Community Detection in Financial Networks for AML Using GNNs

M.S. Minu[1*], S. Eswaran[2], Janisa Ria D[3], V.B. Shreesha[4] and T. Avinash[5]
{ msminu1990@gmail.com[1*], speedypanda45@gmail.com[2], janisariad@gmail.com[3], sha94377@gmail.com[4], avinashtelugu8888@gmail.com[5] }

Assistant Professor, Department of Computer Science and Engineering, SRM Institute of Science & Technology, Ramapuram, Chennai, Tamil Nadu, India[1]
Department of Computer Science and Engineering, SRM Institute of Science and Technology, Ramapuram, Chennai, Tamil Nadu, India[2, 3, 4, 5]

Abstract. Illegal money storing such as financing terrorism, corruption, and organized crime all pose a profound threat to our world economy by laundering money. Anti Money Laundering Protocols fail to keep up with sophisticated methods of scam detection. Using IBM's illicit patterns dataset from Kaggle, this paper investigates a novel approach to AML detection by utilizing machine learning Designed for high-volume transactions in digital economy. The work presented aims to develop and implement machine learning model to prioritize financial transactions for manual investigation, leveraging the IBM AML dataset. Using semi-supervised learning, the model analyzes transaction patterns, sender-receiver profiles, and historical behavior to improve detection accuracy. Additionally, the project explores regulatory frameworks and compliance strategies adopted by key financial agencies to enhance AML effectiveness. The findings aim to provide actionable insights to strengthen existing AML systems and support regulatory compliance. Building on existing literature on automatic detection of financial crimes, this paper also provides recommendations for more efficient and flexible systems for AML work.

Keywords: Graph Neural Network (GNN), Graph Convolutional Network (GCN), Graph Attention Network (GAT), Extreme Gradient Boosting (XGBoost), Anti-Money Laundering (AML).

1 Introduction

Money laundering is a global fraud crime that helps criminals to conceal the source of their unlawfully acquired funds. All banks are required to have an Anti-Money Laundering compliance program. Which use detection mechanisms based on set criteria. The failure to accomplish those operational goals leads to significant false positives and does not meet the more automatic shifts in laundering attempts. Consequently, machine learning and artificial intelligence have turned out to be potent technology in improving the accuracy of detection for AML.

This study creates a data driven AML detection framework from the provided IBM Kaggle synthetic datasets. The dataset contains withdrawal and deposit transactions that have been labelled by known illegal laundering methods through arranged scheme. Collinearity analysis,

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community detection, and cycles detection are used to detect critical transaction patterns suggestive of money laundering.

In the detection of suspicious transactions, Random Forest, Logistic Regression, and XGBoost are usually employed. For Advanced Accuracy, Community Detection Algorithms like Louvain are implemented along with GNNs, used on a large scale because financial transactions are naturally designed as a structure of a network graph, GNN's are used to uncover more complicated and obscure laundering schemes across boundaries of each financial transaction.

A dual graph model is proposed using GCN and GAT for the account data and transaction data respectively along with community detection for the detection of hidden rings and smurfing patterns effectively. These results support the idea that AI driven detection systems for money laundering can be scaled to meet the needs of banks and other financial institutions. This aids in bringing the fight to increasingly advanced, cunning approaches of money laundering strategies.

2 Related Works

Money laundering is a major financial crime that involves disguising illicit funds as legitimate earnings. Traditional AML techniques rely on rule-based systems and machine learning, but they often fail to capture complex transactional relationships. Graph Neural Networks (GNNs) offer an exciting possibility by capitalising on relational structures and improving anomaly detection in financial networks. Zhong Li et al. [1], This project proposes a Multiview graph that has multi level representation learning method called MG-HRL, this is to catch the money laundering groups. Mainly focusing on extracting multi-level representation of transaction subgraphs, user features, and structural features from multiple observational perspectives. Julien Schmidt et al. [2], This project focuses on transactions in the form of directed graph and propose a GNN model for recognition of Transaction laundering. Dawei Cheng et al. [3], This project is built on the idea of deep graph learning, for money laundering detection. Specifically, they design an encoder that focuses on communities which represent the nodes and attribute in transaction graphs for user and give the adjacent gang conduct, then schemes of area-based enhancements to accommodate node with similar transaction features that are aggregated into gangs for downstream detection. Bruno Deprez et al. [4] This project introduces and experiments with a pilot setup to compare and judge the performance of prominent Network analysis methods in a constant setup. It uses the widely popular elliptic dataset. Feature engineering is performed on the datatset along with walk-based methods. Deep learning Graph Neural Networks (DGNN) are used here to perform network analytics.

