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Multi-feature, multi-modal, and multi-source social event detection: A comprehensive survey

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ABSTRACT

The tremendous growth of event dissemination over social networks makes it very challenging to accurately discover and track exciting events, as well as their evolution and scope over space and time. People have migrated to social platforms and messaging apps, which represent an opportunity to create a more accurate prediction of social developments by translating event related streams to meaningful insights. However, the huge spread of 'noise' from unverified social media sources makes it difficult to accurately detect and track events. Over the last decade, multiple surveys on event detection from social media have been presented, with the aim of highlighting the different NLP, data management and machine learning techniques used to discover specific types of events, such as social gatherings, natural disasters, and emergencies, among others. However, these surveys focus only on a few dimensions of event detection, such as emphasizing on knowledge discovery form single modality or single social media platform or applied only to one specific language. In this survey paper, we introduce multiple perspectives for event detection in the big social data era. This survey paper thoroughly investigates and summarizes the significant progress in social event detection and visualization techniques, by emphasizing crucial challenges ranging from the management, fusion, and mining of big social data, to the applicability of these methods to different platforms, multiple languages and dialects rather than a single language, and with multiple modalities. The survey also focuses on advanced features required for event extraction, such as spatial and temporal scopes, location inference from multi-modal data (i.e., text or image), and semantic analysis. Application-oriented challenges and opportunities are also discussed. Finally, quantitative and qualitative experimental procedures and results to illustrate the effectiveness and gaps in existing works are presented.

1. Introduction

A substantial portion of the world's population is actively engaged in Online Social Networks (OSN). In the last two decades, social networks have been transforming the way of life of communities at a global context in every aspect of their civilizational, technological, academic, and economic growth. From a business perspective, social networks represent a great medium for advertising products, boosting company brands, and increasing chances to connect with potential customers. OSNs spread over 200 countries, with over 3.9 billion users worldwide, and average of 8.6 social media accounts per person in 2020.[1] Online social networks can be categorized based on their unique characteristics, such as professional networking, public conversation, creative networking, and innovation. In 2003, LinkedIn[2] was launched as a professional network. The next year, 2004, Facebook[3] started and nowadays it has around 2.7 billion subscribers who share more than 1 billion stories daily. Instagram[4] was launched in 2010 and it is mostly popular for sharing photos and videos. According to recent statistics in 2021, Instagram has one billion monthly active users sharing over 500 million daily stories. Pinterest[5] was also launched in 2010 as an image sharing social network. On the other hand, Twitter is a microblogging and social networking service that allows users to tag geo-locations, images and videos to their posts. Twitter is considered as a more formal social medium and delivers information with less user interaction than Facebook. Therefore, Twitter data streams can provide immediate insights into ongoing occasions, matters, and emerging topics around

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1 https://backlinko.com/social-media-users.
2 http://linkedin.com/.
3 http://facebook.com.
4 http://instagram.com/.
5 http://pinterest.com/.

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Table 1
Statistical result.

Online SN	Year	Monthly active users	Most active countries in 2021
LinkedIn [1]	Feb. 2021	250 Million	America/India
Facebook [2]	Feb. 2021	2.7 Billion	India
Instagram [3]	Feb. 2021	1 Billion	United States
Pinterest [4]	Feb. 2021	459 Million	United States
Twitter [2]	Feb. 2021	187 Million	United States

the world. A brief analysis from the statistics on social networking apps is depicted in Table 1.

OSNs are increasingly reflecting the vibes of real communities. This fact attracted the interest of researchers in studying and classifying the events on social media networks. Discovering social events over OSNs have been studied by many researchers in the last two decades. From a social media mining perspective, an 'event' can be characterized by the occurrence of an unusual real-world happening at a given space and time. Historically, Web blogs were considered as the early platforms for exchanging information. Later, blogs supported the display of postings, which are shown in reverse chronological order, that could contain links to other comments on a some specific topic. Most of the research on blog mining are based on offline algorithms, where each comment in a blog is tagged with an ID, its textual properties, as well as date and time of publication. On the other hand, a micro-blogging platform, e.g., Twitter, is characterized by a continuous stream of data that contain multimedia content as well as user profiles.

Event detection and tracking from social media should reveal the evolution of a certain social happening over space and time. For example, the spread of COVID-19 pandemic in the world has been tagged as a major event that continues in generating a high volume of postings as soon as the pandemic started spreading. The news related to this large-scale event were posted by users on social media, news and health agencies, as well as public and private organizations all over the world. An event like the COVID-19 can be easily detected due to the large volume of users posting about it. However, extracting and clustering all related subtopics, and disseminating insights and deep analysis on such topics, require a variety of data management and mining techniques. Despite the difficulty in detecting events with small-scale bursts of postings, their significance can be of great benefit to local communities (e.g., incident, traffic jam, strike, etc.). According to [5], social media has better coverage of small-scale, or local, events than traditional news media.

The technological development in several domains including big data management and data stream processing, NLP, and machine learning, has driven major contributions in the research field related to event detection from social media. Event detection techniques should ideally be able to analyze the diverse modes of input data (e.g., text, image, etc.), and define the stages and components required for accurately detecting events from different sources of social media. Multiple surveys have recently covered social event detection from different perspectives. Existing surveys rather focus on single-modality (e.g., text [6] or image [7]), single source (e.g., Twitter [8]), and all of them focused on single-lingual techniques, by considering the English language only. In this survey, we focus on providing a comprehensive survey on event detection techniques in the big social data era. We show the importance of considering the full set of features that contribute to accurately defining an event and extracting its properties, such as the textual, visual, semantic and geographical features. The survey also investigates the effect of multi-modal, multi-source, and multi-lingual content on social event detection, and how cross-platform fusion of features that are very dominant in social media can greatly enhance its visibility. Apart from this, we discuss different set of challenges related to event visualization, large-scale data management, and real-time stream processing, which leverage the development of efficient and incremental event detection,

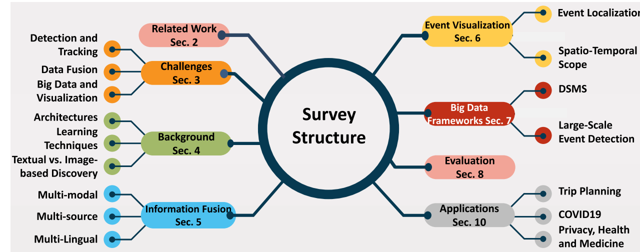

Fig. 1. Survey structure.

and the tracking of their evolution over space and time. To the best of our knowledge, this is the first comprehensive survey to review event detection literature by considering all these perspectives. In particular, the main contributions of this paper are summarized as follows:

1. Examining the open challenges in event detection techniques, information fusion, visualization, and big data design towards an incremental and scalable extraction on a world-wide scale. Moreover, discussing application-oriented challenges and opportunities.
2. Classifying event detection based on the input features, such as the textual, spatial, temporal, and semantic dimensions of an event. Some features can be directly inherited from the stream content or user profile, while others may require complex extraction and fusion techniques.
3. Defining and investigating the event evolution over space and time, which requires implementing an incremental architecture that considers the historical streams to compute the event lifetime and spatial spanning.
4. Conducting a thorough investigation of approaches that employ fusion techniques from multiple data sources, integrate multiple modalities or consider various languages and dialects or language-independent mechanisms.
5. Presenting novel event visualization techniques, with topic-based, spatial and spatio-temporal-based visualizations.
6. Highlighting the need of big data processing tools for event detection. We will also recommend architectures for incremental event detection and tracking over space and time. We believe the scalability and efficiency of such solutions are a key success factor for real-time applications.
7. Conducting a thorough investigation of the performance existing approaches by considering the efficiency and effectiveness of proposed methods.
8. Discussing application domains beyond the discovery of social events from social media and the huge potential of designing event-enriched systems.

To find papers for this survey, we followed a search strategy that consists of three steps. The first step was to conduct a term-based search in the major libraries and search engines, such as IEEE, ACM, Elsevier, Springer, Google Scholar, and ResearchGate. The second step was the crawling-based search, with which we search the papers reviewed by previous surveys about social event detection. In the third step, we applied the inclusion/exclusion criteria to the found papers. The inclusion criteria are: publication year should be from 2010 until 2021, the topic of the paper is in the area of social media event detection, and papers should be written in English. The exclusion criteria are papers that propose detection techniques for non-social media events, and papers with unknown, non-peer reviewed or unclear publication details.

This surveys covers the research studies related event detection from social media sources, and with a focus on data management, fusion, and mining techniques. Other data sources or modalities, such as audio clips

Table 2
Comparison of event detection survey papers.

Reference	Data sources	Detection challenges	Spatial features	Temporal features	Multi-modal	Thematic	Semantic	Data fusion	Multiple platforms	Multi-lingual	Localization	Scalability	Applications	Evaluation
[9]	✓	✓							✓				✓	
[6]	✓		✓										✓	✓
[10]		✓	✓	✓							✓	✓	✓	
[7]	✓	✓			✓				✓					
[11]	✓	✓			✓	✓			✓					
[12]		✓	✓											✓
[13]		✓	✓									✓		✓
[8]		✓	✓	✓		✓								✓
[16]		✓			✓	✓		✓	✓					✓
[15]	✓	✓	✓	✓									✓	
[14]	✓	✓			✓	✓		✓	✓					
This survey	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

and video streaming are out of the scope of this paper. As illustrated in Fig. 1, The rest of the article organized as follows. Section 2 presents related work that depicts existing surveys on social event detection. In Section 3, we discuss the different event detection and tracking challenges. Section 4 overviews the general event detection architecture, and presents the main phases in traditional approaches for event detection. Section 5 presents several dimensions for advanced feature extraction. Section 6 introduces multiple aspects related to information fusion from multiple modalities and multiple media sources. In Section 7, we investigate the visualization techniques for event location and its evolution over space and time. Section 8 depicts the review of existing platforms for big data and streaming processing, as well as large-scale event detection approaches. Then, the performance analysis of existing techniques is explained in Section 9. In Section 10, we unfold the application perspective of event detection in different domains, while Section 11 discusses some possible directions for future research. Finally, Section 12 concludes with the main findings.

2. Related work

The visualization and detection of event-related content from online social networks have been surveyed by a few works, such as, Nurwidyantoro et al. [9], Atefeh et al. [6], Cordeiro et al. [10], Liu et al. [7], Garg et al. [11], Borges et al. [12], Weiler et al. [13], Hasan et al. [8], Yu et al. [14], Liu et al. [15], and Zhou et al. [16] (see Table 2). However, each of these survey paper is focusing on only few aspects of event detection. Nurwidyantoro et al. [9] describe different approaches for detecting disaster, traffic, outbreak, and news by analyzing social media data. But this article does not depict the challenges, future problems, and advanced research areas of detecting events from social media. Atefeh et al. [6] and M. Cordeiro et al. [10] illustrate different event detection techniques to finding occurrences of real-world events that span over time and space from Twitter streams. They also classify event detection techniques based on event type, detection purpose, the methods used, and commonly employed features. They finally highlight some issues and open problems in the event detection in textual data. Moreover, Cordeiro et al. [10] give a clear definition of each organizing content. Apart from this, these papers are not covering the advanced features and new research areas for event detection.

