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A Survey on Fake News Detection in Social Media Using Graph Neural Networks

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ABSTRACT

Nowadays, social media has become the key source of information for anyone seeking about current events across the world. This information may be fake or real news. On social media platforms, fake news negatively impacts politics, the economy, and health, and affects the stability of society. The research on fake news detection has received widespread attention in the field of computer science. There are many effective methods of fake news detection technology including natural language processing (NLP) and machine learning techniques, primarily focusing on content analysis and user behavior. While these methods have shown promise, they often fall short in capturing the complex relational and propagation patterns inherent in social networks. Fake news exhibits distinct features such as misleading headlines, and fabricated content, making its detection challenging. To address these issues, Graph Neural Networks (GNNs) have been introduced as a superior solution. GNNs are particularly effective in processing graph-structured data, allowing them to model the intricate connections and dissemination patterns of news in social networks more accurately. This study provides an overview A variety of false information and their characteristics and discusses various techniques and features used in fake news detection. As well as advanced GNN-based techniques and datasets used to implement practical fake news detection systems from multiple perspectives and future research directions. In addition, tables and summary figures help researchers understand the full picture of fake news detection. Finally, the object of this review is to help other researchers improve fake news detection models using GNNs.

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1. Introduction

Recently, hundreds of news of private and public content delivered the common platforms of social media such as Facebook and Twitter via accessing, commenting, and sharing social network content. It is easier for users or readers to express their own opinions[1]. Therefore, The information obtained from the web and the internet cannot be trusted[2]. There is a chance that you could come across fake news, which could present inaccurate facts to serve political or commercial goals. Furthermore, on social media, false news frequently spreads faster [3]. Researchers found that false information spread 70% more quickly than true information[4].

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Nowadays, people more often use social media to find and consume news than conventional news sources. For instance, 62% of American adults obtained news from social media in 2016, compared to 49% who achieved news in 2012 [5].

It is extremely misleading and hard to distinguish from real news, it is always created by making a few little adjustments to the accurate information[6], which actively aims to mislead the readers for one's benefit. The fake news could have an international effect. For example, The trust of the public in governments has decreased over the years[7]. Also, the Russian Federation's conflict with Ukraine demonstrated how extensively the adversary exploited the global network's capacity to disseminate harmful psychological impacts[9,10], and this problem created economic disturbance and social panic[10] and public health [11], and for example, the COVID-19 epidemic appeared in Wuhan a Chinese city at the end of 2019 and spread over the whole world, and the large number of people lost their lives [12], and which is now a significant source of false information [13].

A rising issue that, because of the volume and complexity of the data, is almost impossible to solve without the aid of AI-based detection techniques[14]. This study provides a graph-based method for identifying fake news that combines data from three sources: the article's content, the content-sharing activities of people who shared it, and users' social networks [15]. With developments in artificial intelligence (AI) and machine learning (ML) algorithms[16]. The performance achieved by Graph Neural Networks(GNNs) in Graph Representation learning tasks such as generating embedding at the node and graph levels [17].GNNs process, this graph data repeatedly Using labeled datasets that contain examples of real and fake news[18].

The primary goal of this research is to lessen the distribution of fake information on social media platforms and reduce it to a minimum. In addition, this study aims to apply a few algorithms in this study to confirm the effectiveness of GNN in detecting authenticity. Finally, it can be able to recognize fake news spreaders and improve the ability to identify rumors [19].

2. Types of fake news

The term "fake news" describes news articles that are published but provide false information to mislead readers intentionally[20], because of malicious intent[21]. The literature shows that there are different types of fake news, as Figure 1 shows. These types included rumors, misinformation, disinformation, hoaxes, and clickbait [20]. A rumor is an unverified or unfounded observation that spreads rapidly[22]. Misinformation is false information that is spread accidentally, while disinformation is false information that is provided to mislead people intentionally [20]. Disinformation is defined as content posted by users to mislead[23]. The spread of false information is the result of spreading information without knowing its origin, it dropped under the type of disinformation. A hoax is a type of fake news in which the writer intentionally misleads the reader. This type involves losing money and deceiving users[24].

Psychological studies provided that one type of fake news that attracts readers is clickbait, which stimulates their curiosity about the news headline, and users are encouraged to click[25]. Clickbait is used to divert users to fake websites in an attempt to attract traffic to those displaying ads. This type of attention-grabbing headline may not accurately represent the content of the article[24].

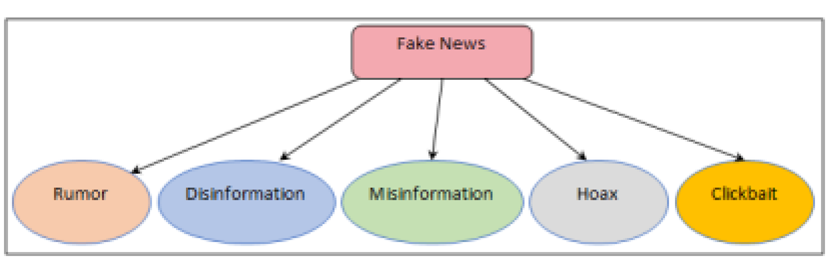

Figure 1. Species of fake news[26]

3. characteristics of fake news

3.1 The effect of an echo chamber: Environments that emphasize the opinions of users who share similar beliefs about political or a topic inclination are known as echo chambers [27]. Interactions with other people reinforce support for these opinions who share the same tendencies and attitudes. Frequency heuristic and Social credibility[27] may be the cause of echo chambers that have been the appearance on social media platforms When there is insufficient information in the news, its truthfulness can be assessed using social credibility. On the other hand, many people continue to believe it to be disseminated and credible, which makes the public accept that such news is credible. When people often hear the news, forms for a frequency heuristic lead to the natural consent of the information —even if it is false information[28].

