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Fake news: a brieftertiary review through health, deep learning, and emerging perspectives

NOTÍCIAS FALSAS: UMA REVISÃO TERCIÁRIA RÁPIDA DAS PERSPECTIVAS DE SAÚDE, APRENDIZADO PROFUNDO E EMERGENTES.

NOTICIAS FALSAS: UN REVISIÓN TERCIARIA RÁPIDA A TRAVÉS DE LA SALUD, EL APRENDIZAJE PROFUNDO Y LAS PERSPECTIVAS EMERGENTES.

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Abstract
Context: The proliferation of fake news represents a significant social threat, especially regarding health information, a problem exacerbated by the COVID-19 pandemic. Deep Learning (DL) techniques are central to detection efforts, with increasing focus on health-related misinformation. **Objective:** This paper extends our previous work, synthesizing secondary studies (SS) on fake news detection, focusing on DL roles, the health domain, and recent trends (2022-2023). **Method:** A rapid tertiary review was conducted, analyzing 15 SS published between 2013 and August 2023, categorized by emphasis: DL applications, health misinformation, or recent publications. **Results:** A consistent dependence on DL and Natural Language Processing for text classification and fabricated media detection was identified. Health-focused or recent trend studies addressed challenges using specific datasets. Key challenges include echo chambers, cross-domain applications, early detection needs, and threats from generative models. Demands for transparency, blocking mechanisms, and Explainable Artificial Intelligence were highlighted. **Conclusion:** This review provides a synthesized view of research on fake news detection, emphasizing intersections with DL and health contexts, confirming the prevalence of core techniques despite diverse methodologies, and pointing to challenges requiring urgent attention.

Keywords: fake news; tertiary review; health; deep learning.

Resumo

Contexto: A proliferação de notícias falsas representa uma ameaça social significativa, especialmente em informações de saúde, problema agravado pela pandemia de Covid-19. Técnicas de Aprendizado Profundo (DL) são centrais nos esforços de detecção, com foco crescente em desinformação relacionada à saúde. **Objetivo:** Este artigo estende o trabalho anterior dos autores, sintetizando estudos secundários (ES) sobre detecção de notícias falsas, focando nos papéis do DL, no domínio da saúde e tendências recentes (2022-2023). **Método:** Foi realizada uma revisão terciária rápida analisando 15 ES publicados entre 2013 e agosto de 2023, categorizados por ênfase: aplicações de DL, desinformação em saúde ou publicação recente. **Resultados:** Identificou-se dependência consistente em DL e Processamento de Linguagem Natural para classificação de texto e detecção de mídia fabricada. Estudos em saúde ou tendências recentes abordaram desafios usando conjuntos de dados específicos. Principais desafios incluem câmaras de eco, aplicações interdomínio, necessidade de detecção precoce e ameaças de modelos generativos. Demandas por transparência, mecanismos de bloqueio e Inteligência Artificial Explicável foram destacadas. **Conclusão:** Esta revisão fornece uma visão sintetizada da pesquisa em detecção de notícias falsas, enfa- tizando interseções com DL e contextos de saúde, confirmando a prevalência de técnicas centrais apesar de metodologias diversas, e apontando desafios que requerem atenção urgente.

Palavras-chave: notícias falsas; revisão terciária; saúde; aprendizado profundo.

Resumen

Contexto: La proliferación de noticias falsas representa una amenaza social significativa, especialmente en información de salud, problema exacerbado por la pandemia de Covid-19. Las técnicas de Aprendizaje Profundo (DL) son centrales en los esfuerzos de detección, con enfoque creciente en la desinformación relacionada con la salud. **Objetivo:** Este artículo extiende el trabajo previo de los autores, sintetizando estudios secundarios (ES) sobre detección de noticias falsas, centrándose en los roles del DL, el dominio de la salud y tendencias recientes (2022-2023). **Método:** Se realizó una revisión terciaria rápida anal- izando 15 ES publicados entre 2013 y agosto de 2023, categorizados por énfasis: aplicaciones de DL, desinformación en salud o publicación reciente. **Resultados:** Se identificó una dependencia consistente en DL y Procesamiento de Lenguaje Natural para clasificación de textos y detección de medios fabrica- dos. Estudios enfocados en salud o tendencias recientes abordaron desafíos usando conjuntos de datos específicos. Los principales desafíos incluyen cámaras de eco, aplicaciones entre dominios, necesidad de detección temprana y amenazas de modelos generativos. Se destacaron demandas de transparencia, mecanismos de bloqueo e Inteligencia Artificial Explicable. **Conclusión:** Esta revisión proporciona una visión sintetizada de la investigación en detección de noticias falsas, enfatizando intersecciones con DL y contextos de salud, confirmando la prevalencia de técnicas centrales a pesar de metodologías diversas, y señalando desafíos que requieren atención urgente.

Palabras clave: noticias falsas; revisión terciaria; salud; aprendizaje profundo.

Introduction

The post-2015 period has witnessed an unprecedented use of social media, an information ecosystem often lacking the quality criteria associated with traditional journalism (Aimeur; Amri; Brassard, 2023). However, this digital landscape has also provided a fertile ground for the proliferation of fake news, a phenomenon that transcends mere misinformation. Fake news has evolved into a powerful tool of manipulation, capable of inflicting damage on the reputations of corporations, governments, and ethnic groups (Meel; Vishwakarma, 2020; Schlicht *et. al.*, 2023).

