ISSN: 2581-3404 (Online) **IF: 5.445 (SJIF)**

International Journal of Innovative Research in Technology and Management, Volume-6, Issue-6, 2022.

A Review on Recent Trends of Fake News Detection on Social Media

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Abstract: *In the past decade, the social networks platforms and micro-blogging sites such as Facebook, Twitter, Instagram and Sina Weibo have become an integral part of our day-to-day activities and is widely used all over the world by billions of users to share their views and circulate information in the form of messages, pictures, and videos. These are even used by government agencies to spread important information through their verified Facebook accounts and official Twitter handles, as it can reach a huge population within a limited time window. However, many deceptive activities like propaganda and rumor can mislead users on a daily basis. In this COVID times the fake news and rumors are very prevalent and are shared in a huge number which has created chaos in this tough time. And hence, the need of Fake News Detection it the present scenario is inevitable. In this paper, we survey the recent literature about different approaches to detect fake news over the Internet. In particular, we firstly discuss about fake news and the various terms related to it that have been considered in the literature. Secondly, we highlight the various publicly available datasets and various online tools that are available and cam debunk Fake News in real time. Thirdly, we describe fake news detection methods based on two broader areas i.e., it's content and the social context. Finally, we provide a comparison of various techniques that are used to debunk fake news.*

Keywords: Fake news detection, machine learning, deep learning, social media, ensemble techniques, N-gram analysis.

Introduction

Fake news is one of the biggest discouragements in our digitally connected world. Fake news spreads at lightning-fast speed impacting millions of people in the form of clickbait, trigrams everyday [1]. Therefore, noticing fake news becomes a vital problem attracting huge research efforts. Detection of fake news from social media always creates a new challenge. It is written on social media to mislead readers. In the 2016 US presidential election, fake news propagated more on Facebook than authentic news [2]. Fake news detection on social media has attracted politicians to researchers. The detection of fake news on social media is very important because fake news can change the mindset of people or society or country. So, it is very important for those readers who read news on daily basis on social media to know whether the news is real or fake. So, they always try to read news from authenticating sites or authors.

In this report, we present a survey on the state of the art pertaining to the type of fake news and solutions that are being proposed. The research in this field has been going on for a long time and in the Indian context, the ill effects of spreading fake news are far from what anyone might think.

Unlike in the context of other countries, WhatsApp is the prime distributor of fake news as compared to other social networking sites like Facebook and Twitter. Due to the increase of internet users in India, which has increased 137million (in 2012) to over 600 million (in 2019) facing unique challenges day by day.

CBSE 12th Date Sheet 2021

Date*	Subject Code & Subject
May 4	67- Multimedia & Web Tech, 72- Mass Media Studies, 735- Food Production IV, 736- Understandi… Evaluation and forms of Mass Media, 743- Retail Operations, 748- Information Storage & Retrieva… Derivative Market Operations, 756- Intro To Hospitality Management, 801- Retail, 811- Banking, 8… Healthcare, 816- Horticulture, 818- Geospatial Technology, 819- Electrical Technology, 823- Cost Accounting, 826- Shorthand (Hindi), 832- Music Production, 834- Food Nutrition & Dietetics, 835-… Media Studies, 628- Autoshop Repair, 779- Textile Chemical Processing, 800- Security … Machines
May 5	73- Knowledge Tradition & Practices, 804- Automotive, 805- Financial M… Wellness, 808- Agriculture, 814- Insurance, 828- Medical Diagnostics, … Dance, 57- Bharatnatyam, 58- Kuchipudi, 59- Odissi, 61- Kathakali
May 6	739- CRTV and COM PRAC MM, 795- Database Management Ap…ation, 4…ainting, 50-… Sculpture, 52- Appl Commercial Art, 768- Electrical Appliances
May 7	37- Psychology
May 8	84- Physical Education
May 10	66- Entrepreneurship, 824- Office Procedures & Practices, … Textile Design, 7… Textile
May 11	796- Web Application- Old, 803- Web Application- New, 821- Me…
May 12	1- English Elective- N, 101- English Elective- C, 301- English Core
May 13	3- Urdu Elective, 22- Sanskrit Elective, 76- National Cadet Corps, 303- Urdu Core, 322- Sanskrit C… Engineering Sciences, 810- Front Office Operation, 827- Air Conditioning & Refrigeration, 830- De… Salesmanship
May 14	46- Engineering Sciences, 79- Library & Information Science- Old, 607- Typography & Computer A… English- Old, 609- Typography & Computer Application Hindi- Old, 747- Library System & Resour… Management, 793- Capital Market Operation, 817- Typography & Computer Application- New, 82… Electronic Technology, 836- Library Information Science- New, 837- Fashion Studies, 778- Printed…
May 17	42- Physics, 625- Applied Physics

Figure 1: CBSE Fake News Date sheet.

