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ANALYSIS OF TOOLS AND TECHNIQUES USED FOR DETECTING FAKE NEWS

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Abstract: It is very easy to propagate fake news in the era of information age as people have become addicted to Internet, WWW, Social Media Platforms and Blogging sites. The fake news has far-reaching implications for politics, society and media credibility. Media literacy campaigns, fact-checking initiatives and the use of Artificial Intelligence (AI) tools & techniques are some of the means for detecting false content. This research paper deliberates on the origin of fake news, factors responsible for spreading them and implications of fake news on society and public opinion. This paper compares the tools and techniques used to detect the fake news. This paper further considers a case study for detecting the fake news with the help of developed Machine Learning (ML) Models using different datasets and then predicting their accuracy level. It is also observed that due to constantly evolving nature of fake news, its spread in different languages and regions, it has become difficult in regulating information flow and controlling the propagation of the fake news.

Keywords: Fake News, Detecting Fake News, Fake News Analysis, Machine Learning Models, Logistic Regression, SVM, Classifiers

I. INTRODAUCTION

The term "Fake news" is used for misleading information deliberately and showing it as legitimate news. It plays the role of forging and misperception of the content [1]. Fake news may range from completely fabricated stories to exaggerated or distorted facts which are circulated through variety of medias such as news outlets, social media or any other platforms. Due to easy accessibility of loosely authenticated data and having little time in hand, people knowingly or unknowingly propagate fake news. Propagation of the fake news affects public opinion, politics and societal trust. It is generally intended to deceive readers for political, financial or social gain [2].

The breakdown of the paper's structure comprises eight sections including Introduction. Section 2 reviews background of the fake news. Section 3 elaborates factors responsible for spreading fake news. Section 4 presents a comparative analysis of computational techniques used for fake news analysis, highlighting their strengths, limitations and real-world applications. Section 5 examines the use of various tools for detecting fake news. Section 6 examines the accuracy of developed models using different datasets. Section 7 focuses on discussion and challenges, followed by conclusion and references.

II. BACKGROUND OF THE FAKE NEWS

The term Fake news has gained momentum with the advent of social media and advanced technologies which enable the manipulations of real content. But the issue of misinformation was always there in the history of mankind. Around 2000 years ago, during a civil war between the Roman Republic and Octavian, Octavian started a 'fake news' campaign against Mark Anthony, who was the adopted son and trusted commander of Julius Caesar. This way, he was able to get public opinion in his favor. Eventually, he ruled Rome for 40 years [3][4]. The invention of printing press in 15th century made it significantly easier to spread both real and fake news compared to handwritten material. In the mid-1700s, the printing press unsuccessfully helped to spread fake news about George II of being ill to harm his public image who was king of Great Britain and Ireland at that time [5]. In 1835, the New York Sun, an American publication, published a series of articles claiming the existence of life on the Moon. Propaganda, a type of fake news, has been used throughout history to change people's opinions for political gains [6]. In 1898, a United States Navy ship, USS Maine, sank in Havana Harbor. Some of the newspapers blamed the Spanish for the sinking using an artist's illustrations of a dramatic explosion and readers were convinced that this was true [7]. The false reports created rift between the Spanish and American which resulted in war between them. In 1917, during the First World War, British newspapers such as the Times and the Daily Mail published a false story claiming that Germans were extracting fat from the bodies of dead soldiers from both sides to make soap and margarine. This propaganda influenced public opinion that the Germans need to be defeated.

In the digital age, economical and easy access to the Internet, rapid growth of social media platforms, democratization of creating information and easy access to digital publishing tools have all contributed to the proliferation of misinformation. Radio and TV presenter Vick Hope shared different types of fake news categorized as Satire, Clickbait, Propaganda and Mistakes [8]. The research [9] categorizes fake news as news satire, news parody, fabrication, manipulation, advertising and propaganda based on levels of facticity and deception. Satires are generally written to joke about the news or famous people. These are meant to be humorous or satirical but mistaken as real news. Clickbait are eye-catching, sensationalized or exaggerated headlines which are used to get more clicks on links or generate more views for a website either to make money or to change public opinion. Its popular example is the 2016 US presidential election. Propaganda is disinformation written with an intent to promote a political agenda or a set of beliefs. Mistakes or misinformation can happen accidentally by a trusted source. Fake news can also be spread through fabricated news Stories or Deepfakes [10]. Fabricated news stories are related to entirely false stories. Deepfakes videos are AI generated videos which convincingly depict people saying or doing things they never actually did. Deepfakes are designed to deceive people by presenting false realities. Fake news was chosen as Collins Dictionary's word of the year in 2017. Since then, it has emerged as a widespread phenomenon, influencing political landscapes, public opinion and even the global economy [11].

