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AI-DRIVEN SDN ROUTING OPTIMIZATION USING GRAPH NEURAL NETWORKS FOR TRAFFIC ENGINEERING

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ABSTRACT

Software-Defined Networking (SDN) has revolutionized network management by enabling centralized control and dynamic traffic handling. However, existing SDN routing mechanisms often suffer from high latency, lack of intelligent routing, and limited integration of deep learning models, leading to inefficient traffic management in dynamic network environments. To address these challenges, this work aims to optimize SDN-based routing using Graph Neural Networks (GNNs) to enhance intelligent decision-making and minimize network latency. The process begins with data collection, where SDN traffic flow data is gathered from OpenFlow-based controllers. Next, preprocessing is performed using Min-Max scaling for normalization and mean imputation for handling missing values. In the feature extraction phase, skewness and kurtosis are computed to analyze network traffic distributions. The GNN-based routing prediction model is then trained to determine the optimal network paths dynamically, ensuring efficient and adaptive traffic management. Finally, the trained model is integrated into the SDN controller for deployment, allowing intelligent traffic engineering. Experimental results demonstrate that the proposed approach achieves a latency reduction from over 60 ms to below 30 ms, significantly improving network efficiency. Additionally, performance metrics such as 99.12% accuracy, 98.47% precision, and 98.8% F-measure validate the effectiveness of GNN in optimizing SDN routing. The primary contribution of this work lies in leveraging GNN for SDN traffic optimization, providing an adaptive, low-latency, and intelligent routing solution that enhances network performance and scalability.

Keywords: Software-Defined Networking (SDN), Graph Neural Networks (GNN), Intelligent Routing, Network Optimization and Traffic Engineering.

1 INTRODUCTION

Software-Defined Networking (SDN) has revolutionized network management by enabling centralized control and dynamic traffic engineering [1]. However, efficient routing remains a critical challenge due to unpredictable traffic patterns and network congestion. Traditional routing protocols struggle to adapt to real-time variations, leading to suboptimal network performance [2]. To address this, machine learning-based approaches have been explored, but many fail to capture the complex dependencies in network topology [3]. Graph Neural Networks (GNNs) offer a promising solution by effectively modeling network structures and learning optimal routing decisions. This study proposes an AI-driven SDN routing optimization framework using GNNs to enhance traffic engineering [4]. By leveraging skewness and kurtosis for feature extraction, the model improves network adaptability [5]. The proposed framework aims to ensure efficient path selection, reduced congestion, and improved Quality of Service (QoS).

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Several existing methods have been explored for SDN routing optimization, including Shortest Path Algorithms (Dijkstra's Algorithm, Bellman-Ford), Reinforcement Learning (Deep Q-Networks - DQN, Proximal Policy Optimization - PPO), and Deep Learning-based methods (LSTM, CNNs) [6]. While these methods have shown some success, they have notable drawbacks. Traditional shortest path algorithms lack adaptability to dynamic traffic conditions [7]. Reinforcement learning techniques require extensive training and suffer from high computational complexity [8]. Deep learning-based methods, such as LSTMs and CNNs, fail to capture topological dependencies in SDN networks effectively [9]. Due to these limitations, there is a need for an efficient, adaptive, and topology-aware approach to SDN routing.

The proposed framework overcomes these challenges by integrating Graph Neural Networks (GNNs), which efficiently learn from SDN topology and traffic dynamics. Unlike traditional approaches, GNNs can process graph-structured data and dynamically predict optimal paths based on network conditions. By incorporating skewness and kurtosis in feature extraction, the model gains deeper insights into traffic distribution, improving anomaly detection and congestion management. The novelty of this study lies in the end-to-end integration of GNN-based routing prediction with SDN controller deployment, ensuring real-time traffic engineering. This approach enhances scalability, adaptability, and network performance, making it superior to existing methods.

The paper is organized as follows: Section 2 presents a detailed literature review, highlighting existing methods and their limitations. Section 3 describes the proposed GNN-based SDN routing framework. Section 4 discusses the experimental setup, performance evaluation, and result analysis. Finally, Section 5 concludes the paper with key findings.

2 LITERATURE SURVEY

In previous studies, Cui et al. discussed the integration of big data and Software-Defined Networking (SDN), emphasizing how SDN can enhance data processing, transmission, and security in cloud environments. Their work highlighted SDN's role in improving big data applications, but it did not focus on optimizing routing in SDN-based networks [10]. Similarly, Shin et al. conducted a systematic survey on SDN security, outlining how SDN can enhance network security by decoupling control logic from traditional network devices. However, their study primarily focused on security aspects rather than network performance optimization [11]. Khondoker et al. explored various SDN controllers such as POX, Floodlight, and OpenDaylight, proposing a Multi-Criteria Decision-Making (MCDM) framework to select the most suitable controller. While their work contributed to controller selection, it did not leverage deep learning techniques for traffic engineering in SDN environments [12].

