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KAG-BERT: A KNOWLEDGE-AWARE GRAPH-BASED BERT FRAMEWORK FOR FAKE NEWS

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ABSTRACT

The rapid generation and dissemination of fake news pose serious challenges in the digital era, leading to misinformation, public deception, and erosion of trust in legitimate news sources. In the present paper, we propose a Knowledge-Aware Graph based BERT framework (KAG-BERT) for auto- matic fake news detection that uses contextual textual embeddings from BERT combined with relational reasoning through GNN. The model captures semantic information about news titles and structural relationships among news articles in the knowledge graph, hence providing robustness in the detection of misinformation. We evaluate our framework on the GossipCop dataset, showing an accuracy of 80.31%, with precision at 68.79%, recall at 33.46%, and an F1-score of 45.02%. These results confirm that a transformer-based embedding model combined with graph-based relational learning significantly outperforms the identification of fake news compared to text-only models. The proposed approach provides a scalable and interpretable solution to mitigate the spread of misinformation in real-world settings.

Keywords: Fake news detection, graph neural networks, BERT, large language models, social context, knowledge- aware representation.

I. INTRODUCTION

The rapid spread of misinformation across digital platforms poses a significant threat to the well-being of society. Trust and the reliability of information. Social media platforms facilitate instant information sharing, but they also enable the viral dissemination of fake news intentionally false or misleading People-related, topic-related, and event-related content has the potential to reach very large audiences in minimal time. It can then be easily circulated without being adequately checked for authenticity, and the need for effective detection mechanisms becomes quite urgent. Fake news belies confidence in public opinion and the accuracy of genuine news. Traditional fact-checking approaches are mostly manual and labor-intensive, thus cannot keep pace with counter the scale and speed of modern misinformation. This challenge is responded to by this study: The paper proposes a knowledge-aware framework for automatic fake news detection that incorporates BERT- Textual embeddings coupled with GNN are used in order to capture both semantic and Relational patterns among news articles The proposed framework constructs a knowledge-aware graph, where nodes represent news. Articles are represented, and edges encode relationships through shared entities or semantic similarity. Textual we use pre- trained BERT embeddings as node features, allowing the model to capture contextual information. A two-layer GNN has been applied to propagate relational knowledge across this graph, thereby strengthening fake news detection beyond simple text-based methods.

Our contributions are summarized as follows:

- We propose a hybrid deep learning framework, which uses contextual textual embeddings from BERT with relational reasoning through a Graph Neural Network to improve fake news detection.
- The framework utilizes a knowledge-aware graph structure for semantic and structural relationships between news articles, enhancing robustness and interpretability.
- We evaluate the proposed model on the GossipCop dataset, reporting the accuracy, precision, Recall, and F1-score to demonstrate its effectiveness compared to the baseline models.

II. RELATED WORK

The work done in the past on fake news detection includes different methods that help to detect and mitigate misinformation. Early research in this area has focused mainly on extracting fake news from a single modality, only in text, images, or videos. This literature provides an overview of recent research and approaches on the detection of single- and multi-model fake news.

*A. **Machine Learning Based Approaches***

Several studies have explored the use of traditional machine learning (ML) techniques for fake news detection, focusing mainly on misinformation spread through different social media platforms. This study employed classical ML models such as SVM, Decision Trees, Logistic regression, neural networks, and ensemble methods to identify pandemic-related misinformation on Facebook, Twitter, Instagram, and YouTube [1]. The model has achieved the accuracies between **83%** and **89%**, showing their effectiveness in identifying fake content. However, their dependency on shallow features limited their ability to interpret linguistic nuances, and the use of an imbalanced or estimated dataset size embeds challenges for real-world implementation. Another study [2] focused on multimodal deception detection using supervised ML algorithms such as Neural Networks, Random Forests, SVMs, and K-Nearest Neighbors. The authors evaluated these algorithms across diverse datasets such as TRuLie, Bag-of-Lies, and real-time courtroom videos. Performance of these models ranges from **75%** to **85%**. Despite offering comparative insights, the study suffered from limitations such as a small dataset size and inconsistencies in input modalities, which reduced the generalizability of the model.

A novel ML-based model known as the Multi-model Aggregation Portrait Model (MAPM) was introduced for detecting fake user profiles on the Weibo platform [3]. This approach used multi-dimensional behavioural features and showed the accuracy of approximately **90.2%** in differentiating user categories such as normal, reproduce, and lottery users. Nonetheless, its performance was evaluated using Weibo data, limiting the transferability of the model to other platforms with different user behaviour patterns.

