International Journal of Computer Science and Information Technology
ISSN: 3005-9682 (Print), ISSN: 3005-7140 (Online) | Volume 3, Number 1, Year 2024
DOI: https://doi.org/10.62051/ijcsit.v3n1.12
Journal homepage: https://wepub.org/index.php/IJCSIT/index

# A Review of Research on Social Network Event Detection Methods

Tianqi Chen

School of Information Engineering, Henan University of Science and Technology, Luoyang 471000, China

## ABSTRACT

In recent years, with the development of technological infrastructure and the use of tech products, internet usage has become widespread globally. Significant advancements have been made in the use of social networks, which are now more readily accessible through Internet and Web 3.0 technologies such as Facebook, Twitter, and Instagram. Consequently, over the past decade, numerous researchers have been developing methods for event detection based on data collected from social media platforms. The methodologies devised for discovering events are typically modular in design and novel in terms of scale and speed. To review the research in this field, we have compiled existing works on social network event detection and conducted a comprehensive and in-depth survey. Methods for social network event detection are elaborated and categorized, with performance evaluations conducted using relevant metrics. Finally, we offer perspectives on future directions.

## KEYWORDS

Social Networks; Information Dissemination; Event Detection

## 1. INTRODUCTION

With the rapid development of the Internet has fundamentally changed significant aspects of our economic and social lives. Social networking platforms such as Instagram, Twitter, and Facebook play a crucial role in disseminating real-time information. These platforms act as real-time for social trends and events [1]. A recent report demonstrated that most real-world events are first reported and spread through these social media platforms rather than traditional media like newspapers or television. Social networks have reshaped the ways people communicate and interact, allowing them to express their opinions and share news and information about ongoing events. Their expressions, discussions, and comments cover various topics, including politics, economics, and entertainment [2]. Conversely, social networks also influence real-world events. For instance, during periods of political and social unrest, millions of people turn to social networks to update and follow major events. The rapid spread of radical statements on Twitter regarding Tunisia's oppressive regime and low living standards eventually led to a national revolution known as the "Arab Spring." Additionally, the 2015 Japanese nuclear crisis resulted in a salt shortage in China due to rumors that iodine in salt could prevent related diseases.

Given the significant role of social network platforms in society, many users post about events on social media [3]. Therefore, detecting events from online social networks like Twitter and Facebook has become essential in social media research. As the name suggests, event detection is a method of identifying events from information posted on social media, such as posts, comments, and shares. It enables people to learn about emergencies faster than traditional media and sometimes discover previously unnoticed events. The first work by Allan et al. [4] developed a new research direction called TDT (Topic Detection and Tracking). In 2002, Kleinberg developed a formal method for modeling burstiness in email data to detect events. In this review, we categorize the event detection methods used in this field into three parts: (1) using burstiness features to identify specific keywords and detect events from them; (2) using social network features such as temporal characteristics, location features, and user interactions to detect events from social networks; (3) using text features of tweets or posts to discover and track events.

Currently, research on event detection has two main shortcomings: first, the definition of events is not clear enough; second, different event detection methods are used for different data types and real-world scenarios, but no relevant literature has provided a detailed summary and analysis of these methods.

In response, this paper defines events, highlighting their connection and distinction from topics, further analyzes various event detection methods, and discusses future development directions.

## 2. DEFINITION OF EVENTS

Events in social media generally refer to significant occurrences in the real world, with data types primarily consisting of text. According to the elements that constitute an event, Tong Wei et al. define an event as something that happens at a specific time and place. Events can be further categorized into new events (New Event Detection, NED) and existing events based on whether they have occurred before. Huang Ying et al. define new event detection as "the first report on a topic in a chronological news stream, that is, identifying new topics."

Most current research does not clearly distinguish between topics and events, with the concepts often used interchangeably [5]. However, some perspectives argue that events and topics are not the same, with topics having a broader scope. Additionally, some articles suggest that an event may encompass multiple topics due to different angles involved in the event's development.

