# Detecting Fake News Propagation Using NLP And GCN

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*The widespread dissemination of fake news on social media has intensified concerns over misinformation and its societal impact. Traditional detection methods, primarily based on textual analysis, fail to account for the propagation dynamics that characterize how misinformation spreads. In this paper, we propose FPN-GCN, a model designed to enhance fake news detection by incorporating multi-hop propagation attention and credibility score embeddings. Our approach leverages graph-based learning to analyze the diffusion structure of misinformation rather than relying solely on content. Experimental evaluations on the GossipCop dataset demonstrate that FPN-GCN significantly enhances fake news detection accuracy by modeling propagation dynamics.*

## 1 Introduction

The rapid proliferation of fake news on social media has raised significant concerns about its impact on public perception, decision-making, and societal stability. With the growing reliance on online platforms for information consumption, misinformation spreads rapidly across user networks, often outpacing fact-checking efforts. Traditional fake news detection methods primarily rely on text-based analysis, which overlooks how misinformation propagates through online interactions. Since fake news often follows distinct diffusion patterns compared to real news, understanding propagation dynamics is crucial for early and effective detection. Graph Neural Networks (GNNs) have shown promise in leveraging social structures for fake news detection, but existing models often fail to capture multi-hop propagation patterns, where misinformation cascades through multiple layers of user engagement. Additionally, they overlook credibility-aware modeling, which considers the reliability of users spreading the information. Integrating both textual and propagation-based features is essential for improving classification accuracy and robustness. This study aims to answer the following key research questions:

- How can Graph Convolutional Networks (GCNs) enhance the detection of fake news propagation on social media by effectively capturing propagation patterns?
- How can the combination of Natural Language Processing (NLP) and Graph Convolutional Networks enhance the detection of fake news propagation by leveraging both textual content and network structures?
- How effectively can a propagation-aware Graph Convolutional Network (PAGN) detect fake news by modeling multi-hop misinformation spread and integrating user credibility?

This paper proposes FPN-GCN, a model that enhances fake news detection by integrating multi-hop propagation attention, credibility score embeddings, and graph-based learning. By modeling misinformation spread and user credibility, FPN-GCN improves classification accuracy and robustness. Experiments on the GossipCop dataset show it outperforms existing methods in distinguishing fake from real news. The next section reviews fake news detection approaches, followed by Methodology, which details FPN-GCN's architecture. Experimentation and Results present the dataset, setup, metrics, and findings. Finally, Conclusion summarizes key insights, limitations, and future directions.

# 2 Related Work

Fake news detection methods fall into three main categories: text-based, graph-based, and propagation-based approaches. While early models relied on linguistic features, recent Graph Neural Networks (GNNs) have integrated social structures and user interactions. However, most existing methods fail to fully capture multi-hop propagation and user credibility, which are crucial for improving detection accuracy.

## 2.1 Text-Based Approaches

Traditional methods used machine learning models (SVMs, Decision Trees, Naïve Bayes) with linguistic features. Deep learning approaches, including CNNs, RNNs, and transformer-based models (BERT, RoBERTa), improved text classification. However, they struggle with manipulated writing styles and ignore propagation dynamics, limiting effectiveness.

## 2.2 Graph-Based Approaches

Graph-based methods model news-user interactions, with GCN-based models (Bi-GCN, DGCN) leveraging engagement patterns. However, most only capture first-order connections, neglecting multi-hop diffusion. While some integrate news credibility, they do not embed trustworthiness signals effectively. Our work addresses this by embedding credibility scores into the graph structure for enhanced classification.

## 2.3 Propagation-Based Approaches

Propagation models analyze misinformation spread using diffusion trees. Methods like GCNSI and AA-HGNN attempt to model these patterns but lack multi-hop propagation attention. FPN-GCN improves propagation modeling by capturing long-range dependencies, though existing versions lack a credibility-aware component.

## 2.4 Our Approach

While text-based methods focus on content, they ignore spread dynamics. Graph-based models capture user interactions but fail to integrate multi-hop propagation and credibility factors. Propagation-based approaches analyze spread patterns but overlook user trustworthiness. To overcome these limitations, FPN-GCN:

- Captures multi-hop propagation to model misinformation diffusion.

