Proceedings of the SMART–2020, IEEE Conference ID: 50582
9th International Conference on System Modeling & Advancement in Research Trends, 4th–5th, December, 2020
Faculty of Engineering & Computing Sciences, Teerthanker Mahaveer University, Moradabad, India

2020 9th International Conference System Modeling and Advancement in Research Trends (SMART) | 978-1-7281-8908-6/20/$31.00 ©2020 IEEE | DOI: 10.1109/SMART50582.2020.9337152

New Politifact: A Dataset for Counterfeit News

Sonal Garg[1] and Dilip Kumar Sharma[2]
[1,2]GLA University Mathura, India
E-mail: [1]sonal.garg@gla.ac.in, [2]dilip.sharma@gla.ac.in

***Abstract*—Fake news is a fictitious article that is intentionally written to deceive people. So it is difficult to detect fake news based on the content of the news article. Online platforms publish these fabricated stories to make more money by enhancing the number of readerships. There is a need to detect fake news as early as possible. The lack of a standard dataset makes this task more challenging. So, In this paper, we proposed a new dataset that is scraped from Politifact websites. This dataset is larger in size in comparison to the existing datasets. We conducted extensive experiments by training state of the art machine learning and deep-learning algorithm. The results depict the effectiveness of our proposed dataset.**

Keywords: Fake news, Machine-learning classifier, Natural language processing.

I. Introduction

Today is a digital era where we spent most of the time on the internet. Social media platforms help to communicate one's thoughts to the rest of the world. This online platform is easily accessible by people who do not have any technical knowledge. People can easily share photos and videos with their friends and relatives. However, since there is a path to grow, there can also be something that can put barriers in it.

Fake news is a combination of two words "fake" and "news" [1]. It is a type of disinformation as it falsifies the basic truthful information intentionally and propagates it[28]. It is used to misguide readers for satisfying their agenda.

With the increase in popularity, there has also been an increase in phony news. Researchers have shown that there has been an exponential growth in the fake news and a spokesperson about this stated in January 2017, for the German government that they "are dealing with a phenomenon of a dimension that they] have not seen before" [2]. Twitter, Facebook, Instagram are rapidly increasing hubs for users to exhibit news, sentiments, opinions, activities, and even there day to day feelings or moods [3]. There is the various definition of Fake news. Authors in paper [4] defined fake news as "a news article that is intentionally and verifiably false. Fake news accounts for many critical real-world problems. The growth of fake news has been so alarming that there are not many developed technologies to control it. It is there for many years. One such example is when the Nazis used false information to spread violent hatred of Jews (anti-Semitism). Recently, it also happened in 2016; a survey showed that the UK Brexit referendum in 2016 was impacted due to the fake news. Alongside other political decisions such as it was so said that in the 2016 US presidential elections, Donald Trump would not have got the seat if there has not been an effect of fake news as well as the alleged interference of Russian trolls [5] [6]. The lives of people also get endangered sometimes like in 2016; there was a shooting in a pizza store in the USA at daylight due to false rumours of paedophile sex rings in the store [7].

Similarly, in 2018, in Mexico, two people were burned to death by a mob due to fake rumours on WhatsApp of child abductors, and later on, the news was proven wrong [8]. The finance and the stock market is also influenced by false news. People tend to believe a message if it is received by them many times by different people that result in influencing them wrongly [9]. In covid19 situation during the lockdown, there have been many cases of mob lynching in which the crowd also murders some innocents due to the circulation of fake news. There are commonly 3V's of data that we have to look into, i.e. Volume, Velocity, and Variety [10]. Apart from them, Veracity is the 4th V, and there are 3 more i.e. Value, Variability, and Visualization. Since there is a massive growth of data, it comes under volume. Velocity focuses on the speed of data generated. There are 500 million daily active stories on Instagram every day as well as, people can make posts in a variety of formats like textual, photos, videos, gifs, etc. In covid19 situation, fake news resulted in mass loss of life. It creates chaos and unrest in people.