The year 2020 was a full pandemic year due to corona virus. So, all the school examinations and university exams had been postponed for some months. As usual, the CBSE 10th and 12th exams are taken in the month of March but due to a pandemic situation, it was extended to May and June. The CBSE board only released the timetable of the exam but on some social media sites, the exact date of each paper was also showing which was false. This fake news distracted the mind of students and they started to follow this fake timetable of the exam. After confirmation of CBSE regarding the timetable of the exam that it has not published yet, all the students get very disappointed. This one example of fake news shows how much fake news can poorly affect human beings' lives. Fake news can suppress the image of society and can change the thinking skill of human beings. Due to this, it is very necessary to detect fake news before spreading it. So a powerful and strong module is required which can be easily available to detect fake news. Also, the module should be less expensive so that it can be available on each and every necessity.

Following are the types of fake news:-

1. for entertainment purpose
2. Use a fake image or title for irrelevant content.
3. Misinterpreted information
4. Completely baseless content.
5. Rumors spread by blind followers

These are such fake news that is easily available on social media. Though most fake news is not defective, they are used only for entertainment purposes but the readers do not understand the fact of this news and they change themselves according to the theme of the news. So it is very difficult for readers to understand the motto of news whether it is released for entertainment purposes or any other purpose. That’s why it is very necessary to develop such model which can easily indicate the motto of news so that readers will not get distracted.

Figure 2: Key terms related to Fake News.

II. Fake News

to Cambridge Dictionary Fake News is defined as “false stories that are created and spread on the Internet to influence public opinion and appear to be true”. Fake news is not a new term and has a long legacy reaching back centuries since the development of the earliest writing systems but with the advent of social media the past decade has seen a shift in how the news is propagated that is quite different from the traditional media. The social media platforms have become fertile ground for computational propaganda, and trolling. There are several terms that are used interchangeably for fake news like satire, yellow journalism, hoax, propaganda, misinformation, disinformation, rumor etc, some of them are described below. Figure 2 gives the visual description about the same.

- **Propaganda:** Propaganda refers to news stories which are created and propagated by a political entity to influence political view.
- **Misinformation:** It is inaccurate information that is deliberately created and is intentionally or unintentionally disseminated disregarding the true intent.
- **Disinformation:** It refers to false or incomplete information that is disseminated with the intention to manipulate facts and mislead the target audience.
- **Rumors and hoaxes:** are interchangeably used to refer to deliberate falsification or fabrication of information that is constructed to seem valid. They present the unverified and inaccurate claims as validated by traditional news outlets.
- **Parody and Satire:** usually use humor to give news updates and typically mimic mainstream news media.
- **Clickbait:** Sensational headlines are often used as clickbaits to draw the attention of users and encourage them to click and thus redirecting the reader to a different site. More clicks on the advertisements mean more money.

The rise in the use of propaganda, hoaxes, satire, along with real news and credible content makes it challenging for regular Internet users to distinguish between real and fake news content. But there are various online tools available for debunking fake news like AltNews, APF Fact Check, BSDetector, Hoaxy, Reverse Image Search, Snopes, PolitiFact, Additionally, there are various IFCN-certified fact-checkers around the world that review and rate the credibility of content on various online platforms. Figure 3 depicts an overall taxonomy of fake news detection approaches

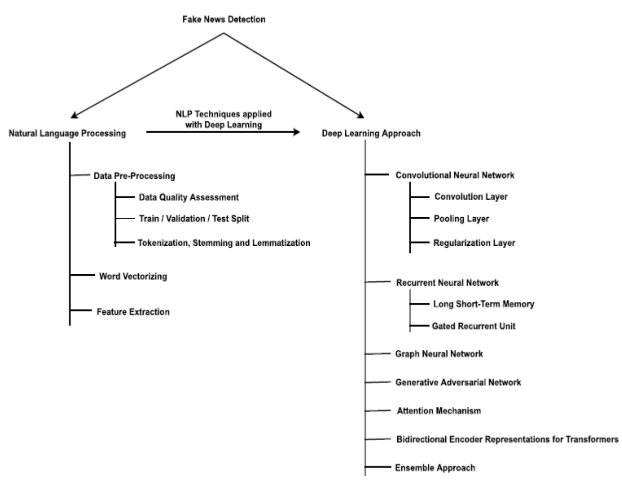

Figure 3: Taxonomy of deep learning-based fake news detection.

