FAKE NEWS DETECTION: A REVIEW

[1]Lata[*], [2]Yogesh Kumar

[1]*Research Scholar, U.I.E.T., M.D. University, Rohtak-124001, Haryana, Bharat*
[2]*Assistant Professor, U.I.E.T., M.D. University, Rohtak-124001, Haryana, Bharat*

***Email ID**: [1]cnhugh.lata@gmail.com, [2]dryogeshkumar.uiet@mdurohtak.ac.in*

Accepted: 21.01.2022 **Published**: 28.02.2022

Keywords: Fake news, Machine Learning, NLP, Sentiment Analysis, social media, Word Embedding.

Abstract

To use social media for consumption of fake news is a double edge sword. On one hand consumers consumes news via social media due to its less cost, easy to access, and instant transmission of information. On the other hand, it allows the broad distribution of "fake news," which is low-quality material that intentionally misleads the public. It has been observed that in today's world, people get their news through search engines and social media than from traditional means like newspapers and magazines. However, there is no way to confirm the accuracy of news found on the internet. Fake news is a major problem that has the ability to cause harm to society. Given the difficulty in spotting false news, many academics are seeking to comprehend the issue statement and its characteristics. This paper summarizes the existing approaches as well as the unique approaches given by researchers. Depending on the nature of content (textual or image-based), several approaches are used to solve the problem.

Paper Identification

**Corresponding Author*

1. Introduction

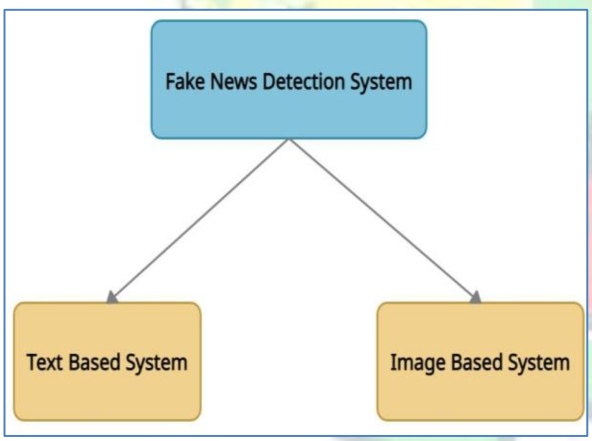
Using on-line social media platforms, sharing of information have been made easy. As the popularity of web-based forums and social platform have been increased, the escalation of fake news has become a warning to different agencies and sectors. It is important to ensure the validity and legitimacy of the news articles before sharing on online social media. Lot of attention has been paid on fake news from many years, since the US presidential elections in 2016. It is difficult for humans to detect whether a news is fake or not. In order to manually detect the authenticity of news article, one has a detailed knowledge of the covered topic. Fake News comprises of intentional and verifiable information which mislead people. Lot of research is done on theme of Artificial Intelligence for detection of fake news. The authenticity of social media articles is frequently questioned. To assist mitigate the negative consequences of fake news, a mechanism to automatically detect it must be developed. Many solutions have been proposed in the field of false news detection to prevent consumers from becoming sufferer of misinformation that escalate like wildfire on social media.

There are lot of challenges in detection of fake news. Fake news usually mixes true stories with false details

It is often that fake news maker blends true story with false details to mislead people. In such case, it is easy to get people's attention about trusted parts without noticing the presence of fabricated ones. Language use is complex in fake news**.** Literature work reveals that a wide range of linguistic factors contribute to the formation of fake news such as subjective, intensifying, and hedging words with the intent to introduce vague, obscuring, dramatizing or sensationalizing language. Therefore, applying most of approaches will be labour-intensive and time-consuming.

Types of Fake News Detection Systems

Fake news detection system can be either textual based or image based. Text based detection of fake news uses propagation features text content features and user features. Propagation feature based uses statistical information from the news articles in propagation process. User feature-based uses user information to check for fake news.[2]



(1) Traditional division of fake news system

Image based detection is a relatively new topic. It involves checking if information in an image, screenshot or poster is true or not. Recently fake news is circulated in image format. People just take screenshot and share it on social media without checking its authenticity. In the pandemic time, people have been sharing information regarding essential resources like oxygen cylinder, medicine, plasma donor on social media platform such as Instagram, Whatsapp, Facebook etc. in image format [2].