Concurrently, deep Learning has emerged as a popular technique since the 2010s. It bypasses manual handcrafting features, which are a laborious and time-consuming but necessary part of traditional machine learning approaches. Thus, deep Learning allows performing complex tasks, such as computer vision, speech recognition, health care monitoring, etc. (Islam *et. al.*, 2020a; Hangloo; Arora, 2022).

Additionally, concerns about health misinformation are significant. The internet has become a widely used and accessible source for health information, often serving as an initial resource for medical advice before consulting a doctor (Schlicht *et. al.*, 2023a; Wang *et. al.*, 2019). As the internet and social media enable diffuse health-related information, they also lower the cost of generating fake news, which started in the pre-COVID-2019 era. For instance, the anti-vaxxer movement, by encouraging individuals not to vaccinate their children, contributed to measles outbreaks in the UK, the US, Germany, and Italy in 2017 (wang, 2017).

This issue increased during the Covid-19 pandemic, in which quarantines increased internet usage (Varma *et. al.*, 2021). The intense flood of real and fake information about Covid-19 through all sources, including social media, was coined as “information epidemic” or “infodemic” (Kim *et. al.*, 2021; Schlicht *et. al.*, 2023). Health authorities even announced that preventing the creation and propagation of fake news about the virus is as essential as alleviating the contagious power of Covid-19 (Kim *et. al.*, 2021).

In response to this challenge, there has been a remarkable growth in the interest in the field, as evidenced by the volume of research with a diverse array of technologies (Meel; Vishwakarma, 2020). In the context of that research area, secondary studies (such as surveys, systematic mapping, or systematic research) have synthesized primary studies and approached the topic under multiple perspectives (Petersen; Vakkalanka; Kuzniarz, 2015), which has generated numerous publications.

This research expands on our previous publication, ‘A Rapid Tertiary Review at the Fake News Domain (Gomes *et. al.*, 2023), presented at the XI Escola Regional de Informática de Goiás. In that initial work, we proposed the methodology of rapid tertiary research within the fake news domain, characterizing it as a tertiary review conducted according to rapid review (RR) protocols (Cartaxo; Pinto; Soares, 2020). The goal of RRs is to accelerate evidence synthesis compared to traditional systematic reviews, thereby delivering timely insights.

The present study delves deeper by investigating specific dimensions, namely health-related disinformation, the role of deep learning, and recent advancements from 2022 to 2023. We observe a divergence in methodologies used by researchers focusing on different sub-topics (‘interest groups’). Despite this methodological variety, the research outcomes show considerable similarity, often concentrating on deep Learning solutions and various facets of the information lifecycle.

Nevertheless, research addressing the primary challenges highlighted in our original review (Gomes *et. al.*, 2023) places significant emphasis on health topics and the most recent literature. Furthermore, our analysis indicates that the development of detailed taxonomies is more common in broader secondary studies than in those focused on specific research niches.

This paper is structured as follows. Section 2 covers the related work and fake news definition; Section 3 presents the research method; Section 4 presents data extraction and results reporting; and Section 5 concludes the paper and points to future work.

Background and related work

This section defines fake news and its related synonyms using (Sharma *et. al.*, 2019). We delineate the main technologies and their taxonomy based on (Hangloo; Arora, 2022) and provide a brief overview of related work.

Definition

Fake news can be defined as fabricated content that mimics real news (Wu *et. al.*, 2022). It is important to note that "fake news" lacks a universally accepted definition, and its interpretation can vary widely (Aimeur; Amri; Brassard, 2023).

Sharma *et. al.* (2019) mention that fake news is news or messages published and spread through the media, containing false information, regardless of the means and motivations that led to its dissemination. This definition allows for capturing the different types of fake news identified in various studies. It allows distinguishing them as fabricated content (completely false), deceptive content (deceptive use of information to frame an issue), imposter content (genuine sources represented by false sources), manipulated con- tent (genuine information or images manipulated to deceive), false connection (hea- dlines, visuals, or captions that do not support the content), and false context (genuine content shared with false contextual information) (Sharma *et. al.*, 2019).

It is possible to subdivide fake information by intention, such as misinformation and disinformation. The former refers to the involuntary dissemination of false information that may result from distortion or misunderstanding due to cognitive biases or lack of comprehension or attention, while the latter refers to false information created and explicitly disseminated to deceive (Aimeur; Amri; Brassard, 2023; sharma *et. al.*, 2019).

Technologies

The main technologies related to fake news are also varied, concentrating in terms of artificial intelligence (AI), natural language processing (NLP), fact-checking (AFC), crowdsourcing (CDS), blockchain (BKC), and graph neural networks (GNN) (Aimeur; Amri; Brassard, 2023).

Artificial Intelligence (AI)

Techniques mainly employ machine learning (ML) or deep learning (DL). ML techniques refer to classical methods in which features are manually extracted for the AI model, such as the number of words or the length of sentences. Methods guided by DL often have the training features extracted. automatically; on the other hand, they are methods that require greater computational capacity (Hangloo; Arora, 2022).

