Comparative Analysis of Graph Neural Network with SAGE Conv, GAT Conv, and GCN Conv Techniques for Fake News Detection

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ABSTRACT

In today's rapidly evolving information landscape, the spread of fake news poses a critical challenge to the integrity of public information. Fake news, characterized by intentionally falsified or misrepresented information, can manipulate public opinion, disrupt political processes, and incite social instability. Consequently, the detection of fake news has become essential for maintaining media integrity and ensuring a healthy democratic function. Traditional methods for detecting fake news, such as decision trees and support vector machines, often fall short due to their inability to capture the relational and structural context of data. To address this, Graph Neural Networks (GNNs) have emerged as promising solutions, offering the ability to process data structured as graphs and retain topological information. This study investigates three GNN models—Graph Convolutional Network (GCN Conv), Graph Attention Network (GAT Conv), and GraphSAGE (SAGEConv)—each with unique strategies for handling graph data in the context of fake news detection. Our comparative analysis reveals that GAT Conv achieves the highest test accuracy of 0.9488 at epoch 86, demonstrating strong learning performance and efficient convergence. SAGE Conv, while slightly less effective, achieves a maximum accuracy of 0.9472 at epoch 93, indicating its potential in specific scenarios. GCN Conv offers a balanced performance with a maximum accuracy of 0.9482 at epoch 99, showcasing its robustness as an alternative approach. These findings underscore the importance of selecting suitable GNN models based on the characteristics of the network, optimizing fake news detection efforts, and contributing to enhanced media integrity and democratic stability.

***Keywords**: GNN, Fake News Detection, Deep Learning*

1. INTRODUCTION

In the rapidly evolving information age, the phenomenon of fake news has emerged as one of the greatest challenges in ensuring the integrity of information received by the public [1]. Fake news, or information that is intentionally falsified or misrepresented, can influence public opinion, manipulate elections, and even incite social instability. Therefore, detecting fake news is crucial not only for media integrity but also for maintaining a healthy democratic function [2], [3].

Fake news is often designed to attract attention, exploiting biases or emotions, thus it can spread quickly through social media and other platforms. This results in the dissemination of misinformation on a scale that can disrupt political processes, damage reputations of individuals or organizations, and cause panic among the public. Consequently, the need to identify and counteract fake news has become increasingly urgent. Manually detecting fake news is a time-consuming and difficult task due to the vast volume of data generated daily and the sophistication with which fake news can be crafted. Automated solutions are necessary to efficiently manage and filter misleading information. However, many traditional approaches rely on natural language processing techniques or machine learning algorithms that do not include the relational or structural context of the data [4].

Current approaches to fake news detection, including decision trees, support vector machines, and regular neural networks, often lack in accommodating the complex structure and relationships present in data. For example, the way fake news spreads through social networks can provide crucial clues not fully utilized by traditional techniques [5], [6].

Conventional techniques are often inadequate in facing complex data structures and the underlying social relationships. They tend to overlook how information spreads through networks, which can be crucial in understanding and identifying fake news. Therefore, methods that can leverage social network structures and analyze information diffusion patterns are greatly needed [7].

Graph Neural Networks (GNNs) have emerged as a promising solution due to their ability to directly process data structured as graphs. Unlike traditional neural networks, GNNs are designed to retain the topological information of data, allowing for a deeper analysis of how entities within a network interact with each other. Among the various types of GNNs, three stand out: Graph Convolutional Network (GCN Conv), Graph Attention Network (GAT Conv), and GraphSAGE (SAGEConv). Each has a unique way of handling graph data representations and interactions, which can be expected to offer specific advantages in the context of fake news detection. GCN Conv, utilizing convolution techniques on graphs, can be effective in integrating information from a node's local neighborhood to make informed decisions about the authenticity (fake or not) of news. This technique can leverage network structures to identify patterns of fake news dissemination. GAT Conv integrates attention mechanisms that allow the model to weigh more heavily on nodes that are more relevant in a given context. In fake news detection, this could mean prioritizing sources or entities that have a greater influence in spreading information. SAGEConv, with its ability to implement various aggregation strategies, provides more flexibility in handling data heterogeneity. This allows the model to better model how fake news spreads through different types of nodes in a social network, enhancing detection accuracy[8], [9], [10].

