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Graph Neural Networks for Traffic Classification in Satellite Communication Channels: A Comparative Analysis

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Abstract: *This paper presents a comprehensive comparison of graph neural networks, specifically Graph Convolutional Networks (GCN) and Graph Attention Networks (GAT), for traffic classification in satellite communication channels. The performance of these GNN-based methods is benchmarked against traditional Multi-Layer Perceptron (MLP) algorithms. The results indicate that GNNs demonstrate superior accuracy and efficiency compared to MLPs, emphasizing their potential for application in satellite communication systems. Moreover, the study investigates the impact of various factors on GNN algorithm performance, providing insights into the most effective strategies for implementing GNNs in traffic classification tasks. This research offers valuable knowledge on the benefits and prospective use cases of GNNs within satellite communication systems.*

Keywords: *Satellite Communication, Graph Neural Network, Traffic classification, GCN, GAT*

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Графовые нейронные сети для классификации трафика в каналах спутниковой связи: сравнительный анализ

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Аннотация: *В данной статье представлено всестороннее сравнение графовых нейронных сетей (GNN), в частности – графовых сверточных сетей (GCN) и сетей внимания к графам (GAT), для классификации* *трафика в спутниковых коммуникационных каналах. Производительность этих методов, основанных на GNN, сравнивается с традиционными алгоритмами многослойного персептрона (MLP). Результаты показывают, что GNN обладают превосходной точностью и эффективностью по сравнению с MLP, что подчеркивает их потенциал для применения в системах спутниковой связи. Кроме того, в рамках исследования изучается влияние различных факторов на производительность алгоритма GNN, предоставляя информацию о наиболее эффективных стратегиях реализации GNN в задачах классификации трафика. Это исследование предлагает ценные знания о преимуществах и потенциальных применениях GNN в системах спутниковой связи.*

Ключевые слова: *спутниковая связь, графовая нейронная сеть, классификация трафика, GCN, GAT*

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1. Introduction

In the realm of modern communication, there exists an intricate web of infrastructure known as a satellite communication system [1]. This system facilitates the transfer of information by means of communication satellites, intertwining various components on the ground, such as antennas, ground stations, and control centers, with the celestial entities themselves.

The demand for high-speed communication and data services has led to the rapid expansion of satellite communication [2] systems, which are particularly useful for providing global connectivity in remote areas where terrestrial infrastructure is limited. Despite their unique advantages, satellite communication channels present distinct challenges, such as global coverage, higher latency, higher cost, atmospheric interference, and limited bandwidth and spectrum allocation. Efficient management of network resources [3] is crucial for satellite communication channels, and expanding capacity may be more feasible in terrestrial networks through the addition of more infrastructure or advanced technologies.

The utilization of satellite communication channels presents notable benefits when compared to alternative channels, particularly in terms of global coverage encompassing even the most remote regions. These channels possess expansive bandwidth capacities that facilitate the seamless transmission of real-time video streams and large-scale data transfers. Moreover, through the implementation of point-to-multipoint communication [4], the dissemination of information to numerous recipients becomes possible. The deployment of satellites is characterized by its expeditiousness and scalability, thereby guaranteeing steadfast and redundant connectivity that operates autonomously from terrestrial networks [5]. Notably, satellites play a pivotal role in enabling long-range and mobile communication [6], while their varied orbital paths confer a remarkable degree of geographical adaptability [7]. It is worth highlighting that satellite communication finds application in various domains, including but not limited to telecommunications, broadcasting, remote sensing, military communications, and disaster response.

In the conventional realm, the process of traffic classification within satellite networks finds its execution primarily within the terrestrial segment, more specifically, at either the Network Operations Center (NOC) or the teleport. Employing techniques such as deep packet inspection, protocol analysis, port-based classification, and quality of service parameters, serves as the customary approach in this regard. The overarching objective of traffic classification is to facilitate the judicious allocation and exploitation of the satellite network's capacity and resources, thereby guaranteeing optimal performance across a diverse array of traffic categories.

One of the critical aspects of managing satellite communication channels is the efficient classification of network traffic, which directly impacts the overall performance and quality of service (QoS) [8]. Consequently, there is a growing interest in the development of advanced traffic classification methods for satellite communication channels.

In addition, an alternative proposition arises, entailing the exploitation of graph neural networks (GNNs) to undertake traffic classification within satellite networks. GNNs, being a distinctive form of deep learning model, demonstrate an inherent capacity to capture intricate relationships and intricate patterns intrinsic to graph-structured data. Through the conceptualization of network traffic as a graph, wherein nodes symbolize data flows and edges signify relationships, the deployment of GNNs holds the potential to enhance the precision and efficacy of traffic classification endeavors.

Graph Neural Networks (GNNs) are a powerful tool for complex problem solving in domains such as computer vision, natural language processing, and network analysis [9, 10]. They can effectively classify network traffic, detect anomalies, and handle large-scale datasets in satellite communication channels [11]. GNNs' adaptability to dynamic changes in network traffic patterns and transfer learning capabilities make them valuable for optimizing bandwidth usage, improving QoS, and enhancing the overall user experience. Furthermore, pre-training on large datasets and fine-tuning on specialized ones can lead to improved classification accuracy and efficiency.

