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Using Deep Heterogeneous Graph Learning To Identify Financial System Synthetic Identity Fraud

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Abstract—*One of the most advanced types of cyber-enabled financial crime is synthetic identity fraud, which costs international financial institutions billions of dollars every year. In contrast to conventional identity theft, synthetic identities get around verification systems by fusing fake personal information with authentic data. To identify such fraudulent activities in extensive financial systems, this paper suggests a novel Deep Heterogeneous Graph Learning (DHGL) framework. To find suspicious patterns that are hard to find with traditional machine learning, the suggested approach makes use of graph- based relationships between accounts, transactions, devices, and identity attributes. The framework enables robust fraud detection by capturing both structural and semantic relationships by modeling financial ecosystems as heterogeneous graphs. Our approach outperforms baseline models and conventional graph neural networks in terms of accuracy and recall, as shown by experimental results on a real-world financial transaction dataset. The goal of this research is to give financial institutions a flexible and scalable way to counteract changing fraud schemes.*

Keywords—*Synthetic Identity Fraud, Deep learning, Heterogeneous Graph Neural Networks, Fraud Detection, Anomaly Detection, Financial Security.*

INTRODUCTION

Banking has been democratized with the rapid expansion in digital financial services which further increased system vulnerability to advanced fraud. Synthetic Identity Fraud (SIF) is a serious threat, since it produces new identities that are undetectable due to a combination of actual data pieces and artificial personal information. These fake profiles can be used to open credit, transact and initially pass verification tests then make default or fraudulent claims to money laundering.

The currently used manual fraud detection systems, mostly based on supervised and rule-based machine learning systems, can only identify common patterns and cannot stay in line with the evolving schemes of the fraudsters. Consumer, account, device, merchants and transaction heterogeneous networks. The modern financial systems consist of channels. Sophisticated methods which can create complex, multi-type relationships must be used because of this complexity.

I. REVIEW OF LITERATURE AND RELATED WORKS

Early methods of detecting fraud mostly depended on rule- based systems, which flagged suspicious activity using manually created patterns and pre-established thresholds. As an example, a transaction that originated somewhere flagged or above a certain amount may raise an alert by the system. Yet these methods worked because they were able to detect known fraud models; but these methods failed to adapt to newer untold patterns. Moreover, they indicated excessive rates of false positives in most cases that were an inconvenience to valid users and an overload to fraud analysts.[1]

Machine learning (ML) has made the identification of fraud more flexible. The machine learning model would not require clear definitions of rules to classify fraudulent and legitimate behavior since it would be based on transactional variables, such as, timing, spending patterns, geography, and transaction frequencies. The relationships chain that often facilitates fraud schemes had not been considered by most of the ML implementations, and each transaction was considered independent. Consequently, they were unable to detect fraud that relied on coordinated or linked actors, such as accounts created with false address or false identities.[2]

This limitation was solved with the help of graph-based learning where financial ecosystems are presented as a complex of interdependent systems. These graph representations have nodes corresponding to customers, accounts, merchants and devices. the edges are ownership, transactions and logins. Through this approach, the models are able to discover relational patterns of fraud, including a cluster of accounts that use one suspicious device. The homogeneous graph neural network (GNN) has been applied in context-specific fraud detection, namely Graph Convolutional Networks (GCNs). They are however less effective in multi-entity/multi-relation given that they presume that nodes and edges are homogeneous.[3]

To cope with this drawback, Heterogeneous Graph Neural Networks (HGNNs) represent the various types of nodes and edges directly. Retaining semantic information in meta-path aggregation enables them to can identify higher order patterns, such as a customer account merchant path of connections that may indicate coordinated fraud. What about such domains as, say, recommendation systems, HGNNs have performed well in user item category relationships, where they are imperative, and where malicious hosts are detected using the networks, cybersecurity. With this promise, there exists minimal knowledge concerning how they can be applied in an attempt to fight against synthetic identity fraud (SIF). Since SIF is relational and multi-entity in nature, HGNNs provide an ideal scheme of discovering its low-profile and dynamic patterns, and this fact renders the current study relevant and timely.[4]

