Misinformation Detection in Social Networks: A Systematic Literature Review

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Abstract. Information quality is becoming an increasingly important issue as social networks have become the primary source for misinformation dissemination. Because of their ease of use, spreading behavior, and low cost, social network platforms are leveraging news consumption. Because of its negative impact on society, this term became more popular and dangerous following the 2016 U.S. presidential election. Many studies have been developed on methods to improve rumor classification, particularly on misinformation detection on social media, with promising results in recent years. Despite the growth of this type of research, it is difficult for a researcher to identify the most up-to-date literature on misinformation detection. To address this challenge, this paper presents a systematic review of the literature that provides an overview of this research area and analyzes high-quality research papers on fake news detection. According to our search protocol, more than 670 articles were discovered during this systematic literature review. Then, we put these studies through a series of scanning stages to ensure that they were of high quality. We chose 76 high-quality studies based on our selection process flow diagram, which is described in this paper. This review describes 10 years of research on social media misinformation and presents the main methods and data sets used in the literature.

Keywords: Misinformation detection · Fact check · Disinformation · Social media

1 Introduction

When compared to more traditional communication methods, such as the printed newspaper, social networks have increased news consumption due to their ease of access, broad audience reach and low cost. They have become the ideal platform for disseminating misinformation. This can have a significant impact on society's

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day-to-day operations, create economic harm, and even affect a nation's political decisions directly or indirectly [90].

On the other hand, detecting fake news on social media, is a difficult undertaking since even people have been known to overlook misinformation. A fake news site also makes an effort to include sensational and very unfavorable phrases in its content. In this regard, the most recent studies in this field reveal that text mining approaches paired with Deep Learning (DL) or Machine Learning (ML) algorithms produce considerable results in terms of detecting disinformation [14,15,58]. Based on the existing work, in the near future, modern society could be able to detect misinformation automatically via information system techniques, allowing for a certain level of information transparency on social networks [50].

As a result, it is critical that users, developers and specialists in Information Systems (IS) are aware of the existing solutions to problems they may encounter throughout the usage or building of the systems. Hence, this systematic review of the literature was created to help with these and other more particular topics, such as analysing the primary sources of information, the primary data-sets used as use cases, and the primary ML and AI algorithms for each scenario. The most relevant publications retrieved in this systematic review process provide answers to these issues.

2 Systematic Review Process

A systematic literature review (SLR) is a study that tries to discover and evaluate a research issue by decreasing superficial information, and analysing and providing the gaps and greatest contributions in a research area [29]. An SLR, according to Kitchenham and Charters [40], is a three-phase process that includes planning, execution, and evaluation. In this study, we conducted a systematic mapping investigation of existing research on misinformation detection and spread in social networks.

This work is structured as follows. Section 3, Sect. 4, and Sect. 5 explain the methodology utilized in this study, including the three phases of the systematic review and the instruments employed in each. Finally, Sect. 6 and Sect. 7 reviews the findings and suggest areas for future investigation.

3 Planning the Review

3.1 Research Questions

The primary purpose of this research is to conduct an SLR on misinformation detection for social networks. The major goal of this research is to answer the following key research issues on this research topic.

- RQ1: How was the distribution of papers on misinformation detection distributed over the years?

- RQ2: What types of publications have been developed in the area of detecting misinformation?
- RQ3: Which social networks are mostly used as a case study?
- RQ4: What are the domains in which the publications are being used?
- RQ5: What type of misinformation exists on social networks?
- RQ6: What kind of approaches are proposed for misinformation detection and spread in social networks?

3.2 Data Sources and Search Criteria

A systematic search strategy is required to identify the whole population of scientific articles that could be related to the selected study topics. We were able to conduct a repeatable and transparent evaluation of external assessments. The first step in the search strategy was to define the search space. The research for this study was performed in six electronic databases.