In this paper, we present a comprehensive analysis of the application of GNNs, specifically Graph Convolutional Networks (GCN) [12] and Graph Attention Networks (GAT) [13], for traffic classification in satellite communication channels. Our study aims to methodically and empirically examine the performance of these GNN models, comparing them with traditional Multi-Layer Perceptron (MLP) algorithms. By evaluating the accuracy and efficiency of these methods, we seek to explore the potential advantages of GNNs in satellite communication systems.

Overall, this paper contributes to the growing body of knowledge on the benefits and potential applications of GNNs in satellite communication systems, particularly in the context of traffic classification. Our findings will not only advance the understanding of GNN-based methods but also pave the way for the development of more efficient and robust traffic classification techniques in satellite communication channels.

2. Literature Review

Satellite resource optimization and management have been extensively researched due to the growth of internet communications. Wenjuan [14] proposed a novel traffic classification routing (TCR) algorithm for Low Earth Orbit Satellite (LEO) satellite networks, which uses traffic classification link-cost metrics (TCM) to optimize network resource utilization for multimedia applications. TCR algorithm introduces a blocking-probability filter mechanism and a server reservation priority queue (SRPQ) mechanism to improve performance and balance traffic load distribution. TCR algorithm outperformed single-service and multiservice routing algorithms in different traffic scenarios, making it a suitable choice for future multimedia satellite networks.

Pacheco et al. [15] developed an ML-based framework for internet traffic classification in satellite communications, with the goal of enhancing QoS management. The hierarchical classification system distinguishes between encryption and flow patterns, surpassing the performance of Deep Packet Inspection (DPI). The proposed system profiles internet communications and sends the data to a Policy-Based Network (PBN) for QoS management.

In 2020, Pacheco et al. [16] developed a framework for internet traffic classification in satellite communications using ML and DL techniques to improve QoS [17]. They proposed a hierarchical classification system that performs well on encrypted, unencrypted, and tunneled traffic. The solution was tested on a cloud-emulated platform and integrates an ILM for each classifier. Results showed improved performance over ntop DPI (nDPI). Future work should consider different types of tunneled protocols and adapt to evolving communication technologies.

Pang et al. [18] introduced a chained graph neural network (CGNN) for traffic classification to overcome challenges posed by Network Address Translation (NAT), port dynamics, and encrypted traffic [19]. Their model uses a chained graph to capture structural and causal relationships in the traffic stream and builds a graph classifier over extracted features. Results show that CGNN improves application and malicious traffic prediction accuracy, outperforming existing neural network-based traffic classifiers on real-world datasets while maintaining robust recall and precision metrics. Huoh et al. [20] proposed a GNN model for encrypted network traffic classification that captures packet relations, raw bytes, and metadata, outperforming traditional CNN and RNN models.

Pang et al. [21] proposed a GNN model for network traffic classification that captures interaction features of packet flows. They designed a graph structure to embed packet contents and sequence relationships into a unified graph and introduced a graph neural network framework for graph classification. The model improves prediction accuracy by up to 37 % for malicious traffic classification and outperforms state-of-the-art deep learning methods. Additionally, it achieves high precision, recall, F1 score, and Matthews Correlation Coefficient, indicating strong correlation between predicted and true values for various types of malicious traffic. Evaluations on real-world traffic data support the efficacy of the proposed model.

This review emphasizes the significance of traffic classification in satellite communications and discusses various techniques proposed to enhance QoS management and optimize network resources. These techniques include TCR algorithm, ML-based frameworks, and GNN models, which outperform traditional methods in terms of accuracy, precision, recall, and F1 Score. These approaches also provide balanced traffic distribution in satellite networks, indicating their potential for improving traffic classification [22]. Future research should address the limitations of these methods and adapt to the changing communication technologies.

3. Method

This investigation utilizes Fig. 1 to demonstrate the methodology for evaluating GNN models in internet traffic classification. The methodology consists of data collection, preprocessing, graph creation, and classification. The acquired internet traffic dataset is preprocessed using standardization and min-max normalization techniques to ensure optimal normalization.

Standardization rescales data to a mean of 0 and a standard deviation of 1, while min-max normalization scales feature values within a range of 0–1 to allow for comparisons among features with varying value ranges. The quality of the data processing [23] is essential for evaluating the effectiveness of multiple GNN models in classifying internet traffic.

After preprocessing the internet traffic data, the next step is to create a graph where each data point is a node and the edges represent relationships between them. This provides insight into the patterns and structures within the data. GNN models are then used to classify the network traffic data based on the information gathered from the graph.

Satellite networks serve as conduits for a diverse range of data, catering to an array of applications and services. The following categories encompass the prevalent types of data transmitted over satellite networks:

+ Voice and Telephony [24]: An essential function of satellite networks lies in facilitating voice communication, particularly in remote regions where terrestrial infrastructure may be limited or absent.

+ Internet Data: Satellite networks assume a pivotal role in providing internet connectivity to areas where terrestrial networks are not readily accessible. By means of satellite links, a broad spectrum of internet data, encompassing web pages, emails, file downloads, and streaming media, can be effectively transmitted. Consequently, individuals, businesses, and organizations gain access to a vast realm of online resources and services, regardless of their geographical location. Notably, the network traffic data set published in reference [25] represents a notable example within this domain.

+ Video and Television Broadcasting [26]: The transmission of television signals constitutes a substantial aspect of satellite network functionality, affording broadcasters the means to disseminate television channels to a wide-ranging audience.

