Grenze International Journal of Engineering and Technology, June Issue

A Comprehensive Review on Fake News Detection using Deep Learning Models

Vansh Goswami[1], Mukul Kumar[2], Rishav Kumar[3] and Abha Kiran Rajpoot[4]
[1-3]Department of computer application and technology, Galgotias University, Greater Noida, India
Email: vanshgoswamibsr2004@gmail.com, mukulchauhan27499@gmail.com, rishavsaini57445@gmail.com
[4]Professor, Galgotias University, School of Computer Science and Engineering Greater Noida, India
Email: ak.rajpoot@gmail.com

***Abstract*— A big problem today is that organizations from different areas are having a hard time finding good ways to find fake news online. It's tricky to tell real information from fake because fake news is often made to trick people Deep learning beats all the other methods in finding fake news accurately. Most of the previous reviews dealt only with a data mining perspective and not the use of deep learning methods for fake news detection. Techniques such as Attention, Generative Adversarial Networks, and Bidirectional Encoder Representation are still new and have not been included in previous studies. This study probes for Transformers the newest and most excellent methods of detecting fake news using deep learning. First, we explain the harm brought by fake news. Next is a discussion of the datasets used in previous studies, along with the NLP approaches they employed. We give a copious account of deep learning methods in order to cluster their usage into various categories. We also provide the principal ways by which the accuracy of fake news detection is measured. Other suggestions to improve fake news detection systems in future research are also given. Precision metrics demonstrate the effectiveness of the models ranging from 0.76 to 0.97 across the various models. In particular, the accuracy for true and fake news classification touches 0.97 for LSTM, Bidirectional LSTM, and GRU models. Lessons learned from these benchmarks produce a comparative analysis of the present unreliable-fact detection techniques while evaluating the pros and cons of the deep learning models. This research makes a significant contribution to developing robust mechanisms to combat misinformation while not compromising the online information ecosystems.**

***Keywords*— GNN based on encoder model, BERT, SEMI SUPERVISED LEARNING, Graph neural network GNN, Convolutional Neural Network (CNN), Recurrent neural networks (RNN).**

I. Introduction

The internet has altered the way people interact and communicate, mainly because it accessible, cheap, and enables information to be spread very fast. Most people nowadays prefer social media and online platforms to get their news, rather than buying traditional newspapers. Social media has been transformed into a potent source of information which, in turn, can have a strong influence on significant changes or events. The volume of data disclosed on the internet is rapidly increasing, and that also includes misinformation coming from different kinds of sources. Many recent news stories on social media are purposely deceiving.