- ACM Digital Library (https://dl.acm.org)
- IEEE Explore (https://ieeexplore.ieee.org)
- Scopus (https://www.scopus.com)
- Springer (https://www.springer.com)
- Web of Science (https://mjl.clarivate.com)
- Wiley (https://onlinelibrary.wiley.com)

After defining the search space, we specified the search phrases that would be used in electronic database search inquiry forms. The search was based on the study questions' keywords, synonyms, and alternate words. The following search string is used:

('misinformation detection' or 'misinformation spread' OR 'misinformation sharing' OR 'disinformation') AND ('social media' OR 'social network') AND ('fact check' OR 'fake news')

3.3 Inclusion and Exclusion Strategy

The inclusion and exclusion criteria have been established in order to accurately assess the quality of the available literature. The authors evaluated and discussed the papers before making an inclusion or exclusion decision. For a paper to be considered for a primary study, it must meet the following criteria:

- Research field: Computer Science
- Language: English
- Publication date 2012 to 2022
- Type of work: Scientific studies
- Availability: Full Text

3.4 Selection Process and Quality Evaluation

We assessed the scientific quality requirements of the chosen studies to determine the relevance of the review results in order to assist the analysis of the results in the included literature and to show the value of conclusions. The results of the included papers' quality rating can identify potential limitations of the current search and lead to further research on the subject. The following criteria were created to compare chosen research for an analysis or corresponding relevance to the topic.

- Are the research goals well-defined?
- What is the research article's year of publication?
- Was the proposed solution explained detailly and clearly?
- What is the distribution of detection techniques across these categories?
- Did the researcher identify which dataset to use?
- What is the size of the validation dataset?
- Do the datasets contain detailed information?
- Are the findings of the study presented in a clear and concise manner?
- Are the results consistent with the objectives?
- What are the study's limitations and recommendations for future research?

The proposed quality assessment process comprises three main measures for quantitative purposes. A 'yes' answer receives a score of 1, a partial answer receives a 0.5 score, and a 'no' answer receives a score of 0, and some questions do not apply to some articles [41]. The aggregated sum of these scores can be used to assess the relevance of the retrieved research articles.

4 Conducting the Review

The second step of our literature review includes the following: (1) searching for primary studies; (2) choosing primary articles by applying inclusion and exclusion criteria; (3) assessing the applicability and relevance; and (4) retrieving information.

The automatic search tools in the digital libraries indicated in the search strategy were used to look for primary research. We utilized a form to categorize and record the information from each document after searching the digital libraries using the stated research string pattern. The results of the search were also saved in an Excel spreadsheet and the Mendeley application.

After extracting the population of scientific publications related to the study topics, the query returned 672 unique results. The articles related to the review purpose were then chosen using the set of criteria specified in Sect. 3.3. The title, abstract, and results of the 672 findings were assessed in the first round. We examined the whole text of each article in a second round and applied quality criteria, resulting in the retrieval of 76 papers. Totally 596 studies were turned down. As a consequence, 76 studies were chosen and placed into the spreadsheet.

Each paper's inclusion and exclusion status is documented for future discussion and reassessment. The systematic review of the literature generated 76 primary studies. We have also included additional works at the time of the final editing of this report to make this study more comprehensive. Quantitative statistics for primary studies are shown in Table 1.

Table 1. Search results after phases

Database	First round	Second round	Third round
ACM Digital Library	217	32	11
IEEE Explore	128	84	33
Scopus	87	58	7
Springer	159	54	18
Web of Science	28	16	4
Wiley	53	12	3

5 Review Results

76 relevant scientific papers were found as a result of the systematic review. These are the key studies that were utilized to address the six research questions defined in Sect. 3.1. Following that, we present the results of each of these questions. All the main results obtained as the output of the SLR are detailed in Table 2 in the Appendix section.

5.1 RQ1: How Was the Distribution of Papers on Misinformation Detection Distributed over the Years?

Figure 1 reflects the intensity of publications that propose to solve the problem of spreading misinformation on social networks. It is seen that the number of papers written on this subject has increased in 2016. It is predicted that one of the biggest reasons for this is the election results in America [14,90]. It has been seen how effective misinformation is in people's political decisions, and as a result, the number of studies has increased. Since the first three months of 2022 were taken into account while conducting the study, the reason for the decrease in the graph is due to the absence of data for the rest of the year.