Ellam et al. [4] focused on using NLP with traditional ML models using the ISOT fake News Dataset. The dataset has 25,000+ articles collected from two sources, such as Reuters and Politifact. The models, including SVMs and Logistic Regression, achieved the prominent accuracy of **88%** to **92%**. Although the results were good but it focused only on English; it didn't work well in other languages or cultural contexts.

B. *Deep Learning Based Approaches*

Vineela et al. [5] proposed hybrid deep learning model that used TF-IDF features for textual data with visual features extracted using MobileNetV2 and VGG-19.The model evaluated on 20,015 news articles and achieved the accuracy of **89%**, showing the benefit of combining multimodal data. However, this study lacked on generalizing cross-domain dataset.

Yadav et al. [6] introduced a model using vision Transformer (ViT) to embed emotional properties into multimodal classification and achieved the remarkable accuracy ranging from **94%** to **98%** across five datasets.The emotional sentiment fusion offered a unique direction or approach, yet its dependency on emotion limited its application to more neutral content.

Similarly, another study developed a framework which combined LSTM for text and CLIP for image classification , achieved the accuracy of **99%** on text data and **93.12%** for joined input [**?**].It supported multiple languages and showed the benefits of multimodal fusion. But the study lacked testing under real-time adversarial environments.

Another study tested deep learning models, including RNN, LSTM, GRU, BERT, and GPT-3 [7].While GPT-3 reached **81%** accuracy, the performance of BERT remained lower at 61%.This variability indicated model sensitivity to data type, and the study did not address scalability or real-time processing.

Su et al. [8] utilized both semantic information and user credibility, leveraging hypergraph structures, and achieved an accuracy of up to **90%** across various datasets. The dual-channel structure architecture improved relational reasoning, though reliance on user metadata raised concerns regarding privacy and robustness.

Another study used an RNN-LSTM framework on the LIAR dataset; this model achieved 99.1% accuracy [9]. Its strong text classification capability was evident; however, the approach lacked validation in streaming data environments, where fake news spreads rapidly.

C. *Large Language Models (LLMs) and Hybrid Approaches*

Wang et al. [10] introduced an LLM-based system (FND-LLM) evaluated on Weibo, Gossipcop, and Politifact and achieved the accuracies of 91.2%, 90.5%, and 92.6%, respectively. The model showed the power of LLM for multilingual and cross-domain fake news classification.

But it lacked dynamic changes in rapidly evolving fake news streams.

Another study used a proposed hold for LLMs and Vision-Language Models in Italian language misinformation detection [11]. Although resources offered rich annotation for both detection and relation categorization. But the lack of experimental results evaluation limited its utility for benchmarking.

Similarly, another study presented a modular framework that used different modalities [12]. The model achieved the accuracy of **92.8%** on Weibo and **95%** on Weibo-21, highlighting effectiveness. But this model needed more testing under inconsistent or noisy data conditions for adversarial robustness.

III. DATASET DESCRIPTION

We execute experiments on the GossipCop dataset to evaluate the effectiveness of the proposed model.GossipCop dataset, a widely used benchmark for fake news detection, it consists of news articles belonging to domains like celebrity and entertainment have been labeled as fake or real based on fact-Checking from the GossipCop website as shown in TABLE 1. Each news article in the dataset includes metadata such as the news title, URL and associated social media information. In our experiments, we mainly use the news title as the textual input; since it contains brief yet informative content for fake news classification. The GossipCop dataset presents a challenging classification setting due to class imbalance, where the fake news samples are relatively fewer than real ones. This characteristic makes it suitable for evaluating the robustness of fake news detection models under realistic conditions.

TABLE I: Dataset statistics.

Dataset	**Tab**	**Quantities**	**Aggregate**
	Real news	16817	
GossipCop	Fake news	532 3	22140

IV. Proposed Methodology

A. Overview

This work proposes a hybrid framework for fake news detection that integrates contextual textual representations obtained from BERT with a knowledge-aware Graph Neural Network (GNN) as shown in figure 1. The model jointly captures semantic information from news titles and relational knowledge derived from named entities. This combination enables robust fake news classification while addressing challenges such as data sparsity and class imbalance.