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III. Benchmark Dataset

In this section, we discuss the datasets used in various studies. For both training and testing, benchmark datasets were utilized. One of the difficulties in identifying fake news is the shortage of a labeled benchmark dataset with trust- worthy ground truth labels and a massive dataset. Based on that, researchers can obtain practical features and construct models [3]. For several usages in DL and ML, such datasets have been collected over the last few years. The datasets are vastly diverse from one another because of different study agendas. For instance, a few datasets are made up entirely of political statements (such as PolitiFact), while others are made up entirely of news articles (FNC-1) or social media posts (Twitter). Datasets can differ based on their modality, labels, and size. Therefore we categorize these datasets in Table 1 based on these characteristics. Fake articles are frequently collected from fraudulent websites designed intentionally to disseminate disinformation. These false news stories are eventually shared on social media platforms by their creators. Malicious individuals or bots and inattentive users who do not care to check the source of the story before sharing it assist in spreading fake news through social media. However, most datasets contain only news content. But cur- rent language features and writing style are not sufficient enough in developing an efficient detection model.

Fake news, Twitter15, and Liar are the most popular datasets that are publicly available. But some studies trained their model with their created dataset [4]. We defined these datasets as self-collected. Since sufficient information is not provided about their self-collected datasets, we find it difficult to compare with other studies properly. Using the benchmark dataset, a comparative study can be established with current state-of-the-art methods for detecting fake news. Kaliyar et al. [5] conducted a comparative study of their suggested model with existing methods using the Kaggle dataset and they reported an accuracy of 93.50% which is the highest, utilizing the same dataset for fake news detection. A pie chart of used benchmark datasets is given in Figure 4.

Table 1: The table provides details of publicly available datasets and corresponding URLs.

Dataset	Modality	Size	Labels	Type	URL
Fake news	Text	20,800	Unreliable, reliable	News articles	https://www.kaggle.com/c/fake-news/data.
Weibo [27]	Text & image	40k tweets	Rumor, Non-rumor	Social media data	https://drive.google.com/file/d/14VQ7EWPiFeGzxp3XC2DeEHi-BEisDINn/view
Twitter15 [28]	Propagation trees	1,381 propagation trees, 276,663 users	Unverified, true, false, non-rumor	Social media data	https://www.dropbox.com/s/7ewzdrbelpmrnxu/rumdetect2017.zip?dl=0
Twitter16 [28]	Propagation trees	1,181 propagation trees, 173,487 users	Unverified, true, false, non-rumor	Social media data	https://www.dropbox.com/s/7ewzdrbelpmrnxu/rumdetect2017.zip?dl=0
LIAR [29]	Text	12.8K	Pants on fire, false, barely true, half-true, mostly true, and true	Political statements	https://paperswithcode.com/dataset/liar
PHEME [30]	Text	5800 tweets	Rumor, Non-rumor	Social media data	https://figshare.com/articles/dataset/PHEME_dataset_of_rumours_and_non-rumours/4010619
FNC-1	Text	75K	Agrees, disagrees, discusses, unrelated	News articles	https://github.com/FakeNewsChallenge/fnc-1
FakeNewsNet [31]	Text	5K	Fake, real	News articles, so-cial media data	https://github.com/KaiDMML/FakeNewsNet
News Aggregator	Text	422,937	Real	News articles	https://www.kaggle.com/uciml/news-aggregator-dataset
Bend the truth [32]	Text	900	Fake, real	News articles	https://github.com/MaazAmjad/Datasets-for-Urdu-news.git
FacebookHoax [33]	Text	15,500	Hoax, non-hoax	scientific news	https://github.com/gabll/some-like-it-hoax/tree/master/dataset
Twitter [34]	Text and Image	992	Rumor, non-rumor	Fact-checked claims	https://github.com/MKLab-ITI/image-verification-corpus/tree/master/mediaeval2015
KaggleFN	Text	13K	Fake	News articles	https://www.kaggle.com/mrisdal/fake-news
FakevsSatire [35]	Text	486	Fake, satire	Political news	https://github.com/jgolbeck/fakenews

