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Comparative Analysis of Graph Neural Networks and Transformers for Robust Fake News Detection: A Verification and Reimplementation Study

Soveatin Kuntur [1,*], Maciej Krzywda [2], Anna Wróblewska [1], Marcin Paprzycki [3] and Maria Ganzha [1]

[1] Faculty of Mathematics and Information Science, Warsaw University of Technology, plac Politechniki 1, 00-661 Warsaw, Poland; anna.wroblewska1@pw.edu.pl (A.W.); maria.ganzha@pw.edu.pl (M.G.)
[2] Faculty of Physics and Applied Computer Science, AGH University of Krakow, 30-059 Krakow, Poland; krzywda@agh.edu.pl
[3] Systems Research Institute, Polish Academy of Sciences, Newelska 6, 01-447 Warsaw, Poland; marcin.paprzycki@ibspan.waw.pl
* Correspondence: soveatin.kuntur.dokt@pw.edu.pl

Abstract: This study compares Transformer-based models and Graph Neural Networks (GNNs) for fake news detection across three datasets: FakeNewsNet, ISOT, and WELFake. Transformer models (BERT, RoBERTa, GPT-2) demonstrated superior performance, achieving mean accuracies above 85% on FakeNewsNet and exceeding 98% on ISOT and WELFake. Specifically, RoBERTa achieved 86.16% accuracy on FakeNewsNet and 99.99% on ISOT, while GPT-2 reached 99.72% on WELFake. In contrast, GNNs (GCN, GraphSAGE, GIN, GAT) exhibited lower performance. GCN achieved 71% accuracy on FakeNewsNet but dropped to 53.30% on ISOT and 50.28% on WELFake, with F1 scores reflecting similar trends. Other GNNs, like GraphSAGE, showed even lower results, particularly on ISOT and WELFake, where performance hovered around 50%. Our findings indicate that while Transformers provide exceptional accuracy and reliability, GNNs offer potential efficiency benefits for resource-constrained scenarios despite their lower predictive performance. This study informs model selection for fake news detection tasks and encourages the exploration of hybrid approaches to balance accuracy and computational efficiency.

Keywords: fake news detection; comparative analysis; transformers; graph neural networks (GNNs); RoBERTa; GPT-2; graph convolutional networks (GCNs); GAT; FakeNewsNet; ISOT dataset

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1. Introduction

In recent years, the rapid spread of news via social media and online platforms has become a double-edged sword. While it allows for easier access to information, it has also led to a rise in information disorders, including misinformation, disinformation, and clickbait. These phenomena, often referred to as fake news, can have serious consequences, such as influencing public opinion, affecting elections, and even inciting violence. As a result, addressing these issues and detecting fake news has become an essential task in today's information-driven society [1–4]. The challenge is not just technological but also social, as fake news undermines trust in media and creates deep divisions in communities. As the volume and complexity of fake news continue to grow, the need for effective detection methods has become increasingly urgent. Detecting fake news is particularly challenging because these articles are often crafted to appear as legitimate as possible, making it difficult to distinguish between true and false information based solely on content. Additionally, the context in which the news is shared—such as the source of the news, the networks through which it spreads, and the patterns of interaction—plays a crucial role in determining its truthfulness [5]. Therefore, machine learning models must not only analyze the text but also consider these contextual factors to accurately detect fake news. Recent advancements in machine learning, particularly with models like Transformers and Graph Neural

Networks (GNNs), offer promising tools for addressing this challenge. Transformers, including models like BERT, RoBERTa, and GPT-2, have shown exceptional performance in various language processing tasks due to their ability to understand complex language patterns [6,7]. On the other hand, GNNs are designed to analyze the structure and relationships within data, making them particularly effective for tasks involving networked information, such as the spread of news on social platforms [8]. Despite advancements, limited research directly compares the effectiveness of Graph Neural Networks (GNNs) and Transformer models in fake news detection. These models differ significantly in how they process data: GNNs leverage the structural relationships in news articles (such as social connections), while Transformers excel at understanding textual context. Comparing these approaches is essential to understand their strengths, weaknesses, and applicability under various conditions, especially as ensuring consistent performance across datasets remains an ongoing challenge.

Our paper presents a comparative analysis of these models, using the ISOT and FakeNewsNet datasets to evaluate their performance. The contributions of this study are as follows:

- Performance Comparison: We systematically compare GNNs and Transformers across key metrics such as accuracy, precision, recall, F1-score, and ROC-AUC, providing a comprehensive view of model effectiveness. The comparison is performed using the same input data, which is the pure text without any other information, ensuring consistency in evaluation.
- Reproducibility: We reimplement all models with standardized settings to ensure robustness and reproducibility. The source code and datasets are available on github (https://github.com/kunturs/comparative-analysis, accessed on: 17 October 2024).
- Insights: We examine the strengths and limitations of GNNs (graph-based) and Transformers (text-based), offering practical recommendations on when each model should be applied, considering both performance and computational cost.

By testing both graph-based and text-based models, we aim to bridge the gap between structural and semantic data in fake news detection, offering a more holistic understanding of the problem. The structure of the paper is as follows. In Section 2, we review the relevant literature to provide context for our study. Section 3 provides an overview of the datasets used in our study, highlighting key characteristics and the sources from which they were obtained. Section 4 details our proposed approach, explaining the methodologies and techniques employed to address the problem of fake news detection. Section 5 presents the results of our experiments, showcasing the performance of different models across various metrics such as accuracy, F1 score, and ROC-AUC. Section 6 offers a comprehensive discussion of the implications of our findings, including the trade-offs between model performance and computational efficiency. Finally, Section 8 summarizes our work, drawing conclusions based on our results and providing potential directions for future research.

2. Literature Review

In recent years, numerous studies have explored methods to tackle misinformation detection, yet there remains a need for research that systematically compares the strengths of different model architectures in this field [9,10]. While advancements have been made, limited work has focused on assessing the robustness and effectiveness of Transformer-based models versus Graph Neural Networks (GNNs) for fake news detection. This comparative analysis is crucial, as each model family offers unique capabilities: Transformers excel in capturing language nuances, whereas GNNs effectively handle relational data, such as social interactions. A thorough comparison of these models across diverse datasets can provide insights into their respective strengths, guiding the development of more resilient misinformation detection systems.

