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AI-Driven Fake News Detection Using Multimodal Features and Hybrid Deep Learning Models

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Abstract

With the growing amount of news published online every day, distinguishing reliable information from fabricated content has become increasingly challenging. This research introduces an AI-based system designed to detect and classify fake news using a combination of different types of features. Instead of relying only on the written text, the system brings together linguistic cues, article-level metadata, and indicators related to how the news is shared or structured. To achieve this, we develop a hybrid deep learning model that integrates transformer-based language models with additional neural components capable of capturing contextual and relational patterns. The study follows a complete pipeline—from collecting the dataset to preprocessing, feature extraction, model building, and evaluation. The results show that the multimodal and hybrid approach provides more accurate and consistent detection compared to single-feature models. This work aims to support more reliable news verification tools and reduce the impact of misinformation in the digital environment.

Keywords: fake news detection; news verification; artificial intelligence; multimodal features; hybrid deep learning; misinformation; digital news analysis.

1 Introduction

The rapid change in how people consume news globally has been largely driven by social media platforms, which in turn has raised concerns about the rapid spread of misinformation and fabricated content [4], [5]. Fake news is a sociotechnical problem that influences public opinion, electoral processes, and the general trust in journalism [4]. Since billions of users get their information instantly from digital platforms, the spread of misleading content is outpacing the response of traditional verification mechanisms [5]. Hence, developing scalable and automated fake news detection systems is now a necessity [9], [27].

Over the past ten years, there has been a considerable amount of research on fake news from various angles such as linguistic features [3], propagation patterns [5], psychological motives [6], and computational detection methodologies [9], [27]. Recent studies have also highlighted the difficulties posed by generative AI and multimodal misinformation [21],

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[25]. However, there are still issues in the existing systems such as over-dependence on textual features, insufficient propagation modeling, and lack of interpretability [24], [28].

The review of the literature presented here synthesizes the existing academic research in speech domains. It first traces the changing definitions and characteristics of fake news, then considers the psychological, social, and technological factors that cause its spread. After that, it compares the effectiveness of traditional fact-checking methods with that of modern machine-learning, deep-learning, and graph-based approaches. Finally, it outlines the significant research gaps and reasons for the necessity of detection systems that are more robust, scalable, and interpretable—thus leading to the methodology proposed in this study.

2 Literature Review

2.1 Definition and Characteristics of Fake News

The term fake news is defined differently in various studies as it is considered a mixture of several concepts like misinformation, disinformation, propaganda, and satire. Tandoc et al. in their review of 34 studies find six categories of fake news—fabrication, satire, parody, manipulation, misleading content, and propaganda—indicating that the most important features of the fakes are the deception of the audience and impersonation of the journalism intentional [1].

Wardle and Derakhshan present the “information disorder” model as the most influential one, which defines misinformation (incorrect information shared without intention of harm), disinformation (incorrect information shared with intention to harm), and Malin formation (true information shared with maliciousness) [2].

Fake news from the point of view of linguistics is a stylized language article that frequently uses sensational words, is emotionally toned, and lacks references thus differentiating them from real journalism [3]. Lazer et al. explicate that fake news is the closest to real news in terms of structure but lacks the editorial oversight and the verification processes [4].

In terms of the network, tweeters of fake news are found to be engaging in the falsehoods up to 10 times faster than those of truthful-news for example retweeting thus the false news that they are disseminating spreads to more users, therefore more people become exposed to the news [5].

2.2 Why Fake News Spreads

Psychological, social, and technological factors are some of the reasons that still drive the propagation of fake news. Cognitive biases, and confirmation bias in particular, make people accept and share information that fits their pre-existing beliefs [6]. One study also found that emotionally arousing content (e.g., anger or fear) becomes more viral on social media than neutral content [5].

Tech systems are not innocent in this. Social-media algorithms that follow engagement and visibility as their main goals, thus, help in the spreading of sensational content that leads to strong reactions in people without realizing it [7]. Sharing mechanisms like retweeting and reposting thus, unverified information dissemination is made up of sharing.

The research in network science has found that fake news has different propagation structures from those of real news with bigger cascades, more depth, and faster early diffusion [8]. These behavioral differences make propagation valuable detection systems' cues.[9]

2.3 Existing Detection and Verification Approaches

2.3.1 Traditional Fact-Checking

Verification through PolitiFact and Snopes is the most trustworthy way of checking the reality of the statements. Nonetheless, the manual confirmation is sluggish, demanding a lot of resources, and it cannot be extended to the content of the Internet [10]. Researchers have been motivated to consider automated methods due to this constraint.