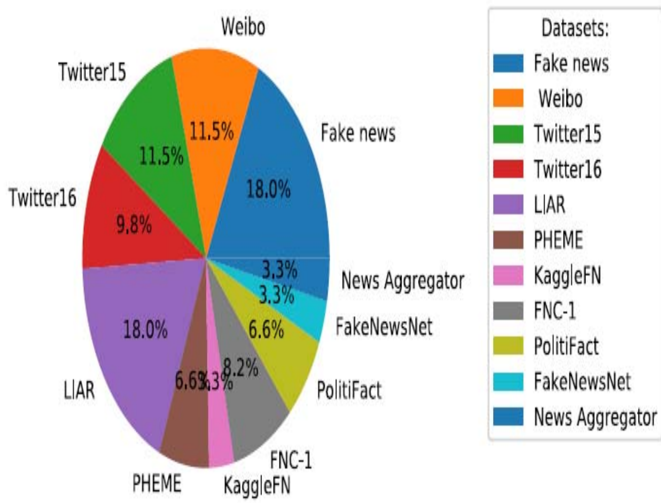

Figure 4: Pie chart of the benchmark datasets of fake news detection.

IV. Related Work

Traditionally, the majority of approaches for detecting fake news focus on analyzing the textual content only and utilized hand crafted textual features for the same. But, with an increasing number of articles which are attached with images over the Internet and the extensive use of social media networks, the multimodal features and social-context play a very vital role in better understanding the overall heuristics of the content. The traditional machine learning and rule-based algorithms are inefficient to detect the patterns in today's information age. Hence, to take advantage of big data Deep learning techniques are investigated for fake news detection.

In 2013, Aditi Gupta, Henmark Lamba and Anupam Joshi achieved more than 90% correct result in identifying false images from twitter of Hurricane Sandy which impacted the United States. Meanwhile, they did a characterization analysis to analyze the impact patterns of the fake pictures by analyzing more than 10,000 images on Twitter. During this time, they worked on NaiveBayes and Decision tree model. After applying these two ML algorithm they arrives at good result having accuracy of 97% by Decision Tree. [6]

In 2017, Elena Kochkina, Arkaitz Zubiaga & Maria Liakata worked on classification of rumor stance on social media platform with the help of sequential classifiers. In this they use Twitter as their social media platform and describe tweets into 4 categories: 1.Support, 2.Deny, 3.query and 4. Comment on an earlier post. They used four sequential classifier-hawkes processes, Long Short Term Memory (LSTM), linear CRF and tree CRF on 8 data sets and all data are related to breaking news. They discover sequential classifiers that use the recitation property in social media interaction outperform non sequential classifiers also LSTM works better than other sequential classifiers. [7]

In 2018, Kalina Bontch., Ahmet Aker, Maria Liakata work on rumour detection using NLP and data mining Methods. They define false news that circulates on social media into two types: long standing rumors and new emerging rumor generate during recent events. They develop a rumor classification system that consists of 4 parts: 1.Detection of rumor, 2.Tracking of rumor, 3. Stances of rumor and 4.Veracity of rumor. And use this system on the PHEME dataset which is publicly available for rumors and non rumors. [8]

In 2018, C.M.M Kotteti, Na Li and Lijun Qian work on increasing the detection of fake news with data imputation. To improve performance they used a novel data preprocessing method to fill the missing value in the raw dataset. With the help of data modeling, they applied missing values for numerical and hierarchical attributes. For hierarchies they select the most frequent value in columns and are numeric for the average value of the column. He did 3 things to cover the missing values. 1. Removed columns with missing values, 2. Missed values with empty text and 3. Used data impersonation techniques to apply missing values and found that multilayer perceptron (MLP) classes improved accuracy by 16%. [9]

In 2018, Supanya Aphiwongsophn and Prabhas Chongstitvatana purpose the ML algorithm to identify fake news. In this paper three popular methods are used: 1.Naive Bayes 2. Support Vector Machine and 3. Neural Network. They used normalization method for cleaning data so that it works better with correct data. In this paper they found that Naive Bayes has an accuracy of 96.08% and the other two complex techniques has an accuracy of 99.90%. [10]