Given the unique strengths of GCN Conv, GAT Conv, and SAGEConv, a comparative evaluation is essential to understand which method performs best under different scenarios of fake news detection. This involves not only comparing their accuracy but also assessing their efficiency in terms of computational resources and scalability. Such comparisons help in pinpointing the optimal approaches for specific types of networks, such as densely interconnected social media networks versus more sparsely connected news citation networks.

2. METODOLOGI

2.1 Developing Method

This section outlines the methodology to be employed in evaluating and comparing the effectiveness of Graph Convolutional Network (GCN Conv), Graph Attention Network (GAT Conv), and GraphSAGE (SAGEConv) in the detection of fake news. The study aims to identify which graph neural network architecture provides the best performance in terms of accuracy, computational efficiency, and scalability.

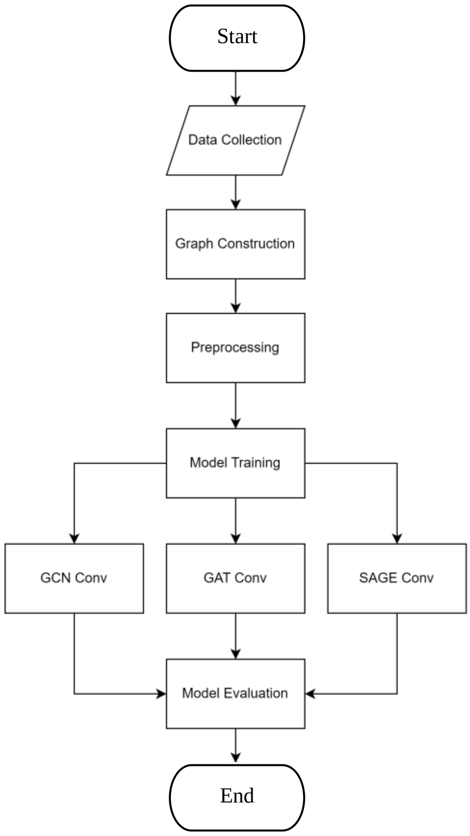

Figure 1. Developing Method Phishing Detection

1. **Data Collection**

Data will be collected from several reputable datasets known for fake news analysis, such as LIAR, FakeNewsNet, and BuzzFeed News. These datasets provide a mixture of textual content and social context, which includes user interactions and propagation networks. Each dataset will be preprocessed to fit a graph-based model where nodes represent articles and edges represent the relationships (e.g., shares, likes, comments) between them. For this research, we use datasets from [11] with amount of training is 1092 examples and the amount of testing examples being 3826 data.

Table 1. Comparison Train and Testing Dataset

Training	Testing
1092	3826

2. **Graph Construction**

Node Representation: Each node (news article) will have feature vectors derived from textual content using NLP techniques such as TF-IDF or word embeddings. Edge Representation: Edges will represent the interactions between articles and users, which could include metrics like shared URLs, user comments, or citations.

3. **Preprocessing**

Splitting Data, The dataset will be divided into 20% training, 10% validation, and 70% testing sets [11].

Loss Function, Binary cross-entropy loss will be used as each news article needs to be classified into fake or real.

Optimizer, Adam optimizer with a learning rate adjustment based on validation loss performance.

4. **Model Training and Implementation**
   GCN Conv is a model using graph convolutional layers to aggregate neighborhood information.
   GAT Conv is a model will utilize attention mechanisms to weigh the importance of neighboring nodes differently.
   SAGEConv is a model to Implementation of different aggregation functions (mean, max, LSTM) to study their impact on fake news detection.
5. **Model Evaluation**
   The trained model is evaluated using the testing subset. The model's performance is measured using evaluation metrics such as accuracy and loss [12].

3. RESULTS AND DISCUSSION

3.1 GAT Conv Model Evaluation

Figure 2 depicts the training and test loss over 100 epochs, highlighting the model's learning and generalization performance. Initially, both losses are high, around 0.7, but they rapidly decrease, indicating effective learning. As epochs progress, the training loss steadily declines, while the test loss shows variability with occasional spikes, suggesting fluctuations in generalization. By the end of the training, both losses converge around 0.2 to 0.3, reflecting stability and a balanced fit between the datasets, with minimal overfitting. The proximity of the curves indicates good generalization, though the test loss variability suggests areas for further optimization.presents the training and validation accuracy of our phishing detection model over a series of epochs.