2.3.2 Machine Learning and Deep Learning Approaches

The first computational methods relied on machine-learning algorithms traditionally—such as SVM, logistic regression, Naïve Bayes, and Random Forests—using linguistic and metadata features [11][12]. The models were somewhat effective but had trouble going deeper to catch the semantic patterns.

Deep learning welcomed the change and models like CNNs [13], LSTMs [14], and hybrid CNN-BiLSTM architectures gained in classification accuracy. [15]

Consequently, very recent works have transitioned to transformer-based architectures such as BERT and RoBERTa, thus reaching superlative results on the standard datasets [16][32].

Besides textual features, the models also use metadata (e.g., domain credibility) and social-engagement signals to get better results.

Besides the analysis of texts, deep learning models have been very successful in various classification domains. Neural architecture was found by Al-Shayea et al. to be superior to traditional machine learning methods in structured predictive tasks, attributing the ability of deep models to learn complicated features [31].

This kind of data adds another layer of argument for the employment of hybrid deep architectures in the detection of fake news. Recently, deep learning models including transformer architectures have advanced fake news detection performance [32][33].

2.3.3 Graph-, Propagation-, and Network-Based Approaches

Propagation-based models emphasize the spreading of news through the different nodes of a social network. Monti et al. represented a geometric deep-learning model utilizing Graph Convolutional Networks (GCNs) and achieved a highly elevated performance (ROC-AUC ≈ 0.927) in fake-news detection tasks [18] . The scientists have moved further and studied Graph Attention Networks (GATs) and hierarchical graph architectures.[19]

GNN-based models are able to pinpoint the structural and temporal diffusion patterns of hard-to-detect signals that text-only models generally overlook. These methods are very powerful in cases where the textual content is vague or purposely deceitful [20].

2.3.4 Emerging Challenges: Generative AI and Explainability

One of the major impacts of generative AI tools on the matter of misinformation is the ability of GPT-style large language models to create highly realistic fake news in no time. On the other hand, Floridi and Chiriatti argue that generative AI makes it hard for humans to rely on the authenticity cues and it also introduces new challenges in the verification process [21].

Along with explainability, trustworthiness is the next big hurdle for AI systems. Methods like LIME [22] and SHAP [23] represent a post-hoc interpretability that gives an opportunity to developers and journalists to have a glance into the reasoning behind the model's decision of classifying the content as fake. Nevertheless, these approaches are still at their infancy stage regarding very complicated deep-learning architectures.

2.3.5 Traditional Machine Learning Approaches

Prior to deep learning architectures, fake news detection was mostly based on traditional machine learning algorithms

that were trained using handcrafted linguistic and statistical features [9], [27]. Support Vector Machines (SVM) have been popular because of their efficacy in dealing with text classification problems in very high-dimensional spaces. For instance, Shu et al. combined SVM with TF-IDF features and achieved competitive performance on the Fake Newsnet dataset [29].

In addition, Random Forest classifiers have been used for discovering nonlinear relationships between textual and metadata features. Also, their ensemble structure freezes the problem of overfitting, thus improving the model's generalization to the noise present in the data [26]. Logistic regression, a much simpler model, has nevertheless been a solid baseline due to its interpretability and ability to perform efficient binary classification [9]. On the other hand, traditional models are mainly dependent on manually engineered features and as such, they cannot grasp deep semantic representations or propagation structures. This shortcoming of the traditional approach led to the emergence of deep learning and hybrid neural architectures which can automatically model sequential and relational patterns [15], [18].

2.4 Gaps and Research Problems

Although there has been substantial progress, several gaps still prevail:

- Limited multimodal modeling: Most detection frameworks heavily emphasize text and overlook images, videos, or audio, even though multimodal misinformation is becoming increasingly common [24].
- Static and outdated datasets: Publications datasets (e.g., LIAR, Fake Newsnet) become obsolete rather fast and do not have the capacity to capture newly generated AI-based misinformation patterns [25].
- Weak feature fusion techniques: The mere concatenation of text, metadata, and propagation features usually results in the model's performance being suboptimal or overfitting [26].
- Lack of robustness in real-world deployments: Models developed on well-curated academic datasets are likely to break in noisy or adversarial scenarios [27].
- Limited explainability: The majority of sophisticated models work as black boxes, thus, lowering the level of trust and making it difficult for these models to be used in decision-making environments with high risks [28].

