Reviewing Machine Learning Algorithms for Fake News Detection

Pradeep Kumar, Saroj Ratnoo

Department of Computer Science and Engineering, Guru Jambheshwar University of Science and Technology, Hisar 125001, India

Corresponding author: Pradeep Kumar, Email: pradeepk0411@gmail.com

With the proliferation of online platforms such as social media, digital media, e-news websites, etc., spreading fake news has become easier than ever before. The fake news may be propagated as political propaganda or for financial gain. Due to the sensational and captivating nature of fake news, many individuals unintentionally forward messages involving fake news. Fake news can be disseminated through manipulated mediums such as photos, videos, click-bait headlines etc. In its entirety, fake news weakens public trust and may cause chaos and confusion among people. Therefore, early detection of fake news is crucial to mitigate the serious implications of people being misinformed. At the same time detecting fake news is becoming increasingly difficult due to the advanced deceptive techniques used to make the fake news sound reliable. Researchers have turned to machine learning algorithms for automated fake news detection. This paper is a state-of-the-art review on identifying fake news using various machine learning algorithms including deep learning, transfer learning and hybrid approaches. It also enlists the frequently used datasets for fake news detection. Furthermore, the paper highlights the challenges in classifying news as genuine or fake, suggesting areas that require further research.

Keywords: Fake news detection, Machine Learning, NLP.

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1. Introduction

Fake news has emerged as a major concern in recent years, primarily due to the expansion of social media platforms and digital news outlets. The dissemination of false information is predominantly facilitated by popular online platforms such as WhatsApp, Twitter, Facebook, Instagram etc. [1]. Notably, fake news is not limited to social media or digital platforms alone; it is also propagated by traditional media houses often due to inadequate fact-checking or biased reporting. Fake news may be motivated by political propaganda or financial gains as well. Fake news captures mass attention and spreads rapidly due to its sensational nature. The consequences of fake news can be far-reaching leading to uncertainty, unwarranted insecurities, and even incidents of public disorder, such as community clashes or, in extreme cases, violence.

For instance, during the COVID-19 pandemic, a rumour suggesting that the vaccine caused infertility, changes in DNA and death fueled mistrust and fear among the public. This resulted in some individuals expressing reluctance towards vaccination.

Numerous similar instances demonstrate how the spread of fake news generates public mistrust, fear, or phobia. Therefore, it is imperative for individuals to critically evaluate messages and news they encounter, verifying their reliability before sharing or acting upon them. However, the sheer volume of online content and the use of sophisticated misinformation techniques make it increasingly challenging to detect fake news through traditional means. Fake news is delivered through anonymous sources, and it is difficult to trace its credibility. Fact-checking resources are limited and by the time fake news is identified; it has often already caused significant harm. Consequently, there is a pressing need to develop automated tools for early detection of fake news. Several machine-learning approaches have been extensively utilized to identify fake news from large amounts of data collected from newsfeeds and online platforms. These techniques encompass traditional machine learning approaches such as Support Vector Machines, Bayesian Classifiers, and Ensemble algorithms. However, recent research has primarily focused on designing deep and transfer learning approaches for fake news identification [2, 3, 4]. Furthermore, some hybrid techniques have also been successfully applied in this domain. Several reviews or survey papers have synthesized the research carried out in this field [5, 6].

In the sequence, this paper systematically reviews the machine learning approaches employed for fake news identification. We have considered the research works carried out from 2016 onwards, encompassing about six and half years. Acquiring a trustworthy and properly labelled dataset is of critical importance when addressing any supervised learning problem. Therefore, we summarize the frequently used datasets to assist practitioners in the field of machine learning in comparing their research to the earlier works. Finally, the paper highlights the challenges faced by researchers in the field of fake news classification, emphasizing the areas requiring further attention.

The paper is organized as follows: Section two summarizes the commonly used datasets for detecting fake news. Section three gives an overview of the methodology and research paper selection. Section four highlights the research contribution in devising machine learning techniques for recognizing fake news. Section five lists the challenges that are yet to be addressed in classifying news items or online messages as authentic or fake. Section six concludes the paper.