III. FACTORS RESPONSIBLE FOR SPREADING FAKE NEWS

In the digital era, anyone with Internet access can create content and disseminate it widely, regardless of accuracy. This democratization of content creation blurs the line between legitimate journalism and user-created falsehoods. Several factors such as social media platforms, echo chambers, clickbait headlines, bots and automated systems, user-generated content and algorithmic bias etc. have contributed to the rapid spread of the fake news in the digital world.

Social media platforms like Facebook, Twitter and Instagram allow for instant sharing of information to millions of users through shares, likes and retweets. Social media encourages users to connect with like-minded individuals and create echo chambers to reinforce their pre-existing beliefs [12]. This helps in spreading fake news without being challenged.

Fake news often exploits emotions such as fear, anger or patriotism to shape public opinion and in some cases, influence elections or policy decisions. Unlike traditional media outlets that adhere to editorial standards, social media platforms lack rigorous content moderation, allowing false narratives to spread as easily as legitimate news. With little incentive to prioritize accuracy over engagement, misinformation can go viral within hours, often without any form of oversight or verification. Influential figures on social media platforms can spread misinformation widely, with followers often taking their statements as truth without verification.

Besides, social media algorithms are designed for prioritizing the content which generates engagement through likes, comments and shares and helps in promoting sensational or emotional content. Clickbait headlines are sensationalized or false advertisements on websites, which are used to attract more clicks generating more revenue for websites. The websites which monetize through engagement with content drive higher revenue through advertisements. This model of revenue incentivizes them to create content that draws attention, regardless of accuracy [13]. People having little time to verify the authenticity of news, help in spreading fake news through these platforms. Basically, social media platforms have fundamentally changed the way in which news is consumed and distributed.

Bots and automated systems also help in propagating fake news by giving it the appearance of widespread popularity or legitimacy. Photos, videos, reviews and blog posts published on a website or social media are considered user-generated content. Earlier images and videos were considered a reliable source of news, but their reliability is now under threat due to morphed images and deepfakes. Deepfakes videos or images are used to create false political statements, incite violence or spread disinformation for personal or financial gain. A viral image from 2016 falsely claimed that Ratan Tata announced Tata Group would stop hiring JNU students, questioning their loyalty to the country. This was repeated in 2020. However, Ratan Tata himself clarified that he had made no such statement.

Algorithmic Bias has been used to have a significant impact on political systems globally. Several reports suggest that fake news have been used as a tool for election interference. Fake news often intensifies political polarization by presenting biased or false narratives that reinforce existing divisions. Fake news has been used as a weapon in geopolitical conflicts and starting information warfare to destabilize other nations or influence international relations. The 2016 U.S. presidential election saw widespread dissemination of fake news, some of which was allegedly linked to foreign actors aiming to manipulate public opinion [14]

IV. COMPARATIVE ANALYSIS OF TOOLS AND TECHNIQUES USED FOR DETECTING FAKE NEWS

Researchers have explored a variety of computational methods to address the issue of fake news analysis, ranging from traditional machine learning techniques to advanced deep learning models. Traditional supervised Machine Learning techniques use labelled datasets i.e., true or false news to train models such as Logistic Regression, Naive Bayes, Support Vector Machines (SVMs), Decision Trees and Random Forests. These models learn the patterns of fake news from training data and predict whether new articles are real or fake. Logistic Regression and Naive Bayes are among the earliest techniques applied to fake news detection. Naive Bayes, being a probabilistic classifier, leverages word distributions to classify text [18-20]. On the other hand, Logistic Regression optimizes classification boundaries to separate fake and genuine news articles effectively. SVMs have been extensively used for text classification tasks, including fake news detection. Studies like those by [21] have demonstrated the effectiveness of SVMs in handling high-dimensional text datasets. They are also Robust to overfitting in small datasets. However, SVM is computationally expensive for large datasets and has limited ability to model complex semantic relationships. Decision Trees and Random Forests are effective at capturing non-linear patterns. Though these approaches are computationally efficient and easy to implement and interpret, they require manual extraction and selection of features. The performance of these models drops for large datasets and complex patterns. Hence these models are not scalable. KNN is also used for fake news classification, but it is slow with large datasets and sensitive to irrelevant features or noisy data [22].