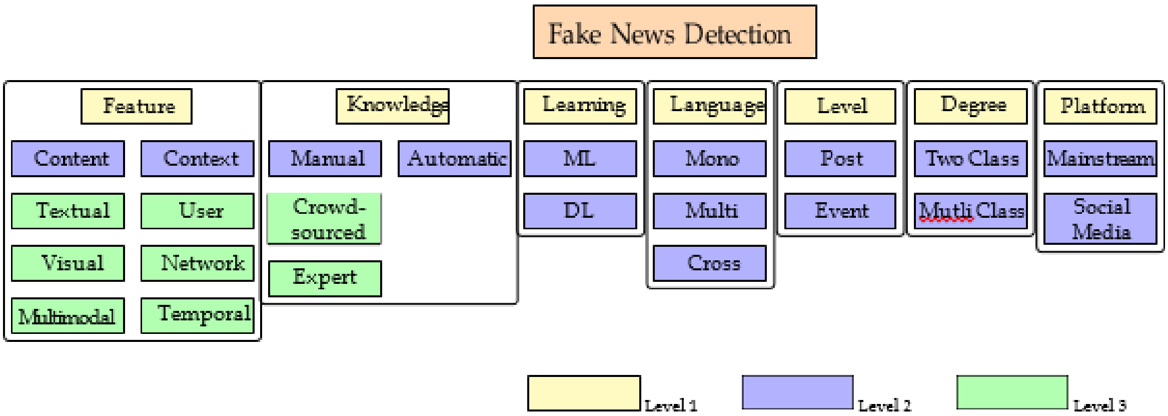

Figure 1 – Taxonomy of fake news detection techniques
Source: Hangloo; Arora, 2022.

Natural Language Processing (NLP) techniques are text-related methods. Fake news can be examined by its textual content, for instance, syntactic, lexical, psycho-linguistic, and semantic. In the syntactic domain, the use of word categories such as nouns, verbs, and adjectives is examined using the Pos-tagging technique. In the syntactic domain, various characteristics such as the number of unique words and their frequencies, the number of sentences, and grammatical errors are extracted to detect suspicious texts. Psycholinguistic information can be obtained using the LIWC statistical system (Reis *et. al.*, 2019). Traditional ML classifiers, such as Logistic Regression, can be paired with NLP techniques such as term frequency-inverse document frequency (TF-IDF) for text analysis.

Fact-checking (FC) techniques verify the textual news through external information, for example, by trying to counter-evidence from a reliable source, which can be carried out manually or automatically. When done manually, the technique can be carried out by **Crowd-sourcing (CDS)** or by experts in the field (Ali *et. al.*, 2022; Kondamudi *et. al.*, 2023; Hangloo; Arora, 2022; Aimeur; Amri; Brassard, 2023).

Blockchain (BKC) is a decentralized ledger that operates on an append-only basis, meaning data is stored across multiple servers without a central authority and can only be added, not deleted or altered. The security of this system is ensured through the verification and cryptographic sealing of blockchain units (blocks) during insertion (Dhall *et. al.*, 2021). Features such as immutability, decentralization, tamper resistance, consensus, record-keeping, and the non-repudiation of transactions are vital aspects that render blockchain technology valuable, not only for cryptocurrencies but also for verifying the authenticity and integrity of digital assets (Ahmad; Aliaga Lazarte; Mirjalili, 2022).

These technologies can be grouped according to their purpose (Ali *et. al.*, 2022; Kondamudi *et. al.*, 2023; Hangloo; Arora, 2022). In this article, we follow (Hangloo; Arora, 2022) as shown in Figure 1, dividing the taxonomy into four main categories: Feature-based (containing Content-based or Social context-based), Knowledge-Based, and Learning-based, with three additional aspects such as language level, detection level, degree of fakeness, and platform.

Feature-based approaches examine characteristics or patterns to detect fake news. For example, sentiment analysis techniques search for a negative sentiment bias in the text. These techniques can be subdivided into content-based or context-based (Hangloo; Arora, 2022).

Content-based technologies analyze the media present in the news, which can be textual, visual, or both (called multimodal). Textual content can be extracted from video and audio through automatic speech recognition systems (ASR), also known as *Speech-to-text*, and from images and videos through OCR.

Context-based techniques, on the other hand, examine the context of the en- environment in which the news is inserted, such as the reactions expressed in comments, responses, and reports, as well as user behavior, such as the time between posts and checking whether the user's behavior resembles that of social network boots. User and posting interactions create a network architecture that can be analyzed using techniques such as blockchain and graphs. It also includes methods considering temporal data on how rumors resurface and credibility data on the news source (Aimeur; Amri; Brassard, 2023; Ali *et. al.*, 2022; Kondamudi *et. al.*, 2023).

Knowledge-based techniques relate to fact-checking techniques, which involve cross-referencing claims with information from trusted sources. As explained previously, fact-checking can be divided into Automatic Fact-Checking and Manual Fact-checking, which can be done through crowdsourcing or expert-based (Ali *et. al.*, 2022; Kondamudi *et. al.*, 2023; Hangloo; Arora, 2022).

Learning-based techniques denote artificial intelligence methods, typically delineated as machine learning (ML) or deep learning (DL) approaches. ML-guided methods are characterized by simplicity, facilitating users' interpretation of intermediate steps, and necessitating minimal data for training. However, they involve manual manipulation of input characteristics, commonly referred to as *feature engineering*. Conversely, DL-guided methods demand a larger volume of data and are often perceived as black boxes due to their complexity and the challenges associated with interpreting intermediate results. Nevertheless, they require less manual data processing and, when a substantial amount of data is available, produce outcomes that exceed those achieved by machine learning (ML) techniques (Garg; Khan; Alam, 2020).