An increase in the use of social media also accelerates the growth of fake information dissemination. Some people like to spread fake news and information for their personal agenda. Since rumours spread faster than the truth because the truth is boring, it is a need of an hour to stop the propagation of fake news as soon as possible to mitigate its impact. Rumours tend to alter thinking or can mislead a person. We read the reviews, look for trending articles, real-time news on the internet, but some of it can be misleading. Rightfully, fake news has attracted the attention of various disciplines, such as computer engineering, psychology, economics, communication, and political science [11].

A. Motivation

Many people fabricate content to gain popularity among friends, group of people and others. Fake news detection is required for improving social media content and intent.

- Character assassination, Propaganda dispersion, Polarization are some serious impact of fake news.
- Facebook, Twitter are putting their efforts to combat fake news.
- Deep fakes are security concerns since its inception.

This paper is further divided into various sections, i.e., Section 2 is based on a Literature review, Section 3 deals with the proposed framework, Section 4 is concerned with Experiments and results, and Section 5 represents a Conclusion and also a next step possible.

II. Literature Review

Many researchers work on the challenge of fake news detection using a multi-label dataset. A past study indicates that it is not easy to make a fake news classifier considering a multi-label dataset.

Olivieri *et al*. in [13], have collected news with the help of Google's custom search feature and obtained a more generalized strategy for task generic features so that they could help in the detection of fake news. They explored a way to obtain metadata about the news that improves the performance as it takes the result given by Google search and uses it as additional features. Their strategy showed an improvement of 3% in F1 score for classification tasks in 6 classes. Authors in paper [14] applied a semi-supervised algorithm for fake news classification. They used the social contextual information and the relationship among the publisher, pieces of news, and the users. This technique aimed at the early detection of fake news and achieved satisfactory results. In paper [15], authors applied network properties for counterfeit news identification. People make similar behavior friends on Facebook or Instagram, and if it is a large community, then every post matters, and thus the false information propagates widely. Authors in paper [16] did emotion analysis to detect whether the news is genuine or fake. The researchers have exploited the emotions of people's comments and the content of the post and used their emotions in detecting fake news. They provide a reliable way to capture the semantic and emotions of the publisher and social signals in the news content. Since the intensity, expression, and various features of fake news .comment and content module differ from the real news, and they have taken that into account. Similarly, in [20], fake news is detected using features of reviews and comments.

In [12], a tool known as Fake News Tracker is made to collect, detect, and visualize fake news. Since it automatically collects fake news articles from social media, it is not required for us to collect data beforehand. It is implemented on two datasets and experiments are done on them. In [17], the authors used a decentralized network, a smart contract-based blockchain technology framework to detect fake news. Blockchain is focused on providing trust and security as it maintains a ledger so that every transaction is logged in it. This technology provides transparency to the system.

User profiles can also lead to the detection and mitigation of fake news [18], we can know the users who are more likely to share fake news than others by observing their behaviors online. The characteristics of these users and how can we use these features to detect other user profiles that share wrongful information.

Fake news can also be detected using the two paths semi-supervised network as focused by [19] on a dataset that is limitedly labeled. It uses CNN in three forms, i.e. shared, supervised, and unsupervised. It gains a high precision rate and f-score in a very less labeled dataset.

Fake news can also be detected using expressions and extreme ratings [21]. The model made in [22] is based on the explanation of fake news detection, i.e. if a piece of news is detected as fake, then "why" it is termed as that. This helps in the better learning of the model and gives the accuracy of 0.83. It also improves efficiency.

A. Motivation

Fake content are extensively used to provoke rage and to polarize the sentiments of people. It has more damaging impacts when it leads to a grave consequence like mob lynching, religious feud and wrong treatment advice to patients.

- Whatsapp had to think about the auto-detection of fake images/video over their platform once it led to mob lynching.
- Deep fakes are security concerns since its inception.
- Fake content needs to be detected and stopped, and consumers need to make aware.

