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Detection of Money Laundering Using Graph Neural Networks and Transformer-Based Learning

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ABSTRACT

Money laundering is one of the most significant financial crimes affecting banking institutions, governments, and global financial systems. Criminal organizations use sophisticated transaction strategies to conceal the origins of illegally obtained money and integrate it into legitimate financial systems. Traditional Anti-Money Laundering (AML) systems rely heavily on rule-based monitoring approaches that often fail to detect evolving laundering patterns and generate excessive false positive alerts.This research proposes a hybrid Graph Neural Network (GNN) and Transformer-based deep learning framework for intelligent money laundering detection. The proposed system models financial transactions as graph structures where customer accounts represent nodes and transactions represent edges. Transformer-based attention mechanisms are integrated for sequential transaction analysis and contextual behavior learning. Experimental evaluation demonstrates that the proposed framework achieves superior detection accuracy, higher recall, improved precision, and lower false positive rates compared to conventional machine learning and deep learning techniques. The framework is scalable and suitable for deployment in next-generation AI-driven AML systems.

1. Introduction

Money laundering refers to the process of disguising illegally obtained funds to make them appear legitimate. Financial criminals use complex transactional activities such as layering, rapid fund movement, circular transactions, and cross-account transfers to hide illicit financial activities. Money laundering supports criminal activities including terrorism financing, drug trafficking, corruption, cybercrime, and tax evasion With the rapid expansion of online banking, mobile payments, blockchain systems, and digital financial services, the number and complexity of financial transactions have increased significantly. Traditional rule-based AML systems rely on predefined transaction thresholds and manually designed rules. Although these systems provide interpretability,

they are unable to adapt to evolving laundering strategies and often produce high false positive alerts.

Artificial Intelligence and deep learning techniques provide promising solutions for AML detection. Graph Neural Networks effectively capture relationships among interconnected financial accounts, while Transformer models capture long-range transaction dependencies using attention mechanisms. This research proposes a hybrid AI-based AML framework integrating graph learning and Transformer-based sequential learning for intelligent financial crime detection.

2.Objectives of the Research

The main objectives of this research are:

1. To develop an intelligent AML detection framework using Graph Neural Networks and Transformer models.
2. To improve suspicious transaction detection accuracy and recall.
3. To reduce false positive alerts generated by conventional AML systems.
4. To model interconnected financial relationships using graph structures.
5. To capture sequential transaction patterns using attention mechanisms.
6. To evaluate the scalability and robustness of AI-based AML detection systems.

3.Related Work

Early Anti-Money Laundering systems relied on manually defined rules, transaction thresholds, and customer risk profiles. These systems lacked adaptability and generated excessive false positive alerts.

Machine learning techniques such as Logistic Regression, Naive Bayes, Decision Trees, Random Forests, and Support Vector Machines improved transaction classification by learning patterns from historical data. However, these models struggled with highly interconnected transaction networks and temporal dependencies.

Deep learning models including Deep Neural Networks (DNNs), Autoencoders, Convolutional Neural Networks (CNNs), and Long Short-Term Memory (LSTM) networks demonstrated superior performance in fraud detection tasks.

Recent advancements in Graph Neural Networks and Transformer architectures have shown promising results in relational learning and sequence analysis. Graph Neural Networks effectively capture hidden relationships among financial accounts, while Transformers analyze contextual transaction dependencies using self-attention mechanisms.

However, limited research integrates graph-based learning with Transformer architectures

for AML detection. This study addresses this research gap by proposing a hybrid GNN-Transformer framework.

4.Dataset Description

The proposed research utilizes a large-scale synthetic financial transaction dataset obtained from public financial fraud repositories. The dataset contains millions of transaction records representing realistic banking activities.