Deep learning techniques include Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTMs) networks, Convolutional Neural Networks (CNNs) and Transformer-based models, such as BERT (Bidirectional Encoder Representations from Transformers) and GPT. RNNs and LSTMs are used for analyzing the sequential nature of text for dependencies between words and phrases to determine the validity of news articles [15]. Attention Mechanisms are also used to check the fake news by focusing on important text and images [16]. The research in [23] has shown that LSTMs capture long-term dependencies effectively. Though these models are suitable for sequence modelling and capturing contextual and temporal dependencies, they are susceptible to vanishing gradient issues and are considered computationally intensive.

CNNs are majorly used for image analysis, but they are also used for text analysis. They detect patterns in text by capturing n-grams or using word embedding features. CNNs can handle multi-modal data combining text and images. [24] has employed CNNs for detecting fake news in social media posts. Transformer-based Models such as BERT and GPT work by capturing contextual relationships in text, so they can be used for fake news detection. [25] has highlighted the use of BERT for sentence-level semantic analysis, achieving state-of-the-art results. These models automate feature extraction, but they require significant labelled data and are limited by high computational cost. These models are good in capturing semantic meaning, dependencies and handling large-scale datasets. but need more resources and lack interpretability.

The hybrid techniques include Graph-based techniques and Multimodal Approaches. Graph-based techniques use network structures to detect communities of misinformation spreaders or sources as fake news often form networks of misinformation, where users or websites are interconnected. Multimodal Approaches employ detection systems that combine text analysis with other data such as images, video or audio. Fake news articles with doctored images or videos can be detected using computer vision techniques. Hybrid techniques combine strengths of traditional and deep learning approaches. For instance, embedding results generated by BERT can be fed into SVMs for classification [26]. These techniques provide enhanced performance and flexibility but need higher computational requirements and are complex to implement.

Natural Language Processing (NLP) techniques have formed the basis for fake news detection. Text representation methods, such as TF-IDF, Word2Vec and FastText, have been employed in studies like those in [27]. These techniques are effective for linguistic pattern analysis and easy to integrate with ML models. But they are limited by contextual understanding and language-specific dependencies as models trained in one language may not be generalized to others.

Network-Based Analysis includes Social Network Analysis (SNA) and Graph Neural Networks (GNNs). SNA examines patterns of news sharing and propagation of fake news as they tend to propagate differently from real news. Tracking speed, reach and patterns of retweets/shares help in identifying disinformation. Bots are also used to spread fake news. Bot detection techniques help in differentiating between real users and automated accounts that spread fake news. Recent studies suggest that the virality of fake news is often amplified by algorithms that prioritize engagement over accuracy [28]. GNNs model relationships and connections in data. [29] has demonstrated the effectiveness of GNNs in capturing relational data for fake news detection. They are effective for social media-based fake news detection and provide insights into dissemination patterns. They are limited by their dependence on large-scale social media data and high computational overhead.

Table I compares fake news detection techniques based on their accuracy, scalability, interpretability, ease of use and resource demand.

The choice of technique for fake news detection depends on a specific application, dataset characteristics and computational resources. Traditional ML techniques are suitable for small-scale problems. Deep learning and hybrid approaches excel in handling large, complex datasets. Network-based analysis and NLP-specific methods provide unique insights, especially for social media data.

Table I. A Comparison of Fake News Detection Techniques

Technique	***Accuracy***	***Scalability***	***Interpretability***	***Ease of Use***	***Resource Demand***
Traditional ML	Medium	Low-Medium	High	High	Low
Deep Learning	High	High	Low	Medium	High
Hybrid Techniques	High	Medium-High	Medium	Medium	High
NLP Techniques	Medium-High	Medium	Medium	High	Medium
Network-Based Analysis	Medium	Low-Medium	Medium	Low	High

V. TOOLS USED FOR DETECTING FAKE NEWS

Since Computer Programs and Bots are widely used to write many posts, Broadcaster Nihal Arthanayake suggests that the validity of a story should be checked by verifying the purpose of a story, reliability of the author sharing the story, reliability of websites through their URLs and the time related to the story. A story should also be checked by verifying its source, followers, verified account having blue ticks and responses of a post. One should also look for clues in the picture and do a reverse image search to find its source. Video can be checked through video checking tools to see the action frame by frame. Figure 1 summarizes the steps required to check the genuineness of the news.

