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Exploring Some Roles of Deep Neural Networks in Fake News Detection: A Mixed-Methods Investigation

Shadan Taha Rashid [1], Mohammad-Reza Feizi-Derakhshi [1]*, And Pedram Salehpour [2]

[1]ComInSys Laboratory, Department of Computer Engineering, University of Tabriz, Tabriz 51666, Iran

[2]Department of Computer Engineering, University of Tabriz, Tabriz 51666, Iran

*** Corresponding author:** Mohammad-Reza Feizi-Derakhshi (E-mail; mfeizi@tabrizu.ac.ir)

Abstract

Given the rapid proliferation of fake news on social media, the need for intelligent methods to detect them has become increasingly urgent. This research aims to investigate the functions of deep neural networks in identifying fake news, developing more effective strategies to combat the spread of misinformation. Employing a mixed-methods approach, this study combined qualitative meta-synthesis and thematic analysis with quantitative t-tests to assess model validity. A systematic literature review of 15 articles identified 14 initial concepts, which were then categorized into three main concepts. Subsequently, semi-structured interviews with 12 experts, analyzed using thematic coding, yielded 21 components, grouped into three factors related to the functions of deep neural networks in fake news detection. The sample T-test results confirmed the validity of the proposed model, with findings ($p<0.0001$) including that the indicators generated were systematically linked, comprehensible, generalizable, and important for designing the model. By integrating the results from both stages, 27 initial concepts were consolidated into four main tasks: text feature extraction, news classification, learning patterns, and system tools. In conclusion, deep neural networks have the potential to play a significant role in combating the spread of fake news. However, achieving a fully accurate and reliable fake news detection system requires a multi-faceted approach that combines various methods and validates them through rigorous statistical analysis.

Keywords: neural networks, fake news, fact-checking, text mining.

1. Introduction

The advent of social media has empowered individuals to create and share content, significantly facilitating the rapid spread of fake news online. This has created an environment conducive to the dissemination of misinformation (Yinikar et al., 2023). Fake news, due to its threat to society, has become one of the most contentious issues of our time (Tarsli, 2023). Fake news is defined as false or misleading information presented in a way that mimics genuine news (Svetenko & Angelopoulos, 2024). That the power of spreading false rumors is rarely greater than that of true news. (Jahanbakhsh & at alm2023). Most fake news is fabricated and has a low level of factual basis. However, after several iterations, the original message becomes distorted, giving rise to a new narrative. Given the existence of media tools, information and communication have reached their highest level of importance in history (Akbari & Momtazi, 2022). The most crucial step in preventing the spread of fake news and saving lives is the "early detection of fake news." Individuals unknowingly share and participate in spreading misinformation. Detecting fake news and its dissemination patterns is of paramount importance to society and governments to prevent such incidents, analyze the motivations behind online news, and develop the ability to distinguish between truth and falsehood (Tarsli, 2023).

Some global regulations encourage platforms to utilize AI to identify and remove harmful content and fake news (Barclay, 2018). Most of the current community detection algorithms tend to find communities in social networks with just considering the topological structures of the networks. (Reihanian & at al ,2023). Due to the capability of DNN in extracting more complex features from unstructured data, DNN has naturally become an important approach to fake news detectionThese are particularly appropriate for text and image analysis and can identify subtle and meaningful patterns that are unnoticeable to human (Shu et al., 2020, Zhang et al., 2021, Devlin et al., 2019). DNNs play indispensable roles in fake news detection, often perform- ing state-of-the-art methods like RNNs and BERT pre-trained model. These systems can understand patterns of text, the structure of a sentence, and even sentiment. For instance, the literature has proven that BERT-based classification model on textual content features is successful in the problem of detection of fake news (J. Almarashy, Feizi-Derakhshi 2023). Additionally, the combination of neural networks and graph studies for prediction-based (prediction) of the spread of misinformation within social media increases algorithms' accuracy (Devlin et al., 2019; Monti et al., 2019). In literatures, it has been reported that these models operating at very high precision with the large data are able toidentifyfake news (Shu et al., 2020). But the complexity of such models, and the voluminous and high quality of the requisite data itself makes this sort of endeavor challenging. All of theseworks show that integrating DNN with other approaches, such as graph analysis, could enhance the performance of detection systems (Monti et al. 2019).