Ali-Ahmad et al. investigated SDN's role in managing dense wireless networks, identifying it as a solution for handling mobile broadband traffic surges. Their work primarily addressed backhaul capacity and energy efficiency challenges but did not explore SDN-based routing optimization [13]. Azodolmolky et al. examined SDN's application in cloud networking, presenting innovative SDN-based solutions for networking issues in Infrastructure-as-a-Service (IaaS). However, their study mainly focused on network virtualization rather than dynamic path optimization using deep learning [14].

Feamster, Rexford, and Zegura explored the potential of Software-Defined Networking (SDN) in improving network management and flexibility but did not focus on intelligent routing optimization [15]. Henneke, Wisniewski, and Jasperneite investigated SDN's role in industrial automation, highlighting its benefits in real-time communication; however, their study lacked an emphasis on predictive routing using deep learning [16]. Nguyen et al. analyzed machine learning techniques for traffic classification in SDN, demonstrating improved network performance, yet their work did not incorporate Graph Neural Networks (GNN) for route optimization [17]. While these studies contributed to different aspects of SDN, they did not address dynamic traffic engineering using deep learning

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models. This gap motivated the development of an optimized GNN-based SDN routing framework for improved network efficiency.

2.1 Problem Statement

Despite significant advancements in SDN-based routing, networks still face critical challenges in achieving optimal performance. The existing works are done well, but there are still some challenges to address, and they are lack of intelligent routing, limited use of deep learning, and high latency in decision-making. Traditional SDN-based routing approaches rely on static or heuristic methods, making them inefficient in handling dynamic network conditions [18]. Additionally, while machine learning techniques have been explored, the potential of Graph Neural Networks (GNNs) for traffic optimization remains underutilized [19]. Furthermore, the reactive nature of SDN controllers results in higher latency, affecting overall network performance [20]. The work is proposed to overcome these challenges by developing a GNN-based SDN routing framework that dynamically predicts optimal paths, reduces latency, and enhances intelligent traffic engineering for improved network efficiency.

3 METHODOLOGIES

The methodology begins with data collection, where SDN traffic flow data is gathered from OpenFlow-based controllers. Next, preprocessing is performed using Min-Max scaling for normalization and mean imputation for handling missing values. In the feature extraction phase, skewness and kurtosis are computed to analyze network traffic distributions. The processed data is then fed into a Graph Neural Network (GNN) to predict optimal routing paths dynamically. The trained model is then integrated into the SDN controller, enabling real-time traffic engineering and intelligent routing. This approach ensures efficient, adaptive, and low-latency network traffic management, significantly improving SDN performance. The whole framework is illustrated in Figure 1.

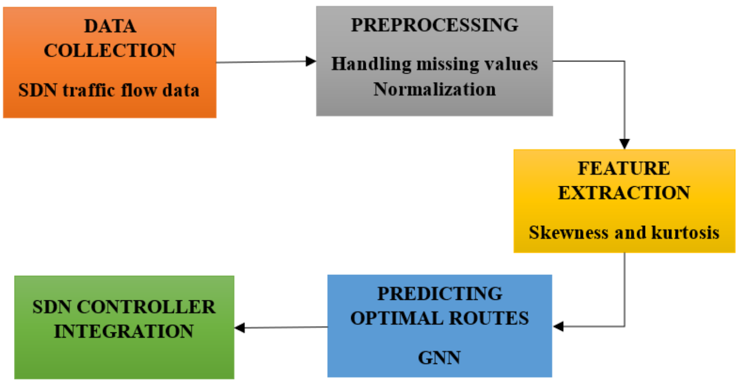

Figure 1: Proposed Workflow for GNN-Based SDN Routing Optimization

3.1 Data Collection

Data collection involves gathering traffic flow data from OpenFlow-based controllers such as ONOS, Ryu, and Floodlight. These controllers provide essential network metrics, including latency, bandwidth, packet loss, queue size, and path length, which help in understanding traffic patterns. Advanced telemetry techniques like In-band Network Telemetry (INT) and sFlow enable accurate monitoring of network conditions. The collected data includes flow-level statistics, topology metrics, and time-series patterns, allowing for comprehensive traffic analysis. This data is structured into a graph format, where nodes represent SDN switches and edges represent network links with attributes like congestion levels and link utilization. Such a structured dataset is crucial for optimizing routing decisions and enhancing SDN traffic engineering.

