

# Hoax News Detection on Social Media: A Survey

1<sup>st</sup>, 2<sup>nd</sup> Priati Assiroj

1<sup>st</sup> Computer Science Department, BINUS  
Graduate Program - Doctor of Computer  
Science

Bina Nusantara University  
Jakarta, Indonesia 11480

2<sup>nd</sup> Information System, Faculty of  
Technology and Computer Science

Buana Perjuangan University Karawang,  
Indonesia

[priati@binus.ac.id](mailto:priati@binus.ac.id)  
[priati@ubpkarawang.ac.id](mailto:priati@ubpkarawang.ac.id)

Meyliana

Information System Department,  
School of Information Systems,

Bina Nusantara University

Jakarta, Indonesia 11480

[meyliana@binus.edu](mailto:meyliana@binus.edu)

Harjanto Prabowo

Management Department, BINUS Business  
School Undergraduate Program, Bina

Nusantara University, Jakarta, Indonesia  
11480

[harprabowo@binus.edu](mailto:harprabowo@binus.edu)

Achmad N. Hidayanto

Faculty of Computer Science, Universitas  
Indonesia

Depok, Indonesia 16424

[nizar@cs.ui.ac.id](mailto:nizar@cs.ui.ac.id)

Harco Leslie Hendric Spits Warnars

Computer Science Department, BINUS  
Graduate Program – Doctor of Computer  
Science

Bina Nusantara University

Jakarta, Indonesia 11480

[spits.hendric@binus.ac.id](mailto:spits.hendric@binus.ac.id)

**Abstract**—Information and Communication Technology (ICT) is a tool to spread and share news effectively. Social media is an Information and Communication Technology product which is a trend of future communication styles, and communication is all about an activity to share the news. The news shared on social media are not always incredible resources, or on the other hand, we can say that most of them are a hoax. According to this condition, research would like to explore what kind of method approach to detect hoax news. This research uses a survey approach to papers published during 2016-2018. By doing this work, we can know the kind of algorithms used for a similar research topic. The most popular approach according to this work is the Classification using Support Vector Machine (SVM), and the most used social media platform is Twitter.

**Keywords**—hoax news; social media; classification; Support Vector Machine; twitter

## I. INTRODUCTION

Nowadays, Information and communication technology (ICT) is overgrowing. ICT become a tool to spread and share news effectively. Social media is an ICT product which is a trend of future communication styles and communication is all about activities to share the story. Social media's popularity is unstoppable. It means no one can stop us to use this way or style to share a fact or fake news. It does influence the whole of human lives, and we can say that human civilization could not be separated from digital life especially from it, social media. Due to the user population, news sharing through social media is the best way because with the massive community of user news could be shared more active and always be in point. On the other side, social media's proliferation is such as two-sided blades. We can get more advantage of it and also more disadvantage by consuming news from social media. Everyone uses social media for work, study, communicate with friends or families, to promote a business and many more good things can be shared from social media. Papadopoulos said in his research [1] that research can combine different computer science with social science in the future to tackle various aspects of

trust and openness of information in social media [1]. But the other condition is many people use social media to share hoax news such as research conducted by Gottfried [2]. Fake news is the synonym of hoax news, thus on this research, we use hoax news term.

Silverman [3] analyzes that most false stories about election shared on Facebook. People can access to an unprecedented number of information –only on Facebook more than 3M posts are generated per minute [4] without the intermediation of journalists or experts, thus actively participating in the diffusion as well as the production of content. Social media has rapidly become the primary information source for many of their users: over half (51%) of US users now get news via social media [5].

The web provides a highly interconnected world-wide platform for each one to spread information for millions of people in the matter of a few minutes, at no cost [6]. Recent surveys have alarmingly shown that people increasingly get their news from social media than from traditional news sources [7, 8], making it of paramount importance to curtail false information on such platforms. With primary motives of influencing opinions and earning money [9, 10, 11, 12], the vast impact of hoax information makes it one of the common dangers to society, according to the World Economic Forum [13].