Given the numerous methods for categorizing events and the lack of clear distinctions among events, topics, and reports, this paper rigorously defines the concepts of event, report, and topic, and elaborates on their interrelationships. Generally, an event comprises four main elements: time, place, person or organization, and action. A report, on the other hand, is a description of an event, which can vary across different media outlets but revolves around the same event, invariably including certain objective information such as time, place, actors, and actions.Topics can be further subdivided into single-event topics, series-event topics, and similar-event topics. A single-event topic pertains to a specific event and includes the event itself, related discussions, and its evolution, often equating to the event itself. A series-event topic encompasses a chain of related events, such as various competitions within the Olympics, all revolving around the central topic of the Olympics. Similar-event topics are composed of similar but unrelated events.

## 3. EVENT DETECTION METHOD CLASSIFICATION

In this section, we review the most advanced event detection work from 2011 to 2021. This survey is based on 25 core papers that use different methods to detect events on social media. From the collected papers, we extracted the references and the citations of these papers. To analyze this in depth, we first categorized the event detection methods based on the features used by each method, as shown in Figure 1. These include burstiness features, social network tweet features, and text features. Then, we describe them in two parts: (1) how they perform event detection; (2) the specific methods used in each paper. Our survey includes 25 core papers, which we compare across five dimensions.

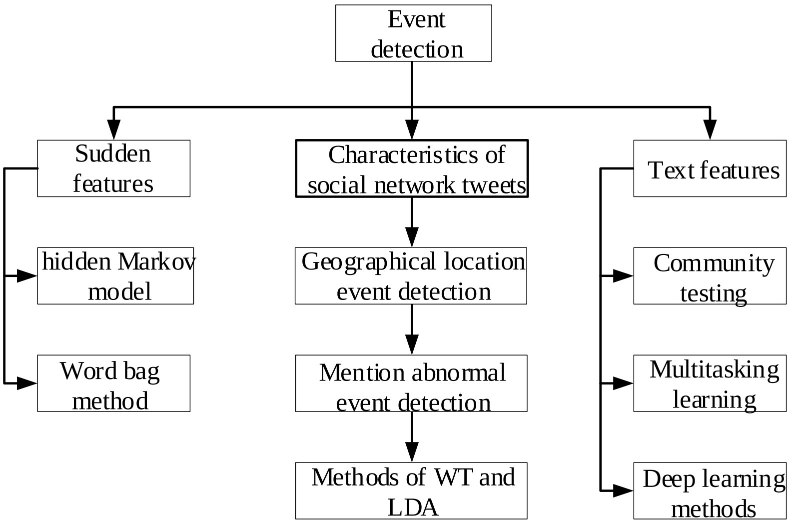


**Figure 1.** Classification of Event Detection Methods

## 3.1. Sudden Features

### 3.1.1. A Method Based on Probabilistic Hidden Markov Hybrid Model

Previous TDT work focused almost exclusively on events and topics detected within a single text stream. However, literature [6] points out that multiple text streams indexed by the same timestamp often cover the same event over a period. Therefore, they proposed a general probabilistic algorithm to align text samples from different streams based on shared time points and use a mixed model to simultaneously discover topics from multiple streams. This method relies on the correlation between the temporal distributions of topics to match topics from different streams. To discover topics from coordinated text streams, they designed a mixed model, which is an extension of Probabilistic Latent Semantic Analysis (PLSA) [7]. They segmented all text streams into equal-length segments based on timestamps. By fitting the mixed model to all text samples at each time point, they obtained the probability distribution of each word, which could be considered as discovered topics. Additionally, they incorporated local dependency parameters into the mixed model to detect topics over continuous time. They also implemented a mutually reinforcing approach to reduce background noise and improve the quality of identified relevant burst patterns.

Literature [8] developed a method for modeling burstiness features. They used an infinite automaton to model text streams. The lower states of the automaton represented lower text arrival rates, while the higher states represented faster rates. Thus, burst events in the text stream could be modeled as transitions from lower to higher states, as the automaton's states vary, potentially existing in any state set at each time point. If each automaton is considered a message sender, its state determines the rate at which messages are sent. This method, based on the Hidden Markov Model, provides a framework for burst detection in text stream analysis. In this paper, they assumed that messages were sent by automatons based on a probabilistic model with multiple states corresponding to different rates. The message sending rate depended on the current state, and to control the frequency of state transitions, they added a transition cost (i.e., the cost of changing from a lower to a higher state) to the cost function. Therefore, short bursts of state transitions were not considered, making it easier to identify long bursts rather than simple state changes.

