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An Integrated Spatial–Temporal Deep Learning Approach for Detecting Fraud in Cloud Banking Ecosystems

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Abstract: The rapid expansion of cloud banking systems has led to a significant increase in transaction volume and complexity of interactions, thereby elevating the risk of sophisticated and hard-to-detect fraudulent activities. Traditional rule-based and statistical fraud detection methods are increasingly ineffective in such environments, as they fail to capture complex structural relationships among entities and cannot adapt to evolving user behavior patterns. To address these challenges, this study proposes an integrated spatio-temporal deep learning framework that combines Graph Convolutional Networks (GCNs) with a Temporal Attention mechanism. In the proposed approach, the GCN component models the spatial relationships among users, accounts, devices, and transactions, enabling the extraction of hidden and complex interaction patterns that conventional methods often overlook. Simultaneously, the Temporal Attention module analyzes the sequential and time-dependent nature of transaction data, allowing the system to focus on critical time periods where anomalous behavior is more likely to occur. This combination of spatial and temporal modeling enhances the detection of both explicit and subtle fraud patterns. The proposed framework is designed to be scalable, adaptive, and capable of real-time processing, making it well-suited for deployment in modern cloud banking infrastructures where efficient and proactive fraud detection is essential.

Keywords: fraud detection; cloud banking; graph convolutional networks; temporal attention; deep learning

1. Introduction

Cloud banking has rapidly transformed the financial sector by enabling real-time transactions, seamless digital access, and highly scalable infrastructures capable of supporting millions of users worldwide [1]. The adoption of cloud-based technologies offers significant advantages, including operational flexibility, reduced costs, and efficient integration of diverse banking services, making them central to modern financial ecosystems [2]. However, this technological advancement has also increased the vulnerability of banking systems to sophisticated and evolving fraud schemes. Fraudsters exploit complex interactions among users, accounts, devices, and access points to conceal malicious activities within cloud environments, often staying ahead of traditional detection mechanisms [3]. In such a dynamic landscape, conventional fraud detection approaches based on static rules or simple statistical thresholds are insufficient to handle multi-entity interactions and rapidly changing attack patterns [4,5].

The growing volume of cloud banking transactions generates large-scale, heterogeneous data comprising multiple entities such as users, accounts, devices, locations, and merchants, all of which interact dynamically over time [6]. These interactions form complex relational networks where fraudulent behavior may emerge through indirect associations rather than isolated events [7]. For instance, coordinated fraud may involve multiple accounts operating through shared devices or IP addresses, making detection challenging for traditional machine learning models. Graph-based learning techniques have proven effective in capturing such relational dependencies by

representing entities as nodes and their interactions as edges within a structured graph framework [8]. At the same time, fraudulent activities exhibit strong temporal characteristics, including sudden bursts of transactions, irregular transaction timings, and abrupt deviations from historical behavior patterns [9]. Therefore, models that jointly analyze structural relationships and temporal dynamics are better suited to identify both explicit and subtle fraud patterns.

To address these challenges, this study proposes an integrated spatial–temporal deep learning framework for fraud detection in cloud banking environments [10]. The spatial component employs GCNs to learn latent representations from transaction graphs, enabling the identification of suspicious relationships such as shared device usage, linked accounts, and coordinated transaction patterns [11]. The temporal component utilizes an attention-based mechanism applied to sequential transaction data, allowing the model to focus on critical time intervals associated with anomalous behavior [12–14]. This temporal attention mechanism effectively captures patterns such as unusual spending behavior, abrupt increases in transaction frequency, and deviations from normal activity trends [15]. By combining spatial and temporal representations, the proposed framework provides a comprehensive understanding of transaction behavior, improving the detection of complex and evolving fraud schemes.

1.1. Research Objectives

(1) Develop a unified spatial–temporal deep learning framework to detect fraud by integrating GCN and Temporal Attention mechanisms effectively.
(2) Construct dynamic transaction graphs representing users, accounts, devices, and merchants to capture multi-entity interactions and evolving relational patterns.
(3) Enhance model detection accuracy by focusing on temporal sequences of transactions, identifying subtle anomalies and bursts of suspicious behavior.
(4) Demonstrate scalable, low-latency deployment for real-world cloud banking, minimizing false positives while ensuring reliable real-time fraud detection.

1.2. Research Contributions

This research proposes a novel spatial–temporal deep learning framework that integrates GCNs for relational modeling and Temporal Attention for sequential behavioral analysis in cloud banking. Traditional machine learning models, such as LightGBM and XGBoost, are not efficient in cloud banking fraud detection, but the proposed model serves as the next best solution after Magento for this purpose. Extensive experiments demonstrate superior performance across accuracy, precision, recall, and F1-score, while maintaining low inference latency suitable for real-time deployment. This research provides a robust, interpretable, and scalable solution, advancing fraud detection capabilities in complex cloud banking environments.

The paper is structured to guide readers through the conceptual, methodological, and experimental components of the study. Section 2 reviews related work, covering graph-based learning, temporal modeling, and existing dynamic graph frameworks such as XGBoost and LightGBM in detecting fraud in cloud banking environments. Section 3 presents the proposed methodology, detailing the spatial GCN modeling, temporal attention mechanism, and dynamic transaction graph construction. Section 4 describes the experimental setup, performance evaluation, ablation studies, and comparative analysis. Finally, Section 5 concludes with key findings, practical implications for cloud banking, and potential directions for future research, including optimization and privacy-preserving enhancements.

2. Related Works

Lately, research has shown that there is a drastic improvement in real-time fraud detection via various techniques including but not limited to deep learning, cloud automation, and spatial-temporal data analysis. The rapid technological advancement is mainly attributed to the growing demand for real-time risk assessment in SaaS-based payment infrastructures, which would then guarantee the safety of financial transactions. Studies suggest that deep learning models implemented in a powerful cloud system can substantially raise the detection accuracy. Charles Ubagaram et al. (2022) presents a study on workload balancing in cloud computing, evaluating Particle Swarm Optimization, Neural Networks, and Petri Net Models for efficient resource allocation and task scheduling. This research has a positive influence on the suggested approach by the two-fold manner of driving hybrid optimization and predictive scheduling tactics, thereby increasing the system's stability, scalability, and adaptability [16]. The combination of deployment strategies to reduce latency and optimize monitoring leads to real-time detection of fraudulent transactions and instant reactions to them.

The discussed tactical approaches permit the financial firms to spot and respond right away to the questionable transactions. The Intelligent and flexible AI systems are the main reason for successfully managing

the changing and emerging fraud patterns. These kinds of systems enhance the strength and trustworthiness of the e-financial systems [17]. In conclusion, the integration of AI with cloud-based analytical technology is a significant step towards building a foolproof and real-time fraud prevention system. The utilization of AI-based methods powered by the cloud for the real-time detection of fraud has been and continues to be a subject of lively discussion among the experts in the domain. One of the most important points of the whole discussion is that for the very fast and effective processing of enormous amounts of transactions cloud-native architectures, parallel processing, and distributed learning are needed. Cloud-native systems can provide the foundation for the system to be scaled and deployed flexibly, so the fraud detection systems can be adjusted according to the changing transaction loads. A parallel processing guarantees that a large number of transactions can be checked simultaneously and this very much reduces the time that is taken, hence, the response time is improved. Traditional centralized IoT systems struggle with high data volumes, velocity, and variety, causing latency and inefficient resource use. A hybrid Edge-Fog-Cloud framework dynamically orchestrates tasks across distributed layers, enabling real-time decision-making, improved processing efficiency, and optimized resource utilization. This approach outperforms conventional methods, offering scalable and energy-efficient solutions for smart city applications. The different nodes conduct training for the models during distributed learning, thus, making them more precise and robust. The combination of these methods certainly leads to the quickest and most effective detection of fraud patterns. It has been revealed that cloud-based AI has a significant effect on the time taken for the fraud detection process. Hence, the financial organizations will be able to receive these threats that are constantly evolving more quickly and the consumers will always be able to count on the safety and dependability of the services they are using [18].