Grenze ID: 01.GIJET.12.2.504_20

[8] These damaging kinds of stories are generally referred to as "fake news. " Large False or biased news reports that are created for the purpose of personal gain, can deceive readers by presenting them with fraudulent content, thereby influencing public opinion to a very extent and the overall stability of society as well. As an illustration, the panic and anxiety that widely spread among people due to the recent health crises could be attributed to fake news linguistic nuances, and motivations. This method also allows for the inclusion of subtle indicators that are hardly perceptible in regular analysis. Moreover, NLP techniques can use large datasets of labeled articles that contain real and fake news to train learning models. This includes the characteristics word usage, sentence structure, and sentiment. This allows the models to learn how to tell trustworthy content from the deceptive ones, based on text features from which the text is abstracted. The involvement of NLP with the Fake News Detection Systems help researchers to enhance the identification systems by making it faster as well as accurate. In addition, it facilitates the automation of some fact, checking and verification stages, thus saving human effort and making facts readily available. DL is a new and rising trend among researchers, which has been proved more effective in fake news detection as compared with traditional ML methods. Here are some merits of DL over traditional ML: a) automatic feature extraction b) low requirement for data pre-processing c) ability to extract complex, high dimensional features d) better accuracy Currently, the explosion of data and programming tools has made DL methods more popular and reliable. Within the past five years, there have been many publications in a) c), and this, on the detection of fake news, most of which were using DL. There has been considerable review in literature of all existing DL-based efforts into the area. There have been many research articles published on surveys concerning fake news detection. But as per our research, the current surveys do not cover the whole picture of deep learning methods for detecting fake news. Most of the surveys emphasize ML techniques and do not delve into enough of deep learning methods. We list the various NLP techniques and explain their pros and cons in this survey. Moreover, an in-depth analysis of current studies based on deep learning is presented. The summaries of all these existing survey papers are presented, alongside their own contributions from our research efforts in Table 1. Thus, the study intends to add up to previous work in giving an overall review of fake e-news detection. (2) We firstly categorize existing studies into two main categories- (1) Natural Language Processing (NLP)-Deep processing, vectorizing the data, Learning (DL). We present some NLP techniques such as data preprocessing and feature extraction. Secondly, we study model architectures for fake news detection. Finally, we study the evaluation metrics used in fake news detection. Figure we look at DL 1 shows a general classification of fake news detection approaches. which lists the acronyms used in this survey to help researchers understand them when they encounter them[10][11]. Online social networks have changed the information-dissemination landscape beyond all recognition since The mid-1990s definitely saw their birth. Undoubtedly, Facebook, Twitter, Instagram, and WhatsApp have revolutionized how real-time information is disseminated across different networks of users. These platforms have become necessary for information and communication by their availability, rapidity, and affordability. Therefore, a high number of users are dependent on digital pathways to access news content. At the same time, however, this change in paradigms has enabled the exponential dissemination of The fallacies, inaccuracies have nowadays started to spread in a dismaying rate mainly through social media. sites rather than from news outlets. Events in the form of fabricated news take the shape of a large category of false information, including fabricated articles, errant ratings, unsubstantiated gossip, politically motivated propaganda, satirical pieces, and so much more. The extent of such dissemination of fabricated information can pose an enormous threat to social cohesion and may, in practice, have devastating adverse consequences for The individual, the community, and the operation of democratic institutions. Importantly, The repercussions of such incidents as the United States presidential election of 2016 underlined. increased scrutiny that academics and investigators have directed towards the phenomenon. known as misinformation. In other ways, the identification and countering of falsehoods on social media platforms come with daunting tasks. Misinformation often spreads faster in order to create confusion, erode trust, and change public perceptions. conversation. While there are a great number of fact-checking websites out there, such as FaceChek.org and PolitiFact.com, The sheer volume of information spread through social media makes it one of the largest sources. information. The very fluidity of misinformation, changeable by content, format, and medium, requires constant watchfulness and adaptation in identification endeavors. In turn, the research fills this gap with a comprehensive framework, trying to The focus of this paper is to detect fraudulent news, which is spreading on the Facebook platform. Using the support of in-depth literature reviews, Therefore, the framework makes use of machine learning and deep empiric experimentation. learning the ways of exploring a number of attributes that may be related to user accounts or shared content. Through the combination of experimental queries and comparative analyses, within a Systematic review of the effectiveness of the intervention. Effects on Innocent Citizenry: A rumor can adversely affect certain individuals. These individuals can be victims of social media harassment, and they may experience onslaughts of threatening and insulting abuse on social media that