Fake news detection tremendously relies upon deep neural networks and employs different approaches (Shu et al., 2020). Convolutional neural networks are efficient at capturing local and important features of text such as the detection of fake sentences or words (Zhang et al., 2021). Besides, transfer learning models, e.g., BERT pre-trained on big corpora, also have the powerful capability in comprehending complex texts and detecting contradictions (Devlin et al., 2019). Also, convolutional and recurrent neural networks were applied to capture local and structural information of text (Kim, 2014, Hochreiter & Schmidhuber, 1997). These models incorporated a social network analysis and, in particular, a neural network to study how fake news spreads and interact in social media (Monti et al., 2019). These developments prove that deep learning is a viable method to cope with the problem of fake news detection.

Recently it has been proved that deep learning techniques are effective in fake news detection. For instance, when using CNNs to detect Persian news distributed over Telegram (with adding the channel ID value into the inputs), the accuracy was 90.46%(Akhgary andMotamadi et al,. 2022). Ibrahim et al. (2021) referred to global trends of criminalizing the circulation of fake news via social media and the Internet. Hashimi et al. (2024) showed that a hybrid model combining CNNs, LSTM layers and FastText embeddings surpassed the baseline for news article classifications in terms of accuracy. In addition, the use of transformer-based models has established their power to decode complex syntactic patterns for deep semantic comprehensionAs LIME and LDA do with Explainable AI, the analysis tools give interpretation and clarifying logic which the detection process requires. An AI misinformation detection system's user interface, boosted with Twitter analytics in real-time, social media activity, and corresponding metadata using LamaIndex's AI, enables users to understand the news and its impact better (Patil et al. 2024). By implementing sentiment and text analysis, ad detection, hate speech, and bot monitoring, this system is able to analyze articles as well as identify fake sponsors. In another study, Hu et al. (2024) explained how today's large language models have not fully usurped the role of small language models tailored for the task of detecting false information. Instead, they designed these advanced models to play the role of an aide, providing multi-angled informative reasoning for the fake news. Troika et al. (2024) proposed a model that used a deep neural network structure for the detection of fake news reliant on social context and textual components, by introducing a new network embedding where a text branch for social context and a social branch for social context content based on previously used, which came out on top of highly publicized small training datasets, beating record models by smaller data frameworks.

The rapid growth of social media platforms that produce massive amounts of content has turned the spread of fake news into a serious problem in the information era. Societies can be divided through manipulation of public perception, trust towards media and fake news. Hence, the creation of sophisticated, automated systems for fake news detection is critically important. One of the most powerful tools of artificial intelligence, deep neural networks, is capable of analyzing multifaceted datasets and identifying underlying structures. However, there are still many unresolved questions regarding the role of deep learning algorithms in the context of detecting fake news. Among these is the absence of a holistic and generic framework for assessing diverse neural network's performance within the scope of information processing, attention to non-English languages and various formats of news, and issues involving unbalanced datasets. Moreover, the dynamic and intricately organized nature of existing information gaps demands new methodologies of falsified fact alleviation.

Accordingly, this paper takes a step forward to explore the effectiveness of deep learning techniques towards detecting falsehoods while filling a few voids revealed from the literature.

The study of the functions of deep neural networks in fake news detection is very important. The epidemic of false information on digital platforms is gravely endangering democracy, national security and social stability. False information can shape public opinion in profound ways, weaken confidence in media and deepen society's divisions. In such a consideration, the requirement for intelligent developments and automatic detection of fake news arises as the need of the hour. Deep neural networks (DNNs), which can automatically learn rich and complex representations based on big data, are considered one of the most promising methods for solving this problem. The results of this study have the potential to promote better detection algorithms for fake news, encourage more media literate users and contribute to working towards a more healthy and reliable information environment.

