Unmasking Deceptive Information: Strategies and Tools for False Information Detection using Machine Learning

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ABSTRACT

The widespread adoption of social media platforms has given rise to a plethora of multimedia content circulating across these networks. The open and unrestricted sharing of information on these platforms has created an environment where data dissemination on the internet is unbounded by considerations of its credibility. Within the realm of social media, the propagation of misinformation, often in the form of false information or rumors, is a prevalent issue. Such unverified information can have dire consequences. Despite the extensive usage of social media platforms, their unregulated nature frequently fosters the generation and diffusion of unverified and speculative content. Consequently, the automatic detection of rumors on social media platforms has emerged as a crucial research domain within the field of social analysis. With this same motivation in mind, this article places its focus on datasets and cutting-edge methodologies employed for rumor detection. Furthermore, it delves into both supervised and unsupervised approaches, as well as delving into the application of deep learning techniques for word recognition.

Keywords

False Information Detection, Machine Learning

1. INTRODUCTION

Traditionally defined, gossip entails withholding information regarding an incident during its dissemination. Platforms like Weibo have provided an even broader reach for the spread of rumors. Notably, statistics from November 2015 indicate Twitter had approximately 340 million monthly users who generated an average of 400 million daily tweets. The unregulated nature of social media platforms offers an opportunity to scrutinize the veracity of rumors by observing how users share and discuss word choices, thereby delving into the mechanics of words and information utilization. Online Social Networks (OSNs) represent one of the internet's most widely used services. Some entities, whether organizations or individuals, employ rumor investigation websites, rumor debunking platforms like snopes.com, twittertrails.com, and factcheck.org, to enable people to fact-check gossip. Nevertheless, these platforms primarily rely on public reports or manual verification to identify rumors. This approach not only demands significant manpower and financial resources but also results in substantial delays in debunking rumors. The absence of systematic efforts by platforms to moderate posts further exacerbates the dissemination of misinformation [14]. According to a Chinese report, over one-third of trending events on microblogs contain false information, with rumors going viral in seconds or minutes [1]. The ensuing examples underscore the harm caused by rumors to political events, the economy, and social stability.

- On May 30, 2018, a rumor circulated on social media suggesting that the deadly Nipah virus was transmitted via broiler chickens. This claim resulted in significant losses for business owners in Tamil Nadu [2].
- On May 5, 2019, a viral video featuring rumors of a massive subway collapse caused panic in Bengaluru. Numerous individuals believed it to be true, as some media outlets reported it as breaking news. However, the Bangalore Metro Rail Corporation Limited (BMRCL) deemed it fake and urged social media users not to share it [3].

Automatic detection of rumors from social media platforms is one of the many studies behind research in the field of social analysis. With the same motivation, this article focuses on the analysis and analysis process of word discovery in social media information.

The automatic detection of rumors on social media platforms is a key area of research within the fiel of social analysis. With the same impetus, this article centers on the exploration and analytical process of word identification within social media content. The article's advantages are manifold. It provides a comprehensive depiction of available options, their classification, and a clear delineation of the selection process steps. Additionally, the article delves into the depth of data analysis concerning chosen words. It offers a meticulous analysis and comparison of state- of-the-art word detection models, encompassing machine learning, deep learning, and hybrid approaches. Furthermore, the article contemplates potential future directions within the realm of selective detection. The content is structured as follows: Section 2 furnishes an overview of the word analysis process and its constituents. Section 3 elucidates the various methodologies for word identification. Section 4 meticulously dissects and contrasts cutting-edge detection techniques. Section 5 unveils the outcomes and hints at future directions in the pursuit of preferred words.

2. RUMOR DETECTION

False information may manifest as a presently circulating narrative or report with questionable or indeterminate accuracy. Furthermore, it can be described as a headline originating from one or multiple sources and evolving over time. The process of identifying and addressing fake news involves a systematic method for assessing the truthfulness of each individual case. In the pursuit of rumor detection, a myriad of challenges must be addressed, including the

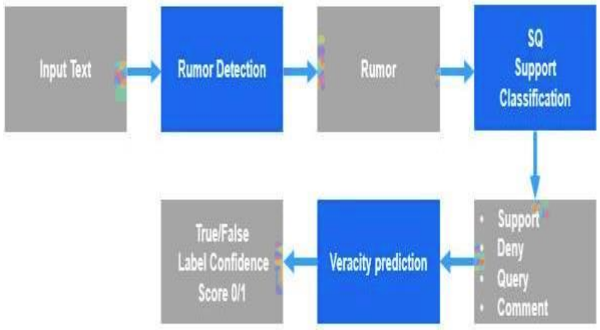

Fig.1.Flow of Rumor Detection and Classification

organization of data, the differentiation of recent rumors from historical data, and the determination of the source or genesis of each rumor, among other complexities.

