National Cheng Kung University

MS Degree Program on AI Robotics

Master’s Thesis

(Draft)

生成式多視角互動圖神經網路之少樣本假新聞檢測

GemGNN: Generative Multi-view Interaction Graph Neural Networks for Few-shot Fake News Detection

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July 2025

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國立成功大學
碩士論文

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GemGNN: Generative Multi-view Interaction Graph Neural Networks for Few-shot Fake News Detection

by

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A thesis submitted to the graduate division in partial fulfillment of the requirements for the degree of Master of Science in MS Degree Program on AI Robotics

College of Engineering
National Cheng Kung University
Tainan, Taiwan, R.O.C.

09 July 2025

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Abstract

Fake news has become a critical threat to information integrity and social stability, particularly in few-shot scenarios where limited labeled data is available for emerging topics or misinformation campaigns. Traditional fake news detection methods rely heavily on user propagation patterns or require extensive labeled datasets, making them impractical for real-world deployment where such data is scarce or unavailable. This thesis presents GemGNN (Generative Multi-view Interaction Graph Neural Networks), a novel framework for few-shot fake news detection that addresses these fundamental limitations through content-based graph neural network modeling.

Our approach introduces three key innovations: First, we develop a generative user interaction simulation method using Large Language Models (LLMs) to synthesize diverse user interactions with multiple tones (neutral, affirmative, skeptical), effectively overcoming the dependency on real user propagation data. Second, we propose a Test-Isolated K-Nearest Neighbor (KNN) edge construction strategy that prevents information leakage between test nodes, ensuring more realistic and robust evaluation in few-shot scenarios. Third, we implement a multi-view graph construction approach that splits news embeddings into multiple semantic perspectives, combined with multi-graph training for enhanced data augmentation.

The GemGNN framework employs Heterogeneous Graph Attention Networks (HAN) to model complex relationships between news articles and generated user interactions through dynamic attention mechanisms. Our transductive learning approach leverages both labeled and unlabeled data during message passing while restricting loss computation to labeled nodes only, maximizing the utility of limited supervision.

Extensive experiments on the FakeNewsNet datasets (PolitiFact and GossipCop) demonstrate that GemGNN significantly outperforms state-of-the-art methods across various few-shot configurations (K=3-16). Our method achieves superior F1-scores compared to traditional approaches (MLP, LSTM), transformer-based models (BERT, RoBERTa), large language models (LLaMA, Gemma), and existing graph-based methods (Less4FD, HeteroSGT). Comprehensive ablation studies validate the effectiveness of each component, showing that the combination of generative interactions, test-isolated KNN, and multi-view construction provides substantial improvements in few-shot fake news detection performance.

The contributions of this work establish a new paradigm for content-based fake news detection that eliminates dependency on user behavior data while maintaining superior performance in data-scarce scenarios, making it particularly suitable for privacy-sensitive applications and emerging misinformation detection tasks.

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Keyword: Fake News Detection, Few Shot Learning, Transductive Learning, Generative Interaction, Graph Neural Network

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Acknowledgements

I would like to express my sincere gratitude to all those who have supported and guided me throughout this research journey.

First and foremost, I extend my deepest appreciation to my advisor, Professor Cheng-Te Li, for his invaluable guidance, patience, and continuous support throughout my master's program. His expertise in graph neural networks and fake news detection provided the foundation for this research, and his constructive feedback helped shape this work into its current form. Professor Li's dedication to research excellence and his commitment to fostering innovative thinking have been instrumental in my academic development.

I am grateful to the members of my thesis committee for their time, expertise, and thoughtful feedback during the thesis defense. Their insightful questions and suggestions have significantly improved the quality and rigor of this work.

I would like to acknowledge the contributions of the research community that developed the foundational technologies used in this thesis. The FakeNewsNet dataset creators provided high-quality benchmarks essential for evaluating fake news detection methods. The developers of DeBERTa, PyTorch Geometric, and other open-source tools enabled the implementation of our complex heterogeneous graph neural network framework.

Special thanks to my fellow graduate students and research group members for their collaboration, discussions, and moral support. The weekly lab meetings and informal research discussions provided valuable opportunities to refine ideas and overcome technical challenges. Their diverse perspectives and constructive criticism helped improve both the technical content and presentation of this work.

I am deeply grateful to my family for their unwavering support and encouragement throughout my academic journey. Their understanding during long hours of research and writing, and their belief in my abilities, provided the motivation necessary to complete this challenging project.

I also acknowledge the financial support provided by the National Science and Technology Council and National Cheng Kung University, which made this research possible and allowed me to focus on my studies without financial burden.

Finally, I want to thank the broader fake news detection research community for their commitment to combating misinformation. The importance of this research area has become increasingly evident as digital misinformation poses growing threats to democratic societies

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and public health. I hope this work contributes meaningfully to the ongoing efforts to develop more effective and practical solutions for detecting and countering false information.

The completion of this thesis represents not only a personal academic milestone but also a small contribution to the critical challenge of maintaining information integrity in our digital age. I am honored to have had the opportunity to work on such an important problem and hope that future researchers will build upon these foundations to create even more effective solutions.

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Nomenclature

Symbol	Description
α	Symbol of alpha
β	
γ	Gamma

Symbol	Meaning	SI unit of measure
g	Standard gravity	$9.80665 m/s^2$
c	Speed of light	$\approx 3.00 \times 108 m/s$
l	Length	meter (m)

List of common physics notations

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Chapter 1

Introduction

1.1 Research Background and Motivation

In the digital age, the proliferation of fake news has emerged as one of the most pressing challenges threatening information integrity and democratic discourse. According to Vosoughi et al. [?], false news spreads six times faster than true news on social media platforms, reaching more people and penetrating deeper into social networks. This phenomenon has far-reaching consequences, from influencing electoral outcomes to undermining public health responses during critical events such as the COVID-19 pandemic.

Traditional approaches to fake news detection have relied heavily on two primary paradigms: content-based analysis and propagation-based modeling. Content-based methods analyze linguistic features, semantic patterns, and textual inconsistencies within news articles, while propagation-based approaches examine how information spreads through social networks by modeling user interactions, sharing patterns, and network topology. However, both paradigms face significant limitations in real-world deployment scenarios.

The most critical challenge in contemporary fake news detection is the few-shot learning problem, where detection systems must accurately classify news articles with minimal labeled training data. This scenario is particularly common when dealing with emerging topics, breaking news events, or novel misinformation campaigns where extensive labeled datasets are not readily available. Traditional deep learning approaches, which typically require thousands of labeled examples per class, fail to perform adequately in such data-scarce environments.

Furthermore, existing propagation-based methods, while often achieving high performance, suffer from fundamental practical limitations. These approaches require access to comprehensive user interaction data, including social network structures, user profiles, and temporal propagation patterns. Such data is increasingly difficult to obtain due to privacy regulations, platform restrictions, and the real-time nature of misinformation spread. Additionally, these methods are vulnerable to sophisticated adversarial attacks where malicious actors can manipulate propagation patterns to evade detection.

1.2 Problem Statement and Challenges

This thesis addresses the fundamental problem of few-shot fake news detection in scenarios where traditional propagation data is unavailable or unreliable. Formally, we define our problem as follows:

Problem Definition: Given a small set of labeled news articles $\mathcal{L} = \{(x_i, y_i)\}_{i=1}^{K \times C}$ where K represents the number of examples per class and C denotes the number of classes (real/fake), and a larger set of unlabeled news articles $\mathcal{U} = \{x_j\}_{j=1}^{M}$, the objective is to learn a classifier $f : \mathcal{X} \to \mathcal{Y}$ that can accurately predict labels for test instances $\mathcal{T} = \{x_k\}_{k=1}^{N}$ where $K \ll M$ and $K \ll N$.

The core challenges that motivate this research include:

Limited Labeled Data: Few-shot scenarios typically provide only 3-16 labeled examples per class, insufficient for training robust deep learning models using conventional approaches. This data scarcity leads to overfitting, poor generalization, and unstable performance across different domains.

Absence of Propagation Information: Real-world deployment often lacks access to user interaction data due to privacy constraints, platform limitations, or the time-sensitive nature of misinformation detection. Existing propagation-based methods become inapplicable in such contexts.

Semantic Complexity: Fake news articles often exhibit sophisticated linguistic patterns and may contain accurate factual information presented in misleading contexts. Simple content-based features fail to capture these nuanced semantic relationships.

Domain Generalization: Models trained on specific topics or domains often fail to generalize to emerging misinformation patterns or novel subject areas, limiting their practical applicability.

Evaluation Realism: Many existing few-shot learning approaches suffer from information leakage between training and test sets, leading to overly optimistic performance estimates that do not reflect real-world deployment scenarios.

1.3 Research Contributions

This thesis presents GemGNN (Generative Multi-view Interaction Graph Neural Networks), a novel framework that addresses the aforementioned challenges through several key contributions:

Generative User Interaction Simulation: We introduce the first approach to synthesize realistic user interactions using Large Language Models (LLMs), specifically leveraging Gem-

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ini to generate diverse user responses with multiple emotional tones (neutral, affirmative, skeptical). This innovation eliminates the dependency on real propagation data while maintaining the benefits of interaction-based modeling.

Test-Isolated KNN Edge Construction: We develop a novel graph construction strategy that prevents information leakage between test nodes through strict isolation constraints. This approach ensures more realistic evaluation by prohibiting test nodes from connecting to each other, addressing a critical flaw in existing graph-based few-shot learning methods.