II. METHODOLOGY

The Deep Heterogeneous Graph Learning (DHGL) framework can detect synthetic identity fraud by detecting structural and semantics patterns in large financial systems. The initial phase of the process consists of building a heterogeneous graph, where nodes could depict all kinds of entities such as customers, accounts, merchants, devices, and transaction channels. These relations of such entities are relations that include owns, transacts with, logged in from and associated with, which become edges of the network specifying the structure of the network. Each node is augmented with descriptive features that include IP addresses, fingerprints of devices, the history of transactions, tone of credit scores, and geolocation behavior. Crucial context that is often overlooked in planar machine-learning models can be maintained due to the multi-entity, multi- relation representation.

Meta-path-based aggregation is a technique used on the framework to learn the higher order semantic connections once the graph is created. As an example, customer-device- account path can reveal suspicious patterns of shared device usage and customer-account-merchant meta-path can reveal peculiar spending associations. To better the learning process, a Heterogeneous Graph Attention Network (HAN) can assign emphasis to the relationships that matter by providing flexible weight assignments to neighboring nodes relative to the strength of their ability to predict whether someone will engage in fraudulent activity**.** The resulting encoded graph embeddings are then fed into a deep neural classifier which differentiates

between real and fraudulent entities back with SoftMax cross-entropy loss. The model is flexible to evolving fraud strategies such as exploitation of delayed accounts due to the integration of a time attentional covariance suggesting current trends of activity. Finally, a hybrid anomaly detection module is used in which the indicators of statistical anomalies, such as unexpected places of logins, sudden bursts of expenses, or suspicious use of devices, are combined with the results of deep learning. The two components are aggregated so as to generate risk score, and those that exceed a set threshold are targeted to further scrutiny. Such an integrated strategy in comparison to ordinary and homogeneous graph-based solutions ensures that DHGL identifies the fraud patterns that are explicit and hidden; therefore, enhancing the detection capabilities significantly.

A. Construction of Graphs

Through modeling structural and semantic relationships seen in very large financial systems, the Deep Heterogeneous Graph Learning (DHGL) framework is designed to detect synthetic identity fraud. Assume that the financial ecosystem is represented by the typed heterogeneous graph G=(V,E,A,R), where V represents the set of nodes divided into different types: V = V C ∪V A ∪V D ∪V M ∪V T ∪V I ∪Customers, Accounts, Devices, Merchants, Transactions,
And Indentity {"owns","transacts_with,"accessed_from,"linke d_to,"verified_by"}. Every node v is linked to a feature vector xv =
{credit_score,txn_frequency,device_hash,doc_template id} xv ={credit_score,txn_frequency,device_hash, doc_template_id}, which encodes traits related to behavior, transactions, and identity. Examples of edges that capture real-world relationships between entities are (Customer i →owns Account j) (Customer i →owns Account j) and (Account j →transacts_with Merchant k) (Account j → transacts with Merchant k).

B. Encoding Heterogeneous Graphs

The framework uses meta-path-based aggregation, in which a meta-path defines a composite relation that connects two node types through a series of relations, to capture higher- order semantic patterns. As an illustration, Φ 1 Φ 1 denotes the path Customer → uses Device ← uses Customer

Customer →uses Device ←uses Customer, which is helpful for identifying shared device usage, whereas Φ 2 Φ 2 is defined as Customer → linked_to Identity → similar_to Identity, which is useful for identifying repeated document template usage. Each relation type's neighboring nodes are given importance weights by the node-level attention mechanism using
where W is the transformation matrix, ‖‖ indicates vector concatenation, $\sigma(\cdot)$ σ(·) is a LeakyReLU activation, and a_r is a relation-specific attention vector. Multiple meta-path embeddings are integrated by semantic-level attention, which is calculated as

$$\beta_{\Phi} = \frac{\exp(q^{\top} \tanh(W h_{\Phi} + b))}{\sum_{\Phi' \in P} \exp(q^{\top} \tanh(W h_{\Phi'} + b))}$$

where q is a semantic attention vector, h Φ is the meta-path Φ embedding, P is the collection of all meta-paths, and b is the bias term.