However, these studies did not compare their methods with any other baselines. They only analyzed the results of coordinated topics detected in news and other datasets. Furthermore, the burst topics discovered in news streams have certain limitations in cross-language information retrieval and integration methods.

### 3.1.2. A bag based method

This category of methods primarily uses the TF-IDF metric to extract the final topics related to burst events, while ignoring other features of the sentence, such as part-of-speech tags. Term Frequency-Inverse Document Frequency (TF-IDF) is a common metric in most topic detection or extraction methods and is described by equations (1) and (2). In these equations, $t$ and $d$ refer to the term and document respectively. In the latter case, the document can be assumed to be a single document containing multiple tweets, which may consist of several tweets or just one tweet. Additionally, *count (t in d)* represents the count of term $t$ occurrences in document message $d$, while *count (d has t)* denotes the count of documents messages where $t$ appears at least once.

Literature [9] uses TF-IDF with a similarity metric to compare two individual tweets. The similarity metric described in equation (3) is used as a scoring function to group new messages. Messages not belonging to any group are considered new groups, and these new groups are populated in the order of the new message classification according to the scoring function. To avoid including irrelevant messages in a group, all messages are compared with the first message and the top k messages in the group.

$$tf\left(t,d\right)=\frac{count\left(t,in\ d\right)}{size\left(d\right)} \tag{1}$$

$$idf\left(t\right)=1+\log\frac{N}{count\left(d\ \ has\ t\right)} \tag{2}$$

$$similarity\left(d_1,d_2\right)=\sum_{t\in d_1} tf\left(t,d_2\right)\times idf\left(t\right)\times boost\left(t\right) \tag{3}$$

The BNgram model introduced in reference [10], together with sentiment classification and part of speech tagging, forms a trend topic detection system. The BNgram model in this study is similar to literature, but the difference is small, with the difference being the boosting factor. If the factor is set to 1.5, the n-gram model contains named entities; otherwise, it is a small number and the corresponding model does not contain named entities. Based on n-gram TF-IDF, rate all tweets and then cluster them into their respective clusters based on these ratings. At each time step, comparing tweets related to time windows with previously published tweets seems to be a simpler implementation method compared to frequent pattern mining algorithms, and in some cases, it achieves good results in outputting topics. In addition to the term frequency inverse document frequency (TF-IDF), there are also methods worth discussing, such as composite component method (CCA) and dual term topic model (BTM), LSH (locally sensitive hashing), Word DFT (discrete Fourier transform), etc.

## 3.2. Characteristics of Social Network Tweets

### 3.2.1. Event detection method based on geographic location

The geographic location of events provides additional insights into the detected events. Literature [5] proposes a spatio-temporal event detection method that detects events along with their occurrence time and geographic location. The first step in this work includes feature extraction and relevance ranking. The relevance ranking step ranks tweets based on their relevance to the event in terms of textual and spatial similarity. These ranked features are then used by a tweet classifier, which is based on a support vector machine. The final step of this method is to estimate the actual location of the classified tweets.

Literature [11] presents another spatio-temporal event detection system with three main stages: detecting new events, ranking events based on their importance, and generating spatial and temporal patterns of the detected and highest-ranked events. This system is built using Java, PHP, and MySQL, and it utilizes the Twitter API and Google Maps to produce user-friendly outputs. The system is constrained to tweets related to crimes and disasters. The Twitter API is used in a query-based manner to retrieve tweets. A set of query rules is required, so some simple rules are used to retrieve tweets, which are then used to populate these rules. Features related to crime or disaster tweets help classify the retrieved tweets, and the classifier achieves an accuracy of 80%, as noted by the authors. The final stage of this method uses content, user, and usage-related features to rank the detected events, while the previous stage focuses on estimating the user's location. The first assumption is that the user's location is in their GPS-tagged tweets (if available). If not, their friends are more likely to be nearby. The last assumption is that their location is mentioned at least once in their tweets. A major issue with this location estimation is that the extracted information may be incorrect in the second and third assumptions.