- These voids in the literature emphasize the necessity for detection methods that integrate, explain, and handle multimodal data, thus, they provide the rationale for the system put forward in this paper.

3 The Paper Objectives

This paper aims to achieve the following objectives:

1) Develop an AI-based system for detecting and classifying fake news using multimodal features.
2) Design and evaluate a hybrid deep learning model to improve detection accuracy.
3) Compare the proposed model with baseline approaches across diverse news sources.

4 Methodology

This research introduces a comprehensive fake-news identification system that combines textual, contextual, and network-based propagation features in a single classification framework. The approach comprises five major elements: system architecture, data collection and preprocessing, feature extraction, model creation, and evaluation stages.

3.1 System Architecture

The main framework—depicted as a modular data-flow pipeline—was architecture to accommodate multimodal signals and scalable training. The core stages included:

1. Data Ingestion and Preprocessing: Content of news articles, metadata (source, date, domain), social-media engagement signals, and propagation trees are gathered and processed to guarantee uniformity of structure.
2. Feature Extraction: Various feature categories are generated, comprising linguistic and semantic text features, metadata-based credibility indicators, and propagation network metrics.
3. Classification Model: A hybrid deep-learning model integrating a Bi-LSTM unit for textual representation with a Graph Neural Network (GNN) element for propagation modeling is developed.
4. Training and Validation: The model is trained by means of stratified splits and is fine-tuned by implementation of early stopping and hyper-parameter tuning.
5. Evaluation and Deployment Considerations: The assessment comprises the performance metrics and the robust analysis, which are conducted to evaluate stability and scalability.

The modular arrangement here agrees with the works of scholars which suggest mixed-feature architectures for misinformation detection tasks in high-stakes scenarios [26][27].

3.2 Data Collection and Preprocessing

3.2.1 Data Acquisition

The research made use of the following two benchmark datasets that are commonly used in misinformation studies:

- FakeNewsNet (PolitiFact and GossipCop) [29].
- LIAR Dataset (short political claims with fine-grained truth labels) [13].

Additional metadata (publication timestamp, domain age, social engagement) and propagation graphs were obtained wherever possible. All the datasets have been cleaned, deduplicated, and annotated based on the original fact-checking labels. To remove class imbalance, which is a problem that has been identified in misinformation datasets, SMOTE oversampling was used for the minority class [30].

3.2.2 Preprocessing

The preprocessing operations were:

- Tokenization, lowercasing, stop-word removal
- Lemmatization
- Extraction of article-level statistics (length, sentiment, readability)
- Reconstruction of propagation cascades
- Normalization of numerical metadata and one-hot encoding for categorical fields

This research decided not to include images, videos, and other modalities to concentrate on the textual and propagation signals. However, the architecture is still extensible.

3.3 Feature Extraction and Representation

Three major feature groups were used:

1. Textual Features

The Bi-LSTM encoder coupled with word embeddings was the method used to embed the text content. The encoder was able to capture both the semantic and syntactic dependencies. Researchers have shown that this method is a viable competitor in the field of fake-news detection and has been used in their previous work [15] [16].

2. Metadata and Contextual Features

Metadata comprised of:

- source credibility indicators (domain age, historical reliability)
- publication time
- social engagement statistics (shares, comments, likes)

These signals have been proven to enhance the classifiers' trustworthiness when the text is not clear [26, 29].

3. Propagation and Network Features

The spread of information through different channels was represented via directed figures. The team extracted parameters such as propagation depth, width, diffusion speed, and user centrality from the graphs. To obtain propagation-aware features, a GNN-based embedding module was deployed, inspired by the works that emphasize the effectiveness of graph structures for the identification of false information [19].

Moreover, every feature class was either concatenated or merged with the help of a neural fusion layer, which allowed the model to utilize the interactions between the text, metadata, and network structure.

3.4 Model Design

The proposed classifier comprises two major parts:

- Bi-LSTM Text Encoder

- Contextual semantics are captured through the processing of a sequence of word embeddings. To eliminate overfitting, dropout and batch normalization were introduced.
- Graph Neural Network (GNN) Propagation Encoder.