2. Commonly Used Datasets

To effectively combat the spread of fake news, it is crucial to understand the process for detecting it. Data gathering, preprocessing, feature engineering, model training, and evaluation are the stages involved in detecting false news. For the detailed process of detecting fake news, readers can refer to [24,25]. Data collection is the very initial step for any machine learning problem. We require a reliable dataset for training any model. Data can be taken from well-known repositories, or it can be collected from various sources and then labelled manually. The latter is very time-consuming and needs the expertise of several domains. Most of the researchers use datasets prepared and labelled by experts. This makes the comparison of various machine learning algorithms feasible for fake news identification.

Table 1 describes some of the commonly used datasets for fake news identification. It gives the name, source, and a brief description of each dataset.

Table 1. Commonly used dataset and their respective sources

Dataset	Source(s)	Description	Reference(s)
Twitter	Twitter-1, Twitter-2	Microblog dataset contains Fake/Real or Rumour/Non-Rumour labelled text samples.	[6,7, 8, 9]
Weibo NER	Weibo-1	The Microblog dataset contains rumour/non-rumour posts from Chinese Twitter called Sina-Weibo. This dataset was used to analyse misinformation during the COVID-19 outbreak in China.	[6,7, 8, 9]
LIAR	LIAR-1, LIAR-2	This is a dataset for fake news detection with 12.8 k human-labelled short statements from Politifact.com APIs.	[7]
Snopes	Snopes	The dataset consists of rumours that are analysed on the Snopes website along with their credibility level.	[10, 11]
Politi-Fact	PolitiFact-1, PolitiFact-2	The PolitiFact dataset contains statements that experts fact-check. These statements are categorised into 6 categories: true, mostly true, half true, mostly false, false, and pants on fire.	[10, 11]
ISOT	ISOT-1, ISOT-2	The ISOT dataset is a collection of numerous fake news and authentic articles sourced from reputable news websites as well as websites flagged as unreliable by politifact.com.	[3]
FNN (Fake News Net)	FNN-1, FNN-2	FNN is collected from two fact-checking websites GossipCop and PolitiFact containing news content with labels annotated by professional journalists and experts, along with social context information.	[3]
Click-bait	clickbait-1, clickbait-2	The dataset comprises headlines labelled as 1 (clickbait) and 0 (not clickbait). The dataset is sourced from diverse news sites including "WikiNews", "New York Times", "The Guardian", "The Hindu", and "BuzzFeed".	[2]

We need to ensure that the distribution of class labels must be balanced otherwise model can be biased towards the majority class. Figure 1 gives the percentage distribution of the datasets used in various research works for fake news identification during the last seven years.

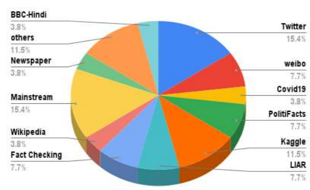
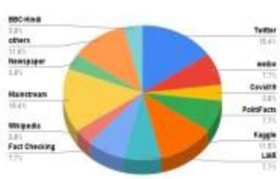


Fig. 1. Dataset source distribution

3. Methodology and Paper Selection

This review examines the research conducted on text classification of Fake/Real news from 2016 onwards. The paper thoroughly explores various machine learning and deep learning algorithms, as well as NLP techniques, utilized to classify text into Fake/Real. The research papers for the review were chosen through a systematic literature search conducted in prominent databases such as IEEE Xplore, Science Direct, and Springer. The search focused on key components including text classification, machine learning, deep learning, and natural language processing. Keywords and terms such as “Fake News classification”, “Fake news identification”, “Detecting fake news using machine learning”, “News classification using machine learning”, Fake news detection using deep learning”, “News classification using deep learning”, “Transformer-Based text classification”, Fake news detection using transfer learning” etc. were utilized to conduct the literature search. The selected papers were examined thoroughly and the ones that met our requirements were included in the study. Figure 2 shows the distribution of research papers according to the type of machine learning technique employed while Figure 3 gives the yearly distribution of the research papers starting from 2016.



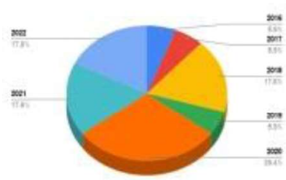


Fig. 2. Distribution of Machine Learning Techniques.

Fig. 3. Year-wise Distribution of papers from 2016.

The deep learning methodology dominates the scene for machine-learning techniques employed for fake news detection, and hybrid machine-learning techniques are also on rise. The number of papers on fake news identification starts increasing significantly from 2020.

