Volume 64 | Issue 02 | February 2025
DOI: 10.5281/zenodo.14864503

Detect & Combat Fake News & Misinformation on Social Media Using Machine Learning

Sohong Dhar[1], Anushka Singh[2]*, Dr. K.K. Shivkumar[3] & Abdula, Ali shiyam[4]

1. Department of Library& Information Science, Jadavpur University, Kolkatta.
Data Scientist Associate, Azure, Microsoft. Email: sohongdhar@gmail.com
2. B.Tech (Major in Mining Engineering, Minor in CSE), IIT Kharagpur.
Software Engineer at Clodura, Pune.
*Corresponding Author Email: anushkasingkgp@gmail.com, ORCID: 0009-0005-6093-0191
3. Associate Professor, Mohan Babu University, Tirupati. Email: Sivakumarccet@gmail.com.
4. Department of Managements, Francis College, USA. Email: sshiam@sfc.edu

Abstract

There are benefits and drawbacks to relying only on social media for news updates. It is true that social media platforms facilitate the rapid dissemination of knowledge among individuals. Still, these kinds of websites might be used to spread misinformation-filled, low-quality content—what is known as "fake news." Because malevolent actors may sway readers with misinformation and false news, social media has grown into an integral part of state security, generating needless discussion on matters that are inherently meaningless to society. This leads to a domino effect, public anxiety, and ultimately risks to the security of the state. Early fake news detection is the most important step in saving people's lives from the spread of false information. People unintentionally contribute to the spread of false information by spreading it. Thus, identifying fake news that has been posted on different social media platforms has recently gained a lot of attention as a developing field of study. The detection of false news on the many social media platforms presents new difficulties that render the algorithms now in use obsolete or inefficient. On the other hand, the original propagators of false news seek to disseminate the misinformation by focusing on innocent individuals. Cutting-edge data sensors and deep learning methods hold considerable promise for facilitating the development of useful solutions to address the issue of false news. However, because of data shortages, such remedies often need improved model generalisation in the actual world. In this research, we address the problem of false news identification by introducing a novel approach that uses a committee of classifiers. Neuronal networks have shown to be an excellent tool among others for identifying bogus news on social media. In this study, a deep learning-based methodology has been used to distinguish bogus news from authentic sources. The suggested model has been constructed using an LSTM neural network. To that purpose, we provide a variety of basic models, each of which has been individually trained on sub-corpora with distinct qualities. Specifically, we use multi-label text-type categorization to aid in the formation of an ensemble. The study was carried out using six distinct benchmark datasets. The findings are encouraging and pave the way for more study.

Keywords: *Social Media Platforms, LSTM Neural Network, Fake News, Misinformation, Algorithms, Model Generalization, Fake News Detection, Neural Networks, Machine Learning, Benchmark Datasets, Base Models, Experiments.*

Volume 64 | Issue 02 | February 2025
DOI: 10.5281/zenodo.14864503

"About three million individuals disseminated about 126,000 rumours. The top 1% of fake news cascades diffused to from 1000 and 100,000 individuals, but the truth seldom diffused to more than 1000 people. This means that false news reached a larger audience than the truth."

Science —

1. INTRODUCTION

Having a certain degree in subject matter, training, or experience no longer prevents someone from sharing their thoughts and pursuing a career in content creation. If they so want, content providers may maintain complete anonymity over the Internet. Still, this has created the conditions for the emergence of the false news phenomenon. Even though the issue of misinformation has been since the dawn of human civilization, the development of online media has fundamentally changed how lies are disseminated (Ahmed et al. 2017) It eventually developed into a very powerful weapon.