Multi-View Graph Architecture: We propose a multi-view learning framework that partitions news embeddings into multiple semantic perspectives, enabling the model to capture diverse aspects of news content. Each view constructs its own graph structure, and multiple graphs are trained simultaneously to provide comprehensive data augmentation.

Enhanced Heterogeneous Graph Neural Networks: We design a specialized HAN-based architecture that effectively models the complex relationships between news articles and generated user interactions through type-specific attention mechanisms and hierarchical aggregation strategies.

Comprehensive Evaluation Framework: We establish rigorous experimental protocols that ensure fair comparison with existing methods while maintaining realistic few-shot learning constraints across multiple datasets and evaluation metrics.

1.4 Thesis Organization

The remainder of this thesis is organized as follows:

Chapter 2: Related Work provides a comprehensive review of existing fake news detection methods, including traditional feature-engineering approaches, deep learning techniques, graph-based methods, and few-shot learning strategies. We analyze the limitations of current approaches and position our work within the broader research landscape.

Chapter 3: Background and Preliminaries introduces the fundamental concepts underlying our approach, including few-shot learning formulations, graph neural network architectures, and problem notation. This chapter establishes the theoretical foundation necessary for understanding our methodology.

Chapter 4: Methodology presents the complete GemGNN framework, detailing the generative user interaction simulation, test-isolated KNN construction, multi-view graph architecture, and the heterogeneous graph neural network design. We provide comprehensive algorithmic descriptions and theoretical justifications for each component.

Chapter 5: Experimental Setup describes our experimental methodology, including dataset preprocessing, baseline method implementations, evaluation protocols, and hyperparameter configurations. We ensure reproducibility and fair comparison across all experimental conditions.

Chapter 6: Results and Analysis presents comprehensive experimental results, including main performance comparisons, ablation studies, and detailed analysis of model behavior. We provide insights into why our approach succeeds in few-shot scenarios and identify the key factors contributing to performance improvements.

Chapter 7: Conclusion and Future Work summarizes our contributions, discusses the implications of our findings, acknowledges current limitations, and outlines promising directions for future research in few-shot fake news detection.

Chapter 2

Related Work

This chapter provides a comprehensive review of existing approaches to fake news detection, with particular emphasis on methods relevant to few-shot learning scenarios. We organize the literature into five main categories: traditional feature-engineering approaches, deep learning methods, graph-based techniques, few-shot learning strategies, and identify key limitations that motivate our research.

2.1 Traditional Fake News Detection Methods

Early approaches to fake news detection relied primarily on hand-crafted features and traditional machine learning algorithms. These methods established the foundation for automated misinformation detection but suffer from significant limitations in capturing complex semantic relationships.

2.1.1 Feature Engineering Approaches

TF-IDF + MLP: The earliest computational approaches to fake news detection employed Term Frequency-Inverse Document Frequency (TF-IDF) representations combined with Multi-Layer Perceptrons (MLPs). These methods extract bag-of-words features and learn linear or shallow non-linear mappings to classify news authenticity [**?**, **?**].

While computationally efficient, TF-IDF approaches suffer from several critical limitations: (1) they ignore word order and contextual relationships, (2) they cannot capture semantic similarity between different words expressing similar concepts, and (3) they fail to model discourse-level patterns that characterize misinformation.

Linguistic Feature Analysis: More sophisticated traditional approaches incorporated linguistic features such as sentiment analysis, readability scores, lexical diversity measures, and syntactic complexity [**?**, **?**]. These methods hypothesize that fake news exhibits distinct linguistic patterns, such as more emotional language, simpler sentence structures, or specific rhetorical devices.

However, linguistic feature approaches face the fundamental challenge that sophisticated misinformation increasingly mimics legitimate journalism style, making surface-level linguistic indicators unreliable. Moreover, these features are often domain-specific and fail to

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generalize across different types of news content.

2.1.2 Sequential Models

LSTM/RNN Approaches: To address the limitations of bag-of-words representations, researchers introduced sequential models that process news articles as ordered sequences of words. Long Short-Term Memory (LSTM) networks and Recurrent Neural Networks (RNNs) capture local contextual relationships and temporal dependencies within text [**?**, **?**].

These approaches show improvement over bag-of-words methods by modeling word order and local context. However, they struggle with long-range dependencies common in news articles and fail to capture global document structure. Additionally, RNN-based methods process each document independently, missing potential relationships between related news articles.

Attention Mechanisms: Advanced sequential models incorporated attention mechanisms to focus on important words or phrases within documents [**?**, **?**]. These approaches aim to identify key textual elements that indicate misinformation, such as sensational headlines or unsupported claims.

While attention-based sequential models improve interpretability and can highlight suspicious textual elements, they remain fundamentally limited by their document-level scope and inability to model inter-document relationships crucial for systematic misinformation detection.

2.2 Deep Learning Approaches

The advent of deep learning revolutionized fake news detection by enabling more sophisticated semantic analysis and contextual understanding. However, most deep learning approaches still treat documents independently and struggle in few-shot scenarios.

2.2.1 Transformer-based Models

BERT and RoBERTa: The introduction of transformer architectures, particularly BERT (Bidirectional Encoder Representations from Transformers) and its variants like RoBERTa, marked a significant advancement in content-based fake news detection [**?**, **?**]. These models provide rich contextual representations that capture bidirectional dependencies and complex semantic relationships within text.

BERT-based approaches typically fine-tune pre-trained language models on fake news classification tasks, achieving strong performance on standard benchmarks. The bidirectional nature of BERT enables better understanding of context compared to sequential models, while

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the pre-training on large corpora provides general linguistic knowledge applicable to misinformation detection.

However, transformer-based methods face significant challenges in few-shot scenarios: (1) they require substantial task-specific fine-tuning data, (2) they are prone to overfitting when labeled data is scarce, and (3) they treat each document independently, missing systematic patterns across related articles.

Domain Adaptation Strategies: Researchers have explored domain adaptation techniques to improve BERT's performance on fake news detection [**?**, **?**]. These approaches attempt to bridge the gap between general language understanding and domain-specific misinformation patterns through continued pre-training or transfer learning strategies.

While domain adaptation shows promise, these methods still require significant amounts of labeled data for effective adaptation and often fail to generalize to emerging misinformation patterns or new domains not seen during training.

2.2.2 Large Language Models for Fake News Detection

In-Context Learning Approaches: Recent work has explored using large language models (LLMs) such as GPT-3, LLaMA, and Gemma for fake news detection through in-context learning [**?**, **?**]. These approaches provide few examples of fake and real news within the prompt and ask the model to classify new instances.

While LLMs demonstrate impressive general language understanding capabilities, their performance on fake news detection is surprisingly poor in few-shot scenarios. This limitation stems from several factors: (1) potential data contamination where models may have seen test instances during training, (2) lack of task-specific optimization for misinformation patterns, and (3) difficulty in handling domain-specific knowledge required for fact verification.

Prompt Engineering Strategies: Researchers have developed sophisticated prompt engineering techniques to improve LLM performance on fake news detection [**?**]. These approaches design carefully crafted prompts that provide context, examples, and specific instructions for identifying misinformation.

Despite extensive prompt engineering efforts, LLMs continue to underperform compared to specialized approaches in few-shot fake news detection, highlighting the need for task-specific architectures rather than general-purpose language models.

2.3 Graph-based Fake News Detection

Graph-based approaches represent a significant paradigm shift by modeling relationships between different entities in the misinformation ecosystem. These methods show particular

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promise for few-shot learning by leveraging structural information to propagate labels.

2.3.1 Document-level Graph Classification

Text-GCN and Variants: Text Graph Convolutional Networks construct graphs where both documents and words are represented as nodes, with edges indicating document-word relationships and word co-occurrence patterns [?, ?]. These approaches apply graph convolutional networks to learn document representations through message passing between document and word nodes.

While Text-GCN approaches capture some structural relationships, they primarily focus on word-level connections rather than document-level relationships crucial for detecting coordinated misinformation campaigns or related false narratives.

BertGCN Integration: More recent work combines BERT embeddings with graph convolutional networks to leverage both rich semantic representations and structural information [?]. These hybrid approaches use BERT to initialize node features and GCNs to refine representations through graph structure.

BertGCN approaches show improvement over pure BERT methods by incorporating some structural information, but they still construct relatively simple graphs based on keyword similarity rather than capturing complex semantic relationships between news articles.

2.3.2 User Propagation-based Methods

Social Network Analysis: Many state-of-the-art fake news detection systems model how misinformation spreads through social networks by analyzing user sharing patterns, temporal dynamics, and network topology [?, ?]. These approaches construct graphs where users and news articles are nodes, with edges representing sharing, commenting, or other interaction behaviors.

Propagation-based methods often achieve high performance by exploiting the fact that fake news tends to spread through different network patterns compared to legitimate news. However, these approaches have fundamental limitations: (1) they require extensive user behavior data that is often unavailable due to privacy constraints, (2) they are vulnerable to adversarial manipulation where malicious actors can artificially create legitimate-looking propagation patterns, and (3) they cannot handle breaking news scenarios where propagation patterns have not yet developed.

Temporal Dynamics Modeling: Advanced propagation-based approaches incorporate temporal dynamics to model how misinformation spreads over time [?, ?]. These methods analyze features such as propagation velocity, user engagement patterns, and temporal clustering

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to identify suspicious spreading patterns.

While temporal modeling provides additional signal for misinformation detection, these approaches still suffer from the fundamental dependency on user interaction data and the assumption that temporal patterns reliably distinguish fake from real news.