In 2018, a. Jain and A. Kasbe work on detecting fake news and they proposed a method so that we can implement this method on Facebook. He used Naive Bayes for forecasting. They used a dataset from Github with 11000 articles divided into (index, text, title and label). Apart from politics, this data contains news related to science and business. For implementation they used both the title and text for their primary source and also added some references by n-gram and then he compared the results and find that Naïve Bayes (on text with n-grams) gives the accuracy of 0.931 and they also showed some ways to improve this model. [11]

In 2019, Deepayan Bhowmik, Oluwaseun Ajao and Shahrzad Zargari proposed a model that identify false news tweets from twitter post using combination of (CNN) and (RNN) models. For the dataset they collected 5,800 tweets centered on five rumor stories: Charlie Hebgo, Sydney Siege, Germanwing Crash, Ottawa Shooting, and Ferguson Shooting. Their proposed work on hybrid of CNN & RNN intuitionally identifies important feature related with false news stories without any prior knowledge of news and achieve more than 80% accuracy. [12]

In 2019, Varshil Mehta and Wenlin Han work on performance evaluation of fake news detection methods. They divide the dataset of fake news into 2 categories. The first is news and the second is the social context model and they divide news into 2 categories of visual (picture, video) and linguistic (text, title) based. They compared performance between traditional ML methods (Naïve Bayes , Random forest) and the latest deep learning methods (LSTM DROP, LSTM-CNN). The purpose of this paper is to provide a basis so that people can choose between these two approaches. They found that the hybrid CNN - RNN model gives better performance/ results. [13]

In 2019, J. C.S. Reece, A. Correia, F. Murai, A. Veloso and F. Benevuto works on searching on a wide variety of features from news articles, posts and stories that can help predict fake news with greater accuracy. He showed the importance of these new features for the evaluation of fake news. Some of those features are bias, reliability / trustworthiness, engagement, domain location, and temporal patterns. They used a dataset containing 2282 BuzzFeed (news articles). They used KNN, Naïve Bayes, Random Forest, Support Vector Machine and XGBoost algorithm for evaluation and to discuss the opportunities and challenges of this approach and they found out that XGBoost work better than all with the accuracy of 0.86. [14]

In 2020, Iftikhar Ahmad, Muhammad Yousaf, Suhail Yousaf and Muhammad Ovais Ahmad classified fake news articles using machine learning models and ensemble techniques (Logistic Regression, Random Forest, Perez- LSVM). In this paper various textual properties are used to differentiate fake new from real news. The experiment was conducted on 4 publicly available dataset which is of different domians and also calculated the performance by performance metrics. The maximum accuracy is 99% achieved by random forest and Perez-LSVM on ISOT Fake News Dataset. [15]

In 2020, C. Yuan, Q. Ma., W. Zhou proposed a model structure-aware multi-head attention network (SMAN) based approach to detect fake news. This method is based on the reliability of both publishers and users. The datasets used for this approach were real-world datasets. This approach can be used for early detection of fake news that optimizes the detection process with the help of asymmetric graphs between publisher and users. They use this model on 3 different dataset (Twitter 15, Twitter 16, Weibo) and find that this model gives very high accuracy. [16]
In 2021, S.M. Shifath, Md. S. Islam and Md. F. Khan proposed a transformer-based approach for detecting COVID-19 fake news. They performed experiments on traditional language models and CNN. The dataset is social media posts related to COVID-19 and labels indicating whether the posts are fake or real. They also experimented with transformer-based models and tested different hyper parameters. The highest accuracy is 0.979 which is shown by RoBERTa. [17]
In 2021 Agrawal, C., Pandey, A. & Goyal proposed, structural features with the Modified Bi-directional Long Short Term Memory (MBi-LSTM) method is proposed to improve the efficiency of Fake news detection. The attention layer is introduced in the Bi-LSTM to update the weight value of the input features and Term Frequency – Inverse Document Frequency (TF-IDF), based on the scalar factor. This weight value is updated in the input gate weight value of the Bi-LSTM that helps to find the relevant feature to store in cell. The proper weight in the Bi-LSTM model stores the features related to reliable information in long-term that helps to improve the classification performance. The structural, user, content, and temporal features were extracted from the Twitter data and applied to the MBi-LSTM method. 33 features were extracted for structural, user, content, and temporal features for the classification. The PolitiFact dataset is collected and used for testing the efficiency of the proposed MBi-LSTM method. Additionally, the CREDBANK dataset is also applied to test the effectiveness of the proposed MBi-LSTM method in the case of a large dataset. The experimental result shows that the proposed MBi-LSTM method has an accuracy of 91% and the Bi-LSTM method has an accuracy of 86.69% in PolitiFact dataset [18].