With the rise of social media, research on the evolution of search terms and proof-of-concept tools has gained popularity. This trend allows both users and professionals to access real-time news and information, but it is susceptible to the dissemination of unverified data.The process of verifying the truth of a claim is a intricate, multi-phase procedure that typically encompasses the following stages:

i. Gathering pertinent information related to the claim in question.
ii. Assessing the significance of each piece of information concerning the claim.
iii. Estimating the reliability and trustworthiness of the collected information.
iv. Making a final determination by amalgamating the outcomes from stages (ii) and (iii) with all the information amassed in stage (i).

The classification methodology comprises four integral components: establishing the classification criteria, appraising the classification results, selecting the appropriate selection function, and making the correct classification decision. When formulating the distribution of rumors, a pivotal determinant is often the time factor, specifically the emergence of new rumors coinciding with breaking news events. Rumors surfacing during breaking news situations are frequently unprecedented. Consequently, it is imperative for word detection and word classification systems to be capable of handling novel, unanticipated words, presuming that training data is available in the recorded language, which may diverge from subsequently encountered information. In such scenarios, early identification and resolution of rumors take on heightened significance, necessitating swifter reporting. Rumors have been a topic of discussion for an extended period, and certain rumors may persist indefinitely without verification. These enduring rumors remain recurrent features of discourse. Furthermore, the system can employ the speech history of selected words to distinguish typical conversations, wherein different words are less frequent. This allows for the continued use of historical data-derived classes with newly acquired data. In contrast to immediate delivery options, long- term options do not impose strict deadlines for completion, as the work typically unfolds in a retrospective fashion.

Figure 1 visually illustrates the classification process, showcasing the accuracy assessment of selection and posture analysis. Inputs and outputs are depicted by white blocks, while blue blocks represent the models utilized in each stage of the process.

3. DATASETS OF RUMOR DETECTION

In this section, we delve into the body of evidence. Table 2 offers a comprehensive breakdown of the search terms associated with the various datasets:

- Qazvinian et al.'s Most-Used Keyword Search Dataset [4]: This dataset comprises over 14,000 tweets related to six different keywords. Each tweet is meticulously categorized to determine whether it is linked to a rumor or not.
- KWON Dataset [5]: Released in 2014, the KWON dataset encompasses 46 carefully selected events and

56 non-rumor events gathered from Twitter. Each event contains a minimum of 65 tweets. Rigorous validation was ensured, with each event being meticulously documented by four participants. Consequently, the dataset includes only events observed by at least four participants and granted collective approval.

- MediaEval Dataset [6]: The MediaEval dataset includes 10,000 target tweets and 7,000 non-target tweets linked to 17 events within the development set. Additionally, it comprises 2,000 tweets associated with 34 events in the test set.
- RUMDECT Dataset [7]: Published in 2017, the RUMDECT dataset incorporates two types of data: Weibo and Twitter. Weibo data encompasses 2,313 rumors and 2,351 non-rumors. The rumors from Weibo were sourced from Sina's social media management office, while non-rumor incidents were collected from the public. As for Twitter data, it consists of 778 events selected by Snopes.com between March and December 2015. For each event, keywords from the Snopes URL were utilized as queries to retrieve relevant Twitter messages [8], [5].
- RUMOUREVAL Dataset [9]: Created for RumourEval 2018 as part of a collaborative project at SemEval 2017, this dataset comprises a training set featuring 297 selected scenarios. It encompasses 298 tweets and 4,322 response tweets. In the test system, there are a total of 1,080 tweets and 1,053 replies, with 28 of them being tweets.
- MULTI Dataset [10]: Released in 2017, the MULTI dataset comprises 4,749 rumors and 4,800 non-rumored instances derived from unconfirmed rumors on Weibo. What sets this dataset apart is its focus on investigating rumors with multimodal content, incorporating not only textual information but also visual content from Weibo platforms.
- LIAR Dataset [11]: Comprising 12,836 concise statements, this dataset is tagged with attributes such as facts, meaning, context/location, speaker, country, political party, and background. An overview of the LIAR dataset is provided in Table 1.
- PHEME Dataset [14]: This repository houses rumors and non-rumors generated on Twitter during breaking news events.
- Fake News Challenge Dataset: This dataset was compiled from diverse sources and Twitter accounts. It comprises approximately 50,000 pairs of word-text references, with text files distributed unevenly.

- Science and Research Research (FEVER) Data: Gathered from Wikipedia, this dataset encompasses around 144,000 data requests, with 56 sparsely distributed records employed for processing educational materials data.

Table 1.The LIAR Dataset statistics [11]

DatasetsStatistics	
Trainingdatasetsize	12,836
Validationdatasetsize	1,284
Testingdatasetsize	1,283
Top-3SpeakerAffiliations	
Democrats	4,150
Republicans	5,687
None(e.g.,FBposts)	2.185

Table2. Datasets for rumor detection.