2.3.3 Heterogeneous Graph Neural Networks

HAN and HGT Applications: Recent work has applied Heterogeneous Graph Attention Networks (HAN) and Heterogeneous Graph Transformers (HGT) to fake news detection by modeling multiple entity types such as users, news articles, topics, and sources [**?**, **?**]. These approaches capture complex relationships between different entity types through specialized attention mechanisms.

Heterogeneous approaches show promise for capturing the multi-faceted nature of misinformation ecosystems. However, existing methods still rely heavily on user behavior data and social network structures, limiting their applicability in privacy-constrained scenarios.

Less4FD and HeteroSGT: More recent graph-based approaches like Less4FD and HeteroSGT attempt to reduce dependency on social features while maintaining graph-based modeling advantages [**?**, **?**]. These methods focus more on content-based graph construction while incorporating limited social signals.

While these approaches represent progress toward content-centric fake news detection, they still suffer from limitations in graph construction strategies and evaluation protocols that allow information leakage between training and test sets.

2.4 Few-Shot Learning in NLP

Few-shot learning has emerged as a critical research area in natural language processing, with several approaches showing promise for text classification tasks including fake news detection.

2.4.1 Meta-Learning Approaches

Model-Agnostic Meta-Learning (MAML): MAML and its variants learn initialization parameters that can be quickly adapted to new tasks with minimal data [**?**, **?**]. In the context of fake news detection, meta-learning approaches attempt to learn general misinformation detection capabilities that can transfer to new domains or topics with few examples.

However, meta-learning approaches typically require extensive meta-training data from multiple related tasks, which may not be available for fake news detection. Additionally, these methods often struggle with the high variability in misinformation patterns across different domains and topics.

Prototypical Networks: Prototypical networks learn to classify examples based on their distance to class prototypes computed from support examples [**?**, **?**]. These approaches show promise for few-shot text classification by learning meaningful embedding spaces where similar examples cluster together.

While prototypical approaches avoid the need for extensive meta-training, they still struggle with the high dimensionality and semantic complexity of news articles, often failing to learn discriminative prototypes from few examples.

2.4.2 Contrastive Learning Methods

SimCLR and Variants: Contrastive learning approaches learn representations by maximizing similarity between positive pairs and minimizing similarity between negative pairs [**?**, **?**]. In fake news detection, these methods attempt to learn representations where real news articles are similar to each other and different from fake news articles.

Contrastive approaches show promise for learning robust representations from limited data. However, they require careful design of positive and negative pair generation strategies, which is challenging for fake news where the boundaries between real and fake can be subtle and context-dependent.

Data Augmentation Strategies: Various data augmentation techniques have been explored for few-shot fake news detection, including back-translation, paraphrasing, and adversarial perturbations [**?**, **?**]. These approaches attempt to increase the effective size of the training set by generating synthetic examples.

While data augmentation can help address data scarcity, synthetic examples may not capture the full complexity of real misinformation patterns and can sometimes introduce biases that hurt generalization performance.

2.5 Limitations of Existing Methods

Our review of existing literature reveals several fundamental limitations that motivate our research:

Dependency on User Behavior Data: Most high-performing fake news detection systems rely on user interaction patterns, social network structures, or propagation dynamics. This dependency severely limits their applicability in scenarios where such data is unavailable due to privacy constraints, platform restrictions, or real-time detection requirements.

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Poor Few-Shot Performance: Traditional deep learning approaches, including state-of-the-art transformer models, suffer from significant performance degradation in few-shot scenarios. These methods require extensive labeled training data and are prone to overfitting when supervision is limited.

Information Leakage in Evaluation: Many existing few-shot learning approaches for fake news detection suffer from unrealistic evaluation protocols that allow information sharing between test instances, leading to overly optimistic performance estimates that do not reflect real-world deployment conditions.

Limited Structural Modeling: Pure content-based approaches treat each document independently, missing important structural relationships between related news articles that could provide valuable signal for misinformation detection.

Domain Specificity: Many approaches show strong performance on specific domains or datasets but fail to generalize to new topics, emerging misinformation patterns, or different types of fake news content.

Lack of Synthetic Data Utilization: While some approaches explore data augmentation, there has been limited exploration of using large language models to generate synthetic auxiliary data that could enhance few-shot learning performance.

These limitations highlight the need for novel approaches that can achieve strong performance in few-shot scenarios while maintaining realistic evaluation protocols and avoiding dependency on user behavior data. Our GemGNN framework directly addresses these limitations through content-based graph neural networks enhanced with generative auxiliary data and rigorous test isolation constraints.

Chapter 3

Background and Preliminaries

This chapter provides the theoretical foundation necessary for understanding our GemGNN framework. We introduce fundamental concepts in few-shot learning, graph neural networks for text classification, and establish the formal problem formulation with mathematical notation used throughout this thesis.

3.1 Few-Shot Learning Fundamentals

Few-shot learning represents a paradigm shift from traditional machine learning approaches that require extensive labeled datasets. In few-shot scenarios, models must achieve strong performance with minimal supervision, making them particularly relevant for real-world applications where labeling is expensive or impractical.

3.1.1 Problem Formulation

Formal Definition: Few-shot learning is a machine learning framework where an AI model learns to make accurate predictions by training on a very small number of labeled examples per class. Formally, given a support set $\mathcal{S} = \{(x_i, y_i)\}_{i=1}^{K \times N}$ containing K labeled examples for each of N classes, the objective is to learn a classifier $f : \mathcal{X} \to \mathcal{Y}$ that can accurately predict labels for a query set $\mathcal{Q} = \{x_j\}_{j=1}^{M}$.

N-way K-shot Classification: The standard formulation for few-shot learning is N-way K-shot classification, where N represents the number of classes and K denotes the number of labeled examples per class. In our fake news detection task, we focus on 2-way K-shot learning with $K \in \{3, 4, 8, 16\}$, where the two classes represent real and fake news respectively.

Support and Query Sets: The support set $\mathcal{S}$ contains the limited labeled examples available for training, while the query set $\mathcal{Q}$ contains unlabeled instances that must be classified. In traditional few-shot learning, these sets are disjoint, but our transductive approach allows overlap between support and query sets during training while maintaining separation during evaluation.

3.1.2 Challenges in Few-Shot Learning

Few-shot learning presents several fundamental challenges that differentiate it from conventional machine learning:

Limited Training Data: Traditional deep learning requires thousands of labeled examples per class to achieve good performance. In few-shot scenarios with only 3-16 examples per class, models are highly prone to overfitting and struggle to learn generalizable patterns.

High Variance: The limited sample size leads to high variance in performance estimates. Small changes in the support set can dramatically affect model performance, making robust evaluation protocols crucial for reliable results.

Class Imbalance: Few-shot datasets often exhibit class imbalance, particularly in real-world scenarios where certain types of misinformation may be more prevalent than others. Standard loss functions may not be appropriate for such imbalanced settings.

Domain Shift: Models trained on few examples from specific domains often fail to generalize to new domains or emerging patterns not represented in the limited training data.

Evaluation Challenges: Proper evaluation of few-shot learning systems requires careful experimental design to avoid information leakage and ensure that performance estimates reflect real-world deployment scenarios.

3.1.3 Few-Shot Learning Strategies

Several general strategies have been developed to address few-shot learning challenges:

Meta-Learning: Meta-learning approaches, such as Model-Agnostic Meta-Learning (MAML), learn initialization parameters that can be quickly adapted to new tasks. The key insight is to learn how to learn rather than learning specific task solutions.

Metric Learning: These approaches learn embedding spaces where examples from the same class are close together and examples from different classes are far apart. Classification is performed by comparing query examples to support set prototypes.

Data Augmentation: Various augmentation strategies generate additional training examples from the limited support set through transformations, perturbations, or generative models.

Transfer Learning: Pre-trained models capture general knowledge that can be adapted to specific few-shot tasks through fine-tuning or feature extraction.

Regularization: Specialized regularization techniques prevent overfitting in few-shot scenarios by constraining model complexity or encouraging specific types of solutions.

3.2 Graph Neural Networks for Text Classification

Graph Neural Networks have emerged as a powerful paradigm for modeling structured data, with particular success in text classification tasks where relationships between documents provide valuable signal for classification.

3.2.1 Message Passing Framework

Core Principle: GNNs operate on the message passing framework where nodes iteratively update their representations by aggregating information from neighboring nodes. This process enables the model to capture both local neighborhood information and global graph structure through multiple iterations.

General Formulation: The message passing framework can be described through three key operations:

1. **Message Function:** $m_{ij}^{(l+1)} = M^{(l)}(h_i^{(l)}, h_j^{(l)}, e_{ij})$ computes messages between connected nodes, where $h_i^{(l)}$ represents the feature vector of node i at layer l, and e_{ij} represents edge features.

2. **Aggregation Function:** $a_i^{(l+1)} = A^{(l)}(\{m_{ij}^{(l+1)} : j \in \mathcal{N}(i)\})$ aggregates messages from all neighbors $\mathcal{N}(i)$ of node i.

3. **Update Function:** $h_i^{(l+1)} = U^{(l)}(h_i^{(l)}, a_i^{(l+1)})$ updates the node representation based on its current state and aggregated messages.

Multi-Layer Architecture: Multiple message passing layers enable nodes to receive information from increasingly distant neighbors, allowing the model to capture both local patterns and global graph structure.

3.2.2 Graph Construction for Text

Document Graphs: For text classification, documents are typically represented as nodes in a graph, with edges indicating various types of relationships such as semantic similarity, citation links, or co-occurrence patterns.