Literature [12] presents an early detection method for emerging events in social networks with location sensitivity. The method considers the places mentioned in messages to determine the location of events and establishes a strong correlation between user location and event location when detecting emerging events. Literature introduces a new method called WhatUp to detect location and fine-grained textual events. It uses self-learning word embeddings to capture linguistic features and hierarchical relationships and statistical data based on frequency measurements. Although these methods can effectively detect events related to different user locations, the performance of current methods is affected by the diversity of social network users and the random public real-time text information on various topics, with metadata often being ambiguous.

### 3.2.2. Event detection method based on mentioning anomalies

Despite the extensive work on event detection and tracking, the vast majority of research focuses on the textual content within social networks. It overlooks the social aspects of social media posts. Mentions on Twitter are dynamically created links intended to engage in discussions with specific users or are automatically created when replying to or retweeting someone. Therefore, literature [13] proposes an event detection method called MABED (Mention Anomaly-Based Event Detection), which pays particular attention to mention behaviors of Twitter users. It relies on three main components. First, MABED analyzes the mention frequency of each word to determine the timing of events and estimate their impact. MABED applies a normal distribution model to the probability of words that appear in tweets with at least one mention. Hence, they define an anomaly function for the mention creation frequency related to word t in time slice $i$ : $anomaly(t,i) = N_t^i - E[t \mid i]$, where $E[t \mid i]$ is the expected value of the normal distribution. Correspondingly, the impact of an event is measured by the integral of the anomaly function.

Literature [14] uses a proposed correlation coefficient to select the most relevant words to describe events based on the similarity between candidate words and main words. Finally, MABED employs two graph structures (i.e., topic graph and redundancy graph) to identify and merge duplicate events. Even in the noisy Twitter content, MABED demonstrates greater accuracy and robustness in event detection.

User-driven short tweets sometimes contain very important information about real-world events, which users post before news media websites and television and radio channels. These short but important pieces of information are unknown and potentially anomalous to event detection systems, as they are not predefined. Enhancing Twitter timing and signal patterns can reveal this fact. For example, a sudden and unexpected increase in the use of a keyword or hashtag may indicate a sudden interest in that topic and reveal real-world events in some way. Due to this setup, ambiguity arises when frequently used hashtags and keywords in daily activity tweets are detected as unseen new events. An effective unspecified event detection algorithm must handle such ambiguity. Literature [15] proposes an event detection system called TwitterMonitor, which identifies emerging topics on Twitter in real-time and provides intentional analytical information that can further be used to extract topics of detected events. StreamListener monitors the Twitter API data stream and detects bursty keywords, then groups these keywords and passes them with an index to the trend analysis module, further identifying anomalies related to events.

### 3.2.3. A Combination Method Based on WT and LDA

Literature [16] propose a continuous wavelet transform based on tag appearances combined with topic model inference using Latent Dirichlet Allocation (LDA). Tags are used to construct wavelet signals instead of individual words, with a sudden increase in tag appearance considered a good indicator of an event occurring at a given time. In this study, tag signals over time are constructed by counting tag mentions in each interval. Due to the noisy nature of tweets, a Kolmogorov-Zurbenko adaptive filter is used to preprocess the signals and remove noise. The continuous wavelet transform is then employed to construct the time-frequency representation of the signal. Wavelet peak analysis and local maxima detection techniques are applied to detect peaks and changes in the tag signal. Finally, when an event is detected within a given time interval, LDA is applied to all tweets associated with the tag in that time series to extract a set of latent topics. Although a list of detected events and related topics is provided, the accuracy or recall rate of this method is not evaluated.

With the rapid development of social media, event detection research has increasingly focused on detecting events from user-generated content (UGC) rather than news stories. Literature [17] proposes a method to detect social events from Flickr photos by leveraging user-provided tags to annotate photos. This method follows the work of literature, which was the first attempt to extract location and event semantics from tags. Literature introduces a method called Scale-Structure Identification (SI) to extract patterns from tag usage. However, SI only considers the temporal distribution of tag usage. To extend this method, literature [18] considers both the temporal and geospatial distribution of tag appearances.Moreover, they apply wavelet transformation to suppress noise in user-annotated tag data and provide a multi-resolution analysis of tag usage distribution.