2. Deep Neural Networks

Deep neural networks, a subset of the field of deep learning, are a class of computational models developed in imitation of the human brain. These models are layered with input, hidden and output layers that collaborate to process data and detect useful patterns. DNNs become more popular because of their capability to process complicated and unstructured data (LeCun, Bengio, & Hinton, 2015) that is useful in the case of fake news detection tasks. DNNs also work with fancy architectures, like Convolutional Networks (CNN) (Schmidhuber, 2015), Recurrent Networks (RNN) and the Transformer architecture, as BERT, to make advanced analyses. CNNs are good at extracting local features, which are beneficial to capturing deceptive keywords or ungrammatical sentences, and RNNs, including LSTM (Hochreiter and Schmidhuber,1997), are robust of modeling sequential and contextual information (Shu et al., 2020; Zhang et al., 2021). Transformer models such as BERT have transformed the landscape of text analysis by encoding complex semantic relationships and are incredibly accurate at fake news detection (Shu el al., 2020; Zhang et al., 2021).

These networks can be of various types (including those based on deep feature extraction, sentiment analysis, and anomaly detection) and they are capable of detecting emotionally charged language, logical inconsistencies, or stylistic differences common in fake news articles (Aggarwal& Zhia,2012). Besides, hybrid models combining CNNs and RNNs or integrating deep learning with classical machine learning approaches, like Random Forest and Gradient Boosting, for enhancing detection accuracy (Kim 2014; Hochreiter & Schmidhuber, 1997). Recent advancements also emphasize the use of Large Language Models (LLMs) trained on extensive datasets, enabling them to adapt to new patterns in misinformation effectively.

3. Fake News

The term "fake news" has emerged to identify misinformation in mainstream media, particularly concerning web-based content. However, research on fake news generally employs a more restricted definition. In a study, (Bandyopadhyay and Marcelloni 2019) defined fake news as a news article deliberately published with demonstrably false information. This definition hinges on two key aspects: intent and veracity. Therefore, fake news articles are those intentionally written to mislead or exploit readers, but whose falsity can be verified using other sources. Several recent studies, such as Conroy et al. (2015), have adopted this definition. Rubin et al. (2015) introduced distinctions between different facets of fake news. Specifically, the authors highlighted serious fabrications, large-scale forgeries, and humorous hoaxes. Serious fabrications represent the archetype of fake news, encompassing articles with malicious intent (e.g., fabricated interviews, pseudo-scientific articles, etc.) that are often virally disseminated via social media. Large-scale forgeries represent deceptive information disguised as legitimate news reports (Rubin et al., 2015).

3.1. Fake News Detection

Deep learning frameworks have obtained superior accuracy compared to the traditional machine learning approaches, by utilizing their ability for automatic feature selection. Feature extraction is a very time-consuming process and can lead to biased features (Ma et al., 2016). This issue is really big in the case of fake news and rumor detection because figuring out the analytical features can be quite challenging. On the other hand, deep learning frameworks can get hidden representations from less complex inputs (Ma et al., 2016). Consequently, the challenge has changed from the input features' relevant characteristics to the network's features, thus making a faster way of solving the problem possible.

3.2. Functions of Deep Neural Networks in Fake News Detection

Detecting fake news using deep learning relies on CNNs, RNNs, and Transformers such as BERT. These models explain the presence of emotionally charged language, illogical arguments, and unreliable sources in texts which are usually indicators of fake news. This work discusses some of the main concerns of these networks.

Text Feature Extraction involves separating text into its constituents, so it can be represented as a numerical or vector format suitable for machine learning algorithms. The aim of the process is to convey linguistic data in a text form that can actually be processed accurately through features like word count, sentiment, grammatical structure, and style (Aggarwal & Zhai, 2012). Certain complexities are later analyzed by advanced models like BERT and GPT at the semantic level. These models relate words and phrases in so many subtle but important ways that they can find logical contradictions in the text. At the same time, stylistic features of the text are analyzed by LSTM and GRU layers who compare the authorship to credible sources and look for anomalies. This is done in a deep network which guarantees that all parts of the text are examined from all possible perspectives.