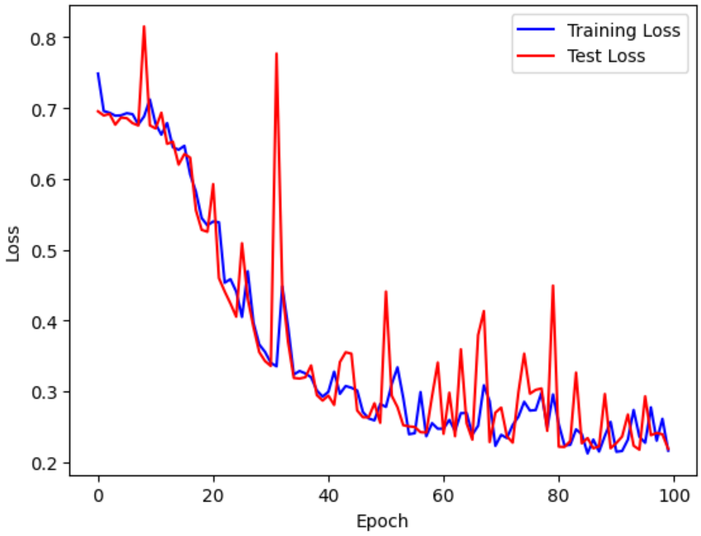

Figure 2. GAT Conv Training and Tess loss

Sedangkan gambar 4 merupakan The graph illustrates the test accuracy of a model over 100 epochs. Initially, the accuracy starts at around 0.5, indicating random performance. There is a sharp increase in accuracy between 10 to 20 epochs, reaching approximately 0.9, signifying rapid improvement in model performance. As training continues, the accuracy fluctuates between 0.85 and 0.9488, demonstrating consistent high performance with some variability. The fluctuations suggest the model may encounter occasional challenges with certain data but generally maintains strong accuracy. Overall, the model achieves high test accuracy, indicating effective learning and good generalization.

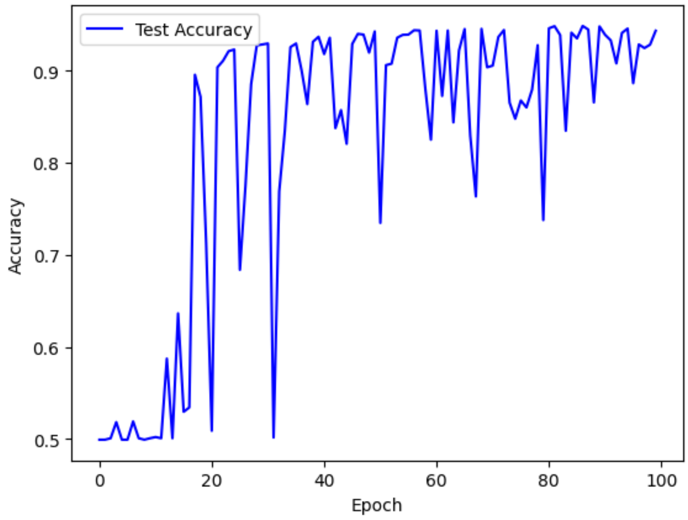

Figure 3. GAT Conv Accuracy Test

The model achieved a maximum test accuracy of 0.9488 at epoch 86. Additionally, the minimum training loss was 0.2120 at epoch 85, while the minimum test loss was recorded at 0.2173 at epoch 94.

3.2 SAGE Conv Model Evaluation

Figure 4. illustrates the progression of training and test loss over 100 epochs, reflecting the model's learning dynamics and generalization ability. Initially, both the training and test losses are high, around 0.7, indicating initial inaccuracies. The losses decrease significantly during the first 20 epochs, showing effective model training. As the epochs progress, the training loss continues to decline gradually, while the test loss exhibits variability with periodic spikes, suggesting challenges in maintaining consistent generalization. By the end of the training, both losses converge to values between 0.2 and 0.3, indicating successful learning with minimal overfitting. The close alignment of the two curves by the final epochs demonstrates a balanced fit between the training and test datasets.