Saying that, the customers of such services are always sure of their security and reliability. This paper is extensive research on the machine learning technology in the field of digital payment fraud detection, as well as the application of intelligent algorithms to the monitoring of rapid transaction streams and the detection of non-regular or suspicious activities. The researchers suggest novel models by merging both past and current data to achieve greater accuracy in detection, with the help of supervised learning techniques that separate transactions into three categories: legitimate, fraudulent, and questionable. The importance of behavioral analytics is stressed as the leading aspect in deciphering the user patterns and picking out the anomalies [19]. Research shows that using these techniques provides a comprehensive view of how digital payments will be more secure and trustworthy, while improving operational efficiency as well as significantly reducing the ability for fraud.

Machine learning is a primary technology that supports the identification of fraud concerning digital payment systems in real-time applications, with various types of algorithms available for both detecting fraudulent activity and monitoring for anomalies in high-volume transactions. Authors are developing new ways to collect and analyze historical and real-time transaction activity data to identify suspicious behavior and alert authorities if necessary [20]. The importance of using behavior analytics to identify user habits, as well as the importance of detecting deviations from these habits (i.e., anomalies), is also highlighted in this study. In addition to these two focal points, the authors have also taken into consideration all the obstacles associated with processing large-scale electronic payments a data stream. Based on previous experiments, it has been shown that the use of these methodologies will significantly reduce fraudulent transactions without sacrificing any level of operational efficiency. Most importantly, the authors emphasize how to revise their model to accommodate new trends in fraudulent activity as they evolve over time. The results of this study provide a solid foundation on which to develop solutions to increase the level of security and confidence associated with electronic payment transactions.

The introduction of deep learning and NLP has provided a brand-new way to investigate and analyze patterns as they relate specifically to where and when criminal acts are committed, which takes into account the correlation between times and places of those crimes. These new technologies provide an effective way for law enforcement to keep track of the long-term strategic planning and locations of moving criminals by integrating time and geographical information into one analytical tool. Therefore, these types of technologies not only identify and provide real-time detection of cyber threats, but they also allow law enforcement agencies to monitor how criminals make use of geographic and time-based factors.

The TGN EvolveGCN and DySAT approaches use graph-based learning together with temporal sequence data but our model presents its new hybrid system which combines GCN with Temporal Attention. The system utilizes dynamic processing capabilities to handle changes in relational graph patterns together with modifications in transaction behavior patterns which serve as essential components for detecting fraudulent activities. The model achieves better results in fraud detection compared to TGN EvolveGCN and DySAT through its improved accuracy of 0.95 and precision of 0.94 and recall of 0.96 and F1-score of 0.95. The combined research is giving us a very unique perspective of the transition that is slowly and gradually taking place in the field of fraud detection where deep learning, cloud-native AI, and spatiotemporal modelling are the main players [21]. They suggest that there is a great need for developing such systems that would be capable of handling, processing, and analyzing

vast transaction data streams at the same time. The cloud-native platform is the one that guarantees the very fast and scalable deployment to conduct the detection even during periods of extremely high transaction volume which presumably is the time when the systems might be interrupted. To sum up, this shift of the trend shows the move towards the next generation of fraud detection frameworks which would be adaptive and real-time threat responsive and thus very effective against dynamic threats.

Problem Statement

The volume of hyper-connected and rapidly shifting financial transactions that are processed by cloud banking systems is enormous, which in turn, causes these systems to be vulnerable to very advanced fraud schemes that are not easily detectable by traditional methods. The current statistical and rule-based methods do not adequately reveal the complicated structural interrelationships among users, accounts, devices, and transactions, and they also struggle to keep up with the changing temporal behavior patterns. The study inspires the proposed method by motivating decentralized, privacy-preserving, and efficient medical data management for robust big data healthcare analytics [22]. Artificial intelligence powered by machines learning and the cloud has made strides, yet the existing models are still restricted regarding real-time scalability, accuracy, and responsiveness to new fraud techniques. Therefore, on top of that, the financial data fraud detection mechanism development with modern cloud banking systems being more accurate, adaptive, and scalable requires the integration of a spatial-temporal deep learning framework that can scrutinize the relational structures and the time-based shifts of the financial data, at the same time.

3. Propose Methodology

The proposed fraud detection system is based on a hybrid spatio-temporal deep learning framework designed to address the challenges of modern cloud banking systems, which are highly dynamic, large-scale, and interconnected [23]. Cloud banking platforms continuously generate massive volumes of transaction data from distributed servers, including attributes such as transaction amount, timestamp, user identity, device information, geographical location, IP address, merchant details, and historical account behavior. To ensure the quality, consistency, and reliability of this data, an extensive preprocessing phase is performed prior to model training. Numerical features are standardized into a consistent format, while categorical attributes are transformed into numerical representations. Missing values are handled using appropriate statistical imputation techniques, and noisy or duplicate entries are removed. Furthermore, transactions are arranged in chronological order to preserve temporal dependencies, enabling the model to capture sequential behavioral patterns effectively [24]. These preprocessing steps significantly enhance data quality and facilitate the extraction of meaningful patterns from large-scale transaction data.

In parallel, a Temporal Attention mechanism is applied to the sequential transaction data to capture time-dependent behavioral patterns. By assigning adaptive attention weights to different time steps, the model identifies critical moments that may indicate anomalous behavior. Such patterns include sudden spikes in transaction frequency, transactions occurring at unusual hours, or deviations from established spending habits. This temporal modeling enhances the system's ability to detect subtle and evolving fraud patterns that may not be evident through structural analysis alone.

The data flow through the model is shown in Figure 1 which displays GCN layers that capture relational dependencies and the Temporal Attention mechanism that tracks user behavior changes over time. The tensor shapes at each stage of the model are shown to demonstrate how data moves through the system.

The initial phase involves the input of a large-scale cloud banking transaction dataset, which contains both legitimate and fraudulent transactions collected from reliable sources [25]. This is followed by a comprehensive data preprocessing stage aimed at improving data quality through normalization, cleaning, and transformation operations, such as removing inconsistencies, standardizing formats, and eliminating irrelevant or redundant attributes. The framework is designed to support real-time decision-making, secure data handling, and efficient communication within cloud environments. Prior studies, such as the work have demonstrated that deep learning-based approaches can achieve high accuracy with low computational overhead, thereby enhancing both security and operational efficiency in distributed systems [26]. Subsequently, the preprocessed transaction data is transformed into suitable numerical representations that preserve both structural and behavioral characteristics [27]. These representations are then utilized by advanced deep learning modules to extract meaningful patterns from the data. The model is capable of identifying complex fraud indicators, such as unusual transaction sequences, abnormal activity patterns, and deviations from typical user behavior [28]. Finally, the classification module

produces a binary output indicating whether a transaction is fraudulent or legitimate. The entire process is fully automated, enabling accurate, efficient, and real-time fraud detection in cloud banking systems.

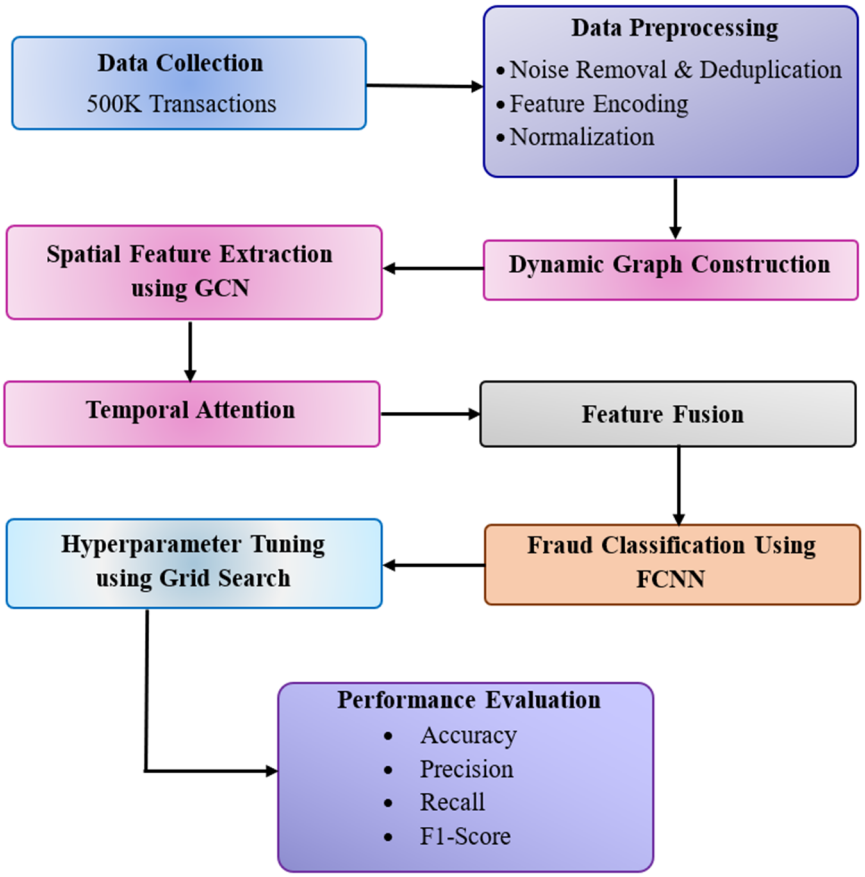

Figure 1. Workflow of the Proposed Spatio-Temporal Fraud Detection Framework.