The hoax news can be spread easily by social media, and it is very influential to real-world thus we have to conduct a deep assess to reduce its impact. There are many hoaxes news shared through social media. This is unfortunate because the existence of this kind of news can make chaos in live society. Hoax news is used to entertain, promote agendas or, stoked on mass by large numbers of bots or sock puppets, attempt to sway public opinion [14]. Hoax news spreads faster than real news, according to a recent BuzzFeed analysis. The hoax is a type of misinformation that aims to deceive the reader [15] deliberately. The example hoax news on social media (Tweeter): *BREAKING! Massive Volcano Eruption Only 32 Miles Away From MAJOR Nuclear Plant! Consciously Enlightened* [16]. Hoax news, as we know, sometimes used as a political weapon [17]. Alternative facts (alt-

facts) are information with no basis in reality while post-truths are defined as beyond the truths or irrelevant information [18]. This research identifies what the approach has done to detect hoax news and what the type of the most popular social media used. There are two surveys conducted by Kumar and Viviani to detect hoax news [35, 49]. By this research Kumar determine the algorithm to detect hoax news and Viviani has detect spam and fake news on online media and microblogging especially on health information. The difference of this research with these both research above is this research proposed to know what the method and approach used and also to mitigate what kind of algorithms, and at last we can know the most popular algorithm used for detecting hoax news.

## II. METHODOLOGY

This research conducted a thorough survey on the research about the hoax news on social media and created a systematic review protocol research with PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-analysis) [19]. This process is classified into five stages, which are: Defining Eligibility Criteria, Defining Information Resource, Literature Selection, Data Collection, and Data Item Selection.

### A. Stage 1: Defining Article Eligibility Criteria

Determined by Inclusion Criteria (IC), which are:

- 1) IC1: the article must be original research that has been studied and written in English.
- 2) IC2: the article has been published between 2016 and 2018.
- 3) IC3: the article has a purpose to analyse the method and approach from another researcher to reduce hoax news on social media and its contributions.

### B. Stage 2: Defining Information Resource

- 1) The literature can be searched on an online database with a significant repository for an academic study such as ACM Digital Library, Elsevier (SCOPUS), Emerald Insight, IEEE Xplore, ScienceDirect, Wiley Online Library, Springer Link and Google Scholar.
- 2) On the articles that eligible to IC, are also searched to find the other research that related to this research.

### C. Stage 3: Literature Selection

- 1) Keyword determination. Firstly is “hoax news and social media” and secondly is “hoax news detection and social media”.
- 2) To explore and select a title, abstract and article keyword obtained from a search result on eligibility criteria that defined before.
- 3) Read the article that not eliminated from the previous stage, full or partially, to determine that the items are eligible for the next review.
- 4) Short-listed articles are re-assessed to find related studies. The articles that reference-listed and

associated with this research will be re-assessed by doing stage 3 to stage 4.

### D. Stage 4: Data Collection

Data are collected manually by creating a data extraction form. This research assesses 73.886 articles based on keywords “hoax news and social media” and 70.550 articles based on keywords “hoax news detection and social media” from all resource and criteria and it all articles, 70 articles are eligible to be a reference candidate according to the title and abstract to answer the research question. After the further study, there are only 38 selected articles that are eligible for this research. Table I shows the data that have been collected.

TABLE I. DATA COLLECTION

Source	Study Found (based on title and keyword)		Candidate	Selected
	Hoax news and social media	Hoax news detection and social media		
ACM Digital Library	67.904	67.917	19	13
IEEE-Xplore	2	1	2	2
Elsevier (SCOPUS)	361	63	10	6
ScienceDirect	90	27	10	3
Emerald Insight	89	31	3	0
Wiley Online Library	44	9	2	2
Springer Link	356	52	3	2
Google Scholar	5040	2450	21	10
Total	73.886	70.550	70	38

### E. Stage 5: Data Item Selection

Data are obtained from short-listed articles that consist of method or approach used for detecting hoax news and article, about the hoax news, distribution on social media.

## III. RESULT AND DISCUSSION

This research has proposed to investigate an approach that used by another researcher to detect hoax news on social media. According to this purpose, research identifies items that can recognize hoax news and provides demographic characteristic and trend literature “Selected Study” such as publication resource, year of publication, variable classification items, items mapping of hoax news and social learning from literature. Table II shows publication resources.