2. Literature Review

[2] uses a naive Bayes classifier to provide a simple strategy for detecting fake news. This method was turned into a software system and put to the test on a collection of Facebook news posts. These classifiers are probabilistic classifiers based on the Bayes theorem.

[4] In order to detect fake news, a deep convolutional neural network (FNDNet) is proposed. Rather than depending on hand-crafted characteristics, this model (FNDNet) uses many deep hidden layers in a neural network to automatically learn the biased characteristics for classification of false. To extract numerous features at each layer, a deep CNN is built.

[12] The authors of this study explain and test the use of word embedding (GloVe) for pre-processing of text so as to build a vector space of words and establish a linguistic relationship. The suggested model, combines the architectures of CNN and RNN and has obtained benchmark results in the prediction of fake news, with the addition of word embeddings completing the picture. Moreover, many model parameters have been used and recorded for the best possible outcomes to make sure the quality of prediction. The addition of a dropout layer, among other things, decreases overfitting in the model, resulting in significantly superior accuracy results.

[15] Author has investigated the detection of fake news with varying degrees of fakeness using several sources in this work. A Multi-source Multi-class Fake news Detection framework is presented, which consists of automated feature extraction, multi-source fusion, and automated degrees of fakeness detection. The suggested framework's efficiency is demonstrated by experimental findings on real-world data, and

additional experiments are done to better understand how it works.

[17] Author has created Detective algorithm, a revolutionary algorithm that uses Bayes inference for detection of bogus news and learns from users' flagging accuracy over time. The method uses posterior sampling to actively balance exploitation (selecting news that maximize the objective value at a particular epoch) and exploration (selecting news that maximize the worth of information to learn about users' flagging accuracy).

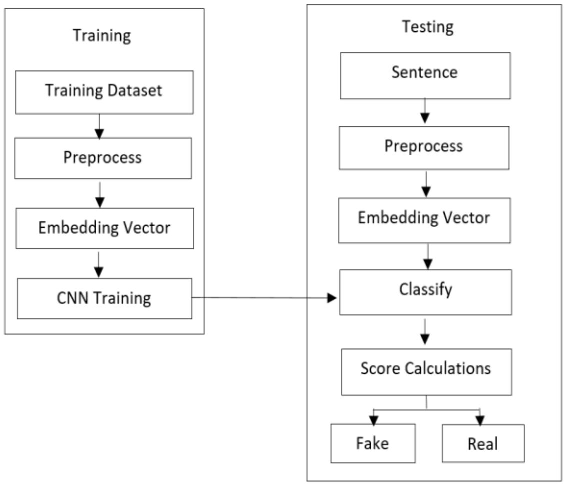
[18] A powerful deep neural network is created that handles both the content of news articles, and also finds the user relationships in social networks. Tensor factorization method is used for proposed approach. A tensor represents the social context of news stories, which is created by combining news, user, and user-group data. On the real-world dataset of FM: BuzzFeed and Faked it, the proposed method DeepNet has been validated. DeepNet improves existing false news detection algorithms by combining news content and social context-based features in a deep net architecture having varying kernel sized convolutional layers

[19] An algorithm is proposed which is based on n-gram analysis and machine learning Two different feature extraction strategies and six different machine learning algorithms for are investigated and compared. TF-IDF as a technique of feature extraction and Linear Support Vector Machine (LSVM) as a classifier produce the best results, with an accuracy of 92 percent.

[20To recognize FN on newly emerged events is the primary issue for FM detection on social media. Unfortunately, most present techniques are ill-equipped to meet this problem, as they tend to learn event-specific properties that cannot be applied to previously witnessed events. To solve this problem, we offer the Event Adversarial Neural Network, an end-to-end architecture that can derive event unvarying features and hence aid in the identification of bogus news on freshly received events. The multi-modal feature extractor, the fake news detector, and the event discriminator are the three primary components. The textual and visual aspects of posts are extracted by the multi-modal feature extractor. It works together with the false news detector to learn the unbiased representation of detection of FN. The event discriminator's job is to retain shared features between events while removing event-specific elements. Extensive experiments are carried out using Weibo and Twitter multimedia datasets. The results reveal that proposed EANN model outperforms existing approaches and can learn transferable feature representations.

