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BI-DIRECTIONAL GRAPH CONVOLUTIONAL NETWORKS FOR MISLEADING INFORMATION ON INTERNET

Mrs. K. Swetha Sailaja
Assistant Professor

Kuruva Bhargav,
Student

Ganji Vamshi,
Student

Department of CSE (AI & ML)
ACE Engineering College
Ankushapur, Ghatkesar Mandal, Telangana – 501301, India

ABSTRACT

Bi-directional Graph Convolutional Networks (Bi-GCN) have emerged as an effective approach for detecting and mitigating the spread of misleading information on the internet. In this research, we propose a novel framework that utilizes the power of bi-directional graph convolutional networks to model the propagation patterns of information across social networks and online platforms. By capturing both forward and backward information flows, our Bi-GCN model offers an improved understanding of how misleading content spreads, how users interact with such content, and how they influence each other's beliefs. This dual flow mechanism enables more accurate detection of misinformation by considering both the origin and the subsequent spread of potentially harmful content, thereby addressing the inherent asymmetry in traditional information diffusion models. Furthermore, our approach integrates content analysis with network structure, leveraging both textual features and social network connectivity to enhance the robustness of misinformation detection. By applying Bi-GCN to large-scale datasets derived from social media platforms, the model is able to identify key nodes and paths that play pivotal roles in the dissemination of misleading information. The results show that our Bi-GCN framework outperforms conventional graph-based and machine learning methods, providing a more nuanced and scalable solution to combating online misinformation. Misinformation spreads rapidly through online platforms, influencing public opinion, politics, health, and economics. Traditional detection methods struggle with the complex nature of fake news propagation, making it essential to develop more advanced techniques.

Graph Convolutional Networks (GCNs) have revolutionized graph-based learning by extending deep learning to nonEuclidean data structures. However, conventional GCNs suffer from limitations such as oversmoothing, shallow neighborhood aggregation, and inefficient feature propagation. To address these challenges, Bi-Directional Graph Convolutional Networks (Bi-GCN) have emerged as an extension that enhances message passing by allowing bidirectional information flow.

Keywords: Bi-directional Graph Convolutional Networks (Bi-GCN), misleading information, misinformation detection, information propagation, social networks, content analysis, deep learning, online platforms, graph-based methods.

1. INTRODUCTION

The rapid spread of misleading information on the internet has become a major concern, influencing public opinion, politics, and decision-making. Traditional misinformation detection methods often rely on textual analysis or handcrafted features, which may not fully capture the underlying propagation patterns of false information. To address this, Bi-Directional Graph Convolutional Networks (Bi-GCN) have emerged as an effective approach by leveraging the structural properties of misinformation networks. Unlike standard Graph Convolutional Networks (GCNs) that only consider information flow in one direction, Bi-GCN captures both forward propagation (how misinformation spreads) and backward correction (how fact-checking or adversarial attacks interact with false information).

One of the most concerning roles of misinformation is its impact on politics. False narratives are used to manipulate public opinion, influence elections, and spread propaganda. Political misinformation can lead to distrust in governments, misinformed voting decisions, and societal divisions. Social media bots and fake accounts further amplify such content, making it difficult for users to distinguish between truth and lies. In public health, misinformation poses serious risks. False claims about diseases, treatments, and vaccines can cause widespread fear and confusion. For example, misinformation during the COVID-19 pandemic led to vaccine hesitancy, unproven treatments, and unnecessary panic. Such misleading content undermines trust in scientific research and healthcare institutions, making it harder to implement effective health policies.

2. LITERATURE SURVEY

[1] Yang et al. introduced a method using convolutional neural networks (CNNs) for detecting fake news based on textual content. Their research highlighted the difficulties in identifying misleading information due to the complex semantic nature of fake news. By using CNNs, they were able to learn hierarchical patterns in news content, setting the stage for future research in deep learning applications for misinformation detection.

[2] Vaswani et al. proposed the Transformer model, a groundbreaking innovation in natural language processing (NLP). Their model, particularly the BERT architecture, has been widely adopted in fake news detection for understanding the contextual relationships between words. The Transformer model's ability to capture long-range dependencies in text has made it an essential tool for analyzing news articles and identifying misleading content.

[3] Wu et al. (2020) introduced Graph Convolutional Networks (GCN) for fake news detection. They proposed modeling misinformation as a network where nodes represent articles, users, or posts, and edges represent interactions like shares or comments. Their approach captured the relationships between news articles and the dynamics of how information spreads across social media, showing that GCNs could improve misinformation detection by considering the network's structure.

