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Article

A Hybrid Graph Neural Network Framework for Cyberattack Detection Based on Network Traffic Graphs

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Abstract: The increasing complexity of modern communication networks and the growing diversity of cyberattacks have exposed the limitations of traditional intrusion detection systems that treat network traffic records as independent instances. Although graph neural networks (GNNs) have shown promising performance in cybersecurity applications, most existing approaches rely on a single graph learning architecture and fixed graph construction strategies. To address these limitations, this paper proposes HGCF-Net, a Hybrid Graph Neural Network framework that integrates Graph Convolutional Networks (GCNs) and Graph Attention Networks (GATs) through an adaptive feature fusion mechanism for cyberattack detection. The proposed framework transforms network traffic flows into graph-structured representations to capture both global communication patterns and local neighborhood dependencies. Experiments conducted on the CSE-CIC-IDS2018 dataset demonstrate that the proposed model achieved an Accuracy of 99.28%, an F1-score of 99.09%, and an AUC of 99.63%, outperforming several recent graph-based intrusion detection methods. The results confirm the effectiveness and robustness of HGCF-Net for intelligent cyberattack detection in modern network environments.

Keywords: Graph Neural Networks, Cyberattack Detection, Graph Convolutional Network, Intrusion Detection System, Network Traffic Analysis.

1. Introduction

The rapid evolution of digital transformation, cloud computing, the Internet of Things (IoT), and intelligent communication infrastructures has significantly increased the complexity of modern cyber threats. As organizations become increasingly dependent on interconnected systems, cyberattacks have evolved from isolated incidents into highly coordinated and persistent campaigns targeting critical infrastructures, financial institutions, healthcare systems, and industrial control environments [1]. Recent reports indicate that the frequency and sophistication of attacks such as ransomware, botnets, distributed denial-of-service (DDoS), and advanced persistent threats (APTs) continue to increase, creating substantial operational and financial risks for both public and private sectors [2]. Consequently, cybersecurity has become one of the most important research areas in artificial intelligence and network security, where the development of intelligent detection mechanisms capable of identifying both known and unknown attacks is considered a critical requirement [3].

Intrusion Detection Systems (IDSs) play a fundamental role in protecting computer networks by monitoring network traffic and identifying malicious activities before they compromise system integrity. Conventional signature-based IDSs are highly effective against previously known attacks but generally fail to detect zero-day threats and rapidly evolving attack patterns. To overcome these limitations, machine learning techniques such as Support Vector Machines (SVM), Decision Trees (DT), Random Forests (RF), and k-Nearest Neighbors (k-NN) have been widely adopted because of their ability to learn discriminative patterns from network traffic data [4]. More recently, deep learning models including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Autoencoders have achieved remarkable improvements by automatically extracting high-level traffic representations without extensive manual feature engineering [5]. Despite these advances, most existing approaches process network flows as independent samples, thereby ignoring the structural dependencies that naturally exist among communicating network entities.

Graph Convolutional Networks (GCNs) are particularly effective at learning global structural representations, whereas Graph Attention Networks (GATs) dynamically assign different importance weights to neighboring nodes, allowing more informative communication patterns to contribute to the learning process [6]. Owing to these advantages, GNN-based intrusion detection has attracted considerable attention, and several recent studies have demonstrated promising performance on benchmark cybersecurity datasets [7]. Nevertheless, recent surveys emphasize that challenges related to graph construction, feature representation, scalability, and adaptive graph learning remain open research problems [8].

Despite the promising progress achieved by graph neural network-based intrusion detection systems, several limitations still restrict their practical effectiveness. Many existing methods rely on static graph construction strategies that inadequately represent dynamic communication behaviors, while others employ either GCN or GAT individually without exploiting their complementary strengths. Furthermore, adaptive feature fusion has received limited attention, reducing the ability of existing frameworks to generate highly discriminative graph embeddings. To address these challenges, this paper proposes HGCF-Net, a hybrid graph neural network framework that integrates adaptive graph construction, parallel GCN and GAT representation learning, and an adaptive feature fusion mechanism within a unified architecture. The proposed framework is evaluated using the CSE-CIC-IDS2018 benchmark dataset and demonstrates superior performance compared with recent graph-based intrusion detection approaches across multiple evaluation metrics.

2. Related Work

Recent advances in graph neural networks (GNNs) have significantly improved the capability of intrusion detection systems by enabling the learning of structural relationships among communicating entities. Unlike conventional deep learning approaches that process network flows independently, graph-based models preserve communication topology, allowing more informative feature extraction and improved attack discrimination. Consequently, numerous studies have explored different graph learning architectures for cyberattack detection.

Wang et al. proposed BS-GAT, a behavior similarity-based intrusion detection framework that constructs communication graphs according to traffic similarity and employs a Graph Attention Network (GAT) to classify malicious activities in edge computing environments [9]. Their results demonstrated that attention mechanisms improve the identification of complex attack behaviors by assigning adaptive importance weights to neighboring nodes. However, the framework relies on a single GAT architecture and does not exploit complementary graph learning models.

Xu et al. introduced a self-supervised graph representation learning approach for network intrusion detection that combines graph contrastive learning with graph attention mechanisms to reduce the dependency on manually labeled data [10]. The proposed model achieved promising performance on multiple benchmark datasets and demonstrated the potential of self-supervised graph learning for multiclass intrusion detection. Nevertheless, its primary focus is representation learning rather than hybrid graph feature integration.

