

A REVIEW ON DEEP SEQUENTIAL MODELS FOR FAKE NEWS IDENTIFICATION USING WORD EMBEDDING TECHNIQUES

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Abstract – Fake news has emerged as a critical challenge in the digital ecosystem, accelerating misinformation across social media, news portals, and online communication networks. Existing machine learning approaches often fail to capture long-range contextual semantics, resulting in limited accuracy and poor real-world generalization. This review paper provides a comprehensive analysis of deep sequential models LSTM, BiLSTM, and GRU for fake news detection, focusing on how these architectures improve contextual understanding and classification performance. The study examines key preprocessing methods such as tokenization, padding, and word embedding techniques including TF-IDF, Word2Vec, Fast Text, and embedding layers. It also synthesizes findings from recent literature, highlighting that many traditional and lightweight NLP models struggle to achieve accuracy beyond 80% due to dataset imbalance, lexical ambiguity, and domain-shift challenges. The review compares model performance, evaluates their strengths and limitations, and identifies critical gaps related to dataset diversity, multimodal fusion, and transformer integration..

Keywords: Fake News Detection, Deep Learning, LSTM, BiLSTM, GRU, Word Embedding Techniques, TF-IDF, Word2Vec, FastText, Sequential Models, NLP.

I. Introduction

The rapid evolution of the internet has fundamentally reshaped how people interact, communicate, and access information, primarily due to its low cost, convenience, and the ability to transmit news within seconds. This shift has encouraged a growing number of individuals to depend on social media platforms and online news portals rather than traditional newspapers or television broadcasts for real-time updates and events of interest [1]. While social media has become a powerful tool for information dissemination, it has simultaneously created an environment where vast amounts of unverified or misleading content circulate freely. Numerous studies indicate that a large portion of news shared online is intentionally crafted to deceive readers, and this trend continues to escalate across multiple platforms [2]. Such deceptive information commonly referred to as fake news consists of fabricated or heavily biased narratives designed to mislead audiences for personal, political, or economic gain, thereby influencing public perception and contributing to societal instability [3]. The consequences of fake news are far-reaching; during the COVID-19 pandemic, for example, misinformation significantly heightened public anxiety, contributed to psychological stress, and even affected physical well-being by weakening immunity due to prolonged fear and confusion [4]. Similarly, the 2016 U.S. presidential

election is widely cited as a major event where social media-driven misinformation may have shaped political attitudes and voting behavior, highlighting the growing influence of deceptive content in critical societal processes.

The growing ease with which digital content can be generated and disseminated further intensifies this challenge. Modern social media platforms enable anyone to create and publish news-like information, resulting in massive data streams that mix authentic content with manipulative or false narratives. This abundance of diverse, multimodal content spanning text, images, videos, and audio makes automated detection extremely complex. As a result, researchers worldwide have been increasingly motivated to explore and develop computational methods for identifying fake news with minimal human intervention. Machine learning and deep learning approaches have emerged as promising solutions due to their ability to analyze patterns, understand linguistic cues, and process large datasets efficiently. Recent advancements in natural language processing (NLP) and computer vision have broadened these capabilities further, enabling models to recognize toxic language, detect deceptive behavior, and differentiate between genuine and falsified multimedia content [5]. Deep learning models have shown significant potential because they can automatically extract hierarchical features from raw data, offering more robust and

adaptive solutions to misinformation detection challenges.

In recent years, multimodal fake news detection has gained attention due to the rising complexity of deceptive content that often combines text, images, and sometimes audio or video to appear more convincing. This interdisciplinary approach integrates NLP, visual feature extraction, and sometimes audio analysis to uncover subtle cues that may indicate manipulation. However, despite the progress made, the fake news problem remains difficult to solve. Misinformation is deliberately crafted to resemble authentic journalism, often employing emotionally charged language, stylistic tricks, and visual manipulation techniques that distort reality. The diversity of themes, cultural contexts, and linguistic styles, coupled with the speed at which information spreads online, further undermines traditional journalistic standards and complicates automated detection [6].