When it comes to **language**, the detection mechanism has the option to consider either one language or multiple languages, whether it be monolingual or multilingual. This is because news that pertains to global events tends to be spread in more than one language and can benefit from being classified across different languages. Another mentioned technique is cross-language learning, where a model trained in a language with rich data, such as English, is used to detect fake news in other languages like Portuguese (Hangloo; Arora, 2022).

Regarding the **detection level**, classification can be performed *a posteriori*, that is, after news circulation. In this case, the claim is analyzed based on the rumor that was spread. Most detection methods are a *posteriori*, not considering this level of related events (Hangloo; Arora, 2022).

Concerning the **degree of fakeness**, a news item can be verified as true or false, with two possible classes, or true, false, and *half false*, with multiple possible classes (Hangloo; Arora, 2022). Liar, the dataset that stands out among the most mentioned in the secondary studies analyzed, has six truth scales: false, not very true, half true, almost true, and true.

From the **platform** perspective, fake news can be analyzed on a specific social network or in the mainstream news media. Facebook, YouTube, WhatsApp, and Instagram lead the way in terms of global user numbers (Dixon, 2024). As we will point out, the population tends to stay in information bubbles and believe the news and journalistic sources that most closely align with the user's worldview. Therefore, the greatest difficulty would be to point out *fake news* associated with the environment in which the individual is inserted on the social network and in the mainstream media.

Related work. While there is a lack of dedicated tertiary studies specifically focused on the phenomenon of fake news, the closest existing tertiary research pertains to sentiment analysis (Ligthart; Catal; Tekinerdogan, 2021). Notably, sentiment analysis techniques hold relevance in the context of fake news detection, as they can be harnessed to identify emotional cues, biases, and hate speech, all of which may indicate the presence of fake news. The findings from this research indicate several key trends and challenges in sentiment analysis, including a growing preference for complex Deep Learning techniques capable of detecting intricate patterns, the necessity for adapting techniques to different domains, and the persistent challenges associated with domain and language dependencies.

Research Method

In this section, we describe our approach to advancing current knowledge and practices in the field of fake news by examining it from three distinct perspectives: deep learning (DL), health, and general. We also compare it with the latest studies from the years 2022 and 2023.

Research questions. To guide our investigation through various phases of the fake news lifecycle and different research angles, we pose the following research questions (RQ):

RQ1: How do different perspectives within peer-reviewed literature define fake news?
RQ2: What techniques, tools, and methods are documented across different perspectives?
RQ3: What are the primary challenges faced in each perspective when addressing fake news?

Search, selection, and extraction. We utilize the search mechanism and studies se- selection from the rapid review of (Gomes *et. al.*, 2023), identifying 15 pertinent secondary studies from the top 50 results of a Google Scholar[1] search conducted on August 29, 2023.

The search string was created using population and intervention (PI). The population is the study area, which comprises fake news, its synonyms, and the intervention is the method intended to be applied in the population, which are secondary studies. We employ the following query:

("fake news" OR misinformation OR rumor OR disinformation) AND
("systematic review" OR "systematic mapping" OR "literature review" OR "survey").

Table 2 presents a comprehensive list of the studies that were identified for review. A total of 13 articles were considered in this study. Of these, a subset of 10 articles was selected based on specific criteria, as detailed in Table 1. Each article selected for inclusion is associated with deep learning (DL), pertains to health, or was published between 2022 and 2023. The subset in question comprises a total of six articles published between the years 2022 and 2023, of which four are specifically oriented towards deep learning (DL) and three pertain to health-related applications.

1 https://scholar.google.com.br/

Reference	Deep Learning	Health	2022-2023
(S1)		✓	✓
(S2)			✓
(S3)			✓
(S5)	✓		
(S6)	✓		
(S9)			✓
(S10)	✓		✓
(S12)		✓	✓
(S13)	✓	✓	

Table 1 – Subset from selected studies that are focused on DL or on health or are from 2022 and 2023
Source: Elaborated by the author.

There are instances of overlapping research areas: (S13) is the only study from the health and DL area; (Ahmad; Aliaga Lazarte; Mirjalili, 2022b; Schlicht *et. al.*, 2023) are both related to the health sector and date from 2022 to 2023, while (S10) focuses on DL technologies within the health field. Nevertheless, none encompasses all three characteristics.

Among the 15 results, 8 (53.3%) were systematic, with an average of 65.5 primary studies being analyzed. (Kim et*. al.*, 2021b; kondamudi *et. al.*, 2023b) forms an outlier with 182 and 218 examined works, leaving these out, the average drops to 49.8 studies.

All three health studies were systematic, forming an average of 64.33 primary studies analyzed. In addition, all three 2023 studies were systematic, making up an average of 107.3 considered research. In the realm of Deep Learning, only (S13) is systematic, which is also health research.

Figure 2 visually represents the citation connections between the chosen secondary studies. It should be noted that the studies by (S10) and (S1) are not cited or cited by the other selected articles.

Within each interest group listed in Table 1, there are no direct or indirect citations between the works. The selected health studies (S1; S12; S13) do not reference each other.