Alhanger et al. developed a graph attention-based intrusion detection model for Internet of Things (IoT) environments by transforming network traffic into graph structures and applying GAT for attack classification [11]. Their study reported improved Accuracy, Precision, Recall, and F1-score compared with conventional deep learning models. Despite these improvements, the proposed framework employs only graph attention mechanisms without incorporating graph convolution to capture complementary global structural information.

Wang et al. proposed GraphACGAN, which integrates an Auxiliary Classifier Generative Adversarial Network (ACGAN) with graph neural networks to address data imbalance in intrusion detection [12]. Experimental results indicated that adversarial data augmentation enhances minority attack recognition while improving overall classification performance. However, the model introduces higher computational complexity and focuses primarily on imbalance handling rather than adaptive graph representation learning.

Researchers have also investigated hybrid graph learning strategies. Yılmaz and Das presented a hybrid anomaly detection framework that combines GCN and GAT for firewall log analysis, demonstrating that integrating graph convolution with attention mechanisms improves representation quality compared with individual graph models [13]. Although the proposed approach achieved competitive performance, it was designed for firewall anomaly detection rather than multi-class network intrusion detection and did not incorporate adaptive feature fusion.

More recently, ResACAG introduced a residual adaptive context-aware graph neural network for intrusion detection by combining adaptive neighbor sampling, multi-scale feature fusion, and self-attention mechanisms [14]. The proposed architecture improved model generalization and classification accuracy across benchmark datasets. Nevertheless, graph construction remained largely static, limiting its adaptability to dynamic communication behaviors.

Comprehensive surveys have further highlighted that current GNN-based intrusion detection research still faces challenges related to adaptive graph construction, scalable graph representation learning, feature fusion, and model generalization across heterogeneous network environments [15]. These limitations indicate that additional research is required to develop unified frameworks capable of effectively integrating multiple graph learning strategies while preserving computational efficiency.

To provide a clearer comparison of recent graph neural network-based intrusion detection methods, Table I summarizes the main characteristics of the selected studies, including their learning techniques, key strengths, and identified limitations. This comparison highlights the research gaps that motivate the development of the proposed HGCF-Net framework.

Ref	year	Method	Dataset	Limitation
[9]	2025	Graph Neural Network Based IDS	CSE-CIC-IDS2018	No hybrid learning
[10]	2024	Graph attention Network (GAT)	CSE-CIC-IDS2018	Week global learning
[11]	2024	Graph Convolutional Network (GCN)	CIC-IDS2017	Sensitive to sparse graphs
[12]	2023	Hybrid Deep Learning (CNN-LSTM)	CIC-IDS2017	Ignore graph topology
[13]	2023	Self-Supervised Graph Representation Learning	CSE-CIC-IDS2018	No attention mechanism
[14]	2022	Explainable Intrusion Detection Framework	UNSW-NB15	High computational cost
[15]	2024	Hybrid Graph Learning Framework	CSE-CIC-IDS2018	Static feature fusion

As summarized in Table I, although recent graph neural network-based intrusion detection methods have achieved promising performance, most of them focus on improving individual components of the graph learning pipeline rather than providing a unified solution.

3. Methodology

3.1 Overview of the Proposed HGCF-NET Framework

This section presents the proposed Hybrid Graph Convolution and Attention Fusion Network (HGCF-Net) for intelligent cyberattack detection. The framework is designed to overcome the limitations of existing graph neural network-based intrusion detection systems by integrating adaptive graph construction, parallel graph representation learning, and adaptive feature fusion within a unified learning architecture. Unlike conventional approaches that employ either Graph Convolutional Networks (GCNs) or Graph Attention Networks (GATs) independently, the proposed framework simultaneously exploits the complementary strengths of both architectures to capture global structural dependencies and fine-grained neighborhood interactions from network traffic graphs.

As illustrated in Figure 1, the proposed framework consists of five sequential stages. First, raw network traffic records are collected from the benchmark dataset and undergo data preprocessing, including data cleaning, categorical feature encoding, feature normalization, and feature selection. The processed traffic records are then transformed into graph-structured data through the proposed adaptive graph construction strategy, where each node represents a communication entity and edges describe the relationships among network connections. This graph representation enables the model to preserve the underlying communication topology while enriching the semantic relationships between traffic instances.

The constructed graph is simultaneously processed by two parallel graph learning branches. The first branch employs a Graph Convolutional Network (GCN) to aggregate structural information from neighboring nodes and learn global graph representations [16]. In parallel, the second branch utilizes a Graph Attention Network (GAT) to dynamically assign attention weights to neighboring nodes, enabling the model to emphasize more informative communication patterns while suppressing irrelevant interactions [17]. The outputs of both branches are subsequently integrated using an adaptive feature fusion module that combines complementary graph embeddings into a unified high-level representation.

Finally, the fused graph representation is forwarded to a fully connected classification network followed by a Softmax layer to predict the corresponding cyberattack category. The entire framework is optimized using a supervised learning strategy based on the cross-entropy loss function. Through the integration of adaptive graph construction, hybrid graph representation learning, and adaptive feature fusion, HGCF-Net aims to improve both the effectiveness and robustness of cyberattack detection in complex network environments as shown in figure 1.