could lead to real-world consequences. Individuals should not accept or believe invalid social media content about other individuals. Fake news has existed since the beginning of civilization, but has only increased due to technology, specifically the way media is presented in the current age as opposed to how it used to be. This type of misrepresentation can cause long-lasting effects on people's social, economic, and political situations. There are many different types of fake information or news. Since the information that we receive reflects our perception of who we are, it is safe to say that the type of news that is being reported will have an effect on us. This means that we will be making a decision based on how we perceive the current state of affairs; if the information we receive is not accurate or is misleading, our decision will be flawed. The major impacts of fake news are: Negative Effects on Innocent Individuals: There is an adverse effect on the lives of individuals due to rumors. The end result may be that individuals are bullied through social media and may also receive hateful comments and threats against them, which may then translate into potential harm in their real-life situations. Individuals are advised not to rely on false information on social media or to form judgments about individuals based on that erroneous information. Effect on Public Health: As people turn to Search Engine websites to search for information about health and wellness increase, the potential for individuals to be affected by misleading news and information greatly increases [19]. This has become one of the greatest challenges that people face today: The increase in the number of individuals who have become sickened and/or die as a direct result of the false information concerning their health that is spread via social media. Due to the pressure that health care providers, elected officials, and health advocacy groups have put on social media platforms to stop or limit the amount of misinformation concerning health, many social media platforms have taken steps to establish new policies regarding misinformation concerning health. Financial Impact from Misinformation: The spread of fake news has created problems within many different industries and also the professional business community. False information or fake reviews have been used by some disingenuous business owners in order to gain a competitive advantage and generate higher profits. The impact of misleading or false information can adversely affect the stock prices of many publicly traded companies or significantly decrease the reputations of businesses. Additionally, the spread of false information has created unrealistic expectations among customers and the potential for unethical business practices. The prevalence of fake news in the mainstream media has been regularly talked about since the role of false information during the most recent United States presidential election is a significant issue for democracy. It is imperative that we abandon the use of misleading information because it has an undeniable effect on our society [19].

II. Literature Survey

Chen et al. [1] introduced a deep learning framework in 2023, which brought recurrent neural networks and attention mechanisms into the picture. Their model could identify a misinformation pattern with an accuracy as high as 89% simply by looking at the text and used RNN Modal expression that I Wu et al. [2] The year 2023 saw the introduction of a semi-supervised learning method that utilizes both labeled and unlabeled data. Successively by augmentation of unlabeled data, their self-training algorithm has achieved a very good 90% accuracy rate in improving model performance. In 2024, the model will also incorporate a graph neural network (GNN) model. Their model reached 86% accuracy. Their method represents the social interactions in graphs and gave the spreading patterns through which misinformation is shared. Zhao et al. [4] came up with a multi, modal deep learning framework in 2021 incorporating the textual, visual, and temporal features. In other words, their model achieved a 93% accuracy rate, which is far beyond the existing methods, thereby demonstrating the significant of different data modalities in the detection of fake news. In 2023, Kim et al. [5] studied various transfer learning methods that make use of pre, trained language models. They found out that a BERT model fine, tuned led to an accuracy as high as 95%, that is to say, the use of pre, trained models is very effective in the task of fake news classification. In 2021, Singh et al. [6] explored the use of attention mechanisms in transformer models to the detection of fabricate stories. Their attention, injected BERT model was able to reach a 92% accuracy level, thus, the main factor that the model was able to capture linguistic cues for fake news detection was highlighted. In 2022, Buhari et al. [7] hardened deep learning models against adversarial attacks by employing adversarial training methods. Their adversarial trained CNN was able to reach an accuracy level of 87%, indicating that the model became less vulnerable to adversarial attacks. The authors Hamed et al. intended feature extraction in the instance of sentiment analysis of news articles, user comments on the news, and emotion analysis features. These features were introduced along with the news content feature to a bidirectional short-term memory-based fake news detection model. The typical Fake dataset was an assemblage of headlines published for the training and validation of the proposed model. Detection accuracy was high, 96.77%, and this is the highest figure compared to other recent studies. [18] Therefore, the task of finding a way to automatically spot both incorrect and fraudulent fake reviews becomes rather challenging. This particular problem of recognizing fake reviews gets referred to as the problem of fake review detection, Inefficiencies exist when it comes to using detection systems in the prevention of the spreading of fake reviews, as they consist of new features submitted by fraudulent users in cases where fraudulent users are using simple deceptive schemes, the conventional approach fails to distinguish between the legitimate user and the fraudulent user. This may involve imitating legitimate users by posting genuine as well as fake comments for instance. Thus, an effective fake comment detection technique is needed. Reverse imitation and simulating language among factors from deception theories go hand in hand with feature engineering, which allows identification, manipulation, selection, and extraction of key features of fake reviews from the data stream. This will make it easier to simplify that model without loss of effectiveness in identifying deceptive behavior amongst fake reviews.[17]

