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Analysis of Heart Disease Prediction using Machine Learning Classification Algorithms

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Abstract: *In 2020, the emergence of the novel Coronavirus (2019-nCoV) led to the dissemination of false information, resulting in significant societal alarm. Fake news frequently utilizes multimedia content, including text and images, to deceive readers and propagate its impact. An essential challenge in identifying false news using multimodal data is to retrieve both the overall properties and combine the inherent characteristics of fake news, such as discrepancies between images and text and picture manipulation. In the digital era, individuals have the ability to get news online through multiple platforms. However, this also leads to the rapid dissemination of incorrect information at an unprecedented rate. Fake news has harmful consequences since it undermines stability in society and public trust, leading to a growing need for fake news detection (FND). Deep learning (DL) has achieved significant success in numerous areas and has also been used to FND tasks, surpassing traditional machine learning approaches and achieving state-of-the-art performance. This survey provides a comprehensive evaluation and examination of current deep learning-based fake news detection systems that concentrate on different aspects, including news content, context in society, and external knowledge. We evaluate the techniques based on the categories of supervised, weakly supervised and unsupervised methods. We conduct a comprehensive assessment of representative approaches for each line, thoroughly examining their utilization of many attributes. Next, we provide a number of frequently employed FND datasets and conduct a quantitative evaluation of the efficacy of DL-based FND techniques on these datasets. Ultimately, we examine the remaining constraints of existing methods and emphasize potential future avenues.*

Keywords: *Fake news, Multimodal, Social media, Tampering, Deep learning*

1. Introduction

The Internet and social media platforms have become essential means for individuals to acquire news in their everyday existence. Public viewers have unrestricted access to consult the news fast and freely, enabling them to do it whenever and wherever they like. As of August 2018, more than 68 percent of Americans obtain their news via social media. Nevertheless; the absence of authoritative censorship diminishes the quality of news disseminated through non-traditional means. The online information ecology is very cacophonous and riddled with deception and fabricated news.

Fake news is a term used to describe news that is deliberately created to deceive people, resulting in harmful consequences for both individuals and society as a whole. It disseminates deceptive or prejudiced narratives for personal gain, significantly impacting public sentiment and societal cohesion. During the COVID-19 pandemic, there has been an abundance of both genuine and false information concerning the outbreak. This influx of information has been so substantial that the World Health Organization has referred to it as a 'information epidemic'.

During the initial quarter of 2020, around 6000 individuals were admitted to hospitals globally as a result of erroneous information on the Coronavirus. Furthermore, researchers have estimated that a minimum of 800 fatalities may have occurred owing to misinformation pertaining to COVID-19. The objective of fake news detection is to automatically identify false information. Current conventional machine learning (ML) methods for fault detection and diagnosis (FND) necessitate the use of feature engineering. The approaches can be categorized into three major categories based on the features used by the models: linguistic features, temporal-structural features, and hybrid features. Linguistic feature-based techniques identify bogus news by analyzing the textual content [1].

For instance, [1] utilized a range of linguistic attributes including special letters, emoticon symbols, and emotive terms. [2] Examined language style characteristics, namely assertive verbs and active verbs. Furthermore, certain techniques investigate the temporal-structural characteristic (such as the propagation feature) derived from social networks for the purpose of identifying counterfeit news [3]. [4] Suggested using Support Vector Machines (SVM) to acquire complex patterns of information propagation. Sampson et al. (2016) utilized implicit connections between segments of discourse to accurately categorize emerging discussions. Additionally, there are proposed hybrid systems that integrate many sorts of features in order to identify bogus news. As an illustration, [5] merged news content, user, and multimedia characteristics. In their study, [6] integrated the temporal fluctuations of content-based, user-based, and diffusion-based characteristics as the dissemination of news develop. While these conventional machine learning algorithms do show promising outcomes, they primarily depend on time-consuming feature engineering. Utilizing deep learning techniques for the detection of fake news has shown success in multiple fields, leading to the development of DL based FND algorithms, which have recently gained considerable attention. Firstly, deep learning may eliminate the need for feature engineering and leverage its robust expressive capabilities to effectively represent the features of input news. As an example, [7] used recurrent neural networks to represent the sequential link between news posts. The authors [8] employed convolutional neural networks to depict complex semantic connections among news posts. In their study, [9] utilized Graph Neural Networks (GCNs) to analyze the spread of rumors. They employed a directed graph structure, consisting of both top-down and bottom-up connections, to understand the patterns of propagation and dispersion. [10] Introduced the multi-modal Variational Autoencoder (MVAE) as a method to uncover the underlying multi-modal representations of multimedia news. Please refer to Figure 1 for a visual representation.