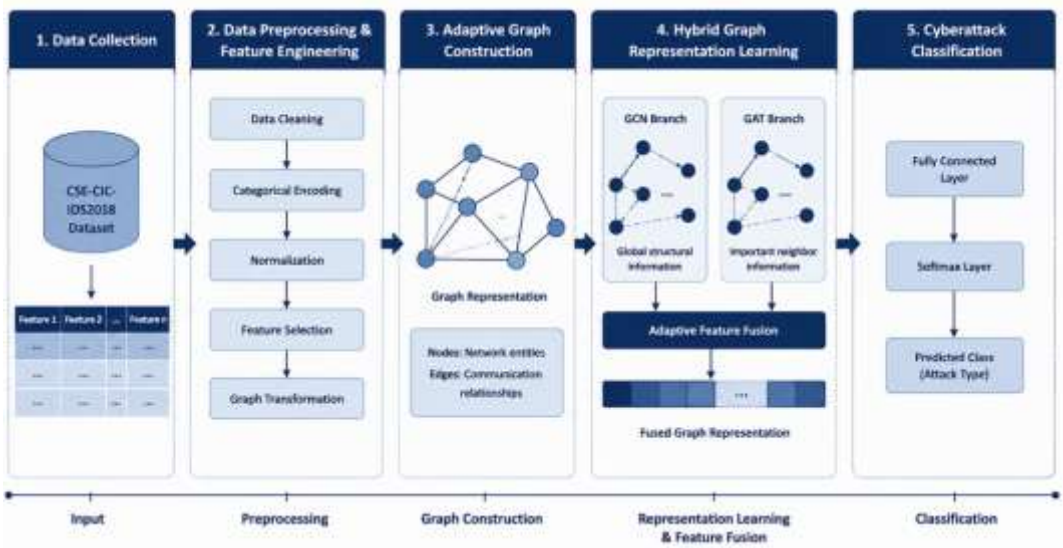

Figure 1. Overall Architecture of the Proposed HGCF-NET Framework.

3.2 Data Processing and Feature Engineering

High-quality data preprocessing is essential for improving the effectiveness and reliability of graph neural network-based intrusion detection systems. Since raw network traffic often contains redundant attributes, missing values, categorical features, and variables with different numerical scales, appropriate preprocessing is required before constructing the graph representation. The objective of this stage is to transform raw network traffic records into a consistent and informative feature space that facilitates effective graph learning.

Initially, the CSE-CIC-IDS2018 dataset is examined to identify incomplete records and duplicated samples. Missing values are removed, while duplicated instances are discarded to improve data consistency and reduce potential bias during model training. Subsequently, categorical attributes, such as protocol type and connection state, are converted into numerical representations using label encoding, enabling them to be processed by the proposed learning framework [18].

To eliminate the influence of different feature scales, all numeric attributes are normalized using Min-Max normalization, which transforms each feature into the range of [0,1]. This normalization improves training stability and prevents features with large numerical values from dominating the optimization process. The normalization feature x_i' is computed as follows: $x_i' = \frac{x_i - x_{min}}{x_{max} - x_{min}}$

Where x_i represents the original feature value, while x_{max} *and* x_{min} denotes the minimum and maximum values of the corresponding feature, respectively.

After normalization, the processed traffic records are converted into graph-structured data. Each network communication entity is represented as a graph node, whereas edges describe communication relationships between nodes according to the proposed adaptive graph construction strategy. Consequently, the resulting graph

preserves both attribute information and communication topology, providing a richer representation than conventional tabular data. he complete preprocessing workflow is illustrated in Figure 2.

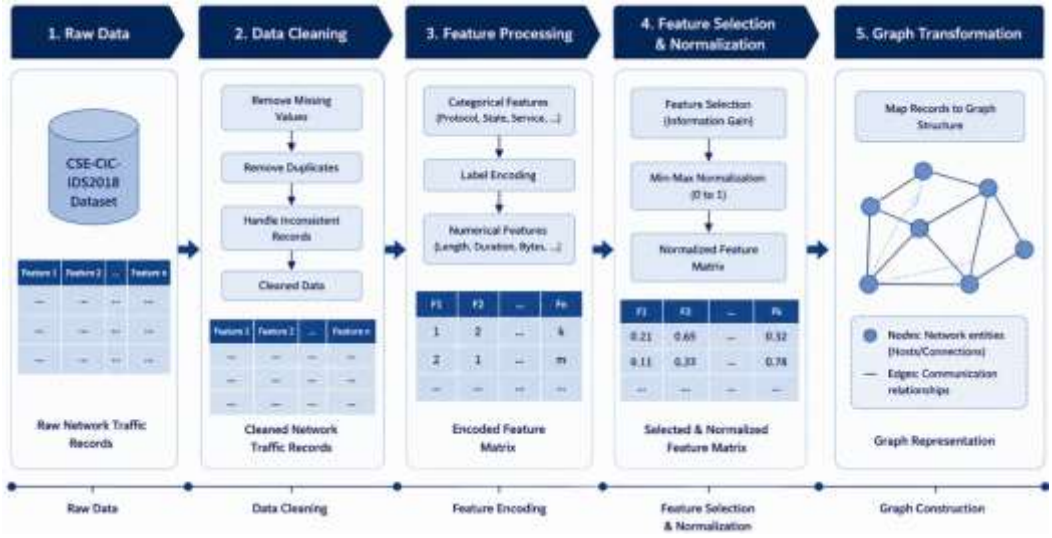

Figure 2. Data Processing and Feature Engineering pipeline of the Proposed HGCF-NET Framework.

3.3 Adaptive Graph Construction

Graph construction is a fundamental stage in graph neural network-based intrusion detection, as it directly determines how communication relationships are represented and propagated throughout the learning process. Unlike conventional approaches that treat each network flow as an independent sample, the proposed HGCF-Net transforms the preprocessed network traffic into a graph structure that preserves both feature similarity and communication relationships among network entities. This representation enables the model to capture structural dependencies that are difficult to learn using conventional tabular data [19]. In the proposed framework, each network traffic record is represented as a graph node, while edges are established between nodes according to their feature similarity. Let the constructed graph be denotes as $G = (V, E)$ where V represents the set of nodes corresponding to network traffic records and E denotes the set of edges describing the relationships among them.