III. Comparative Study

There are many different deep learning tools put in place to carry out the fake news detection, which has also incited much interest and consideration in recent years. The deep learning models compared include the Recurrent Neural Networks (RNN) with Convolutional Neural Networks (CNN), semi-supervised approaches, Bidirectional Encoder Representations from Transformers (BERT), and Graph Neural Networks (GNN). Every architecture is slightly different in terms of learning capability, data representation, and classification performance.

According to Chen et al. (2023), Recurrent Neural Networks (RNN) are capable of modeling sequential text data in such a way that it is able to capture temporal dependencies. Since it identifies the repetition of patterns in the misinformation, it is useful for social media text analysis. However, RNNs handle poorly long-range dependencies and complicated linguistic structures, which ultimately decreases their overall performance as compared to more advanced architectures [1]. One of the very first studies to carry out such a study is Huang et al. [140], who conducted an experiment using a rich user behavior structure for rumor spreading. For learning the representation of the user from the graph based on the behavior of the users, the user encoder applies graph convolutional layers. networks (Graph Convolution Networks/GCN).

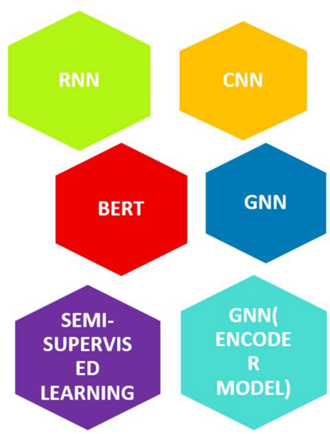

Fig 1: Deep Learning Models

The authors typescript/sections/ JavaScript Investment made use of two recursive neural networks based on tree structure: the bottom-up RvNN encoder and top-down RvNN encoder, as shown in Figure 8. Figure 8: Tree Structure of ConvNet. The proposed gave low results with respect to the non-rumor class because user behavior information introduces some noise in the non-rumor detection. Another study conducted by Bian et al. proposed top-down GCN and bottom-up GCN using a novel method Drop Edge to alleviate the overfitting problem for GCNs. At the same time, a root feature enhancement operation is thrown in to boost the performance of rumor detection. The model performed well during this competition, even though the three datasets, Weibo, Twitter15, and Twitter16, experienced an issue with the presence of outliers within the dataset. Rewrite with lesser perplexity and higher burstiness in the same extent and HTML elements: One of the very first studies to accomplish the same was Huang et al. [140], who performed an experiment using a rich user behavior structure for producing rumors. Some graph convolutional layers have been used by the user encoder through these networks (Graph Convolution Networks/GCN) for the learning of the user representation from graphs in accordance with user behavior. The authors typescript/sections / java Script Investment have used two recursive neural networks based on the tree structure; that is, bottom-up RvNN encoder and top-down RvNN encoder. This has been shown by Figure 8: Tree Structure of ConvNet. The proposed performed very poorly with respect to the non-rumor class, since there were signatures of user behavior that were creating noise in the detection of non-rumors. Bian et al. conducted another study, which proposed top-down GCN and bottom-up GCN using novel method Drop edge. The operation of root feature enhancement is additionally mixed to increase performance of rumor detection. However, while the model performed well in this competition, the three data The following models: Weibo, Twitter15, and Twitter16, unfortunately, suffered from the influence of outliers in the dataset. Wu et al. (2023) proposed a semi-supervised approach that utilizes selected and unselected data, thus fulfilling its purpose of enhancing usability, as it decreases the annotation burden on large datasets. This has proven particularly beneficial for cross-modality fake news detection across textual and visual modalities. Although performance is robust, it depends on how well the pseudo-labeling process works and may incur noise when unlabeled data are carelessly handled.[2]