3.2 Harmful account: Malicious account: currently, news on social network platforms comes from both unreal users and real users. Although false news is primarily spread out by accounts that are not real people, several real users still spread false information. Harmful accounts are mainly created to spread incorrect information [29]. Three primary types of harmful accounts have been classified as social bots, cyborg users, and trolls. In online communities, Trolls are actual users who cause trouble to provoke an emotional response from users of social media platforms [28]. Trolls use disinformation as a way to change the views of others [30], by kindling adverse emotions among users of social media platforms. Therefore, users develop distrust and strongly doubt them; They will get confused and unable to distinguish between what is true and false. Users will start to believe fake and lie information and doubt the truth. Along with automatically posting news, this harmful account may communicate with other users of social networks. Cyborg users are harmful accounts created by real individuals, but they use programs to keep activities functioning. Cyborgs are therefore better able to spread misleading information [28].

3.3 Intention to deceive: The identification of the characteristic depended on the theory that ''no one inadvertently produced inaccurate information in the style of news articles, and the fake news genre is created deliberately to deceive''[31]. Financial, ideological, or political motivations might lead to deception.[32]. However, false news may spread to entertain, to amuse, or, as proposed in[33].

3.4 the information is news: According to reference[29], This characteristic determined whether the information met the requirements to be considered news.

3.5 Authenticity: According to this characteristic, news is either factual or not [29]. It is possible to verify whether a factual assertion is true or false. Only objective opinions are considered true; subjective opinions are not. Factual Statements cannot be untrue. After publishing, a statement is not regarded as factual if it can be disproved[34].

4. Features extraction

Features are crucial in machine learning problems since they directly affect the quality of the results. There are different characteristics have been used by various approaches to identify false information. The features have been categorized into four groups: temporal properties, user information, linguistic features, and user interaction, and are shown in Figure 2. There are two main classifications into which it may be divided: Features based on context and Features based on content. Offer a detailed description of each category below. Additionally, the features are further divided into eight categories: Text-specific, user-specific, message-specific, image-specific, propagation, structural, temporal, and linguistic [35].

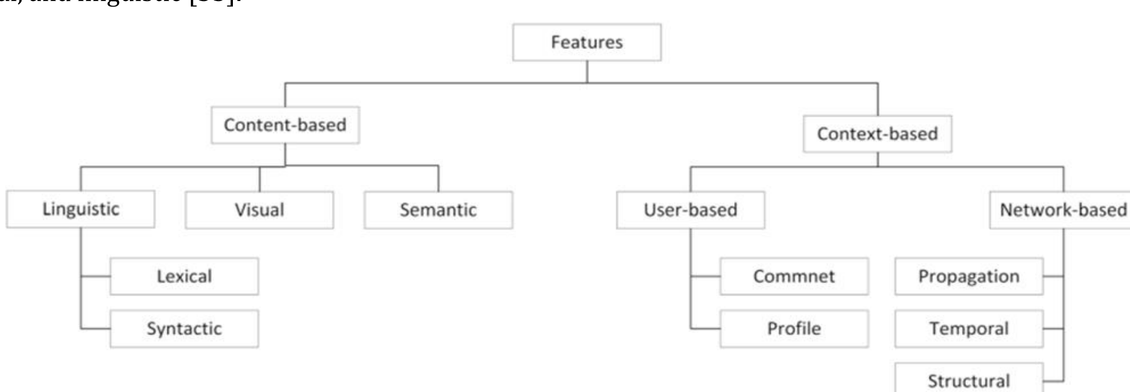

Figure 2. shows the categorization of these features[36]

4.1 Features based on context

Features based on context typically encompassed user information analysis, user responses, structures of the information propagation, and sources of posts[37]. Two groups can be used to classify context-based features:

- Features that are dependent on users: occasionally included the dissemination of misinformation via social media through harmful accounts such as bots. Consequently, it would be helpful to consider user interactions and characteristics when disinformation detection[28]. The most common features based on user included:
  -User profile: On social media platforms, people may publish a photo of themselves and a description of themselves together with other information about themselves. Generally speaking, The user profile may be utilized to extract several features, including the number of posts, the number of friends and followers the verification state of the user account, the age of the user account, and other details[35]. The availability of this data is an important aspect to take into account when using profile-based features. Particular data on people and their social network interactions could not be visible or accessible due to privacy concerns [37].
  - Comments: Users commonly expressed their feelings and thoughts on content posted on social media platforms. Therefore, investigating and analyzing public opinions about certain topics can have an impact on evaluating the authenticity. One of the easiest ways to extract features from user opinions is to analyze sentiments and determine the positions of the users using natural language processing methods and text analysis.
- Features that are dependent on the network: Social media networks include a variety of networks with a wide range of relationships, topics, and interests. Features that are dependent on networks are obtained through analyzing and constructing these special networks, like propagation networks and friendship networks[28]. These features are included in three categories as follows:
  -Temporal features: According to[38], the propagation of true information and disinformation often follows distinct temporal patterns.
  -Structural features: To detect disinformation, investigators the structure and extracted structural features of the information dissemination network like node degree and clustering coefficient.
  -Features of propagation: Research indicates the way false information spreads on social media varies from the way true information. Consequently, building a propagation graph or tree and analyzing its attributes, such as the count of nodes, root level, average node degree, and tree depth, might be helpful [35].

4.2 Features based on content

features based on content are Usually obtained directly from the information. The most of approaches for detecting disinformation relied on features based on content, particularly for textual information. Recent advancements in the tools and approaches used for text analysis have made it easier to access and extract textual features. However, text is not the only important type of content on social networks. Generally, three categories of content-based features exist:

- Semantic features: To extract semantic features related to visual or textual content, certain methods utilize ontologies or knowledge graphs. Finding latent semantic knowledge established in the content can be facilitated by using a knowledge graph[39].

- Linguistic features: According to[38], linguistic features are one of the most commonly utilized features in fake news detection. Usually crafted with the intention of misleading audiences, fake content serves various political or financial objectives. As a result, it is frequently designed to prompt users to share it extensively [28]. Fake news frequently uses attention-grabbing headlines and unique writing styles. Fake news writers use certain words to arouse emotions in their audience. Typical Features of linguistics include:

  -Features of lexical: Bigrams, the surface, and unigrams words formed of the text are examples of lexical features. Analyzing important content phrases or prominent words (such as 3-grams and 2-grams) is considered one of the easiest methods. Furthermore, improving disinformation detection techniques may be achieved by examining the existence of specific terms, word length, suspicious terms, the number of sentences, the frequency of particular terms, and other criteria.
  -Features of syntactic: Features of syntactic are related to the structure and style of text writing. There are many different methods for syntactic features, Including the count of nouns and verbs, adjectives, adverbs,

and syntactic markers like question marks, exclamation points, and periods. Adverbs, negative verbs, and the use of first- or third-person pronouns are examples of additional syntactic elements. [35].