TABLE II. PUBLICATION RESOURCES

No	Title	Year	Type
1	Overview...[1]	2016	Journal
2	Disinformation...[15]	2016	Journal
3	Misleading...[16]	2018	Journal
4	Biomedical...[18]	2017	Journal
5	Coupling...[20]	2017	Conference
6	CSI...[21]	2017	Journal
7	Fake News..[22]	2017	Journal

8	Falling for...[23]	2017	Journal						
9	Hoaxy...[24]	2016	Journal	Wu et.al.	2018	Characterization	Graph Social Media	Mining, Media	Twitter
10	Let's Hate...[25]	2018	Conference			Media Message	Mining, Classification		
11	Satire...[26]	2018	Journal						
12	The fake...[27]	2017	Conference	Ruchansky et.al.	2017	Hybrid Deep Model	Deep Learning		Twitter, Weibo
13	Tracing...[28]	2018	Conference						
14	Worth Its...[29]	2018	Journal	Sen et.al	2018	Characterizing Fake and Organic Likes	Classification		Instagram
15	Audience's...[30]	2017	Journal						
16	Fake News Detection...[31]	2017	Journal						
17	Fake News Mitigation...[32]	2017	Journal						
18	Fake news or truth...[33]	2016	Conference						
19	Fake news...[34]	2018	Journal	Sethi RJ	2017	System Prototype	Graph-theoretic Framework		Common
20	False Information...[35]	2018	Journal	Sinnott RO et.al.	2016	Identify event by sentiment analysis	Data Mining		Twitter
21	Influence...[36]	2018	Journal						
22	Polarization...[37]	2018	Journal						
23	Social Media...[38]	2017	Journal						
24	Some like...[39]	2017	Conference	Volkova et.al.	2018	Linguistics Analysis of Deceptive News	Machine Learning		Twitter
25	Right-click...[40]	2017	Conference						
26	A Computational...[41]	2018	Conference						
27	On the Statistical...[42]	2017	Journal	Zhou et.al.	2017	Topic Modelling	Machine Learning		Twitter
28	Algorithmic...[43]	2018	Journal	Santoso et.al.	2017	Decrease Hoax in Social Media	Data Mining		Common
29	Anatomy...[44]	2018	Journal						
30	Fake News: ...[45]	2017	Journal						
31	Leveraging...[46]	2018	Conference						
32	Mining...[47]	2017	Journal	Pourghomi et.al	2017	Information Quality Metric	Right-click Authenticate		Facebook
33	The rumor...[48]	2018	Journal						
34	Credibility...[49]	2017	Journal						
35	Detecting...[50]	2017	Journal	Bessi A	2016	Forecasting and tracking of viral content and event	Extreme value theory		Facebook
36	Verifying...[51]	2017	Journal						
37	Detection...[52]	2018	Journal						
38	Early...[53][54][55]	2017	Journal						

Table III shows focuses, contributions, approaches and type of social media that are studied by previous researchers to detect hoax news on social media and the internet. Classification is the most used in research to identifying and encountering hoax news. This technique, classification, will very evolve on the next research if it is studied to find a variation effectively. With this approach, researchers want to detect hoax news professionally.

TABLE III. CONTRIBUTION, APPROACH, AND SOCIAL MEDIA PLATFORM

Author	Year	Contribution	Approach	Social Media Platform
Kumar et.al.	2016	Impact, Characteristics, and Hoax Detection	Classification algorithm (logistic regression, support vector machine, random forest)	Wikipedia
Papadopoulos et.al.	2016	Trusted Information Characteristics	Information Retrieval and Discovery	Twitter
Shao et.al.	2016	Platform Architecture	User Activity and URL Popularity	Twitter
Shu et.al.	2016	Characterization and	Data Mining	Twitter, Facebook
Jang et.al.	2017	Fake News Pattern	Evolution Analysis	Tree
Purnomo et.al.	2017	Text-based Hoax News Detection	Sentiment Analysis	Common
Boididou et.al.	2017	Automated Verifying	Classification	Twitter
Boididou et.al.	2017	Automatic Classification on System	Classification	Twitter
Ahmed et.al.	2017	Fake Content Detection Model	Text Classification	Twitter
Farajtabar et.al.	2017	Policy Iteration Method	Point network model	process activity
Tacchini et.al.	2017	Automatic hoax detection system	Classification	Facebook
Vicario et.al.	2018	Framework for Early Warning System	Classification	Facebook
Bovet et.al.	2018	Framework Inferring opinion	Machine Learning	Twitter
Kumar et.al.	2018	Algorithm to detect	Survey	Common