One of the newer technologies that has altered how people see business problems is artificial intelligence. A growing number of businesses are using machine learning and sophisticated analytics to address issues. The advancement of artificial intelligence has brought up a plethora of options for corporations seeking to comprehend human emotions via data. One such opportunity is Natural Language Processing, or NLP (*Reema,2018)*

Social media's ascent has revolutionised information sharing by providing instantaneous worldwide connectedness. But because of real-time sharing and large user bases on sites like Twitter, (*Shu,2019)* it has also contributed to the spread of false information. Twitter's fast reach and short nature make it a popular forum for thoughts and news. However, because of the quick amplification and lack of context, this also leaves it open to false information. It's critical to identify and combat bogus news on Twitter (*Munandar,2019).* Misinformation has the potential to mislead the public, skew conversations, and undermine confidence. Ensuring the accuracy of information is essential for democratic processes, news credibility, and making educated decisions

Due to its accessibility, a lot of individuals utilise various social media sites to keep up with news. For example, social networking platforms are used by almost two thirds of Americans to follow news stories. Said that the biggest source of the news feed in Great Britain is now a variety of digital channels (*Gupta& Kumaraguru,2012)* Social media platforms outperform conventional media because they can quickly disseminate breaking news. But not every news article that is uploaded is accurate (Sunstein, 2001)

The manipulation of information as well as data shifting is a result of several social, political, and economic factors. As a result of the manipulation of the data, news articles are produced that are neither entirely factual nor entirely fake. This ultimately results in false information spreading over social media platforms, creating a number of societal problems. These falsehoods, often referred to as "Fake News," come in a wide range of formats and kinds (Guo,2018).

Some forms of fake news include, for instance, satires, phoney marketing, rumours, and misleading political reports. Since false information tends to become viral faster than real news,

Volume 64 | Issue 02 | February 2025
DOI: 10.5281/zenodo.14864503

many academics are focusing their efforts on developing effective automated methods for spotting false information. A brand-new initiative from Google called "Google News Initiative" is intended to detect and remove false information. Users will be helped by this effort to identify false reports and news (**Zhou & Zafarani, 2019)**. To be honest, it might be difficult to identify bogus news. This study presents an algorithm that is based on a methodical pipeline that is customised to the properties of Twitter data. The methodology starts with compiling a large collection of tweets with news-related information. The model is trained and assessed using this dataset as the basis. Tokenization and normalisation procedures are used to prepare the data, transforming the unformatted text into one that is appropriate for analysis and categorization (M.F,2021). Fake news often goes unnoticed and spreads more quickly. If false news was formerly widely circulated in paper, it has now become much more so with the rise of social media, especially Facebook News Feed. The spread of false news has been linked to post-truth politics and political extremism. With the goal to better understand how false news spreads, the authors of this research examined a data set of rumour floods on Twitter during 2006 to 2017 in an effort to evaluate and understand the effect of fake news on society. The writers also noted the widespread dissemination of false information (*Parikh& Atrey,2018)* A total of 126,000 rumours were spread by 3 million individuals. True news did not reach as many people as false news did. (Meel&Vishwakarma,2019)

Therefore, the goal of exposing false news must be to help the government and advance society at large. Instead than attempting to contain the distribution of fake news after it has already spread, an administrative structure that can counteract the fallout from the spread of false information and prevent society from becoming an enigmatic accomplice in its dissemination is needed. The purpose of this study is to identify and comprehend how false news affects society and the government. Thus, the spread of false news has long been a topic of discussion. The first duty for the good of society is to identify false information. Because of the rapidly expanding social media data as well as new technology, it is crucial and beneficial to identify false news before it begins to circulate widely. (Meel & Vishwakarma,2019)

Nevertheless, the majority of the examined solutions suggest a single-task learning issue for false news detection, where the whole machine learning model is trained mostly from scratch. Furthermore, only a few strategies take domain segmentation into account before detecting false news since most current techniques combine many model types for obtaining features and other classification answers. In order to solve the issue of false news identification, the authors of this work provide a more scalable strategy that involves the formation of a committee of classifiers (Shu,2017) More specifically, the authors suggest a fresh and alternative method whereby the creation of a diverse pool of base models is separately taught on a sub-corpus of texts that have distinct features (arising directly from multi-label categorization). This increases the effectiveness of textual false news identification (Zannettou,2019)

1.1 Objectives

- Look for pertinent characteristics in social media postings that might point to the possibility of false information.
- Take into consideration algorithms like ensemble techniques, deep learning, or natural language processing (NLP) models.
- Consistently update the model in light of fresh knowledge and changing disinformation tendencies.