Graph Convolutional Networks (GCNs), introduced in [11], have become foundational in graph-based learning, enabling node feature aggregation from local neighborhoods to capture complex dependencies within graph structures. GCNs are particularly effective for semi-supervised learning tasks such as node classification but can encounter challenges such as over-smoothing in deeper networks. Despite these limitations, GCNs provide a solid framework for leveraging relational data in misinformation detection.

Graph Isomorphism Networks (GINs), proposed by [12], were designed to address the expressiveness limitations of GCNs by matching the power of the Weisfeiler–Lehman graph isomorphism test. GINs use a simple yet powerful aggregation scheme with a multi-layer perceptron (MLP), allowing them to distinguish between non-isomorphic graphs effectively. This property makes GINs highly suitable for graph-level classification tasks where subtle structural differences are key, providing an advantage in misinformation contexts that require high sensitivity to node interactions.

Graph Attention Networks (GATs), introduced by [13], incorporate self-attention mechanisms to assign varying importance to a node's neighbors during feature aggregation. This adaptability enables GATs to focus on the most relevant connections, improving the model's robustness and flexibility in complex graph structures. GATs have been shown to perform well in social network analyses where the influence of certain nodes varies significantly, making them suitable for capturing the spread dynamics of misinformation.

GraphSAGE, proposed by [14], is an inductive framework that samples and aggregates features from a node's neighborhood. Unlike GCNs, GraphSAGE does not require access to the entire graph during training, enabling it to generalize to unseen nodes in large, evolving graphs. This inductive capability is particularly beneficial for real-time misinformation detection in dynamic social networks where new data points continuously emerge.

Graph Transformers have emerged as a novel approach to combining the strengths of graph-based learning and the self-attention mechanisms of Transformer models [15]. These models adapt the Transformer architecture to operate on graph-structured data, allowing them to capture both local and global node relationships more effectively than traditional GNNs. By leveraging self-attention, graph Transformers can weigh the significance of connections dynamically, improving their ability to model complex interactions within the graph. This makes them particularly valuable for applications like misinformation detection, where the relationships between nodes (such as user interactions) and their attributes are crucial. The TG-Transformer [16] and related models such as SemTGT [17] have demonstrated strong performance by integrating semantic and structural features, providing a comprehensive approach to graph-based learning.

Word embeddings have served as foundational tools for transforming text into dense vectors that capture semantic and contextual meanings, which are crucial for detecting fake news. Techniques such as TF-IDF, Word2Vec, and FastText have shown significant success in enhancing model performance metrics, including accuracy, precision, recall, and F1 score. For instance, the exBAKE model utilizes BERT embeddings to analyze the relationship between headlines and body text, thereby improving classification accuracy. It also employs a Weighted Cross-Entropy (WCE) loss function to address class imbalance, enhancing robustness when handling underrepresented classes in fake news datasets [18].

Transformer-based models, including BERT, RoBERTa, DistilBERT [19], along with graph-based models TG-Transformer [16], SemTGT [17], GTNT [20] and UGformer [21], leverage self-attention mechanisms to capture complex contextual relationships in text, making them particularly effective for multi-class classification in misinformation detection. For example, a DistilBERT-based framework has demonstrated high performance in distinguishing between fake news and satire by utilizing advanced pre-training and tokenization strategies [22]. On the other hand, SemTGT improves classification performance by effectively integrating semantic and structural features and addressing limitations in modeling long-range dependencies. Additionally, models like NewsEmbed provide robust document-level embeddings that perform well across multilingual settings and adapt effectively to shifting topics, such as those seen during major events like COVID-19 [23].

Beyond individual sentences, sentence transformers and document embeddings enhance fake news classification by providing dense vector representations at the sentence and document levels. NewsEmbed, for example, is trained on large-scale, cross-lingual document triplets, enabling it to be resilient across languages and adaptable to topic drift, thus maintaining relevance amid evolving global narratives [23]. Hybrid approaches that combine Transformer models with other deep learning architectures have been successful in integrating both textual and social contexts, leading to more robust misinformation detection. The DANES architecture, for instance, uses a dual-branch approach with a Text Branch for content analysis and a Social Branch to capture user interactions. Tests on datasets like BuzzFace and Twitter16 reveal that combining social and textual features can significantly improve detection accuracy, showcasing the advantages of a multi-perspective approach [24].

Network immunization methods focus on limiting the influence of harmful nodes after misinformation has begun circulating. For example, the minimum-cost weighted directed spanning tree (MCWDST) algorithm identifies and ranks harmful nodes based on their potential to spread misinformation, allowing for targeted real-time interventions. By prioritizing influential nodes within a network, this approach helps contain the impact of harmful content [23,25].

While Transformers are highly effective for analyzing textual content independently, especially in news articles, GNNs offer distinct advantages when social context, such as user interactions and community structures, is integral to the data. By leveraging these relational features, GNNs capture social dynamics that often drive misinformation spread. The emergence of Graph Transformers adds an additional layer of capability by combining the structural understanding of GNNs with the advanced contextual representation of Transformers. This study aims to explore the complementary strengths of Transformers, GNNs, and Graph Transformers, providing a systematic comparison to assess their robustness and effectiveness across various dataset configurations for misinformation detection.

Aside from the points mentioned above, there are also several efforts made by researchers, summarized in the survey paper [26], which combine various techniques to manage the outcomes post-detection. For example, ContCommRTD: This system incorporates network immunization strategies to improve the misinformation detection module. Its goal is to filter out fake news and adapt to changing communities in real-time, effectively managing the spread of accurate information during crisis events [27].

CONTAIN: The CONTAIN algorithm emphasizes community-based immunization by marking and immunizing harmful nodes identified through classification. This method accelerates the process of curbing the spread of harmful content across the network, effectively mitigating the impact of misinformation [28].