		false information		
Gelfert A	2018	Media literacy	-	-
Allcot et.al.	2017	Media Literacy	-	-
Verstraete et.al.	2017	Set model of intervention	-	Common
Tandoc et.al.	2017	Conceptual Framework	Authentication and Verification	Common
Tschiats check. et.al.	2018	DETECTIVE Algorithm	Detection via computational method	Facebook
Rubin et.al.	2016	Detect Potential misleading News	SVM	Common
Kim et.al.	2018	CURB Algorithm	Multi-dimensional counting process	Twitter, Weibo
Viviani et.al.	2017	Detect and assess	Survey	-
Flintham et.al.	2018	Veracity based on reliability	Verification	Facebook
Shao et.al.	2018	Misinformation detection	Verification	Twitter
Liu et.al.	2018	Attention-based approach	Web-mining	Weibo, Twitter
Turenne et.al.	2018	Rumour detection	Classification	Twitter

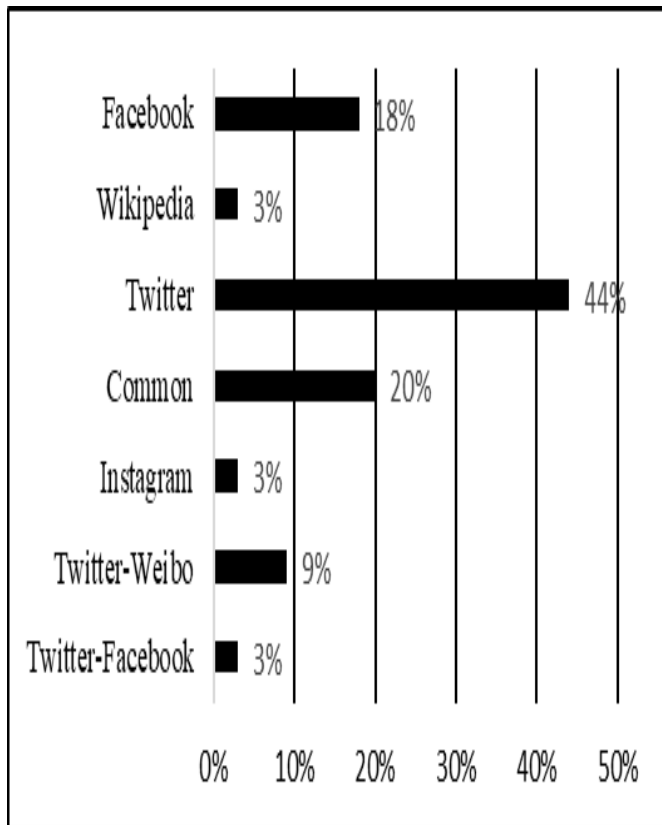


Fig. 1 The most popular Social Media Platform used for research on Hoax Detection in 2016-2018

According to table III above, research analyze that Twitter is the most popular social media platform in hoax news deployment. The percentage detailed as shown on fig. 1, these are the most popular social media platforms during 2016-2018 (on-going).

Twitter is easy to use. This platform provides space to spread information easy and instantly. According to the figure above, a microblogging application, Twitter, also is the most popular social media to research about hoax news. Researchers use information spread data from Twitter, analyze and then determine the information are a hoax or not. The result of this survey can be a reference to the next research to have a new approach focused on data analysis method and made more analysis on many other social media out of Twitter.