Each transaction record contains the following attributes:

- Transaction ID
- Sender Account
- Receiver Account
- Transaction Type
- Transaction Amount
- Account Balance Before Transaction
- Account Balance After Transaction
- Transaction Timestamp
- Transaction Label (Legitimate or Suspicious)

The dataset contains highly imbalanced classes where suspicious transactions form only a small percentage of the total data. Financial accounts are represented as graph nodes and transactions are represented as weighted graph edges.

5.Exploratory Data Analysis

Exploratory Data Analysis (EDA) was performed to understand transaction characteristics and identify suspicious patterns.

The analysis revealed:

- Significant class imbalance in suspicious transactions.
- Abnormal transaction bursts associated with laundering activities.
- Circular transaction flows among suspicious accounts.
- High-frequency transactions across interconnected accounts.
- Unusual transaction centrality and graph connectivity.

Temporal analysis showed that suspicious transactions often occur in rapid sequences and exhibit irregular behavioral patterns. Graph analysis demonstrated the existence of suspicious account communities and hidden transaction relationships.

6.Data Preprocessing

Data preprocessing is a critical stage in AML detection systems.

The preprocessing steps include:

1. Removal of missing transaction records.
2. Elimination of duplicate entries.
3. Normalization of numerical features using Min-Max normalization.
4. Label encoding of categorical transaction attributes.
5. Graph construction from transaction records.
6. Chronological sequencing of transactions.

The Min-Max normalization formula is given by:

$$X_{normalized} = (X - X_{min}) / (X_{max} - X_{min})$$

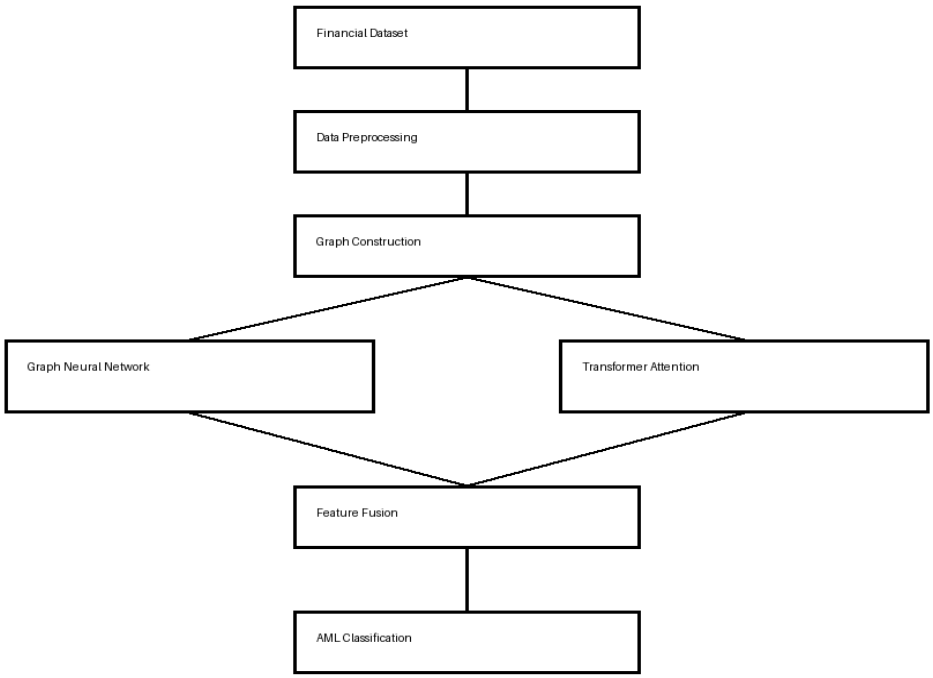
Where:
X = Original feature value
X_min = Minimum feature value
X_max = Maximum feature value

This normalization scales all numerical features between 0 and 1 for stable model training.