Volume 64 | Issue 02 | February 2025
DOI: 10.5281/zenodo.14864503

2. LITERATURE REVIEW

(Zubair, T., Raquib, A., 2019) Misinformation and disinformation have been disseminated across cultures as a result of the rising tendency of sharing and obtaining news via social media sites and the Internet. This tendency has serious ramifications for society in terms of politics, society, ethics, security, and privacy. It also coincides with the area of machine learning's fast advancement, especially with the introduction of methods like deep learning that may be used to produce data. In addition to discussing the technology that have contributed to the growth of issues like filter bubbles, deep fake videos, fake news stories, and social media bots, this paper offers ideas from the Islamic religious system that may help mitigate these issues. After using an Islamic perspective, we conclude that these technology and artefacts transgress the requirement to disseminate truth and refute falsehoods.

(Hangloo, S., 2022) Over the last ten years, there has been a notable increase in the use of social media platforms like Facebook and Twitter, which has greatly enhanced and facilitated interpersonal communication. On the other hand, not all of the information shared and made accessible online is reliable. These platforms provide an ideal environment for the quick spread of false information, including breaking news. The vast quantities of false information that are available on the internet have an opportunity to cause major issues for both individuals and society as a whole. Determining the veracity of provided information is a difficult work, and social media's features make it much more difficult since they facilitate the creation and widespread distribution of material, which results in a massive amount of data that has to be analysed.

(Elsaeed, E., Ouda, O., 2021) Numerous issues arise from online platforms, blogs, and webpages being accessible to anyone. A serious problem that may impact people or whole nations is false news. It is possible to produce and disseminate fake news globally. The US presidential election of 2016 serves as an example of this issue. Regulating social media is thus crucial. Algorithms for machine learning aid in the automated detection of false news. This article suggests a methodology for identifying false news that is built on a collection of voting classifiers, feature extraction, and feature selection algorithms. The suggested method separates legitimate news from bogus news. Initially, we performed pre-processing on the data by removing superfluous letters and digits and lemmatizing the dictionary entries. Second, we used two methods of feature extraction—the phrase to vector technique, a word embedding approach, and the term frequency-inverse document variation methodology—to extract some significant features.

(Choraś, M., Demestichas, K., 2021) Nowadays, fake news poses a serious threat to society and presents a formidable obstacle to those combating misinformation. This phenomena has a detrimental influence on citizens, individual people's or organisations' reputations, and democratic elections (e.g., during the COVID-19 epidemic in the US or Brazil). Therefore, creating powerful tools to combat this issue via the use of cutting-edge Machine Learning (ML) techniques presents a major challenge. The corpus of current research on the use of such intelligent instruments in the battle against misinformation is presented in the article that follows.

(Mohseni, S., Ragan, E., 2019) Several defensive strategies are required to combat false information. While rumour detection and other language analysis algorithms are popular ways to identify fake information on social media, machine learning researchers might investigate additional workable mitigating strategies. In this work, we highlight unresolved problems and

Volume 64 | Issue 02 | February 2025
DOI: 10.5281/zenodo.14864503

promising directions in the study of false news that need more investigation. We begin by going over the many phases of the news life cycle on social media and talking about the fundamental vulnerabilities that news feed algorithms have when it comes to spreading false news, using three instances. Next, we explore how the intricacy and lucidity of the false news issue impede progress in this domain. Our proposal comprises three characteristics of interpretability: algorithmic accessibility, human comprehensibility and the incorporation of corroborating data that might provide diverse advantages for fake news mitigation strategies.

(DSouza, K. M., 2023) False news spreaders spread misinformation that may be detrimental to society and companies alike. Fake news inaccuracies are rapidly amplified by social media's reach. The processes behind such adversarial behaviour and the adversarial machine learning approaches that may be used to identify false news remain largely unexplored in research. Using hostile data, debasing methods are being investigated as a means of countering the production of false news. This study aims to discuss the potential and problems associated with detecting false news.

(Chen, M. Y., Lai, Y. W., 2023) People may now receive and share information more quickly and easily than ever thanks to the widespread use of mobile networked devices. On occasion, however, this leads to the spread of false information that may be hard to discern from the truth. When such information is widely disseminated, it may lead to poor and illogical selections on potentially significant topics. This was in line with the worldwide COVID-19 outbreak in 2020, which is a virus that is very infectious and fatal. The World Health Organisation (also known as the WHO) has already classified the spread of incorrect data about COVID-19 on social networking sites as a "info emic," which presents serious difficulties for international governments trying to contain the pandemic.