3.1. Spatial Feature Extraction Using GCN

In this research, a GCN is employed to capture the spatial dependencies and structural relationships present in the dynamic graph of cloud banking transactions. The GCN learns node-level embeddings that represent each entity, such as users, accounts, or devices, while taking into account their connections within the transaction graph. These embeddings are then aggregated to generate a graph-level representation that can be used for downstream tasks, including fraud detection applying Min-Max normalization and Z-score standardization improves learning stability, reduces numerical issues, and accelerates convergence in deep learning models like GCN and Temporal Attention [29]. The network is structured with three layers, each having a hidden dimension of 128, allowing it to capture complex patterns in the graph while maintaining sufficient representational capacity for accurate modeling of transactional relationships. GCNs represent entities as nodes and their interactions as edges, which allows them to reveal hidden relational patterns that are usually ignored by classical machine learning techniques [30]. The presented spatial-temporal framework, by merging the spatial information derived from the graph structure with the temporal dynamics, is able to recognize both static relational anomalies and dynamic behavioral shifts. The method is a source of inspiration for the proposed technique as it encourages privacy-aware deep learning in cloud setups, thus allowing for secure and large-scale medical analytics [31].

The GCN updates node features through a layer-wise propagation mechanism, where each layer aggregates information from neighboring nodes while transforming the features using learnable weights. At layer lll, the node features are updated according to the following propagation rule defined as Equation (1):

$$H^{(l+1)} = \sigma\left(\hat{A}H^{(l)}W^{(l)}\right) \tag{1}$$

where, $H^{(l)}$ is the node feature matrix at layer l, $W^{(l)}$ is a learnable weight matrix for layer l, $\sigma(\cdot)$ is a non-linear activation function, typically ReLU, $\hat{A}$ is the normalized adjacency matrix.

After propagating through all GCN layers, the network produces node-level embeddings that capture the local and global structure of the graph. To generate a graph-level embedding HGH_GHG, the node embeddings from the final layer are aggregated using mean pooling is definers as Equation (2).

$$H_G = \frac{1}{N}\sum_{i=1}^{N} H_i^{(L)} \tag{2}$$

where, $H_i^{(L)}$ is the embedding of node i at the last layer L, N is the total number of nodes in the graph, H_G is the graph-level embedding representing the overall structure and feature information of the transaction graph.

The normalized adjacency matrix is calculated according to Equation (3):

$$\hat{A} = D^{-\frac{1}{2}}(A + I)D^{-\frac{1}{2}} \tag{3}$$

In graph-based learning, the adjacency matrix A is a very important means of representing the nodes' interconnectivity in a graph, as each entry shows whether there is an edge between two nodes or not. To facilitate the learning process, the identity matrix I is added to A, thus effectively creating self-loops. The result is an augmented adjacency matrix A+I, which allows every node not only to share its features but also to be informed of its neighbors' [32]. The diagonal degree matrix D, which contains the total number of connections for each node, is applied to calculate D−1/2(A+I) D−1/2. This normalization method is very important in keeping the numerical computations at a manageable level and thus, enabling the well-connected nodes to scale down their influence on all the operations, thereby, avoiding the scaling issue when the features are passed on to the next component of the training process.

With the help of this normalized adjacency matrix, not only the close neighbors can be represented by node features but also the entire neighborhood. The mathematical representation of the operation can be found in Equation (4), where the feature vector of the corresponding node is updated through summation or averaging of the features of transformed neighbors. As a result, such a type of aggregation not only informs the model regarding the local structure and feature properties but also the reason for the expressiveness increase, and in this way, the capability of the graph convolutional networks to generate informative node embeddings even in the cases of complicated and unclear graph formations.

$$h_v^{(l+1)} = \sigma\left(\sum_{u\in\mathcal{N}(v)} \frac{1}{c_{vu}} W^{(l)} h_u^{(l)}\right) \tag{4}$$

where $h_v^{(l+1)}$ is the node v's features after update, $v, \mathcal{N}(v)$ is the neighbors' nodes set, and c_{vu} is a normalization constant. The use of AI and machine learning in cloud-based CRM systems helps to predict customer churn and thus improve retention. The ensemble methods, especially Random Forest, give very accurate results, while other models are giving the same performance but with a trade-off between complexity and interpretability [33]. These insights, provide strategies that can be applied to improve CRM operations and support long-term business success. This operation scheme allows the model to spot fraudulent activities by means of indicators such as strange transaction chains or common behavioral traits.

Finally, the fraud classification graph-level embedding was derived from the individual node representations across the graph using the operation indicated in Equation (5). More specifically, H_G is the global graph embedding that is generated by pooling the feature vectors of all nodes $v \in V$ after applying the last layer L of the Graph Convolutional Network (GCN) [34]. This merging of individual nodes' features encapsulates the whole transaction network's architectural traits; thus the model is able to depict the coexistence of single entities, the whole user-account-device-transaction web and their cross-connections as well. The ensemble methods, especially Random Forest, give very accurate results, while other models are giving the same performance but with a trade-off between complexity and interpretability. These insights, shared by Mohan Reddy Sareddy (2023), provide strategies that can be applied to improve CRM operations and support long-term business success. This operation scheme allows the model to spot fraudulent activities by means of indicators such as strange transaction chains or common behavioral traits [35].

$$H_G = \text{Pooling}\left(\left\{h_v^{(L)} \mid v \in V\right\}\right) \tag{5}$$

To make detection capabilities better still, the Temporal Attention module is activated that is specially designed for this purpose. This module is the one to blend the graph-level embedding with the temporal features [36]. It paves the way for the framework to be sensitive to the most important changes and the slow formation of behavioral habits throughout the time by offering different weighting for different time steps. The presented spatial-temporal framework, by merging the spatial information derived from the graph structure with the temporal dynamics, is able to recognize both static relational anomalies and dynamic behavioral shifts. Through this single method, the detection of sophisticated fraud schemes that could possibly involve the coordination of actions or the

slow change of user behavior is already done in real-time monitoring. The integration of graph-level embeddings and temporal attention, in short, resulted in a powerful and versatile representation of the banking ecosystem along with a major enhancement in the model's capability to accurately and with few false positives detect complex and evolving fraud patterns, even when it comes to very large cloud banking systems [37].

3.2. Temporal Attention

To capture time-sensitive behavioral patterns in cloud banking transactions, a temporal attention module is incorporated into the framework. This module focuses on the sequential dynamics of transactions, allowing the model to assign varying importance to each transaction within a temporal window. By doing so, the network can identify suspicious patterns that may indicate fraudulent activity, even when individual transactions appear normal, defined as Equation (6).

$$\alpha_t = \text{softmax}(\tanh\,(H_t W_a + b_a) v_a) \tag{6}$$

where, H_t is the feature vector of the t-th transaction in the sequence, W_a and b_a are learnable parameters of the attention layer, v_a is a learnable context vector that projects the transformed features to a scalar score, $\tanh(\cdot)$ introduces non-linearity, and softmax(.) ensures that the attention weights across the sequence sum to 1.