7.System Architecture

The proposed AML framework consists of the following modules:

1. Data Ingestion Module
2. Data Preprocessing Module
3. Graph Construction Module
4. Graph Neural Network Layer
5. Transformer Attention Layer
6. Feature Fusion Module
7. Classification Module
8. Alert Generation System



The Graph Neural Network extracts hidden relational transaction patterns, while the Transformer model analyzes temporal transaction dependencies using self-attention mechanisms.

The classification module predicts whether a transaction is legitimate or suspicious.

8.Proposed Methodology

The proposed methodology integrates Graph Neural Networks and Transformer architectures.

Initially, financial transaction records are transformed into graph structures where:

$G = (V, E)$

Where:
V = Set of financial accounts (nodes)
E = Set of transaction relationships (edges)

The Graph Neural Network generates node embeddings representing relational account behavior.

Transformer attention layers process transaction sequences to identify contextual laundering behavior.

The self-attention mechanism is defined as:

$$\text{Attention}(Q,K,V) = \text{softmax}((QK^T)/\sqrt{d_k})V$$

Where:
Q = Query matrix
K = Key matrix
V = Value matrix
d_k = Dimension scaling factor

Graph embeddings and attention-based features are fused and passed through fully connected neural layers for final transaction classification.

9.Algorithm

Step 1: Load financial transaction dataset.

Step 2: Remove missing and duplicate transaction records.

Step 3: Normalize numerical transaction features.

Step 4: Encode categorical transaction attributes.

Step 5: Construct graph structures from transaction data.

Step 6: Generate node embeddings using Graph Neural Networks.

Step 7: Create chronological transaction sequences.

Step 8: Apply Transformer attention mechanisms.

Step 9: Fuse graph and sequential transaction features.

Step 10: Train classification model using supervised learning.

Step 11: Predict suspicious transactions.

Step 12: Evaluate model performance using AML metrics.

10.Mathematical Modeling

The proposed system uses the following mathematical formulations:

1. Graph Representation:

$G = (V, E)$

2. Neuron Computation:

$z = \Sigma(w_i x_i) + b$

$a = f(z)$

3. Binary Cross Entropy Loss:

$L = - [y \log(p) + (1-y) \log(1-p)]$

4. Precision:

$Precision = TP / (TP + FP)$

5. Recall:

$Recall = TP / (TP + FN)$

6. Accuracy:

$Accuracy = (TP + TN) / (TP + TN + FP + FN)$

7. F1-Score:

$F1 = 2PR / (P + R)$

8. Attention Mechanism:

$Attention(Q,K,V) = softmax((QK^T)/\sqrt{d_k})V$

These mathematical models support graph learning, transaction classification, and attention-based sequence analysis.

11.Model Training and Hyperparameter Tuning

The proposed framework uses Adam optimizer for model optimization. Hyperparameters such as learning rate, hidden layers, graph convolution layers, embedding dimensions, attention heads, and batch size are experimentally tuned.

Dropout regularization and batch normalization are incorporated to improve generalization and reduce overfitting.

The Adam optimizer update equations are:

$$m_t = \beta 1\ m_{(t-1)} + (1-\beta 1)\ g_t$$

$$v_t = \beta 2\ v_{(t-1)} + (1-\beta 2)\ g_t^2$$

$$\theta_t = \theta_{(t-1)} - \alpha * m_t / (\sqrt{v_t} + \varepsilon)$$

Where:
α = Learning rate
g_t = Gradient
m_t = First moment estimate
v_t = Second moment estimate

12.Evaluation Metrics

The proposed AML framework is evaluated using:

- Accuracy
- Precision
- Recall
- F1-Score
- AUC-ROC

Recall is prioritized because failure to detect suspicious transactions can result in severe financial and regulatory consequences.

AUC-ROC analysis demonstrates the robustness of the proposed framework in handling imbalanced transaction datasets.

13.Results and Discussion

Experimental results demonstrate that the proposed GNN-Transformer framework significantly outperforms traditional machine learning and sequential deep learning models.