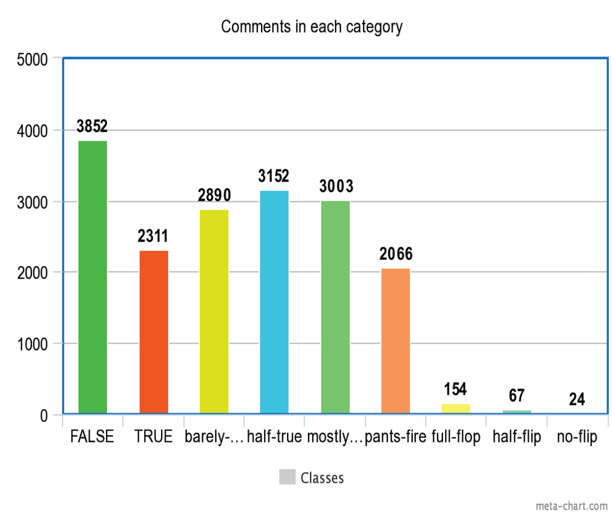

Fig. 1: Statistics of the Scrapped Dataset

Fig. 1 represents the actual dataset after scrapping. It consists of 9 labels but to make the dataset balanced, we convert the dataset to 6 labels (Fig. 2). This will help in removing biased results.

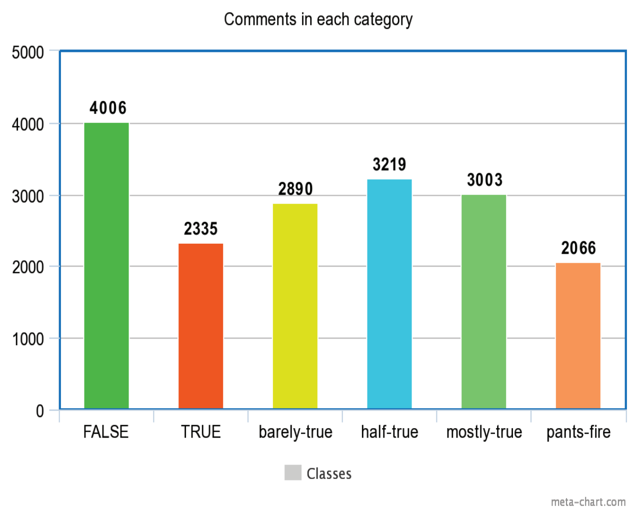

Fig. 2: Statistics of the Dataset after Balancing

B. Machine Learning Model

Machine learning classifier is implemented to identify misinformation .we applied Tf-idf vectorization and used unigram, bigram, and trigram bag of words. Tf-idf is applied to measure the importance of a particular word in a related document. It is calculated by using:

$$tf_{i,j} = \frac{n_{i,j}}{\sum_k n_{i,j}} \tag{1}$$

Where $tf_{i,j}$ is occurrence of i in j document.

tf(w)=(Number of times word w appears in a document/ total number of words in the document)

$$idf(t) = \log \frac{N}{df_t} \tag{2}$$

Where N is the total number of documents and df_t is the number of documents with term t.

C. Naïve Bayes Algorithm

It is a probabilistic classifier that works on the principle of feature independence. It applied the Bayes theorem. A basic classifier i.e. Naïve Bayes, was used in [25] to detect fake news. The dataset used was collected by BuzzFeed News and was used by the classifier for the testing and learning phase. The accuracy obtained was 75.40%.

The mathematical notation used to represent Bayes theorem is-

$$P(c|x) = \frac{P(x|c)P(c)}{P(x)} \tag{3}$$

Where c is a class variable and x is a dependent feature vector.

$P(c|x)$ is a posteriori probability of event x, $P(c)$ is the priori of c.

D. Linear SVM Classifier

This is the most widely used classifier for text classification. Line or hyperplane structure is used to categorize the data into particular categories. It can be described mathematically as-

$$y = (\vec{w}\,\vec{x}) = f\left(\sum_j w_j x_j\right) \tag{4}$$

Here, x is coordinates or features and w is weights that determine the slope of a straight line.

E. Logistic Regression

We applied Logistic Regression for fake news detection. It is a classification algorithm. Logistic regression is used when the dependent variable is categorical.

$$P = \frac{1}{1+e^{-(b_0+b_1 x)}} \tag{5}$$

Here, P is the probability of 1, e is the base of the natural logarithm, b_0 and b_1 are the model parameters.

By using Odd ratio,

$$\frac{P}{1-P} = \exp(b_0 + b_1 x) \tag{6}$$

Probability (P) value always lies in range 0 to 1, but in the case of odd, odd can take the range from 0 to infinity. Odd is defined as the ratio of the probability of an event that will occur to the probability of an event that will not occur.