Considering the distribution of articles by years and digital libraries from Fig. 2, it is seen that there are more articles in IEEE and Springer. In addition, it is clear that the number of all results coming from each digital library has increased after 2016.

5.2 RQ2: What Types of Publications Have Been Developed in the Area of Detecting Misinformation in Social Networks?

Figure 3 represents an overview of which types of primary studies are most published. Conferences and journals are the primary targets of scientific effort, as seen in the diagram. The fact that conferences have a more rigid structure of publication and a smaller scope than journals can explain the larger number of papers published at conferences [41]. Furthermore, at the conferences, technical conversations between researchers take place in technical sessions, significantly enhancing knowledge regarding the conference's issues.

Another factor to consider is that detecting misinformation on social media is a very recent topic. As a result, their works are less likely to be subjected to the more time-consuming process of journal and book review and acceptance.

5.3 RQ3: Which Social Networks Are Mostly Used as a Case Study?

Figure 4 reveals that most of the selected primary studies use Twitter, Weibo, and Facebook as an environment for experimenting with social networks [63,76]. Besides that most used data set is FakeNewsNet [70] for fake news detection [62, 83]. Both of these results are expected because these are the most used social networks with widespread news reading and sharing tools [13,36,45,88].

5.4 RQ4: What Are the Domains in Which the Publications Are Being Used?

Misinformation spreads in a variety of ways, and some studies are attempting to identify domain-specific characteristics [6]. The number of publications by domain is shown in Fig. 5. There are four primary domains that have been discovered.

Papers in this general category provide methods for detecting disinformation in social media posts using common variables such as the number of followers and particular linguistic patterns, etc. This type of method may be used in a variety of domains and is unaffected by domain-specific characteristics [55,68].

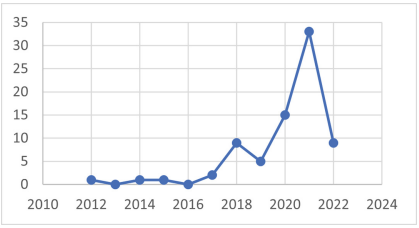

Fig. 1. Papers by year.

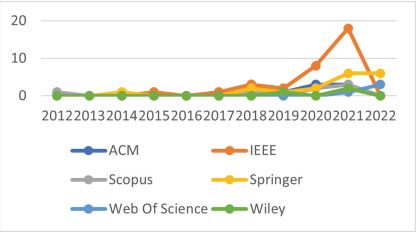

Fig. 2. Papers by year and by source.

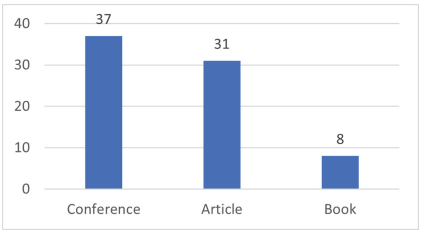

Fig. 3. Papers by publication type.

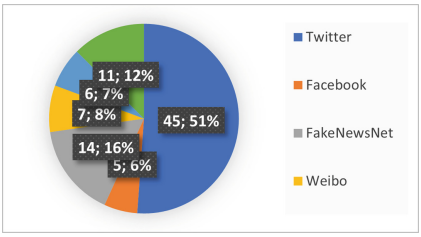

Fig. 4. Papers by dataset.

The techniques in the News category are developed particularly to deal with journalistic news. The majority of fact-checking techniques fall into this category since they aim to uncover false news by extracting and confirming the facts included in the news [12,36].

The health category contains methods for disseminating health-related disinformation. Because of the Covid 19 pandemic, this kind is currently the most prevalent [52,59]. The usage of external knowledge databases is a significant aspect of categorization in both of these efforts, and both employ information from medical databases as ground truth [61,66,81].

The Politics category contains publications which are related to rumor spreading and conspiracy theories. This kind of misinformation can identify people's political decisions and cause polarization in society [14,82].

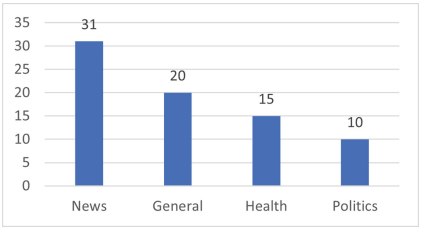

Fig. 5. Papers by domain.