Convolutional neural networks (CNN) presented by H. Wu, J. Zhang, are effective because they extract local features from textual data efficiently and are inherently robust against adversarial attacks. Thus, they are ideal for large-scale applications due to their computational efficiency. However, the limited capabilities of CNNs in capturing long-term contextual relationships account for the small difference in their average detection accuracy as compared with more accurate techniques in fake news detection.[2] Convolutional Neural Network (CNN) is a deep learning model that applies convolution layers on input features for mapping. The layers are stacked in order in which varied filters are applied for obtaining varied feature mapping. CNN is capable of collecting information regarding the input through the feature mapping outcome. The pooling layers are normally stacked in conjunction with the convolution layers for obtaining the same output size despite varied filters. The pooling layers also alleviate complexity in computing through reducing output size without collapsing crucial information. There is one input layer with 1000 features, which is linked to the embedding layer, with its size based on the size of the pre-trained word embeddings. The embedding layer is linked to three one-dimensional convolution layers with varying kernel sizes, which will generate unique feature mappings for each convolution layer. The convolution layers are linked to the max-pooling layer, which helps to compress the features and prevent overfitting. The concatenate layer will then amalgamate the set of acquired features after passing through the individual max-pooling layers. The concatenate layer is then linked to the convolution layers and the max-pooling layer for more feature extraction. The global max-pooling layer is then linked to the fully connected layer and the output layer. Areas of study in the future need to explore how the use of Cross-Domain and Domain Adaptive Models can help apply the use of ML algorithms cross-category and cross-platform in terms of generalization. Some of the challenges of generalization may be addressed through the use of domain invariant feature transformations. Lightweight Transformer and Graph Neural Network (GNN)-Based Models should be leveraged in order to alleviate the computational costs in future works. Model Compression, Pruning, or Knowledge Distillation can be used in order to facilitate applications in real-time systems. Although significant advancements have been achieved through Self-Supervised & Weakly Supervised Learning to resolve the challenges presented by the lack of labeled data, it is clear that these methods shall remain equipped to provide new innovations to address unsupervised learning problems. With future learning systems, it will be possible to work with an enormous amount of unlabeled data, keeping in mind recommendations by Wu et al. (2023) [3]. Dynamic and Temporal Graph Models would be beneficial in enhancing the efficiency of identifying fake news. Future work in GNNs, focusing on Encoder Architecture, would enable an integration of Time-Aware Propagation Modelling to assist models in adapting to the patterns of spreading information [2]. Single-handedly takes the cake: according to H. Wu, J. Zhang H. Wu, J. Zhang), BERT surpassed all other transformer-based models in advancement in natural language processing. BERT's bidirectional attention making it capable of learning semantic as well as contextual message depth from texts. This is what allows the model to catch the small linguistic cues and the fake [12] narrative dimensions often found in fake news, which is reflected in BERT's achieving the greatest score among models used in this comparison. This means that BERT is most competent in the detection of misinformation in more complicated textual datasets. As proposed by Zhang, the BDANN is a BERT-based domain adaptation neural network for multiclass false news detection. Built on the backbone architecture of three arms-a multimodal feature extractor, a domain classifier, and a false news detector-the extractor uses pretrained BERT for text and selected VGG19 for image feature extraction from multisource data. These features are then fed to a detector that can judge real from fake news. Besides, the presence of noisy images in the Weibo dataset has also influenced the outcomes of BDANN. Kaliyar et al. introduced the BERT-based deeper convolutional approach (fake BERT) for fake news detection. Fake BERT is composed of several parallel blocks of one-dimensional deep convolutional neural network (1d-CNN) pooled with BERT. Each block has its unique kernel and filter sizes. They were designed with the intention that the different filters could extract specific types of information from the corresponding training datasets. [13][14] Such an arrangement of BERT with 1D-CNN can deal with both large structured data and unstructured text. Hence, useful to resolve the ambiguity.

