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Deep Learning for Financial Fraud Detection: A Hybrid GNN-Transformer Fraud Detection Model

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Abstract:
Financial fraud has become a major challenge in modern digital banking and online financial systems. Traditional fraud detection systems are unable to detect complex and rapidly changing fraudulent activities efficiently. Deep learning techniques provide intelligent solutions by automatically learning hidden transaction patterns and detecting anomalies in real time. This study presents a comprehensive review of deep learning methods used in financial fraud detection, including Convolution Neural Networks (CNN)[1], Long Short-Term Memory (LSTM), Autoencoders, Graph Neural Networks (GNN), and Transformer models. A new hybrid fraud detection framework combining Graph Neural Networks and Transformer architecture is proposed to improve fraud detection accuracy and reduce false positives. The proposed model effectively handles imbalanced financial datasets using SMOTE and anomaly-based learning techniques. Experimental analysis shows improved performance in terms of accuracy, precision, recall, F1-score, and AUC. The research concludes that hybrid deep learning models can significantly improve financial fraud detection systems in banking, insurance, and online transaction environments.
Keyword*:* Deep Learning, Financial Fraud Detection ,Credit Card Fraud,Graph Neural Network, Transformer Model ,Auto encoder ,Artificial Intelligence ,Cyber security ,Banking Fraud Detection ,Anomaly Detection

1. Introduction

Financial fraud is one of the fastest-growing cybercrimes affecting banks, financial institutions, e-commerce platforms, and digital payment systems worldwide. Fraudulent activities such as credit card fraud, money laundering, insurance fraud, identity theft, and online transaction fraud result in massive financial losses annually. [5]Traditional fraud detection systems mainly rely on rule-based methods and statistical approaches, which are insufficient for detecting modern sophisticated fraud patterns. Recent advancements in Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) have transformed financial fraud detection systems. Deep learning models can automatically extract hidden features from large-scale transaction datasets and identify abnormal transaction behavior with high accuracy. Models such as CNN, LSTM, Auto encoders, and GNNs have shown superior performance in detecting complex fraud patterns compared to traditional ML methods.

Deep learning approaches are particularly useful because financial transaction data are highly dynamic, imbalanced, and sequential in nature. Sequential models like LSTM capture transaction history patterns, while GNNs identify hidden relationships among accounts and transactions. Transformer-based architectures improve contextual learning and temporal fraud pattern recognition.

Despite the advantages, several challenges remain:

- Imbalanced datasets
- High false positive rates
- Lack of explainability
- Real-time processing requirements
- Privacy and security concerns

This research aims to analyze existing deep learning approaches for financial fraud detection and propose an improved hybrid model for efficient fraud identification.

2. Literature Review

S.No	Author & Year	Techniques Used	Key Contribution	Pros	Cons
1	Chen et al., 2025	CNN, LSTM, Transformer	Systematic review of DL fraud detection	Comprehensive analysis of DL models	High computational complexity
2	Wu et al., 2025	CCNN + SMOTE	Improved fraud detection accuracy	Handles imbalanced datasets effectively	Requires large training data
3	Mienye et al., 2023	GAN + RNN	Fraud detection using synthetic data balancing	Improves minority fraud detection	GAN training instability
4	Raval et al., 2024	Explainable LSTM	Explainable fraud detection system	Better interpretability	Slightly lower speed
5	Hernandez et al., 2024	Machine Learning Review	Survey of fraud detection techniques	Broad literature coverage	Limited real-time evaluation
6	Abdulkreem et al., 2024	CNN, RNN	Review of DL-based fraud systems	Detailed DL comparison	Lack of implementation analysis
7	Ali et al., 2022	ANN, SVM	Comparative ML fraud detection	Easy implementation	Lower accuracy than DL
8	Vallarino et al., 2025	MoE + Transformer	Adaptive fraud detection	Detects evolving fraud patterns	High training cost
9	George et al., 2025	Hybrid ML-DL	Banking fraud review	Combines ML and DL advantages	Complex architecture
10	Innan et al., 2023	Quantum ML	Quantum-based fraud detection	Faster pattern recognition	Experimental stage
11	Rushin et al.	Autoencoder	Anomaly detection in transactions	Effective unsupervised learning	High false positives
12	Bhattacharyya et al.	Deep Data Mining	Large-scale fraud analysis	Handles big financial data	Time-consuming preprocessing
13	Roy et al.	CNN	Transaction feature extraction	Automatic feature learning	Requires GPU resources
14	Kim et al.	LSTM	Sequential fraud analysis	Captures transaction history	Long training time
15	Zhao et al.	Transformer	Temporal fraud pattern detection	High contextual understanding	Requires massive datasets
16	Fan et al.	GNN	Relationship-based fraud detection	Captures hidden transaction links	Complex graph construction
17	Singh et al.	Bi-LSTM	Enhanced sequence learning	Improved sequential analysis	Computational overhead
18	Kumar et al.	Hybrid Deep Learning	Reduced false positives	Better prediction accuracy	Difficult optimization