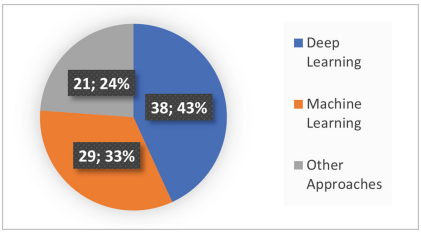

Fig. 6. Papers by solution distribution.

5.5 RQ5: What Type of Misinformation Exists on Social Networks?

Misinformation is merely incorrect information. It can be propagated inadvertently. However, sometimes the source may or may not be aware of the accuracy of the information he or she is sharing [5]. To make the distinction from false information that is shared on purpose, we use the term *disinformation*, and with it we define false information that is generated to deceive the reader on purpose. Disinformation is misleading information spread with the explicit goal of deception. While some authors have listed disinformation as another subcategory of misinformation, such as in [37], we work with an alternative taxonomy presented

in Fig. 7. The authors in [60] also use the term disinformation to differentiate the malicious false news.

Propaganda is news that is produced for a specific audience and is usually utilized in a political setting. In political circumstances, advertisements are frequently used to disparage an opposition party or even a specific country. This method is often employed during political campaigns to persuade voters against the other candidate using entirely fake or partially genuine news, as well as language modifications that confuse people who consume content [82]. Propaganda is often used to polarize societies, and today we also see a rise of fabricated content and the use of deepfakes in media for this purpose.

Stories that seek to explain a situation or incident by evoking a conspiracy without providing evidence are mainly stories concerning acts committed by governments or influential persons. These ideas frequently present information with no known sources or untrusted sources as truths and reject an evidence-based approach [8]. Consideration of authenticity issues as the basic misinformation related analysis is presented in [23].

Rumors consist of news whose veracity is ambiguous or never confirmed. This type of false information is widely spread on social media. Therefore, several studies have analyzed this type of news [46].

Spams are unsolicited communications that are delivered on a mass and repeated basis with the intent of advertising, amusement, or pranking. This is a sort of diffusion circulation in which the message is reiterated so many times at a rapid pace that it begins to mix with the current and relevant data [25].

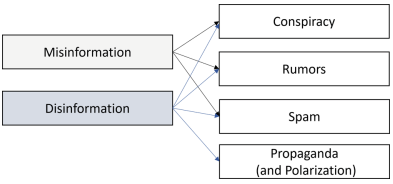

Fig. 7. Misinformation types.

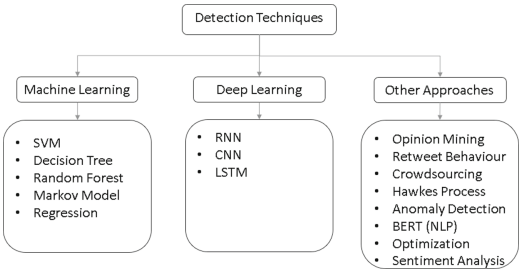

Fig. 8. Misinformation detection approaches.

5.6 RQ6: What Kind of Approaches Are Proposed for Misinformation Detection in the Literature?

Techniques. The numerous methodologies that we have investigated for our research are summarized in Fig. 8. Recently, DL and AI algorithms have been used more heavily. Also, hybrid methods were applied in some articles and better results were obtained in terms of performance. Most of the techniques for detecting misinformation presented in the literature approach the topic as a classification problem, aiming to correlate labels such as misinformation or not.

Researchers have used ML and DL methodologies in the majority of situations, with encouraging outcomes [27,67] (Fig. 6). Other researchers have used alternative techniques, such as Bidirectional Encoder Representations from Transformers (BERT), based on natural language processing techniques, to forecast the class of documents or events, or to assess their validity [38].