Liu et al. [7] analyze events through detection, and categorization over social media. They also discuss the problem of mining relationships between events and social media data based on time, location, and topic. Moreover, the survey gives an overview of textual analysis, and learn multi-modal fusion. However, they did not discuss the semantic, sentimental, linguistic features. Garg et al. [11] analyzed different clustering and topic modeling approaches for event detection, and recommendation over multi-modal social media. Moreover, they present an overview of event detection approaches, and a comparative analysis of statistical findings from related research. Although they focus on the different modalities, they did not give in-depth attention to multi-platform and multi-lingual effects on event detection.

In Weiler et al. [13], a performance evaluation event detection techniques and their quantitative as well as qualitative comparison were presented. They define evaluation metrics to assess the runtime and task-based performance. However, these measures cannot evaluate the effect of platform-based approaches and linguistic-based approaches on event detection. Based on quantitative and qualitative assessment, Borges et al. [12] reviewed the key features for event detection techniques and their usage in the context of smart cities. However, they only identified the key features ignoring the other aspects such as multi-modal, multi-lingual and spatio-temporal effects of event detection.

A review of different event detection methods, which are applied to Twitter data, and their challenges were reviewed by Hasan et al. [8]. The event detection methods were classified based on common traits. Although a structured view of the current event detection methods was presented. they did not touch upon the effect of Big data platform and visualization of events. Moreover, the review did not present ideas on future research directions and challenges. Multi-modal event detection techniques were recently reviewed in [16]. Feature learning from multiple modalities, such as textual, visual, and audio inputs were covered, with methods for learning these features using graph-based, topic-based, and neural network based were presented. Although this last survey covers some common aspects for multi-modal event extraction, it does not consider the other key features, such as data fusion from multiple sources, and the spatio-temporal scope inference and visualization, among others.

Yu et al. [14] review the literature for spatio-temporal event extraction methods and applications. Although the paper discusses the extraction of spatiotemporal social events, the main focus is the detection of general events from sensing devices, such as remote sensing and health sensing. This paper categorizes the events into different types and details the detection method for each type. However, the paper does not discuss fusion of multi-modal social streams, scalability of algorithms, multi-lingual posts, and visualization of events. Liu et al. [15] survey the literature for multi-modal social event detection. The paper describes event representation, detection, evolution and mining. The paper argues that event prediction is an area to be explored by future research works. However, the paper lacks coverage of the effect of spatiotemporal features, multi-lingual social posts, big data characteristics of social media posts, and data fusion.

Each of the previous surveys reviewed some aspects of features and classification strategies affecting the accuracy of event detection, however none of these surveys provided a comprehensive review of the key features, big data management, multi-modality, multi-lingual, data fusion, spatio-temporal and visualization aspects affecting event detection and tracking. To cover up this gap, we provide a detailed and comprehensive study of the effect of single/multiple modalities(textual and visual representations), multiple sources, multiple languages, as well as that of their combination. We identify and discuss challenges of event detection and tracking systems over space and time.

3. Challenges

In online social media, challenges in the design of event detection methods start from the variety of data sources, to content size, to noise reduction, and continuous processing. It is also closely related

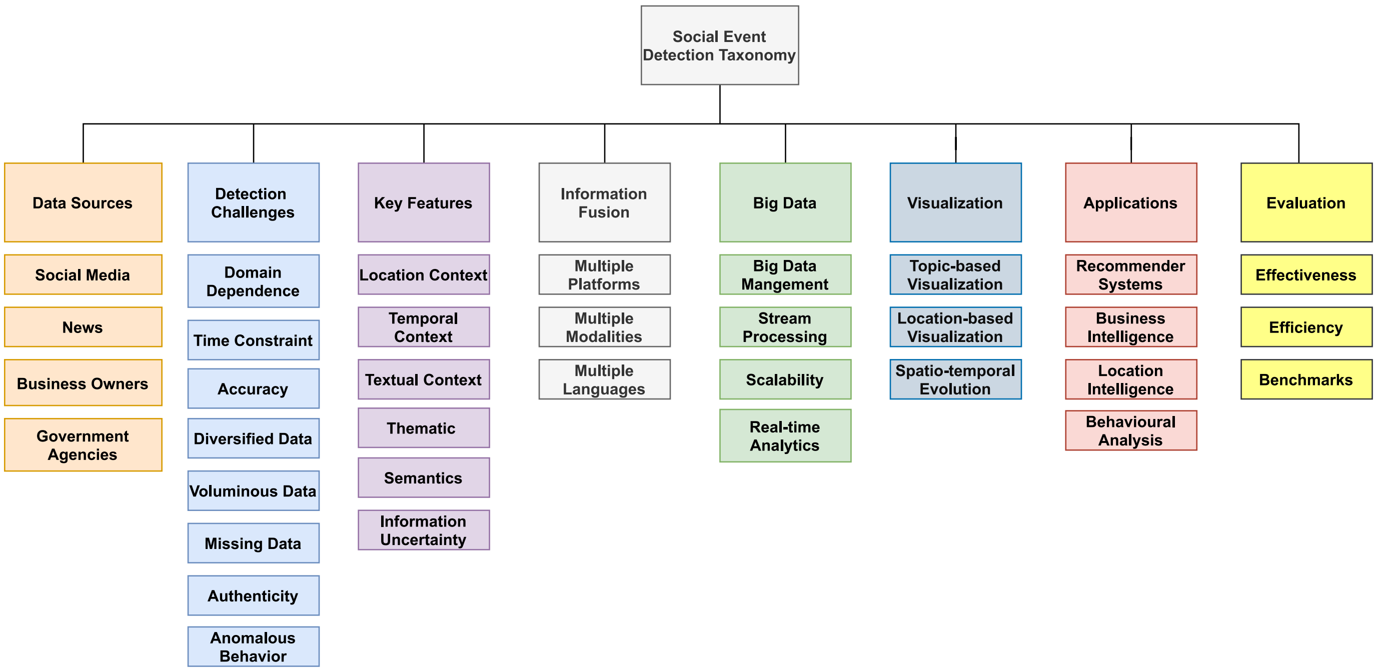

Fig. 2. Taxonomy on event detection from social media.

to topic detection and tracking in different streams, which means to determine new topical trends in the textual and visual streams and their significant evolution. Event detection techniques should face up to and deal with global challenges. As illustrated in Fig. 2, the detection challenges can be categorized into domain dependence, time constraints, detection accuracy, and finding missing data. Moreover, there are other challenges related to the evaluation of the massive explosion of diversified data, high powered computing algorithms, and huge space within a stipulated time frame. Apart from this, other challenges related to choosing appropriate tools and mechanisms while detecting events from diverse unstructured data streams that include textual, images, audio, video, and spatio-temporal content.

Since the use of online social media is increasing day by day, new challenges are posed on its applicability on event detection and evaluation. The taxonomy illustrated in Fig. 2 summarizes the many challenges that are yet to be addressed. The following is a list of challenges that are discussed in this section: (1) Event detection techniques and tasks; (2) Extraction of key features for event detection; (3) Information fusion for event detection; (4) Event visualization and representation on maps; (5) Big data and incremental processing for event extraction; (6) Applications; and (7) Evaluation.

3.1. Event detection technique and task

The event detection task from online social networks faces several challenges, such as domain dependence, time constraint, detection accuracy, diversified data, voluminous data, missing data, authenticity, and anomalous behavior. For example, Twitter data streams are characterized with some unique properties that need to be analyzed. The first of these is the large number of posted tweets, which is approximately 500 million tweets daily. The second is understanding the semantic thoughts from the tweets that are written with a unique conversational style due to the conciseness of the Twitter message. The third is the unbalanced tweet data, where the tweets that contain events constitute only a very small percentage among the social media noise. Finally, the dynamic nature of the topics discussed on the platform. Therefore the challenges to the different tasks of event detection can be generalized to the following:

- Domain dependence: The selection of parameters, input metrics, and output metrics in one domain might not be the same for the other domains. Moreover, these parameters may vary for different applications even in the same domain.
- Time constraint: Event detection techniques should be able to detect the event on an extreme timeline. Depending upon the cruciality of the domain, the timeframe can range from seconds to several minutes. For example, when decision making in critical situations (hospitalization or military decisions), the constraint of the timeline is a crucial consideration.
- Detection accuracy: The event detection methods should have a high degree of precision by maintaining high rate of true-positives, at the same time ensuring a low false-positives.
- Diversified data: Online social networks contributed to a massive explosion of noisy, unstructured and multi-modal data, e.g. textual, images, video, and audio. Such diversity poses a real challenge to effectively determine the relevant data.
- Voluminous data: Event detection algorithms require high power computation and immense storage space, to detect events from massive amount of data.
- Missing data: To accurately detect an event, every data are valuable. The event detection technique must handle the inaccuracies and incompleteness of the input streams.
- Authenticity: Information spread over social media has a limited confidence level. Therefore, extraction algorithms should consider the confidence level while mining events from online social networks.
- Anomalous behavior: Based on the learned predictable patterns of extracted events, some mechanisms should be developed to detect anomalous behavior from raw data, which can result in deviated patterns of such events.

3.2. Extraction of key features for event detection

Geographical information is a rare resource in social media. That is, only between 1% to 3% of tweets are geo-tagged. The key features for extracting events from social media are location, time, space, and semantic information, which are complicated to acquire from social media platforms. However, these key features create new possibilities for location-based social networks. At the same time, they bring new challenges, including user's and message context, dealing with heterogeneous domains, and revealing misrepresentation of data.