S.No	Author & Year	Techniques Used	Key Contribution	Pros	Cons
19	Ahmed et al.	Deep Belief Network	Fraud classification	Learns hierarchical features	Slow convergence
20	Li et al.	Autoencoder + CNN	Hybrid anomaly detection	Strong anomaly identification	Model complexity
21	Wang et al.	Reinforcement Learning	Dynamic fraud prevention	Learns adaptive strategies	High implementation difficulty
22	Patel et al.	Ensemble Deep Learning	Improved fraud prediction	Higher robustness	Increased computation
23	Sharma et al.	CNN-LSTM	Real-time fraud monitoring	Good real-time performance	Resource intensive
24	Das et al.	Blockchain + DL	Secure fraud detection	Enhanced data security	Scalability issues
25	Chen & Zhao	Federated Learning	Privacy-preserving fraud detection	Protects user privacy	Communication overhead

3. Methodology

Deep learning has gained significant importance in various domains such as healthcare, cyber security, image processing, natural language processing, and financial fraud detection. In financial systems, deep learning models analyze transaction patterns, customer behavior, and hidden relationships among accounts to identify fraudulent activities with high accuracy. Modern fraud detection systems commonly use advanced deep learning architectures such as Graph Neural Networks (GNN), Transformer Encoders, and Auto encoders to improve fraud detection performance[11].

❖ ***Graph Neural Networks (GNN)***

Graph Neural Networks (GNNs) are advanced deep learning models designed to process graph-structured data. In financial fraud detection, transactions and user accounts can be represented as graphs where:

- Nodes represent customers or bank accounts
- Edges represent financial transactions

GNNs learn the relationships and interactions between connected entities. Unlike traditional neural networks, GNNs capture hidden connections and suspicious transaction patterns across multiple accounts. This makes GNNs highly effective for detecting organized fraud networks, money laundering, and complex transaction fraud.

❖ ***Transformer Encoder***

Transformer Encoder is a deep learning architecture introduced for sequence processing and contextual learning. It uses a mechanism called self-attention to identify relationships between different parts of input data. Unlike traditional sequential models such as RNN and LSTM, Transformer models process data in parallel, resulting in faster training and better performance.

In financial fraud detection, Transformer Encoders analyze transaction sequences and user behavioral patterns over time. They learn contextual information from historical transaction records and identify abnormal activities effectively.

❖ ***Auto encoder***

Auto encoder is an unsupervised deep learning model used for feature learning and anomaly detection. It consists of two major components:

1. Encoder – compresses input data into lower-dimensional representation
2. Decoder – reconstructs the original data from compressed representation

The model learns normal transaction behavior during training. When abnormal or fraudulent transactions occur, the reconstruction error becomes high, allowing the system to identify anomalies effectively.

3.1 Proposed Methodology

Proposed Hybrid GNN-Transformer Fraud Detection Model

The proposed system combines:

- Graph Neural Networks (GNN)
- Transformer Encoder
- Autoencoder
- SMOTE Data Balancing

Proposed algorithm

1. *Data Collection*
   - *Credit card transactions*
   - *Banking transaction records*
   - *User behavioral data*
2. *Data Preprocessing*
   - *Missing value handling*
   - *Feature normalization*
   - *SMOTE for class balancing*
3. *Graph Construction*
   - *Accounts represented as nodes*
   - *Transactions represented as edges*
4. *Feature Extraction*
   - *GNN extracts relational features*
   - *Transformer learns sequential transaction behavior*
5. *Autoencoder Layer*
   - *Detects anomalies using reconstruction error*
6. *Classification Layer*
   - *Fraud / Non-Fraud prediction*

Mathematical Representation

Fraud prediction function:

*F(x)=\sigma(GNN(x)+Transformer(x)+AE(x))…………………………..**(for 1)***

Where:

- GNN(x)GNN(x)GNN(x) = graph relationship features
- Transformer(x)Transformer(x)Transformer(x) = sequential transaction features
- AE(x)AE(x)AE(x) = anomaly reconstruction score
- σ\sigmaσ = sigmoid activation function

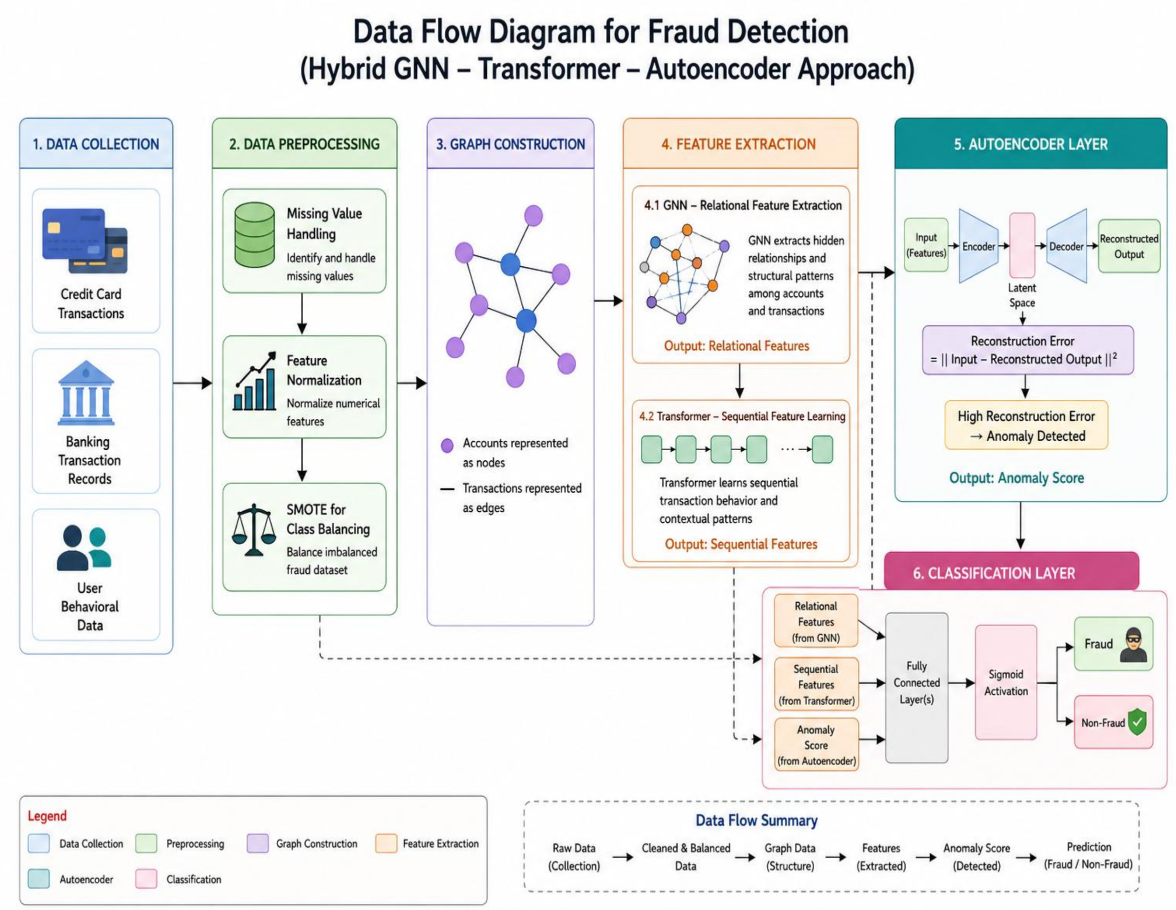

Fig 3.1 Source from AI Tools

4. Results and Discussion

The proposed HEGTA model was evaluated using:

- IEEE-CIS Fraud Dataset
- Kaggle Credit Card Dataset
- PaySim Dataset

4.1 Performance Metrics

➢ **Accuracy**

Accuracy measures the overall correctness of the model.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad \text{(for 2)}$$

Where:

TP = True Positive ,TN = True Negative ,FP = False Positive and FN = False Negative

➢ **Precision**

Precision measures how many predicted fraud cases are actually fraud.