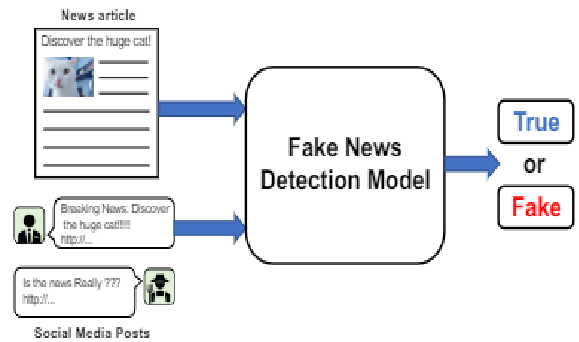

Fig. 1. Fake news detection task

While numerous surveys have been conducted on FND, the majority of them classify the existing research based on different features. For instance, [11] categorized the approaches for identifying fake news into four categories: external knowledge-based detection methods, style-based detection methods, propagation-based detection methods, and credibility-based detection methods. [12] Categorized the detection methods into two groups: those that rely on news content and those that rely on social context. These prior surveys offer valuable information and aid the study process. In recent times, there has been a growing interest in weakly supervised and unsupervised algorithms to address the challenges posed by limited labeled data. It is crucial to address this issue in order to apply it to real-world scenarios, as obtaining a significant number of labeled instances on a wide scale is either too expensive or not possible due to privacy considerations. In addition, we observe that the approaches place varying levels of importance on distinct feature information based on the learning approach used (supervised, weakly supervised, and unsupervised). This compels us to compose this assessment from a fresh standpoint in order to methodically assess and condense the present state of deep learning methods for identifying fake news. Rest of the paper is organized as follows: section 2 review background and related work to contextualize existing methods, in section 3 explains Multimodal fake news detection and its problems, section 4 brief information various datasets available for multimodal fake news detection, in section 5 various challenges and future research direction for multimodal fake news detection are explained, finally we conclude our paper in section 6 which followed by references we used.

2. Related Work

The main difficulty in fake news detection is finding the difference between the news based on features. We can obtain these features from forums, social environments and even from part of accompanying images, so we review the present work in the succeeding three areas: fake news detection based on traditional machine learning, fake news detection based on single modal data, and fake news detection based on multimodal data.

Methods based on hand-crafted features: This method mainly used hand-crafted features to detect fake news. They used feature engineering to extract the emotional polarity, user influence, geographic location, and similarity of dissemination structure in event-related information. Then they used these features to train decision trees, support vector machines, and other classifiers to classify events as fake news and real news [1] used sentiment scores, including the quantity of URLs on Weibo, the quantity of days a user registered, and other characteristics to train the decision tree algorithm to detect rumors. [4] Adopted characteristics such as the geographical location involved in microblog, the client that issued microblog, and the emotional polarity of text symbols, etc., and then used a support vector machine classifier to detect rumors. [13] Evaluated 141 textual features and proposed a new set of features to detect fake news. However, designing effective hand-crafted features requires the knowledge of highly related area and specific events [2]. Meanwhile, this type of method relies on hand-crafted features and the robustness of the obtained feature vectors is not strong enough, since it lacks the knowledge of fake news detection. It is difficult to use hand-crafted features to detect fake news.