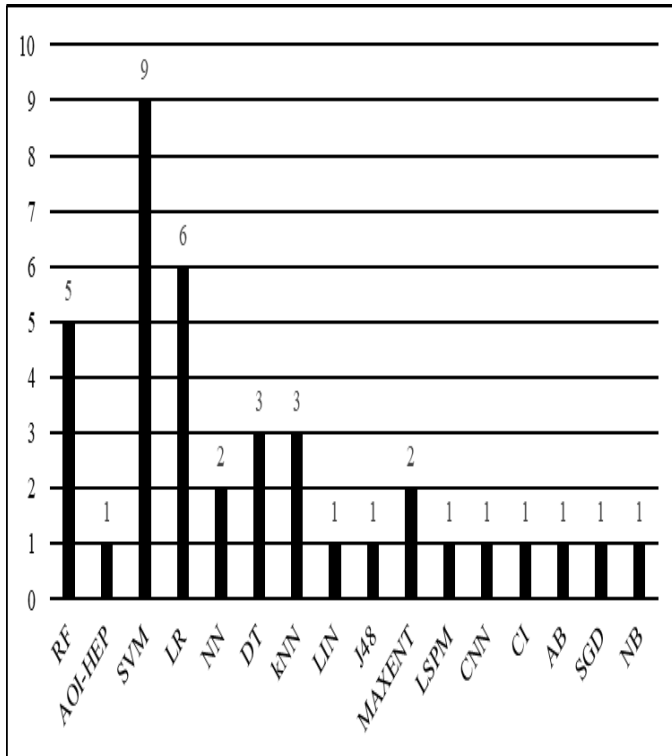
TABLE IV. THE COMBINED ALGORITHMS FOR RESEARCH ON HOAX DETECTION IN 2016-2018

Author	Algorithms															
	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
Kumar et.al	√		√	√												
Sen et.al					√											
Boididou 1 et.al	√		√											√		
Boididou 2 et.al	√		√	√												
Ahmed et.al			√	√		√	√									√
Tachine et.al				√												
Vicario et.al			√	√	√	√	√	√								
Rubin et.al			√													
Turenne et.al	√		√										√			
Shu et.al			√	√		√	√									√
Sinnot et.al			√							√						
Santoso et.al		√														
Volkova et.al	√										√	√	√			
Bovet et.al														√		
Total	5	1	9	6	2	3	3	1	1	2	1	1	1	1	1	1

According to the table IV above, the annotations are A: Random Forest; B: Attribute-Oriented Induction High Level Emerging Pattern (AOI-HEP); C: Support Vector Machine; D: Logistic Regression; E: Neural Network; F: Decision Trees; G: K-Nearest Neighbor; H: Linear Regression; I: J48; J: MaxEntropy; K: Long-Short Term Memory; L: Convolutional Neural Network; M: Collective Influence; N: AdaBoost; O: Stochastic Gradient Descent; P: Naïve Bayes. The conclusion from table IV is shown as on fig. 2.

Fig. 2 shows the most popular algorithm. This research mitigates the most used algorithm to detect hoax news on social media from 2016 until 2018 (on-going).





## REFERENCES

Fig 2. The most popular algorithm to detect hoax news in 2016-2018

According to the fig. 2 above, the most popular approach used for research on detect hoax news is Classification with the algorithms used are Random Forest (RF), Attribute-Oriented Induction High Level Emerging Pattern (AOI-HEP), Support Vector Machine (SVM), Logistic Regression (LR), Neural Network (NN), Decision Trees (DT), K-Nearest Neighbor (KNN), Linear Regression (LIN), J48, MaxEntropy (MAXENT), Long-Short Term Memory (LSTM), Convolutional Neural Network (CNN), Collective Influence (CI), AdaBoost (AB), Stochastic Gradient Descent (SGD), Naïve Bayes (NB), as shown in table IV. The most popular algorithm used to research about hoax news detection on social media in this work is Support Vector Machine (SVM).

## IV. IMPLICATION AND CONCLUSION

The result of this research could be a reference for future research about hoax news, and it can identify approach method trend to hoax news encountering and also the contributions. Some approaches have developed to detect hoax news on the different domain or social media types. The most popular approach according to this work is Classification using the SVM algorithm, and the most used social media platform is Twitter. With its effectivities and versatilities SVM has become very powerful to be used for classification on high dimension data.

The limitation of this work is that the survey conducted to the paper among 2016 until 2018 (on-going), thus on the next research, a researcher can add the duration to improve the accuracy and quality and also elaborate some algorithm to be combined to get more powerful and useful research.