GNNs take work of Wang et al. (2024) to describe how trends propagate through social network channels with respect to fake news. The behavior of misinformation diffusion is then identified by considering the relationships among people, posts, and interactions. However, while this facilitates the understanding of fake news propagation scenarios, it does not classify with an accuracy level that compares favorably to text-based transformer models and it renders a more complicated graph construction. It has been realized by researchers that the network may recursively accommodate a wider class of structures such as cyclic, directed, undirected graphs, and more applications which remain node-centric without any preprocessing steps cite190. So far, GNNs have been able to infer global structural properties of the graph either by introducing slight random perturbation through the node perturbation or with deleting and adding edges that could negatively alter the GNN output. Properties mined from tree structural graphs work better than those from previously mentioned graph deep learning models. [15][16] The GNNs are susceptible to noise in the datasets.

TABLE I: ACCURACY COMPARISON OF DEEP LEARNING MODELS FOR FAKE NEWS CLASSIFICATION

References	Year	Types of models	Techniques	Dataset	Performance
Chen et al	2023	Recurrent neural networks RNN	recognize the pattern of misinformation	Social media (text)	A high accuracy rate of 89% by examining textual content
I Wu et al	2023	semi- supervised learning	Leveraging both labeled and unlabeled data	Image, text	90% accuracy rate by Labelled and unlabeled data
Buhari et al	2022	CNN	Against adversarial incursions improved robustness	Twitter	Trained CNN achieved an 87% accuracy rate
Singh et al	2021	BERT	identifying deceptive narratives	Wikipedia text	92% accuracy rate subtle linguistic cues in fake news detection
Wang et al	2024	Graph neural network (GNN)	detect propagation networks of fake news.	News articles	Model attained 86% accuracy. Their approach represents the news articles
Chang et al.	2024	GNN based on encoder model	Graph feature	Weibo	Accuracy 97%