3. METHOD

3.1 Architecture

We describe the approach's architecture in this portion of the study. then we describe the general procedures for data collection and open media crawls. Lastly, a description of the used document format and categorization is given. Figure 1 displays the framework of the suggested fix (Song,2021). Data harvesters were used to gather the textual data from freely available sources (news providers, for example).

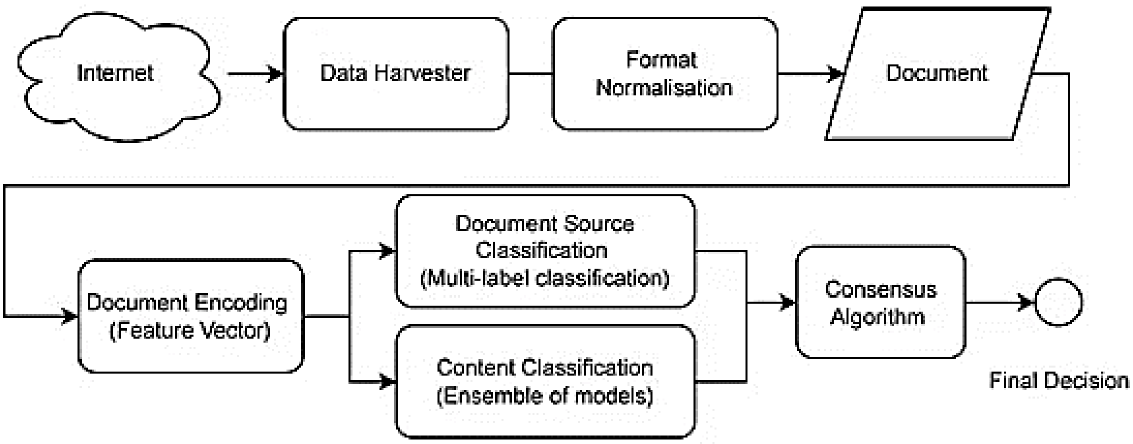

Fig 1: Information flow that the suggested method makes advantage (Stein,2017)

Volume 64 | Issue 02 | February 2025
DOI: 10.5281/zenodo.14864503

Using 3.2 Document Encoding and Classification BERT

A set of benchmark sets, which are often used by different scholars, was produced as part of the study. This made it possible for us to build a combined language archive that finally included several content categories (politics, health, news, etc.).

The issue of feature extraction from documents is distinct as the datasets vary in terms of different attributes (such as text length) (Tan,2019). In order to overcome this, a standardised approach was used for feature extraction across all datasets.

In specifically, word, phrase, and document representation were established using an adaptation of the same BERT model for language (see Figure 2).

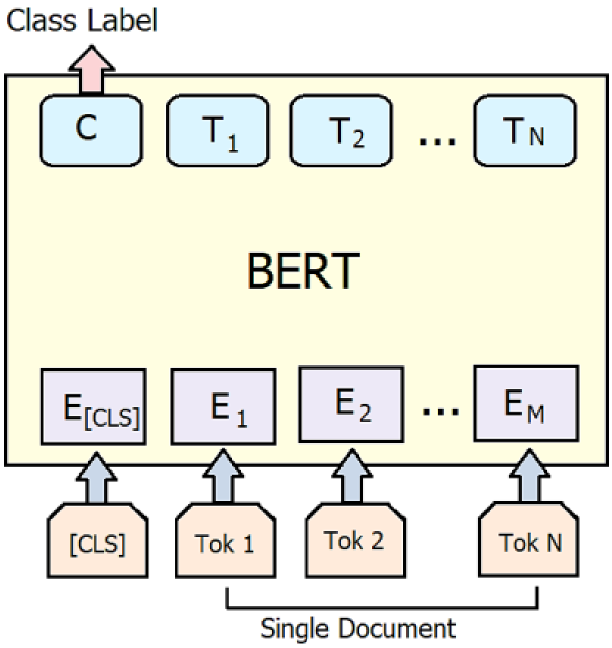

Fig 2: BERT-Based Classification and Representation of Documents

This approach uses traditional two-fold cross-validation and averages the results (Song&Xia,2020) To further underline the differences' significance and variability, the standard deviations from the mean is calculated. A more robust model is achieved by the layered structure of the 5x2-fold Cross-Validation (CV) method (*Vashisht&Dhara,2020)*