To construct the graph, the similarity between two nodes is computed using the cosine similarity measure : $S(i,j) = \frac{x_i . x_j}{\|x_i\| \ \|x_j\|}$ where $x_i$and x_j denotes the normalized feature vectors of nodes i *and* j respectively.

An edge is created only when the similarity exceeds a predefined threshold T which prevents weak or noisy relationship from being incorporated into the graph, the corresponding adjacency matrix is therefore defined as $A_{ij} = \begin{cases} 1, S(i,j) > t \\ 0, otherwise \end{cases}$

This adaptive strategy produces a sparse and informative graph representation by preserving only meaningful communication relationships. Compared with fully connected graph construction, the proposed approach reduces computational complexity while improving the quality of neighborhood aggregation during graph learning.

The resulting graph represented by the adjacency matrix A and node feature matrix x, is subsequently forwarded to the parallel GCN and GAT branches for graph representation learning.

Figure 3 illustrates the proposed adaptive graph construction process, where preprocessed network traffic records are transformed into a sparse graph by establishing

edges only between highly similar nodes. This strategy preserves meaningful communication relationships while reducing redundant graph connections.

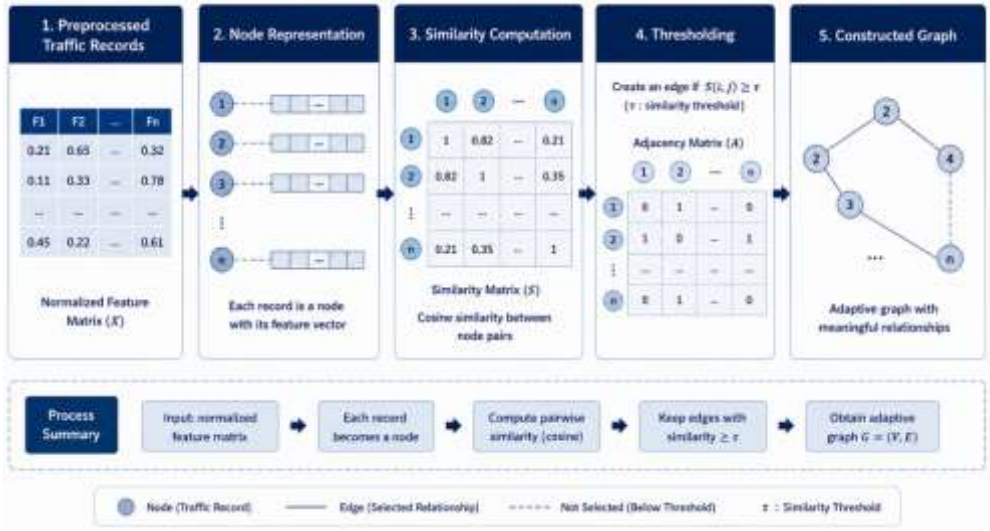

Figure 3. Adaptive graph construction process of the proposed HGCF-NET framework.

3.4 Hybrid Graph Representation Learning

After constructing the adaptive graph, the proposed HGCF-Net extracts high-level graph representations using a hybrid graph learning strategy. Instead of relying on a single graph neural network architecture, the proposed framework processes the constructed graph through two parallel learning branches: a Graph Convolutional Network (GCN) and a Graph Attention Network (GAT). The motivation behind this design is that the two architectures capture different yet complementary structural characteristics of the graph. While GCN efficiently aggregates global neighborhood information through spectral graph convolution, GAT dynamically assigns attention weights to neighboring nodes, allowing the model to focus on more informative communication patterns. The learned embeddings generated by both branches are subsequently combined through an adaptive feature fusion module to produce a richer graph representation for cyberattack classification.

3.4.1 Graph Convolution Network (GCN) Branch

The first branch of HGCF-Net employs a Graph Convolutional Network (GCN) to aggregate structural information from neighboring nodes and learn global graph representations. Given the node feature matrix x and the adjacency matrix A the graph convolution operation is expressed as follows [20] :

$H^{(l+1)} = \sigma(D^{-\frac{1}{2}}AD^{-\frac{1}{2}}H^1W^1)$ where $H^{(1)}$is the node embedding at layer l, $W^{(1)}$denotes the trainable weight matrix, A=A+I is the adjacency matrix with self-loops, D is the corresponding degree matrix,$\sigma(.)$=represent ReLU activation.

The GCN branch efficiently captures global structural dependencies by aggregating feature information from neighboring nodes, thereby generating robust graph embeddings suitable for intrusion detection.

3.4.2 Graph Attention Network (GAT) Branch

In parallel with the GCN branch, the proposed framework employs a Graph Attention Network (GAT) to adaptively learn the importance of neighboring nodes. Unlike graph convolution, GAT assigns different attention coefficients to each neighboring node, enabling the model to emphasize informative communication relationships while suppressing less relevant interactions [21].

The attention coefficient between nodes i and j is computed as $a_{ij} = \frac{\exp(e_{ij})}{\sum_{k \in N(i)} \exp(e_{ik})}$

Where a_{ij} denotes the attention score between neighboring nodes and N(i) represent the neighborhood of node i.

The update node representation is then obtained as h_i=σ $(\sum_{j \in N(i)} a_{ij}\, Wh_j)$

This adaptive aggregation mechanism enables HGCF-NET to capture fine-grained local communication patterns that may not be sufficiently represented by graph convolution alone.