Then, the system looks at the sentiment the text uses. The affective direction of the text, the modulation value of the expressed emotion and the emotional aptness of the text given the topic to be discussed are scored by means of deep-learning techniques. This is crucial as fake news is often disseminated on the grounds of triggering powerful emotions in users. During this, the model also picks up and keeps record of keywords and sentences used frequently in fake news. This is done using Attention Mechanisms – they enable the model to concentrate on the sensitive parts of the text. These include the frequency of individual words (feature extraction), the inclusion of unusual word combinations and recurring patterns. And at every step, the system is learning and adjusting. Every time it takes a new example, it makes an incremental gain in knowing what characteristics are a tip-off for fake news. This incremental learning occurs as a result of feedback loops and weight adjustments in neural network structures, leading to increased system accuracy. The decision layer then performs analysis of the extracted features. In this approach, the discovered features used in identifying fake news area weighted in a deep classifier to determine whether or not the news is fake. Such a procedure is designed to be very dynamic and adaptable in order to follow current patterns of the production of fake news and to overtime refine its quality (Shu et al., 2020).

3.3. News Classification

The problem of news classification has become more important in the context of Fake news detection in the area of NLP and ML to be able to differentiate the fake news from the real news and study the ways in which they are created and propagated. Fake news detection is a challenging task that has attracted a lot of interest from various aspects in the research papers. Earlier research has been focused on the, wherein a 'fake' and 'real' labels were assigned to the news using traditional machine learning methods such as Naïve base and SVM. But in recent years, deep learning models such as CNN and Transformers achieve better performance based on their better feature extraction capabilities for structure of the language. However, there are several open problems in medical image analysis, including imbalanced data distribution and requirement for high-quality labeled datasets. Furthermore, identifying multiple forms of misinformation (e.g., satire, propaganda, distortion) and ascertaining the reliability of classification is a critical research challenge. With the rapidly evolving tactics deployed by fake news creators, the ability to keep up and pin down misinformation is of growing significance. Apart from text analysis, techniques like source detection, audio and video analysis, manipulation detection in images, temporal regularity analysis, and temporal analysis of past news have been used in previous works as complementing methods to gain higher confidence in predicting fakeness of the news.

3.4. Learning Patterns

Contemporary fake news detection used innovative pattern learning methods to recognize and respond to new forms of misinformation approach, pattern discovery approaches, such as clustering and dimensionality reduction, which enables the discovery of hidden patterns in news data, as well as the continual learning method like Elastic Weight Consolidation [9], which permits model to gain new information without catastrophic forgetting. These features are especially important as fake news spreads rapidly across social networks (Monti et al. 2019).

Discriminative classifiers apply neural network architecture with softmax outputs to distinguish real from synthesized patterns and utilize ensemble techniquesto achieve higherquality via the aggregation of multiple models. These pattern integration methods enhance overall system robustness against new deceptions yet, at the same time, enable old jeopardy to do as well as they can. Recent works on meta-learning (Finn et al., 2017) demonstrate how similar approaches are able to implicitly adapt to new fake news features over different cultural and linguistic contexts (Jahanbakhsh et al., 2019).

3.5. Systemic Tools

To combat fake news, an array of complementary methods is needed, each focusing on some particular aspect of a multifaceted problem. Research indicated that hybrid strategy generally works better (Shu et al,. 2020), analogous to the way human fact-checkers combine multiple verification procedures (Hochreiter & Schmidhuber 1997). The recurrent neural networks, especially their LSTM variants, have proven particularly valuable (Shu et al,.2020). At 2018 LSTM implemented for the first time, it could track narrative inconsistencies across entire articles, its ability to maintain long-term dependencies and solving the vanishing gradient issue makes it ideal for spotting sophisticated misinformation.

Table1: Comparison of Artificial Neural Network Tools in Fake News Detection.