Martin Jullum et al. [5] This paper showcases that the common approach of not using a non-reported alert in the training of the model can lead to lower results. The same applies to the use of un-investigated transactions. The model in the project was trained using XGBoost to assess the probability that a new transaction should be flagged for AML. Utku Gorkem Ketenci et al. [6] This model implements a feature set using time-series analysis, which works on a double dimensional representation of transactions in financial networks. Random forest is applied here and to tune hyperparameters, a method called simulated strengthening is used. The dataset on which the algorithm is evaluated on is a real banking dataset. Ashwini Kumar et al. [7] This project applies naïve bayes as the machine learning algorithm to detect money laundering. The data analysis and filtering are implemented via R. The accuracy achieved is 81.25%. Anthony Bonato et al. [8] The project mainly combines methods of community detection using the Louvain algorithm and small cycle detection to find the suspicious transactions pattern below the reporting thresholds. This successfully identifies the cycles of transactions that may indicate layering steps in fraud activity. Valuable tool to enhance the AML (Anti Money Laundering) efforts. Xuan Liu et al. [9] This project introduces a way to recognize activities using scan statistics. Its goal is to help financial institutions find suspicious transactions the algorithm is evaluated using data from commercial banks. M. Alkhalili et al. [10] This project performed many experiments using different machine learning algorithms and concluded that SVM outperforms other algorithms. Because the dataset is nonlinear it used the polynomial kernel and got better accuracy for prediction of transaction decisions and the correlation matrix to show relationships.

K Balaji [11] This paper outlines the difficulties of implementing AI, such as improving the effectiveness and caliber of SAR's while solving security and privacy issues with data. This study makes the case that AI's capability to offer collaborative analytics and risk assessments is helpful for developing Anti Money Laundering frameworks and effectiveness of crime prevention. Pavlo Tertychnyi et al. [12] This project gives a case study of Machine Learning behaviour detection done under the incomplete network information available and the ML patterns inaccessibility. Designed a Machine learning detection system that detect group behaviour and meets scalability requirements. Yan Yang et al. [13] This project adopts data mining techniques along with a density-based clustering algorithm to find shady transactions on financial networks. While implementing link analytics to know the threat of fraud. The project uses the transaction data provided by a bank. Dhiman Sharma et al. [14] This project proposed a system for detecting bank fraud using a community detection algorithm which highlights the pattern that will help you find the bank fraud. Neo4j which is a graph database is used for crafting and demonstrating the data. The graph query language used is cypher query. Chih Hua Tai et al. [15] The method uses here proposes a 2-phase model. It applies machine learning in combination with data analysis methods for flagging anomalies from the transaction data. The initial phase focuses on identifying laundering accounts, with generalized purpose. Then, the final phase focuses on only detecting the highly suspicious clusters.

Mark Cheung et al. [16] This paper probes into the compromise involving the graph topology and the architecture of graph neural networks. The results analyze and showcase the tradeoffs between graph topology and Graph CNNs. Sathish Muppidi et al. [17] Notable characteristic of community is to discover graph nodes are with same interests and keep them firmly connected to derive groups for numerous reasons. This paper shows a semi-supervised learning on graph data for solving community detection. Hiba Hameed et al. [18] addresses the potential of deep learning neural network architectures in estimating parameters of a graph. Graph convolutional neural networks (GCN) have been employed to estimate CDPU number and vertex connectivity of a graph. The results show the promise of recent deep learning architectures in estimating parameters of a graph. Xinyu Wang et al. [19] this paper proposes a hierarchical method of aggregation. Where it aggregates nodes based on hierarchy, region. Selects nodes using random walk. Attention mechanism is implemented here to obtain the final output. Mickael Mohammad et al. [20] This paper explores the effectiveness of GNNs by utilizing various graphical visuals, such as tree and bipartite graphs, to capture and exploit the intricate relationships inherent in medical data. Furthermore, by employing complete graphs and multi-parametric temporal graphs, we can identify anomalies in health values by considering correlation factors.