Sparse Shield: This approach leverages sophisticated classification methods, such as Transformers and Bi-LSTM, to identify harmful speech. Following detection, it applies a network immunization strategy to block harmful nodes, iteratively recalculating the immunization plan to control the spread of harmful content [29].

3. Datasets

The choice of the datasets to perform our comparative study was driven by the need for a common benchmark between two key papers: Phan et al. (2023) [30] and Hu et al. (2022) [31]. Both papers highlight the significance of these datasets in the domain of fake news detection, summarizing their use in various studies. In addition to the previously used datasets, we include the WELFake dataset to broaden the scope and enhance the robustness of our evaluation. Utilizing these datasets ensures consistency in our analysis and allows for a more comprehensive comparison of models within the framework of existing literature. Examples of titles and texts from the FakeNewsNet, Kaggle ISOT, and WELFake datasets, along with summary statistics for all datasets used in this study, are presented in Table 1 and Table 2, respectively.

Additionally, it is important to note that the criteria for labeling articles as "fake" can vary between datasets. For instance, the FakeNewsNet dataset relies on professional fact-checking organizations to validate the veracity of articles [32], whereas the ISOT dataset includes articles sourced from various origins that may lack consistent labeling criteria [33].

Similarly, the WELFake dataset, constructed from multiple sources, reflects a variety of definitions and interpretations of fake news [34]. This variability should be taken into account when interpreting results from these datasets.

Table 1. Example news titles and text from FakeNewsNet, Kaggle ISOT, and WELFake.

Content	FakeNewsNet	Kaggle ISOT	WELFake
Title	Here's What Really Happened When JFK Jr. Met Princess Diana	Fresh Off The Golf Course, Trump Lashes Out At FBI Deputy Director And James Comey	Bobby Jindal, raised Hindu, uses story of Christian conversion to woo evangelicals for potential 2016 bid
Text	During the summer of 1995, John F. Kennedy Jr. secretly met Princess Diana in New York, and ever since, there has been much speculation over exactly what happened in her suite at the Carlyle Hotel that day.	Donald Trump spent a good portion of his day at his golf club, marking the 84th day he's done so since taking the oath of office. It must have been a bad game because just after that, Trump lashed out at FBI Deputy Director Andrew McCabe on Twitter following a report saying McCabe plans to retire in a few months.	A dozen politically active pastors came here for a private dinner Friday night to hear a conversion story unique in the context of presidential politics: how Louisiana Gov. [1]

[1] The text in the WELFake column is truncated due to its length.

Table 2. Summary statistics of datasets with metadata information for the entire dataset not split by categories of fake or real. Metadata refers to additional information available in the dataset, such as the presence of links, authorship data, publication timestamps, and social media interactions. ✗ represents "No", ✓ represents "Yes", and "N/A" means not available. Bullet color coding: ● Kaggle ISOT Fake, ● Kaggle ISOT Real, ● FakeNewsNet GossipCop Fake, ● FakeNewsNet GossipCop Real, ● FakeNewsNet Politifact Fake, ● FakeNewsNet Politifact Real, ● WELFake Kaggle, ● WELFake McIntire, ● WELFake Reuters, ● WELFake BuzzFeed Political.

Dataset	Number of Documents	Average Length (Words)	Number of Sources	Metadata Info
●	23,481	423.2	6	Links: N/A, Authors: N/A, Timestamps: ✗
●	21,417	385.6	2	Links: N/A, Authors: N/A, Timestamps: ✗
●	5323	11.06	4681	Links: 4681, Authors: N/A, Timestamps: ✓, Social Media: ✓
●	16,817	11.30	16,010	Links: 16,010, Authors: N/A, Timestamps: ✓, Social Media: ✓
●	432	11.70	428	Links: 428, Authors: ✓, Timestamps: ✓, Social Media: ✗
●	624	N/A	624	Links: 624, Authors: ✓, Timestamps: ✓, Social Media: ✗
●	20,800	404.4	6	Links: N/A, Authors: N/A, Timestamps: ✗
●	6335	400.5	1	Links: ✗, Authors: N/A, Timestamps: ✗
●	44,898	415.3	1	Links: ✗, Authors: N/A, Timestamps: ✗
●	101	150.2	1	Links: N/A, Authors: ✗, Timestamps: ✗, Social Media: ✗

3.1. FakeNewsNet Dataset

The FakeNewsNet dataset is a comprehensive repository designed to facilitate research in fake news detection. It integrates both news content, such as article headlines and body text, and social context, including user engagement data like shares, comments, and reactions on social media [32]. For example, an article labeled as *fake* in the dataset may include its headline, content, and metadata alongside information on how users interacted with it on social media platforms, such as the number of shares and comments. This combination makes FakeNewsNet a valuable resource for analyzing the spread and impact of misinformation. The dataset is divided into two major sub-datasets:

- GossipCop: Focuses on entertainment news. It includes approximately 20,000 articles labeled as *fake* or *real*, with an average text length of around 500 words [32]. Metadata such as publication date and social engagement metrics (e.g., shares, comments) are also included. The subset is relatively balanced, with a slight bias towards real news, and contains over 50,000 social links, capturing interactions between articles and social media posts.
- PolitiFact: Focuses on political news and consists of around 12,000 articles labeled as *fake* or *real*, with an average text length of approximately 700 words [32]. It includes metadata providing social context, such as user engagement data. The subset is more balanced in terms of the number of fake and real articles, and it features more than 30,000 social links [32].

Both sub-datasets are carefully curated, with labels derived from professional fact-checking organizations, ensuring the reliability of the data for developing and benchmarking fake news detection algorithms.

3.2. ISOT Fake News Dataset

The ISOT Fake News Dataset is a well-known dataset available on Kaggle, used extensively for the development and evaluation of fake news detection models [33]. The dataset is composed of news articles that are labeled as either *fake* or *real*, with a balanced representation of both categories:

- Real News: This subset includes 21,417 articles from credible sources such as Reuters, ensuring that the content is factual and reliable.
- Fake News: This subset consists of 23,481 articles from various sources known for disseminating fabricated or misleading information.