3. Efficient Fake News Identification Model

In this section, a model for Fake News Identification is discussed. For machine learning or deep learning algorithms to work on text data, specific pre-processing is required. To convert text data into a format suitable for modelling, a variety of strategies are commonly utilised. We start with Tokenization This is a procedure that separates the provided text into small fractions. The tokens might be words or numbers or punctuation marks, in addition, they encompass no extrinsic meaning After that, stop words from the text data are removed Words (the most common words in a language that do not provide much context) can be processed and filtered from the text because they are more widespread and carry less useful information. Stop words that are less important and can waste processing time, therefore eliminating them as part of data pre-processing is an important step in natural language processing.



3.1 Preprocessing

3.1.1 Tokenization- It is one of the initial steps in any NLP pipeline. Dividing the raw text into small bits of words or sentences, known as tokens, is what tokenization is all about. It's called 'Word Tokenization' if the text is broken into words, and 'Sentence Tokenization' if the text is split into sentences. 'Space' is typically used for word tokenization, whereas characters such as 'periods, exclamation point, and newline character is typically used for sentence tokenization. We must select the most appropriate strategy for the task at hand. Few characters, such as spaces and punctuations, are ignored during tokenization and will not be included in the final list of tokens.

3.1.2 Stop Word Removal A stop word is a commonly used word (such as "the," "a," "an," or "in") that has been designed to be rejected by a search engine both while indexing and retrieving entries as a result of a search query.

3.1.3 Lemmatization The stemming process is similar to lemmatization. The result of lemmatization is called a 'lemma,' which is a root word rather than a root stem, which is the result of stemming. We will receive a legitimate word that means the same thing after lemmatization.

3.2 Embedding Vector

Word Vector Representation Word2Vec is another cutting-edge approach for converting words to vectors. Word2Vec is a simple neural network that attempts to predict the next word in a context based on a series of words. The vector representation of each word within the context is the weights of the particular link from the input layer node into one of the hidden layer neurons, and Word2Vec effectively represents a vector for each word inside the context. This data is primarily used to encode the contextual information of a specific word within the corpus (collection of texts) on which our word2vec model is trained.

TF-IDF vectorizer

Although the TF-IDF method is old, it is simple and successful in the pretraining phase. The product of term frequency and inverse document frequency is used to calculate TfidfVectorizer. As the name implies, TF-IDF produces values for every word in a document by dividing the frequency of the word in a given document by the percentage of documents in which the word does appear.

4. Analysis

Based on the detection of fake news in the social media and online platform, different techniques for detecting fake news are rendered

[1] **2017 Data mining** Concept of fake news is discussed. Existing fake news detection approach has been revisited from data mining point of view BuzzFeed News and LIAR News of fake news detection in other application

[2] **2017** naive Bayes classifier. classification accuracy of approximately 74%. Facebook news posts.Techniques of AI is preferred to implement problem of fake news detection.

[3] **2018** Machine Learning Techniques, Data Mining, and Natural language processing. Compare and contrast observed results on various datasets through Modals of machine learning. LIAR, FEVER,

and FAKENEWSNET. Approaches based on content may be developed in future.

[4] 2020 F1-score improved by Deep Convolution Neural Network. Glove is used as pre-trained word. accuracy is 98.36% BuzzFeed and Faked it Incorporation of Eco-Ca hamber for fake news classification and many parallel channels based Deep CNN of varying kernel sizes may be used for performing classification task.

[5] 2019 advanced deep learning models depicts an outstanding performance using Char-level C-LSTM in Fake news dataset with its 95% accuracy. Liar from POLITIFACT.COMs API A larger dataset might be utilised to see how traditional models, such as Naive Bayes, compare against highly computational neural network-based algorithms in detecting fake news.

[6]2021 Three parallel blocks of 1d-CNN with varying kernel-sized convolutional layers are combined with BERT to achieve better learning. more precise results are achieved with BERT having an accuracy of 98.90% real-world fake news dataset used U.S. General Presential Election in 2016 future plan is to design a hybrid approach that is mix of content, semantic and temporal based information of newss may be applied for both the binary and multi-class fake news classification.

[7]2017 CSI model is proposed which is combination of three modules: capture, score and integration. CSI gives better result with accuracy of 0.890% Twitter and Weibo future plan is to design a model that includes concepts from crowd sourcing and reinforcement learning.