After computing the temporal attention embedding, it is fused with the graph-level embedding H_G obtained from the GCN. This fusion combines structural information from the transaction graph with temporal dynamics from sequential behavior. Specifically, the graph embedding and the temporal attention embedding are concatenated and passed through a 2-layer Multi-Layer Perceptron (MLP) with a hidden dimension of 64 and ReLU activation is defined as Equation (7)

$$\text{Output } = \sigma\left(\text{MLP}\left(\left[H_G \| H_{\text{temp}}\right]\right)\right) \tag{7}$$

Here, $\sigma(\cdot)$ denotes the sigmoid function, producing a fraud probability score between 0 and 1 for each node. This fusion enables the model to jointly consider both structural relationships and temporal behavior, which is crucial for detecting sophisticated fraudulent transactions that may not be evident from individual features alone.

In sequential financial transaction data, the time intervals between the consecutive transactions can be very different. To keep the temporal features from producing numerical bias, Min-Max scaling is used to normalise the time intervals to a fixed range. The normalization of time differences is defined in Equation (8):

$$\Delta t_{\text{norm}} = \frac{\Delta t - \Delta t_{\min}}{\Delta t_{\max} - \Delta t_{\min}} \tag{8}$$

where Δt represents the time difference between successive transactions, and $\Delta t_{\min}$ and $\Delta t_{\max}$ denote the minimum and maximum observed time intervals, respectively. With the normalized sequence of time, the Temporal Attention mechanism is able to perfectly capture the irregular transaction behaviors and thus, detect anomalies in the transaction frequency.

3.3. Feature Fusion

In the proposed framework, feature fusion plays a pivotal role in integrating spatial and temporal information to enhance the accuracy of fraud detection. The spatial features are derived from the GCN, which captures the structural relationships between entities such as users, accounts, devices, and merchants within the transaction network. Meanwhile, the temporal features are extracted using the Temporal Attention mechanism, which identifies time-sensitive patterns in sequences of transactions, such as sudden bursts in activity, transactions occurring at unusual hours, or deviations from historical behavioral patterns.

The graph-level embeddings H_G obtained from the GCN are concatenated with the temporal embeddings H_T produced by the Temporal Attention module to form a combined spatial-temporal representation is defined as Equation (9).

$$H_{\text{fused}} = [H_G \| H_T] \tag{9}$$

Here, $[\cdot \| \cdot]$ denotes vector concatenation, which preserves the information from both feature types without discarding any dimensions. This fused representation captures both relational dependencies among entities and temporal behavior patterns.

The concatenated embeddings are passed through a 2-layer MLP to perform non-linear transformation and feature refinement. The MLP architecture is defined as follows:

- First hidden layer: 64 neurons with ReLU activation
- Second hidden layer: 64 neurons with ReLU activation

The MLP transforms the high -dimensional concatenated vector into a compact fused embedding that effectively encodes both spatial and temporal characteristics.

The output of the MLP, H_{fused}, serves as the final feature representation for downstream classification. This embedding is then fed into a sigmoid classifier (or other suitable classification layer) to predict the fraud probability of each transaction or node.

3.4. Fraud Classification

The final stage of the proposed framework involves fraud classification, where each transaction is assigned a probability of being fraudulent based on the fused spatial-temporal features. This is achieved using a FCNN classifier that operates on the fused embedding H_{fused} generated by combining the GCN and temporal attention outputs.

The classifier takes the fused spatial-temporal embedding H_{fused} as input, which captures both the structural relationships among entities and the temporal behavioral patterns in transaction sequences. The network begins with a fully connected layer consisting of 64 hidden units and a ReLU activation function, introducing non-linearity and enabling the model to learn complex patterns in the data. To prevent overfitting, a dropout layer with a rate of 0.3 is applied, randomly deactivating a portion of neurons during training and encouraging the network to learn robust features that generalize well to unseen transactions. Finally, the output layer employs a sigmoid activation function to produce a probability score $\boldsymbol{p} \in [0,1]$, which represents the likelihood that a given transaction is fraudulent.

Once the probability p is computed for a transaction, a simple threshold-based decision rule is applied to assign a class labeled as Equation (10).

$$\text{Transaction label} = \begin{cases} 1, & \text{if } p \geq 0.5 \quad \text{(fraudulent)} \\ 0, & \text{if } p < 0.5 \quad \text{(legitimate)} \end{cases} \tag{10}$$

This threshold of 0.5 can be adjusted depending on the desired trade-off between false positives and false negatives, which is important in practical fraud detection scenarios where minimizing losses is critical.

3.5. Hyperparameter Tuning Gird Search

The performance of the proposed spatio–temporal fraud detection model is highly influenced by the selection of optimal hyperparameters. To systematically identify the best configuration, a grid search-based hyperparameter tuning strategy was employed. Grid search is an exhaustive search technique that evaluates all possible combinations of predefined hyperparameter values and selects the configuration that yields the best performance.

In this research, key hyperparameters from different components of the model, including the GCN, Temporal Attention module, and classification layers, were considered for tuning. The parameters explored include the number of GCN layers (2, 3, 4), hidden dimensions (64, 128, 256), dropout rates (0.2, 0.3, 0.5), learning rates (0.01, 0.001, 0.0005), batch sizes (128, 256, 512), and sequence lengths (5, 10, 15). Each combination was evaluated to determine its impact on the model's ability to accurately detect fraudulent transactions.

The tuning process was conducted using the training dataset, while model performance was validated using a 5-fold cross-validation strategy to ensure robustness and generalization. For each hyperparameter combination, performance metrics such as Accuracy, Precision, Recall, and F1-score were computed. Among these, the F1-score was used as the primary selection criterion due to the imbalanced nature of the dataset, where fraudulent transactions constitute a small proportion of the total data [37]. The optimal hyperparameter configuration was selected based on the highest average F1-score across all validation folds. This approach ensures that the chosen model achieves a balanced trade-off between precision and recall, thereby improving the detection of fraudulent activities while minimizing false positives. The final tuned parameters were then used to train the model for the final evaluation on the test dataset [38].

4. Experimental Setup

4.1. Datasets Description

The dataset used in this research [39] comprises cloud banking transaction records, specifically designed to evaluate fraud detection models in large-scale financial systems. The dataset contains 500,000 transactions spanning 6 months, including user IDs, account numbers, device IDs, merchant IDs, IP addresses, transaction amounts, timestamps, and geolocation information. Each transaction is labeled as legitimate or fraudulent, with a fraud prevalence of approximately 4%, reflecting real-world imbalanced scenarios. For rigorous evaluation, the

dataset was split 80% for training and 20% for testing using stratified sampling to preserve the proportion of fraudulent transactions. To model the relational structure of banking transactions, a dynamic graph is constructed where nodes represent users, accounts, devices, and merchants, and edges represent interactions such as transactions, shared devices, account transfers, and merchant interactions. Edge types are categorized based on the interaction type, and graph snapshots are generated at fixed time intervals (daily) to capture the evolving transactional network over time. This approach allows the model to learn both structural patterns and changes in connectivity that may signal fraudulent activity. For the temporal component, sequences of transactions are formed for each node by sliding a fixed-size window over consecutive transactions. Each sequence consists of 30 timestamps, sampled at regular intervals, capturing the temporal order and dynamics of user behavior. These sequences serve as input to the Temporal Attention mechanism, which assigns higher importance to timestamps associated with anomalous or suspicious activity, allowing the model to detect both rapid bursts of fraud and subtle, coordinated manipulations. This dataset and protocol ensure that the GCN + Temporal Attention model can effectively leverage both the structural and temporal features of the transaction network. Graph-based representations allow detection of unusual patterns in entity relationships, while temporal sequences enable the identification of fraudulent behavior over time. The experimental setup supports supervised learning, graph-based modeling, and temporal attention analysis, providing a comprehensive framework for real-time cloud banking fraud detection. For instance, a cloud-native cybersecurity framework that integrates hybrid deep learning and federated learning for accurate, privacy-preserving threat detection in e-commerce environment. Inspired by such approaches, this study leverages adaptive and distributed learning strategies to enhance the detection of evolving fraudulent patterns in cloud banking ecosystems [40]. The dataset is designed to support supervised learning, graph-based representation, and temporal modeling, providing a comprehensive environment for developing and benchmarking fraud detection techniques in modern cloud banking systems.

