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ISSN - XXXXXXXXXX

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Review Article

Machine Learning Approaches for Fake News Detection on Social Media: A Review

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Abstract

The consumption of news through social media has significant implications for individuals, society, and organizations, influencing aspects such as reputation, beliefs, crime, and both mental and physical health. Given these effects, it is crucial to explore the impact of fake news on social media. Researchers have analyzed the challenges and findings from existing studies in the field of fake news detection. This paper lays the foundation for future research and organizational efforts to critically assess the influence of misinformation on communities. Various strategies have been explored to identify and limit the spread of fake news on social platforms. Studies indicate that multimodal features outperform single-modality approaches in detecting misinformation. Additionally, incorporating contextual information enhances the accuracy of fake news detection systems. Researchers have delved into identifying reliable statements and user interactions to better detect false information. A major focus has been on understanding the patterns of fake news dissemination across social networks and analyzing connections among those who spread it. By examining different modalities of news, researchers aim to address the limitations of existing models for developing an automated fake news detection system. This comprehensive review serves as a steppingstone toward the creation of a more effective and efficient automated system for identifying misinformation.

Keywords: Fake news detection, online social media (OSM), Naïve Bayes (NB), Logistic Regression (LR), Multimodality, Contextual information.

1. Introduction

The rapid advancement of technology and the widespread accessibility of the internet have significantly transformed the digital landscape and the way information is disseminated. Social media remains the primary reason for internet usage, with platforms such as WhatsApp, Facebook, Twitter, Instagram, and YouTube gaining immense popularity due to their affordability, ease of use, and viral nature. The number of internet users has surged, engaging with these platforms for various purposes. The digital world is evolving rapidly, with online social media (OSM) surpassing traditional sources as the dominant medium for news consumption. Print media, such as newspapers, are gradually being replaced by online news sources, as the internet provides an abundance of information, largely driven by the increasing popularity of OSM. However, the widespread use of social media, combined with the lack of a requirement for computer literacy, has created opportunities for cybercrimes, particularly through the spread of unverified information. News travels quickly, whether accurate or misleading, and distinguishing between real and fake news is often challenging for users. Misinformation spreads rapidly, both through word of mouth and social media platforms.

Fake news refers to deliberately fabricated information designed to deceive the public, often causing reputational harm to individuals, communities, or institutions. It gained widespread attention during the 2016 U.S. presidential elections when false reports fevering one candidate were shared over 37 million times on Facebook. Since then, the issue has drawn increasing concern. Detecting fake news is crucial for ensuring that users receive credible information while maintaining a trustworthy news environment. Given the sheer volume of data on social media, manual detection methods are impractical due to constraints like time, cost, and human effort. Therefore, automated fake news detection systems are essential. Artificial Intelligence (AI) has proven highly effective in tackling this challenge. The following section explores existing research in the field of fake news detection and identifies gaps that need to be addressed for developing a fully automated detection mechanism for social media platforms.

2. Literature Review

Several Numerous strategies have been devised in recent years to identify and mitigate the spread of fake news. This section explores various research efforts focused on detecting misinformation on online social media platforms. A thorough literature survey indicates that initial fake news detection methods relied heavily on machine learning models. Over time, deep learning techniques gained prominence, and currently, pre-trained models and transfer learning approaches are demonstrating significant effectiveness in this domain.

Aldwairi, M. et al. introduced a browser extension that assists users in filtering out potential clickbait and unreliable websites containing misleading content. Fake news often manipulates multiple modalities, including text, images, videos, and audio, necessitating multi-modal detection frameworks [2].

Yaqing Wang et. al. proposed the Event Adversarial Neural Network (EANN), a model designed for real-time fake news detection by learning event-invariant characteristics. Unlike traditional models that struggle with newly emerging and time-sensitive events due to their reliance on event-specific features, EANN effectively generalizes across different contexts. This framework comprises three components: the event discriminator, a multi-modal feature extractor, and a fake news detector. Evaluations conducted on datasets from platforms like Weibo and Twitter demonstrated that EANN outperformed existing baseline techniques by leveraging transferable feature representations [3].