Single-modal methods based on deep learning: Today, many scholars have tried to use deep learning models to automatically construct deep features to detect fake news. Ma et al. [7] aimed to find out the possibility of using deep neural networks to display tweets by capturing temporal-linguistic features. [14] Added attention mechanisms to recurrent neural networks (RNNs) to focus on different temporal-linguistic features with specific attention. The construction of deep learning models relies on plenty of labeled data, and the data acquisition of fake news has always been the main problem in the field of fake news detection. So the problem of data annotation has become the biggest bottleneck for rumor detection based on deep learning models. Some scholars tried to avoid data labeling and used the idea of unsupervised learning to detect online rumors. [15] Proposed an unsupervised model which added multi-layer RNN to the front end of the autoencoder to detect rumors, it further improved the effectiveness of the model. [16] Proposed a contextualized pre-trained Twitter word embedding based model for irony detection via the transformer architecture. Although the unsupervised learning method avoids the problem of data labeling, the instability of the model brings greater limitations. Single-modal fake news detection based on deep learning improves accuracy compared to traditional methods but ignores news as a collection of multimedia data. The textual and visual information of fake news cannot be effectively used.

Multimodality methods based on deep learning: In recent years, more scholars are focusing on deep learning methods based on multimodal data [17] proposed an image-text consistency driven multimodal approach to analyze the sentiment of social media. [18] Proposed a novel Attentive Recurrent Neural Network (Ante-RNN) with textual and visual fusion for the dynamic interpretable recommendation. [19] Proffered a hybrid deep learning model for fine-grained sentiment prediction in real-time multimodal data. For the data of multiple modalities in news, current researchers use pre-trained deep Convolutional Neural Networks models such as VGG19 to extract the features of the image and merge the obtained visual performance with text information [10]. Specifically, it included social network multimodal content that used Deep Neural Networks to solve the problem of fake news detection. [20] Proposed an end-to-end event-based anti-neural network based on multimodal features to detect emerging fake news event. [10] Proposed a new approach of learning shared representations for multimodal information for fake news detection. Nonetheless, these parts mainly aim at how to integrate different forms of information and ignore the effective modeling of visual content. These visual features used by them are so generic that it is incredibly difficult to indicate the internal features and the missing of fake news detection task-related information from the fake news image, which reduce the performance of visual content in the detection of fake news. At the same time, regarding text, the above models such as TextCNN or LSTM cannot uncover the connection between the text and context well, greatly reducing the ability of fake news detection in the text part [21] put forward an approach to detect fake news by comparing text and image similarity, but the model uses a pre-trained picture description generation model and cannot calculate the similarity of multimodal data, which limits the scene used.

In [22] an interesting approach for multimodal fake news detection, based on a pre-trained BERT model, a ResNet50 model, a data augmentation strategy, and a contrastive learning process is proposed. The BERT model extracts the features of the text of the news while those of the images are extracted by the ResNet50 model. They are concatenated to obtain the final feature representation of the news. To mitigate the problem of operating with a small training set, it is augmented by back-translating the title and abstract of the news so that obtaining additional news (fake and real) with the same semantics but different structures. In order to capture the interacting information between news on a certain topic, contrastive learning is finally used.

In [23], authors propose techniques to identify false information in social media posts by utilizing text and video modalities. The proposal uses self supervised learning to develop expressive representations of combined visual and textual data and defines and offer two deep learning novel approaches based on contrastive learning and masked language modeling (MLM) for the detection of semantic inconsistencies in short-form social media video posts. The two proposed methods, evaluated on a dataset consisting of 160,000 video postings gathered from Twitter, beat cutting-edge techniques both on synthetic data produced by randomly switching positive examples and on real-world data on a new manually labeled test set for semantic misleading. More specifically, results show Contrastive Learning outperforms the method in [24] by 3% on the accuracy, and MLM performs the best overall, outperforming Contrastive Learning by 5.23% on accuracy.

3. Multimodal fake news detection

Misinformation frequently emerges as textual content. The Internet and social media, however, enable the use of several modalities, which can make a misinformation message intriguing in addition to detrimental. For instance, a meme or a video is much simpler to digest, gets a great deal more interest, and disseminates farther than basic text. In this section, we first introduce the multimodal fake news detection problem in the social media setting and after that, we report the main differences with already published surveys on this topic.