[8]2019 Naive Bayes, k-Nearest Neighbours, Random Forests, Support Vector Machine with RBF kernel, and XGBoost With RF accuracy got 85% and with XGB accuracy is 86%BuzzFeed news articles associated with the 2016 U.S. election Future plan is to take larger volumes of labelled data which enable to analyse other deep learning techniques.

[9]2019 semi-supervised learning framework Multidisciplinary contributions are used to detect fake news by enhancing feature engineering, or by giving well-justified machine learning models No dataset is here.

[10] 2019 Ensemble Voting Classifier and X-Gradient Boosting classification X-Gradient Boosting with accuracy 90.53 For pre-processing on dataset NLP technique is performed Deep learning techniques can also be implemented to improve accuracy and test scores.

[11]2020 Bidirectional GRU An increase of accuracy up to 4.2% compared with other Deep Learning Modal. The **Liar** data sets and **PolitiFact** data set to create a larger dataset for fake news and incorporation graph neural network with relation features so as to generate the semantic feature.

[12] 2020 combination of two aspects of deep learning that is recurrent neural network and convolution neural network. The training accuracy is achieved with high performance of 99.54% Kaggle dataset Incorporation of feature like user response, source or author of the article and modal purposed.

[13] 2017 Five algorithms are compared for supervise learning are NB, and DT-J48, K-NN, K* and SVM Algorithm Accuracy NB 79.7 DT-J48 71.6 K* 71.15 SVM **81.35** KNN-IBK (K=3) 70.85 movie reviews datasets, V2.0 and V1.0 Future plan is to expand this study by using other datasets such as eBay dataset and Amazon dataset which uses varying feature selection methods.

[14] 2018 three different variations of neural networks 1. Dense Neural Network Tf-Idf Vectors 2 Bag of Words Vector with Dense Neural Network word embeddings. Accuracy is 94.31% with Tf-Idf with unigrams and bigrams BoW without unigrams and bigrams got accuracy 89.23% Pre-trained embeddings (Word2Vec) fed into dense neural network has accuracy 75.67 Dataset used is FNC-1 Future

plan is to expand this work by doing same analysis on a different dataset such as Facebook and Twitter.

[15] 2018 Multi Source Multi Class Fake News Detection (MMFD) MMFD got accuracy 38.81% LIAR In future research direction is to incorporate more sources such as temporal information, social networks and user interactions

[16] 2019 Gradient Boosting (XGB) and AdaBoost With the help of XGB classifier mean accuracy achieved 88% and F1 score is 0.91. Open sources, Kaggle dataset and George McIntire dataset For better accuracy linguistics features are added to the feature matric

[17] 2018 Detective Algorithm is used for detecting fake news that performs Bayesian inference. accuracy is directly proportional to the veteran user Facebook dataset this algorithm may be used for real-world social system.

[18] 2020 Deep Neural Network with varying kernel sizes convolution layers Accuracy is 95% With the help of News Content and Social Context BuzzFeed and Fakeddit Work can be extended by including the temporal level information for sterling FN detection.

[19] 2017 to represent the context of the document n-gram modelling is used. Accuracy achieved is 87% with n gram and linear SVM classifier and maximum accuracy score 92% is achieved when using Linear SVM classifier and unigram features. Kaggle Work can be extended by running the modal on the dataset which are publicly available for instance Liar data Set.

[20] 2021 Ensemble model which uses Deepfake and XGBoost classifier. Accuracy is 86.49% With BuzzFeed dataset and 88.64% with PolitiFact dataset BuzzFeed and PolitiFact Extending the work by including graph and utilizing the context and content, based features.

[21] 2018 EANN modal which is Event Adversarial Neural Networks comprises of three elements: multi-modal feature extractor, fake news detector, and event discriminator Twitter has Accuracy 71.5% Weibo has Accuracy 82.7%. dataset is Weibo and Twitter.