Reference	Year	Sys.	No.	Title
(S1)	**2022**	Yes	80	A Systematic Literature Review on Fake News in the **Covid-19** Pandemic: Can AI Propose a Solution?
(S2)	**2023**	Yes	61	Fake news, disinformation, and misinformation in social media: a review
(S3)	**2022**	No		Fake News Detection Techniques on social media: A Survey
(S4)	2020	Yes	35	Approaches to Identify Fake News: A Systematic Literature Review
(S5)	2022	No		**Deep learning** for fake news detection: A comprehensive survey
(S6)	2020	No		**Deep learning** for misinformation detection on online social networks: a survey and new perspectives
(S7)	2021	Yes	10	A systematic literature review on disinformation: Towards a unified taxonomical framework
(S8)	2021	Yes	182	A systematic review on fake news research through the lens of news creation and consumption: Research efforts, challenges, and future directions

(S9)	**2023**	Yes	218	A comprehensive survey of fake news in social networks: Attributes, features, and detection approaches
(S10)	**2022**	No		A Brief Survey for Fake News Detection via **Deep Learning Models**
(S11)	2020	No		Fake news, rumor, information pollution in social media and web: A contemporary survey of state-of-the-art, challenges and opportunities
(S12)	**2023**	Yes	43	Automatic detection of **health** misinformation: a systematic review
(S13)	2021	Yes	70	A systematic survey on **deep learning** and machine learning approaches of fake news detection in the pre- and post-**Covid-19** pandemic
(S14)	2021	No		Minimizing the spread of misinformation in online social networks: A survey
(S15)	2020	No		A Survey of Fake News: Fundamental Theories, Detection Methods, and Opportunities

Table 2 – Selected secondary studies and bolded related keywords: deep learning, health. Recent studies, from 2022 and 2023, have the related year bolded in blue. For systematic secondary studies (Sys.), we provide the number of primary studies (No.)
Source: Elaborated by the author.

Similarly, DL articles (S5; S6; S10; S13) do not cite one another. This pattern holds for studies from 2022 and 2023. Only the articles (S3; S9), published in 2022 and 2023, respectively, extend their bibliographies to include works from 2021, in addition to those from 2020, either directly or indirectly.

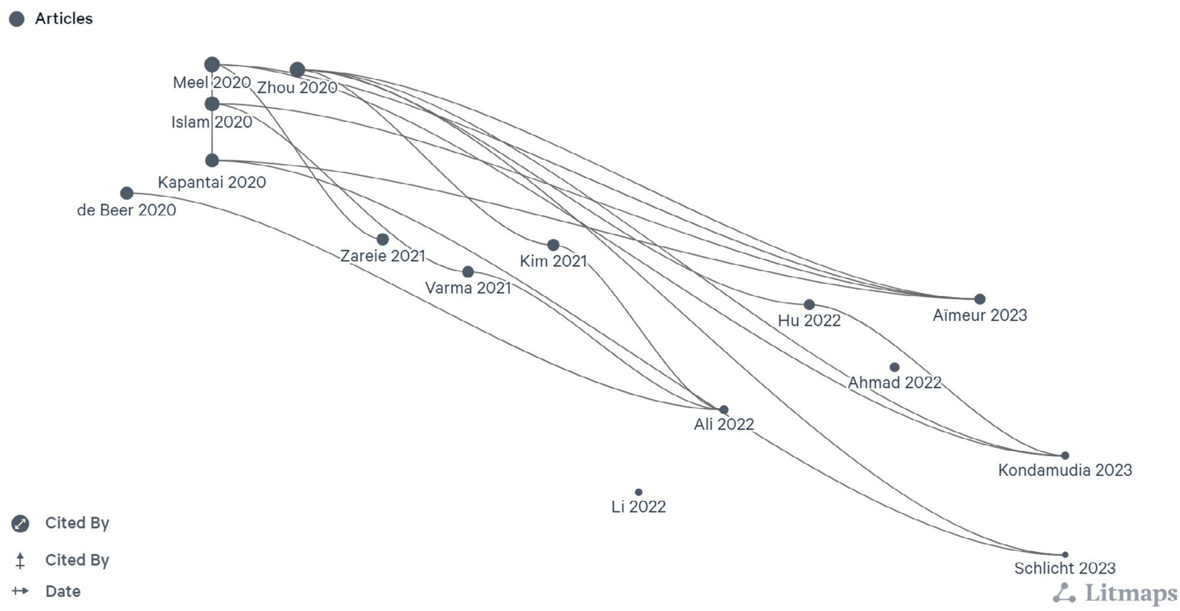

Figure 2 – Visualization of secondary studies, their citation counts, and the temporal citation relationships. Each data point represents a study, with the vertical position indicating the number of citations received, and the horizontal position indicating the publication date. The lines connecting the data points represent the citations between the studies
Source: Elaborated by the author using Litmaps (LTD, 2023).

Research questions (RQs) reported in the secondary studies were also extracted, as shown in Table 3. Five works explicitly stated their research questions (S1; S2; S6; S7; S10; S13). Most of the studies included similar research questions to those raised herein. In the deep learning (DL) domain, most studies identify specific RQs, except for (S5). For each category of RQ (Definition, Techniques, Challenges, and Research Methods), there is one work from DL area and one work from 2022-2023.

In the health sector, most research papers state their research questions, except for the work by (S12), which is an outlier. This observation extends to recent studies from 2022-2023, where only (S3; S9) do not explicitly state their RQs.

Most secondary studies have focused on RQs about technologies, tools, and strategies for detecting fake news (S1; S2; S6; S10; S13): three works were published in 2022- 2023, three related to DL techniques, and two related to health-related studies. Secondly, the RQs affiliated with the primary challenges and future research are stated by three works, two from 2022-2023 (one from the health sector) and another from DL.