Year	Dataset	Rumor	NonRumor
2013	KWON	46	56
2016	MediaEval	10000	7000
2016	Weibo	2351	2350

4. STATE-OF-THE-ART APPROACHES OF RUMOR DETECTION

Figure 2 gives schematic representation of the rumor detection approaches.

1. *Machine Learning Approaches*

Table 3 presents a comparison of machine learning methods for word search. Machine learning techniques are further divided into supervised and unsupervised techniques.

2. *Supervised based Approaches*

Castillo et al. [8] Developed a database for trust learning on Twitter. All themes excluded from the study were analyzed by the review team. A number of features are then extracted to evaluate the credibility of the text. These features are divided into four categories based on messages, users, topics, and ads. They achieved 86% accuracy using the J48 decision tree approach.

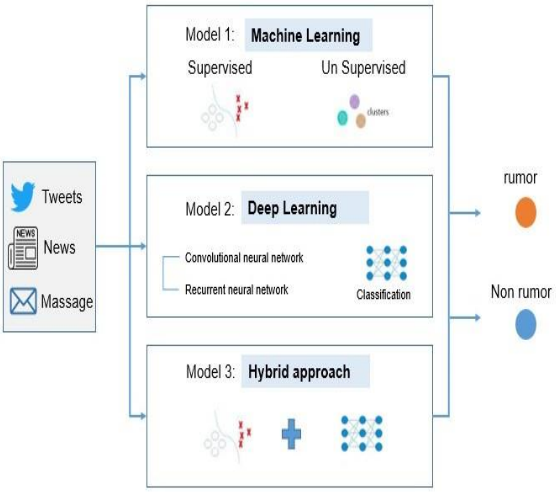

Fig. 2. Approaches of rumor detection

Yang et al. [13] conducted initial investigations in response to the emergence of rumors on Sina Weibo. One facet of their research involved examining a collection of Weibo posts that had been officially debunked as baseless rumors, identified through Sina Weibo's denial of these rumors. They then extracted dense clusters from Weibo data, training a classifier to recognize specific chosen words from this dataset. This endeavor built upon prior studies [8] [14], which had employed numerous methodologies for classification purposes. Additionally, they introduced two novel roles: that of a client and a resident. The experimental results demonstrated the efficacy of their newly proposed features, yielding a reliability rate ranging from 73.5% to 75%. Figure 3 illustrates the machine learning process flow, emphasizing the extraction of optimal features from the input data, subsequently classifying them as either optional or non-optional. Dayani et al. [15] analyzed data stemming from a 2019 keyword search and employed machine learning algorithms, including the nearest neighbor (KNN) and Naive Bayes classifiers, to discern chosen terms for tweets. Their findings, particularly with the Naive Bayes classifier, indicated enhanced word identification accuracy when specific rules were incorporated, achieving an 86% accuracy rate for all supported words and 76% accuracy for rejected and disputed terms [16]. Hamidian and Diab [17] highlighted another research flaw observed in their Twitter feed. They initially identified one rumor as a form of fabricated news and proceeded to dissect this particular chosen rumor. Their exploration focused on evaluating the

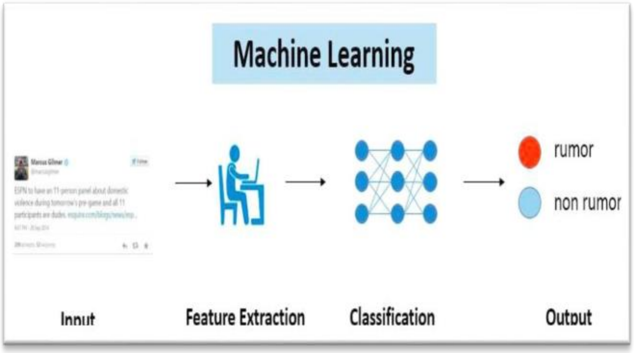

Fig.3.Use of Machine learning for Rumor Detection

Table3. Comparison of Machine learning techniques for rumor detection

Technique	Supervised	Unsupervised	Dataset	Evaluation Parameters	Reference
SVM	√		Sina Weibo	Precision, Recall, F-score	[36]
SEIZ	√		Twitter	SEIZ compartment and RSI	[37]
Decision tree, Random Forest	√		Twitter	Accuracy,Precision,Recall,F1	[38]
Social Spam Analytics and Detection Framework(SPADE)	√		Email, Twitter	True Positive, False Positive, F-measure, Accuracy	[39]
SVM	√		Sina Weibo	P, Recall, F-measure	[29]
Clustering		√	Clinton, Obama	True Positive, Precision, Recall, F1	[21]