Each article in the ISOT dataset includes metadata such as the title, text, and publication date, which provides essential contextual information for analysis. Although the dataset does not inherently contain graph-based information [30], such as relational links between articles or sources, researchers can construct graph representations if needed. Its size, balanced distribution of real and fake news, and diversity of topics make it a robust resource for training and evaluating machine learning models designed to distinguish between authentic and misleading information.

3.3. WELFake Dataset

The WELFake Dataset is a comprehensive data resource developed for enhancing the study and detection of fake news [34]. To mitigate issues of bias and overfitting found in smaller or less diverse data sources, WELFake was constructed by merging four popular datasets: Kaggle, McIntire, Reuters, and BuzzFeed. This combination results in a dataset containing 72,134 news articles, of which 35,028 are labeled as *real* and 37,106 as *fake*.

- Composition: The dataset includes balanced representations of real and fake news, ensuring an unbiased training and evaluation set for machine learning models.
- Features: Each entry contains columns for the title, text, and binary labels indicating the veracity of the news content (real or fake).
- Diversity: By combining different data sources, the WELFake dataset incorporates a variety of writing styles and topics, enabling better generalization in model training.

The WELFake dataset's structure allows for the analysis and extraction of linguistic features, which can be combined with word embedding techniques for effective fake news detection. Its larger size and varied content make it a robust dataset for developing models capable of distinguishing between authentic and misleading information.

4. Our Approach

4.1. Data Preprocessing

In this study, two distinct preprocessing pipelines were employed to prepare the data for Transformer models and Graph Neural Networks (GNNs). Each pipeline is tailored to the specific requirements of the respective models, ensuring that the input data are optimally structured for effective training and evaluation. Importantly, the data splitting strategy was consistent for both pipelines, with the same split applied for Transformer models and GNN models.

4.1.1. Preprocessing for Transformer Models

Transformer models, such as BERT, RoBERTa, and GPT-2, require text data to be processed into a tokenized format that the model can interpret. The following steps were taken to preprocess the data (as illustrated in Figure 1):

- Text Preparation (Tokenization, Masks): The text from each dataset was first tokenized using model-specific tokenizers (e.g., `BertTokenizer`, `RobertaTokenizer`, `GPT2Tokenizer`). This process converts raw text into subword tokens that the Transformer models can understand. Attention masks were generated to indicate which parts of the input sequence should be attended to during training.
- Sequence Formatting (Padding, Truncation): Since Transformer models require input sequences of a fixed length, the tokenized sequences were padded to a maximum length of 128 tokens or truncated if they exceeded this length. This padding ensures that all input sequences are of uniform length, which is necessary for batch processing and allows the model to handle inputs consistently during training and inference.
- Data Splitting: Stratified K-Fold Cross-Validation (https://scikit-learn.org/dev/modules/generated/sklearn.model_selection.StratifiedKFold.html, accessed on: 25 November 2024) was utilized to ensure a robust and comprehensive evaluation. The data were divided into 5 stratified folds, with each fold maintaining the original class distribution to address potential class imbalances. In each iteration, one fold was used as the test set, while the remaining folds served as the training set. This process was repeated for all folds, allowing the model to be trained and evaluated multiple times, ensuring a more reliable estimate of performance. Additionally, a validation set, drawn from within the training portion of each fold, was used to fine-tune hyperparameters and minimize overfitting, providing consistent and unbiased evaluation across different configurations.

4.1.2. Preprocessing for GNN Models

Graph Neural Networks (GNNs) process data in the form of graphs, where nodes represent entities (in this case, news articles) and edges represent relationships between them. The preprocessing steps for GNN models included:

- Text Vectorization (TF-IDF): The text data were converted into numerical features using TF-IDF (Term Frequency-Inverse Document Frequency) vectorization. This method transforms the text into a matrix of features that represent the importance of each word in the document relative to the entire dataset.
- Graph Construction: To create a graph structure suitable for GNNs, edges were generated based on synthetic connections. Nodes in the graph represent individual news articles, while edges were established to define relationships between these articles. This approach allows the GNN to learn patterns of misinformation spread.
- Data Splitting: The same data splitting method as used in the Transformer Section 4.1.1 pipeline was employed.

The preprocessing steps shown in Figure 1 are essential for preparing the data in the right format and structure for each model. By using Stratified K-Fold Cross-Validation consistently across both the Transformer and GNN models, we ensure a fair comparison of their performance. Moreover, the inclusion of a validation set helps us fine-tune the models effectively, reducing the risk of overfitting and ensuring they generalize well during testing.

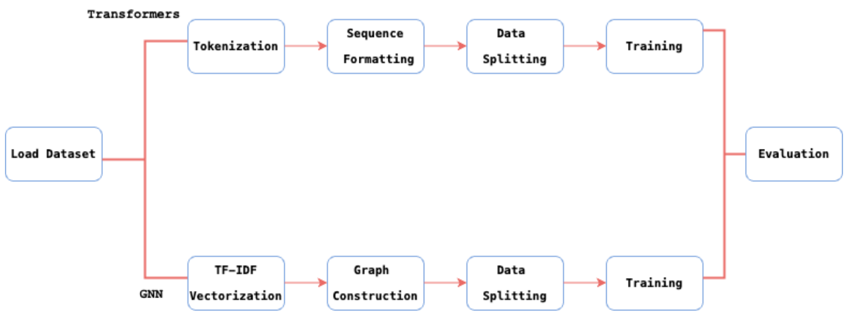

Figure 1. Data preprocessing pipelines for Transformer and GNN models with consistent data splitting to ensure comparability in performance evaluation.

4.2. Model Settings

In this study, we concentrated exclusively on the fundamental architectures of Graph Neural Networks (GNNs) and Transformers for fake news detection, thereby emphasizing their distinct capabilities. This foundational approach provides a basis for future research in the domain.

To ensure a more aligned comparison, we standardized certain preprocessing steps where possible. For example, input data were truncated to the same length for both model types to maintain consistency in text length, and batch sizes were adjusted based on the computational needs of each model. However, due to the inherent differences between GNNs and Transformers, some variation in input handling remains unavoidable. These differences in input processing are discussed further in the limitations section.

The architectures, configurations, and training processes for each model are summarized in Table 3.