+ Data Networks and Virtual Private Networks (VPNs) [27]: Satellite networks offer robust data connectivity for a multitude of applications, including corporate networks, government networks, and remote site connectivity. Through their utilization, wide-area networks (WANs) and virtual private networks (VPNs) can be established, facilitating secure and private data communication between disparate locations.

+ Earth Observation Data: Satellites dedicated to Earth observation contribute significantly to the transmission of data pertaining to the Earth's surface, atmosphere, and environmental conditions. This encompasses a vast array of information, including high-resolution images, weather data, climate data, and other pertinent environmental parameters.

+ Global Navigation Satellite Systems (GNSS) Data: Noteworthy satellite networks, such as the Global Positioning System (GPS), Galileo, and GLONASS, are responsible for transmitting navigation data to user devices. This invaluable data serves as the foundation for precise positioning, navigation, and timing information, thereby enabling a plethora of applications, including navigation systems, geolocation services, and asset or vehicle tracking.

+ Sensor Data and Telemetry: Satellites, equipped with sensors or scientific instruments, fulfill a critical role in the collection and transmission of diverse data types for research purposes. This encompasses a wide range of scientific disciplines, including space exploration, astronomy, climate studies, oceanography, and related domains, thereby contributing to advancements in scientific knowledge.

+ Command and Control Data [28]: In order to effectively manage and operate satellites, satellite networks necessitate the transmission of command and control data.

In this study, we evaluated the classification performance of various GNN models on preprocessed network traffic data [25], which includes five categories: Bulk, Video, Web, Interactive, and Idle. The dataset was provided as pcap files, with features extracted from the raw data. Details of the data are shown in Table 1.

The network traffic dataset used in this study contains pcap files with features extracted from the raw information, categorized into Bulk, Video, Web, Interactive, and Idle. Interactive data refers to real-time applications such as Google Docs or SSH sessions, while Bulk data transfer pertains to applications transferring large data volumes and Web browsing includes traffic generated from browsing web pages. Video playback refers to traffic from streaming applications, and Idle behavior encompasses background traffic from a user's computer.

TABLE 1. Data Set Composition

Category	Num of traces	Duration (s)	Size (MB)
Bulk	19	3599	8704
Video	23	4496	1405
Web	23	4203	148
Interactive	42	8934	30.5
Idle	52	6341	0.69

This research employs label encoding, min-max normalization, and standardization as preprocessing techniques to mitigate the adverse effects of columns with dissimilar value ranges on the performance of regression and classification models. Proper scaling is essential to enhance model efficiency, and established techniques such as min-max normalization and z-score standardization are utilized for this purpose [29].

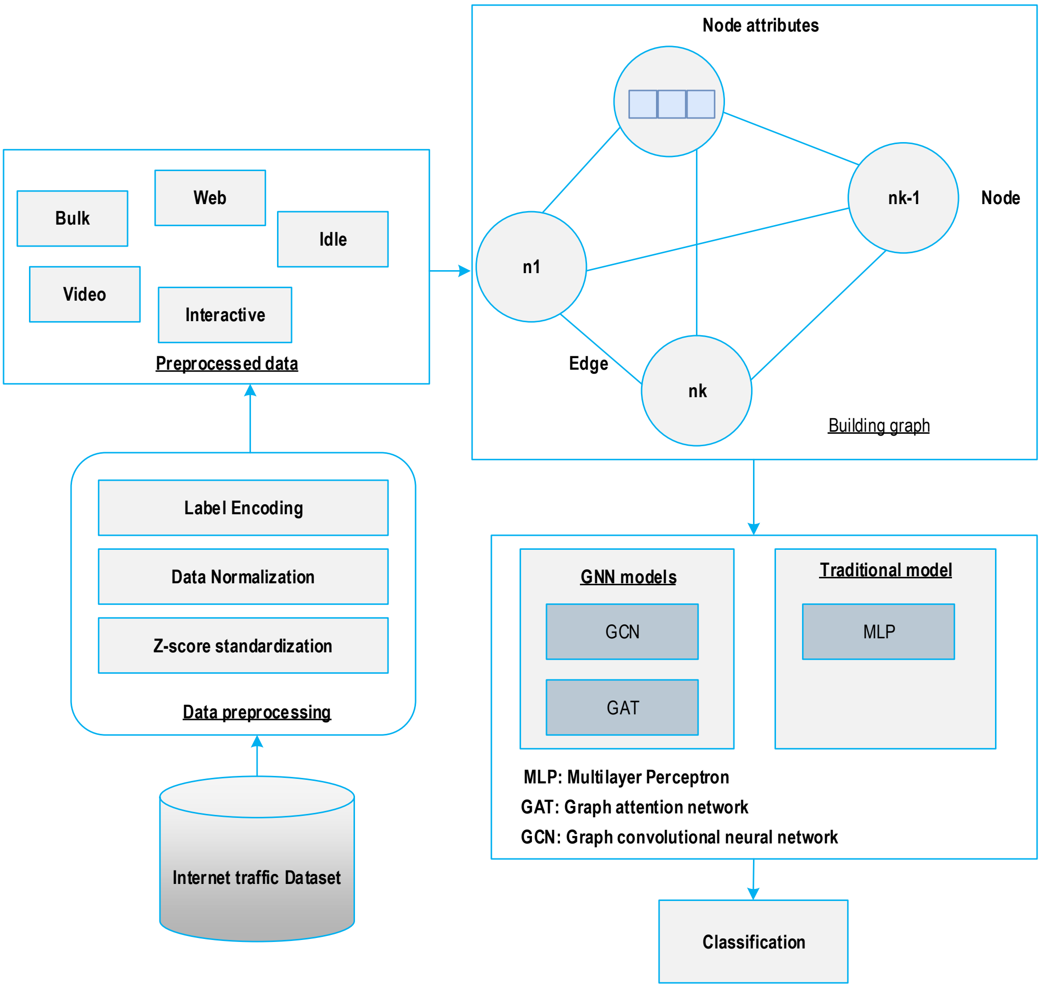

Fig. 1. The Research Flow

Min-max normalization transforms feature values of a dataset into the [0, 1] range using a specific formula:

$$X_{\text{normalized}} = \frac{(X - X_{\text{min\_value}})}{(X_{\text{max\_value}} - X_{\text{min\_value}})}. \quad (1)$$

The min-max normalization formula transforms feature values to fit within the [0, 1] range, with $X_{\text{min\_value}}$ and $X_{\text{max\_value}}$ representing the bounds. On the other hand, *z*-score standardization resizes features to display a normal distribution with a mean of $\mu = 0$ and standard deviation of $\sigma = 1$, represented by the following equation:

$$X_{\text{normalized}} = \frac{(X - \mu)}{\sigma}. \quad (2)$$

After data processing [30], we converted the data into a graph format. We constructed a separate graph for each traffic category, where every packet was treated as a node with a vector of its data. The nodes were connected by sequentially linking adjacent packets as an experiment. (Refer to Fig. 2 for more details.)

This study explores the effectiveness of widely used GNN [31] models, GCN and GAT, for network traffic classification. MLP is included as a conventional model for comparison, with computational time evaluated for all models. GCN and GAT have distinct graph neural network architectures, with unique strengths and weaknesses, and a comparative analysis will provide insights into the best architecture for traffic classification and malware detection. By benchmarking GCN and GAT, this study provides a reference point for developing new GNN models for traffic classification.

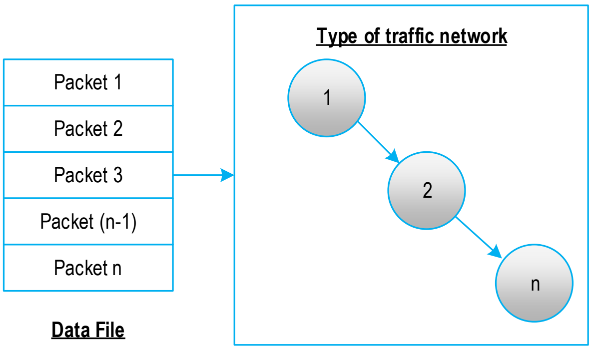

Fig. 2. Represent Data in Graph Form

Comparing GNN models' performance with conventional models like MLP is a fruitful approach for evaluating their effectiveness in traffic classification tasks.

This contrast can reveal the strengths and weaknesses of each approach, enabling the selection of the most appropriate model based on computational constraints, accuracy requirements, and execution time considerations. The following section presents GNN algorithms, including GCN and GAT.

The GCN is a powerful model for graph data learning, particularly in network traffic classification where the goal is to categorize edges. To monitor traffic flow effectively, capturing edge adjacency is crucial, similar to how an adjacency matrix represents node connectivity. The current adjacency matrix $A \in R^{N\times N}$ is central to the GCN [32] model, which uses multilayer graph convolution to process input data at different levels of abstraction. At each time step t, the l^{th} layer of the GCN updates the embedding node matrix $H_t^{(l+1)}$ by utilizing the weight matrix $W_t^{(l)}$ with input from the current adjacency matrix At and embedding node matrix $H_t^{(l)}$.

This mechanism can be formally expressed as follows:

$$H_{\mathrm{t}}^{(l+1)} = G\_\mathrm{CONV}\left(A_{\mathrm{t}}, H_t^{(l)}, W_t^{(l)} = \sigma\left(\hat{A}_t H_{\mathrm{t}} W_t^{(l)}\right)\right). \quad (3)$$

where σ is the activation function (usually ReLU).

The G_CONV layer, a key component of the GCN, is similar to the perceptron, but with a distinct difference: its weight matrix is derived through spectrum filtering of the graph Laplacian matrix. This feature allows the G_CONV layer to effectively capture the graph structure, making it useful for graph-based classification tasks. See the parameterized model in [33].

$$g_\theta * x = U g_\theta U^T x, \quad (4)$$

where the G_CONV layer is similar to a perceptron, but its weight matrix is derived through spectrum filtering of the graph Laplacian matrix.

This allows it to capture the structure of graph data and achieve practical graph-based classification tasks. The model in [34] includes a parameterized framework with a matrix U composed of eigenvectors of the normalized graph's Laplacian matrix, denoted as $\theta \in R^N$.

$$L = I_N - D^{-\frac{1}{2}} A D^{-\frac{1}{2}} = U \Lambda U^T. \quad (5)$$

The Laplacian matrix is constructed using the degree matrix, adjacency matrix, and eigenvalue matrix Λ. Λ is diagonal, and its diagonal values are the eigenvalues. The graph Fourier transform of a signal x is $U^T x$.