- Visual features: Visual features: Visual features are the main method for identifying fake news. When it comes to discovering the truth, people are inherently weak and vulnerable. Thus, to arouse the rage of the audience or other strong emotions, writers frequently used captivating—or even entirely fictional—imagery. Visual aspects in content, including images and videos, are used to extract visual features. These features include, among others, the resolution, detection of objects, image proportion, and histogram.[28].

5. Techniques for identifying fake news

An overview of false news-detecting approaches is shown in Figure 3. The detection of fake news techniques can be broadly classified into main approaches: content-based approaches, which include context-based approaches, Knowledge-driven detection, style-based approaches, propagation-based approaches, multilabel learning-based approaches, and hybrid-based approaches as demonstrated by previous papers [38, 41, 42] For the task of identifying fake news, let ψ^a as one output of the corresponding classes. For instance, ψ^a may belong to {true false} or {unverified rumor, true rumor, false rumor, no rumor} or {real, fake}.

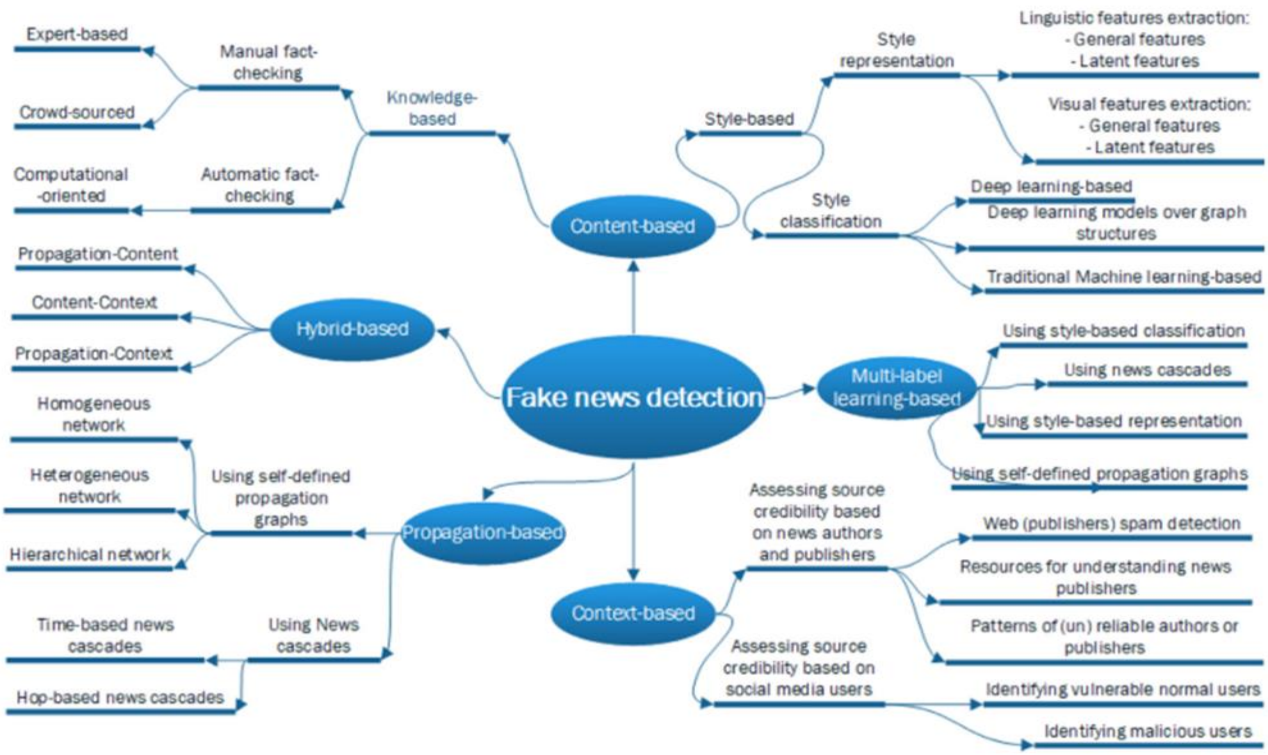

Figure 3. Techniques of fake news detection[42]

5.1 Context-based detection: Given contextual features set of a news item, including text news, publisher news, source news, and interaction news. The goal is to classify whether the news is real or fake. The techniques proposed in this category rely on the negative aspects and characteristics of false news. Determining the reliability of sources used to produce, publish, and distribute news is the goal of source-based strategies [30]. Credibility is defined as the emotional reaction of the public to news that is deemed trustworthy and dependable. The methods are often divided into two categories: (i) evaluating the reliability of sources, with an emphasis on news publishers and authors[44, 45]; and (ii) assessing the credibility of news outlets that spread information based on social media users[43].

5.2 Knowledge-driven detection: A triple, in a knowledge base, represents a collection of news items. K = (S, O, P)[44]. where the collection of subjects taken from news items a is denoted $s = \{s_1,\ s_2, \ldots \ldots, s_k\}$. $O = \{o_1,\ \ o_2, \ldots \ldots, o_k\}$. is a collection of things taken from news item a. $s = \{p_1,\ \ p_2, \ldots \ldots, p_k\}$. is a collection of news sources from news item a.

Thus, knowledge is defined as follows: $s = \{s_i, \ o_i \ p_i\} \in$ K, 1 $\leq$ i $<$ n. The objective of a knowledge-based technique for detecting false news is to assess each triple $s = \{s_i, \ o_i \ p_i\} \in$ K a against triples $kt_1^a = \{st_1, \ ot_1 \ pt_1\}$ using function F. This function assigned a label $\Psi_i^a \in$ [1, 0] to each triple, indicating whether it's real (1) or fake (0). F computes the likelihood that edge pi represents a connection from $\hat{s_i}$ to $\hat{o_i}$ on graph s_i Here, $\hat{s_i}$ and $\hat{o_i}$ are matched nodes corresponding to d s_i and oi on G_k, respectively, determined by a specific threshold ξ. In this category, techniques relied on external sources to validate news statements, aiming to ascertain their authenticity. This process can be executed either manually (expert-based[45] or (computational-oriented[46]), or crowd-sourced [47]) automatically.