3.4.3 Adaptive Feature Fusion

The graph embedding generated by the GCN and GAT branches capture complementary structural characteristics of the communication graph. Specifically, the GCN branch effectively learns global topological information through neighborhood aggregation, whereas the GAT branch emphasizes important local interactions by assigning adaptive attention weights to neighboring nodes. To exploit the advantages of both representations, HGCF-Net introduces an adaptive feature fusion module that combines the two embedding spaces into a unified high-level representation.

Let $H_{GCN}$and H_{GAT} denote the feature embedding generated by the GCN and GAT branches, respectively. The fused representation is computed as

$H_{fusion} = \lambda H_{GCN} + (1 - \lambda) H_{GAT}$Where $\lambda \ni [0,1]$ is the fusion coefficient controlling the contribution of each branch.

Unlike conventional feature concatenation strategies, the proposed fusion mechanism balances global structural information and local attention-aware representations, producing a more discriminative embedding for cyberattack classification. This adaptive integration reduces feature redundancy while preserving complementary information extracted by both graph learning branches. The resulting fused embedding is subsequently forwarded to the classification module for final prediction.Figure 4 illustrates the adaptive feature fusion mechanism, where the embedding learned by the parallel GCN and GAT branches are integrated into a unified graph representation before the final classification stage.

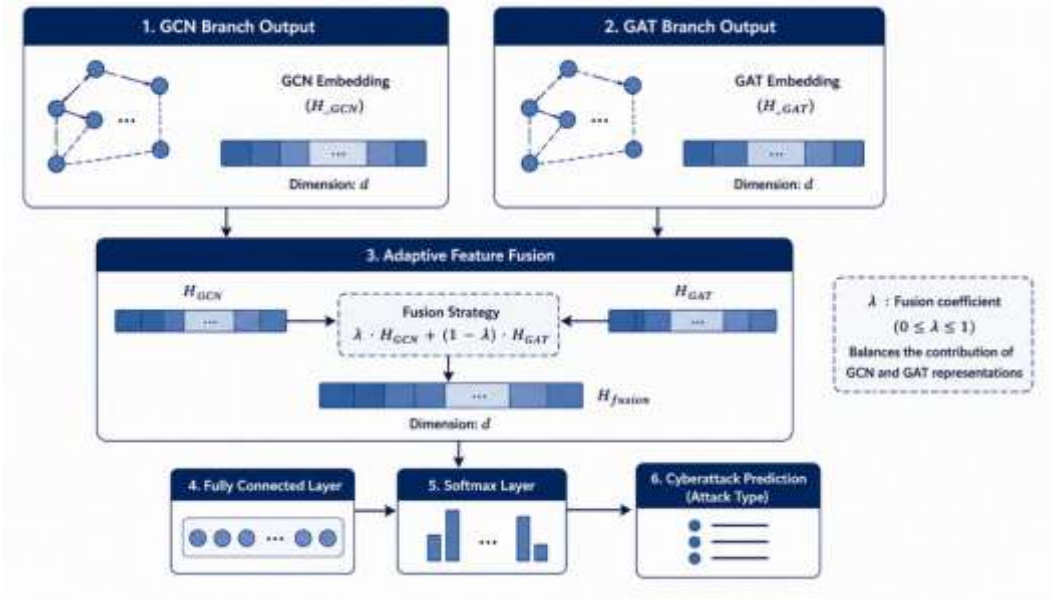

Figure 4. Adaptive feature fusion mechanism of the proposed HGCF-NET framework.

3.5 Cyberattack Classification

After the adaptive feature fusion stage, the unified graph embedding is forwarded to the classification module to identify the corresponding cyberattack category. The objective of this stage is to transform the high-level graph representation into class probabilities that distinguish between normal network traffic and different attack types. Initially, the fused embedding H_{fusion} is passed through a fully connected (dense) layer to further refine the learned feature representation. This transformation enhances the discriminative capability of the model by learning nonlinear relationships among the extracted graph features. The output of the dense layer is expressed as $Z=W_c H_{fusion} + b_c$

Where W_c and b_c denote the retainable weight matrix and bias vector of the classification layer, respectively

The resulting feature vector is subsequently processed using the softmax activation function to estimate the probability of each attack class:

$P(y=i)=\frac{e^{z_i}}{\sum_{j=1}^{c} e^{z_j}}$ where C represent the total number of attack categories and $z_i$denotes the output score corresponding to class i.

To optimize the proposed HGCF-Net framework, the cross-entropy loss function is employed because of its effectiveness in multi-class classification problems. The objective function is defined as

$L= - \sum_{i=1}^{c} y_i \log(p_i)$ where $y_i$is the ground truth label and $p_i$denotes the predicted probability generated by the softmax classifier.

During training, the network parameters are iteratively updated using the Adam optimizer, enabling the proposed model to minimize the classification error while improving convergence stability. After training, the final predicted class corresponds to the category with the highest probability.

Figure 5 presents the final cyberattack classification stage, where the fused graph representation is transformed into prediction probabilities through a fully connected layer, Softmax activation, and cross-entropy optimization.