Veniamin S Bobakov et al. [21] The non-graphical means, which includes support vector machine, decision trees and linear discriminant analysis, demonstrated results comparable to GNNs with a single convolutional layer on the test sample, but overfitting was clearly visible on the validation sample. GNNs were less sensitive to the changes in the number of vertices. Conversely, GNNs showed a large number of false alarms when sorting regular graphs. Xiaoling Li et al. [22] This project showcases a graph neural network-based model which calculates the graph distance and the Wasserstein's center of gravity on the base class tag, this uses K-means method and Llyod's algorithm, and used as the feature extractor and graph neural network is used for the classifications. Zhilin Wang et al. [23] In this paper GNN is combined with LSTM to make better use of the graph data and extract features thereby increasing performance and giving high accuracy in classification tasks. D.P.C.H Pathirana et al. [24] In this paper there are three GNN architecture that includes Graph Convolutional Network, GraphSAGE, and Graph Isomorphism Network are examined Adam and SDG optimizer are used to perform detection of toxic mushrooms and their performance are evaluated. This provides a good way to learn about GNN algorithm and their performance.

Clément Vignac et al. [25] This paper puts forward that models with less features but more training data will beat fewer complex networks. Haoran Shi et al. [26] blends the GCN and GAT based on node characteristics, thus creating an anomaly detection model for anomalous edges. Improving effectiveness. Ziqing Hu et al. [27] helps with the issue of over-smoothing in a graph neural network (GNN) model outperforming other over-smoothing GNN training methods. Zebin Wen et al. [28] it proposes new ways to manage GNN computational complexity and enables GNN applications in scenarios with limited computational resources.

This is important for using GNNs in computational limited environments and making it more efficient. Mahima Raj et al. [29] this study discusses about the technologies such as ML, ANN and CNN to fight against money laundering. This was very instrumental in the implementation of techniques like GNN for our project. Since GNN is very similar to CNN. Sara Makki et al. [30] talks about fraudulent techniques that have arose in the big data era and the data analytics tools to combat financial frauds Investigators needs to navigate through large amount of data from multiple sources which has become an inefficient approach. The paper proposes methods to overcome various financial frauds while processing large data.

3 Methodology

The study's methodology is centered on the design and working of a Anti Money Laundering (AML) using Dual Graph GNNs to produce improvements in the field of money laundering.

3.1 Existing System

The current majority of banks and other financial organizations identify transactions that exceed a certain limit using threshold-based criteria, Basic techniques for tracking transactions that are unable to identify obscure connections amongst accounts. These traditional methods are unable to identify hidden money laundering rings, which results in an ineffective method for Anti Money Laundering. XGBoost and Random Forest are two examples of supervised learning models used by certain institutions of higher learning. calls for tagged data, which is scarce in situations of financial fraud. mostly ignores complete network activity in favor of transaction-level characteristics. A good example is [5] where, the model in the project was trained using XGBoost to foresee that a new transaction should be alerted. XGBoost can undergo class imbalances, if proper care is not taken. It is not as good as GNNs when it comes to learning patterns. [7] Similar to XGBoost, the method implemented here applies the naïve bayes algorithm to classify the money laundering networks, this is very inefficient when dependencies exist between features, leading to poor classification performance. [10] Uses SVM for AML, but SVM suffers from similar drawbacks like the methods mentioned previously. SVM is slow to train on large datasets, requires careful training as it is prone to hyperparameter sensitivity. Too much reliance on data preprocessing, it also suffers from class imbalance. GNNs are used in several studies, however they are usually restricted to single-graph models.