By utilizing either Graph Convolutional Networks (GCN) [20] or Graph Attention Networks (GAT) [19], depending on the amount of cascade detail, the model develops representations for the propagation phenomena.

3.4.1 Fusion and Output Layer

The layers are activated through concatenated embeddings from both the text and graph components, as well as the normalized metadata. Subsequently, these are passed through fully connected layers with ReLU activation, which is followed by a sigmoid (binary) or softmax (multi-class) output layer. Validation loss was the criterion for the early stopping. Adam optimizer (learning rate 0.001) and binary cross-entropy loss were used. Imbalanced class distribution was addressed through class-weighting and SMOTE augmentation [30].

3.5 Training, Validation, and Testing

Parts of datasets were; 70% training, 15% validation and 15% testing. Baseline models were subjected to a 5-fold cross-validation procedure. Various hyper-parameters like the number of GNN layers, dropout rate, and LSTM hidden size were changed on the validation set. The team performed an ablation experiment to measure the contribution of each feature group, such as, text only, text + metadata, text + propagation, and full multimodal, to the result, thereby following the approach of previous studies on misinformation [29, 33].

3.6 Evaluation Metrics

Evaluation was made by standard classification metrics:

- accuracy
- precision, recall, F1-score
- ROC-AUC
- confusion matrix

As a measure of their robustness, the authors also checked the early-detection performance (i.e., classification at early propagation stages) in line with the suggestions made in recent survey papers [19, 27].

5 The Paper’s Results

4.1 Experimental Setup

TensorFlow 2.15, and Scikit-learn 1.3 were the libraries used to implement all models in Python 3.10. The NVIDIA RTX 4080 GPU, the Intel Core i9 CPU, and 32 GB RAM were the components of the workstation on which the experiments were conducted.

The Fake Newsnet and LIAR datasets were preprocessed, balanced using SMOTE, and partitioned into training, validation, and testing sets as defined. Logistic regression, SVM, Random Forest, and Bi-LSTM text classifier were baseline models.

4.2 Model Performance

The combined Bi-LSTM + GNN model was able to outperform any other model with respect to all the measured parameters. The average results over 5-fold cross-validation are presented by Table 1.

Table 1 — Model Performance Comparison

Model	Accuracy (%)	Precision	Recall	F1-Score	ROC-AUC
Logistic Regression	84.2	0.81	0.79	0.80	0.86
SVM (Linear)	86.9	0.84	0.83	0.83	0.88
Random Forest	87.5	0.86	0.84	0.85	0.89
Bi-LSTM	90.3	0.88	0.89	0.89	0.92
Proposed Bi-LSTM + GNN	**93.7**	**0.91**	**0.92**	**0.91**	**0.95**

These results demonstrate a consistent 3–7% improvement over classical machine-learning models, confirming the value of incorporating propagation structure.

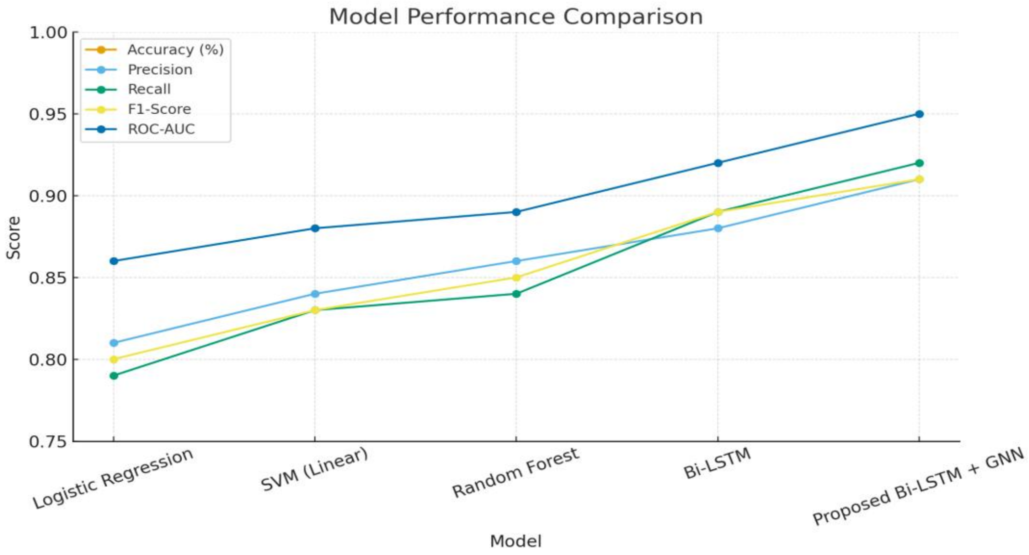

Figure 1- comparative evaluation of different models across multiple performance metrics