- Users' context awareness: Event detection from Location-based social networks requires to consider the user's current location, location history, and location histories of other users.
  - Current location of a user: The current location represented as a level of granularity. Choosing a proper granularity is significant and challenging. These locations, their distances from a reference point and location quality are important features for ranking purposes in recommendation systems. For example, in Travel recommendation systems, discovering future travel destinations depend on the sequential property of locations. Developing an efficient algorithm for addressing this requirement presents a mental challenge.
  - Location History: The user's historical locations can be used by applications to infer the experience, preference, living patterns, and interests of the user. Learning a user's personal interests based on their location history is rather challenging. That is because of the following:
    - Users do not usually share their locations all the time.
    - A single user location may spans multiple kinds of interest.
    - The user's preference has hierarchies and granularity.
  - Location patterns of other users: Based on the historical patterns created by other users, one can generate significant insights and recommendations, this building a public social opinion. Extracting features from users' location patterns faces two challenges:
    - Users present different knowledge degrees on the variety geospatial regions surrounding them. This should be taken into account when comparing users' spatial context.
    - Need for modeling users' distinct locations continuously, so that we can leverage comparable historical patterns.
- Misinterpretation: User location in his/her profile may be misinterpreted as either the actual location or a temporary location that is changing due to travel.
- The heterogeneous domain: The connection between two or more events in a location-based social network needs to determine user-location and location-to-location relationships. A deep analysis should infer those connections and their strength levels.
- Capture cross-modal correlations: To capturing cross-modal correlations effectively and efficiently among the spatial, temporal, and textual aspects of people's daily-life activities.
- Limited ability to estimate event location: Existing methods usually predict event location through single location terms that involve either the user locations or geotags. Instead of individual location terms for event detection in social media, a multinomial spatial scan considers all possible location terms, including user profile, GPS data, and Geo-tags mentioned in the content.
- Polysemous words: Multiple meanings of a word can hinder the actual text interpretation, presenting a challenge to detect, e.g. the sense of hate intent. The semantic features partially addressed this challenge.

3.3. Information fusion for event detection

Fusing information from different social media platforms, various types of data representations and different languages is a serious challenge in social media event detection. Different online social media like Twitter, Facebook, Instagram, etc. share similar events. To fuse information from these various platforms, the system must recognize and match the events despite their different representation and language in the these different platform. Data preparation and integration play a major role in the accuracy of event detection from multiple platforms, multiple modalities and multiple languages.

3.3.1. Multiple platforms

Each social media platform has its unique characteristics. Moreover, each platform has its own information structure, data format, feature naming, data types, unique features, etc. Combining these unique characteristics with user-specified languages is very challenging. These multiple platforms face two main challenges:

- Unstructured Data: online social media data is unstructured and noisy. Additionally, many of fields that are important for event detection are missing in the majority of the postings.
- Characteristics of the social media platform: The generated volume of data, feature naming, data types and unique features vary across platforms, which makes it challenging to organize a connection between them.

3.3.2. Multiple modalities

Most online social networks are multi-modal, but they often rely on one dominant modality. For example, Instagram is a primary image dominant platform, however Twitter is text dominant, and so on. The fusion of information features in textual, visual, and voice data, is one of the crucial challenges to achieve a new insight and better performance in social media event detection.

- With the current computer vision technology, image and video understanding is still an unsolved problem. Therefore, the ability to recognize and localize objects within an image to discover a key feature (e.g. location) used in event detection is quite challenging.
- Data complexity is another challenge in the fusion of multi-modal data. Data in different modalities are incomparable and varies significantly in terms of data characteristics.

3.3.3. Multiple languages

Natural Language Processing becomes even more challenging when considering the language used in online social media. Users often use dialectal languages, which have varying vocabulary, morphology, and spelling. Dialects in each language differ syntactically and phonologically. Furthermore, stop words are represented in numerous ways in the dialects and seen to vary significantly. Sometimes the part of spoken words is not easy to detect, and a person says negative words though he means to say something positive or vice versa. Minimal Machine learning approaches in the English language to identify these types of words while there are only very few, or no, studies in other languages. Therefore, sentimental analysis could be addressed to attain higher estimation capability to identify the true meaning of words and phrases during the process of event detection.

For example, in the case of the Arabic language, which starts from right to left hand, utilizes new and exceptional shapes, imprints and vowels, and Arabic roots that are tri, quad, or confined strictly. A large portion of these roots is trilateral. It makes it challenging to use an algorithm from another language with Arabic. Furthermore, it is challenging to handle the diversity slang due to its linguistic complexity. On the other hand, languages like Japanese and Chinese, which do not rely on word boundaries with whitespaces, and suffer from difficulties in tokenization and geolocation prediction during the process of event detection.

3.4. Event visualization and representation on maps

Visualizing the social media data (e.g. locations, text, etc.) on maps is a challenging task due to its volume and variety. Visualization can be crucial for some applications such as emergency management agencies since they need to make quick decisions to save people's lives. Mining social data can leverage the decision-making process, but its practicality is entirely dependent on the existence of clear and concise characteristics of data. This problem appeared when the volume of data is above the capacity of conventional tools.

The challenging points that should be considered for accurate event visualization are the following:

- The density of events in a specified geographic area.
- Is it reported in any online community?
- The location and spatio-temporal scope of the event.
- Recognizing the location of an event from the post content (text, image, etc.)
- Resolving aliases of geographic locations (United Arab Emirates: UAE).
- Differentiating between the event location and content provider's location.

3.5. Big data and incremental processing for event extraction

Millions of active users in social media share billions of contents. The implementation of the traditional event analysis methods do not scale to Big data. Such massive increase in the amount of data brings many challenging problems.

- Managing Big data: Big data problems are associated with the storage and preprocessing demands of managing velocity, variety and volume. Therefore, event detection system must be implemented on top of Big data platforms.
- Assembling and retrieving posts: Each dataset in social media has a specific level of heterogeneity in terms of type, network organization and structure, content semantics, and other metadata. Retrieving the most informative and representative posts from such a large dataset is a challenging multimedia retrieval problem.
- Redundancy reduction and data compression: Generally, in social media networks, there is a high level of redundancy in the dataset. The reduction of redundancy and data compression effectively reduces the indirect cost of the event detection system.
- Analysis: Big data is incremented every minute. Thus, the analytical component in the event detection system should support present and future datasets and be able to process increasing and more complex datasets. Analyzing these different data within a limited time is challenging.

3.6. Application-oriented challenges

Capturing real-time events from social media opens the doors for interesting location-based applications, such as event-based tourism trip planning, however the challenge is to capture these events accurately in real time. Real-time automatic trip planning depends on many factors, such as travel duration, cost, time, age of tourist, physical condition, and individual interests. All the existing online web or mobile applications have fixed start and end locations for tours. It means the user restricted to selecting her daily tours, accommodations, and public transit hubs among a pre-defined set of sites. The research on real-time trip planning accounts for practical issues like weather conditions, time budget, money budget, which affect the selection of points of interest to visit. Apart from the other challenges like tourist trip planning, applications of recommender systems are required to address the task of maintaining updated information about popular tourist destinations. Moreover, these recommendation systems should provide useful tourist guides that meet users' preferences and consider the popularity and personalization of travel routes at the same time.

3.7. Challenges on evaluation

Highly relying on manually-labeled data to create a training dataset for supervised learning, is a very tedious and time consuming task. That is domain-specific event detection methods, require extensive human input to label social media posts correctly without human bias. Additionally, the typical evaluation methods for information retrieval may not be appropriate for evaluating the results of some domain-specific applications, such as trip planning. More innovative evaluation metrics should be developed that take into consideration the semantics of the data and correctness of the results.

4. Background on event detection techniques

Real-world happenings extracted from social media can be classified based on the *thematic* (e.g., festival or sport events), *temporal*, and *spatial* features, as well as the network structure (e.g., user profiles and social links) [17,18]. Discovering and disseminating events from diverse social networks and with a variety of modes (e.g., text, image) have been the focus in many research studies [6,19]. An event of interest can be defined as follows.

Definition 1 (*Event of Interest*)**.** An Event of Interest (EoI) is an occurrence or happening at a certain place and within a specific time period, that holds several properties and a given level of significance.

Where event properties can include event main topic, related subtopics, occurrence time, duration, location, spatial extent, and its significance level, among others.

Definition 2 (*Social Event Detection*)**.** Given a streaming of social media, social event detection is the process of extracting significant social happenings by analyzing spatio-temporal peaks and emerging topics from data streams.

From the above definition, the input is the social media stream, such as a stream of tweets, and the output is the list of detected events. Since this task is processing streaming social media, the detection of events should be continuous and in a (near) real-time manner.

Over the last two decades, event detection techniques have been covering different media sources, from news-wire, web-forms, blogs, emails, to micro-blogs in social networks. In 1998, Yang et al. [20] have investigated the use of text retrieval and bottom-up clustering approaches in order to detect and track topics of interest from news articles, which was referred to as Topic Detection and Tracking (TDT). Henceforth, many research works have been proposed on event detection multimedia streams. Existing works on event detection are either covering specific [21–24] or generic types of events [25]. They usually focus on inferring social topics and subtopics from online communities. Nevertheless, very few studies have investigated the evolution and spanning of such events over space and time [26]. In addition, existing techniques can find events from snapshots of the social data streams ignoring the incremental and continuous development of such events [27]. Therefore, local events (e.g., accident or small party) may span on a short time period and a limited geographical area, while global events (e.g., storm or election) may remain alive on longer periods (e.g., weeks or months), and over a larger geographical region. Furthermore, most of the existing techniques do not fully leverage continuous stream processing, which is necessary to scale on a worldwide level.

This section presents the major and recent contributions in social event detection. This section is not meant to cover the entire list of papers in this field but rather to highlight the most recent and major contributions, and for the older references, one can be referred to other surveys including [6–8,10,13,28].

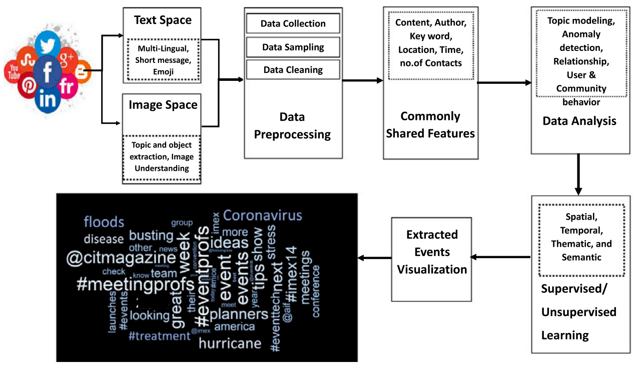

Fig. 3. General overview of event detection process from social media.

4.1. General architectural view of event detection

Event detection typically involves data collection, preprocessing, mining for unusual patterns, and event classification. The distinctive phases involved in the social media analytics process are illustrated in the general architecture for event detection shown in Fig. 3. To describe the architecture of event detection, we usually distinguish the following terminologies.

- Event of Interest (EoI) - An occurrence of an unusual happening at a given place and within a specified time period. An event can hold several properties and a given level of significance. Social events include gatherings, incidents, natural disasters, and emergencies, among others.
- Named Entity - a tag used to classify some content like unstructured text or image in a document such as Facebook, Twitter, etc. These entities are usually associated with properties, such as, entity frequency count, start and end time, etc.