F. Random Forest

Random forest is a supervised algorithm that uses ensemble learning to create a forest. This algorithm could be applied in classification, regression, and other tasks. This algorithm works well on a large dataset.

$$fi_i = \frac{\sum_{j:node\ j\ splits\ on\ feature\ i} ni_j}{\sum_{k \in all\ nodes} ni_k} \tag{7}$$

$$norm\ fi_i = \frac{fi_i}{\sum_{j \in all\ features} fi_j} \tag{8}$$

$$RFfi_i = \frac{\sum_{j \in all\ trees} norm\ fi_{ij}}{T} \tag{9}$$

G. Decision Tree Classifier

A decision tree can be used to perform the task of classification or regression. It works well for both categorical and numerical data.

Gini impurity is used to compute the probability of inaccurate classification of an observation. Gini impurity can be represented by a mathematical notation as follows-

$$G(n) = \sum_{i=1}^{j} P(i) * (1 - P(i)) \tag{10}$$

Where P(i) represents the probability of particular classification i, as per the training dataset.

H. Deep-Learning Model

Deep-learning algorithm worked well for large datasets. Authors in paper[27] compared semantic information which is extracted from an image with the headline text. Authors applied CNN and LSTM to compute the results. We applied the LSTM and Bi-LSTM model for misinformation detection. We used only 2 hidden layers and 64 as batch size. We select 25 as sentence length for fast processing. We ran the classifier on different values of batch size and sentence length but achieved the best results on these settings.

I. Proposed Framework

For preprocessing, we use the NLTK library to remove stop words and to perform stemming. We applied snowball stemmer to convert the word of a sentence into its root form.

Dataset is converted to lower case for further processing. We remove the duplicate news by using the remove duplicate function. The proposed dataset is divided into 80:20 training and testing ratios based on the experimental results.

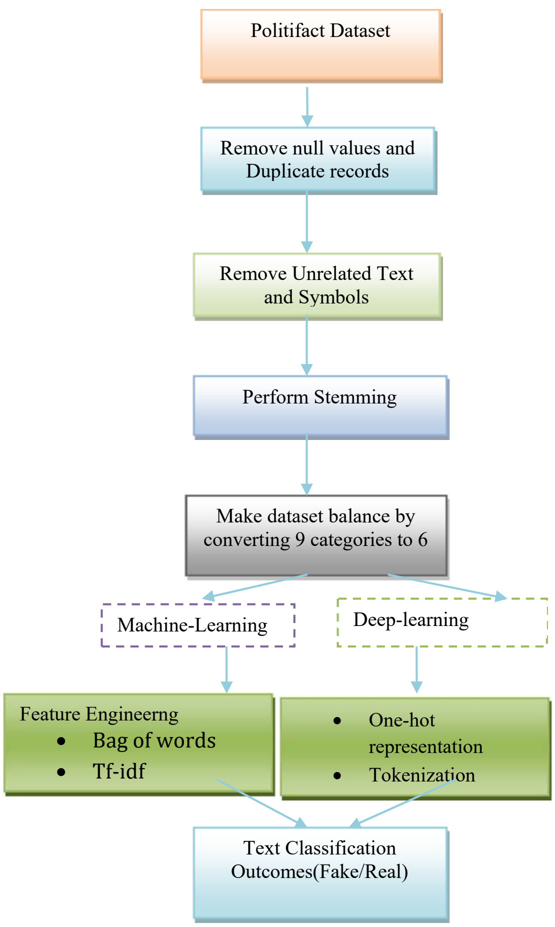

Fig. 3: Proposed Framework

III. Experiments and Results

Google Colaboratory, which is an open-source python notebook environment with a tesla K80 GPU backend is used for training various machine learning models. All ML classifiers achieved 26% accuracy except the decision tree classifier which achieved 23% accuracy. Deep-learning classifier also achieved 26.1% accuracy. Deep learning model

A. Experimental Settings

For experiments, Both LSTM and Bi-LSTM classifier used Softmax activation function, a loss is sparse_ categorical_crossentropy' and Adam optimizer, We applied One-hot encoding representation and pre-embedding to make sentence length equal. We have chosen 40 embedding vector features and sentence length as 25. We have selected these values based on trying different combination to get maximum results. We compared our results in Table 1 with the LIAR benchmark dataset, which is also created from Politifact.com websites. Our dataset is large in size in comparison to the LIAR dataset. We make our dataset publicly available on GitHub platform[1].

