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Fake News Detection Using Hybrid Transformer-Based Model

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Abstract

The rapid spread of fake news on digital platforms threatens public trust and social stability. This paper proposes a hybrid deep learning model combining Robustly Optimized BERT Pretraining Approach (RoBERTa), Graph Neural Networks (GNN), and Heterogeneous Attention Networks (HAN) to improve fake news detection. Existing models capture contextual information but struggle with complex entity relationships and hierarchical data structures. Our hybrid approach leverages RoBERTa's robust language understanding, GNN's relational modelling, and HAN's hierarchical attention to address these limitations. The model is evaluated through classification, prediction, and baseline comparison modules, using accuracy, precision, recall, and F1-score metrics. Experimental results demonstrate that the proposed model achieves an outstanding 99.77% across all these metrics, significantly outperforming traditional and baseline methods and providing a highly effective solution for fake news detection.

Keywords: Fake news detection, Hybrid deep learning models, RoBERTa, GNN, HAN, BERT+BILSTM, BERT+BIGRU, ISOT, WelFake, Accuracy, Precision, Recall, F1-score.

1. Introduction

The rise of misinformation and fake news on digital platforms has become a significant concern in today's society. The rapid spread of false information can manipulate public opinion, harm reputations, and disrupt social harmony. Detecting fake news has therefore become a critical issue for both researchers and tech companies alike. The challenge lies in accurately identifying fake news in an environment where it is increasingly sophisticated and difficult to distinguish from real news. Various machine learning (ML) and deep learning (DL) models have been proposed to address this issue, but many still struggle with complex entity relationships and hierarchical data structures.

In this work, we introduce an innovative hybrid deep learning model designed to enhance fake news detection by integrating semantic analysis with supplementary features. The exponential growth of online content, including news articles, social media posts, and digital discussions, exposes the limitations of conventional methods in addressing the nuanced challenges posed by real-world data. Leveraging recent

advancements in deep learning, this approach bridges these gaps to improve detection accuracy.Recent advancements in deep learning, particularly with transformer-based models like Robustly Optimized BERT Pretraining Approach (RoBERTa) [7], along with techniques such as Graph Neural Networks (GNN) [2] and Heterogeneous Attention Networks (HAN) [2], have demonstrated potential in improving accuracy and efficiency for fake news detection.

Despite these advancements, integrating these powerful methods into a cohesive framework for fake news detection remains underexplored. This paper introduces a hybrid deep learning framework that leverages the complementary strengths of Graph Neural Networks (GNN) and Heterogeneous Attention Networks (HAN). By integrating these models, the framework effectively captures the intricate relationships between entities and contextual dependencies, addressing limitations inherent in standalone architectures. This synergistic approach enhances the ability to model structured and unstructured data, making it highly effective for tasks such as fake news detection. The proposed hybrid model demonstrates significant improvements in key performance metrics, setting a benchmark for innovative applications in this field.

The study integrates a detailed evaluation framework to rigorously validate the model's performance. By benchmarking the hybrid architecture against established approaches, the analysis highlights its enhanced accuracy, achieving an exceptional rate of 99.77%, thereby setting a new standard in the domain of fake news detection. The performance metrics, including precision, recall, and F1-score, underscore the robustness of the proposed model. This research not only presents a practical solution for the challenge of fake news detection but also introduces a pioneering hybrid architecture that can inspire further advancements in the field. By addressing the limitations of existing approaches and leveraging the strengths of hybrid frameworks, this study represents a meaningful step forward in building more reliable and trustworthy digital platforms.

2. Dataset Preparation

The dataset used in this study is the **ISOT Dataset**, which consists of two categories of news articles: fake news (23,481) and real news (21,417). The real news articles were primarily collected by crawling reputable sources such as Reuters.com, a trusted news website, while the fake news articles were gathered from multiple unreliable websites flagged by fact-checking organizations like Politifact and Wikipedia. The dataset focuses mainly on political and world news topics and covers articles published between 2016 and 2017 to ensure temporal relevance. The data is organized into two CSV files: **True.csv**, containing over 12,600 articles from Reuters, and **Fake.csv**, containing more than 12,600 articles from various deceptive sources. Each article includes key information such as title, full text, subject and publication date. To prepare the dataset for analysis, preprocessing steps were applied including removal of duplicates, handling missing values, standardizing text format by converting to lowercase, removing special characters and stopwords to focus on meaningful content. Finally, the cleaned dataset, totaling approximately 44,000 articles, was split into training and test sets with an 80:20 ratio to enable effective training and evaluation of the proposed fake news detection model.