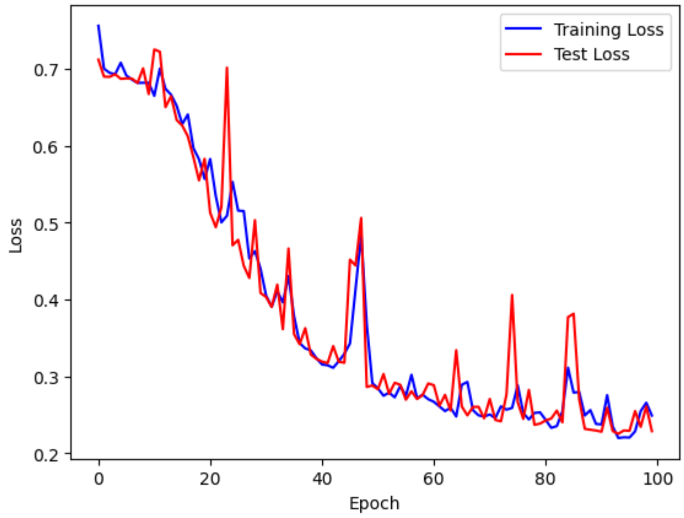

Figure 4. SAGE Conv Training and Test Loss

Figure 5. shows the test accuracy of a model over 100 epochs. Initially, the accuracy begins around 0.5, suggesting random performance. Between 10 to 20 epochs, there is a rapid increase, with accuracy reaching approximately 0.9, indicating significant improvement. As training progresses, accuracy fluctuates between 0.85 and 0.9472, maintaining consistent high performance despite some variability. These fluctuations suggest the model occasionally struggles with certain data but generally demonstrates robust accuracy. Overall, the model achieves strong test accuracy, reflecting effective learning and generalization capabilities.

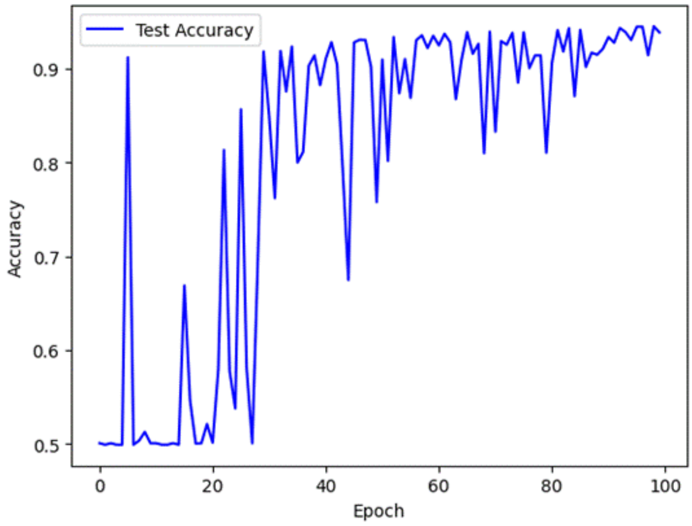

Figure 5. SAGE Conv Test Accuracy

The model achieved a maximum test accuracy of 0.9472 at epoch 9. Additionally, the minimum training loss was 0.2196 at epoch 93, and the minimum test loss was 0.2252, also at epoch 93.

3.3 GCN Conv Model Evaluation

Figure 6. depicts the training and test loss over 100 epochs, showcasing the model's learning progression and generalization. Initially, both losses are high, around 0.7, indicating early stage inaccuracies. A significant decline in both losses is observed within the first 20 epochs, demonstrating effective learning. As training advances, the training loss steadily decreases, while the test loss experiences fluctuations, particularly between epochs 50 and 70, suggesting occasional challenges with generalization. By the end of the training period, both losses converge around 0.2 to 0.3, indicating successful convergence with minimal overfitting. The close alignment of the training and test loss curves suggests a balanced fit and strong model generalization.