3.1 Problem formulation and key concepts

The multimodal fake news detection problem refers to the classification of news with respect to its adherence to real facts, carried out by analyzing the different parts of their information content, which are usually in different formats. News information formats, also called modalities or features, are the following:

- **Text:** Text is a key part of most news. Text classification is a complex process that requires the analysis of its syntactic, semantic, and stylistic aspects. Furthermore, the text appears in different parts of news: (i) title, (ii) description, (iii) links to other digital content (news, web pages, videos, etc.), and (iv) comment from other users.
- **Social features:** News spreading on online platforms (social networks, blogs, and online newspapers) usually report users reaction to the messages posted, sharing, or expressing an appreciation (like, emotions, comments).
- **Audio:** Audio is often included in videos but can also be self-contained information content. Think for example of podcasts, broadcast networks, radio services, and audio files included in the news.
- **Video:** Video content is increasingly included in the news for its high ability to attract the attention of the public. Videos can be extracted from longer-duration sequences (news, documentaries, films, etc.) or captured with mobile devices. The contents of many social media are almost exclusively video-based (e.g. YouTube and Tik-Tok).
- **Images:** Images are often included in the news. They can be captured with mobile devices or extracted from video sequences or from other digital content.
- **Users:** This category includes information about the user that creates the article, in terms of his/her credibility/ reputation, connections in the network, previously created news, and so on.
- **Network and propagation features:** The social network context of news refers to the network characteristics and how the news is propagated via social media, and it is an additional criterion for distinguishing fake news from authentic ones. The propagation feature captures information on the propagation of news, such as the number of replies, and retweets of an article. The propagation graph of news can be represented as a tuple $G = \langle N, E, X \rangle$, where nodes N represent the tweets/retweets of the news and the edges E represent the retweet relationships among them. X is the set of attributes of the nodes.

Accurate classification of the news requires analyzing the single modalities and the correlations among them. The models able to process more than one feature to solve the misinformation detection task are called multimodal classifiers. Much architecture for multimodal classifiers has been designed. The first important classification of multimodal classifiers takes into account the fusion mechanisms used to combine features from different modalities. The main fusion techniques are the following:

- **Early fusion:** This technique is sometimes referred to as feature-level fusion and consists of concatenating features from many data modalities at an early stage. This kind of fusion is frequently referred to as intermediate fusion if it is carried out after feature extraction and before classification. Accordingly, most previous work on multimodal disinformation detection embeds each modality into a corresponding vector representation and then concatenates the vectors to obtain a multi- modal representation that is used for classification.
- **Late fusion:** This technique is also called decision-level fusion and consists in combining the results of the analysis carried out for each data modality separately. In other words, methods like sum, max, average, and weighted average are used to integrate the findings of modality-wise classification. The majorities of late fusion solutions employ hand-crafted rules that are subject to human bias and ignore the quirks of the real world.

4. Datasets for multimodal fake news detection

This section reports a synthetic description of the datasets used to validate the approaches presented in this survey. A detailed description of a larger collection of datasets can be found in [25] that describes 118 datasets related to (i) fake news detection, (ii) fact verification, (iii) satire detection, (iv) news (media) credibility, (iv) check-worthy claims, and (v) claim matching.

- **Weibo:** The Weibo dataset is a collection of posts from Sina Weibo, which is a popular Chinese micro blogging platform similar to Twitter. The dataset includes a large number of posts, with each post containing various types of content such as text, images, videos, and links. The dataset has been used for various research purposes, including sentiment analysis, topic modeling, and user profiling. It can be useful for researchers studying social media behavior in China, as well as for those interested in developing machine learning models to analyze social media data. In this paper two versions of this dataset are mentioned: Weibo A [26] and Weibo B [27].
- **Fakeddit:** Fakeddit [28] is a large multimodal dataset containing over 1 million entries related to several types of fake news. Each entry includes the attributes: (i) submission title, (ii) image, (iii) comments and additional metadata (i.e. score, number of comments, etc.). The samples go through multiple stages of review and are then labeled using distant supervision into 2-way, 3-way, or 6-way classification categories.
- **MediaEval:** The MediaEval dataset [29] is a valuable resource for researchers and developers who are interested in multimedia retrieval and evaluation. It contains a vast collection of multimedia data, including images, audio files, and video recordings, that have been annotated with associated metadata such as timestamps, geo location data, and user-generated tags. The dataset is used to support a series of annual mediaEval benchmarking evaluations, which are organized around a set of shared research tasks or challenges. Each year, researchers are invited to develop algorithms and approaches to tackle these challenges, and then submit their results for evaluation against a set of predefined performance metrics. The MediaEval challenges cover a broad range of topics, including audio event detection, multimedia event detection, social media analysis, and multimedia recommendation systems.
- **FakeNewsNet:** FakeNewsNet [30] is a publicly available dataset designed for research on fake news detection. The dataset includes various types of information related to the creation and dissemination of fake news, including textual content, images, and social net- work information. The dataset is composed of two sub-datasets:
- **PolitiFact:** Contains fact-checking articles from PolitiFact (www.politifact. com), a non-profit organization that evaluates the accuracy of statements made by politicians in the United States [31]. The news articles in the PolitiFact dataset were published from May 2002 to July 2018.