$$Precition = \frac{TP}{TP+FP}. \qquad \text{...............} \ 1$$

$$Recall = \frac{TP}{TP+FN}. \qquad \text{.................} \ 2$$

$$Specificcity = \frac{TN}{TN+FP}. \qquad \text{.................} \ 3$$

$$Balanced\ Accuracy = \frac{sensitivity+specificity}{2} \qquad \text{..................} \ 4$$

$$F1 - Score = 2 \times \frac{precision*Recall}{Precision+Recall} \qquad \text{...................}5$$

$$G - mean = \sqrt{sensivility * specificity}. \qquad \text{..................} \ 6$$

Volume 64 | Issue 02 | February 2025
DOI: 10.5281/zenodo.14864503

4. ANALYSIS

4.1 Information Used in Experiments

All of the tests employed six distinct datasets linked to the topic of detecting false news. Table 1 presents the dataset's specifics along with the numbers that will be used to refer to them in this study.

Table 1: A list of datasets pertaining to the veracity of news

No.	Dataset	Size	Content type	Describe
1	**Covid-19 fake news**	10,500 Items (9,500 Fake, 1,000 Real)	News	False and authentic news reports about COVID-19.
2	**MM-covid**	12,000 Items (7,000 Fake, 5000 Real)	News	False and real news stories having a social background.
3	**Q-prop**	51,000 Articles (40,000 Fake 11,000 Real)	News	Articles classified as "propaganda" or "legitimate"".
4	**ISOT**	44,984 Doc (39,856 Fake 5,128 Real)	News	Verified and fraudulent papers with extra information.
5	**GRAFN**	13,000 Post	News (Global Politics)	Metadata and text from 245 sites.
6	**Pub Health**	Not Specified	Health (public/Biomedical)	Documents pertaining to public health issues that include labels and explanations.

4.2 Dataset Performance in a Single

In this article, we provide the classification accuracy using a BERT-based classifier on the datasets under consideration. Table 2 presents the findings. The authors used a single dataset and five iterations of two-fold Cross-Validation (5x2 CV) in every instance.

Table 2: Performance of a BERT-based classifier that was assessed using the same datasets for training

Dataset	Bal. Acc.	F1	G- Mean	Precision	Recall
Covid.FN	98.6 ± 0.5	98.6 ± 0.7	14.6 ± 1.0	52.6 ± 0.8	42.6 ± 0.8
MMCovid	89.6 ± 0.0	58.9 ± 0.4	15.6 ± 0.4	41.6 ± 0.9	43.6 ± 0.1
QProp	74.5 ± 0.5	74.5 ± 0.4	85.6 ± 0.4	43.6 ±0.6	54.1 ± 0.5
ISOT	58.6 ± 0.4	41.6 ± 0.5	14.5 ± 0.1	69.6 ± 0.1	42.6 ± 0.4
GRAFN	96.6 ± 0.5	45.6 ± 0.8	98.6 ± 0.4	85.6 ± 0.6	46.6 ± 0.4
Pub Health	63.9 ± 0.6	79.9 ± 0.5	56.9 ± 0.5	49.6± 0.2	79.6 ± 0.1

4.3 Accuracy of Text Source Classification

Table 3 lists many metrics for the categorization of multi-label sources. The 5x2 cross-validation was used, as in the other examples, to compare and report the categorization results.

Table 3: The suggested text source categorization model's effectiveness

Dataset	F1	Precision	Recall
Covid.FN	89.6 ± 0.6	85.6 ± 0.4	89.6 ± 0.8
MMCovid	45.6 ± 0.5	74.6 ± 0.5	74.6 ± 0.5
QProp	85.6 ± 0.6	85.6 ± 0.6	58.6 ± 0.2
ISOT	48.9 ± 0.4	47.6 ± 0.4	96.7 ± 0.1
GRAFN	85.6 ± 0.9	89.6 ± 0.4	87.6 ± 0.9
Pub Health	78.9 ± 0.6	58.9 ± 0.5	83.1 ± 0.8
Average	85.6 ± 0.6	79.6 ± 0.6	75.6 ± 0.8
Accuracy	96.6 ± 0.7		
Balanced accuracy	79.6± 0.5		