4. Literature Review

Fake news encompasses various forms, including fabricated stories, attention-grabbing headlines, satirical content masquerading as factual news, and deliberate propaganda. Each type possesses distinct traits and origins. This misinformation can be disseminated through textual content, audio recordings, images, and videos, yielding a significant impact on social media users, both positively and negatively. The use of millions of bots with fake profiles can contribute to the virality of the content, leading to a perception of truth among information consumers who then share it with their contacts. [12]. Recent studies show that the rate at which fake news spreads is unparalleled, resulting in its extensive dissemination. Fake news spreads more rapidly than real news and is often perceived as novel, which may lead to a greater inclination among individuals to share and propagate this type of information [13, 14, 15]. Machine Learning techniques have been extensively used for identifying fake news. Here, we will discuss the research on devising machine learning techniques for identifying fake news.

4.1 Traditional Machine Learning Approaches

Machine learning, a subfield of artificial intelligence, focuses on designing algorithms and statistical models that enable computers to recognize and learn patterns and relationships from vast amounts of data and make accurate predictions. ML algorithms can be trained in a supervised, unsupervised, and reinforcement manner. In our review, we've focused on supervised and unsupervised learning of machine learning algorithms on text data for classification messages or news as Fake/Real. Let us have a look at some benchmark research works carried out using traditional ML approaches. Perez-Rosas et al. (2017) have employed a linear SVM classifier with five-fold cross-validation to identify news articles [16]. They utilize crowd-sourced and web-sourced data, focusing on lexical, syntactic, semantic, and text readability features. Aldwairi et al. (2018) have proposed a user-friendly tool to detect and filter potential clickbait by installing a simple browser extension [2]. The approach utilizes algorithms such as Naive Bayes, BayesNet, Random Tree, and Logistics, achieving impressive precision rates: BayesNet (94.4%), Logistics (99.4%), Random Tree (99.3%), and Naive Bayes (98.7%).

Yang et al. (2019) have employed an unsupervised approach for fake news detection, utilizing an efficient collapsed Gibbs sampling method, and Bayesian network model, and assessing users' credibility [17]. The model achieves moderate accuracies of 75.9% on the LIAR dataset and 67.9% on the Buzzfeed dataset. Its performance is limited due to the unsupervised nature of the approach and the assumptions made about unlabeled data. In contrast to Perez-Rosas et al (2017), Katarya et al. (2022) have suggested the use of MSVM for classifying fake and real review comments [18]. They employ PCA for feature extraction and the firefly optimization method for feature selection. Their objective is to handle multiclass data.

4.2 Deep Learning Approaches

DL, a subfield of machine learning, focuses on training artificial neural networks with multiple layers to extract and learn high-level representations from data. By leveraging multiple layers of interconnected neurons, DL models can extract complex patterns, relationships, and abstractions that might be difficult to extract by traditional ML. DL has applications in image classification, object detection, text generation, text classification, question answering, etc. Some benchmark works using DL for fake news identification have been discussed below.

To begin with, Ma et al. in 2016 presented a novel model that employs recurrent neural networks (RNNs) to effectively capture the intricate contextual information present in the relevant posts [8]. The researchers create two micro-blog datasets from Twitter and Sina Weibo, consisting of rumour and non-rumour categories, to evaluate the proposed approach. Their model demonstrates moderate detection performance, achieving an accuracy of 83.9% for Twitter and 89.0% for Weibo within a 12-hour window. Jiawei et al. (2020) have suggested a novel gated graph neural network called FakeDetector, which consists of representation feature learning and credibility label inference components [11]. The model achieves an accuracy of only 63% on the Politifacts dataset. Li et al. (2020) proposed a multi-level convolutional neural network (MCNN) combined with a sensitive word weight calculation method (TFW) to detect fake news articles [7]. The MCNN-TFW model effectively represents articles using both local convolutional features and global semantic features, enabling accurate identification of fake news. The classifier achieves impressive accuracy rates of 91.67% and 92.08% on two different datasets.