Subsequently, literature [19] presents a novel event detection evolution model to capture the dynamic and evolving behavior of events. The proposed method employs matrix decomposition techniques and LDA to detect events and handle dynamics. The model consists of two main parts: preliminary event detection and event evolution tracking. Preliminary event detection uses matrix decomposition methods to extract initial events from available data. Then, subsequent data is introduced into a non-parametric Bayesian network, specifically a Dirichlet process mixture model, to evolve the initial events. During the evolution process, data can migrate between extracted events or new events can be discovered.Literature proposes a new event-based meta-pattern to characterize the semantic relevance of social events, constructing an event-based heterogeneous information network (HIN) that integrates information from external knowledge bases. Additionally, a new Dirichlet Graph Convolutional Network, called LDA-GCN, is introduced. It uses weighted meta-path instance similarity and textual semantic representation as input to perform fine-grained social event classification and learn the optimal weights of meta-paths for different tasks.

## 3.3. Text Features

### 3.3.1. Community based detection methods

This event detection method is based on graph coverage constructed from the co-occurrence of words in documents. Literature [20] assumes that when there is a thematic relationship between documents, keywords will co-occur. A modularity-based graph partitioning technique is used on the keyword graph to detect and describe events by dividing the graph into subgraphs, each corresponding to an event. They first extracted three types of terms: keywords, noun phrases, and named entities (persons, places, organizations, and monetary amounts). Then, they constructed a graph called KeyGraph using the extracted terms [21]. For each keyword, they calculated term frequency (TF), document frequency (DF), and inverse document frequency (IDF). Consequently, edges between nodes were added after removing keywords with high document frequency. Since nodes within each community are highly connected and there are fewer links between nodes from different thematic communities, they applied community detection on KeyGraph. Community detection techniques remove edges with high betweenness centrality scores until communities are isolated. Keyword communities can be viewed as synthetic documents, and thus, they used cosine similarity to find the original documents representing events.

Event prediction is crucial in social network analysis for studying community evolution patterns. Machine learning (ML) models are typically used to predict events within communities. Researchers have used generative adversarial network (GAN) models to generate realistic sample data to enhance event prediction. Literature [22] proposed an improved GAN model called Generative Adversarial Network Classifier (GAN-C), which includes an additional classifier layer to generate different feature maps. The weights are dynamically adjusted based on the conditions of the predicted events. Specifically, using the entropy values of features to adjust the weights in the classifier layer is a simple method to minimize the classifier loss function. The GAN-C model resulted in up to a 16% loss in up to 10 batches, after which the loss became negligible, allowing the generation of non-overlapping events.

Literature [23] focuses on the problem of detecting communities with internal connections in event-based social networks (EBSN) and proposes a method for community detection using social influence among users. EBSNs include different types of entities and links, and users exhibit more complex behaviors. This method addresses the poor performance of traditional social influence algorithms in EBSNs. To accurately quantify pairwise social influence in EBSNs, literature proposes calculating two types of social influence using users' online social network structure and offline social behavior: structure-based social influence and behavior-based social influence. Specifically, based on the characteristics of EBSNs, behavior-based social influence is measured using user preference similarity in three aspects: topics, regions, and organizers. Then, a weight function combines these two types of social influence to obtain a unified social influence. Literature [24] introduces a community detection algorithm based on social influence called SICD. Inspired by the nonlinear feature learning capability of autoencoders, researchers first designed a deep autoencoder algorithm for neighborhoods to obtain users' latent representations oriented towards nonlinear communities, and then used the K-Means algorithm for community detection, significantly improving the algorithm's effectiveness.