Volume 64 | Issue 02 | February 2025
DOI: 10.5281/zenodo.14864503

4.4 Ensemble of BERT Models

We contrast the suggested strategy with other methods that are well-known from the literature in Table 4:

Table 4: BERT model ensembles' integrated classification performance employing text source classifier

Approach	Balanced Accuracy	Avg. F1
Proposed ensemble method	85.6 ± 0.59	87.6 ± 0.98
Batch MTL	75.9 ± 0.5	79.6 ± 0.4
Majority Voting BERT ensemble	89.6 ± 0.6	79.6 ± 0.9
Weighted BERT ensemble	98.6± 0.6	75.6 ± 0.9

5. CONCLUSION

Sophisticated deep learning methods provide powerful instruments to tackle the problem of misinformation. However, owing to data restrictions, these systems often suffer from poor model generalisation in real-world circumstances. Regretfully, a lot of the solutions that are now in use take a monolithic approach, treating the detection of false news as a single-task learning issue and using several models and classification techniques without taking domain segmentation into account.

In order to address these drawbacks, our study suggests a novel approach to the false news detection problem that involves a committee of classifiers. To that purpose, we provide Cross-validation (CV) technique. This hierarchical CV structure lowers estimate variance and evaluates generalisation a variety of basic models, each of which has been individually trained on sub-corpora with distinct qualities. To assess various methodologies and setups on the studied datasets, we used the 5x2-fold over various data subsets to improve model resilience.

The experimental findings demonstrate the potential of the proposed technique on six distinct benchmark datasets, providing opportunities for future research directions. Specifically, the suggested method shows a 50% improvement in the F1 measure and surpasses the Generalised BERT Ensemble by over 30% in Balanced Accuracy. Additionally, it maintains competition with Batch MTL, as seen by a 0.8% rise in the F1 score.

Future work

The encouraging outcomes and effectiveness point to the direction and importance of using classifier ensembles in disinformation detection systems going forward.

References

1) H. Ahmed, I. Traore, and S. Saad, "Detection of online fake news using N-gram analysis and machine learning techniques," in International conference on intelligent, secure, and dependable systems in distributed and cloud environments, Springer, Cham, pp. 127–138, 2017.

2) A. Reema, A. K. Kar, and P. VigneswaraIlavarasan, "Detection of spammers in twitter marketing: a hybrid approach using social media analytics and bio-inspired computing," in Information Systems Frontiers, vol. 20, no. 3, pp. 515–530, 2018.

Volume 64 | Issue 02 | February 2025
DOI: 10.5281/zenodo.14864503

3) 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, ACM, 2019.

4) D. Munandar, A. Arisal, D. Riswantini, and A. F. Rozie, "Text classification for sentiment prediction of social media dataset using multichannel convolution neural network," in 2018 International conference on computer, control, informatics and its applications (IC3INA), IEEE, pp. 104–109, 2018.

5) A. Gupta and P. Kumaraguru, "Credibility ranking of tweets during high impact events," in Proceedings of the 1st Workshop on Privacy and Security in Online Social Media, ser. PSOSM '12, New York, NY, USA, ACM, pp. 2:2–2:8, 2012.Shu, K.; Wang, S.; Liu, H. Exploiting Tri-Relationship for Fake News Detection. arXiv 2017, arXiv:1712.07709

6) Meyers, M.; Weiss, G.; Spanakis, G. Fake News Detection on Twitter Using Propagation Structures. In Proceedings of the Disinformation in Open Online Media, Leiden, The Netherlands, 26–27 October 2020; van Duijn, M., Preuss, M., Spaiser, V., Takes, F., Verberne, S., Eds.; Springer International Publishing: Cham, Switzerland, 2020; pp. 138–158.

7) Sunstein, C.R. Echo Chambers: Bush V. Gore, Impeachment, and Beyond; Princeton Digital Books+: Princeton, NJ, USA, 2001.

8) Guo, L.; Rohde, J.A.; Wu, H.D. Who is responsible for Twitter's echo chamber problem? Evidence from 2016 U.S. election networks. Inf. Commun. Soc. 2020, 23, 234–251.