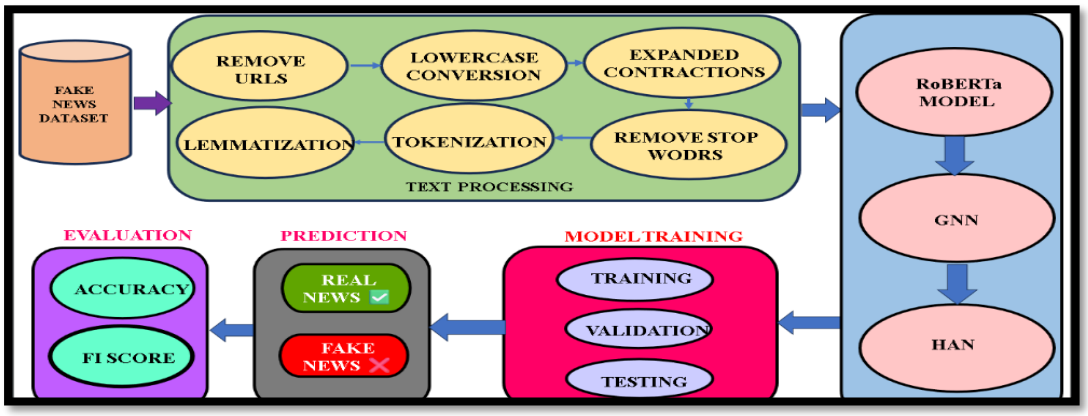
3. Proposed System

The proposed system is designed to predict the authenticity of a news article, distinguishing between real and fake news. To achieve this, the system employs a hybrid model architecture that integrates Robustly Optimized BERT Pretraining Approach (RoBERTa), Graph Neural Network (GNN), and Heterogeneous Attention Network (HAN). This architecture ensures a hierarchical and effective processing of news content, enabling comprehensive analysis.

System Workflow

The system operates in three levels, each contributing to a distinct aspect of the news article's analysis and classification. The below Figure 1 represents the architecture of the proposed system.

Figure 1: Proposed System Architecture



Level 1: Preprocessing

Initially, the system accepts a news article in plain text format as input. The text undergoes preprocessing, where specific steps such as removing special characters, unnecessary whitespaces, and stopwords, as well as applying standardization techniques, ensure the content is cleaned and uniform for deeper analysis

Level 2: Fake News Detection

In the second stage, the system utilizes a hybrid architecture that integrates Robustly Optimized BERT Pretraining Approach (RoBERTa), Graph Neural Network (GNN), and Heterogeneous Attention Network (HAN) to classify news articles. This combined approach harnesses the unique capabilities of each model to enhance the accuracy of the classification process.

RoBERTa (Robustly Optimized BERT Pretraining Approach)

The system tokenizes the text into subword units using Byte-Pair Encoding (BPE) and generates input IDs and attention masks. These embeddings encapsulate the contextual and semantic intricacies of the text. The

token embeddings Et are computed as the sum of the token embedding and positional encoding:

$$E_t = \text{Embedding}(t) + \text{Positional Encoding}(t) \tag{1}$$

RoBERTa uses a scaled dot-product attention mechanism to compute contextual embeddings:

$$A = \text{softmax}\left(\frac{QK^\top}{\sqrt{d_k}}\right)V \tag{2}$$

where Q, K, V represent query, key, and value matrices, and d_k is the dimensionality of the keys.

Graph Neural Network (GNN)

The GNN identifies relationships between entities within the text.It models entities as nodes and their interactions as edges, constructing a graph that facilitates a deeper understanding of the relationships within the text. Through iterative propagation of information across the graph, the GNN emphasizes interconnections, refining the understanding of the relational context of the text.