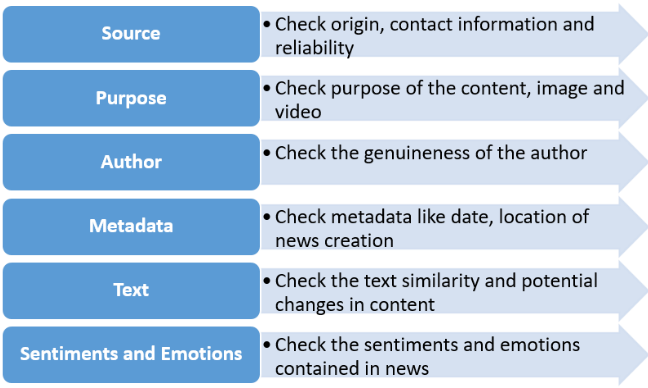

Figure 1. Summarizes the steps required to check the genuineness of the news

Researcher in [17] have suggested roles of different stakeholders in combating the spread of fake news. However, it is not always possible for a common user to follow technical details and steps to verify the information. For this, various detection tools have been developed to identify fake news. Such tools can be classified based on their capability to identify news, which may be content-based or context-based detection tools.

Content-based detection tools are generally based on Linguistic Analysis, Fact-Checking and Text Similarity. In Linguistic Analysis, text is analyzed for misleading writing patterns, such as the use of sensational words, emotional language, grammatical inconsistencies or exaggerated statements. Fact Verification Tools, such as Google Fact Check Tools and ClaimBuster, help to automate the process to verify the accuracy of fake news with matching claims in news articles with trusted fact-checking databases like Snopes, FactCheck.org and PolitiFact, among others. Text Similarity allows users to compare the content of suspicious news articles with reliable sources. If a story deviates significantly from credible reports, it is flagged as fake.

Platforms like Wikipedia or fact-checking communities often rely on crowdsourcing to verify facts and flag misinformation.

Context-based detection tools are mainly based on Source Credibility, User Behavior and Engagement Patterns. Source Credibility refers to the reliability of the news source based on its history, reputation and previous work. It is assumed that unverified websites are more likely to produce fake news. Source credibility can be checked with tools like Whois or DomainTools. User Behavior monitors the behavior of users such as patterns of sharing fake information, bot-like behavior or spreading disinformation systematically. Engagement Patterns work by analyzing how news is shared on social media. Fake news often gets unreasonably high engagement through likes, shares or comments compared to legitimate news. Tools like Hoaxy, Botometer are used to track the spread and influence of the image or video on social media and see if it was amplified by bots or trolls. Table II summarizes commonly used tools and their features.

