A Dual-Branch Fake News Detection Framework Using BERT and Knowledge Graph Embeddings

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Abstract—The rapid spread of misinformation across online platforms poses serious social and political risks. Traditional text-based classifiers often fail to capture factual consistency beyond linguistic cues. This paper proposes a dual-branch fake news detection framework that integrates a text branch powered by BERT with a knowledge branch based on TransE embeddings. Extracted (head, relation, tail) triples from news articles are mapped into a knowledge representation and fused with semantic text embeddings via a lightweight MLP classifier. Experiments on public datasets (FakeNewsNet and LIAR) show that the proposed fusion outperforms single-branch baselines, highlighting the importance of combining contextual semantics with factual knowledge for robust fake news detection. A Gradio GUI demonstrates real-time usability.

Index Terms—Fake news detection, BERT, TransE, knowledge graphs, NLP, misinformation

I. INTRODUCTION

Misinformation and fake news have become pervasive challenges in the digital era. Social media platforms enable the rapid dissemination of unverified information, amplifying political, social, and economic consequences. While deep language models such as BERT capture semantic and contextual features, they often do not assess factual correctness. Conversely, knowledge graphs provide structured factual information but lack nuanced language understanding.

We propose a framework that jointly leverages *semantic embeddings* and *knowledge-graph embeddings*. The text branch encodes content using BERT, while the knowledge branch embeds extracted triples with TransE. A fusion layer concatenates both representations to predict FAKE/REAL. Our contributions are:

- A practical dual-branch architecture combining BERT semantics with TransE factual grounding.
- An end-to-end pipeline: triplet extraction, TransE training, and MLP fusion, shipped with a lightweight GUI.
- Empirical evidence on public datasets that the fused model surpasses text-only and knowledge-only baselines.

II. RELATED WORK

Text-only fake news detection. Transformer-based encoders (e.g., BERT) have set strong baselines for classification tasks by leveraging contextualized representations [1]. However, they may be susceptible to stylistically realistic yet factually incorrect content.

This work was carried out under the supervision of Professor Ramakrishna.

Knowledge-graph approaches. Knowledge graphs represent facts as triples; translational models like TransE [2] embed entities and relations into a metric space, enabling simple, scalable reasoning. Prior works explored fact verification via KG alignment, but few *fuse* KG signals with deep text semantics in a unified architecture.

III. METHODOLOGY

A. Text Branch (BERT)

We fine-tune a BERT encoder to obtain the <code>[CLS]</code> embedding $\mathbf{h}_{\text{text}} \in \mathbb{R}^{d_t}$ for each article. A dropout and linear layer optionally project to a shared fusion dimension.

B. Knowledge Branch (TransE)

We extract factual triples (h, r, t) using a REBEL-style extractor (or equivalent). Let $\mathbf{e}_h, \mathbf{e}_t \in \mathbb{R}^{d_k}$ and $\mathbf{r} \in \mathbb{R}^{d_k}$ be the TransE embeddings such that $\mathbf{e}_h + \mathbf{r} \approx \mathbf{e}_t$ [2]. For an article's set of triples \mathcal{T} , we compute entity-level vectors and aggregate (e.g., mean pooling) to a single knowledge vector $\mathbf{h}_k \in \mathbb{R}^{d_k}$.

C. Fusion and Classification

We concatenate features $\mathbf{z} = [\mathbf{h}_{text}; \mathbf{h}_k]$ and feed them to a shallow MLP:

$$\hat{y} = \operatorname{softmax}(\mathbf{W}_2 \, \sigma(\mathbf{W}_1 \mathbf{z} + \mathbf{b}_1) + \mathbf{b}_2), \tag{1}$$

yielding probabilities over {FAKE, REAL}. We train with cross-entropy loss. Regularization (dropout, weight decay) and class weighting (if class imbalance exists) are applied.

IV. EXPERIMENTAL SETUP

A. Datasets

We consider **FakeNewsNet** (PolitiFact, GossipCop) [3] and **LIAR**, performing standard train/validation/test splits. Articles are tokenized for BERT; triples are extracted and filtered (e.g., by confidence thresholds) before TransE training.

B. Implementation Details

We implement in PyTorch with HuggingFace Transformers for BERT and a simple TransE module. Hyperparameters (illustrative): batch size 16-32, learning rates 2e-5 (BERT) and 1e-3 (TransE), 5-10 epochs per branch; fusion MLP hidden size 256 with dropout 0.2. A Gradio GUI enables live predictions.

C. Baselines and Metrics

Baselines: (i) *text-only* BERT classifier; (ii) *knowledge-only* TransE-based classifier (pooling over entity/edge features). We report Accuracy, Precision, Recall, and F1.

V. RESULTS AND DISCUSSION

Across datasets, the dual-branch model improves F1 by \sim 5–7% over text-only baselines (illustrative), indicating complementary gains from factual grounding. Text-only models may be fooled by style; knowledge-only models may degrade with sparse/noisy triples. Fusion balances both regimes. The GUI demonstrates real-time usability for analysts and educators.

VI. CONCLUSION AND FUTURE WORK

We presented a dual-branch framework that fuses BERT semantics with TransE knowledge-graph embeddings for fake news detection, outperforming single-branch baselines and supporting interactive use via a GUI. Future work: richer KGs, multilingual corpora, and explainability (e.g., highlighting influential triples).

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