### 3.3.2. A method based on multi task learning

Multi-task learning (MTL) methods are used to train on different datasets from multiple related tasks to improve generalization performance. Literature [25] proposes an MTL approach where all tasks are constrained to be close to each other. MTL can also be achieved by sharing a common underlying structure among multiple constrained tasks. These structures can be a set of features, subspaces, or tree-structured models. MTL methods have been applied in fields such as computer vision and biomedical informatics. Consequently, literature [26] proposes a graph-guided multi-task learning method for event detection, assuming two characteristics of event detection. The first characteristic is that some events are more closely related to each other but differ from other events. The second characteristic is that similar events tend to have the same or similar features. Based on these two assumptions an integrated learning framework that utilizes the content information of Weibo texts and captures the relationships between events. They extend traditional non-parametric statistics a new class of scan statistical functions to measure the joint significance of evolving subgraphs and attribute subsets in dynamic multi-dimensional networks, indicating ongoing or upcoming events. Each scan statistical function is then reformulated as a series of subproblems with provable guarantees. Literature [27] proposes two efficient methods based on higher-order network models, namely the recovery high-order network algorithm and the innovation high-order network method, to assist in event detection across different tasks over time in social networks. Given binary sequence data, the multivariate sequence data are first recovered using temporal order, and new multivariate sequence data are developed using logical sequences. By effectively modeling the multivariate sequence data with higher-order network models, common multivariate interaction patterns are obtained to determine the anomaly level of social text events.

Literature [28] uses an entropy-based event task detection framework to identify events and their locations by clustering documents with relatively high density using text data. An entropy maximization inference model is employed to estimate the Shannon entropy of target users, locations, time intervals, and tags, quantifying the spread of events as propagation distance in the real world. Geotagged tweets within a specified time frame are extracted to identify the "when and where" of events and visualize them on a geographic map. Evaluation parameters such as event entropy, clustering score, event detection hit rate, and false alarm rate are determined to demonstrate the effectiveness of the proposed framework.

### 3.3.3. Deep learning based methods

In many applications, such as text classification, information retrieval, and event discovery, feature representation is a critical issue. Traditional feature selection methods, including term frequency, MI, PLSA, and LDA, are used to generate more distinctive features [29]. However, these methods overlook the contextual information or word order in the text . Recently, the rapid development of deep neural networks and the widespread application of word embeddings have provided new potential for various NLP tasks, particularly for text processing in TDT. Literature proposes several deep learning methods using embedding techniques like word2vec to learn word representations, capturing meaningful semantic information in the text. Recurrent neural networks (RNNs) have the advantage of capturing contextual information, but they suffer from a bias where later inputs dominate earlier ones. Conversely, convolutional neural networks (CNNs) can reasonably extract key words from documents using max pooling, making them unbiased. However, the fixed window size of convolutional kernels may limit their performance. Therefore, by combining the advantages of recurrent models and max pooling layers, applying recurrence in this structure to capture as much contextual information from tweets as possible when learning word representations.

Literature [30] integrates syntactic representations of sentences into a graph neural network (GNN) for event detection. Additionally, an entity mention-based pooling method is used to provide specific information about the words mentioning entities. This method involves three steps: first, a BIO-based named entity recognition method is used to assign an entity type label to each word in the sentence and identify dependencies between words. Then, an encoding module represents the input sentence as a matrix. After word embedding, a convolution module performs convolution operations on each word token based on the dependency graph. Finally, entity mention positions are applied to the pooling module to aggregate convolution vectors. Literature First, various types of events are prepared as a training dataset, and a semantically similar sentence tree is constructed using the BERT representation system. Then, event detection is achieved by loading sentence pairs to facilitate the representation of event pairs. Proposes a new event detection method, called Cascaded Context R-CNN [31], based on classic convolutional neural networks. By using a cascaded region-based dense connection network to detect events, they compare the proposed Cascaded Context R-CNN method with traditional template matching methods, showing that R-CNN can achieve better generalization performance during parameter updates.

## 4. FUTURE RESEARCH DIRECTIONS

(1) Co-evolution of Information Dissemination and Social Networks: The impact of changes in the structure of online social networks on existing dissemination models requires further exploration. In fact, social network structures are not static but dynamically evolving. Myers et al. [32] studied the

dynamic relationship between user posting and retweeting behaviors and the network structure in the Twitter network. They found that information cascades in the network significantly alter the local structure of users (i.e., friend relationships) and exhibit burstiness. Existing dissemination models have not accounted for the temporal changes in network structure. Therefore, designing new dissemination models to capture the evolving nature of social networks is a valuable research topic.