V. Challenges and Research Direction

Despite the fact that numerous studies have been conducted on the identification of fake news, there is always space for future advancement and investigation. In the sense of recognizing fake news, we highlight challenges and several unique exploration areas for future studies. Although DL-based methods provide higher accuracy compared to the other methods, there is scope to make it more acceptable.

- The feature and classifier selection greatly influences the efficiency of the model. Previous studies did not place a high priority on the selection of features and classifiers. Researchers should focus on determining which classifier is most suitable for particular features. The long textual features require the use of sequence models (RNNs), but limited research works have taken this into account. We believe that studies that concentrate on the selection of features and classifiers might potentially improve performance.
- The feature engineering concept is not common in deep learning-based studies. News content and headline features are the widely used features in fake news detection, but several other features such as user behavior [19], user profile, and social network behavior need to be explored. Political or religious bias in profile features and lexical, syntactic, and statistical-based features can increase the detection rate. A fusion of deeply hidden text features with other statistical features may result in a better outcome.
- Propagation-based studies are scarce in this domain [20]. Network-based patterns of news propagation are a piece of information that has not been comprehensively utilized for fake news detection [21]. Thus, we suggest considering news propagation for fake news identification. Meta-data and additional

information can increase the robustness and reduce the noise of a single textual claim, but they must be handled with caution.

- Studies focused only on text data for fake news detection, whereas fake news is generated in sophisticated ways, with text or images that have been purposefully altered [22]. Only a few studies have used image features [23], [24]. Thus, we recommend the use of visual data (videos and images). An examination with video and image features will be an investigation region to build a stronger and more robust system.
- Studies that use a fusion of features are scarce in this domain [25]. Combining information from multiple sources may be extremely beneficial in detecting whether Internet articles are fake [22]. We suggest utilizing multi-model-based approaches with later pre- trained word embeddings. Many other hidden features may have a great impact on fake news detection. Hence we encourage researchers to investigate hidden features.
- Fake news detection models that learn from newly emerging web articles in real-time could enhance detection results. Another promising future work is the use of a transfer-learning approach for training a neural network with online data streams.
- More data for a more significant number of fake news should be released since the lack of data is the major problem in fake news classification. We assume that more training data will improve model performance. Datasets focused on news content are publicly available. On the other hand, datasets based on different textual features are limited. Thus research utilizing additional textual features is scarce.
- Instead of a simple classifier, using an ensemble method produces better results [26]. By constructing an ensemble model with DL and ML algorithms, in which an LSTM can identify the original article while passing auxiliary features through a second model can yield better results [27]. A simpler GRU model performs better than an LSTM [28]. Therefore, we recommend combining GRU and CNNs to urge the leading result.
- Many researchers have achieved high accuracy by using CNN, LSTM, and ensemble models [29], [30]. SeqGAN and Deep Belief Network (DBN) were not explored in this domain. We encourage researchers to experiment with these models.
- Transformers have replaced RNN models such as LSTM as the model of choice for NLP tasks. BERT has been used in the identification of fake news, but Generative Pre-trained Transformer (GPT) has not been used in this domain. We suggest using GPT by fine-tuning fake news detection tasks.
- Existing algorithms make critical decisions without providing precise information about the reasoning that results in specific decisions, predictions, recommendations, or actions [31]. Explainable Artificial Intelligence (XAI) is a study field that tries to make the outcomes of AI systems more understandable to humans [32]. XAI can be a valuable approach to start making progress in this area.

VI. Conclusion

Fake news is escalating as social media is growing. Researchers are also trying their best to find solutions to keep society safe from fake news. This survey covers the overall analysis of fake news classification by discussing major studies. A thorough understanding of recent approaches in fake news detection is essential because advanced frameworks are the front-runners in this domain. Thus, we analyzed fake news identification methods based on various strategies. We presented taxonomy of fake news detection approaches. We have given a short description of the experimental findings of previous studies. In this field, we briefly outlined possible directions for future research. Fake news identification will remain an active research field for some time with the emergence of novel deep learning network architectures. There are fewer chances of inaccurate results using deep learning-based models. We strongly believe that this review will assist researchers in fake news detection to gain a better, concise perspective of existing problems, solutions, and future directions.