Tool	**Model Type**	**Sequence Understanding**	**Feature Extraction Capability**	**Language Support**	**Application in Fake News**
CNN	Deep Learning	Low	High	Medium	High
RNN / LSTM	Deep Learning	High	Medium	Medium	Very High
Random Forest	Machine Learning	Low	Manual	Low	Medium
Gradient Boosting	Machine Learning	Low	Manual	Low	High
Hybrid Models	Hybrid	High	High	Medium	Very High
LLMs (e.g., BERT, GPT)	Deep Learning	Very High	Very High	High	Very High

The interesting is how computer vision techniques have been adapted for analyzing texts, one of the techniques that perform well in recognizing images is convolutional neural network, CNN also remarkably effective at detecting suspicious word patterns in news articles by discovering unusual phrasing that appear in fabricated news (Zhang et al,. 2021). Transformer model like Bert that introduced by Devlin's team in 2018, made researcher to pay more attention to simpler tools, still Random Forests and Gradient Boosting have their role, especially when a new platform where training data need interpretable results.

Deep neural networks enable accurate news classification by intelligently. extracting textual features, such as linguistic patterns, writing style, sentiment, and semantic inconsistencies (Al-Kabbi, Feizi-Derakhshi et al,. 2023) and employing advanced systemic tools (e.g., BERT, CNN, and LSTM). These models, through continual learning from data, can identify fake news patterns and enhance classification accuracy through multilayered analysis. The result is an automated, dynamic, and reliable system for combating misinformation.

3.6. meta-synthesis

A meta-synthesis of the research background was also conducted to identify further dimensions and functions. Research Findings the theoretical literature and background were carefully reviewed and analyzed. Initially, a meta-synthesis of all relevant articles published between 2015 and 2024 in domestic and international scientific databases was conducted. The validity of all selected studies was evaluated using the 10 CASP criteria, resulting in the identification of 142 articles. After screening based on titles and abstracts, 66 articles were excluded due to irrelevance to the study's objectives. Subsequently, 32 of the remaining from 76 articles were eliminated due to duplication or an inappropriate study population. Following a full-text review of the remaining 44 articles, 30 were excluded for not meeting the inclusion criteria. Finally, 24 articles that met the inclusion criteria and had a quality score above 31 were included in the analysis. The coding and categorization process were also reviewed multiple times. All these activities were conducted to ensure the quality of the research findings, leading to the identification of the items presented in Table 2 as the functions of deep neural networks in fake news detection.

Table 2: Functions of Deep Neural Networks in Fake News Detection Extracted from the Empirical Literature.

Index	Component	Researcher (Year)
Text Recognition	Extracting semantic features from text, identifying language patterns, extracting text features, sentiment analysis of text, improving data quality	Manzi (2018), Shu et al. (2017), Shu et al. (2020), Monti (2019), Roshandel (1402), Zanjani et al. (1403)
Fake News Review	Detecting fake news based on news sources, identifying fake news based on visual features, detecting fake news based on location information, analyzing social networks	Manzi (2018), Versteet et al. (2022), Vosoughi (2018), Lakshman et al. (2019), Pinaparajo et al. (2020), Alonso (2021), Akhgari (1402),
System Review	Detecting fake news using hybrid models, using recurrent networks (RNN), using convolutional networks (CNN), random forest and gradient boosting algorithms, merging large language models (LLMs),	Manzi (2018), Roth (2022), Kenton and Tauntawa (2019), Tresley (1403), Emami (1402), Zanjani et al. (1403)

Findings revealed that 15 articles yielded 14 primary concepts, which were categorized into three overarching themes, as the primary functions of deep neural networks in fake news detection, as identified from the empirical literature. To ensure content validity, the literature review was assessed by two domain experts. Inter-rater reliability was evaluated using Scott's pi coefficient. Developed by William Scott in 1955, Scott's pi is designed to measure the reliability of nominal data. This method involves two coders (raters) independently coding the data, and reliability is determined based on the correlation between the two coders' ratings.

$$\pi = \frac{OA-EA}{1-EA} \qquad 1$$

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Where, OA (Observed Agreement) is the proportion of items where raters agree, EA (Expected Agreement) is the probability of chance agreement.

$$\pi = \frac{0.864 - 0.50}{1 - 0.50} = 0.728$$

Given that the Scott's coefficient exceeded 0.7, the reliability of the method and evaluation was confirmed.