3.2 Proposed System

To increase detection accuracy, we combine a transaction graph and an account graph implementing a dual graph method. We use advanced method of combining Graph Convolutional Network (GCN) and Graph Attention Network (GAT), Using them, we create a graph network for account and transactions These aids in detecting both direct and indirect laundering. Identifies high-risk accounts using Louvain clustering and centrality-based risk rating. instead of than merely studying individual transactions, we identify complex fraud networks which helps us in detecting unusual transactional behaviour Detects money laundering methods using several accounts rather than single-step payments. Captures circular money flow and evasive layering techniques. The proposed algorithm learns dynamic fraud risk ratings from network structure compared to Traditional machine learning models which make use of static transaction characteristics such as amount and frequency. risk rankings based on account ties, making it easier to justify flagged transactions. Designed for high-volume transactions in today’s digital economy, making it scalable for larger transaction databases.

The architectural diagram in fig 1 depicts a GNN model aimed at leveraging community detection and dual graph model to enhance the detection of frauds in money laundering to promote Anti Money Laundering (AML). The model contains a data layer which is the first step to further processing of graphs. It contains data preprocessing, graph constructions, community detections, data storage. Data preprocessing starts with the extraction of data from the data storage where the data is stored in csv format, the data is extracted and processed and cleaned by removing duplicate transactions, normalizing features using Numpy, missing transactional data is filled. Next the data is converted into a graph using the NetworkX library. Community detection is performed on the graph to group together similar clusters based on modularity. Modularity is defined as the difference between the fraction of edges within communities and the expected fraction of edges in a random graph with the same degree distribution. The Louvain algorithm aims to maximize this modularity.

3.3 Architecture

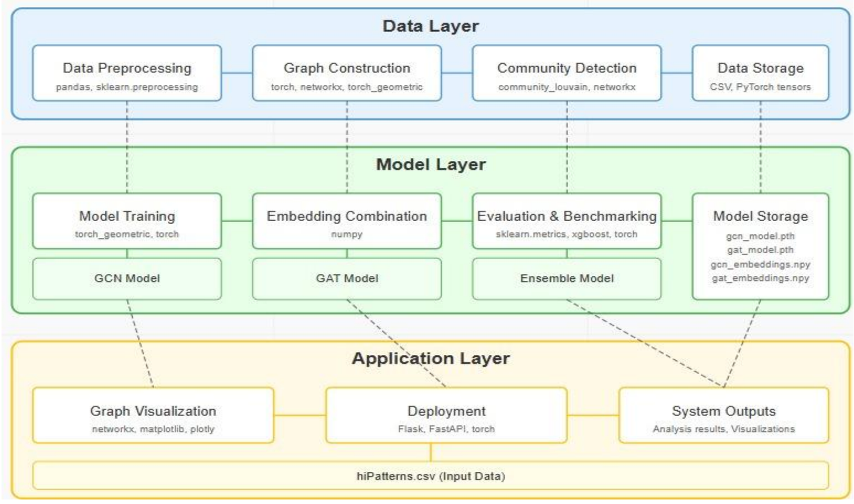

Fig. 1. Architecture Diagram of the Proposed Model.

The model layer works with the construction and training of the GNN. Using Pytorch we convert the graph into pyG format for the construction of GNN, since NetworkX is not optimized for GNN. The GNNs GCN and GAT are constructed using the pytorch library. GNN converts the graph into vector embeddings. 80/20 train-test split is maintained to ensure optimal performance and proper fitting of the GNN. The model performance is benchmarked and evaluated with other machine learning methods like XGBoost, Kmeans to analyze the results and difference in performance. The final layer being the application layer focuses on the output to the end user. The results are visualized using NetworkX which offers many graph visualization techniques, matplotlib can also be used alternatively. A frontend framework like flask may also be used to deploy the visualized data. The system enhances the performance and accuracy of the GNN through the following modules:

Module 1: Data Layer

This module details the data processing and data engineering methodology of the proposed work. Data is stored in the form of CSV values, here the dataset being IBM AML dataset. Data is then processed using Numpy and Pandas which aid in cleaning and filtering outliers of data to aid with proper training of model. Graph is constructed using NetworkX which is a library designed specifically to work with graphs. Community detection is performed on the graph using Louvain algorithm for proper clustering of nodes.