SVM	√		Twitter	Accuracy	[40]
Logistic, Naïve Bayes, random Forest	√		News, Twitter	Precision, Recall, F-measure	[41]
Graph-based pattern Matching algorithm	√		Twitter	Tf– idf	[42]
SVM	√		Sina Weibo	Accuracy	[43]
Information propagation model	√		Sina Weibo	Precision, recall,, F-rate, Accuracy	[30]

effectiveness of a multi-level categorization approach. They employed the J48 decision system, a decision tree-based method supporting various metrics. In [18], the WEKA model was utilized for training and evaluation purposes. Additionally, Kwon et al. [19] scrutinized categorization levels by exploring taxonomy options across different time intervals, spanning from three days to two months. Their structural approach aimed to differentiate between rumors and non-rumors based on user behavior, body language, and speech processing.

4.1.2 Unsupervised based Approaches

Takahashi and Igata [20] adopted an unsupervised methodology to investigate the dissemination of rumors following an earthquake disaster. Their study reveals that retweets prove to be effective in capturing intriguing subjects and mitigating the spread of detrimental rumors originating from them.A group-oriented unsupervised classification technique [21] employs a combination of five models and ranges to identify prominent users. The construction of this approach is bifurcated into two tiers. In the initial stage, tweets featuring permalinks are grouped together. Subsequently, in the second stage, clusters of similar discussions revolving around ongoing news are amalgamated into larger groups, where analogous tasks are recurrently executed. Jain et al. [22] addressed the issue of trust by proposing a method to identify Twitter rumors over time. Their approach is rooted in the belief that verified media sources offer more trustworthy information compared to unverified accounts. Chen et al. [23] assessed false rumors by gauging suspicion and categorized attributes based on audience intelligence, content characteristics, and advertising behavior. They meticulously devised an array of features to detect misleading information in Sina Weibo. Machine Learning is applied for the similar kind of applications[45-49].

4.2 Deep Learning Approaches

Figure 4 illustrates the application of deep learning techniques in the process of keyword retrieval, while

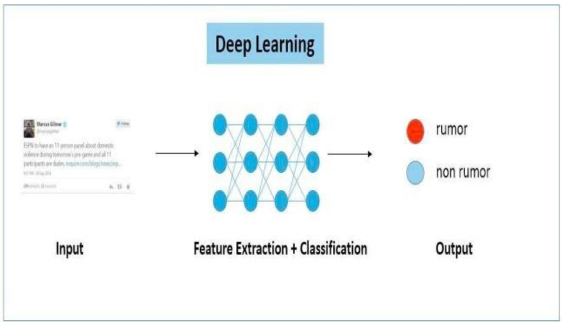

Fig.4. Use of Deep learning for Rumor Detection.

Table4. Comparison of deep learning techniques for rumor detection.

Method	Working	Features	Datasets	References
Two-layer CNN	An input sequence of Convolution Approach for Misinformation Identification (CAMI) is formed of a group of vectors. Then, the vectors are fed to a two-layer Convolution neural networks, gaining the final results of two-class classification.	This model can extract significant Features from an input instance and achieve high performance on the two-Open dataset. Also, this method is Capable of detecting rumors at early stage with limited inputting data.	Twitter and Weibo	[27]
Long Short Term Memory	RNN is employed to extract temporal Representations of articles so user-Features are a unit fed in to totally connected Layer to reason as core. The outputs of the on Top of modules area unit integrated to vector that is employed for classification	This methodology focusses On three characteristics of the rumor data: the text of a writing, the user Response it receives, and also The origin users promoting it.These characteristics signify totally Different aspects ofthe Rumor knowledge, And it's additionally difficult to find Rumor supported one in all them.	Twitter and Weibo	[26],[7]

Bottom-up And top-Down tree-Structured recursive neural network.	The inherent nature of algorithmic models permits them exploitation propagation tree to guide the educational of representations from loudspeaker, like embedding varied indicative signals hidden within the structure, for distinguishing rumors.	This model yield far better performance than alternative strategies via the modelling of interaction structures of posts within the propagation and properly detects false rumor at early stage.	Twitter datasets Released by Ma etal.(2017).	[25]
Combination Of RNN and Auto encoder (AE).	A combination of RNN and AE is employed to find out the conventional behaviours of users.	This method distinguishes rumors as anomalies from other credible microblogs based on user's behaviours.	Dataset contains different Weibos Including both rumors and non-rumors.	[31]
Neural network architecture	Three different variations of neural networks: Tf-Idf with DNN, BOW with DNN, Pre-trained word embeddings with Neural Networks are used to train model.	This method accurately predict stance between a given pair of headline and article body.	Fake News Challenge	[33-34]