Saleh et al. (2021) have devised a model called OPCNN, which utilizes multiple layers to extract high-level and low-level features [3]. The model is optimized using hyperopic optimization and achieves accuracies of 97% on the Kaggle dataset, 95% on the FakeNewsnet dataset, 53.99% on FA-KES5, and 99.99% on the ISOT dataset which have comparatively better performance than MCNN-TFW model by Li et al (2020). Popat et al. (2018) have introduced a model called DeClare that incorporates external evidence articles and considers various contextual factors, the language used, and the reliability of sources [10]. Training a bi-directional LSTM model with multiple datasets, the DeClare model achieves an accuracy of 80%. On the other hand, Singh et al. (2020) have proposed an LSTM network that utilizes tweet text as its primary input and achieves an average F1 score of 86% without additional features. However, when linguistic and user features are included, the average F1 score increases to 88% [9].
Li et al. (2020) and Saleh et al. (2021) have utilized CNN models whereas Abdullah et al. (2020) combine CNN and LSTM layers in a four-layer model, considering linguistic cues and source/historical characteristics. They achieve an accuracy of 97.5% [19]. In contrast, to Abdullah et al. (2020), Umer et al. (2020) use similar architecture except it has PCA for feature extraction and one 1-D CNN layer for useful feature extraction, and an LSTM layer for sequence modelling, achieving an accuracy of 97.8% [20]. Both approaches show promising results in classifying news articles. Despite the success of DL, it was realized by the researchers that training deep neural networks can be computationally intensive and require large amounts of labelled data. Therefore, it is not always the best choice for every problem, traditional ML approaches may still be more suitable for tasks with limited data availability. To reduce the training time, the researcher shifted to the Transfer Learning approach.

4.3 Transfer Learning Approaches

Transfer Learning is a machine learning technique that allows knowledge learned from one task to be leveraged for another task. Instead of training from scratch, a pre-trained model is fine-tuned for new tasks. This approach leverages the existing knowledge in a pre-trained model to improve performance especially when the dataset is limited. Transfer learning has been applied using pre-trained models such as BERT, Roberta, XLNet, etc. for fake news identification as discussed below.

Kula et al. (2021) have focused on classifying fake news articles related to COVID-19 using transformer-based techniques [21]. The researchers explore models such as BERT, Roberta, and XLNet, and find that the Roberta model exhibits slightly better performance with an F1 score of 0.90, compared to BERT (0.83) and XLNet (0.86). Shishah (2022), have presented a model for the classification of Arabic news consisting of three primary components [22]. These components include the BERT model for sequence labelling and encodings, an attention mechanism, and JointBERT, which utilises RFC and NER as shared parameters. The model achieves accuracies of 66% on the ANS dataset, 85% on the COVID-19 dataset, and 80% on the Ara news dataset.

For classifying long-text news in Chinese, Chen et al. (2022) have proposed the LFCN model that leverages DLndigest and BERT embeddings [4]. Their model incorporates the Text-Text Encoder (TTE) layer for converting text into input vectors and utilizes the Local Feature Convolutional (LFC) layer to extract significant local features. A single-layer feedforward network is then employed for category predictions. The advantage of using pre-trained models is that they have been trained on large corpora in multiple languages. As a result, utilizing a multilingual pre-trained model makes it easier to perform classification tasks in different languages.

4.4 Hybrid Approach Approaches

Wu (2018), Li et al. (2021), and Kumar (2022) have employed hybrid approaches for the classification of Fake/Real news. They employ both ML and DL algorithms to compare and evaluate the performance of different models. These studies aim at improving the performance of fake news detection. In a study by Wu (2018), several models such as SVM, XGBoost, TM(DeepWalk), TM(LINE), and TraceMiner were accessed for their effectiveness in classifying social media messages [5]. TraceMiner achieves an F1 score of 0.9, but it would be beneficial to assess model performance using additional metrics.

In this sequence, Li et al. (2021) have devised an unsupervised fake news detection system with their UFNDA model, which involves feature extraction, feature fusion, and an auto-encoder-based approach [6]. Their evaluation, using Twitter and Weibo datasets, employs accuracy measures such as Macro F1 (51.5%), Micro F1 (80.86%), and AUC (64.3%). Kumar (2022) has created a fake news identification model using a dataset of Hindi news articles collected from various sources [23]. Among the three models used (Naive Bayes, logistic regression, and LSTM), LSTM achieved the highest accuracy of 92.36%. The consolidated summary of the various research works for fake news identification is given in the table below.

Table 2. Summary of the various research works for fake news identification.