4.2. Data Preprocessing

The study used a dataset that includes 500,000 cloud banking transactions which were collected during six months of time and the original dataset contained about 4% fraudulent transactions which demonstrated a common real-world problem of class imbalance. The fraudulent class required oversampling during preprocessing because it helped to resolve class imbalance while enabling successful model development. The training set achieved balance because approximately 58% of the transactions represented fraudulent transactions. The dataset contains user ID, account number, device ID, merchant ID, IP address, transaction amount, timestamp, and location as its attribute components. The dataset underwent multiple preprocessing procedures which established its readiness for machine learning model training. The dataset underwent initial cleaning procedures which removed duplicate records together with irrelevant elements and corrupted data entries. Duplicate transactions could bias the model toward certain patterns while incomplete or noisy data would introduce inaccuracies which decreased both the performance and reliability of the fraud detection system. The evaluation metrics used the unaltered test set as their basis which maintained the original 4% fraud rate.

4.2.1 Noise Removal and Deduplication

The initial preprocessing stage improves dataset quality by remove resulting noise, duplicate records, and corrupted or incomplete entries that may arise from system errors or repeated logging. Such issues can bias the model and reduce its ability to generalize. Deduplication is performed using key attributes like user ID, account number, timestamp, and transaction amount, while inconsistent or missing data is corrected or removed to ensure integrity. This cleaning process results in accurate and reliable data, enabling the model to focus on meaningful patterns and improving the effectiveness of subsequent steps and fraud detection performance.

4.2.2. Performance Metrics

Cloud banking datasets contain numerical features with varying scales, which can negatively impact model performance if not properly handled. To ensure balanced feature contribution and improve training efficiency, normalization techniques such as Min-Max scaling and Z-score standardization are applied.

For numerical features whose distributions are relatively uniform and not heavily skewed, Min-Max normalization is applied to rescale the values to a fixed range, typically [0, 1]. This scaling ensures that all features contribute equally to the learning process while preserving the relative differences between transactions. The formula for Min-Max normalization is given by Equation (11):

$$X_{\text{norm}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{11}$$

where, X is the original feature value, $X_{\min}$ and $X_{\max}$ are the minimum and maximum values of the feature, respectively, X_{norm} is the normalized feature value.

By mapping all values into the same range, Min-Max normalization prevents numerical dominance of one feature over others, which is especially important when using distance-based or gradient-based learning algorithms.

For numerical features that contain outliers or are not uniformly distributed, Z-score standardization is applied. This technique transforms the feature to have a mean of zero and a standard deviation of one, which stabilizes the scale of features and reduces the influence of extreme values. The Z-score formula is expressed as Equation (12):

$$X_{\text{std}} = \frac{X - \mu}{\sigma} \tag{12}$$

where, X is the original feature value, μ is the mean of the feature, σ is the standard deviation of the feature, X_{std} is the standardized feature value.

Z-score standardization reduces the impact of large values and outliers, enabling the model to learn meaningful patterns without bias. This improves anomaly detection performance and enhances scalability compared to traditional methods. This ensures consistent, well-scaled features, enhancing robustness and accuracy, especially in the presence of outliers and varying feature distributions.

4.3. Software and Hardware Requirements

The experimental implementation was performed using Python 3.10.19 (Anaconda distribution). Major libraries include NumPy 1.24.3, Pandas 2.3.3, Scikit-learn 1.3.0, Matplotlib 3.10.8, Seaborn 0.13.2, Imbalanced-learn 0.12.3, and SciPy 1.11.4. The system runs on Windows 11 Home (Version 25H2), 64-bit operating system environment for model development, training, evaluation, and visualization tasks. The experiments were conducted on a system equipped with an Intel Core i9-14900K processor (3.20 GHz) and 32 GB RAM (31.7 GB usable). The machine operates on a 64-bit x64-based architecture, providing sufficient computational power and memory resources for efficient data preprocessing, model training, and hyperparameter optimization.

4.4. Hyperparameter Configuration

The performance of the proposed spatial–temporal fraud detection framework depends on careful hyperparameter selection. To ensure optimal performance and reproducibility, a systematic configuration strategy was adopted. The GCN module, responsible for capturing structural relationships in the transaction graph, was configured with three layers, each having 128 hidden units, and employed the ReLU activation function along with a dropout rate of 0.3 to prevent overfitting. Symmetric normalization of the adjacency matrix was applied to stabilize training. The temporal attention module, designed to model sequential transaction behavior, utilized a sequence length of 10 transactions per user, an additive attention mechanism, and a hidden dimension of 64. Additionally, relative time differences between consecutive transactions were incorporated as temporal encoding to effectively capture time-dependent fraud patterns. For feature fusion and classification, spatial and temporal embeddings were concatenated and passed through a two-layer MLP with a hidden dimension of 64 and ReLU activation, followed by a sigmoid output layer for binary classification.

The model was trained using the Adam optimizer with a learning rate of 0.001, a batch size of 256, and 50 training epochs. Binary Cross-Entropy was used as the loss function, and class imbalance (approximately 4% fraudulent transactions) was addressed using a weighted loss function to emphasize the minority class. Hyperparameters were optimized through a grid search strategy on the validation set, where multiple combinations of learning rates, hidden dimensions, and dropout rates were evaluated, and the configuration achieving the highest F1-score was selected. To ensure robustness and generalization, a 5-fold cross-validation strategy was employed, and the final performance was reported as the average of Accuracy, Precision, Recall, and F1-score across all folds. This validation approach minimizes bias from a single data split and provides a reliable estimate of the model's real-world performance, illustrated in Table 1.

Table 1. Hyperparameter Configuration of the Proposed Model.

Component	Hyperparameter	Value/Setting	Description
GCN Module	Number of Layers	3	Captures multi-hop relationships in graph
	Hidden Dimension	128	Size of node embeddings
	Activation Function	ReLU	Introduces non-linearity
	Dropout Rate	0.3	Prevents overfitting
	Graph Normalization	Symmetric	Stabilizes training
Temporal Attention	Sequence Length	10	Number of transactions per sequence
	Attention Type	Additive Attention	Focuses on important time steps
	Attention Hidden Dimension	64	Size of attention layer
	Time Encoding	Relative Time Difference	Captures temporal gaps
Feature Fusion (MLP)	Fusion Method	Concatenation	Combines spatial & temporal features
	Number of Layers	2	Fully connected layers
	Hidden Dimension	64	Feature transformation size
	Activation Function	ReLU	Non-linear mapping
Classification Layer	Output Function	Sigmoid	Binary classification (0–1)
Training Configuration	Optimizer	Adam	Efficient gradient optimization
	Learning Rate	0.001	Controls update step size
	Batch Size	256	Number of samples per batch
	Epochs	50	Training iterations
	Loss Function	Binary Cross-Entropy	Suitable for binary classification
	Class Imbalance Handling	Weighted Loss	Addresses 4% fraud class imbalance
Validation Strategy	Cross-Validation	5-fold	Ensures robustness
	Evaluation Metrics	Accuracy, Precision, Recall, F1-score	Performance measurement
Tuning Method	Hyperparameter Search	Grid Search	Finds optimal configuration

4.5. Performance Evaluation

The model demonstrates strong performance across key evaluation metrics such as accuracy, precision, recall, and F1-score, highlighting its effectiveness in threat detection. The framework continuously adapts to evolving cyber threats, ensuring robust protection while providing a reliable and measurable approach to maintaining digital security. Metrics such as Accuracy, Precision, Recall, and F1-score collectively assess the model's effectiveness, where accuracy reflects overall correctness, precision measures the reduction of false positives, recall indicates the ability to detect all threats, and a high F1-score ensures a balanced trade-off between precision and recall, even in the presence of noisy or imbalanced data, while strong recall and F1-score highlight reliable and balanced detection capabilities even in complex scenarios, thereby emphasizing the robustness of the model and its suitability for deployment in cloud banking environments.