The findings showed that 27 primary concepts (indicators), 4 themes, and main content were identified and determined in the form of deep neural network functions in detecting fake news.

Table 3: Dimensions and final elements of the research.

Main content	**Theme**	**Subcategories**
Functions of deep neural networks in detecting fake news	Text Feature Extraction	Language pattern recognition, stylistic feature recognition, semantic feature extraction, sentiment analysis, style recognition, keyword recognition, text feature extraction, data quality improvement
	News Classification	Classification of news into fake and real categories, detection of different types of fake news, assessment of classification confidence, adaptation to changes in fake news production methods, detection of misleading information, source detection, audio analysis, image analysis, manipulation detection, publication time analysis, news history review
	Learning Patterns	Identification of new patterns, continuous learning, pattern classification, pattern combination and fusion
	System Tools	Fake news detection using hybrid models, using recurrent networks (RNN), using convolutional networks (CNN), random forest and gradient boosting algorithms, fusion of large language models (LLMs),

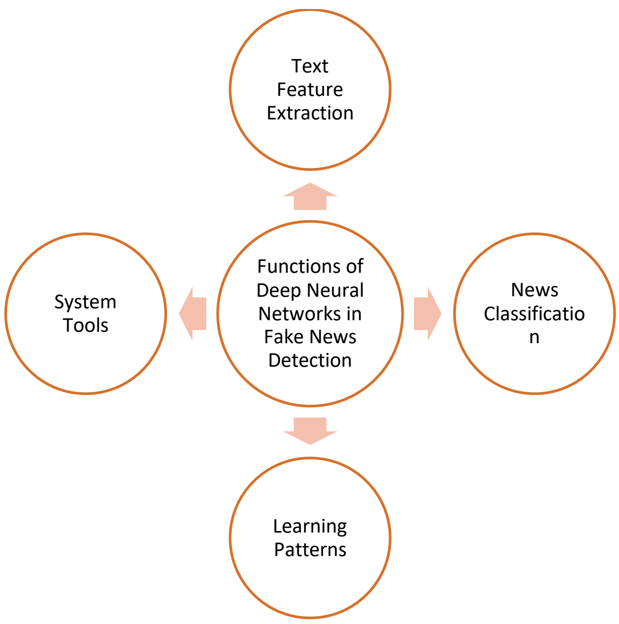

Figure 1- Qualitative model of deep neural network functions in detecting fake news.

Also, to examine the validity of the indicators and the model, the four criteria of Glaser and Strauss (1967) were used, which were based on the opinions of 12 experts from the interview section.

Table 4: Results of the one-sample t-test to determine the validity of the proposed model.

Item	Questions	Average	t	df	Sig.
Application	Are the indicators generated from the data examined?	4.653	14.137	11	0.0001
Comprehension	Are the indicators systematically linked together?	4.124	8.348	11	0.0001
Generalization	Is the model explained in such a way that it takes into account the changing conditions?	4.076	8.924	11	0.0001
Control	Do the theoretical findings seem important for the design of the model?	4.025	5.197	11	0.0001

The results in Table 4 demonstrate that the calculated t-statistic for the constructs of fit, comprehensibility, generalizability, and control is significant at the 0.01 level. Comparing the observed mean with the expected mean indicates that the final model possesses 99% confidence of validity as assessed by experts.

Discussion and Conclusion

In today's fast-paced information age, characterized by the proliferation of social media, fake news has emerged as a significant challenge. Deep neural networks, as one of the most powerful tools in artificial intelligence, exhibit exceptional capabilities in analyzing complex data and identifying latent patterns. Consequently, this technology has garnered significant attention as a promising tool for fake news detection. Accurately identifying the functions of deep neural networks in detecting fake news can enhance the precision and efficiency of fake news detection systems, ultimately enabling a more effective countermeasure against the spread of misinformation in the digital realm. We attempted to study the role of deep neural networks in fake news detection. Based on the results, the 27 concepts (indicators) were grouped into four concepts: text feature extracting, news classify, learning pattern, and system tool. The function of deep neural networks in fake news detection was to detect these. These results suggest that the ability of the model for semantic and pattern information, rather than only at the word and sentence level, supports its performance. Furthermore, this investigation indicates that the use of suitable NN architecture, efficient learning algorithms and state-of-the NLP tools has also an effect on the performance of the fake news detection models. The findings of this study can be used as a reference for further study in this regard and used as a base for creating more evolved systems with higher detection rate to fake news.