Machine Learning Based Classification				
Ref	Author (Year)	Description	Performance	Limitation/Gaps
[16]	P´erez-Rosas et al. (2017)	Linear SVM classifier and five-fold cross-validation for fake news detection	Accuracy: 80% in all features	The performance of the model could be influenced by linguistic property specific to one domain.
[2]	Aldwairi et al. (2018)	An approach to detect and filter out potential clickbait.	Precision: BayesNet: 94.4%, Logistics: 99.4%, Random tree: 99.3%, Naïve Bayes: 98.7%	The method may not be able to filter out all the clickbait in language other than the one analysed in the study.
[17]	Yanget al. (2019)	An unsupervised approach for fake news detection. An efficient collapsed Gibbs sampling is used to detect fake news and users' credibility simultaneously.	Accuracy: LIAR:75.9%, BuzzFeed: 67.9%	Using unlabelled data could lead to the model making assumptions about the data that don't hold.
Deep Learning Based Classification				
Ref	Author (Year)	Description	Performance	Limitation/Gaps
[8]	Ma et al. (2016)	Early detection of rumour using RNN and GRU2 unit on microblog dataset	Accuracy: Twitter: 83.9%, Weibo: 89.0%	The model's generalisability is low, and it may not give good results on long articles.
[11]	Jiawei et al. (2020)	FakeDetector model for fake news detection using feature learning and credibility label	Accuracy: 63%	The performance of the model is not impressive. The model's ability to generalize

		inference.		for other datasets is low.
[7]	Li et al. (2020)	MCNN-TFW model for detecting fake news	Accuracy: Dataset-I: 91.67%, Dataset-II: 92.08%	The model may be overfitting on training data and may be sensitive to changes in language.
[3]	Saleh et al. (2021)	OPCNN model to detect fake news using high-level and low-level features.	Accuracy: Kaggle: 97%, FNN: 95%, FA-KES5: 53.99%, ISOT: 99.99%	The use of multiple layers and hyperparameter optimization can increase the complexity of the model.
[19]	Abdullah et al. (2020)	4-layer model containing 2 CNN, 1 LSTM, and 1 fully connected layer for fake news detection.	Accuracy: 97.5%	The high accuracy achieved in training the model may indicate overfitting to the training data, affecting its performance on new data.
[20]	Umer et al. (2020)	The proposed work used PCA for feature extraction, the 1D CNN layer to extract useful features, and the LSTM layer for sequence modelling.	Accuracy: 97.8%, Precision: 97.4%, Recall: 98.2%, F1-score: 97.8%	PCA is sensitive to the scale of the data. If the data is not pre-processed or standardized, it can lead to a model being biased toward certain features.
[10]	Popat et al. (2018)	Declare model: an end-to-end neural network and Bi-LSTM model trained on four different datasets	Accuracy: Snopes: 78.96%, Politifacts: 67.3%	Type of claim and sources, and language might affect the generalizability of the model.
		Transfer Learning Based Classification		
Ref	Author (Year)	Description	Performance	Limitation/Gaps
[21]	Kula et al. (2021)	Transformer-based approach for fake news detection.	F1-Score: Roberta: 0.90, BERT: 0.83, XLNet: 0.86	Database diversity could limit the model's ability to generalize to other types of fake news.
[22]	Shishah (2022)	jointBERT model along with RFC and NER on Arabic news detection.	F1-Score ANS: 0.66, AraNews: 0.80, CovidFakes: 0.86, Satirial: 0.56	The model will give poor results on news in a different language.

[4]	Chen et al. (2022)	LFCN model to classify Chinese long-text news.	Accuracy: THUCNews: 99.0% MCNews: 96.2%	The model is trained on Chinese text, which makes it less generalized for other languages.
		Hybrid Approaches		
Ref	Author (Year)	Description	Performance	Limitation/Gaps
[5]	Wu et al. (2018)	Proposed a method called Trace-Miner which classifies social media messages. They have also used LSTM-RNN to classify the sequences.	F1 Score: 0.90	They have not proposed any other metrics other than the F1 score. It could have been better to check model performance using different metrics.
[6]	Li et al. (2021)	UFNDA mainly include feature extraction and feature fusion, and the model is based on an autoencoder.	Twitter: Macro F1: 51.5%, Micro F1: 80.86%, AUC: 64.3%	UFNDA may struggle to handle the heterogeneity of features and their integration from different platforms.
[23]	Kumar et al. (2022)	Model trained on Hindi news articles for Hindi news identification.	LSTM Accuracy: 92.36%	Limited size dataset could affect the generalizability of the model.