There are different event detection approaches based on the detection purpose, whether it is related to specific or generic types of events, and the features that are considered in the detection process (e.g., textual, temporal, spatial, etc.). Nonetheless, one can draw a general architecture for event detection with salient components as illustrated in Fig. 3, which includes data crawling and preprocessing, topic modeling and feature extraction, classification, clustering and visualization of events. Event detection includes several stages: (1) data pre-processing phase; (2) feature extraction phase; (3) data analysis; and (4) clustering phase.

- Data preprocessing — aims at creating cleaned and sampled input data for event detection by eliminating noisy components.
- Feature extraction — the features of the textual document can be extracted by different mechanisms, such as, TF-IDF, Named Entity Recognition (NER), and temporal indexing. Extracting features from multi-modal data is usually performed by analyzing word frequencies, mutual information, entropy, etc. The tag annotation may include, hashtags or timestamp, which are filtered along with semantic elements learned from the deep consideration of the text.
- Data Analysis involves approaches for topic modeling and anomaly detection within a set of documents. This can also include other methods to analyze user and community behavior towards taking culture and other semantics into account.
- classification and Clustering based on similarity measures — different similarity measures are considered as a threshold parameter to cluster or compare multimedia content under investigation, such as, textual, thematic, and spatio-temporal similarities. Data clustering should incorporate multiple dimensions and hyperparameters to achieve the best learning experience.

Table 3
Pre-processing technique & tools.

Pre-processing technique	Tools
POS tagging	Gate Twitter POS model [34], Twitter-trained POS tagger [35]
NER	T-NER [30], GEAM event detection system [36]
Slang-word conversion	Porter Algorithm [31]
Resolving temporal expression [32,37]	TempEx, SUTime [38]

- Ranking and visualization — Ranking events of interest based on some criteria related to the popularity of the entities that formed the events, and based on the significance and interaction of these happenings in the real world. Finally, these ranked events should be visualized using multiple ways (e.g., dashboard, word cloud, map-based exploration, etc.) to create a unique browsing experience.

4.2. Event detection from textual streams

Many approaches are used to detect events from social media [7,8,13]. Here, we will present some of the most commonly used techniques. Event extraction from textual data streams can be performed by using different machine learning algorithms and data analysis techniques. These techniques can be classified into supervised, unsupervised, or semi-supervised depending on the way we train and classify events. We present the main contributions in event detection from textual streams, by covering the different phases in the detection process. Event detection from other data modes such as, images, and with multiple modalities will be covered in Section 6.

4.2.1. Data preprocessing

aims at creating cleaned and sampled input data for event detection by eliminating noisy components. Data pre-processing involves removing spaces and filtering the stop-words (words that are removed after text manipulation using Natural Language Processing (NLP) methods, words such as 'the', 'or', 'they', 'and', 'or', 'if', etc.) [29]. Input data is usually pre-processed by using different techniques, such as, part-of-speech tagging, named entity recognition (NER) [30], slang word conversion [31], time expression extraction [32], stemming and removing stop words, URLs, and user-name mentions [33]. Each of the corresponding tools used for this technique depicted in Table 3.

4.2.2. Detection models and techniques

we will discuss the most common models and methods used for event detection in social media. Event detection approaches use NLP methods for topic detection and data analytic purposes. According to the Topic Detection and Tracking initiative (TDT), event detection was identified as a key concept to extract findings from a stream of stories or broadcast news [39]. The goal of event detection is finding the new or old unidentified events that happened at a particular location and specific time [40]. Event detection techniques can be classified into two categories based on the TDT initiative: (i) New Event Detection (NED) and Retrospective Event Detection (RED) [6]. The NED-based techniques focus on identifying events from live stream data or continuous monitoring of data. Most of the NED detection tasks use different similarity metrics in the clustering phase. On the other hand, RED refers to identifying previously unidentified events from a bulk of historical data. The TF-IDF methods or query-based methods are commonly used for the RED detection task.

Research on event detection originates from the area of Topic Detection and Tracking (TDT) [39]. The fundamental task of event detection starts from the topic modeling and anomaly detection. Then, stream clustering or classification is performed by computing similarities of multi-dimensional feature vectors (topic, time, space, etc.). Anomaly detection is the indication of the outlying message within a corpus based on analysis of the terms, segments, and sentiment of that message [41]. An alternative strategy to score novelty on incoming streams is by using First Story Detection (FSD) approach [42]. FSD can categorize newly identified stories into indexed nearest neighbor score or IDF score based on locality sensitive hashing (LSH) technique [43]. Table 4 overviews the recent models and techniques for event detection. We take into consideration several evaluation criteria including: (1) the detection purpose whether it is generic or covers specific types of applications; (2) the detection technique; and (3) learning features whether spatial (SP), temporal (TEM), thematic (TH: topic-based), and/or semantic features are considered. (4) classification models are also reported as supervised (Sp), semi-supervised (SSp), or unsupervised (USp); and finally (5) we also evaluate the social dimensions that may have contributed to the event detection process. It is worth emphasizing that most of specific event detection techniques follow a supervised, or semi supervised learning approach to distinguish among a predefined set of event classes. This is also the case for many studies that are using deep learning as part of the supervised learning strategy. Whereas, unsupervised learning is common in generic detection approaches.

Topic modeling and detection. According to the state-of-the-art in topic-specific event detection and tracking techniques, these approaches mainly rely on feature-pivot (temporal features based), document-pivot (document features), probabilistic models, and frequent pattern matching [6–8,44]. Hence, we will list some common approaches for topic modeling used in event detection.

(1) Document-pivot techniques [10]: classify documents based on cosine similarity on term frequency-inverse document frequency (TF-IDF). For instance, it checks all documents to discover the best match from the already checked document pools, then if the matching score is above a certain threshold, it will create a new group (i.e., cluster), otherwise it will link it to the same cluster. TF-IDF is applied to measure the importance of a word in a given corpus, and to capture the list of documents containing the word. Exploring other data representation and feature extraction techniques was also presented in [3,5,45–52]. However, this method may not be relevant to other scenarios because of cluster fragmentation issue [53]. In addition, for many cases document-pivot techniques rely on arbitrary thresholds to insert a new document to the current topic/cluster.

(2) Feature-pivot techniques: comprise statistical models that discover events by representing a topic in text streams with specific features that are increasing rapidly in frequency [53,54]. Feature-pivot technique is broadly used to identify and extract trending terms, then cluster those terms when possible according to their co-occurrence patterns across other documents. This is referred to as an above-chance frequency of coincidence of two terms from a text corpus in a particular group [55] while measures of co-occurrence are calculated based on KL-Divergence [56].

(3) Probabilistic topic modeling: Probabilistic topic models use generative probabilistic methods that include some of latent (random) variables or hyperparameters which shows terms and topics. [57]. To estimate the probabilistic distribution of a latent variable, sophisticated mathematical models such as the Latent Dirichlet Allocation (LDA) [58] were proposed. Latent Dirichlet Allocation (LDA) is one of the most commonly used topic modeling techniques, where documents are defined as random mixtures over latent topics (words with high probability). Topic models extract topics from a set of relative documents based on a specific word frequency [58]. LDA assumes that documents are represented by the probabilistic distribution of their latent topics, and that topic distribution over documents share a common multivariate beta distribution vector (referred to as Dirichlet prior). Processing data in LDA starts with cleaning it by converting the document to its atomic items, then removing noisy words such as stop-words, and finally joining all words in the relative meaning. The aim of all these studies consists in extracting features from textual data. LDA-based topic modeling excerpts the semantic information from text by applying probabilistic distribution [58]. LDA shows excellent performance comparing to other methods of extracting features from textual data. However, some significant drawbacks of LDA appear in its high reliance on the parameter settings, and the large number of sampling iterations that is required, which leads to a time-consuming task. Many LDA variants were developed later with the aim of improving the extent of topic modeling to other dimensions as summarized in [59].

(4) Frequent Pattern Mining (FPM): A concept introduced in data mining models, where itemsets (correlated set of elements), subsequences (set of tasks), and substructures can considered as frequent patterns in a dataset if they appear with a frequency above a user-specified threshold [60]. For instance, a set of elements, such as apple and orange, which have seen frequently together in a transaction database, is called a frequent itemset. Whereas, buying a smartphone, then a sim card, and then an sd-card, is called a frequent subsequence, if this happens frequently at a seller historical dataset. A substructure is a different structural forms. For example, subgraphs and subtrees could be frequently joined with itemsets or subsequences in a graph database.

4.2.3. Feature extraction

Social textual data streams can help discover the real-world happening at a certain location and time. Extracted features from those streams can reveal the thematic, temporal, spatial, and semantic nature of social events. The input data for an event may be specified or unspecified [6]. The specified input data provides specific pre-determined details and parameters, such as, the time, type, place, and description. Features are classified using different techniques, such as, Gradient boosted decision trees [61,62], Factor graph model [63], Rule-based classifier [48], relevance-based language modeling [64,65], and event modeling approach (ETree) [66]. Conversely, most traditional retrieval and extraction techniques are not appropriate for unspecified data, in which pieces of information are generally missing or hidden, and intelligent inference techniques from data sets are required. Consequently, studies usually rely either on unsupervised or hybrid detection methods. For instance, Becker et al. [48] proposed traditional pre-processing steps stemming, combined temporal, social, topical, and stop-word elimination, along with Twitter-centric feature extraction. In order to enrich the context of incoming tweets, temporal co-occurrence of terms was used in [67] to extract events. The authors in [68] proposed the Symbolic Aggregate ApproXimation (SAX) method to temporally characterize events within periodic windows. From the time window, the bursty terms are identified. Another event detection system presented in [69], that integrates an automata model with a Hidden Markov Model to extract bursty topics. They employed a graph-based clustering mechanism to infer connected components. GeoBurst [70] identifies tweets pivots to generate candidate events ranked based on their spatio-temporal burstiness with real-time continuous monitoring capabilities.

4.2.4. Supervised and unsupervised learning

Different supervised (e.g., classification and neural networks) and unsupervised (e.g., clustering) learning methods have been proposed for event detection from social media. The detection task is a process based on the input data (Specified or unspecified) and the target application for event detection (finding natural disasters, politics, current events, criminal behavior, etc.). Supervised, semi-supervised, and unsupervised detection methods can be witnessed from literature [69]. When a limited number of input and known output pairs are used in training purposes for detecting an event, the learning process is referred to as supervised learning. When only the input data is used in the learning process, without well known output or mapping function, this is called unsupervised learning [71]. This unsupervised process can address the challenge of dependency between learning fields, and reduce the need for using labeled training data. The semi-supervised technique laid in between supervised and unsupervised methods, where only a portion of the input data may be labeled [72]. Classification and regression are examples of supervised learning, whereas, unsupervised learning can be materialized by the clustering methods. Based on the input data (Specified or Unspecified), the use of the detection method can be decided. Event classification of 20 event categories from microblogs has been studied in [73]. The authors proposed a supervised model with multimodal and multi-instance deep neural networks, and weak data labeling. The authors in [74] introduced a model for event detection without manual labeling in the training data, by injecting a bias in the Neural Network with an Attention Mechanism. This aimed at reducing manual efforts in detecting events by using without triggers. A deep learning architecture was also proposed in [75] for traffic-related event detection from Twitter. Words embeddings for feature extraction, in addition to CNN and RNN networks for the classification task.