Module 2: Model Layer

Pytorch which is a machine learning library is used to convert the graph into GNN. Dual graph system is implemented where GCN and GAT are used for account and transactional graphs.

This approach ensures that the advantages of both methodologies are captured effectively. The model is trained using the dataset which is divided into 80/20 ratio for training and testing. It is evaluated with similar which are prevalent in the same domain. Namely, machine learning models like Kmeans, XGBoost and the performance is benchmarked.

Module 3: Application Layer

The output from the previous layer is visualized using NetworkX or matplotlib. This provides easy interpretation of the results since cluster grouping on a large scale can be confusing. These libraries make it easier for the visualization of data in the form of cluster graphs. The visualized data maybe deployed using a framework like flask for application purposes

The above methodology aims to improve performance and propose a new dual graph model for the purpose of Anti Money Laundering in financial systems. This will enhance the detection of frauds in the financial systems and banking sectors and aid in the reduction of frauds. Without manual human monitoring and analysis.

3.4 Implementation

In implementation of the GNN and applying the required algorithm we must establish a techstack that facilitates the project. This section details the required hardware, software, and underlying algorithmic structure.

Hardware and Software Specifications: Specific hardware and software requirements must be met to support the deployment of this work. The hardware requirement includes a computer with at least a GPU which is Nvidia RTX 3060 (or better), any new generation CPU, namely Intel Core i7 or AMD Ryzen 7 processor and 512GB (or more) of SSD space. A reliable Ethernet or WiFi connection is crucial for network connectivity, supported by a minimum of 16 GB of RAM (32 GB+ preferred) to ensure smooth operation. On the software side, the system uses Python as the primary language. Along with several python libraries, hence a python version of 3.8 and above is preferred to avoid dependency issues. Namely, Pandas for data processing, NetworkX, to work with Graphs, Pytorch library to implement Graph Neural Networks, Plotly to visualize them.

Algorithmic Framework: This proposed system's uses Louvain algorithm for community detection to group together nodes based on modularity. The algorithm builds a hierarchical structure of communities. GCN network uses message parsing to aggregate information from neighbours to update the embedding GAT uses attention mechanisms to analyse the impact of the neighbouring nodes to focus on more relevant and important anomalies.

4 Results

Introducing the Community Detection with Dual Graph Model using GCN and GAT. The results are quantified in a series of graphs that present the performance metrics before and after the implementation of our model.

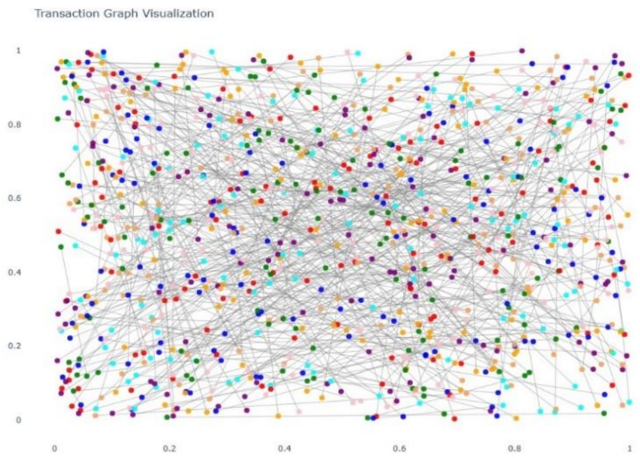

Fig. 2. Transaction Graph Visualization.

Fig 2 depicts the clustering between transactions from one node to another, the nodes being the transaction amount. Similar nodes are coloured with the same colour. This is done by using Graph Attention Network (GAT), the attention score is learned based on the node and its neighbours' features. GAT gives special importance to nodes with high transactional volume, unusual patterns. Anomalous nodes stand out because of their unique feature distribution.