It is important to consider that the performance and limitations given in the table are based on the studies cited in the literature review. Each cited research work has its own strengths and weaknesses. The choice of a specific approach depends on factors such as available data, computational resources, and the specific requirements of the fake news detection task.

5. Challenges

The research in fake news identification using machine learning algorithms has grown manifold in the recent decade. However, there are challenges that need to be addressed. Some of such challenges are listed below.

Data Availability and Quality: There are only limited datasets available in the domain. Obtaining labelled datasets for fake news identification can be challenging due to the lack of ground truth and the dynamic nature of fake news itself. Additionally, ensuring the quality and reliability of labelled data can be difficult, as there may be subjective judgments involved in determining the authenticity of the news. The subjective decisions can introduce a bias in the model. More number of authentically labelled datasets are required to further validation and comparison.

Generalizability: Most of the fake news detection models have been trained on English text data, limiting their effectiveness when applied to other languages. Developing multilingual models is essential to identify fake news across different languages.

Data Diversity: Fake news can take various forms, such as manipulated images, clickbait headlines, and misleading videos. However, existing research predominantly focuses on detecting fake news from text data and neglects the data in other formats. It is crucial to broaden the machine learning approaches to encompass all media types for comprehensive fake news detection.

Identifying Features of Fake News: It is crucial to extract the features that distinguish fake news from genuine ones. The intricate and innovative deception techniques make fake news detection an uphill task. Therefore, further research is required to identify the features of fake news.

Overcoming Deceptive Strategies: Fake news may escape detection because the fake news creators may manipulate the text in ways to deceive the machine learning algorithms. Developing Models that can catch and overcome the bias introduced by such strategies is a significant challenge.

Multidisciplinary Nature: The area of fake news detection is multidisciplinary. Reliable machine learning algorithms for differentiating fake news cannot be developed without input from journalists, linguists, and social scientists. Simply developing black box models for predicting news as fake or reliable cannot be relied on. For successful automated fake news detection, the machine learning community needs to involve other experts for validation of their algorithms for fake news detection.

6. Conclusion

This paper examines the recent research trends for detecting fake news from 2016 onwards. We have included 34 research papers in this review. The datasets used in these papers have been summarized. Initially, researchers applied traditional machine learning approaches, but these failed to achieve up-to-date performance due to a large amount of data and the complexity of identifying patterns in fake news. Subsequently, deep learning approaches gained prominence and improved the performance of fake news detection, However, deep learning needs loads of data for the training phase and has high computational complexity. Later, more powerful models, such as pre-trained transformer models, emerged, which require tuning on a smaller amount of data. These transfer learning models are efficient but may compromise accuracy slightly. Presently, researchers are exploring hybrid models to strike a balance between efficiency and efficacy. In this review, we have also identified certain limitations and gaps that need to be addressed soon. Most of the research conducted thus far has focused on news and messages in the English language. There is a scarcity of research on identifying fake news in other languages, particularly Indian languages. Additionally, given the prevalence of multilingual news and messages, there is a pressing need for a fake news detection algorithm that can effectively handle multiple languages.

References

[1] G. Shrivastava, P. Kumar, R. P. Ojha, P. K. Srivastava, S. Mohan, and G. Srivastava: Defensive modeling of fake news through online social networks. IEEE Transactions on Computational Social Systems, vol. 7, no. 5, pp. 1159–1167, (2020).

[2] M. Aldwairi and A. Alwahedi: Detecting fake news in social media networks. Procedia Computer Science, vol. 141, pp. 215–222, (2018).

[3] H. Saleh, A. Alharbi, and S. H. Alsamhi: Opcnn-fake: optimized convolutional neural network for fake news detection. IEEE Access, vol. 9, pp. 129471–129489, (2021).

[4] X. Chen, P. Cong, and S. Lv: A long-text classification method of Chinese news based on bert and cnn. IEEE Access, vol. 10, pp. 34046–34057, (2022).