5.3 Style-based detection: Given a set f_s^a style features of news item a, where f_s^a is a collection of features related to the items for news. The definition of style-based fake news detection is binary classification to determine if a news item is real or fake. Therefore, find a mapping function F such that $F: f_s^a \to \psi^a$. In this category, the techniques are proposed based on fake news characteristics and the intention. Approaches based on style objective is to capture the distinct writing style used in fake news. Fake news uses distinctive techniques to draw in a large number of people and differentiate it from ordinary news. The writing style capturing step was built automatically. Nonetheless, two techniques —style representation methods [48] and style classification methods [49]—must be followed as standards.

5.4 Detection based on Propagation: Considering article a along with a set of f_p^a Features of news propagation patterns. The definition of False news detection based on propagation is binary classification., which determines if a article is real or fake. This means developing a function for mapping F, such that $F: f_p^a \to \psi^a$. The techniques in this category are suggested based on the characteristics of false news and the echo chamber effect. Techniques based on propagation objective is to capture and extract contents related to false news spread. These methods aimed at fake news detection depended on how users shared it. Often, these techniques can be classified into one of two small categories: (i) using self-defined propagation graphs [50] and (ii) using news cascades [51].

5.5 Multilabel learning-based detection: Multilabel learning-based detection utilized a feature matrix $x \in Rd$, where each news item is represented as vector $a = [a1 \ldots \ldots ad] \in$ x and a label matrix Ψ = [Ψ1, ...Ψl] ∈ Γ, where Γ = {real, fake} and Γ is count of class labels. The goal is to train a function F: x → Γ to predict the labels $\hat{\psi} = F(a)$. A learning method for the training set for each news item associated with a label set is called detect multilabel learning. In this category, the techniques proposed depended on fake news characteristics and the echo chamber effect. The objective of multilabel learning-based techniques is to capture and extract information related to the news latent text and the news content. Techniques are often categorized into four approaches: (i) using style-based classification [54, 55] ;(ii) using news cascades[54]; (iii) using style-based representation[55]; and (iv) using self-defined propagation graphs [56].

5.6 Hybrid-based detection: A modern approach for detecting fake news combines two previous approaches simultaneously, like propagation-context[57], and propagation-content[58].

6. Methods for detecting previous fake news

The identification of false news on social media platforms is still in an early stage, and there are still various challenging issues requiring further investigations. This section reviews the methods and techniques employed in the automated identification of false news.

A recent classification proposed by [59] used fake news detection methods into three categories: content-based, feedback-based, and intervention-based methods. However, upon reviewing the literature on fake news detection in social media platforms, The research that is now available may be classified into broader groups according to two main categories that authors usually examine to identify effective solutions. These aspects revolved around the contextual factors and the news post content. Thus, the reviewed studies can be categorized into three main groups, with a hybrid category included. As illustrated in Figure 5, solutions for fake news detection fall into news content-based approaches, social context-based approaches (further divided into network and user-based approaches), and hybrid approaches. The hybrid category amalgamates contextual approaches and content-based to define solutions.

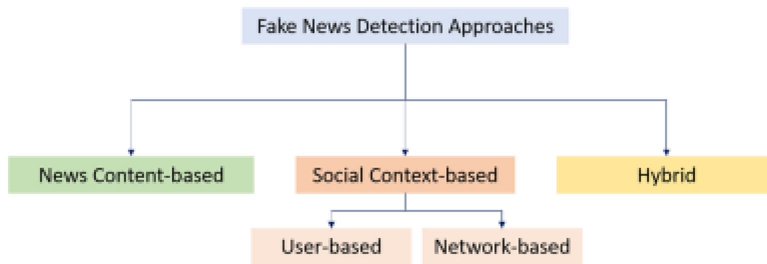

Figure 4. Classification approaches for detecting false news[60]

6.1 The approach based on news content

The approach based on news content for detecting false news utilized information extracted from the news post content, including text and multimedia elements such as videos or images. Researchers in this category focused on exploiting and analyzing the nuances within the news content, including the headline, the source, and the body text. They depended on content-based detection cues, which are features obtained from the text and multimedia components of the news post. Text-based cues are features extracted from the textual content, while multimedia-based cues are obtained from videos and images that are related to the news. Figure 5 outlines the commonly used techniques in this category including machine learning (ML), deep Learning (DL), natural language processing (NLP), fact-checking, crowdsourcing (CDS), and blockchain (BKC)). However, most research in this field primarily relied on text-based cues for false news detection [24].

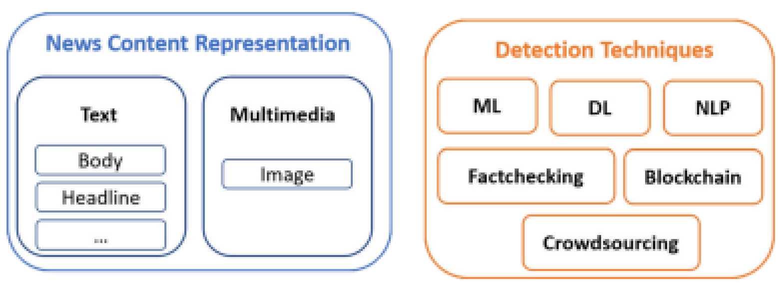

Figure 5. ***The approach based on content*** **including detection techniques and news content representation**[60]

The majority of researchers in this category depend on techniques of artificial intelligence, such as machine learning. deep learning, and natural language processing models, to enhance prediction accuracy. Others utilized alternative methods like crowdsourcing, blockchain, and fact-checking. Particularly, approaches based on AI and ML aimed to extract features from news content for subsequent analysis and training tasks. Feature extraction involved identifying relevant types of information from the content, effectively reducing the size of the data for automatic false news detection. Praised as one of the best approaches, this methodology aims to enhance classification performance by choosing a subset of characteristics from the original set[61].