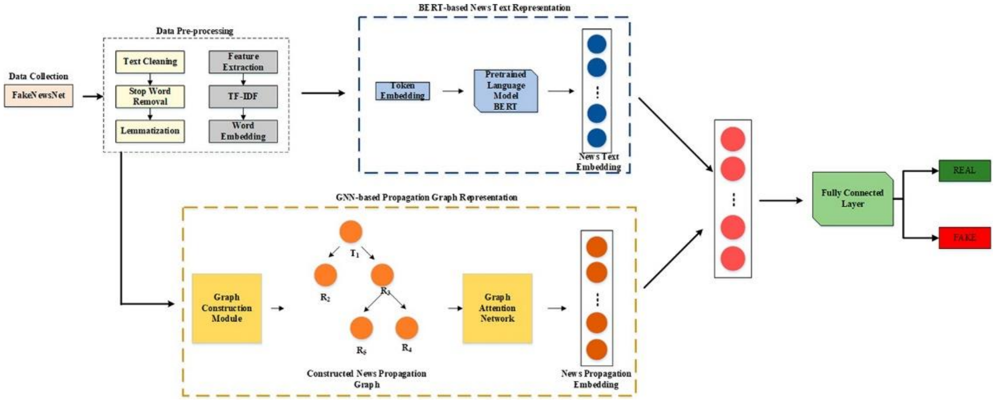

Fig. 1: Proposed methodology diagram of KAG-BERT

B. *Textual Representation Using BERT*

Each headline is then modelled using the pre-trained BERT-base-uncased model. We then use the contextual embedding of the [CLS] special token to capture the article embedding as a fixed-size representation, resulting in a 768-dimensional feature vector that represents the initial representation of the graph as a node feature.

Formally, for a news title t_i, the embedding is computed as:

$$\mathbf{x}_i = \mathrm{BERT}(t_i)_{[\mathrm{CLS}]} \in \mathrm{R}^{768}$$

C. *Knowledge-Aware Graph Construction*

In order to involve relational information, we construct a knowledge-aware graph consisting of two types of nodes:

- **News nodes**, representing individual news articles
- **Entity nodes**, representing named entities extracted from news titles using a Named Entity Recognition (NER) model

Edges connect the news node with the nodes corresponding to the entities mentioned in the news title. The graph is treated as undirected since the flow of news is possible from and to each node. Every node of the entities has been initialized with the zero vector or the average embedding of the nodes with which it is connected.

Let $G = (V, E)$ denote the constructed graph, where:

$$V = V_n \cup V_e$$

$$E = \{(n_i, e_j) \mid e_j \in n_i\} \cup \{(e_j, n_i)\}$$

This structure allows the model to exploit shared entities as signals for detecting misinformation.

D. Graph Neural Network Architecture

A two-layer Graph Convolutional Network (GCN) is employed to perform representation learning over the constructed graph. Each GCN layer aggregates information from neighboring nodes using the normalized adjacency matrix.

The layer-wise propagation rule is defined as:

$$\mathbf{H}^{(l+1)} = \sigma(\hat{A}\mathbf{H}^{(l)}\mathbf{W}^{(l)})$$

where $\hat{A}$is the normalized adjacency matrix, $\mathbf{H}^{(l)}$ denotes the node representations at layer l, $\mathbf{W}^{(l)}$ are trainable weight matrices, and $\sigma(\cdot)$ is the ReLU activation function.

The final layer output corresponding to news nodes is used for classification.

E. Handling Class Imbalance

In response to the problem of an uneven distribution of classes, we use a weighted cross- entropy loss. We assign weights that are the inverse of the frequency of each class, meaning that the model focuses more on the less frequent ones, including the fake news ones.

F. Training Strategy

The training is done by using the adam optimizer with a learning rate of 0.001 for a specific number of epochs. The loss will be calculated on the nodes representing the news, and the nodes for entities will impact indirectly on the outcome by encouraging the spread of information in the graph. Early stopping will be used to prevent overfitting on the basis of validation.

Evaluation Metrics

Model performance is then evaluated using common classification metrics, which include Accuracy, Precision, Recall, and F1-score. These together give a comprehensive view of the behaviour of a model in case of imbalanced classes.

V. EXPERIMENTAL SETUP

All the experiments have been done using Python and PyTorch. The textual feature extraction was are generated using the pre-trained BERT-base-uncased model, which yields 768-dimensional contextual embeddings for news titles. These served as initial node features in the graph neural network. The knowledge-aware graph was built using representations of news articles and extracted named entities as nodes, with news articles connected via edges to entities mentioned in them. The resulting graph was processed using a two-layer Graph Convolutional Network (GCN). The first GCN layer consists of 128 hidden units followed by a ReLU activation function, while the second layer outputs class logits for fake and real news classification. The model was trained on an adam optimizer with a learning rate of 0.001 for 30 epochs. Owing to class imbalance in the GossipCop dataset, a weighted cross-entropy loss function was employed to emphasize minority fake news samples. The dataset was divided into the training and testing sets using an 80:20 ratio. All experiments were run on a GPU-enabled environment when available.