Table 1: Comparison with LIAR Dataset

Dataset	SVM	Logistic Regression
LIAR[26]	0.255	0.247
Proposed dataset	0.26	0.26

Table 2: Classification Report of SVC Classifier

Sr. No	Précision	Recall	F1-score	Support
0	0.29	0.36	0.32	765
1	0.25	0.20	0.22	618
2	0.21	0.21	0.21	623
3	0.37	0.32	0.34	423
4	0.26	0.26	0.26	616
5	0.20	0.20	0.20	459
Accuracy			0.26	3504
Macro avg	0.26	0,26	0.26	3504

Table 3: Classification Report of Multinomial Naïve Bayes Classifier

Sr. No	Precision	Recall	F1-score	Support
0	0.26	0.72	0.39	765
1	0.24	0.04	0.06	618
2	0.22	0.28	0.25	623
3	0.67	0.05	0.34	423
4	0.30	0.23	0.26	616
5	0.27	0.01	0.20	459
Accuracy			0.26	3504
Macro avg	0.33	0.22	0.18	3504

Table 4: Classification Report of Random Forest Classifier

Sr. No	Precision	Recall	F1-score	Support
0	0.27	0.53	0.36	765
1	0.23	0.17	0.20	618
2	0.21	0.18	0.20	623
3	0.40	0.26	0.31	423
4	0.26	0.21	0.23	616
5	0.20	0.12	0.15	459
Accuracy			0.26	3504
Macro avg	0.26	0.24	0.24	3504

[1].https://github.com/sonalgarg174/NewPolitifact-Dataset/blob/main/newpolitifactdataset.csv

Table 5: Classification Report of a Decision Tree Classifier

Sr. No	Precision	Recall	F1-score	Support
0	0.29	0.33	0.31	765
1	0.21	0.19	0.20	618
2	0.22	0.23	0.23	623
3	0.26	0.25	0.25	423
4	0.21	0.20	0.21	616
5	0.18	0.16	0.17	459
Accuracy			0.23	3504
Macro avg	0.23	0,26	0.23	3504