6.2 A approach based on social context

In contrast to solutions based on news content, social context-based approaches captured the skeptical social environment that surrounds Internet news. In addition, news content-based is in contrast to social context-based approaches focused on aspects of the contextual information surrounding the news post rather than solely relying on the content itself. These aspects; provided information on the news post's context for false news detection. It encompassed surrounding data beyond the fake news article, serving as an integral component of automated identification of fake news. Contextual information examples included verifying the credibility by examining the publication date, and the news source, assessing supporting sources; and comparing reporting of similar subjects on multiple online news outlets to ensure consistency[62]. Social context-based aspects can be divided into two subcategories: network-based and user-based. These aspects are utilized for context analysis and training tasks in AI- and ML-based approaches. User-based aspects pertain to information obtained from users of online social networks (OSNs), for example, user profile data[64, 65]. and user activities[65]like user engagement[66] and response[67]. In contrast, network-based aspects involve information obtained through the characteristics of the social network that is used to spread false content and shared like the path of news propagation[68] (e.g., temporal propagation characteristics and propagation times), diffusion patterns [5](e.g., count of shares and retweets), additionally user relationships [69](e.g., friendship relation between users).

6.3 Hybrid approaches

Instead of combining context-and content-based methods, the majority of researchers are concentrating on employing a specific system. This is the result of research by[70], who believed that there are still some difficult restrictions in traditional fusion strategies due to semantic conflicts and existing feature correlations. Consequently, while some studies focused on obtaining information based on content, others captured information context-based into their approaches. However, automating false news detection solely based on one type of feature has proven to be difficult[49]. As a result, present standards for detecting fake news typically include the use of social context-based and news content-based approaches.

7. Fake news detection using the GNN model

The Process for fake news detection using the GNN Model contains four key stages as shown in Figure 6:

Figure 6. The process for detection of fake news using graph neural network[36].

1- Feature extraction: In this stage, there are several difficulties in detecting fake news such as incomplete datasets or problems found in the datasets including visual, textual, and so on. Some of these difficulties might be addressed through discovering important and useful features within the datasets[71].

2- Graph structure: In this stage, a suitable method to Build the graph is chosen, which includes creating of similarity graph, heterogeneous graph, or a propagation graph. Through this process, the original dataset—which was made up of unstructured data—was converted into a structured graph format [36].

3- Graph Neural Network(GNN): A GNN is used to process the graph created in the preceding phase. Every node in the graph has an embedding vector produced by this network. GNNs learn a function that connects a vector for every node, In a low-dimensional vector space. The structure of the network must be mapped in a similarity-preserving way to adjacent nodes in the vector space when two nodes have similar characteristics and structural responsibilities. "Representation" or "embedding" describes the vector that is made for each node.

Figure 7 shows the operation of a graph neural network. First, for every node, a neighborhood is constructed Then, every node and its previous-layer embedding vectors of surrounding neighbors are exposed to are subjected to a linear transformation (trainable weight matrix) and an aggregation operation (sum, average, maximum, minimum, etc.) in each layer. This

embedding is updated repeatedly, with a new embedding for every node calculated at every iteration (layer)[72]. A message-passing system might be used to characterize this process. There are three actions for each node: 1) it collected all the embedding of neighbor vectors (message passing), 2) it processed collected messages using an aggregation function and 3) it updated the embedding vector.

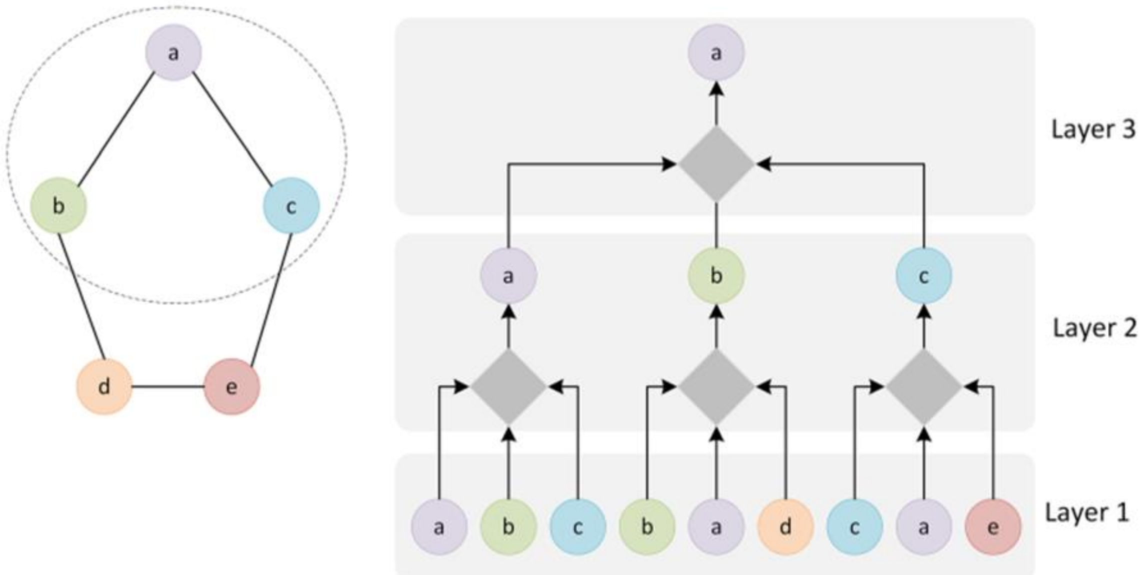

Figure 7. A general diagram of a graph neural network Left: a graph. Right: the embedding produced by a 3-layer GNN for node[72].

4- Classification: several machine learning methods can make use of the embedding vectors generated by the GNN., which serve as feature vectors. These embedding vectors are input into a suitable classifier in the last stage. This study provides evaluation metrics to know the quality of the model. The output of the classifier may be fake or real [36].

8. Related Work

in recent years, the interest in the identification of fake news has increased. many previous studies that have proposed several techniques. Despite the variety of methods used, graph neural networks have had success in detecting fake news, and several related previous works have been selected: a propagation-based technique was provided for detecting false news, which achieved of result Acc: 0.85 on Gossipicop dataset and Acc: 0.81 on PolitiFact dataset. Furthermore, the issue of direct incremental training is unable to be resolved and GNNs trained on a certain dataset may not perform well on fresh data when the graph structure is significantly different[73].