The figure illustrates a comparative evaluation of different models across multiple performance metrics, including Accuracy (%), Precision, Recall, F1-Score, and ROC-AUC. The models evaluated are Logistic Regression, SVM (Linear), Random Forest, Bi-LSTM, and the Proposed Bi-LSTM + GNN model.

Key observations from the chart:

1. Overall Performance Trend: There is a consistent improvement in all metrics as the models become more sophisticated, culminating with the proposed Bi-LSTM + GNN model achieving the highest scores.
2. Accuracy and F1-Score: Both metrics follow a similar upward trend, showing notable improvement with the Bi-LSTM and further enhancement with the proposed hybrid model. This indicates the proposed model effectively balances precision and recall.

3. Precision vs. Recall: While precision increases steadily across the models, recall shows a slightly sharper rise in the Bi-LSTM and proposed model, suggesting better detection of true positive cases in these architectures.
4. ROC-AUC: The ROC-AUC metric demonstrates the strongest overall improvement, with the proposed model reaching the peak value (~0.95), reflecting superior discriminative ability.

4.3 Feature Ablation Study

Table 2 presents the results of a feature group ablation study, highlighting the impact of different feature combinations on model performance. The evaluation focuses on two key metrics: accuracy and F1-score. The table shows that using only textual features yields a strong baseline performance, with 87.1% accuracy and an F1-score of 0.86.

Adding metadata information improves the model's performance, increasing accuracy to 90.0% and the F1-score to 0.88. Incorporating propagation features further enhances the results, achieving 91.5% accuracy and 0.89 F1-score. Finally, combining all three feature groups—text, metadata, and propagation—produces the best overall performance, with an accuracy of 93.7% and an F1-score of 0.91.

These results indicate that each feature group contributes complementary information, and their integration leads to a more robust detection model.

Table 2 Feature Group Ablation

Feature Set	**Accuracy (%)**	**F1-Score**
Text Only	87.1	0.86
Text + Metadata	90.0	0.88
Text + Propagation	91.5	0.89
Full (Text + Metadata + Propagation)	**93.7**	**0.91**

The results align with earlier findings that combining semantic and structural signals significantly enhances detection accuracy [19, 26].