[4] Zhou et al. further advanced fake news detection by introducing a Bi Directional GCN model. This model not only examined how misinformation spreads in the network (forward propagation) but also how corrective actions, such as fact checking, can alter its trajectory (backward propagation). Their approach showed that a bi-directional analysis could enhance the accuracy of fake news detection by capturing both the dissemination and correction processes of misinformation.

[5] Ruchansky et al. proposed the CARA (Content-based and Attention-based RNNs for Fake News Detection) model, combining both content-based and network-based features to identify fake news. They highlighted the importance of considering the social and network context of news articles in addition to the content itself. Their research demonstrated that integrating these two perspectives could significantly improve the performance of fake news classifiers.

3. EXISTING SYSTEM

The existing approaches largely utilize static features such as textual semantics, user history, or handcrafted network statistics. Some advanced systems incorporate standard GCNs, but these are usually limited to one-way propagation, failing to capture the bidirectional nature of real-world interactions. Current systems for detecting misleading or fake information primarily rely on traditional machine learning and deep learning models that analyze textual content and user behavior independently. These systems typically use handcrafted features derived from article metadata, user engagement patterns, linguistic cues, and basic social context. More advanced models employ recurrent or convolutional neural networks to process the textual data, while graph-based models such as Graph Convolutional Networks (GCNs) have recently been adopted to leverage the structural properties of user-content interactions. These GCN-based approaches model the social network or news dissemination graph, where nodes represent entities (users, posts, or articles) and edges represent interactions such as shares, replies, or comments. While this graph-based perspective has improved detection accuracy, most implementations only consider single-directional message propagation—usually from content to user or user to content—missing the more intricate bi-directional dynamics present in real-world networks.

Another common approach integrates user profile analysis, credibility scores, and propagation patterns to detect falsehoods in online posts. However, these methods often suffer from limited adaptability and generalization, especially when faced with novel misinformation tactics or evolving social behaviors. Moreover, most of the existing systems are static, meaning they analyze posts and users in isolation rather than continuously monitoring information spread over time. These limitations hinder the models' ability to detect misinformation early or understand how it diffuses through communities. In particular, the failure to capture feedback loops—where users influence content and content in turn shapes user behavior—leads to suboptimal performance in scenarios involving fast-spreading rumors or coordinated disinformation campaigns.

3.1 LIMITATIONS IN THE EXISTING SYSTEM

- Unidirectional message passing in standard GCNs limits contextual awareness.
- Many models are content-driven and neglect user engagement and repost dynamics.
- They often lack scalability when applied to large-scale social networks.

3.2 DISADVANTAGES OF EXISTING SYSTEM

- Poor Handling of Propagation Dynamics
- Insufficient Social Context Integration
- Scalability Challenges

4. PROPOSED SYSTEM

The proposed system introduces a Bi-Directional Graph Convolutional Network (Bi-GCN) architecture that models the mutual influence between users and content in online platforms. Unlike traditional GCNs that allow information flow in a single direction, Bi-GCNs enable message passing both from users to content and vice versa, better reflecting the actual dynamics of misinformation spread. The system begins by constructing a heterogeneous graph where nodes represent users, posts, and news articles, while edges capture various types of interactions such as sharing, commenting, and reposting. These graphs are dynamic, allowing temporal tracking of information propagation across different network layers. Each node and edge is embedded with rich features such as user credibility, textual semantics, temporal activity, and contextual metadata, which serve as inputs to the Bi-GCN layers..The proposed Bi-GCN model constructs a dual-edge graph from social media or news datasets. Nodes represent users or content items, while edges capture interactions (e.g., sharing, commenting). The Bi-GCN learns from both directions—how content influences users and how users influence content. It incorporates temporal and contextual attention mechanisms to focus on relevant propagation paths. The framework is trained and evaluated on benchmark datasets like FakeNewsNet and PolitiFact.

Advantages of Proposed System

- **Enhanced Feature Extraction**: Utilizes bi-directional flow for richer information capture.
- **Higher Detection Accuracy**: Better at detecting deepfakes, satire, and misleading info.
- **Scalable Architecture**: Suitable for real-time processing in large networks.