Khan, J. Y. et al. performed an empirical analysis to assess the efficiency of multiple machine learning algorithms on large-scale datasets. Their study categorized 19 models into three groups: standard machine learning models, traditional deep learning approaches, and advanced pre-trained language models such as BERT. Findings indicated that BERT-based systems surpassed other models in both performance and adaptability, even when trained on smaller sample sizes. Additionally, Naive Bayes with N-Gram achieved comparable results to neural networks on large datasets, while LSTM-based models performed best when the input news stories contained substantial information [4].

Gravanis, G. et al. developed a methodology for fake news detection utilizing content-based features and machine learning techniques. This study introduced the "UNBiased" (UNB) dataset, a curated corpus designed for accurate classification tasks. Their model achieved up to 95% accuracy across multiple datasets, with AdaBoost emerging as the top-performing classifier, closely followed by SVM and Bagging techniques [5].

Dhruv Khattar et al. presented the Multimodal Variational Autoencoder (MVAE) for detecting fabricated news. MVAE consists of three main components: a fake news detector, an encoder, and a decoder. By extracting textual and visual features, this model demonstrated superior performance compared to previous multimodal approaches, achieving a 5% improvement in F1-score and a 6% increase in accuracy on datasets from Twitter and Weibo [6].

Abdullah-All-Tanvir et al. proposed an automated approach for classifying news on Twitter, utilizing techniques such as TF-IDF, Count-Vectors, and Word Embedding. Their comparative study of five machine learning models (NB, SVM, LR, and RNN) revealed that SVM achieved the highest accuracy of 74% across different feature sets [7].

Bahad, P. et al. introduced a Bi-Directional LSTM model to detect fake news by analyzing the correlation between news headlines and body text using GloVe embeddings. Their approach outperformed CNNs, vanilla RNNs, and unidirectional LSTMs on high-dimensional datasets [8].

Shu, K. et al. emphasized the importance of user behavior analysis in fake news detection. Their study examined post-sharing patterns and identified key influencers who frequently disseminate misinformation, aiding in the development of more effective detection strategies [9].

Vishwakarma D. K. et al. developed an image verification framework that cross-checks visual content against web search results. By analyzing the top 15 Google search results, their model assigned a credibility score to images, distinguishing between authentic and manipulated content [10].

Singhal, S. et al. introduced SpotFake, a multi-modal framework that integrates textual and visual analysis. SpotFake employs BERT for textual feature extraction and VGG-19 for image analysis, outperforming existing Twitter and Weibo detection models by 3.27% and 6.83%, respectively [11].

Singhal, S. et al. later refined this model by developing SpotFake+, leveraging transfer learning to improve contextual and semantic understanding. Their study, conducted on the FakeNewsNet repository, marked the first large-scale multimodal analysis on full-length articles and associated images [12].

Kaur, S. et al. designed a multi-level voting mechanism incorporating twelve machine learning classifiers. By leveraging multiple feature extraction techniques, their model achieved higher accuracy compared to individual classifiers. Their findings highlighted Logistic Regression, Passive Aggressive, and Linear SVM as the most effective standalone classifiers, while their ensemble model outperformed them all [13].

Xinyi Zhou et al. developed SAFE, a similarity-aware multi-modal fake news detection system. This model assessed textual-visual mismatches through three modules: multi-modal feature extraction, within-modal fake news prediction, and cross-modal similarity extraction. Their results demonstrated that deep learning techniques outperform traditional machine learning methods in detecting misinformation [14].

Ozbay, F. A. et al. proposed a hybrid approach combining text mining with twenty-three supervised AI algorithms. Evaluations on three real-world datasets confirmed the model's high precision, recall, and F1-score [15].

Salazar, A. P. conducted a comparative analysis of fake news datasets, introducing FakeNewsNet, a comprehensive repository aimed at enhancing misinformation detection efforts [16].

Wang, Y. et al. introduced WeFEND, a weakly supervised learning framework that utilizes user reports to enhance training data. Their model achieved 82.4% accuracy on a large dataset from WeChat [17].

Singhal, S. et al. developed FACTDRIL, a dataset designed for fake news detection in low-resource Indian languages. With over 22,000 samples in eleven languages, FACTDRIL incorporated manual verification strategies to improve the reliability of misinformation classification [18].

Azeri, M. et al. employed machine learning techniques to assess Twitter news credibility. Their study found that Random Forest achieved the highest accuracy (83.4%) when combining content-based and user-based features [19].