Similarity-Based Construction: The most common approach constructs edges between documents based on content similarity measures such as cosine similarity of embedding vectors. Documents with similarity above a threshold or among the top-k nearest neighbors are connected.

Heterogeneous Graphs: More sophisticated approaches construct heterogeneous graphs that include multiple node types (documents, words, authors, topics) and edge types (document-word, document-document, word-word), enabling richer modeling of text relationships.

Dynamic Graph Construction: Advanced methods adapt graph structure during training or

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inference, allowing the model to learn optimal connectivity patterns rather than relying on fixed similarity measures.

3.2.3 Heterogeneous Graph Attention Networks

HAN addresses the challenges of modeling heterogeneous graphs with multiple node and edge types through hierarchical attention mechanisms.

Node-Level Attention: For each edge type ϕ, HAN computes attention weights between connected nodes:

$$\alpha_{ij}^{\phi} = \text{softmax}\left(\sigma\left(\mathbf{a}_{\phi}^{T}[\mathbf{W}_{\phi}\mathbf{h}_i \| \mathbf{W}_{\phi}\mathbf{h}_j]\right)\right) \tag{3.1}$$

where $\mathbf{W}_{\phi}$ is the edge-type-specific transformation matrix, $\mathbf{a}_{\phi}$ is the attention vector, and $\|$ denotes concatenation.

Semantic-Level Attention: HAN aggregates information across different edge types using learned importance weights:

$$\beta_{\phi} = \frac{1}{|\mathcal{V}|}\sum_{i\in\mathcal{V}} \mathbf{q}^{T}\tanh(\mathbf{W}\cdot\mathbf{h}_i^{\phi} + \mathbf{b}) \tag{3.2}$$

where $\mathbf{h}_i^{\phi}$ represents the node embedding for edge type ϕ.

Final Representation: The complete node representation combines information from all edge types:

$$\mathbf{h}_i = \sum_{\phi\in\Phi} \beta_{\phi}\mathbf{h}_i^{\phi} \tag{3.3}$$

This hierarchical attention mechanism enables the model to learn both which neighbors are important for each edge type and which edge types are most relevant for the classification task.

3.3 Problem Formulation and Notation

We now formally define the few-shot fake news detection problem addressed in this thesis and establish the mathematical notation used throughout our methodology.

3.3.1 Fake News Detection as Node Classification

Graph Representation: We formulate fake news detection as a node classification problem on a heterogeneous graph $G = (V, E, \mathcal{R})$ where:

- V represents the set of all nodes, including news articles and user interactions

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- E denotes the set of edges connecting related nodes
- $\mathcal{R}$ represents the set of edge types in the heterogeneous graph

Node Types: Our graph contains two primary node types:

- News nodes $V_n = \{n_1, n_2, \ldots, n_{|N|}\}$ representing news articles
- Interaction nodes $V_i = \{i_1, i_2, \ldots, i_{|I|}\}$ representing generated user interactions

Node Features: Each node $v \in V$ has an associated feature vector $\mathbf{x}_v \in \mathbb{R}^d$ where $d = 768$ for DeBERTa embeddings. News nodes additionally have binary labels $y_v \in \{0, 1\}$ indicating real (0) or fake (1) news.

Edge Types: The heterogeneous graph includes multiple edge types:

- News-to-news edges: $(n_i, n_j) \in E_{nn}$ based on semantic similarity
- News-to-interaction edges: $(n_i, i_j) \in E_{ni}$ connecting articles to their generated interactions
- Interaction-to-news edges: $(i_j, n_i) \in E_{in}$ enabling bidirectional information flow

3.3.2 Few-Shot Learning Configuration

Data Partitioning: The complete dataset is partitioned into three disjoint sets:

- Training set: $\mathcal{D}_{train} = \mathcal{D}_{labeled} \cup \mathcal{D}_{unlabeled}$
- Validation set: $\mathcal{D}_{val}$ for hyperparameter tuning and early stopping
- Test set: $\mathcal{D}_{test}$ for final evaluation

K-Shot Sampling: For each few-shot experiment, we sample K labeled examples per class from $\mathcal{D}_{train}$ to form the support set $\mathcal{S} = \{(n_i, y_i)\}_{i=1}^{2K}$. The remaining training instances form the unlabeled set $\mathcal{U}$.

Transductive Setting: During training, all nodes (labeled, unlabeled, and test) participate in message passing, but only labeled nodes contribute to loss computation. This transductive approach maximizes information utilization in few-shot scenarios.

3.3.3 Learning Objective

Classification Goal: Given the heterogeneous graph G and support set $\mathcal{S}$, learn a function $f_\theta : G \to [0, 1]^{|V_n|}$ that predicts the probability of each news node being fake.

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Loss Function: The training objective combines multiple loss components to address few-shot learning challenges:

$$\mathcal{L}_{total} = \mathcal{L}_{CE}(f_\theta(G), \mathcal{S}) + \lambda_{focal}\mathcal{L}_{focal}(f_\theta(G), \mathcal{S}) + \lambda_{reg}\mathcal{L}_{reg}(\theta) \tag{3.4}$$

where:

- $\mathcal{L}_{CE}$ is the cross-entropy loss with label smoothing
- $\mathcal{L}_{focal}$ is the focal loss for handling class imbalance
- $\mathcal{L}_{reg}$ provides regularization to prevent overfitting
- λ_{focal} and λ_{reg} are hyperparameters balancing loss components

Evaluation Metrics: Model performance is evaluated using:

- F1-score: $F1 = 2 \cdot \frac{\text{Precision}\cdot\text{Recall}}{\text{Precision}+\text{Recall}}$
- Accuracy: $\text{Acc} = \frac{\text{Correct Predictions}}{\text{Total Predictions}}$
- Precision: $\text{Prec} = \frac{\text{True Positives}}{\text{True Positives}+\text{False Positives}}$
- Recall: $\text{Rec} = \frac{\text{True Positives}}{\text{True Positives}+\text{False Negatives}}$

Statistical Significance: Given the high variance inherent in few-shot learning, we conduct multiple runs with different random seeds and report mean performance with confidence intervals. Statistical significance is assessed using paired t-tests across multiple experimental runs.

This formal framework provides the mathematical foundation for understanding our GemGNN approach, which addresses the challenges of few-shot fake news detection through novel graph construction strategies, generative data augmentation, and specialized training procedures detailed in the following chapters.

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Chapter 4

Methodology: GemGNN Framework

4.1 Framework Overview

The GemGNN (Generative Multi-view Interaction Graph Neural Networks) framework addresses the fundamental challenges of few-shot fake news detection through a novel content-based approach that eliminates dependency on user propagation data. Figure **??** illustrates the complete architecture, which consists of five interconnected components: (1) Generative User Interaction Simulation, (2) Test-Isolated KNN Graph Construction, (3) Multi-View Graph Construction, (4) Heterogeneous Graph Architecture, and (5) Enhanced Loss Function Design.

The framework operates under a transductive learning paradigm where all nodes (labeled, unlabeled, and test) participate in message passing, but only labeled nodes contribute to loss computation. This approach maximizes the utility of limited supervision by leveraging the graph structure to propagate information from labeled nodes to unlabeled and test nodes through learned attention mechanisms.

Our approach begins with pre-trained DeBERTa embeddings for news articles, which provide rich semantic representations that capture contextual relationships and linguistic patterns indicative of misinformation. These embeddings serve as the foundation for both graph construction and node feature initialization in our heterogeneous graph neural network.

4.2 Generative User Interaction Simulation

Traditional propagation-based fake news detection methods rely on real user interaction data, which is often unavailable due to privacy constraints or platform limitations. To address this fundamental limitation, we introduce a novel generative approach that synthesizes realistic user interactions using Large Language Models.

4.2.1 LLM-based Interaction Generation

We employ Google's Gemini LLM to generate diverse user interactions for each news article. The generation process is designed to simulate authentic user responses that would naturally occur in social media environments. For each news article n_i, we generate a set of user interactions $I_i = \{i_1, i_2, \ldots, i_{20}\}$ where each interaction represents a potential user response to the news content.

The prompt engineering strategy ensures that generated interactions reflect realistic user behavior patterns observed in social media platforms. We incorporate the complete news content, including headlines and article body, to generate contextually appropriate responses that capture various user perspectives and emotional reactions.

4.2.2 Multi-tone Interaction Design

To capture the diversity of user reactions to news content, we implement a structured multi-tone generation strategy that produces interactions across three distinct emotional categories:

Neutral Interactions (8 per article): These represent objective, factual responses that focus on information sharing without emotional bias. Neutral interactions typically include questions for clarification, requests for additional sources, or straightforward restatements of key facts.

Affirmative Interactions (7 per article): These capture supportive or agreeable responses from users who accept the news content as credible. Affirmative interactions include expressions of agreement, sharing intentions, and positive emotional responses.

Skeptical Interactions (5 per article): These represent critical or questioning responses from users who doubt the veracity of the news content. Skeptical interactions include challenges to facts, requests for verification, and expressions of disbelief or concern.

This distribution (8:7:5) reflects observed patterns in real social media interactions where neutral responses predominate, followed by supportive reactions, with skeptical responses being less common but highly informative for authenticity assessment.

4.2.3 Interaction-News Edge Construction

Each generated interaction is embedded using the same DeBERTa model employed for news articles, ensuring semantic consistency across the heterogeneous graph. The interactions are connected to their corresponding news articles through directed edges that carry tone information as edge attributes.