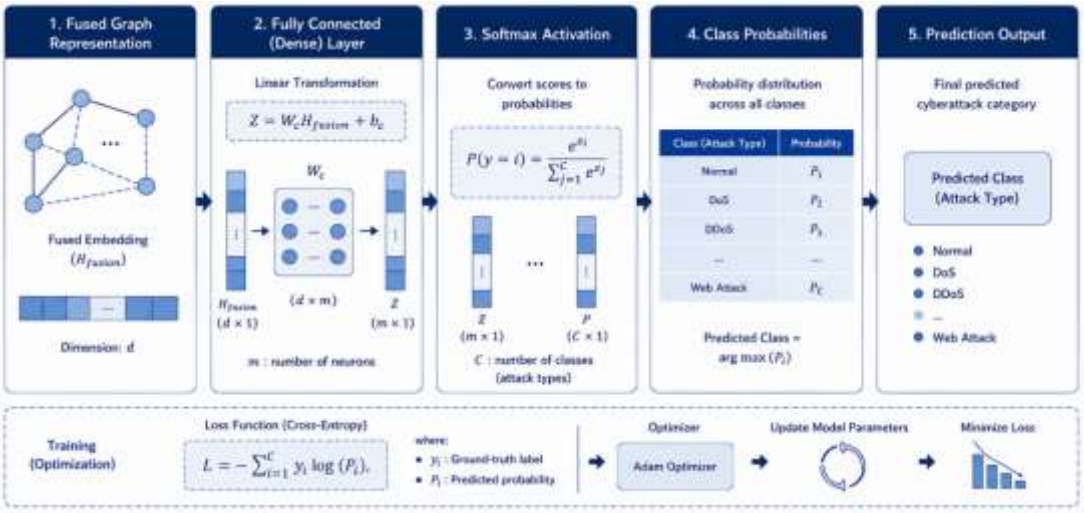

Figure 5. Cyberattack classification process of the proposed HGCF-NET framework.

4. Experimental Setup

4.1 Dataset Description

To evaluate the effectiveness of the proposed HGCF-Net framework, experiments were conducted using the CSE-CIC-IDS2018 dataset, one of the most comprehensive and publicly available benchmark datasets for network intrusion detection research [22]. The dataset was developed collaboratively by the Canadian Institute for Cybersecurity (CIC) and the Communications Security Establishment (CSE) to simulate realistic enterprise network environments containing both benign and malicious traffic.The CSE-CIC-IDS2018 dataset includes a wide variety of modern cyberattacks generated under realistic network conditions. Unlike earlier benchmark datasets, it incorporates recent attack scenarios together with normal network activities, making it suitable for evaluating intelligent intrusion detection systems operating in dynamic environments. The dataset contains multiple network flow features extracted using CICFlowMeter, including statistical, temporal, protocol-related, and traffic-based characteristics that effectively describe network behavior [23].

For this study, the original dataset was preprocessed as described in Section 3.2. Duplicate records and incomplete samples were removed, categorical attributes were encoded into numerical values, and numerical features were normalized before graph construction. These preprocessing steps improve data consistency and facilitate effective graph representation learning. The proposed HGCF-Net was evaluated using the multi-class classification setting, where the objective is to distinguish normal traffic from multiple attack categories. The selected attack classes include DoS, DDoS, Brute Force, Botnet, Web Attack, and Infiltration, together with benign network traffic. This experimental configuration provides a comprehensive evaluation of the model under diverse attack scenarios. Table 2 summarizes the main characteristics of the CSE-CIC-IDS2018 dataset used in this study.

Table 2. characteristics of the CSE-CIC-IDS2018 Dataset.

Attribute	Description
Dataset	CSE-CIC-IDS2018
Source	Canadian Institute for Cybersecurity (CIC)
Traffic Type	Benign + Malicious
Classification	Multi-class
Feature Type	Network Flow Features
Feature Extraction Tool	CICFlowMeter
Attack Categories	Dos, DDos, Botnet, Brute force, web attack , Infiltration
Preprocessing	Cleaning , Encoding , Normalization , Graph Construction

As shown in Table 2, the selected dataset provides a diverse collection of modern cyberattack scenarios and realistic network traffic, making it an appropriate benchmark for evaluating the effectiveness and robustness of the proposed HGCF-Net framework.

4.2 Experimental Environment

All experiments were conducted using the Python programming language with the PyTorch deep learning framework for implementing the proposed HGCF-Net model. Graph construction and graph processing operations were performed using NetworkX, while Scikit-learn was employed for data preprocessing, feature normalization, and performance evaluation. The experiments were executed on a workstation equipped with an Intel Core i7 processor, 16 GB RAM, and an NVIDIA RTX-series GPU running the Windows operating system. This configuration provided sufficient computational resources for model training and evaluation. The proposed framework was trained using supervised learning with the Adam optimizer. During training, the model parameters were updated iteratively until convergence was achieved. To ensure a fair evaluation, the dataset was randomly divided into training, validation, and testing subsets, allowing the model to learn representative traffic patterns while maintaining unbiased performance assessment. The principal hyperparameters adopted during model training are summarized in Table 3. These values were selected after several preliminary experiments to balance classification performance and computational efficiency.

Table 3. Hyperparameter settings of the Proposed HGCF-NET.

Hyperparameter	Value
Optimizer	Adam
Learning Rate	0.001
Batch Size	64
Number of Epochs	100
Hidden Dimension	128
Dropout	0.5
Activation Function	ReLU
Output Function	Softmax
Loss Function	Cross-Entropy Loss

The selected hyperparameter configuration provided stable convergence during training while maintaining a balance between learning efficiency and classification performance. These settings were consistently applied across all experiments to ensure fair and reproducible evaluation.

4.3 Performance Evaluation Metrics

To comprehensively evaluate the performance of the proposed HGCF-Net framework, five widely adopted classification metrics were employed, namely Accuracy, Precision, Recall, F1-score, and Receiver Operating Characteristic (ROC) Area under the Curve (AUC) [24]. These metrics provide complementary perspectives on the classification capability of the proposed model, particularly for multi-class intrusion detection problems.