Table 4 offers a comprehensive comparison of deep learning concerning specific keywords. When juxtaposed with conventional classification methodologies, deep neural networks have demonstrated notable advantages in certain machine learning scenarios. Approaches rooted in neural networks are particularly oriented toward constructing intricate representations of designated data [1]. The diagram in Figure 4 elucidates the deep learning workflow, wherein the most elementary features are

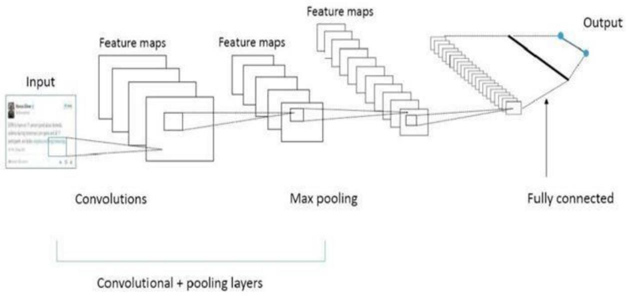

Fig.5.Use of Convolutional neural network for rumor detection

extracted and categorized from the input data provided. In contrast to shallow networks, deep neural architectures can accommodate more intricate models [24]. Deep learning can be categorized into two distinct classes based on various neural network models.

4.2.2 RNN based approaches

In order to establish a concrete connection between linguistic content and communication evidence, Ma et al. [25] introduced a word detection model centered on an iterative neural network framework. In their model, they employ the concept of a spanning tree with its roots embedded in the primary node, and each node within the tree can represent a distinct field of information. Through the iterative progression of this tree-based model, they effectively amalgamate textual content and, as a result, elucidate the relationships therein. They conducted experiments utilizing a global Twitter dataset, yielding results that distinctly outperform conventional search engine performance. Furthermore, their models exhibit cost-effectiveness during the early stages of information dissemination, particularly in the context of rumor investigation, thereby reducing the time required for impact assessment and refutation.

Ruchansky et al. [26] delve into three facets of data selection based on article text, the authors who generated it, and their respective users.

The authors noted that these features render the chosen data highly multifaceted, making it challenging to pinpoint specific words based solely on these attributes. Consequently, their objective is to enhance the precision and automation of search options by integrating all three features into a hybrid model. This model comprises three distinct modules: capture, scoring, and integration (CSI). The primary emphasis revolves around textual content and responses, employing recurrent neural networks to grasp the temporal aspects of user activity. In the second segment, users are characterized by vectors, and their traits are established based on their behavioral patterns. In the third module, the outcomes from the previous two components are fused into a vector, which is subsequently employed for classifying the veracity of the activity, distinguishing between falsehood and truth. Beyond accurate detection, the CSI model collaboratively generates concealed agents for individual users and messages, adaptable for various analyses. Kim et al. [10] introduced a word detection model that amalgamates diverse modalities. In comparison to feature-centric methods, their models demonstrate a remarkable capacity to identify specific terms within multimedia content.

CNN based approaches

Yu and colleagues (Yu et al., 27) observed that Recurrent Neural Networks (RNNs) encountered difficulties in effectively identifying initially selected words when dealing with limited input data and exhibited sensitivity to the introduction of new content within the input sequence. In response to these challenges, they introduced a novel neural network approach grounded in election detection. Their methodology begins by segmenting the chosen context into multiple distinct stages. Subsequently, all pertinent events are consolidated within a collective Weibo post. Each group's representation is then acquired through doc2vec, resulting in a collection of vectors constituting the input sequence for the Convolutional Analysis of Misinformation (CAMI) framework. Lastly, these vectors are input into a two-tiered convolutional neural network, yielding the conclusive outcome of a two-class classification. Remarkably, their models excel in distilling essential features from the input data, leading to exceptional performance when applied to two- dimensional datasets.

In their work, Wang et al. [28] introduced an Innovative Artificial Neural Network (EANN) grounded in Opposite Neural Networks. This EANN encompasses modules for multimodal feature extraction, counterfeit news identification, and event differentiation. The multimodal feature extractor collaborates closely with counterfeit news detection, while simultaneously endeavoring to influence the event separator to apprehend event-invariant representations. In the context of multimodal feature extraction, Convolutional Neural Networks (CNNs) are employed to glean features from both textual and visual content. The counterfeit news detection module is responsible for identifying counterfeit news by leveraging diverse features and acquiring adaptive attributes through the exclusion of specific events. The EANN model employs an event manager to assess distinctions between various events and proficiently expand the scope of occurred events. Figure 5 illustrates the convolutional neural network's flow across various tiers within the model.

4.3 Hybrid approaches

Table 5 provides a comprehensive comparison of hybrid methodologies employed for word retrieval. Essentially, an integrated approach involves amalgamating various techniques and individual approaches to formulate comprehensive proposals, thereby addressing the limitations of existing technologies. When the requisites deviate from expectations due to factual discrepancies and estimations, and where the efficacy of singular methods falls short in verifying facts and approximations, amalgamation aids in attaining meaningful outcomes by synergizing two or more distinct processes.