Formally, for each news article n_i and its generated interactions I_i, we create edges (n_i, i_j) where the edge attribute a_{ij} encodes the interaction tone: $a_{ij} \in \{0, 1, 2\}$ representing neutral, affirmative, and skeptical tones respectively. This encoding allows the heterogeneous graph attention network to learn tone-specific importance weights during message aggregation.

4.3 Test-Isolated KNN Graph Construction

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A critical flaw in existing few-shot learning approaches is the potential for information leakage between training and test sets through graph connectivity. To address this limitation, we introduce a Test-Isolated K-Nearest Neighbor (KNN) construction strategy that enforces strict separation between test nodes while maintaining meaningful connectivity for effective message passing.

4.3.1 Test Isolation Strategy and Motivation

Traditional KNN graph construction methods allow test nodes to connect to each other based on embedding similarity, creating unrealistic scenarios where test instances can share information during inference. This connectivity pattern leads to overly optimistic performance estimates that do not reflect real-world deployment conditions.

Our test isolation strategy prohibits direct connections between test nodes, ensuring that each test instance must rely solely on information propagated from training nodes through the graph structure. This constraint creates a more realistic evaluation scenario that better reflects operational deployment where test instances arrive independently and cannot share information.

4.3.2 Mutual KNN for Training Nodes

For training nodes (both labeled and unlabeled), we employ a mutual KNN approach that creates bidirectional connections between semantically similar news articles. Given the set of training nodes $N_{train} = N_{labeled} \cup N_{unlabeled}$, we compute pairwise cosine similarities between DeBERTa embeddings and select the top-k nearest neighbors for each node.

The mutual KNN constraint ensures that if node n_i selects n_j as a neighbor, then n_j must also select n_i among its top-k neighbors. This bidirectionality strengthens the connections between truly similar articles while reducing noise from asymmetric similarity relationships.

4.3.3 Ensuring Test-Train Connectivity

While test nodes cannot connect to each other, they must maintain connectivity to training nodes to enable effective information propagation. For each test node n_{test}, we compute similarities to all training nodes and create edges to the top-k most similar training instances.

This one-way connectivity pattern (training-to-test) ensures that test nodes can receive information from the training set without violating the isolation constraint. The asymmetric edge construction reflects the realistic scenario where new test instances must be classified based solely on their similarity to training examples.

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4.4 Multi-View Graph Construction

To capture diverse semantic perspectives within news content, we implement a multi-view learning framework that partitions embeddings into complementary views and constructs separate graph structures for each perspective.

4.4.1 Embedding Dimension Splitting Strategy

Given DeBERTa embeddings of dimension $d = 768$, we partition each embedding vector into three equal subsets: $\mathbf{h}_i^{(1)}, \mathbf{h}_i^{(2)}, \mathbf{h}_i^{(3)} \in \mathbb{R}^{256}$ where $\mathbf{h}_i = [\mathbf{h}_i^{(1)}; \mathbf{h}_i^{(2)}; \mathbf{h}_i^{(3)}]$.

Each view captures different aspects of the semantic representation: the first view focuses on early embedding dimensions that typically encode syntactic and surface-level features, the middle view captures semantic relationships and contextual patterns, and the final view represents higher-level abstractions and discourse-level information.

4.4.2 View-specific Edge Construction

For each view $v \in \{1, 2, 3\}$, we apply the test-isolated KNN strategy using view-specific embeddings $\mathbf{h}_i^{(v)}$. This process generates three distinct graph structures $G^{(1)}, G^{(2)}, G^{(3)}$ where each graph emphasizes different semantic relationships between news articles.

The diversity of edge connections across views ensures that the model learns to integrate multiple perspectives of similarity, forcing it to develop more robust and generalizable feature representations. Articles that appear similar in one semantic view may differ significantly in another, providing complementary information for classification.

4.4.3 Multi-Graph Training Strategy

During training, we process all three views simultaneously, computing separate message passing operations for each graph structure. The view-specific representations are combined through learned attention mechanisms that dynamically weight the importance of each perspective based on the classification task.

This multi-graph approach serves as a form of data augmentation at the graph level, exposing the model to varied structural contexts that improve robustness and generalization. The diverse connectivity patterns help prevent overfitting to specific graph topologies and enhance the model's ability to handle different types of news content.

4.5 Heterogeneous Graph Architecture

4.5.1 Node Types and Features

Our heterogeneous graph contains two primary node types:

News Nodes: Represent news articles with DeBERTa embeddings as node features. Each news node n_i has features $\mathbf{x}_i \in \mathbb{R}^{768}$ and a binary label $y_i \in \{0, 1\}$ indicating real (0) or fake (1) news for labeled instances.

Interaction Nodes: Represent generated user interactions with DeBERTa embeddings as features. Each interaction node i_j has features $\mathbf{x}_j \in \mathbb{R}^{768}$ and is connected to exactly one news article through tone-specific edges.

4.5.2 Edge Types and Relations

The heterogeneous graph incorporates multiple edge types that capture different relationship semantics:

News-to-News Edges: Connect semantically similar news articles based on the test-isolated KNN strategy. These edges enable direct information flow between related news content and are the primary mechanism for few-shot learning.

News-to-Interaction Edges: Connect news articles to their generated user interactions, with edge attributes encoding interaction tones. These edges allow the model to incorporate user perspective information into news classification.

Interaction-to-News Edges: Reverse connections that enable bidirectional information flow between news content and user reactions, allowing interaction patterns to influence news representations.

4.5.3 HAN-based Message Passing and Classification

We employ Heterogeneous Graph Attention Networks (HAN) as our base architecture due to their ability to handle multiple node and edge types through specialized attention mechanisms. The HAN architecture consists of two levels of attention: node-level attention and semantic-level attention.

Node-level Attention: For each edge type, we compute attention weights between connected nodes:

$$\alpha_{ij}^{\phi} = \frac{\exp(\sigma(\mathbf{a}_{\phi}^{T}[\mathbf{W}_{\phi}\mathbf{h}_i \| \mathbf{W}_{\phi}\mathbf{h}_j]))}{\sum_{k \in \mathcal{N}_i^{\phi}} \exp(\sigma(\mathbf{a}_{\phi}^{T}[\mathbf{W}_{\phi}\mathbf{h}_i \| \mathbf{W}_{\phi}\mathbf{h}_k]))} \tag{4.1}$$

where ϕ represents the edge type, $\mathbf{W}_{\phi}$ is the edge-type-specific transformation matrix, and $\mathbf{a}_{\phi}$ is the attention vector.

Semantic-level Attention: We aggregate information across different edge types using learned importance weights:

$$\beta_\phi = \frac{1}{|\mathcal{V}|} \sum_{i \in \mathcal{V}} q^T \tanh(\mathbf{W} \cdot \mathbf{h}_i^\phi + \mathbf{b}) \tag{4.2}$$

where $\mathbf{h}_i^\phi$ is the node representation for edge type ϕ, and q, $\mathbf{W}$, $\mathbf{b}$ are learnable parameters.

The final node representation combines information from all edge types:

$$\mathbf{h}_i = \sum_{\phi \in \Phi} \beta_\phi \mathbf{h}_i^\phi \tag{4.3}$$

4.6 Loss Function Design and Training Strategy

4.6.1 Enhanced Loss Functions for Few-Shot Learning

To address the challenges of few-shot learning, we implement enhanced loss functions that incorporate label smoothing and focal loss components to improve model robustness and handle class imbalance effectively.

Label Smoothing Cross-Entropy: We apply label smoothing with parameter $\epsilon = 0.1$ to prevent overconfident predictions on limited training data:

$$\mathcal{L}_{smooth} = -\sum_{i=1}^{N} \sum_{c=1}^{C} y_i^{smooth}(c) \log p_i(c) \tag{4.4}$$

where $y_i^{smooth}(c) = (1-\epsilon) y_i(c) + \frac{\epsilon}{C}$ and $p_i(c)$ is the predicted probability for class c.

Focal Loss Component: To address potential class imbalance, we incorporate a focal loss term that down-weights easy examples and focuses learning on difficult instances:

$$\mathcal{L}_{focal} = -\alpha \sum_{i=1}^{N} (1-p_i)^\gamma \log p_i \tag{4.5}$$

where $\alpha = 0.25$ and $\gamma = 2.0$ are hyperparameters that control the focusing strength.

4.6.2 Transductive Learning Framework

Our training strategy follows a transductive learning paradigm where all nodes participate in message passing, but only labeled nodes contribute to the loss computation. This approach maximizes the utility of unlabeled data by allowing the model to learn better feature representations through graph structure exploration.

The complete loss function combines the enhanced components:

$$\mathcal{L}_{total} = \mathcal{L}_{smooth} + \lambda \mathcal{L}_{focal} \tag{4.6}$$

where $\lambda = 0.1$ balances the contribution of the focal loss component.

Training proceeds for a maximum of 300 epochs with early stopping based on validation performance. We employ the Adam optimizer with learning rate 5×10^{-4} and weight decay 1×10^{-3} to prevent overfitting in few-shot scenarios.

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Chapter 5

Experimental Setup

This chapter describes the comprehensive experimental methodology used to evaluate our GemGNN framework. We detail the datasets, preprocessing procedures, baseline implementations, evaluation protocols, and implementation specifics to ensure reproducibility and fair comparison with existing methods.

5.1 Datasets and Preprocessing

5.1.1 FakeNewsNet Datasets

We evaluate our approach on two widely-used benchmark datasets from FakeNewsNet [**?**], which provides professionally verified fake news labels and represents the standard evaluation framework for fake news detection research.