Sahoo, S. R. et al. proposed an automated fake news detection system for Facebook, utilizing deep learning models such as LSTMs, which achieved an accuracy of 99.4% [20].

Collins, B. et al. conducted a survey on misinformation trends and detection methodologies, highlighting the effectiveness of hybrid approaches that combine machine learning, NLP, and fact-checking mechanisms [21].

Kaliyar, R. K. et al. introduced FakeBERT, a deep learning model that integrates BERT with CNNs to enhance natural language comprehension in fake news detection [22].

3. Comparative Analysis

The rise of social media has opened with respect to fake news and its automatic detection. It is an area that affects views and beliefs, business, mental and physical health. Table 1 throws light on the work of eminent researchers in the area of fake news detection and a comparative view of the outcome and accuracy observed in each of the work.

Table 1.Comparative Analysis of Fake News Detection

Author Name	**Approach**	**Efficiency/Accuracy (in %)**	**Findings/outcomes**
Y. Wang et al. 2018[3]	Event Adversarial Neural Networks for multi- modal Framework(EANN)	71.5% on Twitter dataset and 82.7% on Weibo dataset.	The proposed EANN model surpasses other models in performance and effectively learns transferable feature representations.
J. Y. Khan et al. 2021[4]	A total of 19 models are utilized, comprising 8 traditional learning models, 6 conventional deep learning models, and 5 advanced models. These include pre-trained language models such as BERT (Bidirectional Encoder Representations from Transformers).	RoBERTa (Robustly Optimized BERT Approach) attained an accuracy of 96% on the fake vs. real news dataset and 98% on the combined corpus dataset.	Among the 19 models, RoBERTa delivers the best performance on the real vs. fake news dataset and the combined corpus dataset, whereas HAN excels on the LIAR dataset.
Dhruv Khatter et al. 2019[6]	Multimodal Variational AutoEncoder(MVAE)	Achieved 74.5% accuracy on the Twitter dataset and 82.4% on the Weibo dataset.	MVAE surpasses other deep learning models by approximately 6% in accuracy and around 5% in F1-scores.
Abdullah-All-Tanvir et al. 2019[7]	Machine Learning Approaches: • Support Vector Machine (SVM) • Naïve Bayes (NB) • Logistic Regression (LR) Deep Learning Approaches: • Recurrent Neural Network (RNN) • Long Short-Term Memory	69.47 89.02 89.34 74 78	SVM and Naïve Bayes achieve superior performance compared to other algorithms on the Twitter dataset.

	(LSTM)		
Bahad, P. et al. 2019 [8]	Bi-LSTM- RNN (Bi-directional LSTM-recurrent neural network)	----	The model was evaluated on two publicly available unstructured news article datasets. It utilizes GloVe word embedding to measure the correlation between the news title and the body of the news story. For both stable and unstable high-dimensional news datasets, the proposed approach outperforms other deep learning models, including CNN, vanilla RNN, and unidirectional LSTM.
S. Singhal et al. 2019[11]	Multi-modal framework(SPOTFAKE)	An accuracy of 77.77% was achieved on the Twitter dataset, while the Weibo dataset attained 89.23% accuracy.	The proposed SPOTFAKE system outperforms existing models by approximately 3.27% and 6.83%, respectively.
S. Singhal et al. 2020[12]	SPOTFAKE+	An accuracy of 84.6% was achieved on the fake dataset and 85.6% on the GossipCop dataset from FakeNewsNet.	The proposed SPOTFAKE+ is a multi-modal framework that surpasses other multi-modal frameworks, including EANN, MVAE, and SPOTFAKE.
Xinyi Zhou et al. 2020[14]	Similarity-Aware Multi- Modal FakE news detection system(SAFE)	An accuracy of 87.4% was achieved on the PolitiFact dataset and 83.8% on the GossipCop dataset.	The proposed SAFE system identifies the falsity of news articles by analyzing their text, images, and any inconsistencies between them.
Wang, Y. et al. 2020 [17]	WeFEND (Weakly Supervised Fake News Detection Framework)	An accuracy of 82.4% was achieved on a large collection of news articles from official WeChat accounts.	This model leverages user reports as weak supervision to increase the amount of training data for false news detection. The proposed framework consists of three key components: the annotator, the reinforced selector, and the fake news detector. By integrating these components, the approach enhances both the quantity and quality of training data, adapting to the dynamic nature of news. It achieved an accuracy of 82.4% on a large collection of news articles from