(2) Breaking the Closed World Assumption: A widely accepted assumption in current research on information dissemination in social networks is the closed world assumption: a social network is considered a closed world where information spreads only along the edges within the network, and nodes are not influenced by the external environment. However, Myers et al. [33] observed that information can jump across the network and pointed out that 29% of information dissemination in the Twitter network is influenced by external factors. Quantitative analysis of the impact of external factors on information dissemination within social networks, and subsequently improving the detection of emerging topics, remains an area for in-depth research.

(3) Multi-Source Information Dissemination: Current research on information dissemination in social networks primarily considers the spread of information from a single source. However, in practice, the dissemination process of messages within a topic often results from the combined effects of multiple sources [34]. There is both competition and cooperation among these multiple sources. A better understanding and modeling of multi-source information dissemination can enhance the accuracy of identifying key nodes in the network and predicting the reach of message dissemination.

## 5. CONCLUSION

In this paper, we review event detection methods in social networks over the past decade. First, we introduce the basic concepts of event detection. Next, we categorize the current event detection methods into three main types and provide a comprehensive analysis of the strengths and weaknesses of each method. Finally, we summarize three unresolved issues in the field and analyze the challenges and developments associated with each. In summary, event detection is a crucial research area in data mining in the era of big data, with many key issues that require in-depth and detailed research in the future.

## REFERENCES


[1] Zhou S, Ng S T, Huang G, et al. Extracting interrelated information from road-related social media data [J]. Advanced Engineering Informatics, 2022, 54: 101780.

[2] Zhang W, Zhong T, Li C, et al. CausalRD: A Causal View of Rumor Detection via Eliminating Popularity and Conformity Biases [C]//IEEE INFOCOM 2022-IEEE Conference on Computer Communications. IEEE, 2018: 1369-1378.

[3] Zervopoulos A, Alvanou A G, Bezas K, et al. Deep learning for fake news detection on Twitter regarding the 2019 Hong Kong protests [J]. Neural Computing and Applications, 2022, 34(2): 969-982.

[4] Allan H, Gao Q, Li H, et al. A structural evolution-based anomaly detection method for generalized evolving social networks [J]. The Computer Journal, 2022, 65(5): 1189-1199.

[5] Wang B, Yang C, Chen Y. Detection Anomaly in Video Based on Deep Support Vector Data Description [J]. Computational Intelligence and Neuroscience, 2022, 2012.

[6] Selvi E, Adimoolam M, Karthi G, et al. Suspicious Actions Detection System Using Enhanced CNN and Surveillance Video [J]. Electronics, 2020, 11(24): 4210.

[7] Xia R, Xuan K, Yu J. A state-independent and time-evolving network for early rumor detection in social media [C]//Proceedings of the 2020 conference on empirical methods in natural language processing (EMNLP). 2020: 9042-9051.

[8] Xu K, Zou K, Huang Y, et al. Mining community and inferring friendship in mobile social networks [J]. Neurocomputing, 2016, 174: 605-616.

[9] Sun X, Wu Y, Liu L, et al. Efficient event detection in social media data streams [C]//2015 IEEE International Conference on Computer and Information Technology; Ubiquitous Computing and Communications; Dependable, Autonomic and Secure Computing; Pervasive Intelligence and Computing. IEEE, 2015: 1711-1717.

[10] Chen G, Kong Q, Mao W. Online event detection and tracking in social media based on neural similarity metric learning [C]//2017 IEEE International Conference on Intelligence and Security Informatics (ISI). IEEE, 2017: 182-184.

[11] Cadena J, Chen F, Vullikanti A. Graph anomaly detection based on Steiner connectivity and density [J]. Proceedings of the IEEE, 2018, 106(5): 829-845.

[12] Dionísio N, Alves F, Ferreira P M, et al. Towards end-to-end cyberthreat detection from Twitter using multi-task learning [C]//2020 International Joint Conference on Neural Networks (IJCNN). IEEE, 2020: 1-8.

[13] Gao K, Xu H, Wang J. A rule-based approach to emotion cause detection for Chinese micro-blogs [J]. Expert Systems with Applications, 2015, 42(9): 4517-4528.

[14] Wang H, Gao Q, Li H, et al. A structural evolution-based anomaly detection method for generalized evolving social networks [J]. The Computer Journal, 2022, 65(5): 1189-1199.

