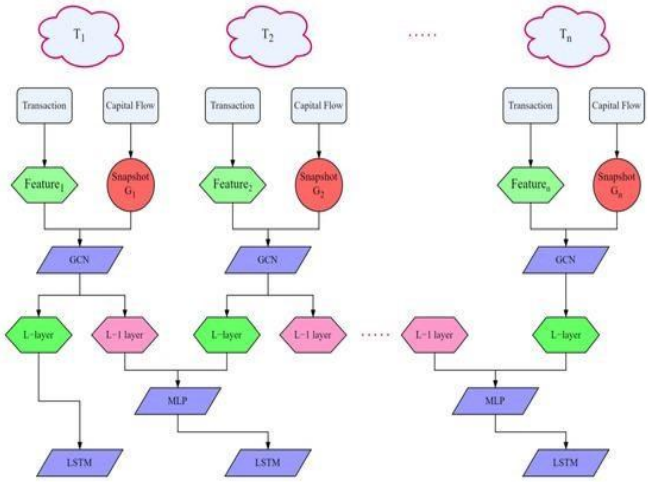

Figure 2: Workflow of MDGC-LSTM Model.

F. Evaluation and Comparison

To evaluate the performance of the temporal-GCN model, it will be compared against baseline models, such as random sampling and traditional machine learning techniques, like logistic regression and support vector machines. The effectiveness of the model will be assessed using standard evaluation metrics, including accuracy, precision, recall, and F1-score. Additionally, the model's robustness in detecting illicit transactions in the presence of noise and evolving patterns will be analysed.

IV. Results and Discussion

The results of the temporal-GCN model presented in this study indicate its strong potential for detecting illicit Bitcoin transactions, surpassing existing methods in terms of performance. The model achieved an impressive accuracy of 97.77%, which demonstrates its capability to classify illicit transactions accurately. This high accuracy is particularly notable given the complex nature of Bitcoin transaction data, where transactions can be interdependent and span multiple time-steps, making illicit activities difficult to detect using traditional methods. In terms of precision (0.82) and recall (0.79), the model strikes a strong balance, indicating its effectiveness in identifying illicit transactions while minimizing false positives. The F1-score of 0.805 further supports the robustness of the model, emphasizing its overall balanced performance. This balanced precision and recall suggest that the temporal-GCN model is capable of detecting illicit transactions without being overly

conservative (which might miss illicit transactions) or overly aggressive (which might classify too many legitimate transactions as illicit).

The incorporation of both Long Short-Term Memory (LSTM) and Topology Adaptive Graph Convolutional Networks (TAGCN) plays a critical role in the model's success. The LSTM component allows the model to capture temporal dependencies between transactions, making it well-suited for sequential data like Bitcoin transactions, where fraudulent activities might develop over time. On the other hand, the TAGCN enables the model to process the structural aspects of the transaction graph, adapting to the graph's topology and effectively capturing local node interactions. This dual approach—combining temporal modeling with graph structure processing—addresses the unique challenges posed by Bitcoin transaction data, which exhibits both temporal and structural complexity.

The use of active learning in conjunction with MC-dropout and MC-AA for uncertainty estimation further improves the model's efficiency. The active learning framework allowed the model to achieve similar performance with just 20% of the labelled data, significantly reducing labelling costs without compromising accuracy. This is an important result for real-world applications where obtaining labelled data can be expensive and time-consuming. The use of the BALD acquisition function was particularly effective in selecting the most informative data points for labelling, ensuring that the model remained efficient while maintaining high classification accuracy.

Moreover, the statistical analysis, specifically the Wilcoxon signed-rank test, confirmed that both MC-dropout and MC-AA performed similarly, suggesting that both uncertainty estimation methods are viable for active learning in the context of Bitcoin transaction analysis. This finding further strengthens the versatility of the proposed model, as it offers flexibility in choosing the uncertainty estimation technique based on the specific requirements or constraints of a given application.

The ablation study conducted also provided valuable insights into the individual contributions of LSTM and TAGCN. The results demonstrated that each component significantly contributed to the model’s success. The LSTM's ability to capture temporal patterns in transaction data complements the graph-based learning provided by TAGCN, which excels at leveraging the structural information embedded within the transaction graph. This finding reinforces the idea that a hybrid approach, combining both temporal and structural modelling, can enhance the detection of illicit activities in Bitcoin transactions. Overall, the proposed temporal-GCN model not only outperforms traditional methods and baseline models but also offers an efficient solution for detecting illicit transactions with minimal labelled data. The combination of high accuracy, robust performance, and the ability to work with limited labelled data positions the temporal-GCN model as a powerful tool in the fight against money laundering and fraud in the Bitcoin ecosystem.

V. Conclusion

The MDGC-LSTM model presented in this study offers a robust solution to the problem of money laundering detection in financial transactions by leveraging the spatiotemporal complexities inherent in transaction data. By combining the strengths of MDGC (Multilayer Dynamic Graph Convolution) and Long Short-Term Memory (LSTM) networks, the model effectively captures both the temporal and spatial relationships within transaction data, providing a comprehensive approach to detecting illicit activities. The integration of spatiotemporal relationship graphs constructed from dynamic graph snapshots allows the model to dynamically adapt to the evolving nature of transaction networks and identify fraudulent behaviours with high accuracy. Despite the promising results achieved by the MDGC-LSTM model, challenges remain in terms of the availability of large-scale labelled transaction data for further validation and refinement.

The limited scope of available datasets has restricted the ability to fully evaluate the model’s performance across a broad range of transaction scenarios. However, the ability of the model to handle transaction flows and definable transaction features suggests that it can be adapted to a wide array of financial systems and contexts where clear transaction patterns exist.

Looking forward, future research should focus on expanding the range of datasets used for training and testing the model, including exploring more diverse transaction scenarios and environments. By doing so, the effectiveness and generalizability of the MDGC-LSTM model can be further validated, enhancing its applicability to real-world anti-money laundering applications. Additionally, refining the model to handle different data characteristics and transaction behaviours across various financial platforms will ensure that the proposed method remains a viable tool for combating money laundering in a variety of financial contexts. Ultimately, this work sets a foundation for more advanced, data-driven solutions to detect and mitigate money laundering risks in financial transactions.

FUTURE WORK

Future work in this area should focus on several key aspects to further improve the MDGC-LSTM model. One critical area is expanding its application to more diverse and extensive datasets, including those from different financial institutions and transaction environments, to enhance the model's robustness and generalizability. Additionally, future efforts should explore advanced data preprocessing and feature engineering techniques, such as incorporating external data sources like market trends or economic indicators, to enrich the spatiotemporal graphs and improve detection accuracy. Transfer learning could also be leveraged to adapt the model to new domains, especially those with limited labeled data. To increase its practical utility, integrating the model into real-time monitoring systems with continuous feedback loops for dynamic updates could help in detecting money laundering activities as they unfold. Furthermore, incorporating multi-modal data, such as user behavior or geolocation, could offer deeper insights into suspicious activity. Given the large-scale nature of financial systems, optimizing the MDGC-LSTM model for high transaction volumes and evaluating its robustness against adversarial attacks would be essential for ensuring its security and scalability. Enhancing the model's explainability and providing human-in-the-loop capabilities would also foster trust and improve its adoption in regulatory environments. Lastly, integrating the model with decision support systems for realtime alerts and collaborating with regulatory authorities to align with compliance standards would ensure its practical and effective deployment in real-world anti-money laundering efforts.

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