From unsupervised learning perspectives, clustering algorithms have been commonly used for event detection, including the hierarchical agglomerative clustering [76], incremental clustering [77], incremental clustering vector expansion (ICVE) [78]. Hierarchical clustering methods differ in their perspective on how to measure inter-cluster dissimilarity at each depth level. Online clustering and Naïve Bayes classifiers applied in [77] to propose a TwitterStand framework as a non-conventional news aggregator. De Boom et al. [79] proposed an augmented semantic information from individual tweets and hashtags in the incremental clustering approach to help in topic labeling. Guille et al. introduced a model named MABED to detect topics based on mentioning anomaly by identifying bursty words in a given time slice [41]. Clustering is then performed to group similar words based on their co-occurrence in related tweets. Hasan et al. [80] presented a similarity threshold-based incremental clustering approach, and developed a framework named TwitterNews+ for news extraction from tweets.

Feature-pivot (or term pivot) is an alternative to document-pivot clustering for event detection. It relies on statistical methods to extract a set of hot bursty features used for clustering [84]. A large number of studies based on feature-pivot techniques for clustering and event detection have been proposed, including infinite-state automation model [85], binomial distribution [84], Hierarchical Dirichlet Processes (HDP) [86], heuristic-based threshold [87], Discrete Fourier Transform [87], Gaussian mixture model [87], and general probabilistic model [88]. They all aim at identifying bursty features and mining correlated bursty topic patterns in order to find events of interest. Another approach presented in [89] that is based on detecting surprising changes in the frequency of n-grams of words to identify topic clusters in news streams. TwitInfo [90], enBlogue [91], EDCoW [92], Twevent [93] are multiple frameworks used for detecting abnormal patterns in the appearance of features. However, feature-pivot techniques suffer from noisy data streams, which can significantly affect the event detection performance [10]. In Twitter, temporal distributions of features are very noisy, and not all bursts are relevant events of interest.

Event Detection using topic modeling approaches based on LDA are also commonly studied. The authors in [36] proposed an unsupervised topic model, GEAM, that distinguishes general words (non-event related opinions) from event-related aspects. GEAM model computes general topics as well as event-related properties, such as time, location, and related keywords. Xie et al. [94] applied the sketch-based topic modeling for early extraction of topics and real-time event detection from Twitter. The Latent Event and Category Model (LECM) presented in [95] used an unsupervised Bayesian model for event classification. The authors in [52] have presented an approach for event analysis to examine their spread and popularity based on hashtag correlation and temporal pattern mining. Morabia et al. [82] present a segmentation based event detection system named SEDTWik, which is based on tweet segmentation, bursty segment extraction and clustering, and event summarization.

The other objective consists in generating clusters of events that are represented with more than the textual properties, such as location, and time. Incorporating spatial and temporal features to extracted events represent another important challenge that can help in tracking and predicting the evolution of such events over space and time. Spatial and spatio-temporal clustering of points representing social streams has been studied in [14,96,97]. Spatial clustering methods include k-means [98], mean-shift clustering [99], and density-based clustering (i.e., DBSCAN [100] and HDBSCAN [101]) have been proposed in event detection to identify the spatial extent covered by the social event. In order to integrate both spatial and temporal properties of events, several spatio-temporal clustering techniques were also developed, such as, the ST-DBSCAN that computes inter-point distances based on spatial, temporal and other attributes separately and with given thresholds [102,103]. A hierarchical spatio-temporal hashtag clustering technique called StreamCube was also presented in [97], where hashtag clusters are organized into data cubes according to their timestamps and geographical information. A spatio-temporal extension of the density-based clustering (DBSCAN) algorithm was proposed in [104]. This approach clusters tweets across space and time with multiple geographical scales, while using LDA for topic modeling. The authors in [25,105,106], have developed a technique for event detection with multiple spatial granularities, such that accidents and traffic conditions are shown at a local scale, while job alerts, elections and natural disasters are shown at higher map scales.

Ahuja, A et al. (2019) proposed a model for spatio-temporal event detection by employing a probabilistic approach to discover events by their associated topic, occurring time, and spatial occurrence from news and Twitter data sources [83]. This work focused on detecting and monitoring the global events that were discussed on news, rather than a generic model to discover all types of events. Another recent work on spatio-temporal event detection has introduced the principle of incremental processing over temporal slices (i.e., hours, days, and weeks), and spatial resolutions (i.e., cities, regions, and countries) [107]. The authors in [108,109] presented a more comprehensive review of spatio-temporal clustering for event detection.

4.3. Image-based event detection

Research on image understanding and automatic knowledge discovery from image data represents a pillar of recent AI and computer vision fields. Online social network platforms such as Facebook, Instagram, and Twitter represent a huge source of image streams, hence the importance of social event detection from image data. Recognizing semantic content from image data can help in proactively identifying inappropriate or harmful content and to keep our community safe. Particularly, event detection from images has been studied in several works [19,110–113]. A semi-supervised learning approach for image classification using visual content and related keywords was presented in [114]. An approach for social event extraction from image collections was proposed in [111], which relies on the user textual input query, available metadata and the actual image content. Event clusters can be refined with spatial, temporal and visual filtering to best match the query input. Cai et al. explored the visual features of images in addition to other tweet properties including text, location, timestamp and hashtags [112]. They studied the impact of tweet images on event detection accuracy. In 2018, Facebook proposed advancing text recognition in images and videos [115]. They identified textual content in images by using a large-scale machine learning system called Rosetta. This architecture uses Faster R-CNN for real-time object detection and to perform word recognition using convolution Neural Network with connectionist temporal classification (CTC) loss to train the sequence model [115]. Fashion analysis and forecasting of fashion-related images using social media have been studied in [19]. Predictive models for

Table 4
Event detection — models and techniques.

Reference	Purpose of detection	Detection technique	Learning features				Other practices	(Un)Supervised			Social dimensions		
			SP	TEM	TH	SE		Sp	SSp	USp	Content	Profile	Topology
Guille et al. (2015) [41]	Generic: topics detected based on term weighting and anomaly detection	Clustering using topic co-occurrence and temporal dynamics		✓	✓		topic clustering, vocabulary dictionary, and time window			✓	✓		
Stilo et al. (2016) [67]	Generic: only trending topics were captured	Symbolic Aggregate Approximation, temporal similarity as a measure of semantic relatedness		✓	✓		SAX, regular expression learning, temporal clustering, complexity evaluation			✓	✓		
Zhang et al. (2015) [69]	Generic: predict event popularity	Hidden Markov model and Graph Clustering			✓		Term frequency, User's social relation		✓		✓	✓	
Ozdikis, O. et al. (2017) [78]	Generic: Online clustering and detection of similar terms in micro-blog posts	Incremental clustering with Temporal Vector Expansion (ICVE)	✓	✓	✓		Term Similarity, Term Historical Analysis			✓	✓		
Giridhar. et al. (2017) [81]	Social Fusion for event monitoring	Expectation–Maximization (EM) Approach	✓	✓	✓		Number of hashtags and tag similarity			✓	✓		
Hasan, M. et al. (2018) [80]	Specific: low computational cost to detect breaking news in real-time	TwitterNews+: random indexing based term vector model with LSH	✓	✓			incremental clustering, a defragmentation module to handle cluster fragmentation.			✓	✓	✓	
Lee et al. (2017) [72]	Specific: Adverse drug event detection	ADE classification from Twitter streams using semi-supervised CNNs			✓		Semi-supervised deep learning model		✓		✓		
Gao et al. (2017) [73]	Specific: Event classification of 20 event classes using deep learning	Multimodal, multi-instance deep neural architecture with social tracking			✓		Supervised deep learning model	✓			✓		
Liu et al. (2019) [74]	Generic: event detection without manual labeling	Biased neural networks with attention			✓		Word embeddings, bias loss, LSTM with attention layers	✓			✓		
Dabiri et al. (2019) [75]	Specific: Traffic event detection using deep learning	CNN+RNN for classification	✓		✓		Word embeddings, supervised deep learning, geocoding	✓			✓		
Fedoryszak, M. et al. (2019) [44]	Specific:- To tackle the problem of event detection	Clustering entities [25] and Summingbird topology		✓			Similarity, Louvain clustering resolution, and Time window			✓		✓	✓
Morabia et al. (2019) [82]	Generic:- to detect newsworthy events from a wide range of categories	SEDTWik:- Segmentation based detection		✓	✓		URL links, hashtags, retweet count, user popularity, follower count and name mention			✓	✓	✓	
S. Liu. et al ., (2019) [74]	Generic :- To reduce the manual effort for detecting events by using the triggerless sentence	Biased Neural Network with an Attention Mechanism			✓	✓	tokenized sentences with NER tags, type-aware event classifier		✓		✓		
Ahuja, A et al. (2019) [83]	Generic :- spatio-temporal event detection	a probabilistic approach to discover events by their associated topics	✓		✓	✓	topics, occurring time, and spatial occurrence from news and Twitter data sources			✓	✓		

style forecasting were developed based on different classifiers and clustering techniques. Mahajan et al. [113] presented on image recognition with deep learning based on hashtags. The authors addressed a large set of public images with hashtags, which approximately 3.5 billion images and 17 000 hashtags. Meanwhile, they achieved 85.4 percentage accuracy on a common benchmarking tool ImageNet.

Several methods for detecting features from visual data, including enhanced sparse coding-based methods [116] and deep learning based anomaly detection [117], with the aim of exhibiting better performance in extracting local feature descriptors from images. Local descriptors can be extracted by using multilevel K-means clustering and bag-of-visual-words (BoVW) for image retrieval and classification [118]. Deep learning techniques can also take advantage of max pooling and Spatial Pyramid Matching (SPM) mechanisms to obtain short descriptions and spatial layout information that help in learning final features and eventually in the event detection process [119].

Event detection through mining image data has been also investigated in the tourism field. Discovering travel routes based on tourists' memorable destinations and geo-tagged photos [51,120]. The event detection carried out by analyzing and exploring significant metadata features from multimedia streams will be covered in detail in Section 6. However, it is worth noting that event detection from pure image data is yet to be fully addressed in the literature.