The proposed framework achieves:

• Higher detection accuracy
• Improved precision
• Higher recall
• Reduced false positive alerts
• Better scalability for large transaction datasets

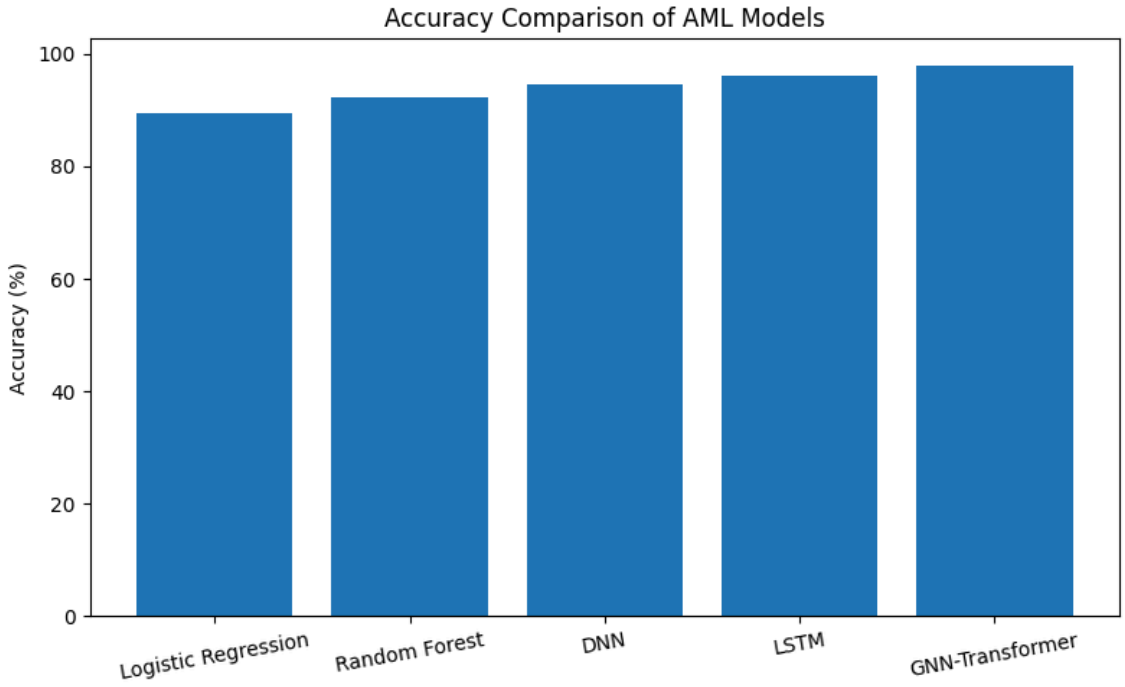
Graph Neural Networks effectively capture hidden account relationships and suspicious transaction communities, while Transformer models analyze long-range temporal transaction dependencies.