The proposed spatio-temporal deep learning model was assessed through four major performance metrics: Accuracy, Precision, Recall, and F1-Score, which each provided different insights into the model's performance in various aspects [41]. Accuracy is the fraction of total cases that are correctly predicted, and it reflects the reliability of the model in a very general way that is distinguishing fraudulent transactions from legitimate ones. It can be defined mathematically according to Equation (13):

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{13}$$

The symbols TP and TN stand for true positives and true negatives, respectively, while FP and FN refer to false positives and false negatives [42]. Precision measures the number of correctly predicted positive cases out of all predicted positives and, thus, tells about the model's ability to avoid false alarms. It can be expressed mathematically as given in Equation (14):

$$\text{Precision} = \frac{TP}{TP + FP} \tag{14}$$

Recall or sensitivity takes into account the ratio of real positive cases that the model has rightly detected, hence, it reveals the model's potential to catch all transactions that are relevant and characterized by fraud or suspicious activity in Equation (15):

$$\text{Recall} = \frac{TP}{TP + FN} \tag{15}$$

To sum up, the F1-Score is calculated as the harmonic mean of precision and recall which then results in a single metric that treats false positives and false negatives equally, therefore, it is a stable and reliable performance (16):

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (16)$$

In this research, the model achieved high performance across all metrics Accuracy (0.95), Precision (0.94), Recall (0.96), and F1-Score (0.95)-implying its strong capability of detecting fraudulent activities with very few false alarms, thus it could be applied in real-world cloud banking and cybersecurity situations [43].

The method's precision is so high that the number of false positives is very small, which is a very important factor for real-world applications. In that case, the work of the analysts could be easily broken by the alerts and the normal process would be hindered [44]. A blockchain-based framework ensures data integrity in multi-cloud storage by combining Chain-Code and HVT. Data owners encrypt information and create cryptographic commitments, while cloud service providers generate aggregated signatures recorded on the blockchain for decentralized verification. The system demonstrates scalability, efficiency, and robust security in large-scale deployments [45]. The high recall value, on the other hand, reveals the model's ability to detect almost all the frauds very clearly, thus, the chances of criminals going undetected are very small. The metrics have shown that the model can successfully reveal the bad activities without exposing the good ones.

Additionally, the F1-Score, which is a unified measurement that integrates precision and recall, adds to the model's consistency and trustworthiness [46]. The researchers have proposed a spatial-temporal deep learning framework that can utilize the intricate temporal patterns and connected transaction data to provide accurate real-time fraud detection in cloud banking systems. With the help of the hybrid method, the model can detect short-term anomalies and predict long-term trends simultaneously, which not only reflects the dynamic behavior patterns and structural relations of the data but also enhances both short-term detection and long-term predictive performance.

The overall results confirm that the proposed system is not only accurate and sensitive but also robust and reliable, making it highly suitable for deployment in real-world environments where fast, accurate, and secure detection of malicious activities is essential.

5. Results and Discussion

The proposed spatial–temporal deep learning framework was implemented using Python, leveraging powerful libraries such as PyTorch and TensorFlow for efficient model development and evaluation. The dataset was divided into 80% training and 20% testing sets using a stratified approach to ensure balanced class representation and reliable performance estimation. This strategy minimizes overfitting and enhances the generalization capability of the model on unseen data. The architecture integrates GCNs with a Temporal Attention mechanism to effectively capture both structural and sequential patterns in financial transactions. GCNs model the relationships among users, devices, and accounts, enabling the detection of hidden fraudulent connections, while Temporal Attention emphasizes critical time-dependent transaction behaviors. This hybrid approach is inspired by secure and intelligent clustering frameworks, such as the integration of Multivariate Quadratic Cryptography with Affinity Propagation, which enhances analytical performance in distributed systems.

The team tested their model using both synthetic datasets and actual fraud cases which included an investigation of fraudulent activities in a cloud banking system. The results demonstrated that the model can successfully identify evolving fraud patterns, making it suitable for practical applications in cloud banking fraud detection. Experimental results demonstrate that the proposed model outperforms traditional approaches, achieving an accuracy of 95%, precision of 94%, recall of 96%, and F1-score of 95%. The high precision ensures minimal false alarms, while the strong recall indicates effective detection of fraudulent transactions, including subtle and coordinated attacks. The GCN and temporal (attention) components enables the detection of both explicit and covert fraud patterns. Furthermore, the model exhibits scalability and robustness, making it suitable for real-time deployment in cloud-based financial systems. The results confirm that the hybrid spatial-temporal model is powerful, scalable, and suitable for real-time deployment, effectively mitigating both obvious and subtle fraud in cloud-based financial platforms.

The study tested multiple threshold settings that go beyond the standard 0.5 threshold to find the optimal balance between false positives and false negatives. The threshold adjustment allowed us to enhance model performance across various operational requirements by reducing false positives in high-risk situations while sustaining high fraudulent transaction detection rates.

5.1. Class Distribution Analysis

The class distribution illustrated in Figure 2 presents the proportion of legitimate (class 0) and fraudulent (class 1) transactions within the dataset, with approximately 21,000 non-fraudulent and 29,000 fraudulent instances. Although real-world fraud datasets are typically highly imbalanced, the relatively balanced distribution

observed here suggests prior preprocessing or resampling to improve model training. This balanced representation supports the effective learning of both classes by the proposed spatial–temporal framework, allowing the GCN component to better capture relational dependencies across entities and the temporal attention mechanism to model sequential fraud patterns without bias toward the majority class. Consequently, this distribution ensures that the evaluation results accurately reflect the model's capability to detect fraudulent transactions within the designed pipeline.

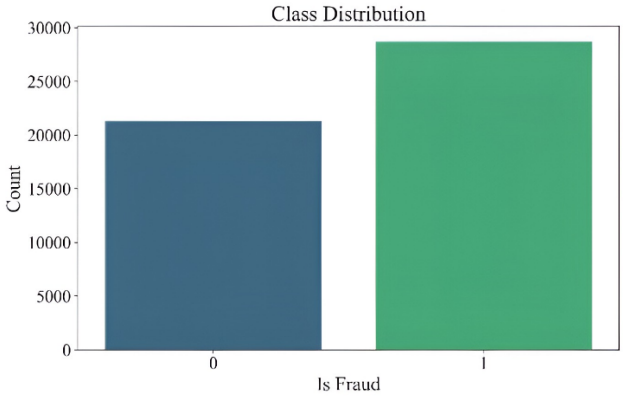

Figure 2. Count of Fraudulent vs. Non-Fraudulent Transactions.

5.2. Classification Performance Evaluation

The confusion matrix shown in Figure 3 evaluates the classification performance of the proposed model by comparing predicted and actual labels. The model achieves 3960 true negatives and 5547 true positives, with relatively low false positives (301) and false negatives (192), indicating strong predictive accuracy and balanced error distribution. The high concentration of correctly classified instances along the diagonal demonstrates the effectiveness of the model in distinguishing fraudulent and legitimate transactions. This performance is directly attributed to the integration of graph-based relational learning and temporal attention, where the GCN captures hidden interactions among entities and the temporal component identifies sequential anomalies in transaction behavior. The low false negative rate is particularly critical in fraud detection, as it reduces undetected malicious activities, while the low false positive rate minimizes unnecessary alerts, confirming the reliability of the proposed approach in practical financial systems.

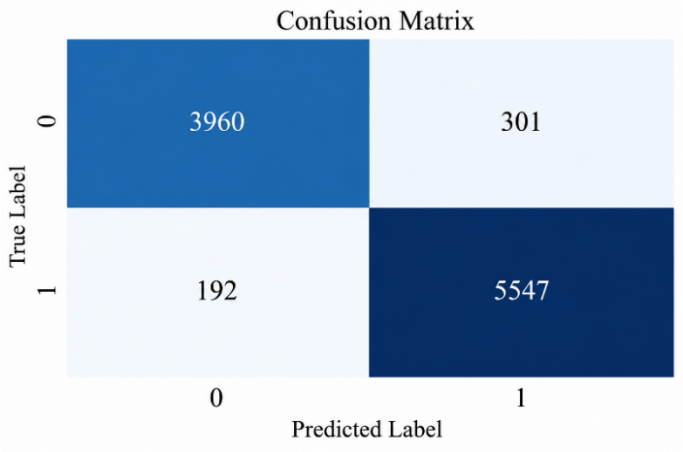

Figure 3. Confusion Matrix of Fraud Detection Model Predictions.