In equation (4), the function g_θ depends on the Laplacian matrix eigenvalues. However, computing the Laplacian eigenvalue decomposition is computationally expensive. To address this, a truncated expansion of the Chebyshev polynomial $T_k(x)$ is used to approximate $g_\theta(\Lambda)$ up to the k^{th} order:

$$g_{\theta'}(\Lambda) \approx \sum_{k=0}^{k} \theta'_k T_K(\widetilde{\Lambda}), \quad (6)$$

where the Chebyshev polynomials are utilized to approximate $g_\theta(\Lambda)$ up to the k^{th} order, denoted by $\theta' \in R^k$. The matrix $\widetilde{\Lambda}$, obtained by scaling and shifting the Laplacian matrix Λ, captures the highest eigenvalues, and L denotes the number of eigenvalues encapsulated by it.

The Chebyshev polynomials can be defined as follows:

$$T_k(x) = 2x T_{K-1}(x) - T_{K-2}(x), \quad (7)$$

where $T_0(x) = 1, T_1(x) = x$.

Equation (8) show cases the GCN model, which is built using convolutional layers arranged in a stacked multilayer equation:

$$g_{\theta^*} * x \approx \sum_{k=0}^{k} \theta_k T_K(\tilde{L}), \quad (8)$$

where $\tilde{L} = \frac{2}{\lambda_{\max}} L - I_N$.

In this context, we set a constraint on the convolution layer such that k equals 1, that is:

$$g_\theta * x \approx \theta'_0 T_0(\tilde{L}) x + \theta'_1 T_1(\tilde{L}) x = \theta'_0 x + \theta'_1 \tilde{L} x. \quad (9)$$

Taking the approximation $\lambda_{\max} = 2$, we can get:

$$g_{\theta'} * x \approx \theta'_0 x + \theta'_1 (L - L_N) x = = \theta'_0 x - \theta'_1 D^{-\frac{1}{2}} A D^{-\frac{1}{2}} x. \quad (10)$$

Furthermore, to prevent overfitting, the number of trainable parameters could be restricted:

$$g_\theta * x \approx \theta \left(I_N + D^{-\frac{1}{2}} A D^{-\frac{1}{2}}\right) x. \quad (11)$$

Note that $\theta = \theta'_0 = -\theta'_1$ in (6).

The range of feature values of $I_N + D^{-\frac{1}{2}} A D^{-\frac{1}{2}}$ is [0, 2]. In the context of deep neural network models, it has been observed that repetitive application of a particular operation may lead to unstable values and gradient explosion.

To mitigate this issue, a novel normalization technique is proposed in [34]:

$$I_N + D^{-\frac{1}{2}} A D^{-\frac{1}{2}} \to \widetilde{D}^{-\frac{1}{2}} \tilde{A} \widetilde{D}^{-\frac{1}{2}}, \quad (12)$$

where $\tilde{A} = A + I_N, D_{ii} = \sum_j \tilde{A}_{ij}$.

The attention mechanism has demonstrated considerable potential in various sequence-based tasks. In this section, the theoretical derivation of the GAT will be explicated, along with a discussion of its advantageous applications. GAT comprises a solitary graph attention layer, while any graph attention network can be created by integrating numerous layers.

To calculate the attention coefficient for the node pair (i, j) in this layer, the following formula is employed:

$$\mathrm{sum}_N = \sum_{k \in N_i} e^{\{\mathrm{LeakyReLu}\,[a^T (W h_i \| W h_j)]\}},$$

$$\alpha_{i,j} = e^{\{\text{LeakyReLu}\,[a^T(Wh_i \| Wh_j)]\}} \,/\, \text{sum}_N. \tag{13}$$

The GAT employs a single graph attention layer, which serves as the building block for constructing any graph attention network by stacking multiple layers. The attention coefficient, denoted as $\alpha_{i,j}$, for node j in relation to node i, where N_i denotes the neighbor node set of nodes i in the graph, is calculated by employing the concatenated vectors notation ||, and the formula provided in (13). The GAT's input node features are denoted by $h = \{h_1, h_2, \cdots, h_N\}$, where $h_i \in R^F$. The weight matrix $W \in R^{F \times F}$ enables weight-sharing linear transforma-tion among nodes. The weight vector $a \in R^{2F}$, representing a single-layer feedforward neural network [35], is normalized with the softmax activation function and the LeakyRelu function is used for nonlinearity. The normalized attention coefficient $\alpha_{i,j}$ is used to compute each node's final output eigenvector h', using formula:

$$h'_i = \sigma\left(\sum_{j \in N_i} \alpha_{ij} W h_j\right). \tag{14}$$

GAT uses the activation function $\sigma\,(.)$ for nonlinearity and employs multi-head attention with K independent mechanisms to compute hidden state vectors for each node.

The resulting vectors are concatenated to obtain the final output, as expressed in the mathematical formula for multi-head attention:

$$h'_i = \|_{k=1}^{K}\, \sigma\left(\sum_{j \in N_i} \alpha_{ij}^k W^k h_j\right). \tag{15}$$

In GAT, multiple attention mechanisms are used to compute hidden state vectors for each node, which are concatenated to obtain the final output. Equation (15) involves concatenation using the || symbol and employs a normalized attention coefficient and weight matrix.

To address the issue of multiple eigenvectors in the final output, the average method is used, as shown in the formula:

$$h'_i = \sigma\left(\frac{1}{K}\sum_{k=1}^{K} \sum_{j \in N_i} \alpha_{ij}^k W^k h_j\right). \tag{16}$$

GAT applies the average method to compute the final output eigenvector for each node, which contains F' fused feature vectors. This simplifies the feature aggregation process and improves the model's performance by preserving the important graph features.