References

[1] Yang, Shuo, et al. "Unsupervised fake news detection on social media: A generative approach." Proceedings of the AAAI Conference on Artificial Intelligence. Vol. 33. 2019. on Social Media: A Generative Approach".

[2] Shu, Kai, et al. "Fake news detection on social media: A data mining perspective." ACM SIGKDD explorations newsletter 19.1 (2017): 22-36

[3] K. Shu, D. Mahudeswaran, S. Wang, D. Lee, and H. Liu, ''FakeNews- Net: A data repository with news content, social context and spatial- temporal information for studying fake news on social media,'' 2018, arXiv:1809.01286.

[4] Y.-C. Ahn and C.-S. Jeong, ''Natural language contents evaluation system for detecting fake news using deep learning,'' in Proc. 16th Int. Joint Conf. Comput. Sci. Softw. Eng. (JCSSE), Jul. 2019, pp. 289–292.

[5] R. K. Kaliyar, A. Goswami, P. Narang, and S. Sinha, ''FNDNet— A deep convolutional neural network for fake news detection,'' Cog- nit. Syst. Res., vol. 61, pp. 32–44, Jun. 2020.[Online]. Available: http://www.sciencedirect.com/science/article/pii/S1389041720300085

[6] A. Gupta, H. Lamba, P. Kumaraguru and A. Joshi, "Faking sandy, identifying fake images of hurricane sandy on twitter," in In proceedings of the 22nd international conference on World Wide Web. ACM, 2013.

[7] A. Zubiaga, E. Kochkina, M. Liakata, R. Procter, M. Lukasik and I. Augenstein, "Discourse-Aware Rumour stance classification in social media using sequential classifier.," Information Processing & Management, vol. 54, pp. 273-290, 2017.

[8] A. Aker, A. Zubiaga, K. Bontcheva, M. LIakata and R. oricter, "Detection and Resolution of rumours in social media: A survey," ACM comput., vol. 51, p. 36, Feb 2018.

[9] C. M. M. Kotteti, X. Dong, N. Li and L. Qian, "Fake News Detection Enhancement with Data Imputation," in IEEE 2018 IEEE 16th Intl Conf on Dependable, Autonomic and Secure Computing, 16th Intl Conf on Pervasive Intelligence and Computing, 4th Intl Conf on Big Data Intelligence and Computing, 2018.

[10] S. Aphiwongsophon and P. Chongstitvatana, "Detecting fake news with Machine Learning methods," in 15th international conference on Electronics, computer, Telecommunication and Information Technology, 2018.

[11] A. Jain and A. Kasbe, "Fake News Detection," in 2018 IEEE International Students' Conference on Electrical, Electronics and Computer Sciences, 2018.

[12] O. Ajao, D. Bhowmik and S. Zargari, "Fake news Identification on Twitter with combination of CNN and RNN models," in International conference on social media & society, Copenhagen,Denmark SMSociety, 2018.

[13] W. Han and V. Mehta, " Han, Wenlin; Mehta, Varshil (2019). [IEEE 2019 IEEE International Conference on Industrial Internet (ICII) - Orlando, FL, USA (2019.1Fake News Detection in Social Networks Using Machine Learning and Deep Learning: Performance Evaluation.," in IEEE 2019 IEEE International Conference on Industrial Internet (ICII), Orlando, FL, USA, 2019.

[14] J. C. S. Reis, A. Correia, F. Murai, A. Veloso, F. Benevenuto and E. Cambria, "Supervised Learning for Fake News Detection," in IEEE Intelligent Systems, 2019.

[15] I. Ahmad, M. Yousaf, S. Yousaf and M. O. Ahmad, "Fake News Detection Using Machine Learning Ensemble Methods," vol. 2020, p. 11, 2020.