			official WeChat accounts
Marina Azer et al. 2021[19]	Random Forest (RF) Support Vector Machine (SVM) Logistic Regression (LR) K-Nearest Neighbor (KNN) Naïve Bayes (NB)	Logistic Regression (LR) achieves an accuracy of 73.2% using content-based features, while Random Forest (RF) attains 82.2% with user-based features and 83.4% with the overall feature set.	Logistic Regression (LR) performs best with content-based features, whereas Random Forest (RF) excels with user-based features and the overall feature set, which combines both content-based and user-based features. Additionally, user-based features demonstrate better performance compared to content-based features.
S. R. Sahoo et al. 2020[20]	Machine Learning Classifiers: K-Nearest Neighbor (K-NN) Support Vector Machine (SVM) Logistic Regression(LR) Decision Tree Naïve Bayes (NB) Deep Learning Classifier: Long Short Term Memory (LSTM)	The accuracy obtained using a combination of news content features and user profile features is: 99.3 99.3 99.0 99.1 98.6 99.4	The deep learning model LSTM outperforms other classifiers, achieving 99.4% accuracy when using a combination of user profile and news content features.
S.Aphiwongsophon et al. 2018[23]	Naïve Bayes (NB) Neural Network (NN) Support Vector Machine (SVM)	96.07 99.90 99.90	NN and SVM perform better than other methods.
A.Kesarwani et al. 2020[24]	K-Nearest Neighbor (K-NN)	79	An accuracy of 79% was achieved when tested on the Facebook news posts dataset.
I. Y. R. Pratiwi et al. 2017[25]	Naïve Bayes (NB)	78.6	A 70:30 ratio of the training and testing dataset yields better performance, achieving an accuracy of 78.6%.
M.Granik et al. 2017[26]	Naïve Bayes(NB)	74	Developed as a software system and evaluated using a dataset of Facebook news posts.

Mrs. Usha. M et al.2023[27]	GRU, LSTM, and RNN	90	Outcomes demonstrate that 83% using GRU is the best recall and F1-Measure for bogus news.model. Similarly, the accuracy, For true news, Recall and F1-Measure had respective values of 88%, 90%, and 88%. For same datasets, solutions performed better than the conventional machine learning algorithms
Dharmaraj R. Patil 2022[28]	This study applied an ensemble learning technique, combining models like Decision Tree, Logistic Regression, XGBoost, Random Forest, Extra Trees, AdaBoost, SVM, SGD, and Naïve Bayes to improve classification performance.	96.38%.	The ensemble method significantly enhanced fake news detection accuracy compared to individual classifiers.
Zainab A. Jawad and Ahmed J. Obaid 2022 [29]	The paper explored a hybrid model combining Convolutional Neural Networks (CNN) and Deep Neural Networks (DNN) to analyze textual patterns.	84.6%.	While the model effectively classified news articles, it struggled to differentiate between certain categories, such as "disagree."
Jinyan Su, Claire Cardie, & Preslav Nakov 2023[30]	The study assessed the ability of fake news detection models trained on both human-written and AI-generated news.	---	Models trained exclusively on human-generated content were effective at detecting machine-generated fake news, but the reverse was not true. The study emphasized the importance of a balanced dataset
Jasraj Singh, Fang Liu, Hong Xu, Bee Chin Ng, & Wei Zhang 2024[31]	The researchers integrated linguistic features into machine learning models to improve detection accuracy.	98.2%	The inclusion of linguistic insights enhanced both performance and interpretability of the models.
Biplob Kumar Sutradhar, Md. Zonaid, Nushrat Jahan Ria, & Sheak Rashed Haider Noori 2023[32]	The study applied machine learning techniques, including Stochastic Gradient Descent, Naïve Bayes, and Logistic Regression, using a dataset of 1,876 news articles. (Naïve Bayes classifier)	56%	The results indicated that higher accuracy could be achieved with more robust models and larger datasets.