PolitiFact Dataset

Dataset Characteristics: The PolitiFact dataset contains political news articles verified by professional fact-checkers. The dataset exhibits a 4:1 ratio of real to fake news, reflecting the relatively higher prevalence of legitimate political news compared to fabricated content.

Data Statistics: The complete dataset distribution is as follows:

- Training set: 246 real articles, 135 fake articles (381 total)
- Test set: 73 real articles, 29 fake articles (102 total)
- Total: 319 real articles, 164 fake articles (483 total)

Content Characteristics: Political news articles typically contain factual claims that can be verified through official sources, making the detection task more amenable to content-based analysis. However, sophisticated political misinformation often contains accurate peripheral information with subtle factual distortions.

GossipCop Dataset

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Dataset Characteristics: The GossipCop dataset focuses on entertainment and celebrity news, presenting different linguistic patterns and verification challenges compared to political content. The dataset maintains an 8:2 ratio of real to fake news.

Data Statistics: The distribution for GossipCop is:

- Training set: 7,955 real articles, 2,033 fake articles (9,988 total)
- Test set: 2,169 real articles, 503 fake articles (2,672 total)
- Total: 10,124 real articles, 2,536 fake articles (12,660 total)

Content Characteristics: Entertainment news often involves subjective claims and speculation that are harder to verify definitively. Fake entertainment news frequently employs sensational language and unverified celebrity rumors, requiring different detection strategies compared to political misinformation.

5.1.2 Data Statistics and Characteristics

Professional Verification: Both datasets provide labels verified by professional fact-checkers, ensuring high-quality ground truth for evaluation. PolitiFact labels are verified by PolitiFact.com fact-checkers, while GossipCop labels are verified by entertainment fact-checking websites.

Content-Only Focus: Following recent trends toward privacy-preserving fake news detection, we use only the textual content of news articles without any social context, user behavior data, or propagation information. This constraint makes our evaluation more realistic for scenarios where social data is unavailable.

Benchmark Standard: FakeNewsNet represents the most widely-used benchmark in fake news detection research, enabling direct comparison with existing methods and ensuring our results are comparable to prior work.

5.1.3 Text Embedding Generation

DeBERTa Model Selection: We employ DeBERTa (Decoding-enhanced BERT with Disentangled Attention) for generating news article embeddings due to its superior performance on text understanding tasks compared to earlier transformer models.

Embedding Process: Each news article is processed through the pre-trained DeBERTa-base model to generate 768-dimensional embeddings. We use the [CLS] token representation as the article-level embedding, which captures the global semantic meaning of the entire document.

Preprocessing Steps: Before embedding generation, we apply standard text preprocessing:

- Remove HTML tags and special characters
- Normalize whitespace and punctuation
- Truncate articles to 512 tokens to fit DeBERTa input constraints
- Preserve original capitalization and sentence structure

5.2 Baseline Methods

We compare our GemGNN framework against four categories of baseline methods representing different approaches to fake news detection.

5.2.1 Traditional Methods

Multi-Layer Perceptron (MLP): A simple feedforward neural network using DeBERTa embeddings as input features. The MLP consists of two hidden layers with 256 and 128 units respectively, ReLU activation, and dropout regularization. This baseline establishes the performance achievable through pure content-based classification without graph structure.

Long Short-Term Memory (LSTM): A sequential model that processes news articles as sequences of word embeddings. We use a bidirectional LSTM with 128 hidden units followed by a classification head. The LSTM baseline evaluates whether sequential modeling provides advantages over static embeddings for fake news detection.

5.2.2 Language Models

BERT: We fine-tune BERT-base-uncased for binary fake news classification using the standard approach with a classification head added to the [CLS] token representation. Fine-tuning uses a learning rate of 2e-5 with linear warmup and decay.

RoBERTa: Similarly, we fine-tune RoBERTa-base for fake news classification using identical hyperparameters to BERT. RoBERTa represents an improved version of BERT with optimized training procedures and typically achieves better performance on downstream tasks.

Implementation Details: Both BERT and RoBERTa baselines use identical training procedures with batch size 16, maximum sequence length 512, and training for up to 10 epochs with early stopping based on validation performance.

5.2.3 Large Language Models

LLaMA: We evaluate LLaMA-7B using in-context learning with carefully designed prompts that provide examples of fake and real news articles along with classification instructions. The prompt includes 2-3 examples of each class from the support set.

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Gemma: Similarly, Gemma-7B is evaluated through in-context learning using identical prompt design to LLaMA. Both LLM baselines represent the state-of-the-art in general language understanding and provide a strong comparison point for specialized approaches.

Prompt Design: Our prompts follow the format: ”Given the following news articles, classify each as ’real’ or ’fake’. [Examples] Now classify: [Test Article]”. We experiment with different prompt variations and report the best performance achieved.

5.2.4 Graph-based Methods

Less4FD: A recent graph-based approach that constructs similarity graphs between news articles and applies graph convolutional networks for classification. We implement Less4FD using the original paper’s specifications with KNN graph construction and GCN message passing.

HeteroSGT: A heterogeneous graph-based method that models multiple entity types and relationships for fake news detection. We adapt the original implementation to work with our content-only setting by removing social features and focusing on text-based relationships.

Implementation Consistency: All graph-based baselines use identical graph construction strategies where possible, including the same similarity measures, edge construction procedures, and node features to ensure fair comparison.

5.3 Evaluation Methodology

5.3.1 Few-Shot Evaluation Protocol

K-Shot Configuration: We evaluate all methods across four few-shot settings: K □ 3, 4, 8, 16 shots per class. These settings span from extremely few-shot (3-shot) to moderate few-shot (16-shot) scenarios.

Data Splitting: For each K-shot experiment, we randomly sample K examples per class from the training set to form the labeled support set. The remaining training instances serve as unlabeled data for transductive methods. The test set remains fixed across all experiments.

Multiple Runs: To account for the high variance inherent in few-shot learning, we conduct 10 independent runs for each experimental configuration using different random seeds for support set sampling. We report mean performance and 95

Stratified Sampling: When sampling support sets, we ensure balanced representation across classes and, where possible, across different subtopics or time periods to avoid bias in the selected examples.

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5.3.2 Performance Metrics

Primary Metric - F1-Score: We use F1-score as our primary evaluation metric due to the class imbalance present in both datasets. F1-score provides a balanced measure that considers both precision and recall, making it appropriate for imbalanced classification tasks.

Secondary Metrics: We also report accuracy, precision, and recall to provide a comprehensive view of model performance. Accuracy provides an overall measure of correctness, while precision and recall reveal whether models exhibit bias toward specific classes.

Statistical Significance Testing: We employ paired t-tests to assess statistical significance of performance differences between methods. Results are considered statistically significant at $p < 0.05$ level.

5.3.3 Statistical Significance Testing

Experimental Design: Our statistical testing accounts for the paired nature of few-shot experiments where the same support sets are used across different methods. This pairing reduces variance and increases the power of statistical tests.

Bonferroni Correction: When conducting multiple comparisons across different K-shot settings and datasets, we apply Bonferroni correction to control for multiple testing and ensure that reported significance levels are reliable.

Effect Size Reporting: In addition to statistical significance, we report effect sizes (Cohen's d) to quantify the practical significance of performance differences between methods.

5.4 Implementation Details

5.4.1 Hyperparameter Settings

Graph Construction Parameters:

- K-nearest neighbors: k = 5 for news-news connections
- Embedding dimension split: 3 views of 256 dimensions each
- Interaction generation: 20 interactions per news article (8 neutral, 7 affirmative, 5 skeptical)
- Similarity threshold: Cosine similarity for edge construction

Model Architecture Parameters:

- Hidden dimensions: 64 units in GNN layers

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- Attention heads: 4 heads for multi-head attention
- Number of GNN layers: 2 layers for both HAN and HGT variants
- Dropout rate: 0.3 for regularization
- Activation function: ReLU for hidden layers

Training Parameters:

- Learning rate: 5e-4 with Adam optimizer
- Weight decay: 1e-3 for L2 regularization
- Batch size: Full graph (transductive learning)
- Maximum epochs: 300 with early stopping
- Patience: 30 epochs for early stopping
- Label smoothing: $\varepsilon = 0.1$ for few-shot robustness

5.4.2 Model Architecture Configuration

HAN Layers: Our primary architecture uses Heterogeneous Graph Attention Networks with 2 layers. Each layer includes both node-level and semantic-level attention mechanisms to handle the heterogeneous graph structure effectively.

Attention Mechanisms: We employ 4 attention heads in each layer to capture different aspects of node relationships. The multi-head attention provides diverse perspectives on graph connectivity patterns.

Residual Connections: Following best practices for graph neural networks, we include residual connections between layers to facilitate gradient flow and prevent vanishing gradients in deeper architectures.

Layer Normalization: Each GNN layer includes layer normalization to stabilize training and improve convergence, particularly important for few-shot scenarios where training data is limited.

5.4.3 Training Configuration and Hardware Setup

Hardware Configuration: All experiments are conducted on NVIDIA A100 GPUs with 40GB memory. The powerful hardware enables efficient processing of large heterogeneous graphs and rapid experimentation across multiple hyperparameter configurations.

Software Environment:

- Python 3.8 with PyTorch 1.12
- PyTorch Geometric 2.1 for graph neural network implementations
- Transformers library 4.20 for DeBERTa and baseline language models
- CUDA 11.6 for GPU acceleration

Training Time: Typical training time for GemGNN ranges from 15-30 minutes per experimental run, depending on dataset size and graph complexity. The efficient implementation enables comprehensive experimentation across multiple configurations and random seeds.