- Incorporates credibility scores to improve classification accuracy.
- Combines text, network, and propagation analysis for a more robust detection framework

# 3 Methodology

The figure below illustrates the dataset structure, providing an overview of its composition and features. float

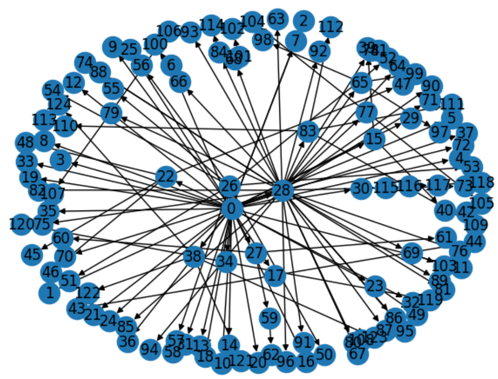

Figure 1: Dataset

## 3.1 Data Collection and Pre-processing

We utilized publicly available fake news datasets, including GossipCop from UPFD, to evaluate our models. The dataset was preprocessed to ensure an equal distribution of fake and real news for both training and testing sets. float

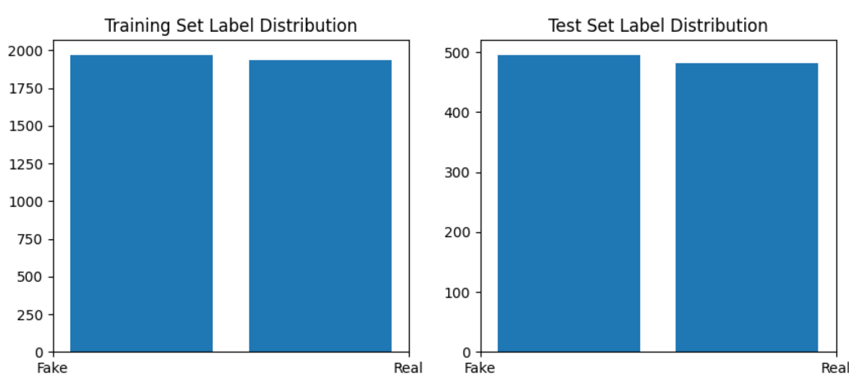


Figure 2: Balanced Label Distribution in Training and Test Sets for Fake News Detection

For textual preprocessing, NLP techniques such as tokenization, stopword removal, and vectorization were applied. Additionally, profile features were extracted, encoding metadata such as account creation date, follower count, and location into a 10-dimensional vector to identify bot activity and influential users in fake news spread. Spacy Word2Vec was used to convert users' historical tweets into 300-dimensional embeddings, capturing linguistic patterns and engagement behaviors. The final 310-dimensional content feature was a combination of these representations. To enhance our model's ability to assess credibility, we generated credibility scores based on node degrees, using engagement-based credibility as a heuristic. These scores were validated and reshaped to ensure proper integration into the model. In terms of graph construction, social media posts were modeled as graphs where nodes correspond to articles, and edges capture propagation patterns among users. The propagation structures were leveraged to enrich the model's understanding of how fake news spreads across networks. The figure below illustrates the overall process, highlighting the Exogenous Context Encoder for social context extraction and the Endogenous Preference Encoder for news content representation: float

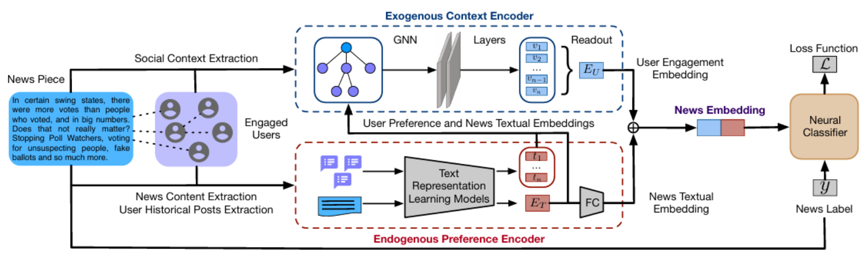


Figure 3: Overview of the proposed fake news detection model, integrating social context (exogenous) and textual content (endogenous) to generate a fused news embedding for classification.

## 3.2 Model Architectures

1. GCN: Captures local and global dependencies in the news propagation network.
2. FPN-GCN: A novel propagation-aware GCN that:
   - Implements Multi-Hop Propagation Attention to track how misinformation spreads across users.
   - Integrates Credibility Score Embeddings to incorporate user trustworthiness into the model.
   - Uses Graph-Based Learning to analyze diffusion patterns instead of relying solely on text.