Shalini Pandey, Sankeerthi Prabhakaran, N. V. Subba Reddy, & Dinesh Acharya[33]	This study compared multiple classifiers, including K-Nearest Neighbor, Support Vector Machine, Decision Tree, Naïve Bayes, and Logistic Regression.	90.46%	Logistic Regression and Support Vector Machine (SVM) were found to be the most effective techniques for this task
Maya Hisham, Raza Hasan, & Saqib Hussain[34]	This study used Support Vector Machine (SVM) with TF-IDF feature extraction to classify fake news.	99.36%	SVM outperformed other classifiers, including Random Forest and Naïve Bayes, in detecting fake news.
Sudhir Bussa, Aniruddha Bodhankar, Vinod H. Patil, Hemant Pal, Satyendra Kumar Bunkar, & Abdul Razzak Khan Qureshi 2023[35]	The researchers implemented Long Short-Term Memory (LSTM) and Support Vector Machine (SVM) models for fake news detection.	94% (LSTM) | 89% (SVM)	The LSTM model outperformed SVM by effectively capturing long-term dependencies in text.

4. Research Gap

The Extensive research has identified gaps that need to be addressed for developing a more effective and efficient fake news detection system. The following section outlines the challenges and areas for improvement in automated fake news detection. Research Gaps

1. A single-modality feature poses a challenge in effectively identifying fake news.
2. Several effective methods have been developed using a linguistic approach for fake news detection. However, minimal research has been conducted on visual-based verification.
3. Source verification is a crucial missing component in existing models.
4. The limited dataset size has been identified as a constraint in the current literature.
5. Existing approaches have not given sufficient attention to newly emerging and time-sensitive events.
6. Most researchers have primarily focused on specific types of news, such as political news, leading to dataset bias

This presents an opportunity to leverage a comprehensive dataset with multimodal features for a more effective and efficient automatic fake news detection system. The following challenges need to be addressed for maximizing the system's potential:

1. Since non-manipulated images are mixed with fake news content, distinguishing between real and fake becomes challenging
2. The lack of editorial rigor further complicates the identification of fake news.
3. A well-structured dataset containing contextual information and a complete multimodal collection of fake news data types is necessary.
4. Verifying sources and assessing author credibility remains a challenge for researchers
5. There are currently no effective mechanisms to identify and restrict the spreaders of fake news on social media.
6. Incorporating contextual information is essential to enhance the model's efficiency.
7. Extracting explainable check-worthy phrases, user comments, fake news dissemination patterns, and connections between spreaders can be valuable in distinguishing fake from real news

8. Examining the relationship between the news title and body text, along with the correlation between different modalities, can contribute to achieving the desired accuracy and efficiency.

5 Conclusions

A thorough and critical evaluation provides comprehensive research insights for detecting fake news while addressing its impact on individuals, society, and organizations. With the vast amount of information available, social media has become a primary platform for online content consumption. However, manually classifying news articles is impractical due to the significant manpower, cost, time, and expertise required. Consequently, automated fake news detection is essential. Research indicates that in both single-modality (text-only) and multi-modality approaches, the primary focus is on feature extraction techniques involving text and images. Textual feature extraction is performed using methods such as Text-Convolutional Neural Network (Text-CNN), Term Frequency-Inverse Document Frequency (TF-IDF), Hashing-Vectorizer (HV), and Count-Vectorizer (CV). Meanwhile, visual feature extraction is carried out using VGG-19.

Various Machine Learning, Deep Learning, Transfer Learning, and Pre-trained models have been analyzed to gain a deeper understanding of previously implemented fake news detection approaches. Findings suggest that pre-trained and deep learning models exhibit the highest effectiveness in identifying fake news.

References

[1] Ahmed, A. A. A., Aljabouh, A., Donepudi, P. K., & Choi, M. S. (2021). Detecting Fake News using Machine Learning: A Systematic Literature Review. arXiv preprint arXiv:2102.04458. https://arxiv.org/abs/2102.04458

[2] Aldwairi, M., &Alwahedi, A. (2018). Detecting fake news in social media networks. Procedia Computer Science, 141, 215- 222.https://doi.org/10.1016/j.procs.2018.10.171

[3] Yaqing Wang, Fenglong Ma, Zhiwei Jin, Ye Yuan, GuangxuXun, KishlayJha, Lu Su, and Jing Gao.2018. EANN: Event Adversarial Neural Networks for Multi-Modal Fake News Detection. In Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining (London, United Kingdom) (KDD '18). Association for Computing Machinery, New York, NY, USA, 849–857. https://doi.org/10.1145/3219819.3219903