The authors proposed A novel graph neural network with adversarial active learning (AA-HGNN), integrated a hierarchical attention mechanism to address the heterogeneity of News-HIN, enabling it to learn both textual and structural information concurrently. Experimental findings showcase AA-HGNN's superiority over text-based and other graph-based models with less labeled data. AA-HGNN is well-suited for early-stage fake news detection with limited training data and demonstrates strong generalizability[74].

The task of utilizing social media platforms to detect fake news without supervision is considered. Unsupervised detection of fake news is much harder compared to its supervised counterpart since there is no tagged data to support modeling. GTUT (Graph-based Unsupervised Fake News Detection Technique) has developed a graph-based approach to operate in three stages. Initially, a collection of legitimate fake articles must be identified that exploited high-level observations of behavior among users to spread fake news in the first phase, the second and third phases are gradually expanded to include all articles in the dataset. Their technique is based on graph-based methods, such as identification graph-based feature vector learning, and label propagation. It detected fake news with accuracy rates approaching 80%, by Siva Charan Reddy & et al (2020)[75].

Van-Hoang Nguyen&et al. proposed Factual News Graph (FANG) introduces a novel approach to fake news detection, prioritizing representation learning over performance metrics. It boasts scalability during training, eliminating the need to manage all nodes, and maintains efficiency during inference without necessitating the reprocessing of the entire graph. Empirical findings validate FANG's proficiency in capturing social context. However, the flaw of the Factual News Graph (FANG) framework is that errors from upstream tasks, like stance detection or textual encoding, can carry over to FANG. Consequently, any inaccuracies or inconsistencies during the initial preprocessing phases could impact the effectiveness of FANG's learned representations. Moreover, the dataset employed for contextual fake news detection could swiftly become obsolete, given that hyperlinks and social media platform traces at the time of publication might no longer be accessible. This could restrict the utility and adaptability of FANG over time[76].

In [2021] Chenggang Song & et al proposed A unique design for temporal news propagation graphs called TGNF for false news detection to address this issue. It carried out in-depth tests on three real-world datasets, and the outcomes showed that the suggested framework is effective on all three: 0.923 on the Twitter dataset, 0.968 on the Webio dataset, and 0.935 on the fake news network. There are several shortcomings with their prototype. First of all, it is challenging to quickly spread information to nearby nodes for each interaction. Second, TGNF requires more time to execute than baseline methods since it can only evaluate several tweets for a single item of news at a time[77].

Yingtong Dou & et al proposed User preference-aware for detecting fake news(UPFD) used internal and external information to predict the accuracy of news on social media. However, the work is limited somewhat to exploring user p preference for detecting false news. The results presented that removing any component from the UPFD can reduce its performance. Moreover, joint encryption of internal and external information achieved the best performance (Acc: 84.62 on Politifact and Acc: 97.23 on Gossipicop). This result further confirmed the importance of modifying internal user preferences.[78].

The authors introduced a new graph-based method for fake news detection, focusing on the growing need to combat the spread of fake information and its social repercussions. The proposed approach utilizes a summarization technique based solely on internal document information. It constructs a graph to capture the relationships between sentences and computes the reflection rate of contextual information among them using an attention mechanism. Furthermore, the method enhances fake news detection by leveraging summary information as a crucial aspect of the document. Experimental results highlight the effectiveness of the proposed method, reaching a high accuracy of 91.04%[79].

Samyo Rode-Hasinger & et all presented a simple efficient GNN approach for the detection of false news on social media. This model employed pre-trained language models to encode text features of social media for messages and user profile descriptions. Modeling the relations between users and their tweets as well as users who shared similar content, GNN architecture outperformed text-based models and also models that combined text and user features from pre-trained language models. In addition, this model can apply knowledge to unseen data without the need for retraining. An f1-score of 0.94 on FakeNewsNet and 0.486 on the Covid-19-Disinfo datasets showed that their approach has limitations in settings with insufficient training data [14].

In [2022] Pallabi Saikia & et al used the technique of hybrid graph neural network-based to examine the social context of false news identification. To learn the text features, this hybrid model integrates a bi-directional encoder representation from the transformers model with a graph neural network on the propagation of news. With an f1-score of 0.91 on Politifact and 0.93 on the Gossipicop dataset, their suggested strategy can outperform baseline models by learning both the content and context characteristics[80].

In[81], the authors suggested a new hypergraph neural network model–Hypergraph for Fake News Detection(HGFND). Experiments conducted on two real-world benchmark datasets for the identification of false news—the Politifact dataset (Accuracy& F1-score: 91.1) and the Gossipicop dataset (Accuracy& F1-score: 96.4)—show that the suggested model performs significantly better than the most advanced techniques for both complete and limited sets of labeled data

Giorgio Barnabo & et al presented a highly demanding, large-scale multilingual benchmark dataset for detecting fake news(FbMultiLingMisinfo), a recently developed demanding multilingual benchmark dataset for the identification of misinformation. Six cutting-edge models are used in their experiments. In the greatest situation, an accuracy of 83%

was obtained on FbMultiLingMisinfo. In contrast 98% on Gossip cop and 87% on Politifact. Regarding Gossipicop, the most extensive benchmark dataset for detecting false news, also it was demonstrated that a minuscule training set enables 97% accuracy with 5 models out of 6, raising doubts about its true discriminative ability[82].

Mohit Mayank & et al suggested DEAP-FAKED, which is a knowledge graph-based framework for fake news detection. Their approach embedded a tensor decomposition model and natural language processing (NLP) encoded news articles. A range of these encodings provides their detector an additional benefit. DEAP-FAKED achieved an F1-score of 88% and 78% for the two datasets(KFN-UB and CoAID-UB), indicating an improvement of around 21% and 3%, respectively, demonstrating the performance of the method[83].

Mudit Dhawan & et al proposed a framework based on Graph Neural Networks, designed to be end-to-end trainable. It facilitates intricate interactions within and between different modalities, to improve the acquisition of resilient data representations for identifying false news(GAME-ON). Two available datasets were used to achieve results (Acc:0.958) on Twitter and (F1:0.874) on Weibo for detecting fake news. it was expanded to include longer articles[84].