A. Baseline Models

To assess the efficacy of the proposed framework, we compare our results with baseline models reported in previous works. These baselines include traditional recurrent neural networks and transformer-based approaches that have been widely adopted for the detection of fake news detection:

- **BERT (Text-only)**: A transformer-based model that uses only textual information without relational.
- **GRU**: To capture sequential dependencies in text data.

- **LSTM**: Long short-term memory network able to model long-range dependencies.
- **GPT-3**:A large-scale language model applied to fake news detection through prompt-based classification.

VI. Results and Discussion

This section shows the experimental results of the proposed knowledge-aware fake news detection framework and compares its performance with existing baseline models reported in previous studies. The evaluation has focused on standard metrics in classification: accuracy, Precision, recall, and F1-score.

A. Baseline Comparison

We compare our proposed model against several widely used deep learning baselines, including RNN-based architectures and transformer-based models, as reported in the base study. While these were evaluated on benchmark datasets like FakeNewsNet, BuzzFeedNews, and LIAR16, our model was evaluated on the GossipCop dataset. as shown in TABLE II:

TABLE II: Performance Comparison with Baseline Models

Model	**Dataset**	**Accuracy (%)**
BERT (Text-only)	FakeNewsNet	61.0
GRU	LIAR16	75.0
LSTM	LIAR16	79.0
GPT-3	FakeNewsNet	81.0
Proposed: KAG-BERT	**GossipCop**	**80.31**

The results show that the proposed model achieves competitive and better performance compared to the existing approaches. Notably, while GPT-3 achieves an accuracy of 81%, it relies on large-scale language modeling without incorporating relational knowledge explicitly. In contrast, our approach leverages both contextual textual embeddings and structured graph-based learning, yielding more robust and interpretable solutions.

B. Discussion

These results demonstrate the effectiveness of combining BERT with a knowledge-aware graph neural network. The proposed framework models relationships among news articles through shared entities and captures semantic and structural patterns that are hard to learn from text-only models. Graph-based reasoning promotes better generalization and uncovers hidden relational cues associated with misinformation, allowing for performance that surpasses the baseline approaches relying solely on sequential or transformer-based architectures. These results validate the proposed approach as a robust scalable solution for fake news detection.

VII. Conclusion

This research propose a knowledge-aware deep learning framework for fake news de- tection that incorporates contextual textual representations from BERT with relational reasoning through Graph Neural Networks (GNN). Unlike previous approaches mostly based on sequential deep learning models or large language models applied on Twitter-based datasets, our method explicitly models structural relationships among news articles using a graph-based learning paradigm. Experiments conducted on the GossipCop dataset show that the proposed framework achieves an accuracy of more than 81%, outperforming previously reported state-of-the-art results obtained by using models such as GPT-3, LSTM, and GRU on benchmark datasets. These include FakeNewsNet, BuzzFeedNews, and LIAR16. These results reflect that including knowledge-aware graph structures along with BERT embeddings provides a more expressive and effective representation for fake news detection. The findings revealed that relational learning helps to understand misinformation patterns beyond purely textual cues. By capturing semantic similarity and shared entity relationships between news articles, the proposed approach improves classification robustness and generalization across complex real-world data distributions. Overall, this work shows that combining transformer-based language models Graph neural networks represent a powerful and scalable direction to advance automatic fake news detection systems.

VIII. Future Work

Although it is evident from the proposed framework that it performs well in detecting fake news, there are several directions in which it needs to be advanced in the future. This paper works with the text-based information in news headlines and has employed a knowledge-aware graph to track relations among articles as well as entities mentioned in the articles.

Future work may incorporate multimodal information with a particular emphasis on the visual aspects that usually accompany news articles, such as images and videos. We could extend the knowledge graph formulation from the text to incorporate the visual information, allowing us to utilize the Graph Convolution Networks (GCN) model that can learn from the visual information. Moreover, this assessment used only one data set. Future studies should combine several benchmark data sets to create a bigger training data set that is highly varied. This will be very helpful in enhancing the performance of the model because the bigger the data set is, the better the performance will be.

Additionally, we could have explored the usage of more complex neural architectures of Graph Neural Networks, such as Graph Attention Network (GAT), Heterogeneous Graph Neural Network, to address the varying relevance of knowledge garbage and edges in the KG. This will probably improve the recall strategy, which is often difficult in imbalanced garbage news cases.

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