## 3.3 Training and Evaluation

To train the FPN-GCN model, we used the cross-entropy loss function, optimized with the Adam optimizer with a learning rate scheduler to ensure stable convergence. The model was trained for multiple epochs with early stopping to prevent overfitting. The training pipeline consisted of the following steps:

1. Graph Construction and Feature Extraction: Nodes were initialized with text embeddings and credibility scores, while edges captured the propagation structure.
2. Forward Pass: The FPN-GCN model applied multi-hop propagation attention to refine node representations.
3. Backward Pass and Optimization: The model weights were updated using Adam optimization with gradient clipping to prevent exploding gradients.
4. Evaluation Metrics: We assessed the model's performance using accuracy, precision, recall, and F1-score, in addition to a confusion matrix to analyze classification errors.
5. Hyperparameter Tuning: We experimented with different learning rates, dropout values, and attention mechanisms to maximize performance.

The final trained model was validated using unseen test data, ensuring generalizability to real-world misinformation detection scenarios.

# 4 Experimentation and Results

To evaluate the performance of FPN-GCN, we analyzed the Confusion Matrix to assess classification accuracy and misclassification trends. float

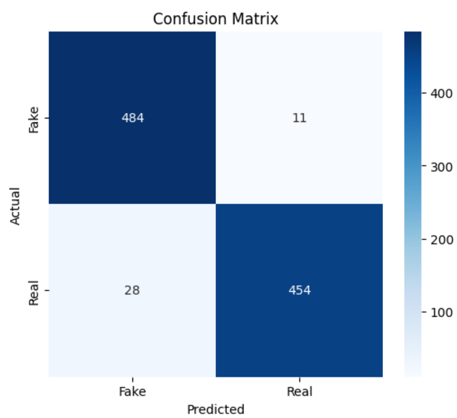


Figure 4: Confusion Matrix for Fake News Classification Performance

Additionally, we tracked Training vs. Test Loss Over Epochs to ensure model stability and detect potential overfitting. float

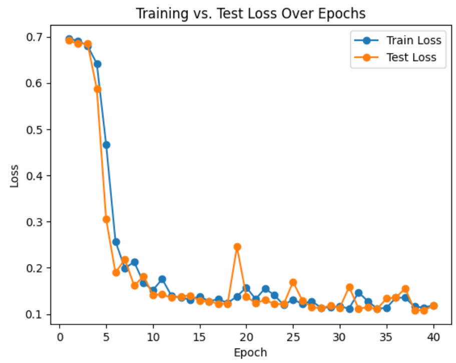


Figure 5: Training vs. Test Loss Over Epochs for Fake News Detection Model

### 4.1 Performance Comparison

| Model | Accuracy |
|---|---|
| GCN | 94% |
| FPN-GCN | 96% |
| RoBERTa-GCN | 98.6% |
| CT-BERT+BiGRU | 98.4% |
| BerConvoNet | 97.4% |
| FNDNet | 98.3% |
| BERT | 90.0% |
| BanglaBERT | 83.4% |
| XLM-RoBERTa | 93.31% |
| KMAGCN | Various (up to 84.9%) |

Table 1: Comparison of Model Accuracies

### 4.2 Key Findings

FPN-GCN outperformed GCNs by leveraging multi-hop propagation attention and credibility score embeddings, leading to improved accuracy and fewer misclassifications. The model demonstrated stable convergence and consistently high evaluation metrics, confirming its effectiveness in propagation-aware fake news detection.

# 5 Conclusion

## 5.1 Summary

This study introduces FPN-GCN, a novel propagation-aware model that enhances fake news detection by incorporating multi-hop propagation and credibility-based embeddings. Our results demonstrate that analyzing news diffusion patterns significantly improves classification accuracy compared to traditional GCN-based models.

## 5.2 Limitations

The effectiveness of FPN-GCN relies on labeled datasets, which limits scalability to new, unseen data. Additionally, the multi-hop analysis increases computational complexity, making real-time detection more challenging.

## 5.3 Future Improvements

Future work should explore advanced credibility assessment methods beyond node degrees and integrate hybrid models combining transformers with GNNs. Additionally, improving the interpretability of propagation-aware detection frameworks will enhance model transparency and trustworthiness.

## 5.4 References


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