Weizhi Xu & et al. proposed a unified graph-based approach for detecting fake news named GET. To discover the intricate semantic structure, the information propagation depends on the long-distance semantic dependencies established by evidence graphs and claims. Moreover, to obtain finer-grained semantics that is more advantageous for the claim-evidence interaction downstream, an effective and simple structure learning module is implemented to eliminate redundant information. Additionally, they have verified that GET performs well in detecting false news, with results of 0.90 for Snopes and 0.76 for Politifact [2022] [6].

Sathyanarayana K B & et al suggested A three-level approach, in which one mean-pooling layer and two GCN layers are used as the graph encoder to create GCNFN. Additionally, it provided a comparison of several machine learning techniques with the suggested technique (FDUP), and achieved a success rate of 97.5% in determining which news was fake and which was true, which is a superior result overall. It also demonstrated that, for text embedding, the BERT approach outperformed the word2vec technique. Through their research, it was demonstrated that it was challenging to distinguish between true and fraudulent news information[2].

In[85], the authors proposed DECOR, a novel approach to social graph optimization a system for detecting false information. The foundation of decoration is adaptability. The degree-corrected stochastic block model (DCSBM) is extended. It accomplished this concurrently using a generative model of the graph. Examine the effects of node labels and degrees on tractable probability in a ballistic manner. It achieved a score of 0.93 from Gossipicop and 0.94 from the Politifact dataset (2023).

Table 1: shows a summary literature Survey

Authors, Year, reference	Methodology	Dataset	Results	Drawbacks
Yi Han Shanika, et al (2020)	GNN	FakeNewsNet	Acc:0.811 on Politifact and Acc:0.853 on Gossipicop datasets	GNNs trained on a given set of data may not achieve better performance on new data with considerably different graph structures.
Yuxiang Ren, et al (2020)	GNN	Politifact and BuzzFeed	Accuracy of 0.61 on Politifact and 0.73 on the BuzzFeed dataset.	The AA-HGNN model could have low recall even if it might have exhibited high accuracy. This might mean that while the model excels at correctly classifying samples as genuine or bogus (high accuracy), it may not be able to recognize all of the authentic samples that

				are there (poor recall). This implied that the model may miss some true news articles because it tended to classify them as fake.
Siva Charan Reddy Gangireddy (2020)	GTUT	FakeNewsNet	Accuracy:0.80 for Politifact datasets and Accuracy:0.77 for Gossipicop datasets	Unsupervised fake news identification of this method is much harder than its supervised counterpart since there is no tagged data to support modeling.
Van-Hoang Nguyen, et al (2020)	GNN	Twitter dataset	AUC score of 0.7518 on the Twitter dataset.	A flaw of the Factual News Graph (FANG) framework is that errors from upstream tasks, like stance detection or textual encoding, can carry over to FANG. Consequently, any inaccuracies or inconsistencies during the initial preprocessing phases could impact the effectiveness of FANG's learned representations. Moreover, the dataset employed for contextual fake news detection could swiftly become obsolete, given that hyperlinks and social media platform traces at the time of publication might no longer be accessible. This could restrict the utility and adaptability of FANG over time.
Shuzhi Gong, et al (2021)	TGNF, GCN, etc.	Twitter, FakeNewsNet	TGNF: Accuracy:0.968 for the Weibo dataset Accuracy: 0.935 for the FakeNewsNet dataset and Accuracy: 0.923 for Twitter.GCN:Accuracy:0.865for Twitter ,Accuracy:0.873 for FakeNewsNet Accuracy:0.932for Weibo	First of all, it is challenging to quickly spread information to nearby nodes for each interaction. Second, TGNF required more time to operate than baseline techniques since it can only evaluate several tweets for a single item of news
Yingtong Dou, et al (2021)	GNN	FakeNewsNet	ACC:84.62 for the Politifact dataset and ACC:97.23 for the Gossipcop dataset	There is a limitation in exploring the preference of users for fake news
Gihwan Kim, et al (2021)	Baseline Graph Model	HDSF dataset	91.04% on HDSF dataset	reliance graph-based fake news detection method relies solely on internal document information. While this approach simplifies the process by focusing on the text itself, it may overlook important

				external factors or contextual cues that could contribute to more accurate detection. Additionally, although our method achieved high accuracy in experimental settings, its effectiveness in the real world remains to be fully validated.
Samyo Rode-Hasinger, et al (2022)	GNN	FakeNewsNet, Covid-19-Disinfo	F1 scores 0.9467 of FakeNewsNet and F1 scores 0.4868 of Covid-19-Disinfo	There is a limitation in settings with insufficient training data
Pallabi Saikia, et al (2022)	GNN	Politifact and Gossipicop	F1score of 0.91 on Politifact and F1-score of 0.93 on Gossipicop dataset	The majority of these methods are unable to handle synthetic material that is ultra-realistic synthesized media and generated using generative models.
Ujun Jeong, et al (2022)	GNN	FakeNewsNet	Accuracy& F1-score: 91.11 of Politifact and Accuracy& F1-score: 97.46 of Gossipcop datasets	The information type of each hyper-edge is not considered in the framework, which can potentially misguide the inference when more types of hyper-edges are added
Giorgio Barnabo, et al(2022)	GNN	FakeNewsNet	Acc: 98% on Gossipcop and Acc: 87% on PolitiFact and around Acc: 74% up to 82%for FbMultiLingMisinfo	Accuracy on the FbMultiLingMisinfo dataset has not exceeded 83%, which cannot achieve the real validity of the proposed
Mohit Mayank, et al (2022)	GNN	KFN-UB and CoAID-UB	F1-score of 88% and KFN-UB and F1-score of 0.78 of CoAID-UB datasets	It has not achieved the requirements of sources for the data
Weizhi Xu, et al (2022)	GNN	Snopes and PolitiFact	R-T:0.764 for the Politifact dataset and R-F:0.902 for the Snopes dataset	Unable to capture high-order semantics from long evidence due to the aggregation of features limited to the 1-hop neighborhood. Moreover, the absence of redundancy reduction might impact other relevant claim-related information as they are fused through neighborhood propagation.
Mudit Dhawan, et al (2022)	GNN	Twitter, Weibo	Acc:0.958 of Twitter and F1: 0.901 of Weibo datasets	Necessity to expand their work to include longer articles

Sathyanarayana K B, et al(2023)	GNN	FakeNewsNet	Acc:84.13 for the Politifact dataset and Acc:97.50 for the Gossipcop dataset	Need to fine-tune hyper-parameters and increase hidden layers for neural networks.
Jiaying Wu, et al (2023)	GNN	FakeNewsNet	Rec: 0.952 for the Politifact dataset and Acc:0.9333 for the Gossipicop dataset	Need to design and refine more complex multi-relational social graphs for fake news detection

9. Datasets for detecting fake news

This research presented popular datasets that have been utilized recently to identify fake news in this area:

9.1 LIAR: It is an English dataset of 12,836 brief political statements collected from internet streaming and social media platforms such as Facebook and Twitter, between 2007 and 2016[42]. It is divided into a training set size of 10,269, a testing set size of 1,283, and a validation set size of 1,284 [86].