[22] 2019 unsupervised fake news detection (UFD) UFD has Accuracy 75.9% LIAR BuzzFeed There is future plan for improvising the performance of unsupervised modal with the help of semi supervised learning modal

[23] 2019 Merged cosine similarity Tf-idf sentiment analysis Tf-Idf Vectorizer- Cosine Similarity has Accuracy 81.6% Kaggle, PolitiFact and Emergent datasets apply different neural network

[24] 2021 **Cross-SEAN** modal which is a semi-supervised cross-stitch based attention neural model accuracy is 94% CTF, Twitter .There is future plan to include meaningful information from different forms of media like images, videos or GIF which are provided using tweets

[25] 2018 hybrid machine-crowd approach In Neural Network model accuracy is achieved 81.64%. There is no big dataset. There is title in which corpus of words is used and description part of the news articles There is future plan for analysing the credibility of social media news provider through crowd workers .

[26] 2019 sentiment-aware fake new detection algorithm LSTM HAN(Twit) classifier has 86% Accuracy Pheme Labelled Twitter dataset With this approach sentiment is not enhanced up to large extent so this can be done by Additional sources of sentiment extracted from, e.g., visual media such as animations images, embedded text in the images

[27] 2018 Fake Detector And Deep Walk Model. In the multi-class scenario Accuracy is 40% higher than the other methods. PolitiFact Dataset is used here.

[28] 2018 weak supervision method using XGBoost F1 score is 0.78 and 0.94 Twitter API Here the vital problem is of collecting training datasets for required size so this is overcome by accepting a certain amount of labelled noise that will yield well performed classifier.

[29] 2018 with the method of Trans and binary Trans knowledge graph embedding algorithm is used Trans FML has F1 score **0.77** Kaggle To combine content driven and file driven approach, even with inadequate and imperfect knowledge graph. It provides explanation about the results of fake news detection

[30] 2017 Three levelled hierarchical attention networks: 3HAN is used accuracy is 96.77%. PolitiFact. A web application based on 3HAN has been released that detects bogus news and learns in real time from manually reviewed articles on the internet.

[31] 2019 reinforced weakly supervised fake news detection framework., We FEND Accuracy is 82.4% WeChat is used here.

[32] 2020 deep diffusive network model FAKEDETECTOR real-world fake news dataset is used here.

[33] 2019 **Bayesian machine learning system** Accuracy is **63.333%** locally generated dataset Future research plans include adding an attribution function in order to create systems that can not only detect FN, but also influence-based information intended to persuade a target audience to make erroneous decisions.

[34] 2018 **Lid stone smoothing for Naive Bayes** Accuracy is 83.16% Kaggle dataset is used here.

[35] 2021 supervised machine learning algorithm accuracy is 92% LIAR adding numeric statistical values.

[36] 2017 LSTM model 41.5% accuracy is achieved and LIAR dataset is used here.

[37] 2019 hierarchical propagation network PolitiFact accuracy is 84.3% And Gossip Cop accuracy 86.1% PolitiFact, Gossip Cop Deep learning models can be used to improve the detection of FN.

[38] 2018 Natural Language Processing, Machine Learning Techniques, and Deep Learning Techniques Precision is 75% Kaggle data set is used here.

[39] 2018 Deep LSTMs with two layers, each with 100 cells PolitiFact-67 BuzzFeed -74.2 PolitiFact and BuzzFeed dataset is here.As it is done in a streaming way, the proposed framework might be modified to detect FN in real time.

[40] 2019 Machine learning, semantics, and natural language processing are all combined.Accuracy is increased by 5 to 10 % by adding semantic features Liar Data Set Semantic feature to be taken into consideration for detection of Fake news. exploitation of graph network with the relational features.

[41] 2019 FESCR Algorithm is used (Feature Extraction System for Customer Review)Naïve base accuracy is 85.49%, in K-Nearest Neighbor Accuracy is 65.03 and in DT is 69.38% E-Commerce Web sites such as Flipkart, Amazon, Snapdeal Review summary should be present so as to get the informed decision can be taken.

[42] 2020 Fake Detector 97.8 FNC-1 data set is used.

[43] 2020 Multi-Layer Perceptron Fake News AMT-54.3 Celebrity-68. Fake News AMT and Celebrity Extending the problem of fake news detection from uni domain to multidomain.

[44] 2021 Dense deep learning model with two LSTM and two GRU 89.8 LIAR dataset Other FN datasets should be used to test the model.