- **GossipCop:** Contains articles from GossipCop, a website that reports false news about celebrities and entertainment in magazines and on the internet in the United States. It assigns a 0–10 scale to each article depending on its credibility, with 0 indicating that the rumor is wholly untrue or fictive and 10 indicating that the news is 100 per cent factual.
- Each sub-dataset includes both fake and real news articles, and all entries are labeled accordingly. The dataset also includes social network information for some articles, such as the number of retweets and likes on Twitter. FakeNewsNet aims to provide researchers with a standardized and reliable dataset for developing and evaluating fake news detection models. It can be useful for researchers working in the fields of natural language processing, machine learning, and data mining.
- **BuzzFeed:** The BuzzFeed News dataset is a collection of news articles and their corresponding metadata from BuzzFeed News (https://www.buzzfeed.com/), a popular news and media website. The dataset contains over 200,000 articles published between 2014 and 2018, covering a wide range of topics including politics, entertainment, and technology. The dataset includes several different types of information for each article, including the article title, author, publication date, URL, text content, and images. Additionally, the dataset includes social media engagement metrics for each article, such as the number of Facebook likes, comments, and shares. The BuzzFeed dataset has been used for various research purposes, including topic modeling, sentiment analysis, and fake news detection.
- **PHEME:** The PHEME dataset [32] is a publicly available dataset designed for research on rumor detection and veracity prediction in social media. The dataset includes tweets related to nine different events, such as the Boston Marathon bombing, and the Charlie Hebdo shooting, and is divided into four sub-datasets:
  - ➢ Rumors Contains tweets that were posted during the events and were classified as either true or false.
  - ➢ Non-rumors Contains tweets that were posted during the events but were not related to rumors.
  - ➢ Thread structure Contains information about the structure of tweet threads related to the events, such as the number of tweets in each thread and the number of retweets.
  - ➢ Stance Contains information about the stance of tweets related to the events, such as whether the tweet supports, denies, or is neutral towards a rumor.

Each tweet is labeled according to its veracity status (i.e. true or false) and its stance (i.e. support, deny, or neutral). The dataset also includes additional metadata for each tweet, such as the date and time of the tweet, the Twitter user who posted the tweet, and the location of the tweet.

5. Challenges and future directions

Fake news affects both online and offline social com- munities and different proposals exist in the recent literature investigating at different levels and with different strategies the problem. Multimodal approaches for fake news detection have been proven to be a viable effective approach to address disinformation, however, many are still challenges that remain to be addressed.

- **Datasets:** Different multimodal datasets exist, but they are often related to two or a few modalities such as text and images. These datasets have generally small sizes, expose content in just one language, and often are imbalanced either in the fake or real news. An addi- tional issue is that, in order to cope with different styles and different topics, datasets from heterogeneous plat- forms should be available. Therefore, urgent is a need for real and complete multimodal datasets containing different modalities such as text, images, video audio, social content, and temporal and network propagation features.
- **Finer classification:** Existing fake news detection models are mainly binary classifiers that determine whether a piece of news is false or not. This strategy is often not sufficient and a multi-class classification or even a regression task should be used. The final aim should allow enabling prioritized reasoning and consequent strategies in the presence of fake news detection.
- **Scalability:** Since deep neural networks are complex and costly to build, and as most existing multimodal mod- els use multiple deep neural networks (one per modality), they are not scalable as the number of modalities grows. Furthermore, many existing models require extensive computing resources, including large amounts of memory storage and processing units. As a result,

when developing new architectures, the scalability of proposed models should be considered.