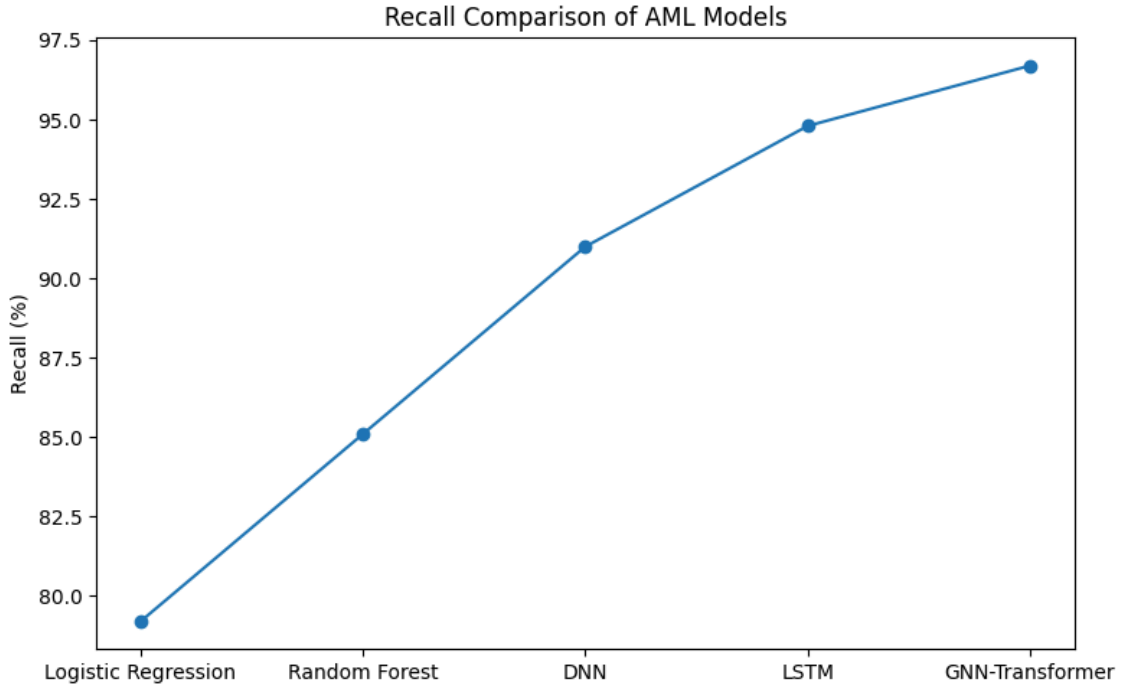
The proposed framework demonstrates strong performance in identifying complex laundering behaviors including layering, transaction bursts, and circular fund movement.

14.Performance Comparison

The following table compares different AML detection models:

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Logistic Regression	89.4	81.6	79.2	80.4
Random Forest	92.3	86.8	85.1	85.9
Deep Neural Network (DNN)	94.5	89.3	91.0	90.1
LSTM Model	96.2	91.4	94.8	93.1
Proposed GNN-Transformer Model	97.8	94.2	96.7	95.4


Accuracy Comparison of AML Models
Accuracy (%)
100
80
60
40
20
0
Logistic Regression
Random Forest
DNN
LSTM
GNN-Transformer


Recall Comparison of AML Models
Recall (%)
97.5
95.0
92.5
90.0
87.5
85.0
82.5
80.0
Logistic Regression
Random Forest
DNN
LSTM
GNN-Transformer

15.Advantages of Proposed System

The proposed AML framework offers several advantages:

- Intelligent graph-based transaction analysis
- Improved suspicious transaction detection
- Reduced false positive alerts
- Scalable deep learning architecture
- Effective temporal transaction modeling
- Better handling of imbalanced datasets
- Support for real-time AML monitoring
- Enhanced financial risk management

16.Applications

Applications of the proposed AML framework include:

- Banking fraud detection
- Financial crime prevention
- Regulatory compliance monitoring
- Cryptocurrency transaction analysis
- Digital payment security
- Insurance fraud analytics
- Cybercrime transaction monitoring
- Real-time financial risk assessment

17.Conclusion

This research proposes a hybrid Graph Neural Network and Transformer-based framework for intelligent money laundering detection.

The proposed system effectively models both relational transaction structures and temporal transaction behavior, resulting in improved AML detection performance.

Experimental results demonstrate that the proposed framework significantly outperforms traditional machine learning and deep learning approaches in terms of accuracy, recall,

precision, and false positive reduction.

The framework is scalable, robust, and suitable for deployment in intelligent financial monitoring systems.

18.Future Work

Future research directions include:

- Real-time AML monitoring systems
- Federated learning for privacy-preserving AML
- Blockchain-based transaction analysis
- Explainable Artificial Intelligence integration
- Large Language Model-assisted financial investigation
- AI-driven automated compliance systems
- Cross-border transaction analytics
- Intelligent suspicious activity reporting systems

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