[45] 2021 Efficient Deep Diffusive Network 92.3 BuzzFeed and PolitiFact For more precise classification, temporal data with content and social context features could be used

[46] 2020 HGAN: Hierarchical Graph Attention Network is used Accuracy is 37.57% using PolitiFact dataset PolitiFact and BuzzFeed There is future plan to construct a new modal by integrating other powerful modals in natural language processing

[47] 2019 Spot Fake is a multimodal system for detecting FN. With Twitter accuracy is 77.77% and with Weibo is 89.23% Twitter and Weibo Longer articles and more complex fusion approaches can yet be improved to better understand how different modalities play a role in detecting FN.

[48] 2017 Inclusion of speaker profile into LSTM Modal for fake news detectionAccuracy is 41.5%

LIAR dataset Hierarchical Interaction structure may be considered for representing semantic conflicts.

[49] 2018 TICNN modal is used which combine the image and text information. Accuracy is 92.20% news about American presidential election Future plan is to explore more data on France Nation Election for finding the difference between Real and Fake news in Other Language

[50] 2018 TCNN-URG: Two level convolution network with user response generator algorithm is used. Weibo and Twitter dataset is usd.

5. Conclusion and Future Scope

Fake news has a number of negative consequences for society, and it is becoming a hot research topic. Many academics have proposed new theories and systems for detecting fake news. In this study, these frameworks/systems have been presented and contrasted. The classification of fake news, its impact, datasets, and the core model of a detection system were also covered. To get better results in the future, more features should be added to existing systems.

RÉFÉRENCES

1. Granskogen, T., Gulla, J.A.: Fake news detection: Network data from social media used to predict fakes. CEUR Workshop Proc. 2041, 59–66 (2017)
2. Granik, M., Mesyura, V.: Fake news detection using naive Bayes classifier. 2017 IEEE 1st Ukr. Conf. Electr. Comput. Eng. UKRCON 2017 - Proc. 900–903 (2017). https://doi.org/10.1109/UKRCON.2017.8100379
3. Oshikawa, R., Qian, J., Wang, W.Y.: A survey on natural language processing for fake news detection. Lr. 2020 - 12th Int. Conf. Lang. Resour. Eval. Conf. Proc. 6086–6093 (2020)
4. Kaliyar, R.K., Goswami, A., Narang, P., Sinha, S.: FNDNet – A deep convolutional neural network for fake news detection. Cogn. Syst. Res. 61, 32–44 (2020). https://doi.org/10.1016/j.cogsys.2019.12.005
5. Khan, J.Y., Khondaker, M.T.I., Afroz, S., Uddin, G., Iqbal, A.: A benchmark study of machine learning models for online fake news detection. Mach. Learn. with Appl. 4, 100032 (2021). https://doi.org/10.1016/j.mlwa.2021.100032
6. Kaliyar, R.K., Goswami, A., Narang, P.: FakeBERT: Fake news detection in social media with a BERT-based deep learning approach. Multimed. Tools Appl. 11765–11788 (2021). https://doi.org/10.1007/s11042-020-10183-2
7. Ruchansky, N., Seo, S., Liu, Y.: CSI: A hybrid deep model for fake news detection. Int. Conf. Inf. Knowl. Manag. Proc. Part F1318, 797–806 (2017). https://doi.org/10.1145/3132847.3132877
8. Reis, J.C.S., Correia, A., Murai, F., Veloso, A., Benevenuto, F., Cambria, E.: Supervised Learning for Fake News Detection. IEEE Intell. Syst. 34, 76–81 (2019). https://doi.org/10.1109/MIS.2019.2899143
9. Nordberg, P., Kävrestad, J., Nohlberg, M.: Automatic detection of fake news. CEUR Workshop Proc. 2789, 168–179 (2020)
10. Mahabub, A.: A robust technique of fake news detection using Ensemble Voting Classifier and comparison with other classifiers. SN Appl. Sci. 2, 1–9 (2020). https://doi.org/10.1007/s42452-020-2326-y
11. Braşoveanu, A.M.P., Andonie, R.: Integrating Machine Learning Techniques in Semantic Fake News Detection. Neural Process. Lett. (2020). https://doi.org/10.1007/s11063-020-10365-x
12. Agarwal, A., Mittal, M., Pathak, A., Goyal, L.M.: Fake News Detection Using a Blend of

Neural Networks: An Application of Deep Learning. SN Comput. Sci. 1, 1–9 (2020). https://doi.org/10.1007/s42979-020-00165-4