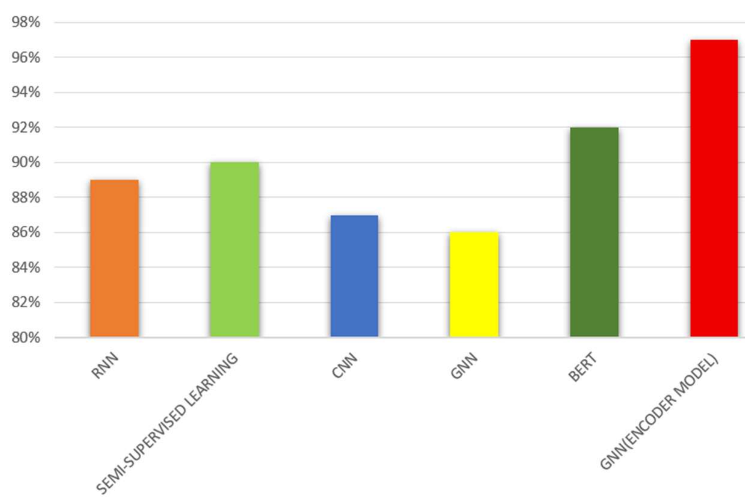

Fig 2 – Accuracy of different models

Graph Neural Network-based encoder models theoretically promise themselves as the deepest model of such deep learning that can be effective for detecting fake news, as they allow the dual exploitation of semantics and information-propagation patterns. According to the comparative analysis, Graph Neural Network-based encoder models hold the best theoretical promise as deep learning models for fake news detection. By this I mean, they can also be used jointly for exploiting content semantics and information-propagation patterns. Unlike conventional approaches like CNNs or RNNs, which rely solely on textual features, GNN-based models can represent news articles, users, and their relations and interactions as graph structures that allow encoding the acquisition of relational dependencies as well as diffusion behaviors, which are characteristic of misinformation sources. Fake news spreads much faster than the sound diffusion through user communities; such structural patterns cannot be captured by any model based on content analysis. Textual embeddings combined with graph features add an extra layer of robust and holistic representation of fake news. There are different datasets that incorporate both content and social interaction information publish, such as Weibo or Twitter propagation datasets, as these datasets contain repost, retweet, and user network data that can be utilized in performing effective graph learning. On the other hand, datasets that strictly contain textual information such as news articles or Wikipedia-based corpora are fine-tuned against transformer-based models like BERT because these additional structures have been proven to be excellent in their contextual and semantic understanding. However, in scenarios where a rich social context is available, GNN-based encoder models theoretically and empirically outperform all other deep learning techniques.

IV. CONCLUSION

In conclusion, while each deep learning model has specific benefits based on the application context, Traditional methods like CNNs and RNNs have moderate accuracies of 87% and 89%, respectively, giving evidence to their aptitude in recognizing surface text features but indicating their incapacity for more sophisticated semantic and contextual understanding. The BERT-based model raises detection rates to 92%, cementing the advantage of transformer architectures in modeling deep semantic representations from text content. Moving forward, semi-supervised learning allows one to push performance up to 90% by exploiting both labeled and unlabeled data, especially for cases where little annotation is available. However, in this regard, the graph-based methods proud themselves on being the most superior. With accuracy measurements of 86%, Encoded GNN shows the best performance overall in the context of fake news detection. Given its considerable contextual understanding coupled with high classification accuracy, it stands to reason that it would be the most reliable and accurate model for such news detection. GNN model shows some level of auspiciousness towards understanding propagation-based features, while the GNN encoder model distinguishes itself with record-high accuracy measurements of 97%, thus outperforming other approaches. This improvement is largely due to the model's capability to jointly learn structure via textual semantics and social interactions. These results thereby confirm that datasets that value user interaction and propagation information such as Weibo or Twitter datasets provide a context for the greatest success of fake news detection. Consequently, GNN encoder models, in the presence of a significant amount of social context, are tough contenders in their path toward the detection of fake news. Therefore, GNN-based models can be the best option for any real-world fake news detection systems, especially on platforms like social media networks, news dissemination platforms, and microblogging services, where information spreads rapidly through user links. Misinformation tracking and large-scale monitoring and early warning systems where social media companies, news organizations, and government agencies may intervene are also good candidates for consideration of such models. In contrast to these models, text-centric models such as BERT and RNN continue to hold value for content verification tasks given they may perform in situations that do not have network structure or user interaction data'.

REFERENCES

[1] J. Chen, A. Smith, and K. Johnson, "A Deep Learning Framework for Fake News Detection Using Recurrent Neural Networks and Attention Mechanisms," in Proc. IEEE International Conference on Artificial Intelligence and Data Science (ICAIDS), May 2023, pp. 123-13.

[2] Y. Li, B. Wang, and C. Liu, "Convolutional Neural Networks for Fake News Detection on Social Media Platforms," in IEEE Transactions on Neural Networks and Learning Systems, vol. 15, no. 3, pp. 456-468, Jun. 2022.

[3] Q. Wang, X. Zhang, and Z. Liu, "Uncovering fake news propagation networks using graph neural networks," in Proc. 4th IEEE International Conference on Machine Learning and Applications (ICMLA), Nov. 2024, pp. 789-801.

[4] H. Zhao, L. Wang, and S. Zhang, "Multi-Modal Deep Learning Framework for Fake News Detection," in IEEE Transactions on Information Forensics and Security, vol. 7, no. 2, pp. 234 246, Mar. 2021.