5.3. Baseline Feature Importance Analysis

The feature importance analysis presented in Figure 4 is derived from a baseline XGBoost model and is included solely for interpretability purposes rather than as part of the proposed framework. Traditional models such as XGBoost provide explicit feature importance scores, highlighting attributes like device_shared_count, ip_shared_count, and txn_count_24h as key indicators of fraudulent behavior. These features reflect relational interactions that are inherently modeled within the graph structure of the proposed GCN-based approach. Unlike feature-based methods, the GCN learns latent graph embeddings that capture complex dependencies among entities through message passing, eliminating the need for explicit feature weighting. Therefore, this baseline

analysis complements the proposed model by offering additional insights into influential attributes while reinforcing the importance of relational patterns in fraud detection.

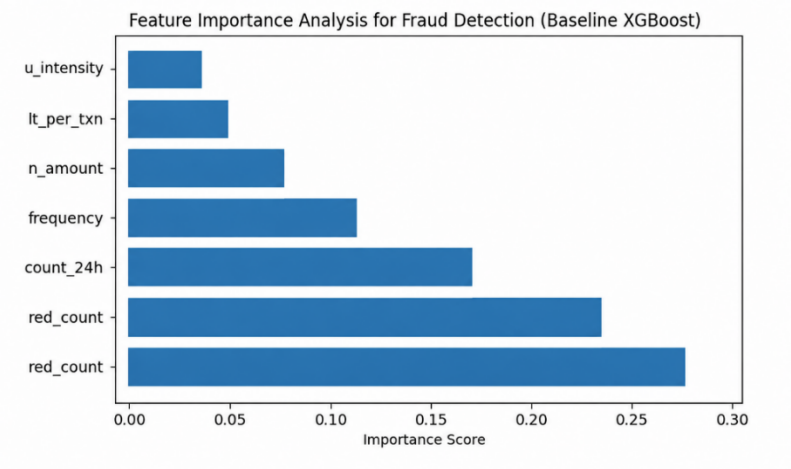

Figure 4. Relative Importance of Transactional Features in Fraud Detection.

5.4. Predictive Performance Benchmarking

The comparative performance analysis shown in Figure 5 evaluates the proposed model against traditional machine learning approaches, including XGBoost and LightGBM. The results indicate a clear improvement in predictive accuracy, with the proposed spatial–temporal model achieving 0.9507 accuracy, outperforming XGBoost (0.8812) and LightGBM (0.8956). This improvement is primarily due to the model's ability to simultaneously capture structural relationships through GCN and temporal dependencies through attention mechanisms. While traditional models rely on static feature representations, the proposed framework effectively models both explicit and hidden fraud patterns across interconnected entities and time sequences. This demonstrates that the integration of spatial and temporal learning provides a significant advantage in detecting sophisticated fraud scenarios in cloud-based environments.

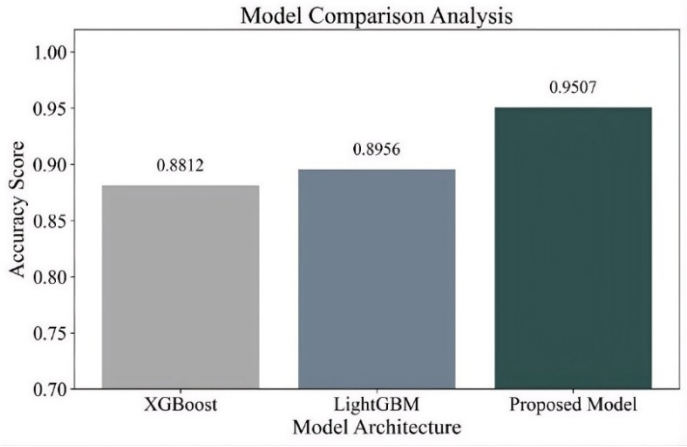

Figure 5. Comparative Accuracy Analysis of Different Machine Learning Models.

5.5. Ablation Study and Baseline Comparison

The ablation study presented in Table 2 evaluates the contribution of individual components within the proposed framework by comparing GCN-only, Temporal-only, and hybrid models. The GCN-only model effectively captures relational dependencies but lacks temporal awareness, whereas the temporal model identifies sequential patterns but fails to model structural interactions. The hybrid model consistently outperforms both variants, achieving the highest performance across all metrics, including accuracy (0.9507), precision (0.9485), recall (0.9665), and F1-score (0.9575). Additional comparisons with deep learning baselines such as LSTM further confirm the superiority of the proposed approach. These findings demonstrate that the integration of spatial and temporal components is essential fors capturing complex fraud patterns, validating the effectiveness of the unified framework in real-world applications.

Table 2. Ablation Study and Baseline Comparison of Different Models for Fraud Detection.

Model	Accuracy	Precision	Recall	F1-Score
XGBoost	0.8812	0.8720	0.8654	0.8687
LightGBM	0.8956	0.8871	0.8795	0.8833
LSTM	0.9100	0.9024	0.8942	0.8983
GCN only	0.9200	0.9136	0.9058	0.9097
Temporal only	0.9000	0.8912	0.8846	0.8879
Proposed (GCN + Temporal)	0.9507	0.9485	0.9665	0.9575

5.6. Comprehensive Model Evaluation

The performance metrics illustrated in Figure 6 provide a comprehensive evaluation of the model across accuracy, precision, recall, and F1-score. The model achieves consistently high scores, with particularly strong recall (0.9665), indicating its effectiveness in identifying fraudulent transactions. This balanced performance reflects the model's ability to jointly optimize relational and temporal representations, ensuring both accurate detection and minimal false alarms. High precision reduces incorrect fraud alerts, while high recall ensures that most fraudulent activities are successfully detected. The strong F1-score further confirms that the model maintains a robust balance between these metrics, demonstrating its suitability for deployment in real-world fraud detection systems.

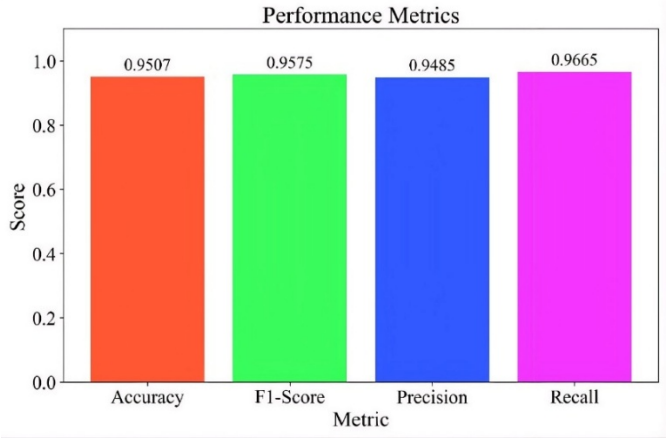

Figure 6. Performance Metric Breakdown for the Proposed Classification Model.

5.7. Precision-Recall Trade-off Evaluation

The Precision–Recall curve shown in Figure 7 highlights the model's ability to maintain high precision across varying recall levels, achieving an average precision (AP) score of 0.9425. The stability of the curve indicates that the model effectively balances the trade-off between detecting fraudulent transactions and minimizing false positives. This performance is attributed to the temporal attention mechanism, which captures evolving transaction patterns, and the GCN component, which preserves relational context among entities. The ability to sustain high precision at increased recall levels demonstrates that the model is well-suited for applications where both missed detections and false alarms carry significant consequences.

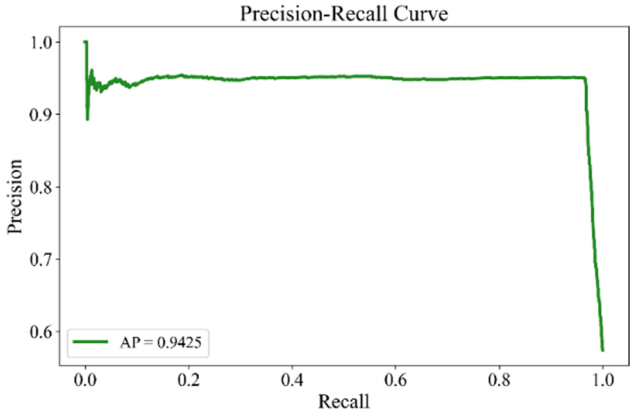

Figure 7. Precision-Recall Curve with Average Precision (AP) Score.