13. Elmurngi, E., Gherbi, A.: Detecting Fake Reviews through Sentiment Analysis Using Machine Learning Techniques. DATA Anal. 2017 Sixth Int. Conf. Data Anal. Detect. 65–72 (2017)
14. Masciari, E., Moscato, V., Picariello, A., Sperli, G.: A Deep Learning Approach to Fake News Detection. Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics). 12117 LNAI, 113–122 (2020). https://doi.org/10.1007/978-3-030-59491-6_11
15. Karimi, H., Roy, P., Saba-Sadiya, S., Tang, J.: Multi-Source Multi-Class Fake News Detection. Proc. 27th Int. Conf. Comput. Linguist. 1546–1557 (2018)
16. Agarwal, H., Husain, F., Saini, P.: Advances in Computing and Data Sciences. Springer Singapore (2019)
17. People Who Share, T.: The State of the Sharing Economy: Food Sharing in the UK Tracking the State of the Sharing Economy: It is here to stay. 517–524 (2013)
18. Kaliyar, R.K., Kumar, P., Kumar, M., Narkhede, M., Namboodiri, S., Mishra, S.: DeepNet: An efficient neural network for fake news detection using news-user engagements. Proc. 2020 Int. Conf. Comput. Commun. Secur. ICCCS 2020. (2020).
19. Ahmed, H., Traore, I., Saad, S.: Detection of Online Fake News Using N-Gram Analysis and Machine Learning Techniques. Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics). 10618 LNCS, 127–138 (2017).
20. Kaliyar, R.K., Goswami, A., Narang, P.: DeepFakE: improving fake news detection using tensor decomposition-based deep neural network. J. Supercomput. 77, 1015–1037 (2021). https://doi.org/10.1007/s11227-020-03294-y
21. Wang, Y., Ma, F., Jin, Z., Yuan, Y., Xun, G., Jha, K., Su, L., Gao, J.: Eann. 849–857 (2018). https://doi.org/10.1145/3219819.3219903
22. Yang, S., Shu, K., Wang, S., Gu, R., Wu, F., Liu, H.: Unsupervised fake news detection on social media: A generative approach. 33rd AAAI Conf. Artif. Intell. AAAI 2019, 31st Innov. Appl. Artif. Intell. Conf. IAAI 2019 9th AAAI Symp. Educ. Adv. Artif. Intell. EAAI (2019).
23. Bhutani, B., Rastogi, N., Sehgal, P., Purwar, A.: Fake News Detection Using Sentiment Analysis. 2019 12th Int. Conf. Contemp. Comput. IC3 2019. 1–5 (2019).
24. Paka, W.S., Bansal, R., Kaushik, A., Sengupta, S., Chakraborty, T.: Cross-SEAN: A cross-stitch semi-supervised neural attention model for COVID-19 fake news detection. Appl. Soft Comput. 107, 107393 (2021).
25. Shabani, S., Sokhn, M.: Hybrid machine-crowd approach for fake news detection. Proc. - 4th IEEE Int. Conf. Collab. Internet Comput. CIC 2018. 299–306 (2018).
26. Division of Computing Science and Mathematics , University of Stirling , Stirling , FK9 4LA , UK. 2507–2511 (2019)
27. Meneses Silva, C. V., Silva Fontes, R., Colaço Júnior, M.: Intelligent Fake News Detection: A Systematic Mapping. J. Appl. Secur. Res. 16, 168–189 (2021).
28. Helmstetter, S., Paulheim, H.: Weakly supervised learning for fake news detection on Twitter. Proc. 2018 IEEE/ACM Int. Conf. Adv. Soc. Networks Anal. Mining, ASONAM (2018). https://doi.org/10.1109/ASONAM.(2018).

29. Xiao, G., Kontchakov, R., Cogrel, B., Calvanese, D., Botoeva, E.: Efficient handling of SPARQL OPTIONAL for OBDA (Extended Version). Springer International Publishing (2018)

30. Singhania, S., Fernandez, N., Rao, S.: 3HAN: A Deep Neural Network for Fake News Detection. Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics). 10635 LNCS, 572–581 (2017).

31. Wang, Y., Yang, W., Ma, F., Xu, J., Zhong, B., Deng, Q., Gao, J.: Weak Supervision for Fake News Detection via Reinforcement Learning. Proc. AAAI Conf. Artif. Intell. 34, 516–523 (2020).