[15] Vivek Joe Bharath A, Thirumarimurugan M. Analysis and implementation of certain multivariate statistical process monitoring Tools for fault detection and isolation (FDI) task in a laboratory scale shell-tube heat exchanger [J]. Journal of Intelligent & Fuzzy Systems, 2022, 43(1): 1651-1668.

[16] Bhuvaneswari A, Valliyammai C. Information entropy based event detection during disaster in cyber-social networks [J]. Journal of Intelligent & Fuzzy Systems, 2019, 36(5): 3981-3992.

[17] Aynehband M, Hosseinzadeh M, Zarrabi H, et al. Accuracy and availability modeling of social networks for Internet of Things event detection applications [J]. Wireless Networks, 2019, 25: 4299-4317.

[18] Persia F, Helmer S. A framework for high-level event detection in a social network context via an extension of iseql [C]//2018 IEEE 12th International Conference on Semantic Computing (ICSC). IEEE, 2018: 140-147.

[19] Hu W, Wang H, Qiu Z, et al. An event detection method for social networks based on hybrid link prediction and quantum swarm intelligent [J]. World Wide Web, 2017, 20: 775-795.

[20] Hasni S, Faiz S. Real-time Event localization and detection over social networks using Apache Intelligence [C]//2017 IEEE/ACS 14th International Conference on Computer Systems and Applications (AICCSA). IEEE, 2017: 264-271.

[21] Unankard S, Li X, Sharaf M A. Emerging event detection in social networks with location sensitivity [J]. World Wide Web, 2015, 18: 1393-1417.

[22] Zhu T, Li J, Hu X, et al. The dynamic privacy-preserving mechanisms for online dynamic social networks [J]. IEEE Transactions on Knowledge and Data Engineering, 2020, 34(6): 2962-2974.

[23] Zhou H, Yin H, Zheng H, et al. A survey on multi-modal social event detection [J]. Knowledge-Based Systems, 2020, 195: 105695.

[24] Nguyen T, Grishman R. Graph convolutional networks with argument-aware pooling for event detection [C]//Proceedings of the AAAI Conference on Artificial Intelligence. 2018, 32(1).

[25] Ahmad F, Abbasi A, Kitchens B, et al. Deep learning for adverse event detection from web search [J]. IEEE Transactions on Knowledge and Data Engineering, 2020, 34(6): 2681-2695.

[26] Yuan J. Learning context-aware representation for event detection [C]//2021 17th International Conference on Computational Intelligence and Security (CIS). IEEE, 2021: 600-603.

[27] Miao Y, Chen C, Pan L, et al. Machine learning–based cyber-attacks targeting on controlled information: A survey [J]. ACM Computing Surveys (CSUR), 2021, 54(7): 1-36.

[28] Wu G, Guo Z, Li L, et al. Video Abnormal Event Detection Based on CNN and LSTM [C]//2020 IEEE 5th International Conference on Signal and Image Processing (ICSIP). IEEE, 2020: 334-338.

[29] Shin S, Choi M, Choi J, et al. Stexnmf: Spatio-temporally exclusive topic discovery for anomalous event detection [C]//2017 IEEE International conference on data mining (ICDM). IEEE, 2017: 435-444.

[30] Zeng Y, Feng Y, Ma R, et al. Scale up event extraction learning via automatic training data generation [C]//Proceedings of the AAAI Conference on Artificial Intelligence. 2018, 32(1).

[31] Sun P, Zhang R, Jiang Y, et al. Sparse R-CNN: An end-to-end framework for object detection [J]. IEEE transactions on pattern analysis and machine intelligence, 2023.

[32] Kaur R, Singh S. A comparative analysis of structural graph metrics to identify anomalies in online social networks [J]. Computers & Electrical Engineering, 2021, 57: 294-310.

[33] Yan L, Luo C, Shao R. Discrete log anomaly detection: a novel time-aware graph-based link prediction approach [J]. Information Sciences, 2023, 647: 119576.

[34] Ni W, Sun H. Research on Visual Communication Page Design Theory of Multi-Source Information Fusion Using Deep Web Crawlers [C]//2023 International Conference on Applied Physics and Computing (ICAPC). IEEE, 2023: 455-459.