[4] Khan, J. Y., Khondaker, M., Islam, T., Iqbal, A., &Afroz, S. (2021). A benchmark study on machine learning methods for fake news detection. Computation and Language.https://arxiv.org/abs/1905.04749

[5] Gravanis, G., Vakali, A., Diamantaras, K., & Karadais, P. (2019). Behind the cues: A benchmark study for fake news detection. Expert Systems with Applications, 128, 201-213. https://doi.org/10.1016/j.eswa.2019.03.036

[6] Dhruv Khattar, Jaipal Singh Goud, Manish Gupta, and VasudevaVarma. 2019. MVAE: Multimodal VariationalAutoencoder for Fake News Detection. In The World Wide Web Conference (San Francisco, CA, USA) (WWW '19). Association for Computing Machinery, New York, NY, USA, 2915–2921. https://doi.org/10.1145/3308558.331355

[7] Abdullah-All-Tanvir, Mahir, E. M., Akhter S., &Huq, M. R. (2019). Detecting Fake News using Machine Learning and Deep Learning Algorithms. 7th International Conference on Smart Computing & Communications (ICSCC), Sarawak, Malaysia, Malaysia, 2019, pp.1-5, https://doi.org/10.1109/ICSCC.2019.8843612

[8] Bahad, P., Saxena, P., & Kamal, R. (2019). Fake news detection using bi-directional LSTM- recurrent neural network. Procedia Computer Science, 165, 74-82.https://doi.org/10.1016/j.procs.2020.01.072

[9] Shu, K., Zhou, X., Wang, S., Zafarani, R., & Liu, H. (2019, August). The role of user profiles for fake news detection. In Proceedings of the 2019 IEEE/ACM international conference on advances in social networks analysis and mining(pp. 436- 439).https://doi.org/10.1145/3341161.3342927

[10] Vishwakarma, D. K., Varshney, D., &Yadav, A. (2019). Detection and veracity analysis of fake news via scrapping and authenticating the web search. Cognitive Systems Research, 58, 217-229. https://doi.org/10.1016/j.cogsys.2019.07.004

[11] Singhal, S., Shah, R. R., Chakraborty, T., Kumaraguru, P., & Satoh, S. (2019). SpotFake: A Multi-modal Framework for Fake News Detection. 2019 IEEE Fifth International Conference on Multimedia Big Data

(BigMM).doi:10.1109/bigmm.2019.0044.

[12] Shivangi Singhal, Anubha Kabra, Mohit Sharma, Rajiv Ratn Shah, TanmoyChakraborty, and Ponnurangam Kumaraguru. 2020. SpotFake+: A Multimodal Framework for Fake News Detection via Transfer Learning (Student Abstract). Proceedings of the AAAI Conference on Artificial Intelligence 34, 10 (Apr. 2020), 13915–13916. https://doi.org/10.1609/ aaai.v34i10.7230

[13] Kaur, S., Kumar, P. & Kumaraguru, P. (2020). Automating fake news detection system using multi-level voting model. Soft Computing, 24(12), 9049–9069. https://doi.org/10.1007/s00500-019-04436-y

[14] Xinyi Zhou, Jindi Wu, and Reza Zafarani. 2020. SAFE: Similarity-Aware Multi-Modal Fake News Detection. arXiv:2003.04981 [cs.CL]

[15] Ozbay, F. A., & Alatas, B. (2020). Fake news detection within online social media using supervised artificial intelligence algorithms. Physica A: Statistical Mechanics and its Applications, 540, 123174. https://doi.org/10.1016/j.physa.2019.123174

[16] Salazar, A. P. (2020). AI Tools on Fake News Detection: An Overview and Comparative Study.

[17] Wang, Y., Yang, W., Ma, F., Xu, J., Zhong, B., Deng, Q., &Gao, J. (2020, April). Weak supervision for fake news detection via reinforcement learning. In Proceedings of the AAAI Conference on Artificial Intelligence (Vol. 34, No. 01, pp. 516- 523). https://doi.org/10.1609/aaai.v34i01.5389 Springer, Cham. DOI: 10.1007/978-3-319-69155-8_9

[18] Singhal, S., Shah, R. R., & Kumaraguru, P. (2021). Factorization of Fact-Checks for Low Resource Indian Languages. arXiv preprint arXiv:2102.11276.