The MLP is a neural network with an input layer, one or more hidden layers, and an output layer. The input layer feeds the network with input variables, while the output layer generates the final output. Hidden layers are between the input and output layers. The MLP is widely used in various fields and is composed of interconnected neurons in a one-way and one-directional manner.

The mathematical description of each layer can be represented by Eq:

$$O_i^{(\ell)} = \varphi\left(u_i^{(\ell)}\right) = \varphi\left(\sum_{j=1}^{n_\ell} O_j^{(\ell-1)} w_{j,i}^{(\ell)} + w_{0,}^{(\ell)}\right), \quad 1 \le \ell \le L, \tag{17}$$

where $\varphi(.)$ plays a crucial role in determining the output of a neural network.

For hidden layers, the activation function is typically a nonlinear tangent hyperbolic function, while a linear function is used for the output layer. In a neural network with L non-input layers, the real layer is identified by index l, and the output of neuron i in the real layer l is denoted as O_i^l. The weights associated with the connections between neurons in adjacent layers are represented by $w_{j,1}^{(\ell)}$. The final output of the network is represented by $O^{(L)} = y$, where L is the index of the final layer and n_L is its length. The basic architecture of an MLP neural network is shown in Fig. 3.

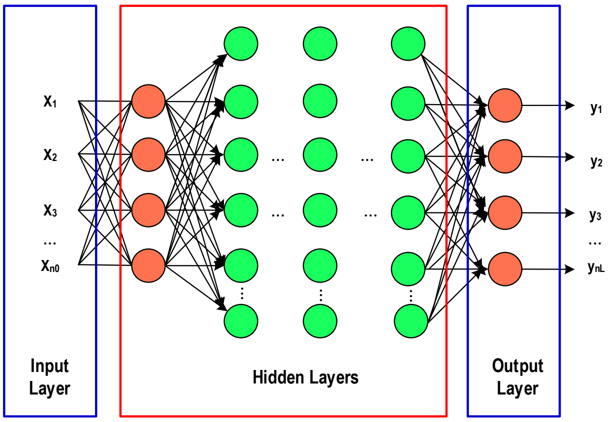

Fig. 3. Basic Architecture of an MLP Neural Network

4. Results

This study aimed to evaluate the effectiveness of GNN algorithms in network traffic classification, focusing on two popular algorithms: GCN, GAT, and a traditional MLP. The dataset was divided into three parts: training, validation, and test data, with an 8:1:1 ratio. The experiment involved classifying network traffic into five categories (*Idle, Interactive, Web, Video, Bulk*) and evaluating the results through a multi-classification problem. In the experiment we will use measures such as $F1$-score, Recall and Precsision to evaluate the results.

The Fig. 4 displays the loss value obtained while training the model using GCN, GAT, and MLP algorithms. The results indicate that MLP had the lowest loss value, followed by GCN, and then GAT. Furthermore, the loss values began converging from the 80th epoch onwards. These findings suggest that all three algorithms effectively classify network traffic, with MLP being the most efficient in reducing loss, followed by GCN and GAT. Notably, GNN algorithms, such as GCN and GAT, demonstrated effectiveness in classifying network traffic, which has practical applications in network security and intrusion detection.

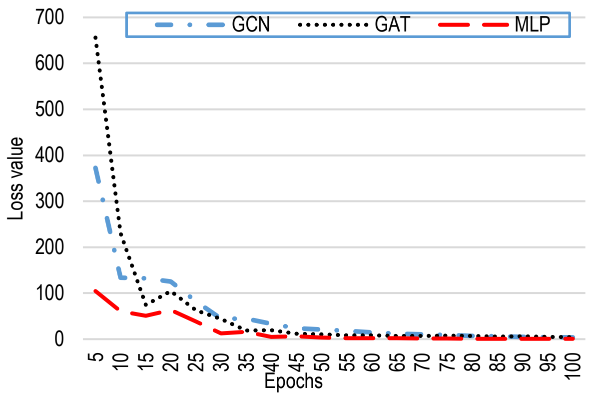

Fig. 4. Loss Value for Training Data of Algorithms

The Fig. 5 presents the accuracy of the validation dataset for each epoch. The study found that GCN achieved the highest accuracy of 92,2 %, followed by GAT with an accuracy of 91,12 %, and MLP with an accuracy of 79,5 %. These results indicate that GCN outperformed GAT and MLP in terms of accuracy, which could be attributed to GCN's ability to capture higher-order dependencies between nodes in the graph. GAT, a more recent GNN architecture, performed slightly worse than GCN but still better than MLP, suggesting its potential in this domain.

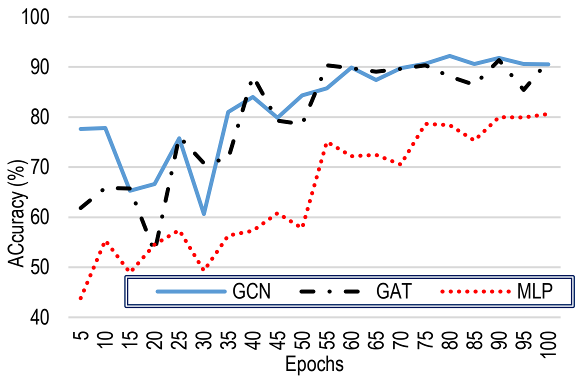

Fig. 5. Accuracy of Validation Data via Each Epoch of Algorithms

Training time is crucial when selecting a model for classification tasks, especially when handling large datasets or limited computational resources. Fig. 6 shows that the GCN algorithm had the shortest training time, followed by MLP, and then GAT. Consequently, GCN may be a more suitable choice for scenarios where speed is critical. However, it is essential to consider other factors, such as dataset size and complexity, computational resource availability, and the required level of interpretability, when selecting an appropriate algorithm for classification tasks.