Table 3. Architectures, configurations, and training processes for GNN and Transformer models.

Model Type	Architecture	Configurations and Training Process
GNN	2 GCNConv (GCN) 2 SAGEConv (GraphSAGE) 2 GATConv, 8 Heads (GAT) 2 GINConv (GIN)	Hidden Size: 64 Learning Rate: 0.001 Weight Decay: 5×10^{-4} Batch Size: Full Graph 5 epochs (Pre-training) 3 epochs (Fine-tuning) Optimizer: Adam Loss Function: Cross-Entropy
Transformer	12 Layers (BERT, RoBERTa, GPT-2)	Hidden Size: 768 Learning Rate: 2×10^{-5} Dropout: 0.1 Batch Size: 16 3 epochs Optimizer: AdamW Loss Function: Cross-Entropy

4.3. Training Procedure

The training procedure for the GNN and Transformer models adhered to the following structure:

- Optimizer: The training of the GNN models utilized the Adam optimizer [35] with a learning rate of 0.001 to handle the gradient-based optimization effectively. The Transformer models (BERT, RoBERTa, and GPT-2) employed the AdamW optimizer [36], which is known for its decoupling of weight decay and learning rate, with a learning rate set at 2×10^{-5} to maintain stability during training.

- Loss Function: All models employed Cross-Entropy Loss as the primary loss function to address the binary classification task (i.e., classifying news as fake or real). This choice is suitable for probabilistic outputs and allows for direct optimization of classification accuracy.
- Batch Size: For the Transformer models, a batch size of 16 was selected, which balances training speed and memory constraints. The GNN models were trained using a batch size of 1, processing one graph at a time, due to the intrinsic nature of the graph data representation.
- Training Epochs: The Transformer models were trained for a total of 3 epochs, which was found sufficient due to their pre-trained nature and ability to converge quickly. The GNN models followed a two-phase training approach: an initial pre-training phase of 5 epochs for link prediction using Mean Squared Error (MSE) loss, followed by a 3-epoch fine-tuning phase focused on classification using cross-entropy loss.
- Cross-Validation Strategy: Both GNN and Transformer models were evaluated using 5-fold stratified cross-validation to ensure robustness and generalizability across different data splits. Each fold's results were averaged, and the mean and standard deviation for metrics such as accuracy, precision, recall, F1-Score, and ROC-AUC were calculated.

4.4. Evaluation Metrics

To evaluate model performance, the standard classification metrics of accuracy, recall, precision, F1 score, and ROC-AUC were employed, which is consistent with established practices in classification research [30,31,37].

- Accuracy: Measured as the proportion of correctly classified samples (real vs. fake news) to the total number of samples in the test set.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

where TP = True Positives, TN = True Negatives, FP = False Positives, FN = False Negatives.

- F1-Score: Computed to provide a balance between precision and recall, especially in cases of class imbalance. The formula is:

$$\text{F1} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

- Precision and Recall: Precision measures the accuracy of fake news predictions, while recall evaluates the model's capacity to identify all instances of fake news:

$$\text{Precision} = \frac{TP}{TP + FP}, \quad \text{Recall} = \frac{TP}{TP + FN}$$

- ROC-AUC: Measures the model's ability to distinguish between classes (real vs. fake news). The ROC curve plots the true positive rate (TPR $= \frac{TP}{TP+FN}$) against the false positive rate (FPR $= \frac{FP}{FP+TN}$) at various threshold settings, and AUC is the area under the curve. The ROC-AUC value ranges from 0.5 (no discrimination) to 1 (perfect discrimination).

It is important to note that these metrics were not calculated manually but were executed automatically through the model evaluation process.

5. Results

5.1. Transformer Models

BERT, RoBERTa, and GPT-2 achieved high accuracy and F1 scores across all datasets. On the Kaggle ISOT dataset, RoBERTa achieved an accuracy of 99.99% $\pm$ 0.0002. BERT maintained robust performance on FakeNewsNet with an accuracy of 85.28% $\pm$ 0.01 and on WELFake with 98.87% $\pm$ 0.002.

5.2. Graph Neural Network (GNN) Models

GNN models, including GCN, GraphSAGE, GIN, and GAT, exhibited lower accuracy and F1 scores, particularly on the Kaggle ISOT dataset. GraphSAGE achieved $\sim$51% accuracy and a $\sim$35% F1 score, indicating limited learning. On FakeNewsNet, GIN performed better, with an accuracy of 74% $\pm$ 0.31 and an F1 score of 72.60% $\pm$ 0.29.

5.3. Variability Analysis

The standard deviations for GNN metrics were higher, indicating greater variability compared to Transformer models. In Table 4, we provide an overview of the models utilized for fake detection. Table 5 showcases the performance of our models in comparison to state-of-the-art solutions.

Table 4. Summary of model performance metrics. The table presents the mean and standard deviation for accuracy, F1 Score, ROC-AUC, precision, and recall across datasets. *Dataset Legend:* 🔴 FakeNewsNet, 🟢 Kaggle ISOT, 🔵 WELFake.