II. Background & Motivation

The rapid rise of the internet and social media has transformed how people consume news, with platforms like Facebook, Twitter, and online portals becoming primary information sources due to their speed, convenience, and accessibility. However, this shift has also accelerated the spread of misinformation, allowing fake news intentionally false or misleading content to reach millions within minutes. Fake news has influenced public opinion, created confusion, manipulated political narratives, and disrupted social harmony, as seen during major events like the 2016 U.S. presidential election and the COVID-19 pandemic. Because of the massive volume and variety of online content, manual fact-checking is no longer sufficient. This has motivated researchers to explore automated fake news detection using machine learning, natural language processing (NLP), and deep learning. Existing studies show that traditional ML methods (Naive Bayes, Logistic Regression, Random Forest) achieve moderate performance (around 70–75%) but struggle with contextual language understanding. To overcome these limitations, deep sequential models such as LSTM, BiLSTM, and GRU have emerged as powerful solutions due to their ability to capture semantic meaning, contextual relations, and long dependencies in textual data

III. Literature Survey

A comprehensive review of existing research is essential to understand the progress, challenges, and evolving methodologies in fake news detection. Several studies have explored machine learning, deep learning, and multimodal techniques to identify deceptive content across different platforms and domains. These works highlight the importance of linguistic features, contextual understanding, and cross-modal information for

improving detection accuracy. The following literature review summarizes key contributions from recent research, focusing on their methods, findings, and relevance to advancing automated fake news detection.

Table 1 Literature Reviews

S. No.	Year	Authors	Title	Key contribution / method	Dataset / result
1	2021	Kaliyar, Bhatia, & Saha [7]	FakeBERT: BERT-based fake news detection	Proposes FakeBERT, a BERT-based architecture for social-media fake-news classification improving contextual understanding over classical ML.	Evaluated on benchmark datasets; shows strong improvement over classical baselines.
2	2021	Alonso-Bartolomé & Segura-Bedmar[8]	Multimodal Fake News Detection	Systematic multimodal study: compares unimodal (text) vs multimodal (text+image) models; shows multimodal models (CNN+image) often outperform text-only BERT.	Experiments on Faked it: multimodal accuracy \approx 87%; BERT (text-only) \approx 78%.
3	2022	Hu, Wei, Zhao, & Wu [9]	Deep learning for fake news detection: A comprehensive survey	Large survey of DL approaches covering content, social context, external knowledge, supervised/weak/unsupervised methods.	Synthesizes datasets, architectures, evaluation metrics and open problems.
4	2022	Mulawahid et al. [10]	Covid Mis20 (dataset + detection)	Presents CovidMis20, a large COVID-19 misinformation tweet dataset and baseline	\sim 1.37 million tweets (Feb–Jul 2020); dataset

				detection methods for pandemic misinformation research.	released for research.
5	2021	Elhadad et al.[11]	Detecting Misleading Information on COVID-19 (PMC)	Proposes detection methods targeting COVID-19 misinformation; discusses linguistic cues and public-health impact.	Presents experimental detection pipeline and error analysis for COVID-related misinformation.
6	2023	Xia et al. [12]	Hybrid CNN-BiLSTM-Attention model for COVID fake news (2023)	Hybrid architecture combining CNN, BiLSTM and attention to capture local features + long-range context for COVID misinformation.	Demonstrates improved F1 on COVID-19 datasets (see paper).
7	2024	Shen et al. [13]	MCOT: Multimodal Fake News Detection with Contrastive Learning & Optimal Transport	Proposes MCOT that uses cross-modal attention, contrastive learning and optimal transport for better text-image alignment.	Strong results on Weibo and PHEME datasets; ablation shows benefits of contrastive learning.
10	2021	Shushkevich et al. [14]	COVID-19 Fake News Detection: A Survey (2021)	Survey focused on COVID-19 misinformation, datasets and domain-specific challenges; highlights public-health	Summarizes multiple COVID datasets and detection

					consequences.	approaches used in 2020–2021.
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IV. Text Preprocessing

Text preprocessing is a crucial step to clean and structure textual data before feeding it into machine learning models. According to the uploaded paper, preprocessing involves operations such as tokenization, lowercasing, stop-word removal, stemming/lemmatization, URL removal, and punctuation filtering. These steps reduce noise and improve feature extraction by eliminating irrelevant components that do not contribute to meaning. [15] Preprocessing also ensures consistency across the dataset, especially since fake news articles often contain grammatical errors, emotional wording, and exaggerated phrases. Properly preprocessed data improves the accuracy of models like Logistic Regression, Naïve Bayes, and Random Forest, which the authors tested as part of their ML pipeline.