5. Advanced dimensions for event extraction

This section presents the main dimensions that are considered in the event detection process. We can mainly categorize these dimensions from the perspective of event extraction as spatial, temporal, thematic, and social context. Thinking naturally about an event as a social occurrence associated with an attraction or some user(s) at a specific time and place. Therefore, not only event location and time are fundamentals in the extraction process, but also the spatio-temporal evolution of extracted events, which defines what we refer to as, *'spatial scope'* and event *'time-to-live'* or *'duration'*. Location related contents have a crucial role in accurate real-time event detection. In addition to spatial and temporal dimensions, we should consider the semantic and contextual features as well as the social network structure. The thematic dimension considers the trending topic modeling and tracking that can help in extracting related events. The social context is reflected by the user profile, interactions, and some information flow and patterns between the user's connections that may impact the extraction process. We discuss these dimensions and their significance in the following subsections. Table 5 summarizes the contributions with respect to the dimensions considered in these research studies for event detection.

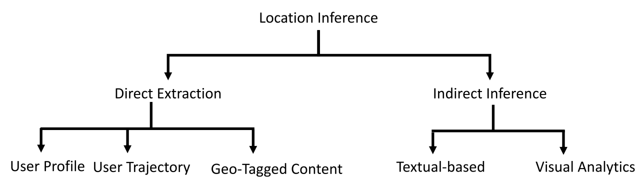

Fig. 4. Location inference from social media.

5.1. *Location inference and spatial scope*

Location-based social network services are usually based on geo-tagged social data, but also on moving object (e.g., a pedestrian or vehicle) locations and Trajectories. From event detection perspectives, most approaches assume having the user enabling the geo-tagging service for enriching the published media content such as text, photos, and videos with their locations. The geo-tagging networking services are Flickr, Pinterest, Yelp and Foursquare, vitalize users to share their current location and discover social activities around their areas of interest. Thus, the current location of a user plays a vital role in event detection recommendation. We classify location inference techniques into many categories as shown in Fig. 4. We distinguish between direct extraction of geo-locations and indirect inference of a location.

However, more challenging studies have investigated the potential of inferring location from the multimedia content itself, whether it consists of text, image or video [121–123]. The reason behind this trend, is that most social networks do not recommend sharing geotags by default because of privacy concerns. For example, today, only around 1% to 3% of all tweets are explicitly geotagged [124]. As a result, recent research on text-based geolocation prediction has primarily focused on defining language-specific lexicons that can be a powerful indicator of location information.

5.1.1. *Point location inference*

Zheng et al. (2018) [125] summarized the prediction of location information into three categories: (i) user home location, (ii) tweet location, and (iii) mentions locations. These categories are identified based on user profiles and/or tweets content. User's home location can be collected from self-declared profiles. Tweet location is usually extracted from both the user's profile and the geotag property. The tweet location gives a detailed pattern of a user's mobility. Some of the location names are also mentioned in tweet content or hashtags; this mentioned location provides a better understanding of the whereabouts of events. Tweet content and Twitter network can also be used for home location prediction. Word-centric approaches that are applied to tweet content, are distinguished by local word identification and spatial word usage modeling. For the Twitter network, we usually study relationships between users' home locations that are delineated by their connections and interactions. User-mention-based location prediction from tweet content uses mentioned location recognition and location disambiguation methods. In general, there are Distance-based metric and Token-based metrics for location evaluation. In Distance-based metric, locations are depicted by geographical coordinates, while token-based metrics represent locations as discrete symbols.

Abali et al. (2018) [126] used a location recognizer based on manually created Geonames file. Then, similarity checking is performed on tweet texts to identify place names. Geographical databases and gazetteers including DB-pedia [127], the USGS database [128], and the US census TIGER Gazetteers [129]. The authors [130] used a hybrid approach by detecting spatial indicators and assigning weights based on geographical interpretation, and by using the USGS location database to deal with ambiguous location names. However, such methods are comparatively slow when it comes to efficiency. Besides, users may write the abbreviation of the location while gazetteers contain the official names only.

The Hybrid and multi-elemental location inference method introduced in [131] suggests predicting tweet location by considering other inherently linked metadata. The final location of a tweet is extracted based on the importance of content-based location, place-labeled tweets and profile-based location. For the experimental evaluation, the accuracy of the proposed method is assessed by using the Haversine formula. Haversine (or great circle) distance is calculated based the shortest distance between two points on a sphere surface. Predicting geo-location in the English language had lower accuracy than non-English language. The experimental result calculates the class entropy with respect to a language on training data and perceive class entropy on English data is the largest. In contrast, Thai and Turkish have much smaller entropy. It is clear that non-English languages had a strong bias towards a small number of cities.

5.1.2. *Spatial scope*

After extracting the social content's geographical coordinates (e.g., ⟨latitude, longitude⟩ for a given place, organization, city name, street name, and landmarks), there is a need to define the spatial evolution and geographical extent of such an event at a given time. The authors in [25,132] described the spatial scope of an event at different map resolutions so that event with higher significance would appear on multiple map zoom levels, whereas local events with a lower significance appear only on a detailed zoom level of the map. Therefore, a smooth integration and map browsing experience can be achieved by visiting events related to districts, cities, countries, and worldwide levels.

5.2. *Temporal scope*

Social media streams are continuously updated, thus urging the exploration of real-world events in a timely manner. Tweets from several hours ago may not be as important as the newly published ones. Therefore, temporal intervals and the posted social streams during these intervals are very influential factors. In event detection, local time is more useful to characterize tweets or other streams rather than coordinated universal time. Several studies have incorporated the temporal dimension by using different mechanisms, including the mean time of occurrence [83], statistical unsupervised approaches such as Poisson modeling along with smoothing over time-series data [133], weighted graph with symbolic temporal entities [17,134], and wavelet transformation and normalized wavelet entropy [92,134–136].

The authors in [32] propose representing time expressions as single pseudo-tokens, with unique vector representations that encode easily retrievable time parameters. CNN filters were use to focus on generalizable time patterns from within lengthy time expressions. Stilo et al. [67] present a technique for temporal analysis and discretization of the temporal series of terms by using temporal sliding windows and clustering of co-occurring patterns. This algorithm is based on transforming word temporal series into string symbols for discovering events from large micro-blog streams. After this technique, Li et al. (2017) [137] proposed an approach for analyzing temporal signals of tweets, so they can classify them based on their content, and determine old event clusters that should be filtered out. Rule-based temporal identification module identifies the temporal information such as tweet creation time, and the duration depicted by the difference between the creation time and current time. Afyouni et al. [2] proposed sliding window strategies that classify tweet terms by calculating similarity class wise with word embeddings, which is learned from vocabulary corpora. They then define the *'time-to-live'* or *temporal scope* of events by merging topics spreading over multiple sliding windows, thus incrementally updating their temporal evolution.

Table 5
Advanced dimensions for event extraction.

Reference	Location inference	Spatial Scope		temporal scope		Semantics
		Uniscale	Multiscale	Start Time (ST)	Time To Live (TTL)	
L, Farhad et al. (2016) [131]	Inference from textual content, user profile, and place labels.		Regional level	NA	NA	NA
Tartir, S. et al. (2017) [138]	NA		Country level	NA	NA	Keyword information
Hua, T. et al (2016) [139]	Geo-tags, profile, and content		City Level	NA	NA	Only similarity basis
AL-Smadi, M.,(2017) [140]	NA		Country level	NA	NA	NER (Named entity Recognition) & Topic modeling.
Ozdikis, O et. al, (2017) [78]	Textual Content.		Country level	1 min	1 min (time window/bucket)	No. Only similarity.
Q. Li et al. (2017) [137]	Textual content	Temporal significance		NA	NA	Word embedding
Y. Wang et al. (2017) [141]	Geo-tagged tweets.	Spatial and temporal significance		NA	NA	NA
A. Tonon et al. (2017) [142]	Text content in tweet	Spatial significance (based on country level)		NA	NA	Users semantic queries
Abali, Gizem et al.(2018) [126]	Text		Regional level	NA	NA	NA
Y. Huang et al. (2018) [104]	Geo-tagged tweets		Cities	100 min	30 min	Word frequency and topic model
Shah, Z. et al. (2019) [107]	User defined text and user profile		Country, city, region	NA	NA	Similarity
Ahuja, A et al. (2019) [83]	Content of Tweet and News	Spatial and temporal significance		NA	NA	NA
Zhou, Z. et al. (2019) [143]	Geo-tagged textual content		Local area	NA	NA	Docvec model
Han et al. (2019) [144]	Geo-tagged tweet		City level	NA	30 min	Word embedding
Wei et al. (2019) [17]	Text content in the tweet		Cities	NA	NA	No semantic measures
George, Y. et al. (2019) [133]		Spatial and temporal significance	City Level	NA	NA	NA

5.3. Spatio-temporal scope

Most of the existing approaches on event detection from social media deal separately with time and space dimensions, in addition to the textual content analysis. The combination of spatial and temporal dimensions would make it easier to find the source of events, monitor their peaks in space and time, and identify separate events where location and time extents differ. Dynamic spatio-temporal indexing techniques were presented in literature to cope with this gap [2,65,97,107]. Mao et al. (2015) [145] proposed a spatio-temporal approach to detect the abnormal events related to environmental pollution. They evaluated the temporal dependency by using Markov chains and Bayesian Networks for spatial dependency. For the Spatio-temporal correlation, they adopted a decentralized algorithm based on a probabilistic graphical model (PGM). A PGM combines the probabilistic theory with graph theory, which easily hand out the occurring problems of uncertainty and complexity of modeling the real world events. However, the proposed algorithm was applied to wireless sensor networks, thus was not directly used for social event detection.

Kim et al. (2016) [146] studied the problem of spatio-temporal autocorrelation of keywords that can be clustered together in order to infer local topics by considering their spatio-temporal relationships and dynamic point patterns. A comprehensive review of statistical approaches used to classify spatio-temporal point patterns can be found in [147]. These techniques can offer advantages with respect to performance in case they are coupled with efficient spatio-temporal indexing of events.

Hua et al. (2016) [139] propose a semi-supervised learning approach in Twitter for domain-specific Spatio-temporal Event Detection (ATSED). The proposed algorithm automatically learns the features from historical tweet labels to identify the hidden patterns and relationships from the source and target datasets. Then, the algorithm detects ongoing events from real-time Twitter data streams by using the generated pseudo labels and features. The relevancy between tweets and events is based on textual, spatial, and temporal similarities.

Wang et al. (2017) [141] mapped TF-IDF based feature words into spatio-temporal dimensions, and machine learning classifiers for event detection from Twitter. The tweets were classified based on category names of multi-functional building forms by k-NN in eight time periods, which are divided by an interval of three hours. Another approach use geotagged tweets to trace the development and visualize specific spatio-temporal events in real-time [26]. A small scale spatial–temporal event detection mechanism from textual content was proposed in [104]. Spatial–Temporal Clustering algorithms are usually used to cluster tweets across time and space dimensions as described in Section 4.2.4.