The results of this research indicate that deep neural networks can play a dominating role in fake news detection. By learning text features (e.g., language patterns, writing style, semantics, and sentiment), the model discriminates subtle differences between real and fake news. Detecting Fake News is a challenging one for models as it is hard to classify news into two main types (fake and real), and there are many subtypes of fake news that models have to tackle. It shows how these models can be further extrapolated to increase their confidence in the classification and robustness to the changes in the way fake news is produced. In addition, identifying misinformation, sources, audio-visual analysis, and tracing the history of the news helps in modelling the news in a holistic manner. In the learning patterns domain, the discovery of new patterns, lifelong learning, and the combination and integration of patterns illustrate the possibilities of deep learning and of enhancing performance when new data are presented. At the other extreme, the application of system methods such as hybrids, RNNs, CNNs, random forest, and gradient boosting, and the inclusion of LLMs, reveal the wide range and complexity of means that can be applied for fake news detection.

In line with this and in line with recent work (Shu et al., 2020; Zhang et al., 2021; Devlin et al., 2019), this work also reinforces the need for precise text feature extraction to capture linguistic, stylistic, and semantic features. Second, our results on the use of diverse deep neural network models, such as RNNs, CNNs, and pre-trained

BERT, are consistent with what has been reported in the literature. For example, it has been proved in the past that the integration of convolutional neural networks and recurrent neural networks improves the accuracy of fake news detection (Kim, 2014; Hochreiter and Schmidhuber, 1997). As mentioned in prior studies, this research demonstrates the importance of social network analysis and the use of graph neural networks in order to enrich the understanding of the ways in which fake news spread through social networks (Monti et al., 2019) that Persian rumors are often expressed in three SA classes including narrative, question, and threat, and in some cases with the request SA (Jahanbakhsh & at al,2019). Furthermore, as per the internal studies such as those of Akbari & Memarzi (2022), Ibrahimi et al. (2021), Hashemi et al. (2024), Patil et al. (2024), Ho et al. (2024), and Troika et al. (2024), and the studies supports the continuing progress of these studies in Iran and also the consistency between our findings and these previous studies. By utilizing the findings of existing researches and introducing new methods, the work has provided some insights about the role of deep neural networks in fake news detection, which serves as an indicative reference for researchers and developers of fake news detection systems.

The finding shows that DL model of different feature learning, classifying and learning methods has strong potential for detecting fake news. Yet comprehensive studies, such as enlarging size and diversity of training data in addition to novel algorithms, as well as the effect of social and cultural factors on the fake news propagation, are needed to improve model performance. Furthermore, due to the dynamic and complicated characteristic of fake news, fake news detection models need to be updated and enhanced regularly. Already then, deep neural networks can be considered as an important technique against the recent infodemics. However, a comprehensive and effective fake news detection system cannot be guaranteed by merely incorporating any single methodology of the fake news detection. This research is subject to limitations, including the dependence of models on the quality and quantity of training data. Imbalanced and insufficient data can significantly impact model performance. The ongoing evolution of fake news generation techniques necessitates continuous model updates. Therefore, future research should focus on developing reinforcement learning methods to enhance model performance with limited data. Another research is essential to identify novel and more complex features of fake news, such as employing deep linguistic analysis and graph neural models. Based on the results, it is recommended to utilize the developed models for constructing automated fake news detection tools on social media and news platforms. Furthermore, these models can assist search engines in ranking search results based on the credibility and accuracy of the news. Moreover, this research can contribute to the development of policies to combat the spread of fake news and enhance public awareness in this area.

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