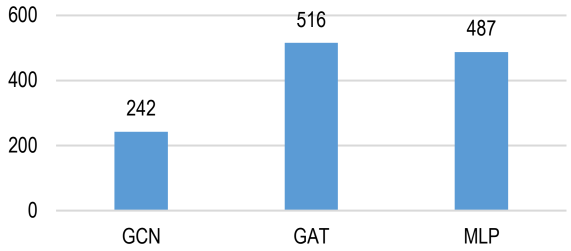

Fig. 6. Time Training of Algorithms

Next, we will evaluate the classification of each pair of categories together. There are some reasons for these experiments.

+ Detailed analysis: Assessing the classification performance for each pair of categories individually allows for a more in-depth analysis of the models' strengths and weaknesses. This approach can reveal specific areas where the models perform well or struggle, providing valuable insights for further improvements.

+ Identifying challenging category pairs: Some pairs of categories might be more challenging to distinguish than others due to overlapping or similar traffic patterns. Evaluating the classification of each pair separately can help identify these challenging cases, informing potential strategies to address these issues.

+ Model selection: By comparing the performance of different algorithms for each pair of categories, we can identify the most suitable model for each pair, allowing for a more targeted and efficient application of the algorithms in real-world scenarios.

+ Robustness evaluation: Investigating the performance of the classifiers for each pair of categories can provide insights into their robustness and adaptability when handling various types of traffic patterns. This can be especially important when the classifiers are deployed in dynamic environments where traffic patterns might change over time.

+ Fine-grained performance metrics: Evaluating the classification of each pair of categories together allows for calculating fine-grained performance metrics such as precision, recall, and *F*1-score for each category pair. These metrics can provide a more comprehensive understanding of the classifiers' performance and help identify areas for improvement.

Fig. 7a provides a detailed view of the performance metrics for the three algorithms (MLP, GCN, and GAT) when classifying between the *Idle* and *Interactive* categories. MLP and GCN achieved a precision of 0,98, while GAT had a slightly lower precision of 0,97. This indicates that MLP and GCN were slightly better at correctly identifying true positive cases as a proportion of all the predicted positive cases. MLP and GAT achieved a perfect recall score of 1, while GCN had a slightly lower recall of 0,99. This means that MLP and GAT could identify all true positive cases as a proportion of the total positive cases. GCN, on the other hand, missed a small proportion of true positive cases.

Fig. 7. Loss Value for Training Data of Algorithms

The *F*1-score, the harmonic mean of precision and recall, was 0,99 for MLP and 0,98 for GCN and GAT. This suggests that MLP provided a better balance between precision and recall in classifying *Idle* and *Interactive* categories, followed closely by GCN and GAT.

MLP achieved the highest accuracy of 0,98, while both GCN and GAT had a slightly lower accuracy of 0,97. This indicates that MLP was the best-performing algorithm in correctly classifying both *Idle* and *Interactive* categories as a proportion of all cases.

In conclusion, based on the performance metrics provided, **MLP demonstrated a slightly better overall performance in classifying between the *Idle* and *Interactive* categories** when compared to GCN and GAT. However, all three algorithms showed strong performance, with only minor differences in the metrics.

Fig. 7b provides a detailed view of the performance metrics for the three algorithms (MLP, GCN, and GAT) when classifying the *Idle* and *Web* categories. MLP exhibits the highest precision (0,98), but its recall (0,87) and accuracy (0,85) are considerably lower than those of GCN and GAT.

This suggests that while MLP effectively identifies *Idle* and *Web* traffic cases, it struggles to capture all true instances within the dataset. On the other hand, GAT achieves perfect recall (1) and the highest $F1$-score (0,98) and accuracy (0,97), indicating a balanced performance in terms of correctly identifying and classifying *Idle* and *Web* traffic cases. GCN closely follows GAT, with an $F1$-score of 0,97 and an accuracy of 0,94.

In summary, **GAT demonstrates the best overall performance for classifying *Idle* and *Web* categories**, closely followed by GCN. While MLP has the highest precision, its lower recall and accuracy suggest it may be less suitable for this specific classification task.

Fig. 7c compares MLP, GCN, and GAT for Idle and Video traffic classification, revealing similar performance among the algorithms, with only minor differences in precision and recall. $F1$-scores are identical at 0,98, and accuracy scores are equal at 0,97 for all three models. This suggests strong performance across the board, with the choice of the best algorithm depending on the specific application requirements and constraints.

In Fig. 7d, the comparison of Idle and Bulk categories is presented. GCN demonstrates a slight edge over MLP and GAT, with an accuracy of 0,99 and an $F1$-score of 0,99. MLP and GAT show almost identical performance with accuracy and $F1$-scores of 0,97 and 0,98, respectively. These results indicate that **GCN is the most effective in this specific classification task**, but all three algorithms exhibit strong performance. The optimal choice should be determined based on the application's requirements and constraints.