Table II. Comparative study of Commonly used Tools for detecting Fake News

Content/ Context	***Tool Name***	***Category***	***Type of Tool***	***Description***
Content based	Google Images	Reverse Image Search	Search engine	This tool searches for similar images across the web to verify the source or original context. It also helps in finding out whether the image has been edited, cropped or altered.
Content based	TinEye	Reverse Image Search	Website	This tool tracks where an image appears online and checks for alterations.
Content based	Yandex Images	Reverse Image Search	Search Engine	It is better at finding similar faces or places in images (especially Russian sources).
Content based	FotoForensics	Meta data Analysis	Search engine	This tool doesn't just state whether an image is real or fake, it also identifies hidden pixels, provides Error Level Analysis (ELA) and metadata details.
Content based	EXIF.tools	Metadata Analysis	Website	It reads EXIF metadata from images like camera information, GPS, timestamps.
Both Content & Context based	InVID Verification Plugin	Meta data Analysis	Browser extension	InVID is a plugin available for Chrome and Firefox. It analyzes video metadata, allows reverse image search, does keyframe analysis.
Context based	NewsGuard	News Source Credibility	Browser Extension	It rates news websites for reliability based on journalistic standards.
Context based	Hoaxy	Bot detection	Website	It visualizes the spread of articles and tweets to detect coordinated disinformation through network analysis.
Context based	Botometer	Bot detection	Website	It tracks the spread and influence of the image or video on social media and see if it was amplified by bots or trolls.
Context based	SunCalc/ Wolfram Alpha	Geolocation tools	Website/App	Both tools are used to verify videos by matching the direction of shadows to the time of day when the video was recorded.
Context based	Google Maps/ Google Earth or Wikimapia	Geolocation Tool	App/App/ Website	These tools are used to compare the landmarks, buildings, roads or terrain features in the image or video with the real-world location.
Both Content & Context based	Truepic	Meta Data Analysis	App	It captures and verifies images at the point of creation using secure camera technology, ensuring authenticity through metadata validation, geolocation and timestamps. It is frequently used in journalism, insurance and compliance.
Content based	YouTube Data Viewer	Meta data Analysis	Website	This tool extracts metadata (upload time, video ID) and generates thumbnails for reverse image search, helping to verify original upload date and detect re-uploads or manipulation.
Content based	FakeImageDetector	Metadata Analysis and ELA Analysis.	Website	It uses machine learning algorithms to detect signs of image tampering or manipulation. It focuses on visual anomalies and deepfake detection in images.
Content based	Fawkes	Deepfakes	App	These tools are used to identify deepfakes.
Context based	Whois Lookup Tools	Domain Information	Website	It gives domain registration info to identify suspicious or fake sources.
Context based	CrowdTangle (by Meta)	Social Media Monitoring	Platform Tool (Facebook)	It tracks how content spreads across social platforms. It is mainly used by journalists.
Context based	ClaimReview / FactCheck.org / Snopes	Fact Checking	Website	It provides verified info on common fake news stories and claims.
Content Based	Forensically, JpegSnoop	Image Forensics analysis/ Metadata Analysis	Website/App	These tools are used to detect signs of manipulation, such as inconsistent lighting, shadows, pixels, compression or noise.

The Governments of various countries are coming forward in combating spread of fake news and are trying to create awareness, draft regulations and restrict the circulation if it is harming the society or situations. The social media platforms should also use techniques to authenticate news before it is uploaded. And finally, the users or readers should self-assess the news and try to stop the spread.

VI. Comparison of Accuracy of Developed ML Models using Different Datasets

The major challenges faced in Machine Learning models, especially with reference to fake news analysis is data dependency. The poor quality of data or biasness in the data can lead to inaccurate results. Moreover, a model trained using dataset of one region cannot be used for prediction of fake news for another region. The domain of data collected for making a model also makes it different.

In the current research paper, the development of a model and prediction of fake news for cross region is explored and analyzed. For this, two different datasets belonging to different regions are considered. The first Fake news dataset, considered in the current research is available at https://www.kaggle.com/code/ahmedtronic/fake-news-classification/notebook#About-the-data. The major features taken for building models and analysis are id, title, authors, text and label. If the value of the label is 0, it is considered real news. If value of label is 1, it is labelled as fake news.

The second dataset, BharatFakeNewsKosh, available at https://www.kaggle.com/datasets/man2191989/bharatfakenewskosh. This dataset is India's first public benchmark dataset of fake news incidents and contains 26,232 news samples. It has 19 columns. The major features taken for analysis are id, title, author and Eng_Trans_News_Body. The label value is either FALSE or TRUE. From the dataset, only selected features(columns) viz. id, title, author, text and label are selected. The label value FALSE is converted to numeric 1 and TRUE to numeric 0.

Both data sets are considered for building models and making predictions. To verify the role of data dependency in fake news analysis, first the model is developed and then accuracy is noted for first dataset. The same steps are followed for the second dataset. Then, both the datasets are combined to check the results.

Table III shows the comparison of various models on both individual data sets as well as on the combined dataset, with values expressed as percentages. A graphical representation of this comparison is provided in Figure 2, which illustrates the performance of different models across the datasets.