Wei et al. [17] presented a learning methodology for cross-modal search on geotagged tweets. The LeGo-CM model combines textual words, time units, and locations. They extracted the spatial entities (locations of interest) are identified using a clustering algorithm, publish time of tweet as temporal entities, and textual entities (keywords and phrases) extracted by stop-word removal. Then, Kullback–Leibler divergence was used to evaluate the correlation between the probability from the co-occurrence graph and the probability from the initial embedding. Zhang et al. (2017) [148] used co-occurrences between location, time, and text in tweets to learn embeddings and this framework was named as 'ReAct'. In this method, the location is represented in the form of regular grid cells. However, the assumption of a uniform distribution of spatial data may not fit well with real-life social data. Recently another Spatio-temporal framework for event detection introduced in [107] represented time using three temporal features (e.g., hour, day, and week), in addition to the spatial features that include the city, state, and country. They analyzed events by applying the regression model, and proposed mapping unexpected changes in incoming data based on spatio-temporal lattice.

Han et al. (2019) [144] introduced event detection from geo-tagged tweets with multiple spatial levels using power-law distribution for time series data. They presented experiments on spatio-temporal statistical distributions power-law basic and advanced algorithms. The power-law basic algorithm did not consider the content of each tweet, and it only checks the power-law distributions in the time-series data at multiple spatial resolutions. In contrast, the advanced algorithm integrates the power-law verification with semantic analysis by using word embedding of tweets, which was demonstrated to be significantly improving the precision and recall. George et al. (2019) [133] integrated the quad-tree spatial indexing with a Poisson model to detect events at different spatio-temporal scales. The geographical space is partitioned into multi-scale regions based on data stream density, and using the quad-tree and Poisson distribution with a smoothing technique applied to those regions. Moreover, the proposed method used semantics to assess the integrity and correctness of the detected events. The detection approach proposed a strength index to measure how precise the extracted event is, by using Twitter and Flickr datasets.

5.4. Semantics

Data stream semantics and contextual features are depicted by the thematic dimension, as well as the social content of users. Thematic dimension-based event detection techniques were proposed along with different supervised classification mechanisms [59], such as SVM [48], conditional random field (CRF) [63], n-gram based content analysis [66], and Gradient boosted decision tree [62], and unsupervised algorithms [3,146,149]. Dynamic time warping concept [150] and Graph cut algorithm [151] are used based on the online social network structure.

ArmaTweet is a semantic tweet analysis system proposed by Tonon et al. (2017) [142]. The ArmaTweet draws out a structured model from tweets' content, and integrates it with DBpedia and WordNet to produce the RDF knowledge graph. The proposed system can then classify events by producing semantic queries over the knowledge graph. These semantic queries define the relationships between entities in tweets and provide better results compared to the keyword-based search method. The drawback of this work is that it only focuses on longer and explicit texts. In 2019, Event detection based on semantic keyword information proposed by Yu et al. (2019) [152]. The semantic keyword information method easily identifies the trending events from social media. The semantic properties are distinguished and help in clustering hot events by using The affinity propagation algorithm. Another approach developed in [143], which presents a semantic-aware document embedding technique aiming at reducing the visual clutter of geo-tagged social media data. A doc2vec model is proposed to construct the semantic correlation of geo-tagged data and transform documents into high dimensional vectors. The doc2vec uses one-hidden-layer neural networks to convert words into real-valued vectors. The doc2vec model avoids the dimension disaster problem (i.e., high-dimensional space) thus improving the efficiency of the classifier training task. By comparing the experimental results, this doc2vec model bringing extra semantic features to fit for short texts and effectively enhances the performance of long text contents.

A recent research on semantic features aimed at detecting hate intents from social media. Senarath et al. (2020) [153] conducted a study of hate speech detection by using three features, such as corpus-based semantic features, declarative knowledge-based features, and FrameNet features [154]. The corpus-based semantic feature uses Bag-of-Word techniques for tweet pre-processing. The declarative knowledge-based feature provides a sensible interpretation of the words in a natural language content from the human-engineered external knowledge bases. The last feature is FrameNet; it provides a rich linguistic resource of text with similar latent meaning under the semantic frame categories. The utilization of semantic features can help in improving data analysis in different domains, such as public safety, governance, and journalism.

5.5. Information uncertainty

Social event detection is highly dependent on the quality of data. Retrieving accurate events of interest out of social media news requires cross checking those media streams with verified sources, and employ techniques for fighting fake news [155]. The SpotFake framework considers the textual and visual features of the Twitter and Weibo articles, but was only focused on fake news detection [156]. This framework uses bidirectional Encoder Representation from Transformers (BERT) for textual representation and VGG-19 pre-trained on ImageNet dataset for visual representation. These features are fused by using a simple concatenation technique to attain the proper news representation.

Another multi-modal fake news detection framework based on Weibo and Twitter networks is proposed by Khattar et al. [157]. The framework uses an encoder, decoder, and news detector. The encoder discovers feature representations from textual and visual modalities. The textual encoder extract features by using recurrent neural networks with Long–Short Memory cells, and the visual encoder is trained using convolutional neural networks (CNNs). Just opposite to the encoder, the decoder reconstructs data from the sampled multi-modal representation.

With the aim of fighting misinformation during the COVID19 pandemic, the authors in [158] proposed a model for fake-news event distribution predictors amongst social media users using Nigeria as a case study. The authors describe the result of a Nigerian sample social media posts containing related to fake news events. The proposed framework investigated the fake news events, which was motivated by

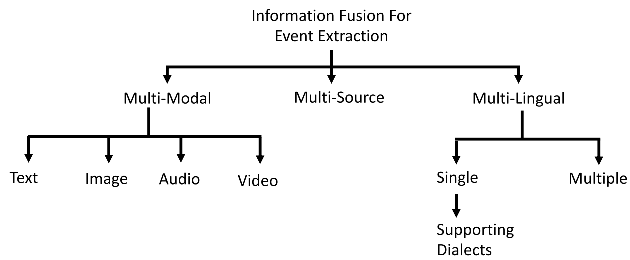

Fig. 5. Information fusion for social event detection.

"altruism". The model used Partial Least Squares to evaluate the effect of some parameters on the sharing of fake news. The study found that the prediction of fake news sharing of COVID-19 is mainly affected by altruism. However, the research failed to assess the impact of fake media sharing on cultural context, age and gender. Because Nigeria is a country with multiple cultural and ethnic groups.

6. Information fusion for event extraction

Discovering events from social media can be greatly enhanced with the integration of multimedia data streams that can be derived from multiple modalities (e.g., text, image, video), multiple languages, and multiple social network sources (see Fig. 5). Data fusion methods are required to integrate events from different sources and different modes, thus offering a better performance and more enriched knowledge compared to individual network approaches [159]. This is also motivated by the ongoing trend of users sharing their interest and content over multiple social networks simultaneously. For instance, one can share a textual message about an event over Twitter, while sharing related photos and videos with hashtags over Instagram.

Definition 3 (*Data Fusion For Social Event Detection*)**.** Given multiple streams of multimodal social media, data fusion is the task of identifying and combining the relationships between the different multimodal social media posts, such as texts and images, with the purpose of merging data at an early or later stage to improve the effectiveness of the event detection process.

For the above definition, the input is multiple social media streams of different modalities, such as a stream of texts and images. The output is the detected events. This task improves the process of event detection by combining features and relationships of multi-modal posts that are related to a given spatio-temporal event in order to improve the effectiveness of event detection in real-time.

Recent works on social media event detection extract their data from a single social media platform with single modality. Hardly a few research papers proposed a combination of the multiple modalities, multiple languages, and from different platforms. This combination is very critical, as well as challenging. We present in the following sections the details on these important aspects and their impact on the event detection process.

6.1. Multi-modal

Traditional social event tracking methods are mainly based on analyzing textual data, with a few studies on social data mining from images as described in Section 4. However, the popularity and growth of social media leveraged the development of multi-modal data processing techniques, that may include text, image, audio, and video content [7]. With the aim of achieving better performance in social event detection, recent studies extracted features from both texts and images using data fusion and machine learning techniques. Data fusion is the process of incorporating multiple data sources so that we can produce more consistent, accurate, and enriched information than insights derived from a single data source.

Early research approaches focused on multi-modal feature representation rather than traditional single model feature extraction. One of the previous learning methods, Canonical Correlation Analysis (CCA) [160], was used for multi-modal data representation, but it was only considered for correlation between variables and does not take into account the relationships among variables. Multiple Kernel Learning (MKL) [114] established a kernel function for text and image data, and it achieved the fusion of features by combining different kernel functions. Corr-LDA and multi-modal LDA models capture the relationships among images and their annotations on the topics, which are represented by textual and visual modalities in the topic space. Besides, some authors include URLs and geographic information. A multimodal data fusion framework for extraction of cross-media topics has been presented in [161]. Hybrid models based on topic models, word embedding, and deep learning also been used in multi-modal feature representation.

Table 6 illustrates the main contributions related to information fusion for social event detection. Zeppelzauer et al. (2016) [162] presented the experimental analysis of the fusion of textual and visual data from Instagram. They employ a hierarchical approach for the fusion of textual and visual representations. For the textual representation, two popular features, namely, TF-IDF and LDA are used. For the visual description, they choose global features (GSIT) and local features (SIFT descriptors). They further classify the textual and visual feature combination using an SVM classifier with a radial basis function kernel (RBF kernel) and RUSBoost. Yilmaz, et al. (2018) [163] focus on hashtags in text and geolocation features on Twitter. The proposed model is an unsupervised probabilistic generative modal, and it uses the expectation–maximization (EM) algorithm to find the model parameters and generative latent variable model for access time and spatial features.

A multi-modal an end-to-end deep neural network framework for sentimental scrutiny in Twitter was proposed in [164]. They introduced a new residual model to merge text and image features and propose two combined strategies for enhancing and differentiate more feature depictions. Later, an extension to this approach was proposed based a hierarchical semantic attention network, integrating image captioning for multi-modal sentiment exploration [165]. This was the first mechanism that uses image slogans extracted from visual semantic features as the additional information for text in multi-modal sentiment exploration task. Qian et al. (2019) [166] present a technique to fuse the location, appearance, semantic, and temporal features to extract the location of interest and merge the visual representativeness, significance, and season relevance to rank images for each POI. The popular viewpoints termed as locations of interest in each POI are extracted by using Location-Appearance-Semantic-Temporal (LAST) clustering method. Each location of interest is summarized with textual and image data properties. Another approach for rapid mapping of image data from social networks to spatio-temporal queries in case of emergency [167]. They are extracting the temporal and spatial whereabouts of images in order to better manage and analyze emergency events.