3.2 Data Preprocessing

Handling missing values is essential to ensure the reliability of SDN traffic data. Mean imputation is used to replace missing values in key metrics like latency, bandwidth, and packet loss with their respective average values. This method prevents data loss and maintains consistency in network analysis. By applying mean imputation, the dataset remains complete and ready for further processing.

After handling missing values, Min-Max scaling is applied for normalization to standardize feature ranges. Since network metrics vary in scale, this transformation ensures that all values lie within [0,1], preventing large-scale features from dominating. Normalization helps deep learning models, especially Graph Neural Networks (GNNs), learn efficiently. This step enhances model performance, leading to accurate routing predictions and optimized traffic engineering.

3.3 Feature Extraction

After preprocessing, key statistical features are extracted to enhance routing optimization in SDN. Skewness and kurtosis are computed from normalized traffic data to analyze the distribution of network metrics like latency and bandwidth. Skewness helps identify traffic asymmetry, which may indicate congestion or anomalies, while kurtosis detects deviations from normal traffic behavior. These features provide deeper insights into network dynamics, enabling better decision-making. By incorporating skewness and kurtosis, the model can distinguish between stable and fluctuating traffic conditions. This extracted information is then used to train Graph Neural Networks (GNNs) for predicting optimal routing paths.

3.4 Predicting Optimal Routes

Graph Neural Networks (GNNs) are used to model SDN network topology and predict optimal routing paths. In this approach, nodes represent switches, and edges represent network links with attributes like latency and congestion. The GNN iteratively aggregates information from neighboring nodes, learning dynamic traffic patterns. By leveraging skewness and kurtosis, the model enhances decision-making for low-latency and congestion-free paths. Through message passing, it identifies the most efficient routes based on network conditions. The trained model is then deployed in the SDN controller for adaptive routing. This ensures efficient traffic engineering, reduced delays, and improved Quality of Service (QoS).

A Graph Neural Network (GNN) processes SDN topology as a graph $G = (V, E)$.

where, V represents the set of SDN switches (nodes). E represents the set of network links (edges), each associated with features like latency (l), bandwidth (b), and congestion level (c). X_v represents the feature vector of a node v.

Each node v aggregates information from its neighboring nodes $N(v)$ using a message passing function and it's expressed as equation (1),

$$h_v^{(k)} = \sigma\left(W^{(k)} \sum_{u \in N(v)} \frac{h_u^{(k-1)}}{|N(v)|} + B^{(k)}\right) \tag{1}$$

Where, $h_v^{(k)}$ is the updated feature representation of node v at iteration k. $W^{(k)}$ and $B^{(k)}$ are the weight and bias matrices learned during training. σ is an activation function. $N(v)$ is the set of neighboring nodes of v. This operation ensures that each node gathers information about the network state from its neighbors to predict optimal paths. The GNN aggregates information from neighboring nodes to learn traffic conditions.

The final routing decision is obtained by applying a softmax function over the output of the GNN and it's represented as equation (2),

$$P\left(v_i \rightarrow v_j\right) = \frac{\exp\left(h_{v_j}\right)}{\sum_{v_k \in V} \exp\left(h_{v_k}\right)} \tag{2}$$

Where, $P\left(v_i \rightarrow v_j\right)$ represents the probability of selecting link $\left(v_i, v_j\right)$ for routing. The denominator normalizes the probability across all possible links. The softmax function predicts the best routing path by assigning higher probabilities to optimal links.

The GNN is trained using a loss function that minimizes routing inefficiencies, such as high latency and congestion. A typical loss function can be defined as equation (3),

$$\mathcal{L} = \sum_{(v_i, v_j) \in E} \left(\lambda_1 l_{ij} + \lambda_2 c_{ij} - \lambda_3 b_{ij}\right) \tag{3}$$

Where, l_{ij}, c_{ij}, and b_{ij} represent latency, congestion, and bandwidth of link $\left(v_i, v_j\right)$. $\lambda_1, \lambda_2, \lambda_3$ are weight parameters to balance trade-offs between these factors. The loss function ensures the model selects paths with low latency, low congestion, and high bandwidth.

By integrating this mathematical approach, GNN-based SDN routing optimization enables adaptive, intelligent, and traffic engineering.