For the *Interactive* and *Web* categories (Fig. 7e), GCN outperforms the other algorithms with an accuracy of 0,87 and an $F1$-score of 0,84. MLP shows moderate performance with an accuracy of 0,81 and an $F1$-score of 0,76. In contrast, GAT's performance is notably lower, with an accuracy of 0,61 and an $F1$-score of 0,65. These results suggest that **GCN is the most suitable algorithm for this classification task**, while GAT may not be as effective in this specific context. As always, the choice of the algorithm should be guided by the unique requirements and constraints of the application.

When classifying between Interactive and Video categories (Fig. 7f), both GCN and GAT excel with an accuracy of 0,97 and $F1$-scores of 0,97. MLP lags with an accuracy of 0,78 and an $F1$-score of 0,71. The recall for MLP is considerably lower at 0,56, while GCN and GAT maintain high recall rates of 0,95 and 0,97, respectively. These results highlight **GCN and GAT as the preferred algorithms for this classification task**, while MLP may not be the optimal choice. It is crucial to consider the application's unique requirements and constraints when selecting an algorithm.

For the Interactive and Bulk categories (Fig. 7g), GCN stands out with an accuracy of 0,99 and an $F1$-score of 0,98. MLP and GAT have similar accuracies (0,91 and 0,90, respectively) but differ in recall and $F1$-score. While MLP has a higher recall (0,8) and $F1$-score (0,89) than GAT, both algorithms have perfect precision (1). Given the results, **GCN is the best choice for classifying between *Interactive* and *Bulk* categories**, while MLP and GAT may be suitable alternatives depending on the specific context and requirements.

When comparing the algorithms for the Web and Video categories (Fig. 7h), GCN outperforms MLP and GAT with an accuracy of 0,85 and an $F1$-score of 0,87. MLP has a significantly higher recall (0,98) but lower precision (0,62), resulting in an $F1$-score of 0,76 and accuracy of 0,66. GAT demonstrates the lowest performance, with an accuracy of 0,52, precision of 0,67, recall of 0,29, and an $F1$-score of 0,4. In this case, **GCN is the most suitable choice for classifying *Web* and *Video* categories**, while MLP could be considered if a high recall is prioritized. In comparing the algorithms for the Web and Bulk categories (Fig. 7i), GAT performs the best with an accuracy of 0,92 and an $F1$-score of 0,92. GCN follows closely with an accuracy of 0,90 and an $F1$-score of 0,91, exhibiting a particularly high recall of 0,97. MLP has the lowest accuracy of 0,86 and an $F1$-score of 0,86. Based on these results, **GAT is the preferred choice for classifying the *Web* and *Bulk* categories**, while GCN can be a viable alternative, particularly when a high recall is desired.

For the Video and Bulk categories (Fig. 7j), GCN outperforms the other algorithms, achieving an accuracy of 0,99 and an $F1$-score of 0,99, with near-perfect precision and recall. GAT is the next best option, with an accuracy of 0,98 and an $F1$-score of 0,98. MLP, although performing well in precision, has lower recall and thus shows a lower accuracy of 0,91 and an $F1$-score of 0,88. Based on these results, **GCN is the optimal choice for classifying the *Video* and *Bulk* categories**, with GAT as a strong alternative.

In conclusion, the performance of the three algorithms (MLP, GCN, and GAT) varies depending on the specific pair of categories being classified. However, some general trends can be observed.

First of all, GCN consistently achieves high performance across most category pairs, making it a reliable and effective choice for network traffic classification tasks. GCN is the best choice for classifying between Video and Bulk, Interactive and Bulk, and Interactive and Video categories.

Secondly, GAT performs strongly in several cases, such as classifying between Idle and Interactive, Idle and Video, and Video and Bulk categories. While it may not always outperform GCN, GAT is a promising alternative, especially considering its ability to capture higher-order dependencies.

Third, MLP demonstrates competitive performance in some cases, such as classifying between Idle and Interactive and Idle and Web categories. However, it tends to be outperformed by GCN and GAT in other scenarios. MLP may be a suitable choice when computational resources are limited or when dealing with specific category pairs where it shows strong performance.

Ultimately, the choice of the best algorithm for network traffic classification should consider the specific requirements and constraints of the application, including computational resources, desired level of interpretability, and the relative importance of precision, recall, and accuracy.

5. Conclusions

Evaluating network traffic classification methods utilizing graph neural networks in satellite communication channels has yielded promising outcomes for enhancing the user experience. The conducted experiments employing GNN models, such as GCN and GAT, have demonstrated their capability to classify network traffic data and pinpoint areas needing optimization accurately.

GNN models' capacity to consider spatial and temporal dependencies in data renders them highly suitable for analyzing traffic data within satellite communication channels. By detecting patterns and anomalies, network operators can optimize the network to reduce latency and packet loss, ultimately leading to significant improvements in user experience.

Future research in this field could explore applying GNN models for network traffic classification in other communication networks, including cellular networks and IoT networks. Moreover, there is potential for investigating alternative neural network architectures for traffic classification, such as recurrent neural networks and convolutional neural networks.

In conclusion, examining network traffic classification methods using graph neural networks in satellite communication channels demonstrates that GNN models hold considerable potential for significantly enhancing user experience. This study lays the groundwork for further exploration of GNN models' application in network traffic classification and optimization across various communication networks.

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