[16] C. Yuan, Q. Ma, W. Zhou, J. Han and S. Hu, "Early Detection of Fake News by Utiliz ing the Credibility of News, Publishers, and Users Based on Weakly Supervised Learning," arXiv:2012.04233v2 [cs.CL], p. 11, 2020.
[17] S. Shifath, M. F. Khan and M. S. Islam, "A transformer based approach for fighting COVID-19 fake news," arXiv:2101.12027v1 [cs.CL], p. 9, 2021.
[18]. Agrawal, C., Pandey, A. & Goyal, S. Fake news detection system based on modified bi-directional long short term memory. Multimedia Tools Application 81, 24199–24223 (2022) https://doi.org/10.1007/s11042-022-12772-9
[19] J. Ding, Y. Hu, and H. Chang, ‘‘BERT-based mental model, a better fake news detector,’’ in Proc. 6th Int. Conf. Comput. Artif. Intell., New York, NY, USA, Apr. 2020, pp. 396–400, doi: 10.1145/3404555.3404607.
[20] L. Wu and H. Liu, ‘‘Tracing fake-news footprints: Characterizing social media messages by how they propagate,’’ in Proc. 11th ACM Int. Conf. Web Search Data Mining, Feb. 2018, pp. 637–645.
[21] X. Zhou and R. Zafarani, ‘‘Fake news detection: An interdisciplinary research,’’ in Proc. Companion World Wide Web Conf., May 2019, p. 1292.
[22] A. Giachanou, G. Zhang, and P. Rosso, ‘‘Multimodal multi-image fake news detection,’’ in Proc. IEEE 7th Int. Conf. Data Sci. Adv. Anal. (DSAA), Oct. 2020, pp. 647–654.
[23] D. Mangal and D. K. Sharma, ‘‘Fake news detection with integration of embedded text cues and image features,’’ in Proc. 8th Int. Conf. Rel., INFOCOM Technol. Optim., Trends Future Directions (ICRITO), Jun. 2020, pp. 68–72.
[24] P. Qi, J. Cao, T. Yang, J. Guo, and J. Li, ‘‘Exploiting multi-domain visual information for fake news detection,’’ in Proc. IEEE Int. Conf. Data Mining (ICDM), Nov. 2019, pp. 518–527.
[25] R. Kumari and A. Ekbal, ‘‘AMFB: Attention based multimodal factorized bilinear pooling for multimodal fake news detection,’’ Expert Syst. Appl., vol. 184, Dec. 2021, Art. no. 115412.
[26] S. S. Jadhav and S. D. Thepade, ‘‘Fake news identification and clas- sification using DSSM and improved recurrent neural network classi- fier,’’ Appl. Artif. Intell., vol. 33, no. 12, pp. 1058–1068, Oct. 2019, doi: 10.1080/08839514.2019.1661579.
[27] S. Deepak and B. Chitturi, ‘‘Deep neural approach to Fake-News identification,’’ Proc. Comput. Sci., vol. 167, pp. 2236–2243, Jan. 2020. [Online]. Available: http://www.sciencedirect. com/science/article/pii/S1877050920307420
[28] M. Bugueño, G. Sepulveda, and M. Mendoza, ‘‘An empirical analysis of rumor detection on microblogs with recurrent neural networks,’’ in Proc. Int. Conf. Hum.-Comput. Interact., Jul. 2019, pp. 293–310. [Online]. Available: https://link.springer.com/chapter/10.1007/978-3-030-21902- 4_21
[29] M. Umer, Z. Imtiaz, S. Ullah, A. Mehmood, G. S. Choi, and B.-W. On, ‘‘Fake news stance detection using deep learning architecture (CNN- LSTM),’’ IEEE Access, vol. 8, pp. 156695–156706, 2020
[30] S. M. Padnekar, G. S. Kumar, and P. Deepak, ‘‘BiLSTM-autoencoder architecture for stance prediction,’’ in Proc. Int. Conf. Data Sci. Eng. (ICDSE), Dec. 2020, pp. 1–5
[31] A. Nascita, A. Montieri, G. Aceto, D. Ciuonzo, V. Persico, and A. Pescape, ‘‘XAI meets mobile traffic classification: Understand- ing and improving multimodal deep learning architectures,’’ IEEE Trans. Netw. Service Manage., early access, Jul. 19, 2021, doi: 10.1109/TNSM.2021.3098157.
[32] A. Adadi and M. Berrada, ‘‘Peeking inside the black-box: A sur- vey on explainable artificial intelligence (XAI),’’ IEEE Access, vol. 6, pp. 52138–52160, 2018.