Table5.Comparison of hybrid techniques for rumor detection

Model	**Dataset**	**Evaluat ionPara meters**	**Refe rence**
Unsupervised (combination of autoencoders and Recurrent neural networks)	Weibo	Precision, Recall	[31]
LSTM and CNN	Twitter	Precision, Recall, F-Measure	[32]
Hybrid approach deriving community-based features With meta data, content and interaction based features	Twitter	Detectionrate, False positive rate, F-score	[45]
Hierarchica lclustering	Weibo	Precision, Recall, F-measure	[29]
Hybrid CNN for integrating text and meta data	LIAR		[11]
CSI model(Capture,Score and Integrate)	Twitter and Weibo	F-score	[26]
Graph kernel based hybrid SVM classifier	Weibo	Precision, Recall	[43]

Certain analyses undertake a balanced approach, blending diligence with nonchalance in their research endeavors. Cai et al. [29], for instance, delve into specific inferences drawn from user responses, including comments and posts pertaining to specific events, for scrutinizing selected statuses on the Weibo platform. Their method entails collating topical information and fusing it with Weibo-derived data to discern spurious rumors within a cluster of tweets. Employing cluster analysis, they dissect text excerpts extracted from retweets and comments. Their tests underscore the efficacy of the novel features proposed for classification, emphasizing the pivotal role of excluding words and punctuation in the pursuit of specific terms. In a novel study presented by Liu et al. [30], an exploration of user characteristics on online media platforms is conducted to identify targeted keywords. Beyond the content attributes of messages, their approach posits that the intent to disseminate specific messages hinges on individual user characteristics. Their novel information disclosure model underscores the distinctiveness between trust messages and the information disclosure model itself. To unravel this query, an intricate data model consolidates users into k groups through a propagation process, harnessing user state-sensitive attributes.

Their methodology aptly segregates rumors from credible content on social media. The authors affirm the feasibility of analyzing selected terms from microblogging platforms based on the pattern elucidated via a multi-occurrence model.

Chen et al. [31] propound an unsupervised model that amalgamates autoencoders and centralized networks. This model leverages user behavior to discern suspicious rumors across diverse microblogging platforms. Features predicated on user comments are freshly prepared and subsequently scrutinized at the time of dissemination, thereby enhancing the selection process. The authors report an impressive model performance, with a test accuracy rate of 93.49% and an F1 score of 88.16%.

Ajao et al. devise a hybrid model amalgamating recurrent neural networks and convolutional neural networks [32]. They meticulously observe and categorize fake news within Twitter messages to pinpoint fake news-related features, all without prior expertise in the domain. Initially, their method harnesses a blend of RNNs and CNNs to autonomously identify features within Twitter messages, irrespective of topical familiarity or subject matter. Subsequently, the model detects spurious news on Twitter, drawing insights from both textual and visual content. The utilization of deep learning facilitates automatic feature extraction, allowing for the assimilation of word relationships within the pseudo text, sans explicit network training. Their approach attains a commendable accuracy rate of 72%.

5. CONCLUSION

Due to the extensive utilization of social media platforms for the dissemination of information and news, research into the investigation of rumors has experienced a surge in interest. Numerous studies have concentrated on the detection of sources of gossip and the identification of such rumors. Given the rapid propagation of rumors in the online sphere, the development of tools designed to pinpoint and uncover false information has become of paramount importance. This article offers an overarching view of keyword analysis, database registration, application registration, and the comparative examination of techniques for researching keywords in their current state.

Upon conducting an exploration of pre-existing keywords, it becomes evident that greater attention should be directed towards the extraction of keywords from lengthy textual content. Furthermore, the existing automated systems for rumor detection primarily aim to render a conclusive verdict on whether the provided information qualifies as a rumor or not. Instead, this process should also prioritize the presentation of substantiating evidence as to the origins of the rumor, with the ultimate objective of preventing the dissemination of false information in future instances. Rumors have the potential to propagate through diverse media formats encompassing text, images, audio, and video, thus necessitating a multimodal approach that incorporates words as components of this multifaceted media landscape.

6. REFERENCES

[1] Cao,Juanetal.(2018).“AutomaticRumorDetectionon Microblogs: A Survey.” arXiv preprint arXiv:1807.03505.

[2] Nipah Virus, https://mumbaimirror.indiatimes.com/news/india/nipah-virus/

[3] BMRCL,https://timesofindia.indiatimes.com/

[4] Zubiaga,Arkaitzetal.(2018).“Detectionand Resolution of Rumours in Social Media: A Survey.” ACM Computing Surveys (CSUR) 51(2): 32.