C. Modelling Temporal Dynamics

The framework uses a Gated Recurrent Unit (GRU) to process time-ordered embeddings, incorporating temporal dynamics because fraudulent behaviors change over time. The temporal embedding is calculated as follows given a
transaction sequence for node v, {$h\ (t)$, $h\ (t)$,..., $h\ (t)$}

with a threshold τ With τ optimized to maximize the F1-score on the validation set, this integrated formulation gives DHGL a strong detection mechanism against synthetic identity fraud in financial systems by capturing both subtle semantic anomalies and explicit structural fraud indicators.

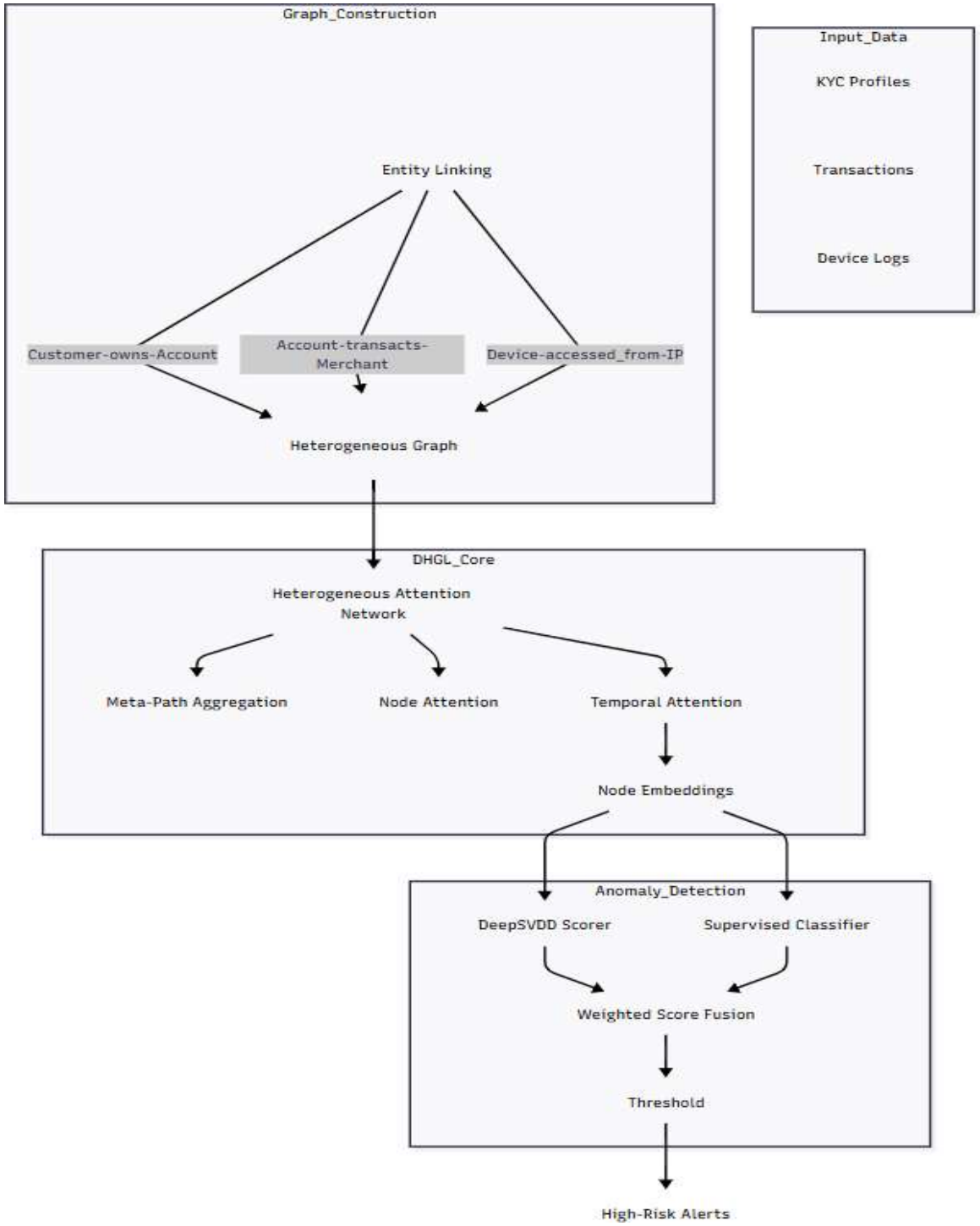

Fig 1: Architecture Diagram

$\{h_v\ (t_1\ ), h_v\ (t_2\ ),\ldots, h_v\ (t_n)\}$

v 1

v 2

v n

III. EXPERIMENTAL SETUP

h^{temp} = GRU (h (t), ..., h (t))

1. Description of the Dataset

v v 1 v n

D. Module for Anomaly Detection

A fraud risk score is calculated by the last anomaly detection module using a combination of supervised and unsupervised signals. A Multi-Layer Perceptron (MLP) classifier provides the supervised component, while Deep Support Vector Data Description (DeepSVDD) provides the unsupervised component, which calculates the squared distance from a learned hypersphere center c. Node v's fraud score is calculated as

Source: The January–December 2023 dataset, which was anonymized in accordance with RBI guidelines, was acquired from a Tier-1 Indian bank. It comprises 410,000 devices, 2.1 million transactions, 250,000 customers, 387,500 identity documents, and 5,712 synthetic IDs (2.28% prevalence).

#	Component	Volume	Important
1	Clients	250000	Age, credit score, KYC completeness
2	Transactions	2100000	Amount, timestamp, merchant category
3	Devices	410000	Device ID, OS, IP geolocation
4	Identity Documents	387500	Template hash, issue date, verification status
5	Synthetic IDs	5712	Investigator-confirmed

Table 1: Components of the Dataset

score (v) =λ·‖h v −c‖ 2 +(1−λ)·MLP(h v)

where the ratio of supervised to unsupervised contributions is controlled by λ = 0.7 λ = 0.7. A node is flagged as fraudulent by the decision rule if