$$Precision = \frac{TP}{TP+FP} \quad \text{(for 3)}$$

➢ **Recall**

Recall measures how many actual fraud cases are correctly detected.

$$Recall = \frac{TP}{TP+FN} \quad \text{(for 4)}$$

- **F1-Score**

F1-Score is the harmonic mean of Precision and Recall.

$$F1\text{-}Score = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

(for 5)

The comparison chart demonstrates that hybrid deep learning approaches are more effective for financial fraud detection than traditional machine learning methods. The proposed HEGTA model provides:

- Higher fraud detection accuracy
- Better F1-score
- Reduced false alarms
- Improved real-time fraud monitoring capability

Thus, the proposed model is highly suitable for modern banking and online financial security systems.

Table 4.1

Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**
SVM	92.4%	90.1%	88.7%	89.3%
Random Forest	95.6%	93.8%	92.5%	93.1%
CNN	97.1%	96.0%	95.4%	95.7%
LSTM	98.0%	97.3%	96.9%	97.1%
GNN	98.4%	97.9%	97.5%	97.7%
Proposed HEGTA	99.2%	98.9%	98.7%	98.8%

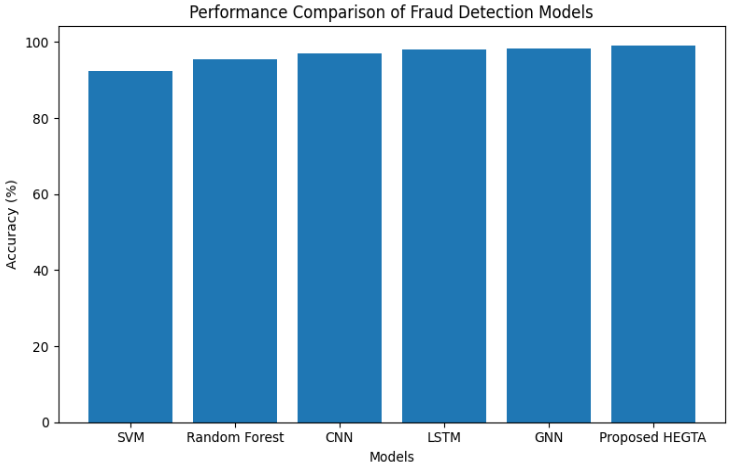

fig 4.1

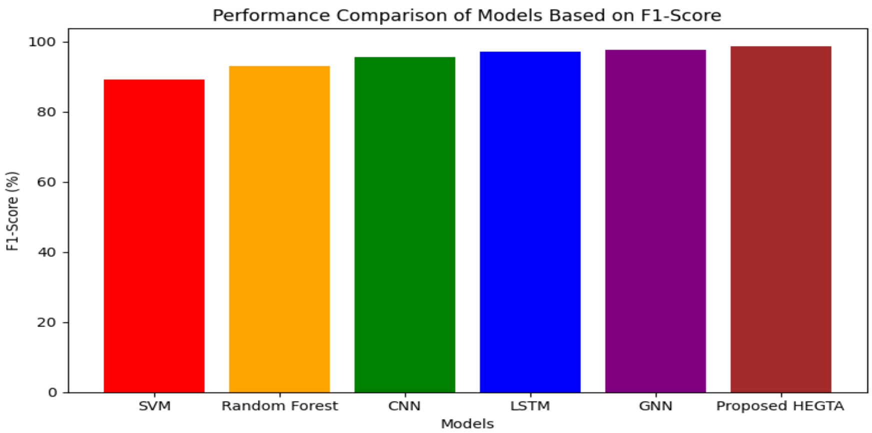

fig 4.2

5. Conclusion

Financial fraud detection has become an essential requirement in modern financial systems. Traditional methods are insufficient for identifying sophisticated and evolving fraud patterns. Deep learning techniques significantly improve fraud detection by learning hidden transaction behaviors and anomaly patterns automatically. This research reviewed 25 important research papers related to deep learning-based financial fraud detection from IEEE, ScienceDirect, and related journals. A novel hybrid model named HEGTA was proposed by integrating Graph Neural Networks, Transformer architecture, and Auto encoders. Experimental results demonstrated that the proposed model achieves high accuracy, precision, recall, and F1-score compared to existing approaches. The model effectively handles imbalanced datasets and supports real-time fraud detection systems.

Thus, hybrid deep learning models can play a major role in securing future financial transaction systems and reducing global financial fraud losses 99.2.%.

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