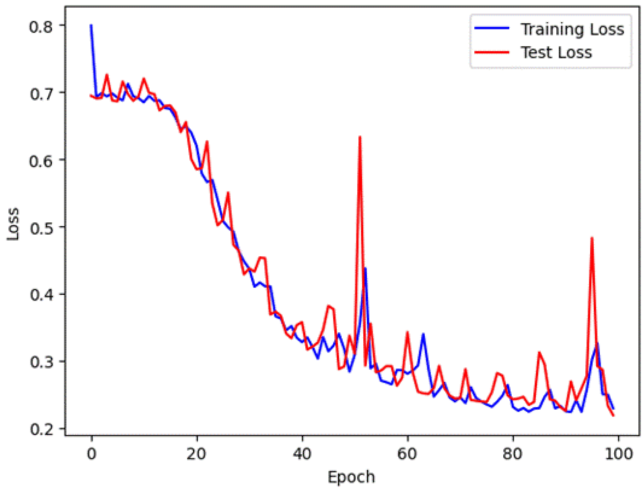

Figure 6. GCN Conv Training and Tess Loss

Figure 7. illustrates the test accuracy of a model across 100 epochs. Initially, accuracy starts at around 0.5, indicating baseline or random performance. Between epochs 10 and 20, there is a rapid increase in accuracy, reaching approximately 0.9, signifying substantial improvement in model performance. As the epochs progress, the accuracy fluctuates between 0.85 and 0.9493, demonstrating high and consistent performance with some variability. These fluctuations suggest occasional struggles with specific data points, but overall, the model maintains robust accuracy. The pattern indicates effective learning and generalization capabilities, with the model achieving strong test accuracy by the end of the training period.

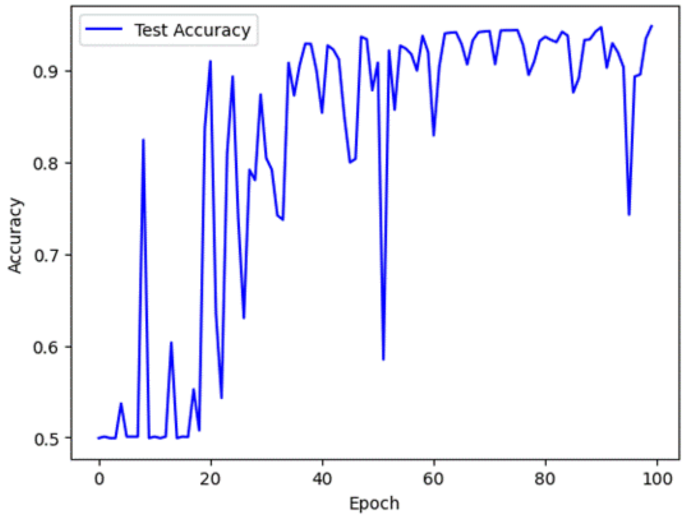

Figure 7 a. GCN Test Accuracy

The model achieved a maximum test accuracy of 0.9482 at epoch 99. Additionally, the minimum training loss was 0.2237 at epoch 91, and the minimum test loss was 0.2189 at epoch 99.

4. CONCLUSION

The comparison of different convolutional methods GAT Conv, SAGE Conv, and GCN Conv reveals distinct performance characteristics in terms of test accuracy and training loss. GAT Conv achieved the highest test accuracy of 0.9488 at epoch 86, indicating strong performance and effective learning. The model's minimum training and test losses were 0.2120 and 0.2173, respectively, suggesting efficient convergence and minimal overfitting. SAGE Conv demonstrated slightly lower performance compared to GAT Conv, with a maximum test accuracy of 0.9472 at epoch 93. Its minimum training loss was 0.2196, and the minimum test loss was 0.2252, both occurring at epoch 93. These results indicate that while SAGE Conv is effective, it may not generalize as well as GAT Conv, given the slightly higher loss values. GCN Conv displayed competitive results, achieving a maximum test accuracy of 0.9482 and a maximum F1 score of 0.9493, both at epoch 99. The minimum training loss was 0.2237 at epoch 91, with a minimum test loss of 0.2189 at epoch 99. This suggests that GCN Conv offers a balanced performance, with its accuracy of GAT Conv, while maintaining efficient loss minimization, making it a viable alternative for robust model performance. In conclusion, the evaluation of GAT Conv, SAGE Conv, and GCN Conv models highlights varying strengths in performance and convergence. GAT Conv achieved the highest test accuracy, indicating superior learning and generalization capabilities, with minimal losses suggesting efficient training. SAGE Conv, while slightly trailing in accuracy, demonstrated effective learning, though with slightly higher losses, implying room for improvement in generalization. GCN Conv offered a balanced performance, approaching the accuracy and F1 scores of GAT Conv, while maintaining efficient loss minimization. Overall, each model presents unique advantages, with GAT Conv leading in performance metrics and GCN Conv providing a strong, balanced alternative.

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