Fig. 3. Account Graph Visualization.

In Fig. 3 depicts the clustering between accounts from one node to another, the nodes being the accounts. Similar nodes are coloured with the same colour. Graph Convolutional Network (GCN) is used for the feature aggregation of the accounts. Unlike GAT this treats all neighbour nodes as equal, averaging features from all accounts. Smooths features from the connected network, learning network patterns. Great for capturing general patterns which are common in accounts.

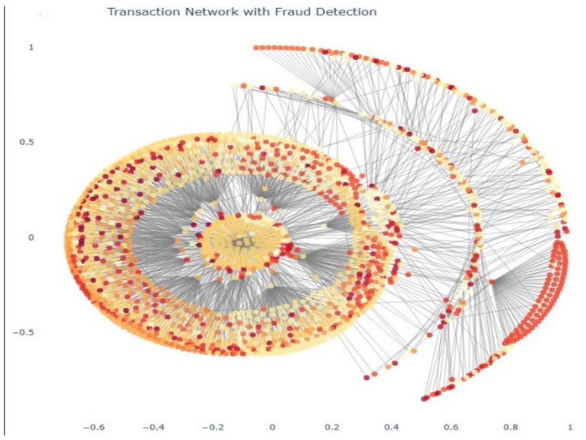

Fig. 4. Final Output after Graph Fusion.

In Fig 4, the final output after the fusion of both graphs is represented using a cluster graph. A colour scheme is implemented to showcase the severity of the suspicious activity with red being the most severe and white being the least severe.

Fig. 5. Benchmarking with other methods.

Lastly, in Fig 5, the graph showcases a marked improvement in evaluation metrics with accuracy of the proposed system to 92, precision to 94 and F1 score to 89. Compared to commonly used ML models for AML. This improvement indicates the streamlined efficiency of the proposed system, which is a direct benefit of the system's automated features.

5 Discussion

The increase in money laundering and frauds aligns with our hypothesis that creating a method to automate the capture of money laundering rings and anomalies would greatly speed up the process of capturing criminals in the modern world. The automation of anti-money laundering not only speeds up the analysis of transactions but also reduces the human error involved in the analysis of the financial data, thereby saving human resources, money and improving accuracy. GNNS and Anti-Money Laundering are both evolving fields. Every passing year there is a new invention in the field of GNNs. GNNs are being explored thoroughly in the field of Anti-Money Laundering. There are some future works and enhancements that could be done to improve the project. Mainly focusing on improving accuracy and reducing the false positives. Money laundering often involves relationship between entities, a Heterogenous Graph Neural Network (HGNN) could be used to improve performance and diversify the relationships between entities. Temporal Graph Neural Network (TGNN) is useful in capturing evolved patterns from data. Since money laundering patterns evolve over time, this could prove to be a future implementation in the efforts to combat money laundering. Future improvements could focus on the explainability and interpretation of the output graph using explainable AI. GNNExplainer or PGExplainer could be used to identify key nodes and edges. Graph Counterfactual Explainers could be used to improve the debugging of the GNNs.

6 Conclusion

In conclusion, this research study has developed a method that leverages the capabilities of GNNs for the domain Anti-Money Laundering. The proposed model makes use of a dual graph system by using both GCN and GAT compared to traditional methods which only make use of a single Graph Neural Network. The method used aims to make improvements in AML by detecting hidden patterns, smurfing and other anomalous activities in the financial network system. The study has succeeded in providing an alternative method and has improved the efficacy of traditional ML algorithms. Future work will refine this model to overcome emerging challenges and enhance its efficiency and reliability. It highlights the potential of GNN in the field of Anti-Money Laundering, as fraud techniques evolve so does the techniques against them evolve. This project aims to contribute to anti-crime methods by combating the ever-growing crime of money laundering and frauds. Thereby improving the technology used in Anti-Money Laundering and Graph Neural Networks.

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