[5] L. Wu and H. Liu: Tracing fake-news footprints: Characterizing social media messages by how they propagate. In: Proceedings of the eleventh ACM international conference on Web Search and Data Mining, pp. 637–645, (2018).
[6] D. Li, H. Guo, Z. Wang, and Z. Zheng: Unsupervised fake news detection based on autoencoder. IEEE Access, vol. 9, pp. 29356–29365, (2021).
[7] Q. Li, Q. Hu, Y. Lu, Y. Yang, and J. Cheng: Multi-level word features based on cnn for fake news detection in cultural communication. Personal and Ubiquitous Computing, vol. 24, pp. 259–272, (2020).
[8] J. Ma, W. Gao, P. Mitra, S. Kwon, B. J. Jansen, K.-F. Wong, and M. Cha: Detecting rumors from microblogs with recurrent neural networks. In: Proceedings of 25th IJCAI, pp.3818-3824, Research Collection School of Computing and Info. Systems (2016).
[9] J. P. Singh, A. Kumar, N. P. Rana, and Y. K. Dwivedi: Attention-based lstm network for rumor veracity estimation of tweets. Information Systems Frontiers, pp. 1–16, (2020).
[10] K. Popat, S. Mukherjee, A. Yates, and G. Weikum: Declare: Debunking fake news and false claims using evidence-aware deep learning. arXiv preprint arXiv:1809.06416, (2018).
[11] Z. Jiawei, D. Bowen, and S. Y. Philip: Fakedetector: Effective fake news detection with deep diffusive neural network. In Proceedings of the 2020 IEEE 36th International Conference on Data Engineering (ICDE'20), pp. 1826–1829, (2020).
[12] A. Gupta, N. Kumar, P. Prabhat, R. Gupta, S. Tanwar, G. Sharma, P. N. Bokoro, and R. Sharma: Combating fake news: Stakeholder interventions and potential solutions. Ieee Access, vol. 10, pp. 78268–78289, (2022).
[13] X. Zhou and R. Zafarani: A survey of fake news: Fundamental theories, detection methods, and opportunities. ACM Computing Surveys (CSUR), vol. 53, no. 5, pp. 1–40, (2020).
[14] K. Shu, S. Wang, and H. Liu: Beyond news contents: The role of social context for fake news detection. In Proceedings of the twelfth ACM international conference on web search and data mining , pp. 312–320, (2019).
[15] Y. Luo and J. Ma: The influence of positive news on rumor spreading in social networks with scale-free characteristics. International Journal of Modern Physics C, vol. 29, no. 09, p. 1850078, (2018).
[16] V. P´erez-Rosas, B. Kleinberg, A. Lefevre, and R. Mihalcea: Automatic detection of fake news. arXiv preprint arXiv:1708.07104, (2017).
[17] S. Yang, K. Shu, S. Wang, R. Gu, F. Wu, and H. Liu: Unsupervised fake news detection on social media: A generative approach. In Proceedings of the AAAI conference on artificial intelligence, vol. 33, no. 01, pp. 5644–5651, (2019).
[18] R. Katarya, D. Dahiya, S. Checker et al.: Fake news detection system using featured-based optimized msvm classification. IEEE Access, vol. 10, pp. 113184–113199, (2022).
[19] A. Abdullah, M. Awan, M. Shehzad, and M. Ashraf: Fake news classification bimodal using convolutional neural network and long short-term memory. Int. J. Emerg. Technol. Learn, vol. 11, pp. 209–212, (2020).
[20] M. Umer, Z. Imtiaz, S. Ullah, A. Mehmood, G. S. Choi, and B.-W. On: Fake news stance detection using deep learning architecture (cnn-lstm). IEEE Access, vol. 8, pp. 156695–156706, (2020).
[21] S. Kula, R. Kozik, M. Chora´s, and M. Wo´zniak: Transformer based models in fake news detection. In: Proceedings of the 21st International Conference on Computational Science (ICCS 2021), Part IV Krakow, Poland, June 16–18, 2021, Springer, pp. 28–38, (2021).
[22] W. Shishah: Jointbert for detecting Arabic fake news: IEEE Access, vol. 10, pp. 71951–71960, (2022).
[23] S. Kumar and T. D. Singh: Fake news detection on Hindi news dataset. In: Proceedings of Global Transitions, vol. 3, no. 1, pp. 289–297, (2022).
[24] Detecting Fake News with Natural Language Processing, https://www.analyticsvidhya.com/blog/2021/07/detecting-fake-news-with-natural-language-processing/, last accessed 2023/07/04.
[25] Step-by-Step Text Classification.https://medium.com/tokopedia-data/step-by-step-text-classification-fa439608e79e, last accessed 2023/07/05.