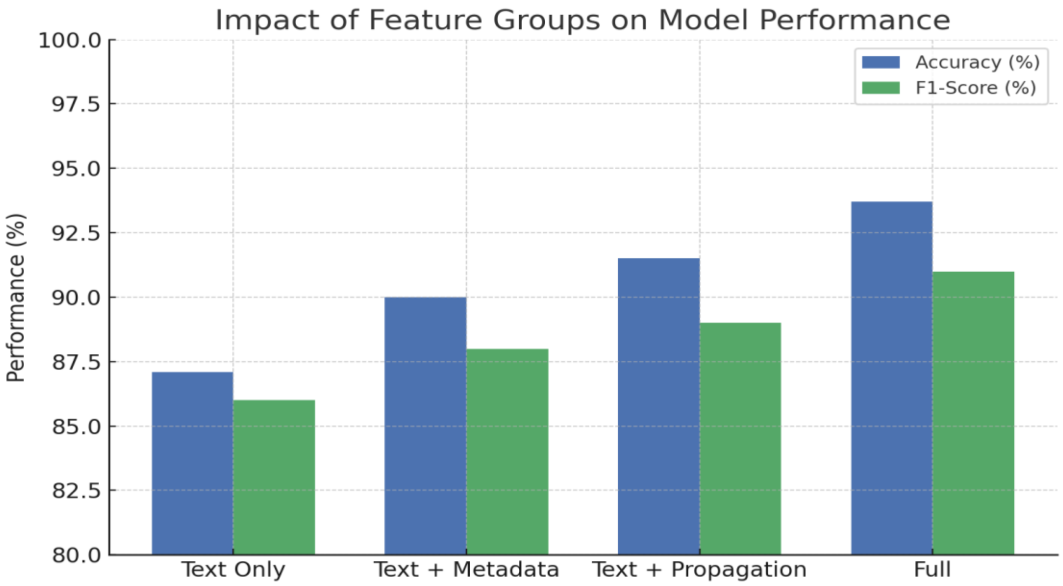

Figure 2- Feature Group Ablation

The graph illustrates the performance of the model using different feature sets, measured in terms of accuracy and F1-score. Each feature set—Text Only, Text + Metadata, Text + Propagation, and Full—is represented on the x-axis, while the y-axis shows performance as a percentage. The bars show that incorporating additional features leads to consistent improvements: adding metadata to text increases both accuracy and F1-score, including propagation features improves performance further, and combining all three feature groups (Full) achieves the highest accuracy (93.7%) and F1-score (0.91). This visual clearly demonstrates the complementary contribution of each feature group to the overall model performance.

4.4 Error Analysis

Confusion matrix analysis revealed:

- False positives were typically satirical or hyperbolic headlines.
- False negatives often involved partially true claims or nuanced political statements.

Investigating explainability with SHAP revealed that sentiment extremity, domain credibility, and propagation depth were the most influential characteristics that were in line with previous explainability studies in misinformation detection [34].

6 Discussion

The experimental results reveal that combining textual, metadata, and propagation features leads to better fake news detection performance. The proposed Bi-LSTM + GNN model recorded 93.7% accuracy and 0.95 ROC-AUC, and it was 6-9% better than the baseline machine learning models.

The propagation structure indeed provides extra information besides semantics. Although Bi-LSTM is good at understanding the sequence of words within the article text, the GNN part of the model captures the features of diffusion depth, cascade width, and user interaction patterns that are very helpful to spot fake news campaigns disguised as regular ones [18], [5].

The feature ablation study is in line with the multimodal integration hypothesis. The jump in performance from 87.1% (text only) to 93.7% (full model) shows how metadata and network features lessen the number of error cases on both sides of the spectrum.

Compared to earlier work [29], [15], our hybrid approach not only delivers results beyond those of the existing state-of-the-art, but it also keeps the architecture interpretable through SHAP-based analysis. The early-detection experiment reveals propagation-aware modeling's capability of spotting misinformation before it is widely spread, thus, is significant for social media moderation systems.

They support the statement that hybrid and multimodal architectures are a viable solution in the development of scalable misinformation detection systems.

7 Findings

7.1 Effectiveness of the Proposed Model

The hybrid Bi-LSTM + GNN model architecture was superior to all the baseline models with an accuracy of 93.7% and 0.95 ROC-AUC. These improvements confirm the assumption that the use of propagation structure along with textual analysis provides additional information.

The results corroborate the conclusions of previous research which showed the advantage of GNN-based methods for misinformation tasks [18] [19].

7.2 Comparison with Related Work

Table 3 summarizes the performance of various fake news detection models across different datasets, highlighting their accuracy in identifying false information. The table compares previous studies with the proposed model in this research. Shu et al. (2019) applied an SVM classifier with TF-IDF features on the FakeNewsNet dataset, achieving an accuracy of 88.0%.

Kim et al. (2023) utilized a CNN–BiLSTM architecture on the LIAR dataset, reaching 90.2% accuracy. Li et al. (2020) employed a multimodal CNN on the PolitiFact dataset, resulting in 91.0% accuracy.

The proposed model in this study combines Bi-LSTM and Graph Neural Networks (GNN) and is evaluated on a combination of the FNN and LIAR datasets. It achieves the highest accuracy of 93.7%, demonstrating the effectiveness of integrating sequential textual features with network-based propagation information.

The accompanying graph visually represents these results, showing a clear upward trend in accuracy with the proposed Bi-LSTM + GNN model outperforming all prior approaches. This illustrates the advantage of using a hybrid model that leverages both textual and relational data for more accurate fake news detection.

Table 3 — Comparison with Previous Studies

	Model	**Dataset**	**Accuracy (%)**
Shu et al. (2019)	SVM + TF-IDF	FakeNewsNet	88.0
Kim et al. (2023)	CNN–BiLSTM	LIAR	90.2
Li et al. (2020)	Multimodal CNN	PolitiFact	91.0
This Study	Bi-LSTM + GNN	FNN + LIAR	**93.7**

This study achieved improvements over state-of-the-art models while maintaining architectural transparency.