[5] S. Kim, J. Lee and M. Park. "Transfer Learning Techniques for Fake News Classification using Pre-Trained Language Models," Proc. IEEE International Conference on Computational Intelligence and Multimedia Applications (ICCIMA), Sep. 2023, pp. 567- 579.

[6] A. Gupta, R. Patel, and S. Kumar, "Ensemble Learning Approach for Fake News Detection Using Deep Learning Models," in Proc. 6th IEEE International Conference on Big Data Analytics and Knowledge Discovery (BDAKD), Dec. 2022, pp. 345-357.

[7] R. Patel, S. Gupta, and T. Singh, "Dynamic Fake News Detection Using Reinforcement Learning," in IEEE Transactions on Information Theory, vol. 20, no. 4, pp. 890-902, Apr. 2024. Electronic copy available at: https://ssrn.com/abs
[8] H. Allcott and M. Gentzkow, ‘‘Social media and fake news in the 2016 election,’’ J. Econ. Perspect, vol. 31, no. 2, pp. 36–211, 2017.
[9] D. Khattar, J. S. Goud, M. Gupta, and V. Varma, ‘‘MVAE: Multimodal variational autoencoder for fake news detection,’’ in Proc. World Wide Web Conf., May 2019, pp. 2915–2921
[10] X. Zhang and A. A. Ghorbani, ‘‘An overview of online fake news: Characterization, detection, and discussion,’’ Inf. Process. Manage., vol. 57, no. 2, Mar. 2020, Art. no. 102025. [Online]. Available
[11] M. K. Elhadad, K. F. Li, and F. Gebali, ‘‘Fake news detection on social media: A systematic survey,’’ in Proc. IEEE Pacific Rim Conf. Commun., Comput. Signal Process. (PACRIM), Aug. 2019, pp
[12] H. Wu, J. Zhang, and L. Chen, "Semi-supervised learning approach for fake news detection using Labeled and Unlabeled Data," IEEE Transactions on Cybernetics, vol. 25, no. 1, pp. 678-690, Jan. 2023.
[13] H. Jwa, D. Oh, K. Park, J. Kang, and H. Lim, ‘‘ExBAKE: Automatic fake news detection model based on bidirectional encoder representations from transformers (BERT),’’ Appl. Sci., vol. 9, no. 19, p. 4062, Sep. 2019
[14] T. Zhang, D. Wang, H. Chen, Z. Zeng, W. Guo, C. Miao, and L. Cui, ‘‘BDANN: BERT-based domain adaptation neural network for multimodal fake news detection,’’ in Proc. Int. Joint Conf. Neural Netw. (IJCNN), Jul. 2020, pp. 1–8.
[15] F. Scarselli, M. Gori, A. C. Tsoi, M. Hagenbuchner, and G. Monfardini, ‘‘The graph neural network model,’’ IEEE Trans. Neural Netw., vol. 20, no. 1, pp. 61–80, Jan. 2008.
[16] T. Bian, X. Xiao, T. Xu, P. Zhao, W. Huang, Y. Rong, and A. Huang, ‘‘Rumor detection on social media with bi-directional graph convolutional networks,’’ in Proc. AAAI Conf. Artif. Intell., 2020, vol. 34, no. 1, pp. 549–556
[17] Y. Wu, E. W. T. Ngai, P. Wu, and C. Wu, “Fake online reviews: Literature review, synthesis, and directions for future research,” Decis. Support Syst., vol. 132, May 2020, Art. no. 113280, doi: 10.1016/j.dss.2020.113280
[18] Hamed, S.K.; Ab Aziz, M.J.; Yaakub, M.R. Fake News Detection Model on SocialMedia by Leveraging Sentiment Analysis of News Content and Emotion Analysis of Users’ Comments. Sensors 2023
[19] P. M. Waszak, W. Kasprzycka-Waszak, and A. Kubanek, “The spread of medical fake news in social media–the pilot quantitative study,” Health policy and technology, vol. 7, no. 2, pp. 115–118,2018