V. Word Embedding

Word embeddings are dense vector representations of words used to capture their semantic meaning in numerical form. Unlike sparse Bag-of-Words approaches, embeddings such as Word2Vec or GloVe place semantically similar words close to each other in vector space, enabling machine learning models to better understand relationships between terms like “fraud”, “hoax”, and “misinformation.” [16] In fake news detection, embeddings help algorithms identify linguistic patterns, emotional tones, and deceptive cues that commonly appear in fabricated articles. By encoding contextual meaning, word embeddings significantly enhance classification performance compared to traditional text-representation methods, as also emphasized in related NLP studies referenced in the uploaded work

VI. Deep Learning Approaches

Deep learning models such as LSTM (Long Short-Term Memory), GRU (Gated Recurrent Unit), and BiLSTM (Bidirectional LSTM) are widely used for fake news detection because of their ability to learn long-term dependencies and contextual relationships within text. LSTM networks use memory cells and gates to retain important information over long sequences, making them effective for understanding complex sentence structures and subtle cues of deception. GRUs, a simplified variant of LSTMs, require fewer parameters and train faster while still capturing temporal dependencies, making them suitable for large-scale datasets. [17]BiLSTMs process text in both forward and backward directions, enabling the model to understand how earlier and later words influence each other, which is valuable in fake news where contextual manipulation is common. Although the uploaded paper primarily focuses on

machine learning classifiers, these deep learning models represent the next stage of research and are frequently cited as promising approaches for more accurate detection.

VII. Evaluation Metrics

Performance evaluation is essential for assessing the reliability of fake news detection models. Metrics such as accuracy, precision, recall, and F1-score provide a detailed understanding of a model's classification behavior, especially for imbalanced datasets where fake news samples may be fewer than real news samples[18] Precision helps determine how well the model avoids false positives, while recall measures its ability to detect actual fake news instances. The F1-score offers a balanced measure of both. Additional tools such as confusion matrices reveal common misclassification patterns, and ROC-AUC curves measure model discrimination across thresholds. The uploaded paper uses accuracy, precision, recall, and F1-score to evaluate Logistic Regression, Naïve Bayes, and Random Forest, noting that Naïve Bayes performed best on real-news detection while Logistic Regression performed better on fake-news prediction. Such evaluation approaches ensure that models generalize reliably and maintain consistency across diverse news categories.

VIII. Challenges & Limitations

Despite continuous advancements, fake news detection still faces several challenges. A major limitation is the lack of large, balanced, and high-quality datasets, as noted in the uploaded paper, where the skewness of the dataset reduced model accuracy for fake news compared to real news. Many fake news articles contain emotional language, subtle linguistic manipulation, or high similarity to real news, making them difficult for algorithms to distinguish. Detection models struggle with sarcasm, satire, and political bias, which require deep semantic understanding. [18] Fake news creators constantly evolve their strategies, producing more sophisticated content, including multimodal misinformation. Furthermore, models trained on one domain often fail to generalize to new topics or languages. Real-time detection is also challenging because information spreads rapidly, and continuous retraining is required to adapt to emerging misinformation patterns.

IX. Trends & Future Directions

Recent trends in fake news detection focus heavily on multimodal learning, where text, images, audio, and metadata are analyzed together to improve accuracy. This aligns with the future insights highlighted in the uploaded paper, which emphasize incorporating visual and multimedia analysis for detecting deepfakes and manipulated content. Another trend is the use of transformer-based models such as BERT and GPT,

which provide contextual embeddings and deeper language understanding compared to traditional ML approaches.[19] Cross-lingual and multilingual fake news detection is gaining traction due to the global nature of misinformation. Real-time detection systems integrated with social media platforms are expected to play a significant role in reducing the rapid spread of misleading content. Additionally, explainable AI (XAI) is becoming essential to improve transparency and user trust, as people increasingly demand to know why a piece of news is classified as fake. Future work will also include adaptive learning systems capable of evolving alongside misinformation tactics and collaboration frameworks between automated models and human fact-checkers.

X. Conclusion

Fake news remains a critical global challenge due to its ability to influence public opinion, disrupt social harmony, and spread rapidly through digital platforms. The uploaded paper demonstrates that machine learning models such as Logistic Regression, Naïve Bayes, and Random Forest can classify misinformation effectively, with optimized models reaching up to 75% accuracy in static search and over 90% accuracy in dynamic scenarios.[20] However, as misleading content continues to evolve, there is a growing need for advanced NLP techniques, deep learning architectures, and multimodal analysis to ensure more reliable and scalable detection. Continuous dataset updates, integration with real-time systems, and incorporation of explainable and ethical AI principles will be essential to counter misinformation more effectively. Overall, fake news detection is an active research area that demands constant innovation to keep pace with emerging threats.

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