Parameters. We also want to point on the parameters used for misinformation detection. Of course, the *type of account* is at the front of studies. For example, an interesting work that states that misinformation is spread more widely and deeply than truthful information and it is more likely to be spread by humans than bots is presented in [80]. Thus, while doing studies on misinformation detection running the experiments with considering bots and without them will give, needless to say, also important information on misinformation detection but also spreading. Work on the type of users that spread misinformation is also presented in [30]. Another differentiating parameter that studies should consider is also the validated or non-validated types of accounts, e.g. for studies on Twitter. *Evidentiality* is another parameter that comes at the forefront of studies in both misinformation detection and misinformation spreading, such as presented in [91]. *Network indices*, such as centrality indices, are used as parameters when studying influential nodes in misinformation detection and spreading studies as well, e.g., in [60]. Homophily is also considered as a parameter in detection of misinformation and spreading patterns, e.g., [73].

6 Threats to Validity of Research

As with any systematic review process, the results of this study may contain flaws arising from the execution and analysis process and analytical imperfections. It is about quality and relevance criteria that may not be satisfactory to conceptualize a study as relevant because of the subjective criteria that each researcher develops based on his/her profile.

One of the inclusion/exclusion criteria in our work is considering works written in English only. In a way, this limits the contribution of authors who may have written in another language. Another one is the research area limited to computer sciences. This may have caused some articles that may be relevant to be excluded from the review process.

7 Conclusion and Future Work

The benefit of using a comprehensive systematic review process is that out of context publications that made it through the screening step may be deleted in the subsequent phases before the quality evaluation. This emphasizes the need of doing a thorough and systematic literature review.

The major goal of this SLR is to provide a list of the most important and relevant works on misinformation as well as their specific topics and categorizations. The responses to our study questions revealed that Twitter, Weibo,

Youtube, and Facebook are the most popular social media sites for misinformation detection studies. In addition, we can conclude that DL and AI algorithms have been widely used in the detection process in recent years, which adds value to the literature and practical applications. Finally, it was determined that using various forms of data, such as social, temporal, or emotional resources, together with, or in addition to text analysis, can increase the correctness of the offered solutions.

Finally, the findings of this systematic review revealed potential areas for future research. There are few publications focused on presenting studies for non-English language misinformation. This is unsurprising given the large group of people working on natural language processing technologies for English. As a result, future studies with this goal will be regarded as notable by the scientific community for their unique qualities, even if their detection findings do not differ significantly from those reported in this SLR. As another result of the research, fake news and video detection, spammer, and bot detection issues stand out as problems that need to be solved. Also, there hasn't been much progress in developing real-time detection systems. Last but not the least, network dynamics based on time analysis is also of crucial importance so that data about how long does misinformation survive within the network and what are the related parameters of influence can better inform our societies of the misinformation spreading dynamics and issues.

A Appendix A

Table 2. Systematic literature review results.

Ref	Year	Source	Type	Dataset	Method	Domain
[54]	2012	Scopus	Conference	Twitter	DL	News
[43]	2014	Springer	Conference	Twitter	ML	Health
[25]	2015	IEEE	Book	Twitter	DL	News
[19]	2017	IEEE	Book	Twitter	DL	General
[14]	2017	ACM	Conference	FakeNewsNet	NLP + DL	Politics
[74]	2018	Scopus	Book	Twitter	DL	General
[11]	2018	Springer	Artice	LIAR	NLP	General
[83]	2018	ACM	Conference	FakeNewsNet	ML	News
[15]	2018	IEEE	Book	Twitter	ML + NLP	News
[76]	2018	ACM	Conference	Weibo, Twitter	DL	Politics
[35]	2018	IEEE	Book	Twitter	DL	News
[2]	2018	IEEE	Book	Twitter	NLP	News

(*continued*)

Table 2. (*continued*)