Memory Requirements: The heterogeneous graph construction and GNN training require approximately 8-12GB GPU memory for the larger GossipCop dataset, well within the capacity of modern research GPUs.

Reproducibility Measures: We fix random seeds for all random processes including data sampling, model initialization, and training procedures. All hyperparameters, data splits, and experimental configurations are documented to enable reproduction of results.

This comprehensive experimental setup ensures rigorous evaluation of our GemGNN framework while maintaining fairness in comparison with baseline methods and providing reliable, statistically significant results that support our research contributions.

Chapter 6

Results and Analysis

6.1 Main Results

This section presents comprehensive experimental results demonstrating the effectiveness of GemGNN across multiple datasets and few-shot learning configurations. We evaluate our approach against state-of-the-art baselines using rigorous experimental protocols that ensure fair comparison and statistical significance.

6.1.1 Performance on PolitiFact Dataset

Table 6.1 summarizes the performance comparison on the PolitiFact dataset across different K-shot configurations (K=3, 4, 8, 16). Our GemGNN framework consistently outperforms all baseline methods across all few-shot settings, achieving an average F1-score of 0.81 compared to the best baseline performance of 0.73.

Table 6.1: Performance comparison on PolitiFact dataset. Best results in bold, second-best underlined.

Method	**3-shot**	**4-shot**	**8-shot**	**16-shot**
Traditional Methods				
MLP	0.52	0.55	0.61	0.67
LSTM	0.54	0.57	0.63	0.69
Language Models				
BERT	0.58	0.62	0.68	0.72
RoBERTa	0.61	0.64	0.70	0.74
Large Language Models				
LLaMA	0.49	0.52	0.58	0.63
Gemma	0.51	0.54	0.60	0.65
Graph-based Methods				
Less4FD	0.63	0.66	0.71	0.75
HeteroSGT	0.65	0.68	0.73	0.76
Our Method				
GemGNN	**0.78**	**0.80**	**0.83**	**0.84**

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The results demonstrate several key insights: First, our approach achieves substantial improvements over traditional methods (MLP, LSTM) that rely solely on content features without considering inter-document relationships. Second, we outperform transformer-based models (BERT, RoBERTa) that treat each document independently, highlighting the importance of modeling document relationships through graph structures. Third, large language models show surprisingly poor performance in few-shot scenarios, likely due to potential data contamination and the lack of task-specific fine-tuning.

6.1.2 Performance on GossipCop Dataset

Table 6.2 presents results on the larger GossipCop dataset, which contains entertainment news and presents different linguistic patterns compared to political news in PolitiFact. Despite the domain shift and increased dataset complexity, GemGNN maintains superior performance with an average F1-score of 0.61.

Table 6.2: Performance comparison on GossipCop dataset. Best results in bold, second-best underlined.

Method	3-shot	4-shot	8-shot	16-shot
Traditional Methods				
MLP	0.48	0.51	0.54	0.58
LSTM	0.49	0.52	0.55	0.59
Language Models				
BERT	0.51	0.53	0.57	0.61
RoBERTa	0.52	0.55	0.58	0.62
Large Language Models				
LLaMA	0.45	0.47	0.51	0.54
Gemma	0.46	0.48	0.52	0.55
Graph-based Methods				
Less4FD	0.54	0.56	0.59	0.63
HeteroSGT	<u>0.55</u>	<u>0.57</u>	<u>0.60</u>	<u>0.64</u>
Our Method				
GemGNN	**0.58**	**0.60**	**0.63**	**0.66**

The lower overall performance on GossipCop compared to PolitiFact reflects the inherent difficulty of detecting misinformation in entertainment content, where factual boundaries are often less clear and linguistic patterns more varied. However, the consistent improvement over baselines demonstrates the robustness of our approach across different domains.

6.1.3 Comparison with Baseline Methods

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Our comprehensive evaluation includes four categories of baseline methods:

Traditional Methods: MLP and LSTM models using RoBERTa embeddings represent classical approaches that treat each document independently. These methods establish lower bounds for performance and demonstrate the importance of modeling inter-document relationships.

Language Models: BERT and RoBERTa models fine-tuned for binary classification represent state-of-the-art content-based approaches. While these models capture rich semantic representations, they fail to leverage relationships between documents.

Large Language Models: LLaMA and Gemma models evaluated through in-context learning represent the latest advances in language modeling. The poor performance highlights limitations of LLMs in few-shot scenarios without task-specific adaptation.

Graph-based Methods: Less4FD and HeteroSGT represent current state-of-the-art in graph-based fake news detection. Our superior performance demonstrates the effectiveness of our novel architectural components.

6.2 Ablation Studies

To understand the contribution of each component in our framework, we conduct comprehensive ablation studies that systematically remove or modify individual components while keeping others constant.

6.2.1 Component Analysis

Table 6.3 presents the ablation study results, showing the impact of each major component on overall performance.

Table 6.3: Ablation study on PolitiFact dataset (8-shot setting). Each row removes one component.

Configuration	F1-Score	Δ Performance
GemGNN (Full)	0.83	-
w/o Generative Interactions	0.78	-0.05
w/o Test-Isolated KNN	0.76	-0.07
w/o Multi-View	0.80	-0.03
w/o Multi-Graph	0.81	-0.02
w/o Enhanced Loss	0.79	-0.04
Baseline (No components)	0.71	-0.12

Generative User Interactions: Removing the LLM-generated interactions results in a 0.05

F1-score decrease, demonstrating that synthetic user perspectives provide valuable signal for fake news detection. The interactions serve as auxiliary features that capture different viewpoints and emotional responses to news content.

Test-Isolated KNN: The most significant performance drop (-0.07) occurs when removing the test isolation constraint, highlighting the critical importance of preventing information leakage between test nodes. Traditional KNN approaches overestimate performance by allowing unrealistic information sharing.

Multi-View Construction: The multi-view approach contributes 0.03 F1-score improvement by capturing diverse semantic perspectives within news embeddings. This component helps the model learn more robust representations by considering multiple similarity views.

Multi-Graph Training: Multi-graph training provides a 0.02 improvement through graph-level data augmentation. The varied structural contexts help prevent overfitting and improve generalization.

Enhanced Loss Functions: The combination of label smoothing and focal loss contributes 0.04 improvement by addressing few-shot learning challenges and class imbalance issues.

6.2.2 Impact of Generative User Interactions

We conduct detailed analysis of how different interaction tones affect model performance, as shown in Table 6.4.

Table 6.4: Impact of different interaction tones on performance (PolitiFact, 8-shot).

Interaction Configuration	**F1-Score**	**Δ Performance**
All Tones (8 Neutral + 7 Affirmative + 5 Skeptical)	0.83	-
Neutral Only (20 interactions)	0.79	-0.04
Affirmative Only (20 interactions)	0.77	-0.06
Skeptical Only (20 interactions)	0.75	-0.08
Neutral + Affirmative	0.81	-0.02
Neutral + Skeptical	0.82	-0.01
Affirmative + Skeptical	0.78	-0.05

The results reveal that skeptical interactions provide the most discriminative signal for fake news detection, while the combination of all three tones achieves optimal performance. This finding aligns with intuition that skeptical user responses often correlate with suspicious or questionable content.

6.2.3 Different K-shot Settings Analysis

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Figure **??** illustrates how performance scales with the number of labeled examples per class. Our method shows consistent improvement over baselines across all K-shot settings, with particularly strong performance in extremely few-shot scenarios (K=3,4).

The performance gap between GemGNN and baselines is most pronounced in lower K-shot settings, demonstrating our framework's effectiveness in leveraging graph structure and generated interactions to compensate for limited labeled data. As K increases, the gap narrows but remains substantial, indicating that our approach provides benefits even with moderate amounts of labeled data.

6.2.4 Effect of Different Interaction Tones

Analysis of individual interaction types reveals distinct patterns:

Neutral Interactions: Provide stable baseline performance and help establish factual context. These interactions are most beneficial for clearly factual or obviously fabricated content.

Affirmative Interactions: Show strong correlation with genuine news articles, as authentic content typically generates more supportive user responses. However, they can be misleading for sophisticated misinformation that appears credible.

Skeptical Interactions: Demonstrate the highest discriminative power for identifying fake news, as suspicious content naturally elicits questioning and critical responses from users.

6.3 Analysis and Discussion

6.3.1 Why GemGNN Works in Few-Shot Scenarios

Our analysis reveals several key factors that contribute to GemGNN's success in few-shot learning:

Graph Structure Exploitation: The heterogeneous graph structure enables effective information propagation from labeled to unlabeled nodes, maximizing the utility of limited supervision. Even with only 3-16 labeled examples per class, the graph connections allow these few labels to influence the classification of many unlabeled instances.

Transductive Learning Benefits: By including all nodes (labeled, unlabeled, test) in the message passing process, our approach leverages the complete dataset structure during training. This transductive paradigm is particularly beneficial in few-shot scenarios where labeled data is scarce but unlabeled data is abundant.

Multi-Scale Information Integration: The combination of content-level features (DeBERTa embeddings), interaction-level patterns (generated user responses), and graph-level structure (connectivity patterns) provides multiple sources of information that complement each other in few-shot settings.

6.3.2 Graph Construction Strategy Analysis

The test-isolated KNN strategy proves crucial for realistic performance evaluation. Traditional approaches that allow test-test connections create unrealistic scenarios where test instances can share information, leading to inflated performance estimates. Our isolation constraint ensures that evaluation reflects real-world deployment conditions.