[5] Kwon,Sejeongetal.(2013).“Prominent Features of Rumor Propagation in Online Social Media.” In2013 IEEE 13th International Conference on Data Mining, 1103–8.

[6] Boididou, Christinaetal.(2014).“Challenges of Computational Verification in Social Multimedia.” In Proceedingsofthe23rdInternationalConferenceonWorld Wide Web, 743–48.

[7] Ma,Jingetal.(2016).“Detecting Rumors from Microblogs with Recurrent Neural Networks.” In Ijcai, 3818–24.

[8] Castillo,Carlos,MarceloMendoza,andBarbaraPoblete. (2011). “Information Credibility on Twitter.” InProceedingsofthe20th International Conferenceon World Wide Web, 675–84.

[9] Derczynski, Leon etal. (2017).“SemEval-2017 Task8: RumourEval:Determining Rumour Veracity and Support for Rumours.” arXiv preprint arXiv:1704.05972.

[10] Jin,Zhiweietal.(2017).“Multimodal Fusion with Recurrent Neural Networks for Rumor Detection On Microblogs.” InProceedings of the 25th ACM International Conference on Multimedia, 795–816.

[11] Wang,WilliamYang.(2017).“Liar,LiarPantson Fire’: A New Benchmark Dataset for Fake News Detection.”arXivpreprintarXiv:1705.00648.

[12] Ma,Jing,WeiGao,andKam-FaiWong.(2018). “Detect Rumor and Stance Jointly by Neural Multi-TaskLearning.”InCompanionoftheTheWebConference 2018 on The Web Conference 2018, 585–93.

[13] Yang,Fan,YangLiu,XiaohuiYu,andMinYang. (2012). “Automatic Detection of Rumor on Sina Weibo.”In Proceedings of the ACM SIGKDD Workshop on Mining Data Semantics, 13.

[14] Greenhill,KellyM,andBenOppenheim.(2017). “Rumor Has It: The Adoption of Unverified InformationinConflictZones.”InternationalStudies Quarterly 61(3): 660–76

[15] Dayani,Raveena,NikitaChhabra,TarunaKadian,and RishabhKaushal. (2015). “Rumor Detection in Twitter:AnAnalysisinRetrospect.”In2015IEEE International Conference on Advanced Networks and Teecommuncations Systems (ANTS), 1–3.

[16] Alzanin,SamahM,andAqilMAzmi.(2018).“Detecting Rumors in Social Media: A Survey.” Procediacomputerscience142:294–300.

[17] Hamidian, Sardar, and Mona T Diab. (2015). “Rumor Detection and Classification for Twitter Data.” InProceedingsoftheFifthInternationalConferenceon Social Media Technologies, Communication, andInformatics(SOTICS),71–77.

[18] Hall,Marketal.(2009).“TheWEKA DataMining Software: An Update.” ACM SIGKDD explorations newsletter 11(1): 10–18.

[19] Kwon,Sejeong,MeeyoungCha,andKyominJung. 2017. “Rumor Detection over Varying Time Windows.”PloSone12(1):e0168344

[20] Takahashi,Tetsuro,andNobuyukiIgata.(2012). “Rumor Detection on Twitter.” In The 6th InternationalConferenceonSoftComputingandIntelligent Systems, and The 13th International Symposium on Advanced Intelligence Systems, 452–57.

[21] Chang,Cheng,YihongZhang,ClaudiaSzabo,and Quan Z Sheng. (2016). “Extreme User and Political Rumor Detection on Twitter.” In International Conference on Advanced Data Mining and Applications, 751–63.

[22] Jain,Suchita,VanyaSharma,andRishabhKaushal. (2016). “Towards Automated Real-Time DetectionofMisinformationonTwitter.”In2016International Conference on Advances in Computing, Communications and Informatics (ICACCI), 2015–20.

[23] Chen, Weiling, Chai Kiat Yeo, Chiew Tong Lau, and Bu Sung Lee. (2016). “Behavior Deviation: An Anomaly Detection View of Rumor Preemption.” In 2016 IEEE 7th Annual Information Technology,ElectronicsandMobileCommunicationConference (IEMCON), , 1–7.

[24] Pathak, Ajeet Ram, ManjushaPandey, and SiddharthRautaray. (2018). “Application of DeepLearningforObjectDetection.”ProcediaComput.Sci132: 1706–17.

[25] Ma, Jing, Wei Gao, and Kam-Fai Wong. (2018). “Rumor Detection on Twitter with Tree-Structured Recursive Neural Networks.” In Proceedings of the 56th Annual Meeting of the Association forComputationalLinguistics(Volume1:LongPapers),1980– 89.

