ABSTRACT:

The rapid spread of misinformation through social media platforms has become a major societal concern, influencing public opinion and political stability. Traditional fake news detection methods primarily focus on text content analysis, often ignoring the complex interaction patterns among users, posts, and shared information. This paper presents a graph-based approach for detecting fake news using Graph Neural Networks (GNNs). By modeling social media data as a heterogeneous graph, where nodes represent users and posts and edges represent user engagements, the proposed model effectively captures both textual and structural features. A Graph Convolutional Network (GCN) architecture is implemented using the PolitiFact dataset to classify news items as real or fake. Experimental results demonstrate that the GNN-based model achieves improved accuracy and generalization compared to traditional deep learning baselines such as CNN and LSTM. The findings highlight the potential of leveraging relational structures in social networks for enhanced fake news detection and early misinformation control.

INTRODUCTION

The rapid growth of social media platforms such as Twitter and Facebook has made it easier to share information globally. However, this convenience has also led to the spread of *fake news*, which can mislead users and influence public opinion. Detecting such misinformation is a major challenge because fake news often spreads through complex social interactions rather than just through text content.

Traditional fake news detection methods mainly rely on text-based features using models like CNN and LSTM, but they ignore how news propagates through user networks. To overcome this limitation, this study employs *Graph Neural Networks (GNNs)*, which can model relationships among users, posts, and interactions.

In this paper, a *Graph Convolutional Network (GCN)* is implemented using the PolitiFact dataset to classify news as fake or real. By combining textual and structural information, the proposed model improves detection accuracy compared to traditional deep learning approaches.

RELATED WORK

Fake news detection has been widely studied using **text-based methods**, including traditional machine learning algorithms like SVM and Naïve Bayes, and deep learning models such as CNN and LSTM [1], [2]. While effective in analyzing content, these approaches fail to capture how misinformation spreads through social interactions.

To address this limitation, **graph-based approaches** have emerged, modeling news propagation and user interactions as graphs. Graph Neural Networks (GNNs), including Graph Convolutional Networks (GCN) and Graph Attention Networks (GAT), can learn both textual and structural features from social networks, improving detection accuracy [3], [4], [5].

Despite progress, few studies implement GNNs on real-world datasets to evaluate practical performance. This paper fills this gap by applying a GCN model to the PolitiFact dataset, combining content and social interaction features for effective fake news detection.

METHODOLOGY

The proposed approach employs a **Graph Convolutional Network (GCN)** to detect fake news by leveraging both textual content and social network structure.

Dataset: The PolitiFact dataset is used, containing labeled news articles and user interactions such as shares and comments. Textual preprocessing includes tokenization, stopword removal, and embedding using TF-IDF and word2vec.

Graph Construction: News articles and users are modeled as nodes, with edges representing interactions (e.g., reposts, comments). Node features combine textual embeddings and user engagement metrics, while the adjacency matrix encodes connections.

GCN Model: Each GCN layer updates node features based on neighbors :

$$H^{(l+1)} = \sigma(\widetilde{D}^{-\frac{1}{2}}\tilde{A}\widetilde{D}^{-\frac{1}{2}}H^{(l)}W^{(l)})$$

where $\tilde{A}$is the adjacency matrix with self-loops, $\widetilde{D}$is the degree matrix, $H^{(l)}$is the feature matrix, and $W^{(l)}$is the trainable weight matrix. The final layer uses softmax for binary classification (fake vs. real).

Implementation: *The model is implemented in **PyTorch Geometric**, with 2 graph convolution layers, 128 hidden units, learning rate 0.001, and dropout 0.5. Evaluation metrics include **Accuracy, Precision, Recall, and F1-score**.*

IMPLEMENTATION

*The proposed GCN model for fake news detection is implemented using **PyTorch Geometric**. The key steps include:*

1. ***Data Preprocessing:***
   - *Load the **PolitiFact** dataset.*
   - *Clean textual content (tokenization, stopword removal).*
   - *Convert text to embeddings using **TF-IDF** and **word2vec**.*
2. ***Graph Construction:***
   - *Represent users and news articles as nodes.*
   - *Create edges for user-post interactions (shares, comments, replies).*
   - *Build the **adjacency matrix** and combine node features (text + user engagement).*
3. ***GCN Model Setup:***
   - *2 Graph Convolution layers with **ReLU** activation.*
   - *Hidden dimension: 128 units.*
   - *Dropout rate: 0.5 for regularization.*
   - *Optimizer: **Adam**, learning rate: 0.001.*

4. **Training & Evaluation:**
    - Train for **100 epochs** with 70/15/15 train-validation-test split.
    - Evaluate performance using **Accuracy, Precision, Recall, and F1-Score**.

The model effectively combines **structural relationships** and **textual information**, enabling robust detection of fake news even when content alone is ambiguous.

RESULTS AND DISCUSSION

The proposed GCN model was evaluated on the **PolitiFact** dataset and compared with CNN and LSTM baselines. The dataset was split into **70% training, 15% validation, and 15% testing**, and evaluation metrics included **Accuracy, Precision, Recall, and F1-Score**.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN	85.2	84.7	83.1	83.9
LSTM	87.6	86.5	85.9	86.2
GCN	**91.8**	**90.9**	**91.3**	**91.1**

Table I. Performance comparison of different models

The results show that the GCN outperforms text-based models by effectively leveraging **social interactions and propagation patterns**. Visualization of node embeddings indicates that fake and real news form distinct clusters, demonstrating the model's ability to capture both content and structural features.

Although the GCN achieves superior accuracy, it has **higher computational costs** due to graph construction and message passing. Future work may explore **Graph Attention Networks (GATs)** or **LightGCN** to improve efficiency.

CONCLUSION AND FUTURE WORK

This paper presented an implementation-based approach for detecting fake news on social media using **Graph Neural Networks (GNNs)**, specifically the **Graph Convolutional Network (GCN)** model. Unlike conventional text-based methods that rely only on linguistic features, the proposed approach incorporates both textual and structural information from user-news interactions. By modeling the dataset as a graph, the system captures how misinformation spreads through social connections and community structures.

Experimental results on the **PolitiFact** dataset demonstrate that the GCN model outperforms traditional deep learning models such as CNN and LSTM in terms of accuracy, precision, recall, and F1-score. The findings confirm that social context and network connectivity play an essential role in distinguishing fake news from genuine information.

Despite the promising results, certain limitations remain. The computational complexity of graph-based models and the limited availability of large, labeled datasets restrict scalability. In future work, this study can be extended by:

1. Implementing **Graph Attention Networks (GATs)** to better capture relationship importance between users and posts.
2. Exploring **temporal graph networks** to model the evolution of news propagation over time.
3. Applying **cross-platform learning** to generalize detection models across multiple social media networks.

Overall, this work highlights the potential of graph-based deep learning in combating misinformation and sets the foundation for further advancements in social network analysis and trustworthy AI systems.

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