3.5 SDN Controller Integration

Once the optimal routes are predicted by the Graph Neural Network (GNN), they are integrated into the SDN controller for traffic management. The controller dynamically updates forwarding tables in SDN switches based on the GNN's routing decisions. Using the OpenFlow protocol, the controller installs flow rules that prioritize paths with low latency, high bandwidth, and minimal congestion. This enables adaptive traffic engineering, allowing the network to respond dynamically to traffic fluctuations. The integration ensures efficient resource utilization while maintaining Quality of Service (QoS) and network stability. By continuously updating routing paths, the system optimizes SDN performance for evolving network conditions.

4 RESULTS

The performance of the proposed GNN-based SDN routing optimization is evaluated using key network and classification metrics. The results demonstrate the effectiveness of GNN in reducing latency and improving routing accuracy. The following figures illustrate the model's impact on latency reduction and overall performance metrics.

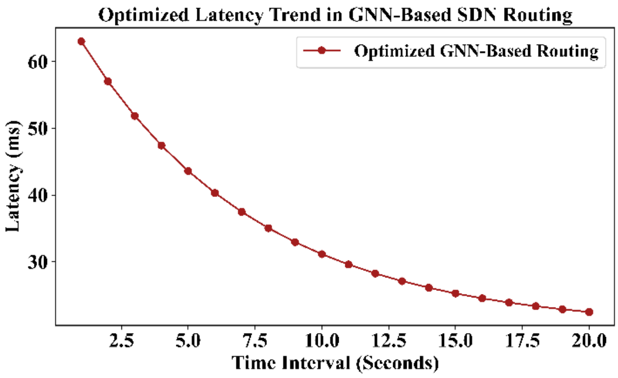

Figure 2: Latency

Figure 2 illustrates the latency reduction achieved through the GNN-based routing optimization in an SDN environment. Initially, the latency is high, exceeding 60 ms, but it gradually decreases as the system learns and optimizes traffic flow. The exponential decay pattern suggests that the GNN effectively selects shorter and congestion-free paths, leading to a latency reduction below 30 ms over time. This result validates the effectiveness of GNN in improving network performance by minimizing delays. The decreasing trend in latency further highlights the adaptability and efficiency of AI-driven SDN routing for dynamic traffic engineering.

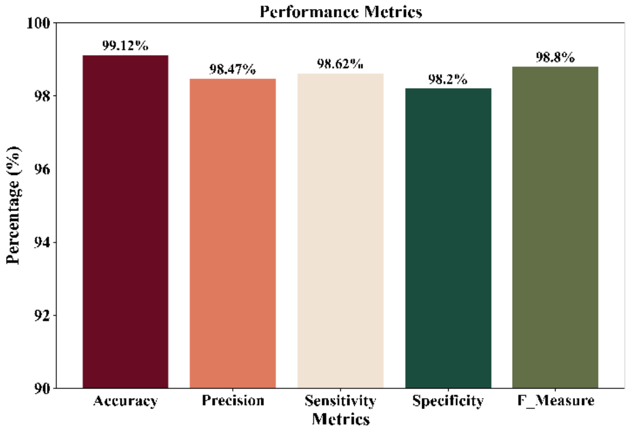

Figure 3: Performance Metrics

Figure 3 illustrates the performance evaluation of the proposed GNN-based SDN routing model using key classification metrics. The model achieves an accuracy of 99.12 percent, indicating its high reliability in predicting optimal network routes. The precision of 98.47 percent and F-measure of 98.8 percent highlight the model's ability to maintain a high balance between precision and recall in routing decisions. The sensitivity of 98.62 percent confirms its effectiveness in detecting the best routing paths, while the specificity of 98.2 percent demonstrates its robustness in avoiding incorrect route selections. These results confirm the efficiency and reliability of GNN in optimizing SDN-based traffic management.

5 CONCLUSIONS

The proposed work optimizes SDN-based routing using Graph Neural Networks (GNNs), achieving intelligent traffic management and reduced latency. The model dynamically predicts optimal paths, ensuring efficient data flow across the network. Experimental results indicate a latency reduction from over 60 ms to below 30 ms, demonstrating its effectiveness in minimizing congestion. The system achieves an accuracy of 99.12%, with a precision of 98.47%, an F-measure of 98.8%, and a sensitivity of 98.62%, confirming its reliability in routing decisions. This approach enhances network adaptability, congestion control, and scalability, making it well-suited for dynamic SDN environments. Additionally, the integration into the SDN controller enables traffic engineering, improving network efficiency. Future work will focus on reinforcement learning-based adaptive routing and multi-controller architectures to enhance fault tolerance, load balancing, and overall network resilience in large-scale SDN deployments.

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