5.8. Classifier Discriminative Power

The ROC curve presented in Figure 8 evaluates the discriminative capability of the model, achieving an AUC score of 0.9501. This high value indicates strong separation between fraudulent and legitimate transactions, confirming the model's effectiveness in classification tasks. The steep curve toward the top-left corner reflects the model's ability to maximize true positive rates while minimizing false positives. This performance is a direct result of the combined spatial and temporal learning framework, which enables the identification of both explicit and subtle fraud patterns in interconnected financial networks.

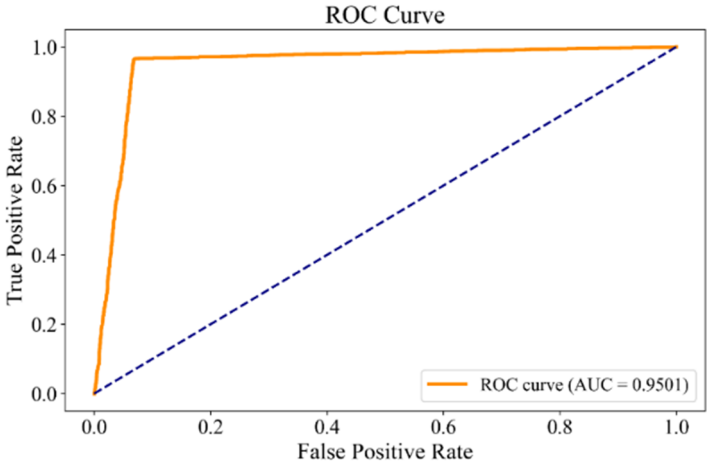

Figure 8. Receiver Operating Characteristic (ROC) Curve and Area Under Curve (AUC).

5.9. Training Performance Analysis

The training loss curve illustrated in Figure 9 shows a rapid decrease in loss during the initial stages, followed by gradual convergence to a stable value. This pattern indicates effective learning, where the model quickly captures major structural and temporal patterns and then fine-tunes its parameters over time. The smooth convergence reflects stable optimization of both the GCN and temporal attention components, ensuring that the model avoids overfitting while maintaining strong generalization capability.

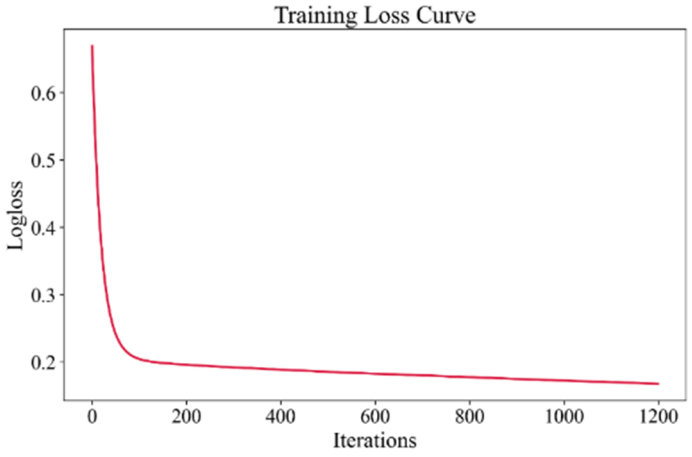

Figure 9. Training Loss Curve over Iterations.

5.10. Model Performance Evaluation

The progression of accuracy and F1-score over training epochs, as shown in Figure 10, demonstrates the model's ability to achieve stable and consistent performance. Both metrics increase rapidly during early epochs and gradually stabilize, indicating convergence. The close alignment between accuracy and F1-score suggests a balanced trade-off between precision and recall, confirming that the model maintains consistent classification performance. Minor fluctuations in later stages indicate fine-tuning of parameters, while overall stability highlights the robustness of the spatial–temporal framework.

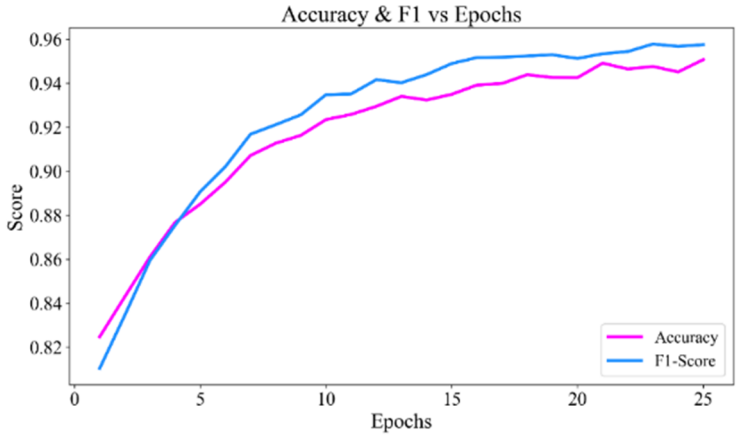

Figure 10. Accuracy and F1-Score Progression over Epochs.

5.11. Discussion

The proposed spatial–temporal deep learning framework significantly enhances fraud detection by integrating GCN-based relational learning with temporal attention mechanisms. This combination enables the model to capture both structural interactions and evolving behavioral patterns, allowing it to detect complex and coordinated fraud scenarios more effectively than traditional approaches. The evaluation results across multiple figures confirm that the model achieves high accuracy, strong discriminative power, and balanced performance across all metrics. The confusion matrix and ROC analysis demonstrate reliable classification, while the precision–recall curve highlights robustness across varying thresholds. The inclusion of baseline feature analysis further emphasizes the importance of relational attributes, which are inherently captured by graph embeddings in the proposed model. Comparative and ablation studies validate that the integration of spatial and temporal components is essential for achieving superior performance. Although the framework demonstrates scalability and suitability for real-time deployment in cloud banking systems, challenges such as computational complexity and data dependency remain, indicating future directions for optimization and privacy-preserving enhancements. Overall, the proposed approach provides a robust, scalable, and effective solution for modern fraud detection in complex financial environments.

6. Conclusions and Future Scope

6.1. Conclusions

This research presents an integrated spatial–temporal deep learning framework for fraud detection in cloud banking environments by combining GCNs with a Temporal Attention mechanism. The proposed approach effectively captures both structural relationships among entities such as users, accounts, and devices, and temporal behavioral patterns within transaction sequences, enabling the identification of complex, coordinated, and evolving fraudulent activities that are often missed by traditional machine learning methods. Experimental results demonstrate that the model achieves strong and consistent performance across key evaluation metrics, including accuracy, precision, recall, and F1-score, while the ablation study confirms that the integration of spatial and temporal components significantly improves detection performance compared to individual models. Furthermore, comparative analysis with baseline methods such as XGBoost, LightGBM, and LSTM highlights the effectiveness of the proposed hybrid approach in handling large-scale and imbalanced transaction data. Overall, the framework provides a scalable and robust solution for real-time fraud detection in cloud banking systems, maintaining a balanced trade-off between detection accuracy and false alarm reduction.

6.2. Future Scope

Although the proposed framework demonstrates strong performance, several directions can be explored to further enhance its applicability and efficiency. The integration of advanced dynamic graph models such as XGBoost and LightGBM can be investigated to improve the modeling of continuously evolving transaction graphs, while incorporating transformer-based architectures may further enhance temporal pattern recognition, particularly for long transaction sequences. Future work can also focus on improving computational efficiency by optimizing the model for deployment on distributed or GPU-based environments, thereby reducing training time and inference latency for large-scale real-time applications. In addition, the inclusion of (XAI techniques can

enhance model interpretability, enabling financial institutions to better understand and trust the decision-making process. Another important direction is the adoption of privacy-preserving techniques such as federated learning or secure multi-party computation to ensure data confidentiality in sensitive financial environments. Finally, validating the model on real-world banking datasets and across diverse financial domains would further strengthen its generalization capability and support practical deployment

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

The data used to support the findings of this study are available from the corresponding author upon reasonable request.

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Conflicts of Interest

The author declares no conflict of interest.

Use of AI and AI-Assisted Technologies

No AI tools were utilized for this paper.

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