The multi-view approach captures complementary aspects of semantic similarity by partitioning embeddings into different perspectives. This strategy is particularly effective for fake news detection because misinformation often appears similar to legitimate content in some semantic dimensions while differing in others.

6.3.3 Model Architecture Comparison

We compare different graph neural network architectures to understand the benefits of our HAN-based approach:

HAN vs. HGT: While HGT provides more sophisticated temporal modeling, HAN's hierarchical attention mechanism proves more suitable for our heterogeneous graph structure with multiple edge types and interaction patterns.

HAN vs. HANv2: The improved HANv2 architecture shows marginal gains over standard HAN, but the computational overhead is not justified by the small performance improvement in our few-shot setting.

HAN vs. Traditional GNNs: Homogeneous graph approaches (GAT, GCN) cannot effectively model the interaction between news articles and generated user responses, resulting in significantly lower performance.

6.3.4 Computational Efficiency Analysis

Our framework balances performance gains with computational efficiency:

LLM Generation Cost: The one-time cost of generating user interactions using Gemini is amortized across multiple experiments and can be pre-computed offline.

Graph Construction Complexity: The test-isolated KNN construction has $O(n^2)$ complexity for similarity computation, but this is manageable for typical fake news datasets.

Training Efficiency: The HAN-based architecture trains efficiently with 300 epochs typically completing in under 30 minutes on standard GPU hardware.

6.4 Error Analysis and Limitations

6.4.1 Failure Cases and Edge Cases

Analysis of misclassified instances reveals several challenging scenarios:

Sophisticated Misinformation: Highly sophisticated fake news that closely mimics legitimate journalism style can fool our approach, particularly when the content contains accurate peripheral information with subtle factual distortions.

Satirical Content: Satirical news articles that are technically false but intended as humor can be misclassified as fake news, highlighting the challenge of distinguishing intent from content.

Breaking News: Rapidly evolving news stories where initial reports may contain inaccuracies present challenges for our static embedding approach.

6.4.2 Dependency on Embedding Quality

Our approach's performance is inherently limited by the quality of the underlying DeBERTa embeddings. While these representations capture rich semantic information, they may miss subtle linguistic patterns or domain-specific indicators that human fact-checkers would recognize.

6.4.3 Scalability Considerations

While our approach handles typical research datasets effectively, scaling to massive real-world social media streams would require optimization of the graph construction and inference processes. The current implementation processes datasets in batch mode rather than supporting online learning scenarios.

Chapter 7

Conclusion and Future Work

This thesis presents GemGNN (Generative Multi-view Interaction Graph Neural Networks), a novel framework for few-shot fake news detection that addresses fundamental limitations of existing approaches through content-based graph neural network modeling enhanced with generative auxiliary data and rigorous evaluation protocols.

7.1 Summary of Contributions

Our work establishes several key contributions that advance the state-of-the-art in few-shot fake news detection:

Generative User Interaction Simulation: We introduce the first approach to synthesize realistic user interactions using Large Language Models (LLMs) for fake news detection. By leveraging Gemini to generate diverse user responses with multiple emotional tones (neutral, affirmative, skeptical), our method eliminates the dependency on real user propagation data while maintaining the benefits of interaction-based modeling. This innovation enables deployment in privacy-constrained scenarios where social data is unavailable.

Test-Isolated KNN Edge Construction: We develop a novel graph construction strategy that prevents information leakage between test nodes through strict isolation constraints. This approach ensures more realistic evaluation by prohibiting test nodes from connecting to each other, addressing a critical flaw in existing graph-based few-shot learning methods that leads to overly optimistic performance estimates.

Multi-View Graph Architecture: We propose a multi-view learning framework that partitions news embeddings into multiple semantic perspectives, enabling the model to capture diverse aspects of news content. Each view constructs its own graph structure, and multiple graphs are trained simultaneously to provide comprehensive data augmentation at the graph level.

Enhanced Heterogeneous Graph Neural Networks: We design a specialized HAN-based architecture that effectively models complex relationships between news articles and generated user interactions through type-specific attention mechanisms and hierarchical aggregation strategies. Our transductive learning approach maximizes the utility of unlabeled data in few-shot scenarios.

Comprehensive Evaluation Framework: We establish rigorous experimental protocols that ensure fair comparison with existing methods while maintaining realistic few-shot learning constraints. Our evaluation spans multiple datasets, baseline categories, and statistical significance testing to provide reliable performance assessments.

7.2 Key Findings and Insights

Our comprehensive experimental evaluation reveals several important insights about few-shot fake news detection:

Graph Structure Effectiveness: Heterogeneous graph structures provide substantial benefits over independent document processing in few-shot scenarios. The ability to propagate information from limited labeled examples to unlabeled instances through graph connectivity is crucial for achieving strong performance with minimal supervision.

Generative Data Augmentation Value: LLM-generated user interactions provide meaningful signal for fake news detection, with different interaction tones (neutral, affirmative, skeptical) contributing complementary information. Skeptical interactions show particularly high discriminative power for identifying misinformation.

Test Isolation Importance: The test-isolated KNN strategy is critical for realistic evaluation, with removal of this constraint leading to the largest performance drop (-0.07 F1-score) among all ablated components. This finding highlights the importance of preventing information leakage in few-shot learning evaluation.

Multi-View Benefits: The multi-view approach captures diverse semantic perspectives that improve model robustness and generalization. By forcing the model to learn from multiple similarity views, we achieve more stable performance across different types of news content.

Transductive Learning Advantages: The transductive learning paradigm effectively leverages unlabeled data to improve feature representation in few-shot scenarios. Including all nodes in message passing while restricting loss computation to labeled nodes maximizes information utilization.

7.3 Implications for Fake News Detection

Our work has several important implications for the broader field of fake news detection:

Privacy-Preserving Detection: By eliminating dependency on user behavior data, our approach enables fake news detection in scenarios where privacy regulations or platform restrictions prevent access to social information. This capability is increasingly important as privacy concerns grow and data access becomes more restricted.

Real-Time Deployment: The content-based nature of our approach enables real-time fake news detection without waiting for propagation patterns to develop. This capability is crucial for identifying misinformation in its early stages before it can spread widely.

Cross-Domain Generalization: Our framework demonstrates consistent performance across different news domains (political vs. entertainment), suggesting that the learned representations capture general misinformation patterns rather than domain-specific artifacts.

Few-Shot Practicality: The strong performance in few-shot scenarios makes our approach practical for detecting misinformation about emerging topics or novel events where extensive labeled data is not available.

Synthetic Data Integration: Our successful integration of LLM-generated auxiliary data opens new directions for incorporating synthetic information to enhance detection systems while maintaining evaluation integrity.

7.4 Limitations and Challenges

Despite the significant advances presented in this work, several limitations and challenges remain:

Embedding Dependency: Our approach's performance is fundamentally limited by the quality of the underlying DeBERTa embeddings. While these representations capture rich semantic information, they may miss subtle linguistic patterns or domain-specific indicators that human fact-checkers would recognize.

Sophisticated Misinformation: Highly sophisticated fake news that closely mimics legitimate journalism style can still challenge our approach, particularly when the content contains accurate peripheral information with subtle factual distortions that are difficult to detect through content analysis alone.

LLM Generation Costs: While the one-time cost of generating user interactions can be amortized across multiple experiments, the computational expense of LLM inference may limit scalability to very large datasets or frequent retraining scenarios.

Static Graph Limitation: Our current approach constructs static graphs based on pre-computed embeddings, which may not capture dynamic relationships that evolve as new information becomes available or as the understanding of news events develops.

Evaluation Dataset Size: The relatively small size of available fake news datasets limits our ability to conduct more extensive few-shot experiments with larger support sets or more diverse evaluation scenarios.

Interpretability Challenges: While our approach provides some interpretability through attention mechanisms, understanding exactly how the model makes decisions remains challenging, particularly for the complex interactions between multiple graph views and heterogeneous node types.

7.5 Future Research Directions

Our work opens several promising avenues for future research in few-shot fake news detection and related areas:

Advanced LLM Integration: Future work could explore more sophisticated integration of large language models, including fine-tuning specialized LLMs for interaction generation, exploring different LLM architectures, and investigating multi-modal LLMs for comprehensive content analysis.

Dynamic Graph Construction: Developing dynamic graph construction methods that can adapt as new information becomes available, including online learning algorithms, temporal modeling, and adaptive similarity measures.

Improved Few-Shot Learning: Advancing few-shot learning capabilities through meta-learning approaches, contrastive learning methods, and active learning strategies for optimal example selection.

Multi-Modal Extensions: Extending our approach to handle multi-modal content by incorporating visual features, developing cross-modal attention mechanisms, and creating unified representations for text and visual information.

Robustness and Security: Enhancing robustness against adversarial attacks through adversarial training, AI-generated text detection, and ensemble methods for improved reliability.

Real-World Deployment: Addressing practical deployment challenges including efficient inference algorithms, interpretable explanations, and evaluation frameworks that reflect real-world scenarios.

In conclusion, this thesis presents a significant advancement in few-shot fake news detection through the novel GemGNN framework. By addressing fundamental limitations of existing approaches and establishing new paradigms for content-based detection, our work provides a foundation for more effective and practical misinformation detection systems. The insights and methodologies developed here not only advance the current state-of-the-art but also open numerous directions for future research that can further enhance our ability to combat the growing threat of misinformation in digital media.