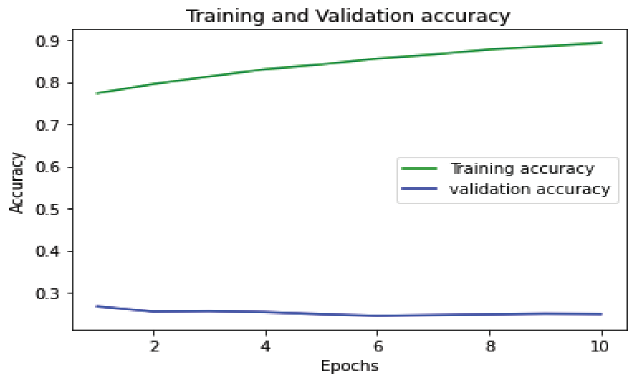

Fig. 4: Training and Validation Accuracy of LSTM Model

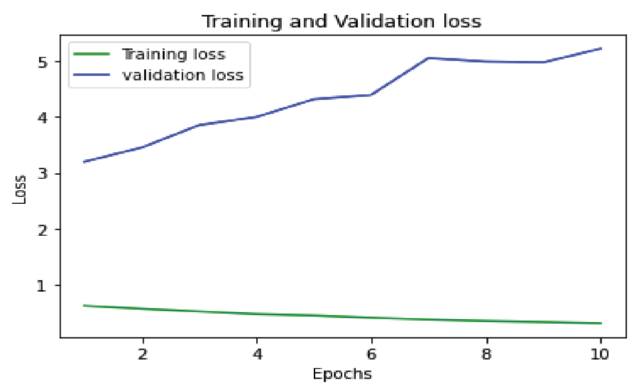

Fig. 5: Training and Validation Loss of LSTM Model

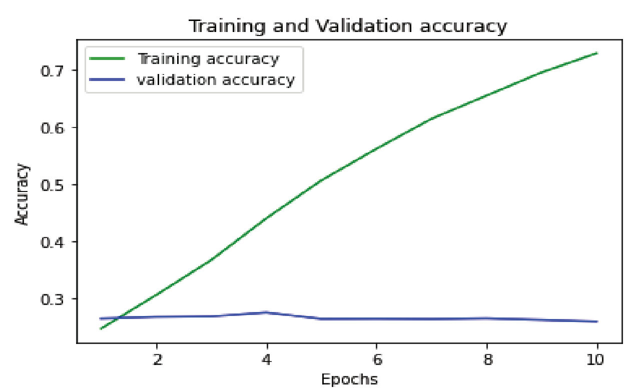

Fig. 6: Training and Validation Accuracy of Bi- LSTM Model

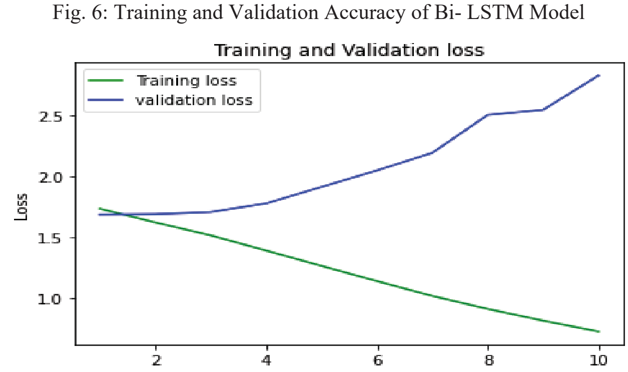

Fig. 7: Training and Validation Loss of Bi-LSTM Model

IV. Conclusion and Future Work

In this paper, we have adopted machine learning approaches to our proposed dataset. This is the extended version of the LIAR dataset. We achieved the highest of around 26% accuracy by using the machine learning model and deep-learning model. There is a scope to add transformers by using six-labels to enhance the performance of the model further.

Acknowledgment

The authors generously acknowledge the funding from the Council of Science and Technology, Lucknow, UP, India in Dept of Computer Engineering & Applications, GLA University Mathura. The title of the research project is “Identification of unreliability and fakeness in Social Media posts”.

References

[1] Gelfert, A. (2018). Fake News: A Definition. Informal Logic, 38 (1), 84–117. https://doi.org/10.22329/il.v38i1.506 8

[2] Karishma Sharma, Feng Qian, He Jiang, Natali Ruchansky, Ming Zhang, and Yan Liu. 2018. Combating Fake News: A Survey on Identification and Mitigation Techniques. ACM Trans. Intell. Syst. Technol. 37, 4, Article 111, (August 2018).

[3] F Masood, G Ammad, A Almogren, A Abbas, H Khattak, I Ud Din, M Guizani, M Zuair, “Spammer Detection and Fake User Identification on Social Networks”, IEEE Access, 2019.

[4] Buntain, C., & Golbeck, J. (2017, November). Automatically identifying fake news in popular Twitter threads. In *2017 IEEE International Conference on Smart Cloud (SmartCloud)* (pp. 208-215). IEEE.

[5] F Pierri, S. Ceri, “False News On Social Media: A Data-Driven Survey”, June 2019.

[6] Grinberg, N., Joseph, K., Friedland, L., Swire-Thompson, B. & Lazer, D. Fake news on Twitter during the 2016 U.S.presidential election. Science 363, 374–378 (2019).

[7] Marubeni.com. (2019). 19 Real Events Caused by Fake News in the US | Marubeni Corporation. [online] Available at: https://www.marubeni.com/en/insight/p otomac/backnumber/19.html [Accessed 9 Oct. 2019].

[8] BBC News. (, 2019). Burned to death because of a rumour on WhatsApp. [online] Available at: https://www.bbc.com/news/world-latin- america-46145986 [Accessed 9 Oct. 2019].