Concern with definition is that it focuses; no secondary studies selected from 2022 to 2023 explicitly identified the definition as a specific research question. The elements pertain to the definition of the concept in question (Table 3). Of relevance are two aspects, namely, “health” and “deep learning.” In the context of health and deep learning, the S10 study was distinguished by its incorporation of an additional query, a feature that is not present in another research (S10). The inquiry into the employed research methodologies within the extant literature is of paramount importance.

Research question	Secondary study	Intereset subset
Definition	(S2) (S6) (S7)	2022-2023 DL-
Techniques, tools, and methods	(S1) (S2) (S6) (S10) (S13)	**Health, 2022-2023** 2022-2023 DL **DL**, **2022-2023** **DL**, **Health**
Main challenges/Future research	(S1) (S2) (S6)	**Health**, **2022-2023** 2022-2023 DL
Research Methods	(S10)	**DL**, **2022-2023**

Table 3 – Research questions in reported secondary studies
Source: Elaborated by the author.

In terms of data extraction, from the variables in (Gomes *et. al.*, 2023), we make a view from the studies between the considered domains: General, Health, Deep Learning, and the most recent studies (2022-2023). The variables extracted for each study are listed below:

V1 Year
V2 Complete reference
V3 Research questions of the study
V4 Is it systematic?
V5 If it is systematic, the number of primary studies
V6 Focus of the study
V7 Aspects of the ecosystem and information lifecycle covered
V8 Tasks covered
V9 Covered techniques
V10 Architectural solutions (and technologies) mentioned
V11 Mentioned techniques, tools, and methods
V12 Public datasets
V13 Public models

V14 Explicit research gaps
V15 Implicit research gaps

Data Analysis

The subsequent section is an exposition of the results of the investigation into the research questions of this tertiary study, with an examination of the research questions from three angles: deep learning (DL), health, and general. Comparisons have also been made with studies from 2022 and 2023.

RQ1: HOW DO DIFFERENT PERSPECTIVES WITHIN PEER-REVIEWED LITERATURE DEFINE FAKE NEWS?

Generalist fake news studies tend to define fake news approaches according to its technology and content, as explained in Section 2 (S2; S3; S4; S9; S11; S15).

As noted in (Gomes *et. al.*, 2023), fake news issues are often examined in the literature regarding health and deep learning techniques.

Within the domain of deep learning (DL), (S5) classifies fake news based on characteristics such as news content, social context, and external knowledge, categorizing DL techniques into supervised, weakly supervised, and unsupervised methods. (S13) Assess DL techniques in terms of the pre- and post-COVID-19 pandemic.

After the pandemic, research on detecting fake news related to health took off. (S1) and (S13) are two studies on this. (S1) looks at misinformation about COVD-19 on social media. (S13) uses deep learning techniques to compare pre- and post-pandemic scenarios. (S12) looks at health misinformation more broadly. It identifies analogies and differences between COVD-19 and other health datasets.

(S11; S7; S12; S14) research on taxonomy. Three of them (S11; S7; S14) are out of the interest group in Table 1, making up half of the six studies that are not from 2022-23 and do not focus on health or DL. (S12) is the only paper from the interest group, a health and recent study, that searches upon taxonomy.

As noted in (Gomes *et. al.*, 2023), the fake news information cycle is distributed in key phases: Propagation (37%), Creation (33.3%), and Consumption (29.7%). The distribution of fake news information cycle is like interest subsets: Health, DL, and 2022-2023. However, consumption is explored more in secondary work related to health.

Table 3 illustrates the fake news task mentioned in the secondary work. Studies are divided into four groups: all, Health, DL, and recent (2022-2023 publication year). The distribution is similar between all groups. The most cited tasks are textual classification, followed by fabricated media detection. However, technologies to deal with the detection of fabricated media are rarely mentioned (S11). Intervention and prevention of fake news are less frequently discussed in the literature, with no mentions in the Health, DL, and recent subgroups.

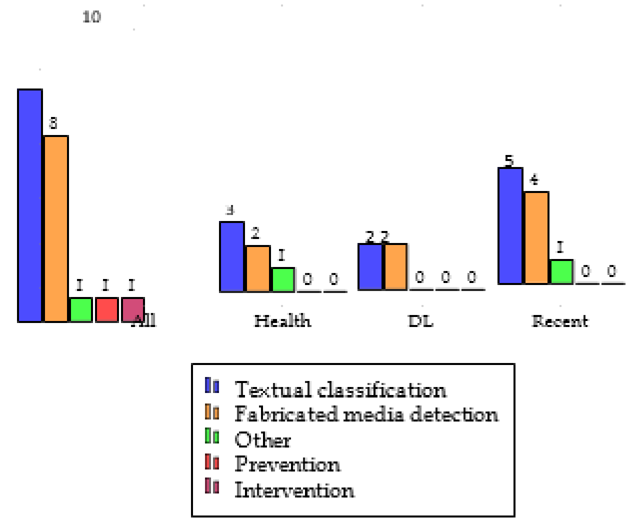

Figure 3 – Fake news task stage covered
Source: Elaborated by the author.