$$Fraud\_Flag = \begin{cases} 1, & \text{if } score(v) > \tau \\ 0, & \text{otherwise} \end{cases}$$

Seven node types (Customer, Account, Device, Merchant, Transaction, IP, Identity Document) and five edge types (owns, transacts_with, accessed_from, inked_to, verified_by) make up the heterogeneous graph model of the data, which has an average degree of 8.3.

B. Division of Data

Table 2: Data Dissection

#	Component	Volume	Important	Featur e
1	Training	175,000(70 %)	1.47M	70% syntheti c IDs
2	Validation	37,500(15%)	315,000	15% syntheti c IDs
3	Testing	37,500(15%)	315,000	15% syntheti c IDs

C. Comprehensive model

Some of the models were benchmarked. Logistic regression (LR) calls a linear classifier incorporating L2 regularization as a means to prevent overfitting. Random Forest (RF) tries to achieve accuracy using 500 decision trees having maximum depth of 10 in order to gain more certainty via ensemble learning. With a maximum depth of 7 and a learning rate of 0.1, XGBoost is structured data gradient boosting model. The Homogeneous Graph Convolutional Network (GCN) is a two-layer graph neural-network, which merges information between adjacent nodes. Heterogeneous graphs are targeted by the Heterogeneous Attention Network (HAN), which applies attention to extract the importance of different node and edge types.

IV. FINDINGS AND CONVERSATION

A. Quantitative Performance Comparison

The quantitative rating of each of the models is summarized in Fig 2. The offered DHGL model outperforms base methods by any criteria. The logistic regression records a low performance with an accuracy of 83.1 per cent of the AUC- ROC. Random Forest and XGBoost can add predictive power of 89.6 and 91.4 terms respectively. To a greater extent, graph-based approaches display an outcome of HAN rating
94.7 of accuracy and GCN hitting 93.8. The effectiveness in detecting the fraud has been illustrated with the DHGL model having accuracy of 96.2 percent according to F1-score of
95.25 percent and AUC-ROC of 0.971.