- **Enhancement of basic multimodal classifiers:** Many deep learning advanced techniques have been applied in order to improve the performance of multimodal classifiers for misinformation detection. The concatenation of vector representations does not always result in an effective multimodal embedding. Thus, some recent works used the attention mechanism to focus on relevant parts of images or texts. In order to get the most out of embed- dings, using an attention mechanism is preferable since it results in richer multimodal representations. One of the most relevant problems when training classifiers using supervised approaches is the lack of labeled and balanced datasets. In order to solve this problem, generative models have been used. They are trained to learn the patterns that characterize misinformative content and can be used to create synthetic balanced datasets or augment existing ones. As a result of their effectiveness in detecting fake news, Graph Neural Networks (GNNs) are now being studied for their potential to detect misinformation in many media. Users, multimodal content, and relation- ships among them are modeled by means of a GNN. The learning process derives embeddings for users and multimodal content that can be used by a classifier to detect misinformative content.
- **Source verification and author credibility:** Only a limited number of existing approaches evaluate either author's credibility or the veracity of the source of the news article. Those two tasks should be deeply explored in future research. Source credibility is a key point when evaluating fake news as well as author credibility as this last allows an automatic system to retrieve the chain of news authored by the same author or group of authors.
- **Cross-domain:** When trained on vast volumes of labeled data on events of interest, deep learning-based models perform well, but when instructed on different events due to domain shift, their performance tends to decline. Because it is challenging to get large-scale labeled information, detecting fake news on emergent events poses substantial challenges for current detection algorithms. Furthermore, including new information from emerging events necessitates either creating an entirely new model from scratch or continuing to refine an existing one, both of which can be difficult, expensive, and unrealistic for use in real-world contexts.
- **Explainability:** The Explainability of models is largely unexplored. This task is relevant and should be focused on future methods in order to obtain transparent models that provide decisions/suggestions explainable and trans- parent. More specifically, fake news detection systems have to fulfill some general requirements: they have to provide decisions/suggestions, but also justify how and/ or why the provided decisions/suggestions have been given. The justification should be provided by flagging the different pieces of the news with the corresponding truth value (true or false or using a finer granularity) and presented in an easy way. In addition, justification in the output should also include ethical considerations. Concerning this specific task, it should be noticed that, to the best of our knowledge, no dataset exists that contains fake news accompanied by the justification of disinformation.
- **Enhancing the integration of news content features** (either text, image or video) with network and propagation features in DL models Features related to the creator of the news, the characteristics of the network in which the news spreads and the propagation-based information are not fully explored in combination with news con-tent in current DL proposals and are research directions on which the community should investigate more in the next future. A more depth analysis of network and propagation-based features and their fusion with well- known adopted modalities would improve fake information detection.
- **Enhancing the exploitation of emotions expressed in the texts to detect fake news:** The use of the emotions extracted from the text combined with additional modalities could enhance the task of fake news detection. The motivation relies on some studies in the literature showing that fake news triggers different emotions in users compared to real news. More specifically showed that generally false rumors on Twitter caused followers to react with fear, disgust, and astonishment whereas true rumors caused them to respond with joy, grief, trust, and

anticipation. A more in-depth analysis of this specific issue and the embedding of well- known techniques used to catch emotions from a text, such as those based on lexicon or on neural networks could improve fake news detection.

- **Enhancing the exploitation of statistical features to detect fake news** Statistical features can provide a synthetic representation of the relevant information and easily allow evidencing the quantitative distribution patterns that characterize fake and real news. This specific issue could be profitably used to complement the information provided by the different modalities, such as image, video, and audio, as well as social content.

6. Conclusion

The paper provided a rigorous and in-depth survey on a very specific topic related to the use of deep learning for multimodal fake news detection on social media. The paper analyzed a large number of deep learning approaches and provided, for each work surveyed, an analysis of the rationale behind the approach, highlighting some relevant features such as the DL method used, the type of data analyzed, the datasets used, the fusion strategy adopted and the eventual domain-invariant features. The survey also discusses the main limitations of the current approaches and the challenges that remain to be addressed by future research works including effective use of cross-domain fake news detection strategies.

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