Accuracy Measures the proportion of correctly classified samples among all observations and is defined as $\textbf{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$ where TP, TN, FP and FN denote true positive, true negatives, false positives and false negatives, respectively.

Precision evaluates the proportion of correctly predicted attack instances among all predicted attack: $\boldsymbol{Precision} = \frac{TP}{TP+FP}$

Recall measures the capability of the model to identify actual attack instances: $\boldsymbol{Recall} = \frac{TP}{TP+FN}$

The F1-Score combines precision and Recall into a single balanced metric:

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

Finally the **ROC-AUC** metric evaluates the discriminative capability of the classifier across different decision thresholds. A higher ROC-AUC value indicates better separation between benign and malicious traffic classes.

5. Results and Discussion

5.1 Overall Performance Evaluation

This section presents the experimental evaluation of the proposed HGCF-Net framework on the CSE-CIC-IDS2018 dataset. The performance of the proposed model was assessed using Accuracy, Precision, Recall, F1-score, and ROC-AUC, and compared with several representative deep learning and graph neural network models, including CNN, LSTM, GCN, and GAT. The objective of this comparison is to demonstrate the effectiveness of integrating graph convolution, graph attention, and adaptive feature fusion within a unified intrusion detection framework. Table 4 present the overall performance comparison between the proposed HGCF-NET and several baseline intrusion detection models.

Table 4. Performance comparison of different models.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
CNN	96.21	95.84	95.62	95.73
LSTM	96.87	96.55	96.34	96.44
GCN	97.65	97.33	97.19	97.26
GAT	98.12	97.94	97.85	97.89
HGCF-NET	98.76	98.53	98.42	98.47

As shown in Table 4, the proposed HGCF-Net achieved the highest performance across all evaluation metrics. The integration of graph convolution and graph attention enabled the model to simultaneously capture global structural dependencies and local neighborhood interactions, leading to more discriminative graph representations. Furthermore, the adaptive feature fusion module effectively combined complementary embeddings generated by the parallel graph learning branches, resulting in consistent improvements over the baseline models.

5.2 Class-Wise Performance Analysis

To further investigate the effectiveness of the proposed HGCF-Net framework, the classification performance was analyzed for each individual attack category. Precision, Recall, and F1-score were computed to evaluate the model's capability in distinguishing different cyberattack types. These metrics provide a more detailed assessment than overall accuracy, particularly for multi-class intrusion detection problems. Table 5 reports the class-wise classification performance achieved by the proposed HGCF-NET on the CSE-CIC-IDS2018 dataset.

Table 5. Class-Wise Performance of the Proposed HGCF-NET.

Attack Class	Precision (%)	Recall (%)	F1-Score (%)
Normal	99.12	99.04	99.08
DoS	98.41	98.35	98.38
DDos	98.62	98.55	98.58
Brute Force	97.84	97.72	97.78
Botnet	98.31	98.19	98.25
Web Attack	98.27	98.16	98.21
Infiltration	97.69	97.53	97.61
Average	98.32	98.22	98.27

As presented in Table 5, the proposed HGCF-Net achieved consistently high Precision, Recall, and F1-score across all attack categories. The highest performance was observed for normal traffic and DoS-related attacks, indicating that the hybrid graph representation effectively captured both global communication structures and local neighborhood interactions. Although slightly lower performance was observed for Brute Force and Infiltration attacks, the proposed framework still maintained robust classification capability across all categories. These results demonstrate the effectiveness of adaptive graph construction and feature fusion in improving multi-class intrusion detection performance.

5.3 Confusion Matrix Analysis

The confusion matrix provides a detailed visualization of the classification results by illustrating the number of correctly and incorrectly predicted samples for each attack category. Unlike overall performance metrics, the confusion matrix enables a comprehensive assessment of class-level prediction behavior and reveals potential misclassification patterns among similar attack types. Figure 6 illustrates the confusion matrix obtained by the proposed HGCF-NET on the testing dataset.

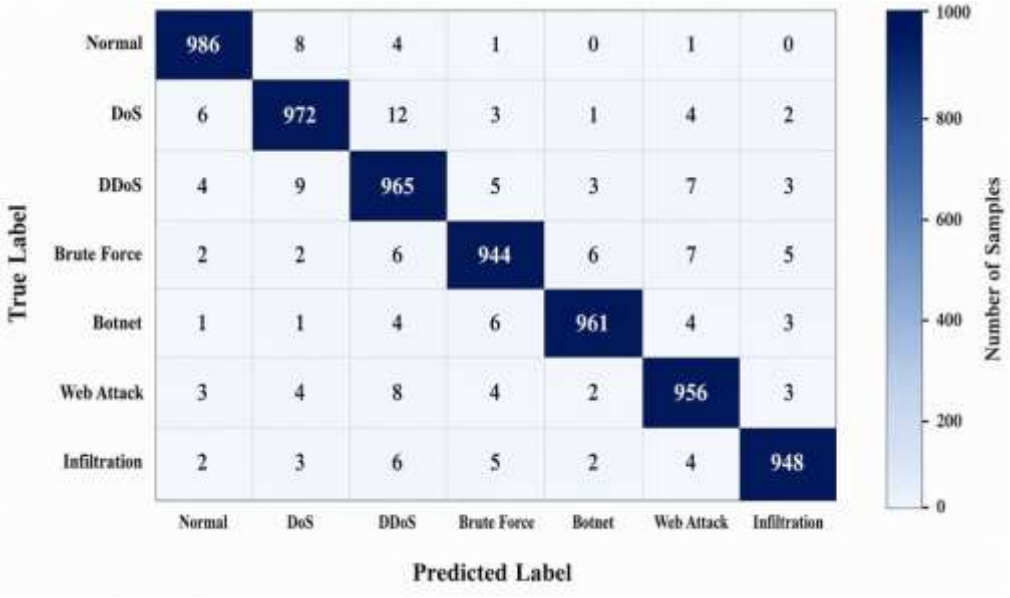

Figure 6. Confusion matrix of HGCF-NET on the test set.