Model	Dataset	Accuracy (%)	F1 Score (%)	ROC-AUC (%)	Precision (%)	Recall (%)
BERT	🔴	85.28 $\pm$ 0.01	85.00 $\pm$ 0.008	78.78 $\pm$ 0.02	85.22 $\pm$ 0.006	85.28 $\pm$ 0.01
	🟢	99.94 $\pm$ 0.001	99.94 $\pm$ 0.001	99.94 $\pm$ 0.001	99.94 $\pm$ 0.001	99.94 $\pm$ 0.001
	🔵	98.87 $\pm$ 0.002	98.87 $\pm$ 0.002	98.87 $\pm$ 0.002	98.87 $\pm$ 0.002	98.87 $\pm$ 0.02
RoBERTa	🔴	86.16 $\pm$ 0.008	85.66 $\pm$ 0.007	78.56 $\pm$ 0.02	85.91 $\pm$ 0.006	86.16 $\pm$ 0.008
	🟢	99.99 $\pm$ 0.0002	99.99 $\pm$ 0.0002	99.99 $\pm$ 0.0002	99.97 $\pm$ 0.0002	99.96 $\pm$ 0.0002
	🔵	99.43 $\pm$ 0.008	99.43 $\pm$ 0.008	99.43 $\pm$ 0.008	99.43 $\pm$ 0.007	99.43 $\pm$ 0.008
GPT-2	🔴	84.94 $\pm$ 0.01	84.51 $\pm$ 0.009	77.58 $\pm$ 0.02	84.75 $\pm$ 0.008	84.94 $\pm$ 0.01
	🟢	99.93 $\pm$ 0.0004	99.93 $\pm$ 0.0004	99.93 $\pm$ 0.0004	99.93 $\pm$ 0.0004	99.93 $\pm$ 0.0004
	🔵	99.72 $\pm$ 0.001	99.72 $\pm$ 0.001	99.72 $\pm$ 0.001	99.72 $\pm$ 0.001	99.72 $\pm$ 0.001
GCN	🔴	71 $\pm$ 0.35	68.10 $\pm$ 0.37	52.22 $\pm$ 0.04	67.69 $\pm$ 0.37	71 $\pm$ 0.35
	🟢	53.30 $\pm$ 0.02	34.98 $\pm$ 536 $\times 10^{-5}$	50.00 $\pm$ 5.00	31.59 $\pm$ 0.1	51.37 $\pm$ 0.02
	🔵	50.28 $\pm$ 0.01	33.68 $\pm$ 0.01	50.00 $\pm$ 0	25.30 $\pm$ 0.01	50.28 $\pm$ 0.01
GraphSAGE	🔴	41 $\pm$ 0.44	34.92 $\pm$ 0.45	50.00 $\pm$ 0	32.85 $\pm$ 0.43	41 $\pm$ 0.44
	🟢	51.67 $\pm$ 0.01	35.98 $\pm$ 0.004	50.28 $\pm$ 0.007	38.59 $\pm$ 0.16	51.67 $\pm$ 0.01
	🔵	49.30 $\pm$ 0.01	34.06 $\pm$ 0.01	50.02 $\pm$ 0.0002	44.06 $\pm$ 0.1	49.30 $\pm$ 0.01
GIN	🔴	74 $\pm$ 0.31	72.60 $\pm$ 0.29	58.33 $\pm$ 0.15	87.24 $\pm$ 0.05	74 $\pm$ 0.31
	🟢	51.43 $\pm$ 0.02	35.49 $\pm$ 0.02	50.08 $\pm$ 0.001	38.23 $\pm$ 0.14	51.43 $\pm$ 0.02
	🔵	50.27 $\pm$ 0.01	34.62 $\pm$ 0.01	49.96 $\pm$ 0.001	35.58 $\pm$ 0.1	50.27 $\pm$ 0.001
GAT	🔴	75 $\pm$ 0.36	70.03 $\pm$ 0.38	50.00 $\pm$ 0	68.85 $\pm$ 0.37	75 $\pm$ 0.38
	🟢	51.38 $\pm$ 0.02	34.91 $\pm$ 0.02	50.00 $\pm$ 0.0001	32.79 $\pm$ 0.1	51.38 $\pm$ 0.002
	🔵	50.84 $\pm$ 0.01	34.28 $\pm$ 0.01	49.98 $\pm$ 3.02 $\times 10^{-5}$	25.86 $\pm$ 0.01	50.84 $\pm$ 0.01

Table 5. Comparison of accuracy (%) for models on ISOT and FakeNewsNet datasets. Models are sorted from the highest to the lowest accuracy within each dataset.

Model	Accuracy (%)
ISOT Dataset	
BERT (OUR)	99.94 ± 0.001
CT-BERT [38]	99.9
DeBERTa [38]	99.9
RoBERTa [38]	99.9
XLNet [38]	99.9
GPT-2 (OUR)	99.93 ± 0.0004
BERT [38]	98.7
ELECTRA [38]	98.5
GraphSAGE (OUR)	51.67 ± 0.01
GIN (OUR)	51.43 ± 0.02
GAT (OUR)	51.38 ± 0.02
FakeNewsNet Dataset	
C-CNN [39]	99.90
DOCEMB BART (BiGRU) [40]	99.80 ± 0.12
DOCEMB BART (LSTM) [40]	99.79 ± 0.06
DOCEMB BART (GRU) [40]	99.77 ± 0.07
FakeBERT [41]	98.90
FNDNet [42]	98.36
MisRoBÆRTa (BiLSTM-64) [43]	97.85 ± 0.23
MisRoBÆRTa (LSTM-64) [43]	97.84 ± 0.50
MisRoBÆRTa (BiLSTM-128) [43]	97.58 ± 0.73
MisRoBÆRTa (BiLSTM-32) [43]	97.57 ± 0.29
MisRoBÆRTa (LSTM-32) [43]	97.56 ± 0.29
MisRoBÆRTa (LSTM-128) [43]	97.55 ± 0.38
DOCEMB BERT (LSTM) [40]	96.31 ± 0.72
DOCEMB ROBERTA (BiGRU) [43]	93.12 ± 1.29
DOCEMB ROBERTA (LSTM) [43]	93.52 ± 0.78
DOCEMB WORD2VEC CBOW (BiLSTM) [40]	93.81 ± 0.39
DOCEMB WORD2VEC SG (BiLSTM) [40]	93.14 ± 0.50
DOCEMB FASTTEXT CBOW (BiLSTM) [40]	93.52 ± 0.30
DOCEMB GLOVE (GRU) [40]	88.83 ± 0.76
RoBERTa (OUR)	86.16 ± 0.008
DeBERTa [38]	85.3
BERT (OUR)	85.28 ± 0.01
CT-BERT [38]	85.0
BERT [38]	85.3
XLNet [38]	84.4
GPT-2 (OUR)	84.94 ± 0.01
GAT (OUR)	75 ± 0.36
GIN (OUR)	74 ± 0.31
GCN [44]	73.3
GCN (OUR)	71 ± 0.35
GraphSAGE (OUR)	41 ± 0.44

To provide further context, we include Table 6, which highlights a significant disparity in inference time between GNNs and Transformer models. This substantial difference arises from the fact that GNNs were executed using a CPU, leading to longer inference times compared to the GPU-accelerated runs of the Transformer models.