[26] Ruchansky, Natali, SungyongSeo, and Yan Liu. (2017). “Csi: A Hybrid Deep Model for Fake News

Detection.”InProceedingsofthe2017ACMonConference on Information and Knowledge Management,797–806

[27] Yu,Fengetal.(2017).“AConvolutionalApproachfor Misinformation Identification.”

[28] Wang,Yaqingetal.(2018).“Eann:EventAdversarial Neural Networks for Multi-Modal Fake News Detection.”In Proceedings of the 24th ACM SIGKDD Detection.” In 2015 12th Web Information System and Application Conference (WISA), 53–58.

[29] Wang, Shihan, and Takao Terano. (2015). “Detecting Rumor Patterns in Streaming Social Media.” In 2015 IEEE International Conference on Big Data (Big Data), 2709–15.

[30] Wu,Ke,SongYang,andKennyQZhu.(2015).“False Rumors Detection on SinaWeibo by Propagation Structures.”In 2015 IEEE 31st International Conference on Data Engineering, 651–62.

[31] Granik, Mykhailo, and VolodymyrMesyura. (2017). “Fake News Detection Using Naive BayesClassifier.”In2017IEEEFirstUkraineConferenceon Electrical and Computer Engineering (UKRCON),900–903.

[32] InternationalConferenceonKnowledgeDiscovery & Data Mining, 849–57.

[33] Cai, Guoyong, HaoWu, andRuiLv. (2014). “Rumors Detection in Chinese via Crowd Responses.” In Proceedingsofthe2014IEEE/ACMInternationalConference on Advances in Social Networks AnalysisandMining,912–17.

[34] Liu,Yang,andSonghuaXu.(2016).“Detecting Rumors through Modeling Information PropagationNetworksinaSocialMediaEnvironment.”IEEE Transactions on computational social systems 3(2):46–62.

[35] Chen,Weilingetal.(2018).“UnsupervisedRumor Detection Based on Users’ Behaviors Using NeuralNetworks.”PatternRecognitionLetters105: 226–33.

[36] Ajao, Oluwaseun, DeepayanBhowmik, and ShahrzadZargari. (2018). “Fake News Identification onTwitterwithHybridCnnandRnnModels.”InProceedings of the 9th International Conference on SocialMediaandSociety,226–30.

[37] Thota,Aswini,PriyankaTilak,SimratAhluwalia,and NibratLohia. (2018). “Fake News Detection: ADeepLearningApproach.”SMUDataScienceReview1(3) : 10.

[38] Boididou,Christinaetal.(2015).“Verifying Multimedia Use at MediaEval 2015.” In MediaEval,.

[39] Yang,Fan,YangLiu,XiaohuiYu,andMinYang. (2012). “Automatic Detection of Rumor on Sina Weibo.”In Proceedings of the ACM SIGKDD Workshop on Mining Data Semantics, 13.

[40] Jin, Fang et al. (2013). “Epidemiological Modeling of News and Rumors on Twitter.” In Proceedingsofthe7thWorkshoponSocialNetworkMininga nd Analysis, 8.

[41] Kwon, Sejeong et al. (2013). “Prominent Features of Rumor Propagation in Online Social Media.” In2013 IEEE 13th International Conference on Data Mining, 1103–8.

[42] Wang,De.(2014).“AnalysisandDetectionofLow Quality Information in Social Networks.” In 2014 IEEE30thInternationalConferenceonDataEngineering Workshops, 350–54.

[43] Liu,Xiaomoetal.(2015).“Real-TimeRumor Debunking on Twitter.” In Proceedings of the 24th ACM Internationalon Conference on Information and Knowledge Management, 1867–70.

[44] Yang,Zhifanetal.(2015).“EmergingRumor Identification for Social Media with Hot Topic.

[45] Sharma, T., Prasad, S.K. Enhancing cybersecurity in IoT networks: SLSTM-WCO algorithm for anomaly detection. Peer-to-Peer Netw. Appl. 17, 2237–2258(2024). https://doi.org/10.1007/s12083-024-01712-z

[46] Sharma, T., Pal, A., Kaushik A., Yadav, A., Chitragupt, A., A Survey on Flood Prediction Analysis Based on ML Algorithm using Data Science Methodology 2022 IEEE Delhi Section Conference, DELCON 2022.

[47] Sharma, T., Prasad, S.K., Sharma, V., Research Challenges of Block chain in 6G Network ,2022 IEEE Delhi Section Conference, DELCON 2022.

[48] Prasad, S.K., Sharma, T., Performance Comparison of Multipath routing Protocols for Mobile Ad hoc Network International Journal of Systems, Control and Communications, 2022, 13,(1), pp.82-98.

[49] Sharma, T., Kumar, V., Congestion Aware Link Cost Routing for MANETS, International Journal of Computer Networks and Communications, 2016, 8(3), pp.167-179.