9) Zhou, X.; Zafarani, R. Fake News Detection: An Interdisciplinary Research. In Proceedings of the Companion Proceedings of the 2019 World Wide Web Conference, WWW '19, San Francisco, CA, USA, 13–17 May 2019; Association for Computing Machinery: New York, NY, USA, 2019; p. 1292.

10) Mridha, M.F.; Keya, A.J.; Hamid, M.A.; Monowar, M.M.; Rahman, M.S. A Comprehensive Review on Fake News Detection with Deep Learning. IEEE Access 2021, 9, 156151–156170.

11) Parikh, S.B.; Atrey, P.K. Media-Rich Fake News Detection: A Survey. In Proceedings of the 2018 IEEE Conference on Multimedia Information Processing and Retrieval (MIPR), Miami, FL, USA, 10–18 April 2018; pp. 436–441.

12) Tin, P. T. (2018). A study on deep learning for fake news detection. [11] Meel, P.; and Vishwakarma, D. K. (2019). Fake News, Rumor, Information Pollution in social media and Web: A Contemporary Survey of State-of-the-arts, Challenges and Opportunities. Expert Systems with Applications.

13) Vosoughi, S.; Roy, D.; Aral, S. (2018). The spread of true and false news online. Science359, 1146–1151.

14) Shu, K.; Sliva, A.; Wang, S.; Tang, J.; and Liu, H. (2017). Fake news detection on social media: a data mining perspective. SIGKDD Explor. 19(1), 22–36.

15) Zannettou, S.; Sirivianos, M.; Blackburn, J.; and Kourtellis, N. (2018). The web of false information: rumors, fake news, hoaxes, clickbait, and various other shenanigans.

Volume 64 | Issue 02 | February 2025
DOI: 10.5281/zenodo.14864503

16) Zubair, T., Raquib, A., &Qadir, J. (2019). Combating Fake News, Misinformation, and Machine Learning Generated Fakes: Insight's from the Islamic Ethical Tradition. ICR Journal, 10(2), 189-212.

17) Hangloo, S., & Arora, B. (2022). Combating multimodal fake news on social media: methods, datasets, and future perspective. Multimedia systems, 28(6), 2391-2422...

18) Elsaeed, E., Ouda, O., Elmogy, M. M., Atwan, A., & El-Daydamony, E. (2021). Detecting fake news in social media using voting classifier. IEEE Access, 9, 161909-161925.

19) Choraś, M., Demestichas, K., Giełczyk, A., Herrero, Á. Ksieniewicz, P., Remoundou, K., ...&Woźniak, M. (2021). Advanced Machine Learning techniques for fake news (online disinformation) detection: A systematic mapping study. Applied Soft Computing, 101, and 107050.

20) Mohseni, S., Ragan, E., & Hu, X. (2019). Open issues in combating fake news: Interpretability as an opportunity. arXiv preprint arXiv:1904.03016.

21) DSouza, K. M., & French, A. M. (2023). Fake news detection using machine learning: an adversarial collaboration approach. Internet Research.

22) Chen, M. Y., Lai, Y. W., &Lian, J. W. (2023). Using deep learning models to detect fake news about COVID-19. ACM Transactions on Internet Technology, 23(2), 1-23.

23) Song, Y., Zhang, T., Wang, Y., & Lee, K.-F. Zen 2.0: Continue training and adaption for n-gram enhanced text encoders. arXiv preprint arXiv:2105.01279.

24) Stein-Smith, K. (2017). Librarians, information literacy, and fake news. Strategic Library, 37.

25) Tan, M., Chen, B., Pang, R., Vasudevan, V., Sandler, M., Howard, A., & Le, Q. V. (2019). Mnasnet: Platform-aware neural architecture search for mobile. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition (pp. 2820–2828).

26) Tian, Y., Song, Y., & Xia, F. (2020). Joint chinese word segmentation and part-of-speech tagging via multi-channel attention of character n-grams. In Proceedings of the 28th international conference on computational linguistics (pp. 2073–2084).

27) Vashisht, V., &Dharia, P. (2020). Integrating chatbot application with qlik sense business intelligence (BI) tool using natural language processing (NLP). In Micro-electronics and telecommunication engineering (pp. 683–692). Springer.