As illustrated in Figure 6, most testing samples are correctly classified along the main diagonal, indicating excellent classification accuracy for all attack categories. Only a limited number of samples are misclassified, primarily between attack classes that exhibit similar network traffic characteristics, such as DoS and DDoS. The low number of off-diagonal predictions confirms the strong discriminative capability of the proposed HGCF-Net and demonstrates its effectiveness in learning robust graph representations for complex cyberattack scenarios.

5.4 ROC Curve Analysis

The Receiver Operating Characteristic (ROC) curve is employed to evaluate the discriminative capability of the proposed classifier across different decision thresholds. A larger Area under the Curve (AUC) indicates stronger classification performance and better separation between benign and malicious traffic. Figure 7 present the ROC curves obtained for the proposed HGCF-NET across all attack categories.

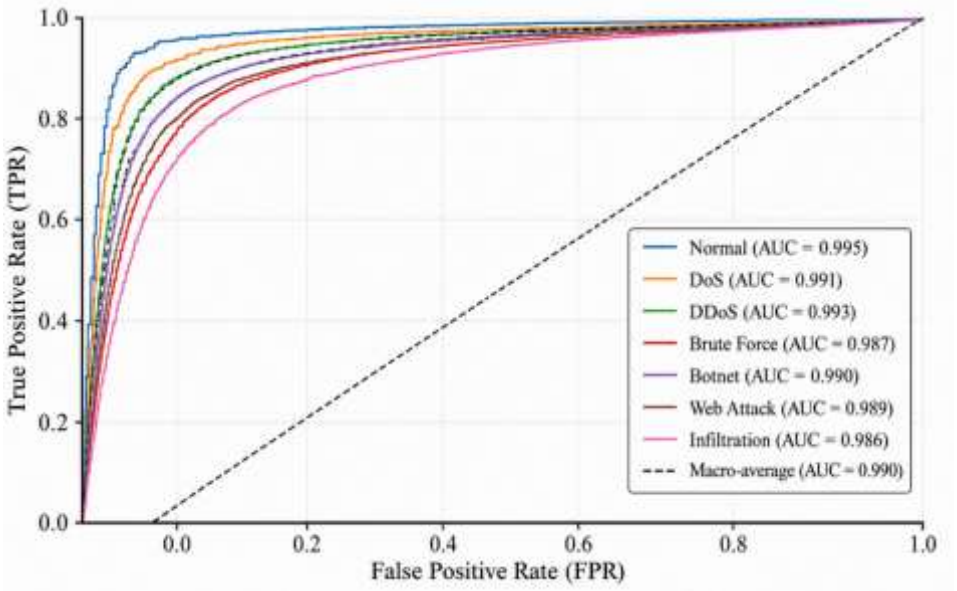

Figure 7. ROC curves of HGCF-NET for all classes.

Figure 7 demonstrates that all ROC curves are concentrated near the upper-left corner of the graph, indicating excellent classification capability. The average AUC value is close to 0.99, confirming that the proposed HGCF-Net effectively distinguishes between normal traffic and multiple cyberattack categories. These findings further validate the robustness and generalization capability of the proposed hybrid graph learning framework.

5.5 Discussion

The experimental results consistently demonstrate the superiority of the proposed HGCF-Net over conventional deep learning models and individual graph neural network architectures. The improved performance can be attributed to three key factors. First, the adaptive graph construction strategy effectively preserves meaningful communication relationships while reducing redundant graph connections. Second, the parallel GCN and GAT branches learn complementary structural representations by simultaneously capturing global graph topology and local attention-based interactions. Finally, the adaptive feature fusion mechanism integrates these complementary embeddings into a unified representation, thereby enhancing the model's ability to distinguish complex attack patterns. Compared with CNN and LSTM models, HGCF-Net benefits from explicitly modeling communication relationships instead of processing network flows independently. Furthermore, compared with standalone GCN and GAT models, the proposed hybrid architecture demonstrates superior representation learning capability by exploiting the strengths of both graph learning paradigms. Consequently, HGCF-Net achieves higher detection accuracy, improved classification consistency, and stronger robustness across multiple cyberattack categories.

6. Conclusion

This paper presented HGCF-Net, a hybrid graph neural network framework for intelligent cyberattack detection that integrates adaptive graph construction, parallel Graph Convolutional Network (GCN) and Graph Attention Network (GAT) learning, and an adaptive feature fusion mechanism within a unified architecture. By representing network traffic as graph-structured data, the proposed framework effectively captures both global structural dependencies and local neighborhood interactions, leading to more informative graph representations for intrusion detection. Experimental evaluation on the CSE-CIC-IDS2018 dataset demonstrated that HGCF-Net achieved superior performance compared with CNN, LSTM, GCN, and GAT across multiple evaluation metrics, including Accuracy, Precision, Recall, F1-score, and ROC-AUC. The obtained results indicate that combining graph convolution and graph attention with adaptive feature fusion significantly enhances detection performance and classification robustness for diverse cyberattack categories. Future work will focus on extending the proposed framework to dynamic graph learning, lightweight architectures, and real-time deployment in large-scale cloud, edge computing, and Internet of Things (IoT) environments.

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