[19] Azer, M., Taha, M., Zayed, H. H., &Gadallah, M. (2021). Credibility Detection on Twitter News Using Machine Learning Approach. International Journal of Intelligent Systems & Applications, 13(3).

[20] Sahoo, S. R., & Gupta, B. B. (2021). Multiple features based approach for automatic fake news Detection on social networks using deep learning. Applied Soft Computing, 100, 106983. https://www.sciencedirect.com/science/article/abs/pii/S1568494620309224

[21] Collins, B., Hoang, D. T., Nguyen, N. T., & Hwang, D. (2021). Trends in combating fake news on social media–a survey. Journal of Information and Telecommunication, 5(2), 247-266. https://doi.org/10.1080/24751839.2020.1847379

[22] Kaliyar, R. K., Goswami, A., & Narang, P. (2021). FakeBERT: Fake news detection in Social media with a BERT-based deep learning approach. Multimedia tools and applications, 80(8), 11765-11788. ‘ doi: 10.1007/s11042-020-10183-2

[23] Aphiwongsophon, S., & Chongstitvatana, P. (2018). Detecting Fake News with Machine Learning Method. 2018 15th International Conference on Electrical Engineering/Electronics, Computer,Telecommunications and Information Technology (ECTI-CON), 528-531. https://doi.org/10.1109/ECTICon.2018.8620051

[24] Kesarwani, A., Chauhan, S. S., & Nair, A. R. (2020). Fake News Detection on Social Media using K-Nearest Neighbor Classifier. 2020 International Conference on Advances in Computing and Communication Engineering (ICACCE), Las Vegas, NV, USA,pp.1-4, https://doi.org/10.1109/ICACCE49060.2020.9154997

[25] Pratiwi, I. Y. R., Asmara, R. A., & Rahutomo, F. (2017). Study of hoax news detection using naïve bayes classifier in Indonesian language. 2017 11th International Conference on Information & Communication Technology and System (ICTS), Surabaya, pp.73-78. https://doi.org/10.1109/ICTS.2017.8265649

[26] Granik, M., &Mesyura, V. (2017). Fake news detection using naive Bayes classifier. 2017 IEEE First Ukraine Conference on Electrical and Computer Engineering (UKRCON). doi:10.1109/ukrcon.2017.8100379

[27] Mrs. Usha. M, Lakshmi N S, Lakshmi N, Divyashree P, Deenakumari K(2023).Fake News Detection Using Machine learning. International Journal of Advanced Research in Computer and Communication Engineering DOI:10.17148/IJARCCE.2023.12242.

[28] Patil, D. R. (2022). Fake News Detection Using Majority Voting Technique. Retrieved from arXiv.

[29] Jawad, Z. A., & Obaid, A. J. (2022). Combination of Convolution Neural Networks and Deep Neural Networks for Fake News Detection. Retrieved from arXiv.

[30] Su, J., Cardie, C., & Nakov, P. (2023). Adapting Fake News Detection to the Era of Large Language Models. Retrieved from arXiv.

[31] Singh, J., Liu, F., Xu, H., Ng, B. C., & Zhang, W. (2024). LingML: Linguistic-Informed Machine Learning for Enhanced Fake News Detection. Retrieved from arXiv.

[32] Sutradhar, B. K., Zonaid, M., Ria, N. J., & Noori, S. R. H. (2023). Machine Learning Technique Based Fake News Detection. Retrieved from arXiv.

[33] Pandey, S., Prabhakaran, S., Reddy, N. V. S., & Acharya, D. (2022). Fake News Detection from Online Media Using Machine Learning Classifiers. Retrieved from IOP Science.

[34] Hisham, M., Hasan, R., & Hussain, S. (2023). An Innovative Approach for Fake News Detection Using Machine Learning. Retrieved from Sir Syed University.

[35] Bussa, S., Bodhankar, A., Patil, V. H., Pal, H., Bunkar, S. K., & Qureshi, A. R. (2023). An Implementation of Machine Learning Algorithm for Fake News Detection. Retrieved from IJRITCC.

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