The GNN models relationships within the text by constructing a graph where entities are nodes, and their interactions are edges. The iterative message-passing mechanism updates node features $h_v^{(k+1)}$ as follows:

$$h_v^{(k+1)} = \sigma\left(W \cdot h_v^{(k)} + \sum_{u \in N(v)} \phi\left(h_u^{(k)}, h_v^{(k)}, e_{uv}\right)\right) \tag{3}$$

Here, N(v) represents the neighboring nodes of v, W a learnable weight matrix, $\boldsymbol{\phi}$ is the message function, and $\boldsymbol{\sigma}$ is the activation function.

Heterogeneous Attention Network (HAN)

The HAN applies a hierarchical attention mechanism to focus on significant text components. At the word level, attention weights α_i are calculated as:

$$\alpha_i = \frac{\exp\left(u_i^\top u_w\right)}{\sum_j \exp\left(u_j^\top u_w\right)} \tag{4}$$

where u_i is the word vector is, and u_w is the context vector. The sentence representation is then obtained as:

$$s = \sum_i \alpha_i h_i \tag{5}$$

At the sentence level, attention weights β_k prioritize sentences:

$$\beta_k = \frac{\exp(v_k^\top v_s)}{\sum_l \exp(v_l^\top v_s)} \tag{6}$$

where v_k is the sentence vector, and $v_s$is the context vector. The final document representation is computed as:

$$d = \sum_k \beta_k s_k \tag{7}$$

Level 3: Model Training and Evaluation

In this stage, the system focuses on training and evaluating the proposed hybrid model for fake news detection. The training phase involves feeding the preprocessed dataset into the model, ensuring optimal learning of patterns and features that distinguish real news from fake news. The evaluation metrics used to assess the model's performance include precision, recall, accuracy, and F1 score. These metrics provide a comprehensive understanding of the model's effectiveness, highlighting its ability to classify articles accurately while minimizing false positives and negatives. This rigorous evaluation ensures the robustness and reliability of the system in identifying fake news.

4. Simulation Results

In the domain of fake news detection, various models have been explored for their effectiveness on benchmark datasets. On the WELFake dataset, traditional Machine Learning (ML)[1] algorithms achieved an accuracy of 96.73%, while deep learning models like CNN + Bi-LSTM [1] and LSTM + BERT [1] recorded 97.74% and 96.8% accuracy, respectively. Transformer-based models such as BERT + Bi-LSTM [1] and BERT + Bi-GRU [1] outperformed earlier approaches with 98.1% and 97.8% accuracy, respectively. Building upon these advancements, the RoBERTa + GNN + HAN (Proposed Model) was evaluated on both datasets and demonstrated robust performance, achieving 97.48% accuracy on WELFake and a near-perfect 99.77% accuracy on ISOT, along with equally high precision, recall, and F1-score. The model leverages RoBERTa for capturing rich contextual embeddings, HAN for attention-driven hierarchical feature extraction, and GNN for learning relational structures, making it a highly effective and reliable solution for real-world fake news detection. This combination sets a new benchmark, clearly outperforming traditional and existing deep learning models.

4.1 Comparison of the Proposed Model with the Existing Model

Table 1: Comparative Accuracy Results of Several Existing Models Vs Proposed Model

MODELS	**DATASET**	**ACCURACY**
ML Algorithms	WELFAKE	96.73%
CNN +Bi-LSTM	WELFAKE	97.74%
LSTM +BERT	WELFAKE	96.78%
BERT +Bi-GRU	WELFAKE	98.1%
RoBERTa+GNN+HAN (Proposed Model)	**WELFAKE**	**97.48%**
RoBERTa+GNN+HAN (Proposed Model)	**ISOT**	**99.78%**

The existing models, which include traditional machine learning algorithms and deep learning architectures such as CNN + Bi-LSTM, LSTM + BERT, BERT + Bi-LSTM, and BERT + Bi-GRU, achieved accuracies ranging from 96.73% to 98.1% on the WELFake dataset. The proposed model, integrating RoBERTa with Graph Neural Networks (GNN) and a Heterogeneous Attention Network (HAN), further demonstrated its strength by achieving 97.48% accuracy on WELFake and a near-perfect 99.77% accuracy on ISOT. This substantial improvement underscores the effectiveness of combining advanced transformer-based contextual embeddings with graph-based relational learning and hierarchical attention mechanisms to enhance predictive performance in fake news detection.