32. Zhang, J., Dong, B., Yu, P.S.: FakeDetector: Effective fake news detection with deep diffusive neural network. Proc. - Int. Conf. Data Eng. 2020-April, 1826–1829 (2020).

33. Traylor, T., Straub, J., Gurmeet, Snell, N.: Classifying Fake News Articles Using Natural Language Processing to Identify In-Article Attribution as a Supervised Learning Estimator. Proc. - 13th IEEE Int. Conf. Semant. Comput. ICSC 2019. 445–449 (2019).

34. Soni, V.D.: Prediction of Geniunity of News using advanced Machine Learning and Natural Language processing Algorithms. (2020).

35. Vijayaraghavan, S., Wang, Y., Guo, Z., Voong, J., Xu, W., Nasseri, A., Cai, J., Li, L., Vuong, K., Wadhwa, E.: Fake News Detection with Different Models. (2020)

36. Long, Y., Lu, Q., Xiang, R., Li, M., Huang, C.-R.: Fake News Detection Through Multi-Perspective Speaker Profiles. Proc. Eighth Int. Jt. Conf. Nat. Lang. Process. Volume 2:, 252–256 (2017)

37. Shu, K., Mahudeswaran, D., Wang, S., Liu, H.: Hierarchical propagation networks for fake news detection: Investigation and exploitation. Proc. 14th Int. AAAI Conf. Web Soc. Media, ICWSM 2020. 626–637 (2020)

38. Kaliyar, R.K.: Fake news detection using a deep neural network. 2018 4th Int. Conf. Comput. Commun. Autom. ICCCA 2018. 1–7 (2018).

39. Shu, K., Mahudeswaran, D., Liu, H.: FakeNewsTracker: a tool for fake news collection, detection, and visualization. Comput. Math. Organ. Theory. 25, 60–71 (2019). https://doi.org/10.1007/s10588-018-09280-3

40. Braşoveanu, A.M.P., Andonie, R.: Semantic Fake News Detection: A Machine Learning Perspective. Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics). 11506 LNCS, 656–667 (2019). https://doi.org/10.1007/978-3-030-20521-8_54

41. Gaurav, D., Yadav, J.K.P.S., Kaliyar, R.K., Goyal, A.: Detection of false positive situation in review mining. Springer Singapore (2019)

42. Zhang, J., Dong, B., Yu, P.S.: FakeDetector: Effective fake news detection with deep diffusive neural network. Proc. - Int. Conf. Data Eng. 2020-April, 1826–1829 (2020). https://doi.org/10.1109/ICDE48307.2020.00180

43. Saikh, T., De, A., Ekbal, A., Bhattacharyya, P.: A Deep Learning Approach for Automatic Detection of Fake News. (2020)

44. Aslam, N., Ullah Khan, I., Alotaibi, F.S., Aldaej, L.A., Aldubaikil, A.K.: Fake Detect: A Deep Learning Ensemble Model for Fake News Detection. Complexity. 2021, (2021).

45. Kaliyar, R.K., Goswami, A., Narang, P.: EchoFakeD: improving fake news detection in social media with an efficient deep neural network. Neural Comput. Appl. 1, (2021).

46. Ren, Y., Zhang, J.: Fake News Detection on News-Oriented Heterogeneous Information Networks through Hierarchical Graph Attention. (2020)
47. Singhal, S., Shah, R.R., Chakraborty, T., Kumaraguru, P., Satoh, S.: SpotFake: A multi-modal framework for fake news detection. Proc. - 2019 IEEE 5th Int. Conf. Multimed. Big Data, BigMM 2019. 39–47 (2019).
48. Wu, L., Rao, Y.: Adaptive interaction fusion networks for fake news detection. Front. Artif. Intell. Appl. 325, 2220–2227 (2020).
49. Yang, Y., Zheng, L., Zhang, J., Cui, Q., Li, Z., Yu, P.S.: TI-CNN: Convolutional Neural Networks for Fake News Detection. (2018)
50. Qian, F., Gong, C., Sharma, K., Liu, Y.: Neural user response generator: Fake news detection with collective user intelligence. IJCAI Int. Jt. Conf. Artif. Intell. 2018-July, 3834–3840 (2018).