Table III. A Comparison of various Models on Datasets

Model	*Dataset I*	*Dataset II*	*Combined Dataset*
Logistic Regression			
Training Accuracy	98.84	79.04	91.07
Testing Accuracy	97.11	61.74	76.16
SVM			
Training Accuracy	99.96	97.71	98.34
Testing Accuracy	98.48	62.30	77.83
Decision Tree Classifier			
Training Accuracy	99.75	69.30	88.80
Testing Accuracy	99.47	61.06	74.58
Random Forest Classifier			
Training Accuracy	98.22	65.72	83.99
Testing Accuracy	96.92	60.85	75.80

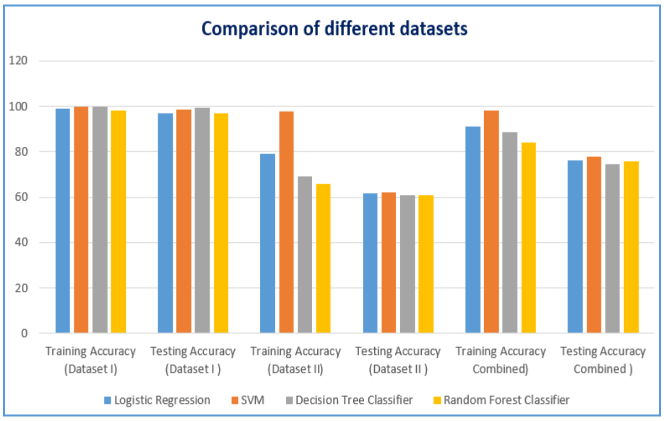

Figure 2. Comparison of different models on different Datasets

From the results of training and testing accuracy, it is observed that the accuracy varies from data to data. It also means prediction data of one region may not produce reliable accuracy when model developed using dataset of another region is used.

VII. Discussion and Challenges

Fake news spread faster in this digital era than it can be fact-checked. Once viral, it becomes difficult to correct, even after the truth is revealed. Growing public distrust in traditional media outlets has created a vicious cycle where people are more likely to rely on unverified sources for information. This can be termed as technological arms race. People are more likely to believe and spread fake news that aligns with their existing beliefs leading to more polarized societies.

Regulation of fake news presents legal and ethical challenges too, as many countries grapple with issues of free speech and censorship. Defining what constitutes fake news without infringing on civil liberties is a complex issue.

Social media platforms are criticized for their role in spreading fake news. Algorithms that prioritize engagement often amplify emotionally charged content, irrespective of its accuracy. While platforms like Facebook and Twitter have implemented fact-checking features and flagged misleading content, these efforts are not sufficient to completely stop the spread of fake news.

Misleading information often blends accurate facts with subtle falsehoods, making it challenging to isolate and identify the deceptive elements within a news article. The growing use of sophisticated AI tools to generate hyper-realistic fake content, including deepfakes, has further complicated detection efforts. Although advancements in ML and NLP have significantly improved fake news detection, several challenges remain.

Techniques for fake news detection have continuously evolved over time. Static models built over time get obsolete very soon and cannot be used in the long term. The availability of labelled data for fake news detection is often limited. Creating high-quality datasets is very time-consuming. Since data is labelled by humans, it also adds to bias during data labelling. Dataset from a specific domain is not suitable for another domain. Fake news can spread across any language, making it challenging to develop a universal solution for detecting and preventing its propagation in multilingual contexts. Detection algorithms can be influenced by biases in the training data, potentially skewing the results. As fake news detection techniques advance, so do the strategies used by people spreading disinformation, making it an ongoing and dynamic challenge. Continuous research is essential to enhance detection models, especially in identifying nuanced content such as satire and opinion pieces.

Collaboration between governments, regulatory bodies and technology platforms is crucial to establish clearer policies and frameworks for combating misinformation. Additionally, promoting media literacy and public awareness is vital. Educating individuals to critically evaluate news sources can significantly reduce the spread and impact of fake news at the grassroots level.

VIII. CONCULUSION

The digital age has revolutionized how news is produced, consumed and disseminated, creating an environment where fake news can spread rapidly across borders. To address this issue, a robust fake news detection system requires a multi-layered approach, combining content, context, user behavior and network analysis. While efforts to combat fake news have grown in response, the rapidly evolving landscape of misinformation, combined with the incentives of social media platforms, continues to pose significant challenges. In this environment, fostering media literacy, developing advanced detection technologies and promoting trust in verified sources will be essential for curbing the spread of fake news.

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