- [1] S. Papadopoulos, K. Bontcheva, E. Jaho, M. Lupu, and C. Castillo, "Overview of the Special Issue on Trust and Veracity of Information in Social Media," *ACM Trans. Inf. Syst.*, vol. 34, no. 3, pp. 1–5, 2016.
- [2] J. Gottfried and E. Shearer, "News Use Across Social Media Platforms 2016," *Pew Research Center*, May 2016.
- [3] C. Silverman, "This analysis shows how fake election news stories outperformed real news on Facebook," BuzzFeed, available at: [https://www.buzzfeed.com/craigsilverman/viral-fake-election-news-outperformed-real-news-on-facebook?utm\\_term=.wsBVKGogk#.bxANM8qLe](https://www.buzzfeed.com/craigsilverman/viral-fake-election-news-outperformed-real-news-on-facebook?utm_term=.wsBVKGogk#.bxANM8qLe) (accessed 16 February 2017).
- [4] R. Allen, "What happens online in 60 seconds?," Website, 2017. [Online]. Available: <https://www.smartinsights.com/internet-marketing-statistics/happens-online-60-seconds/>
- [5] N. Newman, R. Fletcher, A. Kalogeropoulos, D.A Levy, and R.K Nielsen. Reuters institute digital news report 2017. 2017.
- [6] T. Berners-Lee, R. Cailliau, J.F Groff, and B. Pollermann. "World-wide web: The information universe," *Internet Research*. 20(4):461–471, 2010.
- [7] A. Perrin, "Social Media Usage," *Pew Research Center*, 2015.
- [8] E. Shearer and J. Gottfried, "News Use Across Social Media Platforms 2017," *Pew Research Center*, September 2017.
- [9] Planet Money: Episode 739: Finding the fake=news king. <http://www.npr.org/templates/transcript/transcript.php?storyId=504155809>
- [10] D. Kumar and D. Makhija, "Reviews and ratings fraud detection in e-commerce," 2015.
- [11] M. Luca and G. Zervas, "Fake it till you make it: Reputation, competition, and yelp review fraud," *Management Science*, 62(12):3412–3427, 2016.
- [12] A. Smith and V. Banic, "Fake news: How a partying Macedonian teen earns thousands publishing lies," *NBC News*, 2016.
- [13] L. Howell et al, "Digital wildfires in a hyperconnected world," *WEF Report*, 3:15–94, 2013.
- [14] A. Bessi and E. Ferrara, "Social bots distort the 2016 U.S. Presidential election online discussion," *First Monday* 21, 11, 2016. <https://doi.org/10.5210/fm.v21i11.7090>
- [15] S. Kumar, R. West, and J. Leskovec, "Disinformation on the Web: Impact, Characteristics, and Detection of Wikipedia Hoaxes," *WWW*, pp. 591–602, 2016.
- [16] S. Volkova and J.Y Jang, "Misleading or Falsification? Inferring Deceptive Strategies and Types in Online News and Social Media," *WWW*, pp. 575–583, 2018.
- [17] H. Berghel, "Alt-News and Post-Truths in the "Fake News" Era," *IEEE Computer*, vol. April, pp. 110–114, 2017.
- [18] M.H Purnomo, S. Sumpeno, E.I Setiawan, D. Purwitasari, "Keynote Speaker II: Biomedical Engineering Research in the Social Network Analysis Era: Stance Classification for Analysis of Hoax Medical News in Social Media," *Procedia Comput Sci [Internet]*. 2017;116:3–9. Available from: <https://doi.org/10.1016/j.procs.2017.10.049>
- [19] D. Moher, A. Liberati, J. Tetzlaff, D.G Altman, "The PRISMA Group (2009). Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement," *PLoS Med* 6(7): e1000097. doi:10.1371/journal.pmed1000097
- [20] X. Zhou, X. Tao, M.M Rahman, J. Zhang, "Coupling topic modelling in opinion mining for social media analysis," *Proc Int Conf Web Intell - WI '17 [Internet]*. 2017;533–40. Available from: <http://dl.acm.org/citation.cfm?doid=3106426.3106459>
- [21] N. Ruchansky, S. Seo, Y. Liu, "CSI: A Hybrid Deep Model for Fake News Detection," 2017;797–806. Available from: <http://arxiv.org/abs/1703.06959v0Ahttp://dx.doi.org/10.1145/3132847.3132877>
- [22] K Shu, A. Sliva, S. Wang, J. Tang, H. Liu, "Fake News Detection on Social Media : A Data Mining Perspective," 2016;19(1):22–36.
- [23] M. Flintham, C. Karner, K. Bachour, H. Creswick, N. Gupta, S. Moran, "Falling for Fake News: Investigating the Consumption of News via Social Media," 2018;1–10.