Ref	Year	Source	Type	Dataset	Method	Domain
[79]	2018	ACM	Conference	Twitter	ML	Politics
[63]	2018	Springer	Article	Weibo	NLP	General
[77]	2019	IEEE	Book	Reddit	Hawkes	General
[7]	2019	Wiley	Conference	Twitter	ML	General
[64]	2019	ACM	Conference	Facebook	ML	News
[10]	2019	IEEE	Conference	LIAR	ML	News
[82]	2019	Springer	Article	Twitter	DL	General
[88]	2020	ACM	Conference	Weibo, Twitter	DL	News
[60]	2020	Springer	Article	FakeNewsNet	DL	News
[20]	2020	IEEE	Conference	Twitter	DL	Health
[49]	2020	Scopus	Article	Twitter	ML	General
[46]	2020	Scopus	Conference	Twitter	DL	Health
[78]	2020	IEEE	Conference	Twitter	ML	News
[68]	2020	Springer	Article	Twitter	ML	General
[85]	2020	ACM	Conference	Twitter	DL	News
[55]	2020	ACM	Conference	FN-COV	DL	News
[3]	2020	IEEE	Article	LIAR	DL	Health
[75]	2020	IEEE	Book	Koirala, FNSD	ML, NLP	News
[90]	2020	IEEE	Conference	Twitter	ML	Politics
[27]	2020	IEEE	Conference	Twitter	ML, DL	Politics
[23]	2020	IEEE	Conference	Twitter	NLP	News
[8]	2020	IEEE	Article	Twitter	DL	General
[13]	2021	IEEE	Conference	FakeNewsNet	ML	News
[62]	2021	IEEE	Conference	FakeNewsNet	DL	General
[4]	2021	Wiley	Article	Twitter	ML	General
[48]	2021	Springer	Article	Twitter	PageRank	News
[44]	2021	Scopus	Article	Instagram	DL	Politics
[28]	2021	IEEE	Conference	FakeNewsNet	ML	News
[87]	2021	IEEE	Conference	FakeNewsNet	ML, NLP, DL	Health
[17]	2021	ACM	Conference	Twitter	ML + DL	News
[1]	2021	IEEE	Article	philstar.com	ML	General
[89]	2021	IEEE	Conference	Twitter	ML	Health
[31]	2021	IEEE	Conference	Facebook	ML	News
[72]	2021	IEEE	Conference	Twitter	ML	News
[56]	2021	Springer	Article	Twitter	ML	Health
[18]	2021	IEEE	Conference	FakeNewsNet	DL	General
[86]	2021	Scopus	Article	Facebook	Optimize	General
[24]	2021	WebOfScience	Article	Twitter	DL	General
[22]	2021	IEEE	Conference	Twitter	ML, NLP	Health

(*continued*)

Table 2. (*continued*)

Ref	Year	Source	Type	Dataset	Method	Domain
[26]	2021	IEEE	Conference	Liar, Fakenews	Sentiment	Health
[21]	2021	IEEE	Conference	FakeNewsNet	DL	Politics
[71]	2021	IEEE	Conference	Liar	DL	Politics
[33]	2021	IEEE	Conference	FakeNewsNet	DL	News
[9]	2021	Springer	Article	Twitter	DL	Health
[12]	2021	Springer	Article	FakeNewsNet	DL	News
[47]	2021	Springer	Article	Twitter	DL	News
[36]	2021	ACM	Conference	Weibo, Twitter	DL	News
[16]	2021	Wiley	Article	Twitter	DL	General
[84]	2021	ACM	Conference	Twitter	Text Mine	General
[38]	2021	IEEE	Conference	Fake News AMT	NLP	Health
[67]	2021	IEEE	Article	Weibo	NLP	News
[42]	2021	Springer	Article	Twitter	DL	General
[66]	2021	Scopus	Article	Youtube	ML	Health
[34]	2021	IEEE	Conference	Twitter	ML + NLP	Health
[61]	2021	IEEE	Conference	Twitter	NLP	Health
[58]	2022	Springer	Article	LIAR	NLP + DL	News
[32]	2022	Springer	Article	Twitter	ML	General
[57]	2022	Springer	Article	Twitter	DL	News
[39]	2022	WebOfScience	Article	Twitter	ML	Politics
[45]	2022	WebOfScience	Article	Twitter, Weibo	DL	General
[51]	2022	Springer	Article	Twitter	DL	News
[65]	2022	Springer	Article	FakeNewsNet	ML	Politics
[69]	2022	Springer	Article	Twitter	DL	Health
[53]	2022	WebOfScience	Article	Weibo	Regression	News

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