Table 6. Summary of model parameters and inference time across datasets; conducted using Google Colab *Dataset:* 🔴 FakeNewsNet, 🟢 Kaggle ISOT, 🔵 WELFake.

Model	Dataset	Num Parameters (M)	Inference Time (ms)
BERT	🔴		1.959958575
	🟢	110 M	1.97158281
	🔵		2.97158281
RoBERTa	🔴		2.012654269
	🟢	125 M	2.012654269
	🔵		4.795929272
GPT-2	🔴		3.705212435
	🟢	124 M	3.705975748
	🔵		6.795929272
GCN	🔴		2.204942703
	🟢	0.34 M	42.35391617
	🔵		147.2014904
GraphSAGE	🔴		1.867437363
	🟢	0.61 M	323.0213642
	🔵		820.9738255
GIN	🔴		1.739025116
	🟢	0.61 M	348.1784821
	🔵		811.0843182
GAT	🔴		2.980279922
	🟢	0.40 M	178.8868904
	🔵		551.1020184

6. Discussion

This study provides a comprehensive evaluation of the performance of Transformer models (BERT, RoBERTa, GPT-2) and Graph Neural Networks (GCN, GraphSAGE, GIN, GAT) in the context of fake news detection.

The results demonstrate that Transformer models consistently deliver superior performance across all datasets. On the Kaggle ISOT dataset, BERT, RoBERTa, and GPT-2 achieved near-perfect metrics, with accuracy, F1 score, precision, recall, and ROC-AUC all exceeding 99%. For example, RoBERTa recorded an exceptional accuracy of 99.99% $\pm$ 0.0002, suggesting that the ISOT dataset may be relatively straightforward for Transformer models or that these models leverage their self-attention mechanisms effectively to extract nuanced features from the text.

Even on more challenging datasets such as FakeNewsNet and WELFake, Transformer models maintained high performance, with BERT achieving 85.28% $\pm$ 0.01 accuracy on FakeNewsNet and 98.87% $\pm$ 0.002 on WELFake. These results underscore the robustness of Transformers in handling various types of data and their ability to generalize well across datasets. The consistently high precision and recall further highlight their capability to accurately classify fake news while minimizing false positives and ensuring comprehensive detection.

In contrast, GNNs exhibited more variability and generally lower performance. On the Kaggle ISOT dataset, GNN models such as GCN and GraphSAGE achieved results close to random baseline levels (e.g., GraphSAGE: $\sim$51% accuracy, $\sim$35% F1 score), indicating potential challenges in effectively learning the necessary features to distinguish between real and fake news. This observation aligns with the reviewer's comments and suggests that the graph structures or node features used in this study may not fully capture the intricacies of the dataset.

GNNs performed moderately better on the FakeNewsNet dataset, with GIN achieving 74% $\pm$ 0.31 accuracy and 72.60% $\pm$ 0.29 F1 score. However, even with these improvements, their performance remained below that of Transformer models, highlighting a gap in GNNs' ability to match the effectiveness of self-attention-based architectures. The higher standard deviation in GNN metrics compared to Transformers suggests greater variability and less consistent learning across cross-validation folds.

The results reveal a significant performance gap between Transformer models and GNNs, indicating that Transformers are better suited for tasks requiring deep contextual understanding and sequence modeling. Their self-attention mechanisms enable them to capture complex relationships in the text, leading to higher precision, recall, and F1 scores. For GNNs to close this gap, enhancements in graph construction and richer node features are essential.

From the results presented in Table 5, it is evident that transformer-based models do not face significant challenges with the ISOT dataset, achieving near-perfect accuracy. Our implementations of BERT and GPT-2 attain accuracies of 99.94% and 99.93%, respectively, which are comparable to state-of-the-art models such as CT-BERT, DeBERTa, RoBERTa, and XLNet reported by [38]. In contrast, the FakeNewsNet dataset appears more difficult for our state-of-the-art models, as reflected in the generally lower accuracies. Despite this increased difficulty, graph-based models perform better on FakeNewsNet than on ISOT; however, none of the graph models, including our implementations of GraphSAGE, GIN, GAT, and GCN, surpass transformer-based models in performance. BERT-based models rank highly across both datasets, reaffirming their effectiveness in fake news detection tasks. GPT-2 also performs well, ranking closely with BERT-based models yet marginally below the top-performing models. Methods leveraging advanced embeddings, such as DOCEMB [40], demonstrate exceptional performance on the FakeNewsNet dataset. Among them, DOCEMB BART combined with BiGRU achieves the highest accuracy of 99.80%, followed closely by LSTM (99.79%) and GRU (99.77%), underscoring the adaptability of BART embeddings in conjunction with sequential classifiers. C-CNN [39] also performs remarkably well, reaching 99.90%, while transformer-based models such as FakeBERT [41] and FNDNet [42] achieve strong results of 98.90% and 98.36%, respectively, but remain slightly behind the top DOCEMB configurations. MisRoBæRTa [43] variants, such as BiLSTM-64, exhibit competitive performance with a maximum accuracy of 97.85%. However, they are outperformed by DOCEMB BART models, which leverage the attention mechanisms of transformer-derived embeddings to handle the FakeNewsNet dataset's complexities better.

While the near-perfect performance of Transformers on the ISOT dataset may point to dataset simplicity or potential overfitting, the comparatively lower scores of GNNs, particularly on ISOT, suggest limitations in feature representation and graph structure.

This study emphasizes that while Transformer models are highly recommended for applications where accuracy and comprehensive text analysis are crucial, GNNs could be optimized for cases where real-time performance and computational efficiency are priorities. Future research should explore improvements in GNN input structures and feature engineering to enhance their performance in text classification tasks.