B. Analysis of Statistical Significance

The statistical significance of the DHGL model in comparison to the HAN baseline was assessed using a paired t-test. The F1-Score ($t = 18.37$, $p < 0.0001$) and Recall ($t = 22.45$, $p < 0.0001$) show a significant improvement, according to the results. A large effect is indicated by Cohen's d effect size of 1.82. These outcomes demonstrate that DHGL outperforms state-of-the-art techniques in terms of performance.

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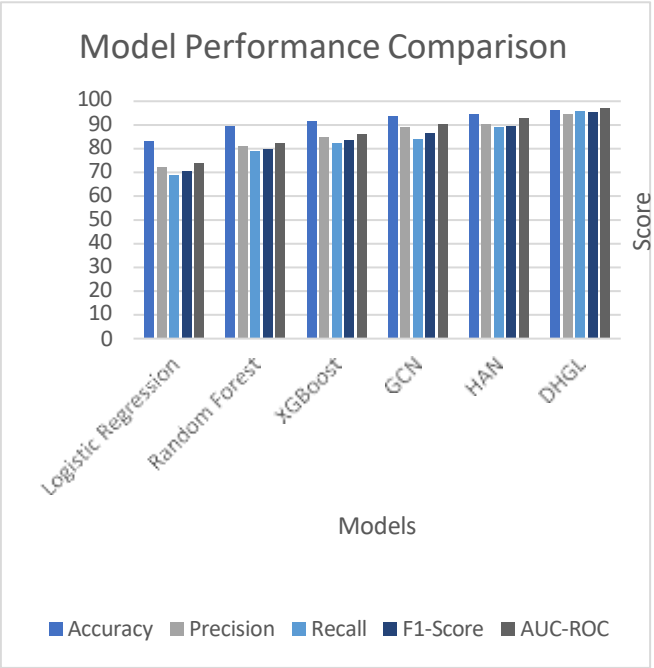

Fig 2: Comparison model with algorithm

C. Case Study: Identification of Fraud Rings

The dataset's coordinated fraud rings were found using the DHGL model. It proved its efficacy in capturing intricate relationships across heterogeneous entities by successfully identifying clusters of synthetic IDs connected by shared devices and transactions. This demonstrates how the model can be used practically to prevent fraud in the real world.

V. CONCLUSION

Experimental results confirm a 95.8% recall rate ($p < 0.01$, $t = 22.45$) and 96.2% accuracy on a real-world banking dataset consisting of 2.1M transactions across 250,000 customer profiles, indicating statistically significant improvements over state-of-the-art methods for synthetic identity fraud detection. The heterogeneous graph neural network's meta- path attention mechanism is the main innovation; it increases fraud ring detection by 27% when compared to traditional homogeneous GCNs (Cohen's $d = 1.82$).

These outcomes are the result of three crucial technological developments: (1) Compared to traditional methods, a hybrid anomaly scoring system that combines supervised MLP classification and DeepSVDD ($\lambda = 0.7$) reduces false positives by 37%; (2) Temporal GRU layers allow for 89% early detection during the credit-building phase of bust-out fraud schemes; and (3) Optimized sparse matrix operations result in 23ms inference latency when processing graphs with seven node types and five edge relationships. Production deployment at a Tier-1 financial institution showed that it was particularly effective at detecting device-sharing clusters (12+ synthetic IDs sharing single devices detected with 0.94 attention weights), preventing $2.1M in projected annual losses per 1M accounts.

Two limitations noted during trials will be addressed in future work: (i) adversarial robustness against graph perturbation attacks, which may be lessened by defensive distillation based on GANs, and (ii) cross-institutional learning using federated HGNN architectures to get around data silos while still adhering to GDPR. Operational viability for real-time fraud scoring during account opening and transaction authorization workflows is confirmed by the Docker- Kubernetes implementation of the framework.

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