- [24] C. Shao, G.L Ciampaglia, A. Flammini, F. Menczer, "Hoaxy : A Platform for Tracking Online Misinformation," :745–50.
- [25] D. Lottridge, F.R Bentley, "Let's Hate Together," Proc 2018 CHI Conf Hum Factors Comput Syst - CHI '18 [Internet]. 2018;1–13. Available from: <http://dl.acm.org/citation.cfm?doi=3173574.3173634>
- [26] M. Bedard, "Satire or Fake News : Social Media Consumers Socio-Demographics Decide," 2018;2:613–9.
- [27] E. Mustafaraj, P.T Metaxas, "The Fake News Spreading Plague: Was it Preventable?," Proc 2017 ACM Web Sci Conf - WebSci '17 [Internet]. 2017;(June):235–9. Available from: <http://dl.acm.org/citation.cfm?doi=3091478.3091523>
- [28] L. Wu, H. Liu, "Tracing Fake-News Footprints," Proc Elev ACM Int Conf Web Search Data Min - WSDM '18 [Internet]. 2018;637–45. Available from: <http://dl.acm.org/citation.cfm?doi=3159652.3159677>
- [29] I. Sen, A. Aggarwal, S. Mian, S. Singh, P. Kumaraguru, A. Datta, "Worth its Weight in Likes: Towards Detecting Fake Likes on Instagram," 2018;(5):205–9. Available from: <https://doi.org/10.1145/3201064.3201105>
- [30] E.C Tandoc, R. Ling, O. Westlund, A. Duffy, D. Goh, L. Zheng Wei, "Audiences' acts of authentication in the age of fake news: A conceptual framework," New Media Soc. 2017.
- [31] S. Tschiateck, A. Singla, M.G Rodriguez, A. Merchant, A. Krause, "Fake News Detection in Social Networks via Crowd Signals," 2017;517–24. Available from: <http://arxiv.org/abs/1711.09025>
- [32] M. Farajtabar, J. Yang, X. Ye, H. Xu, R. Trivedi, E. Khalil, et al. "Fake News Mitigation via Point Process Based Intervention," 2017;(lcm1). Available from: <http://arxiv.org/abs/1703.07823>
- [33] V. Rubin, N. Conroy, Y. Chen, S. Cornwell, "Fake News or Truth? Using Satirical Cues to Detect Potentially Misleading News," Proc Second Work Compute Approaches to Decept Detect [Internet]. 2016;7–17. Available from: <http://aclweb.org/anthology/W160802>
- [34] A. Gelfert, "Fake news: A definition," Informal Log. 2018;38(1):84–117.
- [35] S. Kumar, N. Shah, "False Information on Web and Social Media: A Survey," 2018;1(1). Available from: <http://arxiv.org/abs/1804.08559>
- [36] A. Bovet, H.A Makse, "Influence of fake news in Twitter during the 2016 US presidential election," 2018;1–23. Available from: <http://arxiv.org/abs/1803.08491>
- [37] M. Del Vicario, W. Quattrociocchi, A. Scala, F. Zollo, "Polarization and Fake News: Early Warning of Potential Misinformation Targets," 2018; Available from: <http://arxiv.org/abs/1802.01400>
- [38] H. Allcott, M. Gentzkow, "Social Media and Fake News in the 2016 Election," J Econ Perspect [Internet]. 2017;31(2):211–36. Available from: <http://pubs.aeaweb.org/doi/10.1257/jep.31.2.211>
- [39] E. Tacchini, G. Ballarin, M.L Della Vedova, S. Moret, L. de Alfaro, "Some like it Hoax: Automated fake news detection in social networks," In CEUR-WS; 2017.
- [40] P. Pourghomi, A.A Halimeh, F. Safieddine, W. Masri, "Right-click Authenticate adoption: The impact of authenticating social media postings on information quality," In: 2017 International Conference on Information and Digital Technologies (IDT) [Internet]. Institute of Electrical and Electronics Engineers Inc.; 2017 [cited 2018 May 26]. p. 327–31. Available from: <http://ieeexplore.ieee.org/document/8024317/>
- [41] S.M Jang, T. Geng, J-Y Queenie Li, R. Xia, C-T. Huang, H. Kim, et al. "A computational approach for examining the roots and spreading patterns of fake news: Evolution tree analysis," Comput Human Behav [Internet]. 2018 Jul [cited 2018 May 26];84:103–13. Available from: <http://linkinghub.elsevier.com/retrieve/pii/S0747563218300906>