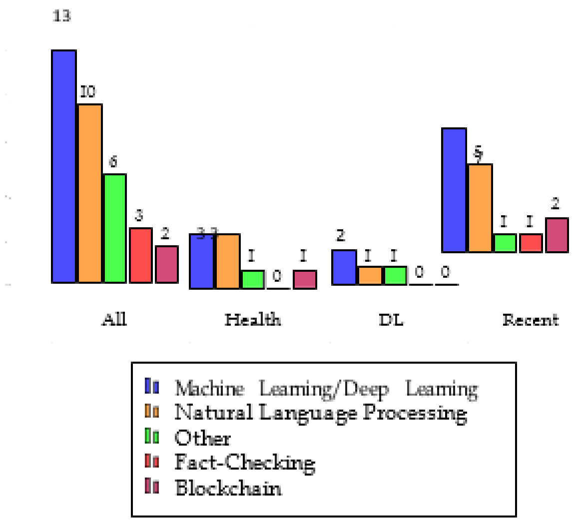

Figure 4 – Mentioned technologies
Source: Elaborated by the author.

RQ2: WHAT TECHNIQUES, TOOLS, AND METHODS ARE DOCUMENTED ACROSS DIFFERENT PERSPECTIVES?

The technologies mentioned are listed in Table 4[2], which is divided into four groups: Health, DL, and recent (published between 2022 and 2023). Machine Learning/Deep Learning has been cited most frequently, followed by Natural Language Processing in all its subgroups. (S12) reports that 33% of medical studies used Deep Learning, 28% used Machine Learning, and 37% used a combination of the two. In studies involving deep learning methods, pretrained Transformers generally surpassed other models in performance, while ensemble techniques such as random forests were more effective than most conventional machine learning approaches.

2 In this work, we consider Crowdsourcing as Fact-checking.

Dataset	Mentioned by	Size	Source
FakeNewsNet (SHU *et. al.*, 2018)	(S2; S3; S5; S6; S11; S10; S15)	23k Statements'	GossipCop Polifact
LIAR (WANG, W. Y., 2017)	(S2; S5; S3; S6; S11; S15)	12,8k Statements'	Polifact
CREDBANK (MITRA; GILBERT, 2015)	(S3; S5; S6; S11; S15)	6M Tweets'	Twitter/X
FacebookHoax (TACCHINI *et. al.*, 2017)	(S3; S5; S6; S11; S15)	15,5 Posts	Facebook

Table 4 – Most mentioned public datasets by secondary studies
Source: Elaborated by the author.

The most frequently referenced public datasets, as indicated in Table 4, include FakeNewsNet, which is cited in 7 secondary studies, LIAR, noted in 6 studies, Credbank, mentioned in 5 studies, and FacebookHoax, also cited 5 times. Credbank, FakeNewsNet, LIAR, and FacebookHoax were published between 2015 and 2018.

Fake News Net contains 23K Gossip Cop (About […], c2019) and Politi Fact (Polifact, c2020) fact-checking websites (Shu *et. al.*, 2020). LIar composes 12.8K human-labeled short statements from the fact- checking website PolitiFact (Wang, 2017). Each news is labeled with six-grade truthfulness: true, false, half-true, part-true, barely-true, and mostly-true. Credbank is a large crowd-sourced dataset of 6M tweets over 96 days starting from October 2015 (Mitra; Gilbert, 2015). FacebookHoax contains information about posts on Facebook pages associated with scientific news (non-hoax) and conspiracy pages (hoax), gathered using the Facebook API. The data collection includes 15.5K postings from 32 pages (Tacchini *et. al.*, 2017).

(S5; S6; S11; S15) cite all four datasets, CREDBANK, FakeNewsNet, LIAR, and FacebookHoax. (S5; S6) are DL-focused works, and only (S5) is an article from 2022 and 2023.

It is worth noting that only (S12; S5) list six datasets more recent than 2018, all related to Covid-19. Among these datasets, four are in English and have more than 100 citations as of October 10th, 2023: CoAID, FakeCovid, FakeHealth, and ReCOVery (Cui; Lee, 2020; Shahi; Nandini, 2020; Dai; Sun; Wang, 2020; Zhou *et. al.*, 2020).

Dataset	Mentioned by	Size	Source
CoAID (Cui; Lee, 2020)	(S12; S5)	5K News 297K interactions 1K posts	Multiple media outlets
FakeCovid (Shahi; Nandini, 2020)	(S12; S5)	7.6K news articles	Poynter
FakeHealth (Dai; Sun; Wang, 2020)	(S12; S5)	6M Tweets'	HealthNewsReviews
ReCOVery (Zhou; Mulay, *et. al.*, 2020)	(S12; S5)	2K news articles	NewsGuard21

Table 5 – Health mentioned public datasets
Source: Elaborated by the author.

CoAID, which stands for "Covid-19 Healthcare Misinformation Dataset", includes 5,216 news articles, 296,752 related user engagements, and 958 posts on social networks (Cui; Lee, 2020). FakeCovid consists of 7,623 fact-checked news articles from 105 countries, sourced from Poynter-listed fact-checkers (The Corona […], 2025) and Snopes ([2025?]) , covering Covid-19 and collected between April 1st, 2020, and January 7th, 2020 (Shahi; Nandini, 2020).

FakeHealth encompasses two datasets: HealthStory and HealthRelease, representing- ing news stories and news releases data from HealthNewsReview (c2022). HealthStory contains 1.69K news articles, while Health Release contains 606 news articles (Dai; Sun; Wang, 2020). ReCOVery is a Covid-19-correlated multimodal fake news detection dataset, including news-related images, textual content, and social context, sourced from the News- Guard21 website, comprising 2,000 news articles and 1.4 million tweets (Zhou *et. al.*, 2020).