7. Reproducibility

Ensuring reproducibility was a cornerstone of this study, which evaluated the comparative performance of Transformer models (BERT, RoBERTa, GPT-2) and Graph Neural Networks (GCN, GraphSAGE, GIN, GAT) in fake news detection across the FakeNewsNet, Kaggle ISOT, and WELFake datasets. The distinct approaches in preprocessing and data handling for each model type were essential for a thorough analysis. Transformers required tokenization, padding, and truncation to process text, while GNNs involved transforming text into TF-IDF representations and using k-Nearest Neighbors (k-NNs) to create edges for the graph structures. This difference in data processing provided an opportunity to highlight how each model type functions optimally within its respective domain: Transformers for capturing deep contextual relationships and GNNs for exploiting relational structures.

The computational requirements were another aspect critical to reproducibility. Transformer models, such as BERT and GPT-2, demanded significant GPU memory due to their complexity and ability to model long-range dependencies in the text. These computationally intensive processes were balanced by their superior ability to capture linguistic nuances, justifying the resource investment. On the other hand, GNNs like GraphSAGE and GAT proved more efficient in terms of resource usage and were suited for scenarios emphasizing relationships between data points, such as news articles. This contrast highlighted an important trade-off between computational cost and model performance, showcasing that GNNs can serve as resource-efficient alternatives while maintaining reasonable accuracy in specific tasks.

A key success in this study was achieving consistency across various hardware and software environments. Even with potential differences in GPU types and software versions (e.g., PyTorch 2.0), we minimized discrepancies by carefully documenting our setups and ensuring detailed records of all experimental configurations. This meticulous approach reduced variability, enabling consistent and reliable results across different experimental runs and reinforcing the study's reproducibility.

Dataset preprocessing played a vital role in maintaining reproducibility. We leveraged widely used benchmark datasets—FakeNewsNet, Kaggle ISOT, and WELFake—and documented distinct preprocessing methods tailored for each model type, from text cleaning for Transformers to graph construction for GNNs. By openly sharing our entire preprocessing pipeline, we set a replicable standard that future researchers can follow, thereby minimizing variability in dataset handling and enhancing the reproducibility of subsequent studies.

Managing hyperparameter tuning was another crucial aspect. Transformer models, with their high computational demands, posed challenges for comprehensive tuning. However, despite these constraints, we documented our process thoroughly to ensure reproducibility and identified hyperparameter settings that provided robust performance for both model families. This transparency offers a practical reference for future researchers and demonstrates that reproducible and meaningful results are achievable, even when extensive hyperparameter searches are not feasible.

Limitations

This study provides valuable insights into the comparative performance of GNNs and Transformers for fake news detection; however, several limitations may affect the generalizability and scope of the findings.

First, the analysis was conducted using three primary datasets: FakeNewsNet, Kaggle ISOT, and WELFake, all of which classify articles strictly as either fake or real. While these datasets are widely recognized and reliable for benchmarking fake news detection, the definitions of "fake" and "real" may differ depending on the criteria used by the annotators. These differences in annotation practices can introduce variability in how fake and real news are interpreted across datasets. This may limit the models' ability to generalize to other datasets or real-world scenarios where the distinction between fake and real news is more subjective or nuanced.

Another significant limitation lies in the nature of the GNN models used in this study. Unlike Transformer models, which were pre-trained on large textual corpora, the GNNs were not pre-trained. This lack of pre-training restricts their ability to capture deep contextual and positional information within the text, as GNNs typically process the text more like a bag-of-words. Consequently, this may have resulted in the loss of important semantic details, impacting their overall performance when compared to the more context-aware Transformer models.

The performance of GNNs also heavily relies on the graph structures generated from the relationships between articles. The dependence on graph construction methods, such as k-Nearest Neighbors (k-NNs), introduces potential biases because the similarity metrics used may not always reflect true relationships. Fine-tuning these graph construction processes remains a challenge, as minor changes can lead to different graph topologies and, in turn, affect the model's performance.

Computational constraints further influenced the extent of hyperparameter tuning in this study. For Transformer models, especially BERT and GPT-2, the significant computational cost limited the range of hyperparameter tuning to a narrow set of configurations, such as batch size and learning rate. This restriction may have prevented the identification of optimal settings that could enhance performance.

Lastly, more advanced models such as GPT-3 or GPT-4 were not included in this study due to resource and access limitations. Future research that includes these models could provide deeper insights and potentially more robust results, especially regarding contextual understanding and language processing. Their inclusion would also allow for an exploration of how different definitions of fake and real news, as determined by varying annotation criteria, impact model performance.

8. Conclusions

8.1. Implications

The implications of this work extend beyond fake news detection. The consistently superior performance of Transformer models reaffirms their position as the dominant architecture for text-heavy classification tasks. Over the past five years, Transformer models have become the standard for achieving state-of-the-art results across a wide range of natural language processing (NLP) tasks and have consistently topped leaderboards. Their powerful self-attention mechanism allows them to capture deep contextual representations, making them highly effective for text-based datasets that require nuanced language understanding.

For GNN models, their strength lies in capturing relationships between data points, such as articles, through graph structures. This makes them particularly suitable for tasks where relational information is paramount. However, applying them to purely text-based classification tasks presents challenges and may require further research and optimization to bridge the performance gap with Transformers. Enhancements in graph construction methods and feature representation could help improve GNN performance in scenarios where both relational and textual information are crucial.

8.2. Future Work

Future research could explore several promising directions. First, testing the models on more diverse datasets, particularly those with ambiguous or subtle fake news examples, would enhance the generalizability of the findings. Second, integrating hybrid models that combine GNNs' ability to model relational structures with Transformers' contextual understanding could improve performance in more complex scenarios. Thirdly, Future research could explore optimizing transformer structures to improve model efficiency [45]; this approach would require significant modifications to the architecture of the proposed method. Graph Neural Networks can also be optimized in structure cases [46] and training processes [47], which, based on research, can enhance the quality of research. Finally, future work should explore the potential of advanced architectures, such as BERT-based GNN hybrids or models like GPT-3, to push the boundaries of fake news detection, particularly in terms of scalability and accuracy. The need for post-detection solutions remains critical because achieving high classification accuracy does not mark the end of the fake news detection challenge. Addressing the post-detection phase with effective management strategies is essential for ensuring long-term mitigation of misinformation.

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