[9] Kogan, Shimon and Moskowitz, Tobias J. and Niessner, Marina, Fake News: Evidence from Financial Markets (April 15,2019). Available at SSRN: https://ssrn.com/abstract=323776 3 or http://dx.doi.org/10.2139/ssrn.3237 763

[10] Xichen Zhang and Ali A. Ghorbani, Information Processing and Management, “An overview of online fake news: Characterization, detection, and discussion”, 2019

[11] Tandoc, E. C. The facts of fake news: A research review. Sociology Compass 13, (2019).

[12] Shu K, Mahudeswaran D., Liu H. , “FakeNewsTracker: a tool for fake news collection, detection, and visualization”, Computational and Mathematical Organization Theory, 2018

[13] Olivieri, A., Shabani, S., Sokhn, M. & Cudré-Mauroux, P. Creating Task- Generic Features for Fake News Detection. Proceedings of the 52nd Hawaii International Conference on System Sciences (2019). doi:10.24251/hicss.2019.624.

[14] Kai Shu, Suhang Wang, and Huan Liu. 2019. Beyond News Contents: The Role of Social Context for Fake News Detection. In The Twelfth ACM International Conference on Web Search and Data Mining (WSDM ‘19), February11–15, 2019, Melbourne, VIC, Australia. ACM, New York, NY, USA,10 pages. https://doi.org/10.1145/3289600.329099 4.

[15] Shu, K., Bernard, H. R. & Liu, H. Studying Fake News via Network Analysis: Detection and Mitigation. Lecture Notes in Social Networks Emerging Research Challenges and Opportunities in Computational Social Network Analysis and Mining 43–65 (2018). doi:10.1007/978-3-319-94105- 9_3.

[16] Chuan Guo, Juan Cao, Xueyao Zhang, Kai Shu and Miao Yu, "Exploiting Emotions for Fake News Detection on Social Media", 2019.

[17] Qayyum, A., Qadir, J., Janjua, M. U. & Sher, F. Using Blockchain to Rein in the New Post-Truth World and Check the Spread of Fake News. IT Professional 21, 16–24 (2019).

[18] Shu, K., Wang, S. & Liu, H. Understanding User Profiles on Social Media for Fake News Detection. 2018 IEEE Conference on Multimedia Information Processing and Retrieval (MIPR) (2018). doi:10.1109/mipr.2018.00092

[19] Dong X., Uboho V., Chowdhury S., Lijun Q., "Deep Two-path Semi- supervised Learning for Fake News Detection", 2019

[20] Liu, W. et al. A Method for the Detection of Fake Reviews Based on Temporal Features of Reviews and Comments. IEEE Engineering Management Review 1–1 (2019). doi:10.1109/emr.2019.2928964

[21] Vanta T., Aono M., "Fake Review Detection Focusing on Emotional Expressions and Extreme Rating", the Association for Natural Language Processing. 2019.

[22] Shu, K., Cui, L., Wang, S., Lee, D. & Liu, H. dEFEND. Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining - KDD 19 (2019). doi:10.1145/3292500.3330935

[23] Reis, J. C. S., Correia, A., Murai, F., Veloso, A. & Benevenuto, F. Explainable Machine Learning for Fake News Detection. Proceedings of the 10th ACM Conference on Web Science-WebSci 19(2019). doi:10.1145/3292522.3326027

[24] Saikh, T., Anand, A., Ekbal, A. & Bhattacharyya, P. A Novel Approach Towards Fake News Detection: Deep Learning Augmented with Textual Entailment Features. Natural Language Processing and Information Systems Lecture Notes in Computer Science 345–358 (2019). doi:10.1007/978-3-030-23281-8_30 .

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

[26] Wang, W.Y. (2017). " liar, liar pants on fire": A new benchmark dataset for fake news detection. arXiv preprint arXiv:1705.00648.

[27] Mangal, D., & Sharma, D. K. (2020, June). Fake News Detection with Integration of Embedded Text Cues and Image Features. In 2020 8th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions)(ICRITO) (pp. 68-72). IEEE.

[28] Sharma, S., & Sharma, D. K. (2019, November). Fake News Detection: A long way to go. In 2019 4th International Conference on Information Systems and Computer Networks (ISCON) (pp. 816-821). IEEE.