RQ3: WHAT ARE THE PRIMARY CHALLENGES FACED IN EACH PERSPECTIVE WHEN ADDRESSING FAKE NEWS?

Six secondary studies intersect with the primary challenges, including two within the health sector (S1; S12) and three that were published between 2022 and 2023 (S1; S2; S12). The literature identifies these primary challenges as outlined by (Gomes *et. al.*, 2023):

Bridging echo chambers (S1; S2; S8; S11): People typically seek out information that confirms their existing beliefs and ignore evidence that contradicts them (S1). Such tendencies lead to the creation of information bubbles or echo chambers (S11).

Cross-domain, cross-platform, multilingual datasets and frameworks (S11; S12; S15): The nature of fake news is characterized by its perpetual evolution and intricacy. It manifests in diverse forms, encompassing a myriad of content, linguistic variations, thematic nuances, methodologies of dissemination, and geographical origins. A significant aspect of its sophistication is the ability to appear authentic, thereby evading immediate detection and recognition. Nevertheless, numerous current methods for its detection tend to concentrate solely on single facets like content, dissemination, style, or language (S2; S11; S12; S15). **Real-time learning and Early detection of fake news** (S2; S11; S12): The social networks allow fast spread of content, and fake news, due to its structure and social bots, hence there is a need for early detection (S2). A potential search direction is user profiling, in which the capture of contextual information on user behavior derived from social media users and the network can provide additional useful information to increase detection accuracy (S2; S12). Another direction is real--time detection, utilizing web ap- applications for fact-checking that can continuously learn from newly fact-checked articles, providing real-time identification of fraudulent information (S11).

We also extracted other challenges, such as:

Generative models (S11; S6; S15): Six studies characterize generative content, particularly deepfakes (S2; S6; S7; S8; S11; S15), describing these as manufactured images or videos. However, only two of these studies (S11; S15) emphasize the challenge of detecting such fabricated media. Among these, (S6) is one of the earliest secondary studies in the deep learning domain and the only one that discusses text generators, citing GPT-3 as a tool capable of automating the creation of fake news.

Transparency and blocking (S8; S15): The limited coverage of fact-checking websites and regulatory approach necessitates the provision of a more transparent communicative interface for news consumers to access and comprehend the algorithm results. News consumers often rely on algorithmic decision-making instead of their own judgment due to the lack of transparency in the regulations (e.g., warning labels) (S8). To effectively prevent the proliferation of false information, it is necessary to implement new policies and regulations. Furthermore, a successful strategy to block and mitigate the spread of fake news can be based on the structure of the network or users (S15).

Explainable detection (S12; S15). There is also a need to make the fake news detection explainable to users, or via model interpretability or mining social feedback (S12; S15). Biomedical claims, which are usually taken from scientific literature, can be difficult for regular users to understand. Text simplification is a promising area of research that could provide simplified explanations of these claims (S12).

Conclusion

This paper is a Rapid Tertiary study of fake news, in which we built upon our previous work, analyzing health, deep learning, and emerging perspectives (Gomes *et. al.*, 2023). A review of the selected studies reveals that two-thirds of them pertain to health or deep learning, with the remainder published between 2022 and 2023. Findings from research questions across all studies and specific interest groups in general were consistent, as illustrated in Figures 3 and 4. The tasks most frequently referenced included textual classification and fabricated media detection, regardless of whether the focus was solely on Deep Learning, Health, recent studies, or a broader scope. Similarly, Machine Learning/Deep Learning and Natural Processing techniques were predominantly cited not only in general and deep learning-focused research but also in recent and health-related studies.

Variations between groups are primarily observed in the research methodologies discussed in Section 3. All health studies were systematic. These studies were unique in referencing datasets newer than 2018, particularly those concerning COVID-19, although some of these studies were among the least recent overall. The sole systematic study specific to Deep Learning also pertains to the health sector.

In the studies from 2022-2023, all those from 2023 were systematic, and as illustrated in 2, there is a noticeable decrease in citations among these studies. We speculate that the growing volume of publications in recent years, as identified in our preliminary findings, reduces the likelihood of authors citing one another, given the increased number of available works. Also, a significant issue for taxonomy is evident in general secondary studies, which do not belong to any specific interest group.

Health and recent papers (S1; S2; S12) play a major role in the interest groups in the main challenges stated in (Gomes *et. al.*, 2023). In this study, we augment the scope of our inquiry by addressing three additional challenges: The following topics will be discussed: first, generative models; second, transparency and blocking; and third, explainable detection. Among these studies, (S6) is noteworthy as one of the earliest secondary studies in the deep learning domain, and it is the only study that discusses text generators for automating the creation of fake news. Citing GPT-3 as a tool capable of automating the creation of fake news. **Limitations and Future Work.** As an extension of (Gomes *et. al.*, 2023), our work inherits its limitations. Notably, this rapid review may have omitted relevant secondary studies. To mitigate this concern, we prioritized the most pertinent secondary studies identified through the Google Scholar algorithm. Moving forward, future endeavors should focus on (i) refining the procedures for conducting rapid reviews within the context of tertiary studies and (ii) replicating this study with an expanded pool of secondary studies. Enhancements in the search string are necessary to minimize irrelevant results, and the inclusion of additional scientific databases could further enrich our findings.

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