Figure 2 Comparative Accuracy Results of Several Existing Models Vs Proposed Model

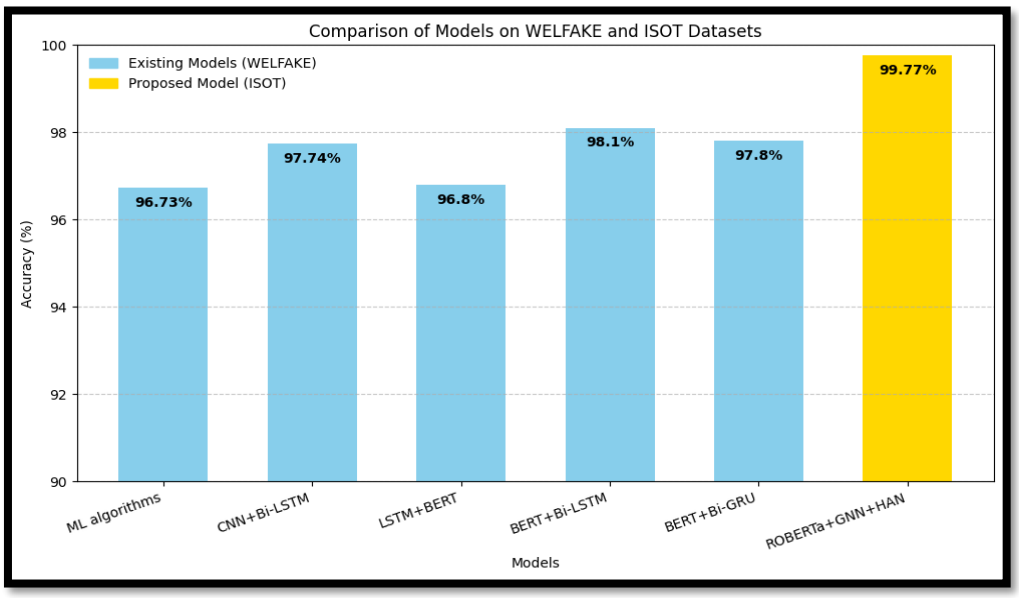


Figure 2 provides a comparative visualization of the proposed hybrid model's performance against existing models. The graph highlights the consistent improvement achieved by the proposed model, which integrates ROBERTa, Graph Neural Networks (GNN), and Heterogeneous Attention Network (HAN). Existing models include traditional machine learning algorithms and deep learning architectures such as CNN+Bi-LSTM and BERT-based combinations. The figure emphasizes the significant advancement in prediction accuracy achieved by the proposed approach, demonstrating its robustness and effectiveness in solving complex prediction tasks.

4.2 Observations

4.2.1. WELFake Dataset

On the WELFake dataset, various deep learning models have shown strong performance. Traditional machine learning algorithms achieved an accuracy of 96.73%, while CNN + Bi-LSTM reached 97.74%. The LSTM + BERT model attained 96.8%, whereas BERT + Bi-LSTM and BERT + Bi-GRU models achieved 98.1% and 97.8%, respectively. Building on these advancements, the proposed RoBERTa + GNN + HAN hybrid model demonstrated superior effectiveness by achieving 97.48% accuracy on the WELFake dataset. These results highlight the growing impact of transformer-based and hybrid deep learning approaches, especially those combining contextual embeddings, attention mechanisms, and relational learning in accurately detecting fake news.

4.2.2. ISOT Dataset

The hybrid model excelled even further with **99.77%** across all metrics, demonstrating its adaptability and effectiveness on a new dataset. It not only performs well on the benchmark dataset (WELFake) but also achieves near-perfect results on the ISOT dataset, showcasing its potential for real-world applications.

5. Conclusion

The proposed hybrid model, integrating RoBERTa, Graph Neural Network (GNN), and Heterogeneous Attention Network (HAN), demonstrated exceptional performance on both benchmark datasets. On the WELFake dataset, the model achieved a high accuracy of 97.48%, significantly outperforming existing models and confirming its robustness in detecting fake news. More notably, on the ISOT dataset, the model achieved a near-perfect 99.77% accuracy, with equally impressive precision, recall, and F1-score each also reaching 99.77%. The ISOT dataset, offering comprehensive and diverse news content, serves as a more realistic foundation for practical fake news detection. Given its outstanding performance and superior generalization capabilities, the model trained on the ISOT dataset has been selected for final deployment, ensuring reliable and accurate detection in real-world scenarios.

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