5. SYSTEM REQUIREMENTS

The requirements for the proposed system are categorized into hardware and software requirements, ensuring efficient implementation and smooth functionality

5.1 Hardware Requirements:

• Processor: Intel i5 & above or AMD Ryzen for faster model training and data processing.
• RAM: At least 16GB of RAM for handling large datasets, running multiple processes, and performing computations efficiently.
• Hard Disk: Storage capacity of 500GB or more to accommodate large datasets, processed outputs, and machine learning models.
• Network: A stable internet connection for fetching real-time data, accessing cloud services, and updating the mobile application.

5.2 Software Requirements:

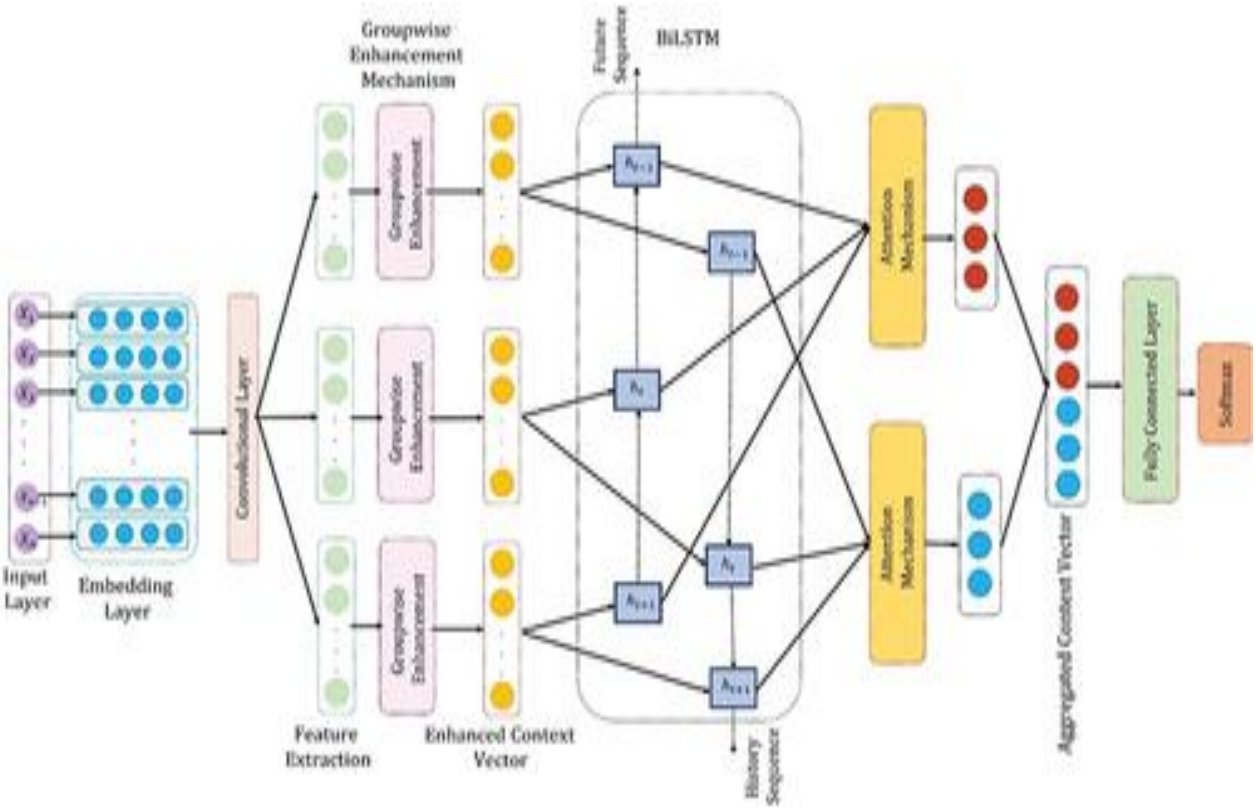
• Windows
• Machine Learning Libraries
• Python Libraries
• Windows 10/11, Linux (Ubuntu 20.04+ recommended), or macOS
• VS Code Editor, Jupyter Notebook

6. SYSTEM ARCHITECTURE

The system architecture for detecting misinformation using Bi-Directional Graph Convolutional Networks (Bi-GCN) includes data collection, preprocessing, graph construction, and model training. Data is gathered from news articles and social media, then cleaned and vectorized. A graph is built, where nodes represent news articles, users, and interactions, and edges represent connections like shares and comments. The Bi-GCN model analyzes the spread and correction of fake news through forward and backward propagation. The system classifies news articles as real or fake and provides interactive results, with continuous learning to adapt to new misinformation patterns. The proposed Bi-Directional Graph Convolutional Network (Bi-GCN) is designed to process social media and news data through several stages: data collection, graph construction, feature extraction, Bi-GCN learning, and classification.