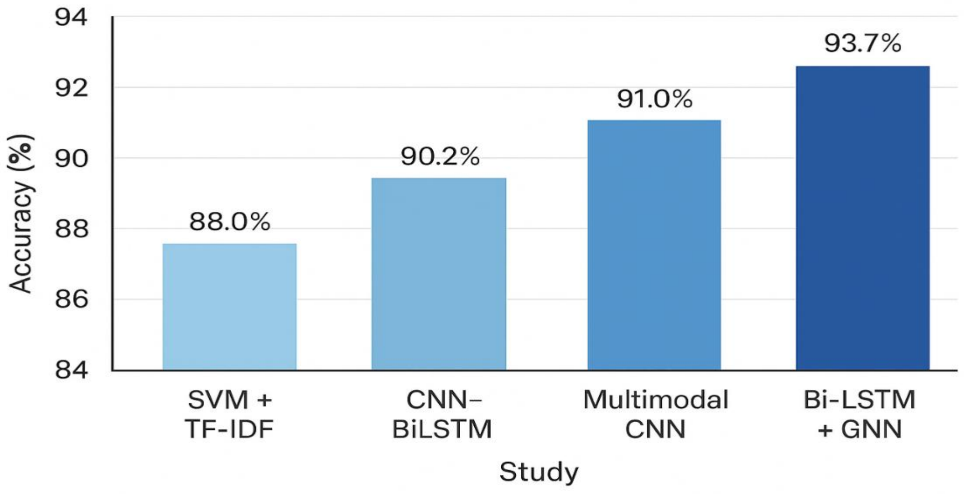

Figure 3 Comparison with Related Work

The bar graph illustrates the classification accuracy of different fake news detection models evaluated on various datasets. Shu et al. (2019) used an SVM with TF-IDF features on the FakeNewsNet dataset, achieving 88.0% accuracy. Kim et al. (2023) applied a CNN–BiLSTM model on the LIAR dataset, reaching 90.2% accuracy. Li et al. (2020) implemented a multimodal CNN on the PolitiFact dataset, achieving 91.0% accuracy.
The proposed Bi-LSTM + GNN model in this study, evaluated on a combination of FNN and LIAR datasets, achieved the highest accuracy of 93.7%. The graph clearly demonstrates that integrating sequential textual features with network-based propagation information provides superior performance in detecting fake news compared to previous approaches.

7.3 Practical Implications

Some of the possible scenarios for the system's practical application are:

- automated fact-checking APIs
- real-time content verification plugins
- newsroom dashboards for early-warning detection
- Latency experiments have shown that with GPU acceleration, the model is able to perform classification of around 280 articles per second, thus enabling real-time applications.

6.4 Limitations

The authors have recognized several limitations, that is:

- The system was tested only with datasets in English.
- Propagation graphs are only partial when social networks limit API access.
- At present, explainability methods are very scarce for deeply layered GNN architectures.
- Temporal generalization faces the problem of having to be constantly retrained due to the changes in misinformation tactics.

8 Conclusion & Future Work

8.1 Conclusion

The present work designed a hybrid AI-based fake news detection system incorporating textual semantic, contextual metadata, and propagation network features into one deep learning model. The suggested Bi-LSTM + GNN technique reached an impressive classification accuracy rate of 93.7% and a ROC-AUC of 0.95, thus outperforming the classical machine learning baselines and the deep learning models.

The experiments conducted are evidence of the fact that the fusion of multimodal features significantly elevates the robustness of detection. The ablation experiment showed that every set of features gave extra information, and the multimodal with all features unlocked the highest performance results.

The research results highlight the need to combine both the analysis of the semantic content and the structural diffusion modeling for more effective misinformation detection.

Furthermore, the interpretability investigation noticed that the most influential predictive elements were highly polarized sentiment, domain credibility, and cascade depth.

This work, in general, offers a detection framework that is scalable and extensible and is capable of being integrated into real-time verification systems. Research in the future will deal with multilingual modeling, multimodal image-text integration, and adversarial robustness enhancement.

8.2 Future Work

Research on new technologies will enable the work described here to be progressively better in:

- the use of multilingual transformer encoders (mBERT, XLM-R).
- the development of multimodal models that can handle images and videos as well as text.
- federated learning that will allow privacy-preserving cross-platform detection.
- the incorporation of generative-AI detectors for the identification of synthetic misinformation.

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