9.2 Fake-NewsNet: It is a public standard for identifying false information. The dataset includes links to Twitter posts that discuss news stories from two fact-checking websites, which are PolitiFact and Gossipcop contain news, spreaders of news, sources of news, reply propagation graphs, and retweets, etc[87].

Gossipcop is a website that checks reports about celebrities and entertainment, while PolitiFact is a website that checks political statements[15]. It is made up of the BuzzFeed and PolitiFact real-world datasets. 15,257 users connected with Buzz Feed's 90 actual and 90 false news stories by retweeting or liking the content. PolitiFact has 23,865 users interacting with the news 120 actual news stories and 120 fake news stories[88].

9.3 BuzzFeed: A curated dataset near the U.S. presidential election of 2016 represents sample news from 9 news agencies, posted on Facebook over a week. Datasets containing false news and true news have 12 characteristics and 91 observations[90, 91].

9.4 Weibo: The dataset was initially retrieved from Sina Weibo, the most prominent social media platform in China, and used for rumor classification. There are 2312 phony news items and 2351 true news items in the raw dataset. Several news stories with more than 2000 nodes are eliminated, due to GPU resource limitations[77].

9.5 The Twitter dataset: It consists of two datasets (twitter15 and tweet 16). Twitter15 contains tweets from popular sources that were retweeted or very replied to (in 2015) beside graphs of the propagation (replies and retweets). Twitter16 shares the same process collection of data with Twitter15 but was based on data in 2016[91]. True rumors and non-rumors are selected as fake news and real news respectively. Twitter datasets are preprocessed in the same way as Weibo and FakeNewsNet datasets [77].

9.6 PHEME: The dataset talks about politics and society, it was gathered from Twitter for 4842 tweets and 330 rumors. The dataset is available in both English and German[42]. It contained two variants: PHEME9 and PHEME-5. PHEME-9 was gathered from nine news events (and domains) in 2018, whereas PHEME-5 was gathered from five news events spanning five domains in 2016. In the propagation graphs, only responses are gathered[92].

Table2: show statistics of dataset[92]

Feature	Twitter15	Twitter16	PHEME-9	Weibo	BuzzFeed	PHEME-5	Gossip cop	PolitiFact	LIAR
Number of source news	**1,490**	**818**	**6,425**	**4,664**	**-**	**5,802**	**22,140**	**1,056**	**12,836**
Number of users	**276,663**	**173,487**	**50,593**	**2,746,881**	**15,257**	**49,435**	**345,292**	**345,440**	**3,767**
Number of posts	**331,612**	**204,820**	**105,354**	**3,805,656**	**634,750**	**103,212**	**1,396,548**	**564,129**	**2589**
Number of	**4**	**4**	**2**	**2**	**2**	**2**	**2**	**2**	**6**

the classes									
Number fake news	**-**	**-**	**3830**	**2,313**	**91**	**1,972**	**5,323**	**432**	**150**
Number real news	**-**	**-**	**4023**	**2,351**	**91**	**2,351**	**16,817**	**624**	**182**
Average number of news/posts	**223**	**251**	**-**	**816**	**182**	**-**	**-**	**-**	**332**
Maximum number of news/posts	**1,768**	**2,765**	**-**	**59,318**	**-**	**-**	**-**	**-**	**-**
Minimum number of news/posts	**55**	**81**	**-**	**10**	**-**	**-**	**-**	**-**	**-**
average number of time length/ news	**1337 hours**	**848 hours**	**-**	**2,461 hours**	**-**	**-**	**-**	**-**	**-**

10. Discussion

Many previous studies have proposed several techniques based on GNNs in Table 1. The majority of datasets cover a narrow range of topics, often of health, economic, and political nature. Data sets must be updated frequently in terms of data set size, topic areas, and other factors because fake news takes many different forms. the majority of diffusion-based detection techniques simplify the Fake-NewsNet dataset. This research outlined the basic techniques, benefits, and drawbacks of GNN-based methods for detecting false news. UPFD provided the best performance of the other models, due to the greater ability to extract significant characteristics to detect bogus news.

Therefore, to improve the new potential of the models based on GNN, a better focus should be paid to obtaining excellent features while constructing useful standard data.

11. Conclusion and Future Directions

Graph Neural Networks (GNNs) have made significant progress in the field of false news detection by identifying intricate patterns that would have been missed by more conventional techniques. Many techniques have been developed to improve the performance of GNNs, such as using social network analysis to comprehend the propagation of false information and more efficiently evaluating patterns and correlations. Previous studies have proved that GNN models are highly accurate in identifying false news; using datasets like Politifact and Gossipicop, some models have been proven to exceed 90% accuracy in this regard. This indicates that they can manage huge and intricate datasets

with ease. Even with their efficacy, GNN models face challenges in generalizing to new data and adapting to changes in graph structures. It requires constant innovation to solve these problems:

_Enhanced Data Organization: Increasing the effectiveness of data structure may significantly improve GNN models to recognize and understand patterns, producing results that are more reliable and accurate.

_ Hierarchical Graph Structures: Information about user interactions, content qualities, and temporal trends may all be captured at multiple levels by using hierarchical graph structures. This can lead to the detection of better capabilities.

By focusing on these future ways, researchers might enhance the accuracy and effectiveness of GNN models in the identification of fake news, hence enhancing the strength of fake news detection systems.

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