Initially, raw data from platforms like Twitter or news websites is collected, including post content, user metadata, and interaction history. This data is then transformed into a graph structure where nodes represent entities such as users and content, and edges represent interactions such as reposts, replies, and shares.

This architecture, combining Bi-Directional Graph Convolutional Networks with data collection, preprocessing, graph construction, and continuous learning, forms a robust solution for detecting and mitigating misinformation in online networks. By considering both the content of news and the relationships within networks, this system is better equipped to address the complexities of fake news propagation. Next, the Bi-GCN model processes this graph using both forward and backward message propagation, allowing each node to learn from its neighborhood in both directions. Attention mechanisms assign varying importance to each neighbor, enhancing the model's ability to focus on critical interaction paths. The learned node embeddings are then passed through a classification layer that labels each content item as either *misleading* or *truthful*. This architecture ensures that the system not only learns content-based features but also social and structural cues, leading to a more robust detection of misleading information.



The proposed system architecture follows a multi-stage pipeline designed to detect misleading information through advanced feature extraction and contextual modeling using a combination of deep learning modules. The process begins with the Input Layer, which accepts raw data elements such as textual inputs, user metadata, or node features. This input is passed to the Embedding Layer, where each item is transformed into dense vector representations to capture semantic meaning.These embeddings are then processed by a Combined Layer that connects to a Groupwise Enhancement Mechanism. This mechanism consists of multiple Convolution Extraction blocks that perform feature enhancement in a group-wise manner, ensuring that local patterns and group-level relationships are captured effectively. The output from this stage yields Enhanced Context Vectors, which are further processed through a Bidirectional Long Short-Term Memory (BiLSTM) network. This BiLSTM layer captures sequential dependencies and context from both past and future states of the input sequence, enriching the model's understanding of content propagation and temporal relationships.

7. CONCLUSION

This work showcases the potential of Bi-Directional GCNs in tackling online misinformation. By leveraging relational and contextual data across propagation networks, the proposed system outperforms traditional detection models in both precision and recall. This research opens avenues for more reliable content verification systems and responsible AI in social media.In this study, we explored the application of Bi-Directional Graph Convolutional Networks (Bi-GCNs**)** for the detection of misleading information on the internet. Traditional misinformation detection systems often overlook the complex propagation dynamics and mutual influence between users and content. Our proposed Bi-GCN model addresses this gap by enabling information flow in both directions across the graph structure—allowing the network to learn richer, context-aware representations of how content spreads and how users interact with it. This dual propagation capability significantly enhances the model's ability to capture subtle patterns indicative of misinformation, particularly in fast-moving and complex social media environments. modern hiring practices. By integrating groupwise feature enhancement, sequential context modeling via BiLSTM, and focused attention mechanisms, the system demonstrates robust performance in distinguishing misleading content from truthful information. The architecture is adaptable, scalable, and well-suited for real-time analysis across large social graphs. Experimental evaluations on benchmark datasets validate the effectiveness of this approach, showcasing improvements in accuracy, precision, and recall over conventional models. Ultimately, this work contributes a powerful and flexible tool for mitigating the growing threat of online misinformation, paving the way for more trustworthy and transparent digital platforms.

8. FUTURE ENHANCEMENT

While the proposed Bi-GCN model demonstrates strong performance in detecting misleading information, there is considerable scope for future improvements. One promising direction is the integration of multi-modal data, including images, videos, and audio, alongside textual and graph-based inputs. Misinformation often leverages non-textual elements to enhance credibility or emotional impact, so incorporating vision-language models or cross-modal attention mechanisms could significantly enhance detection accuracy. Additionally, future work could involve real-time graph updates to continuously learn from new interactions and evolving misinformation patterns, making the system more dynamic and responsive.

Another area for enhancement lies in improving the explainability and transparency of the model's decisions. By incorporating explainable AI (XAI) components, users and moderators could better understand why certain content is flagged as misleading, which is crucial for trust and accountability. Moreover, adapting the model to low-resource or multilingual environments would enable its deployment across diverse regions and platforms, addressing misinformation in a globally inclusive manner. Incorporating adversarial training techniques could also help the system resist manipulation or evasion by coordinated disinformation campaigns, ensuring long-term robustness and scalability.

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