- [42] A. Bessi, "On the statistical properties of viral misinformation in online social media," Phys A Stat Mech its Appl [Internet]. 2017 Mar [cited 2018 May 26];469:459–70. Available from: <http://linkinghub.elsevier.com/retrieve/pii/S0378437116308160>
- [43] S.O Soe, "Algorithmic detection of misinformation and disinformation: Gricean perspectives," J Doc [Internet]. 2018 Mar 12 [cited 2018 Jun 8];74(2):309–32. Available from: <http://www.emeraldinsight.com/doi/10.1108/JD-05-2017-0075>
- [44] C. Shao, P-M Hui, L. Wang, X. Jiang, A. Flammini, F. Menczer, et al. "Anatomy of an online misinformation network," Barrat A, editor. PLoS One [Internet]. 2018 Apr 27 [cited 2018 Jun 8];13(4):e0196087. Available from: <http://dx.plos.org/10.1371/journal.pone.0196087>
- [45] N. Rochlin, "Fake news: belief in post-truth," Libr Hi Tech [Internet]. 2017 Sep 18 [cited 2018 Jun 8];35(3):386–92. Available from: <http://www.emeraldinsight.com/doi/10.1108/LHT-03-2017-0062>
- [46] J. Kim, B. Tabibian, A. Oh, B. Schölkopf, M. Gomez-Rodriguez, "Leveraging the Crowd to Detect and Reduce the Spread of Fake News and Misinformation," In: Proceedings of the Eleventh ACM International Conference on Web Search and Data Mining - WSDM '18 [Internet]. New York, New York, USA: ACM Press; 2018 [cited 2018 Jun 8]. p. 324–32. Available from: <http://dl.acm.org/citation.cfm?doi=3159652.3159734>
- [47] Q. Liu, F. Yu, S. Wu, L. Wang, "Mining Significant Microblogs for Misinformation Identification: An Attention-based Approach," 2017;9(5). Available from: <http://arxiv.org/abs/1706.06314>
- [48] N. Turenne, "The rumour spectrum," Amblard F, editor. PLoS One [Internet]. 2018 Jan 19 [cited 2018 Jun 8];13(1):e0189080. Available from: <http://dx.plos.org/10.1371/journal.pone.0189080>
- [49] M. Viviani, G. Pasi, "Credibility in social media: opinions, news, and health information—a survey," Wiley Interdiscip Rev Data Min Knowl Discov. 2017;7(5).
- [50] H. Ahmed, I. Traore, S. Saad, "Detecting opinion spams and fake news using text classification," Secur Priv [Internet]. 2017;(November):e9. Available from: <http://doi.wiley.com/10.1002/spy2.9>
- [51] C. Boididou, S.E Middleton, Z. Jin, S. Papadopoulos, D.T Dang-Nguyen, G. Boato, et al. "Verifying information with multimedia content on twitter: A comparative study of automated approaches," Multimed Tools Appl. 2017;1–27.
- [52] C. Boididou, S. Papadopoulos, M. Zampoglou, L. Apostolidis, O. Papadopoulou, Y. Kompatsiaris, "Detection and visualization of misleading content on Twitter," Int J Multimed Inf Retr [Internet]. 2018 Mar 4 [cited 2018 Jun 8];7(1):71–86. Available from: <http://link.springer.com/10.1007/s13735-017-0143-x>
- [53] I. Santoso, I. Yohansen, Nealsen, H.L.H.S Warnars, K. Hashimoto, "Early investigation of proposed hoax detection for decreasing hoax in social media," 2017 IEEE Int Conf Cybern Comput Intell [Internet]. 2017;175–9. Available from: <http://ieeexplore.ieee.org/document/8311705/>
- [54] Warnars, H.L.H.S 2016. Using Attribute Oriented Induction High level Emerging Pattern (AOI-HEP) to mine frequent patterns. International Journal of Electrical and Computer Engineering (IJECE), 6(6), 3037-3046.
- [55] Warnars, H.L.H.S., Trisetarso, A. and Randiatoamanana, R. 2018. Confidence of AOI-HEP Mining Pattern. Telkomnika, 16(3), 1217-1225, June 2018.