To tackle the multi-modal data complexity, a multi-modality graph was designed in [168] with similarity measures, which effectively leverage the complementary cross-media insights to achieve significant improvement of topic detection performance. A multimodal fusion approach along with a feature coding mechanism were presented in [169], to extract events from Flickr data based on a multimodal clustering algorithm introduced earlier in [170]. The authors in [171] developed an approach for summarizing Flickr images and textual data from blogs. They trained a model to predict grammatically correct sentences with a long explicit storyline that appears acceptable. Qian et al. [172] present a multi-modal event topic model (mmETM). It adopts an incremental learning strategy to learn the correlation between visual and textual modalities, and obtain informative social event monitoring and their evolution trends.

Deep learning approaches were adopted for image understanding and captioning purposes. For instance, the authors in [173] developed a model based on Recurrent Neural Networks (RNN) with an attention mechanism to capture the relations between visual and textual features for rumor detection. They evaluated the performance of this model with Weibo and Twitter datasets. A binary classifier was finally used to distinguish rumors in micro-blogs. Huang et al. (2018) [174] also work on textual and visual information to extract the most relevant and useful data. Canonical Correlation Analysis (CAA) is a classical approach of the basic paradigm and foundation of multi-modality representation learning. This work uses a Deep Canonical Correlation Analysis(DCCA), which is more flexible than the CCA Kernel. In another model [175], topic are learned over time automatically from multi-modal data. This model reduces the undesirable updates by using the multi-expert minimization restoration scheme. Furthermore, it helps in alleviating the drift problem that is common in social data and thus affect the correctness of tracking events. Qi et al. (2019) [176] presents a fake news detection framework by utilizing visual information. Apart from the previous research works, Multi-domain Visual Neural Network (MVNN) combines the data of pixel and frequency domain. The frequency-domain uses by CNN with the ability to capture spatial structure characteristics, and the pixel domain employs a multi-branch CNN-RNN network to extract the features. The MVNN model evaluates on Weibo data due to the limited distinctive images in the existing Twitter multimedia dataset.

6.2. Multi-source

Early studies on fusing or summarizing content from different social media platforms are presented in [175,177,178]. Zhang et al. [177] developed a probabilistic multi-event tracking algorithm across multiple domains to obtain evolution trends and informative summary from Google News and Flickr. Shah et al. [178] focused on summarizing the contextual information from Flickr and Wikipedia. Their system leverages Wikipedia as an event background knowledge to automatically generate summaries in real-time about events of interest. The proposed method needs attention to missing essential aspects of an event that are missing in Wikipedia. Multi-modal clustering and fusion algorithms had been previously proposed in [179–181] where features are heterogeneous.

Satya et al. (2017) [182] proposed three different approaches to merging information from various social media such as Twitter and Tumblr. They presented an event detection model within real-time temporal constraints (i.e., detecting the event a few minutes after its occurrence) inferred from multiple streams. The techniques for fusing data streams from multiple sources are based on three main scenarios [168,182]: (i) Graph Generation Scenario; (ii) Graph Filtering Scenario; and (iii) Post Clustering Scenario:

1. Graph Generation Scenario. The graph generation scenario is a straightforward model, by joining two or more data sources into one stream. The whole textual content from both sources is gathered at a single time interval. However, for each data stream, tokenization, data cleaning and other data processing is performed individually. A graph connecting co-occurring words is usually built based on all existing tokens. The problem in this technique is that each data streams is coming from a different platform and may have different features (i.e., the properties and metadata published in each API). Thus, when the streams are treated equally, some features might be lost. Losing some features may later impact the quality of generated event clusters.

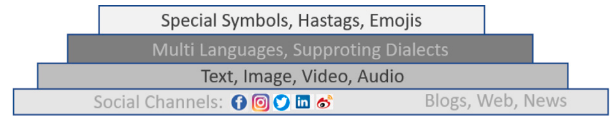

Fig. 6. Hierarchical perspective of multi-modal and multi-lingual channels in social media.

2. Graph Filtering Scenario. In this scenario, for each source, the data stream is processed separately, and a separate graph of tokens is created for each data streams. At the end, the generated graphs are merged based on specific token properties and a similarity measure to introduce one merged graph. Consequently, there is only one merged graph that is used for clustering and event tracking purposes. However, the resulting merged graph can be complex and more sophisticated to build than the individual graphs. The number of generated clusters from the merged graph is fewer comparing to those generated from individual graphs, where each cluster represent one event.
3. Post Clustering Scenario. In this technique, each data stream undergo the whole process separately, including graph clustering and event tracking. The fusion is performed here by merging the generated event clusters at the end of the event detection phase.

The approach developed in [183] focuses on multi-modal clustering of social streams from Flickr and Twitter. A feature fusion strategy is implemented along with distance metrics that help in constructing a singly multi-modal affinity matrix. Different clustering techniques were tested using the ReSEED dataset for multimodal data such as a modified DBSCAN, spectral clustering and incremental clustering. Wang et al. (2017) [141] used an unsupervised learning approach to integrate Twitter and Instagram data streams and then select the best detection performance from both sets. The approach first identifies all potentially related posts from each source in a given period. Secondly, it decides on the similarity of potentially co-related posts, whether they represent real events or otherwise the similarity would be accidental. It is suggested here that event detection from Instagram may suffer from a high number of false negatives because of its sparsity, while Twitter data event detector may present many false positives, due to the short messages and high percentage of noise. Therefore, both detected events from these different modalities are fused, and then the resulting events are tracked. Another approach to integrating information from Twitter and Instagram was proposed in [81]. They developed a fusion algorithm for identifying and geo-locating real-world events. They also used the Expectation–Maximization (EM) algorithm to find the relevant variables, unknown parameters for the coherence, and location names. The evaluation of performance was done using existing event detection techniques for Twitter and Instagram individually as baselines, so that the fusion model was assessed and showed a better accuracy performance.

6.3. Multi-lingual

The language of a social media user interface is the language that the user chooses to interact with. There are 123 different languages for interfacing. English, Japanese, Spanish, Arabic, Russian, Korean, French and Chinese are among most frequently used languages. Most text-based geolocation and event detection studies are carried out in a basic English setting. English language identification and processing tools are readily available, thus allowing for highly accurate event detection techniques. Here we investigate the language influence on event detection in the online community (see Fig. 6).

Table 6
Information fusion for event detection: Modalities and types of streams.

Reference	Modality		Language			Type of stream		Technique
	Uni-modal	Multi-modal	Uni-lingual	Multi-lingual	Dialect support	Uni-source	Multi-source	
Zhitao Wang et al. (2014) [184]	Text		Chinese			Weibo		Rule Set Model (RSM)
Zhang and Xu (2014) [177]		Image & Text	English					CO-PMHT (CO-Probabilistic Multi-Hypothesis Tracking)
Yılmaz, Y., & Hero, A. O. (2018) [163]		Text & geolocation	English			Twitter		Generative Latent Variable model
Quian et al. (2015) [172]		Image & Text	English			Google News		multi-modal Event Topic Model (mmETM)
Jin, Z. et al. (2017) [173]		Text & Image	English				Weibo & Twitter	att-RNN
Huang et al. (2017) [174]		Metadata, text & image.	English			Twitter		Canonical Correlation Analysis (CCA)
Satya et al. (2017) [182]	Text		English				Twitter & Tumblr	Event Detection at Onset (EDO)
Giridhar et al. (2017) [81]	Text		English				Twitter & Instagram	Expectation–Maximization (EM) Algorithm
Wang et al. (2017) [141]	Text		English				Twitter & Instagram	Fusing the events based on similarity from Duplexing and Event Monitoring Algorithm
Abdulkareem and Tiun et al. (2017) [185]	Text			Iraqi, Egyptian, & Lebanese	Yes	Twitter		Sentic, PoS, Modification, Negation feature in KNN, NB and decision tree algorithm.
Alayba et al. (2017) [186]	Text		arabic			Twitter		Unigram and bigram features applied on the several machine learning algorithms along with deep and convolutional neural networks
El-Masri et al. (2017) [187]	Text		Arabic				Different reviews	Supervised sentiment classification in sentence level and document level.
Hathlian et al. (2020) [188]	Text		Arabic		Yes	Twitter		Text classification (features are frequency, n-grams, & tweet label) by machine learning techniques

(*continued on next page*)

6.3.1. *Single language*

Wang et al. (2014) [184] investigated identifying the characteristics of Chinese words, emoticon elements, and hierarchical structure of Chinese micro-blogs. As a result, a new sentiment word mining method was developed. They also implemented a visualization technique to study the relationship between online sentiments and real-life users' behaviors. The next approach in the Chinese language was to identifying event rumors on Weibo [193]. The authors focused on detecting

Table 6 (continued).

Reference	Modality		Language			Type of stream		Technique
	Uni-modal	Multi-modal	Uni-lingual	Multi-lingual	Dialect support	Uni-source	Multi-source	
Xu et al. (2017) [164]		Image & Text	English			Twitter		Merged Neural Network, (MNN), and early Residual MNN and Late Residual MNN
Xu (2017) [165]		Image & Text	English			Twitter		Hierarchical Semantic Attention Network (HSAN)
Lo et al. (2017) [149]	Text		English			Twitter		DPMM(Dirichlet process Mixture Model) Clustering
Tiwari et al. (2018) [159]		Text & Image	English				Twitter, Instagram, & Flickr	Markov Random Fields
Abali et al. (2018)[126]	Text		Turkish			Twitter		Naïve Bayes Classifier
Qian et al. (2018) [175]		Image & Text	English				Google News & Flickr	Online Multi-modal Tracking Model & Online multi-modal multi-expert learning
O'HalloranEtAl2018 et al. (2018) [189]		Image, Text & Video	English			Wikipedia		multi-modal Event Topic Model (mmETM)
Alkouz et al. (2018) [190]	Text			English & Arabic		Twitter		TrafficClassifier
Modha et al. (2018) [191]	Text			English, Hindi (Romanized & Devanagiri script)	Yes		Facebook, & Twitter	
Singhal et al. (2019) [156]		Text & Image		English & Chinese			Twitter & Weibo	FBERT & VGG-19
Khattar et al. (2019) [157]		text & Image		English & Chinese			Twitter & Weibo	MVAE
Qi et al. [74] (2019) [176]	Image		NG				Twitter & Weibo	MVNN
Liu, Y. et al. (2020) [192]	Text			English, Chinese, French, German, & Japanese			Twitter, Weibo, WeChat, worldwide Publishing House & Forum.	MLEM (Multi-lingual event mining model)
Alkouz et al. (2020) [24]	Text			English & Arabic	Yes		Twitter & Instagram	SNSJam

rumors in Chinese via crowd response under emergency scenarios. They proposed detecting event rumors from a mixed set of valid news and false information, and extracting the features from the re-posts and comments. Lastly, they classify the rumors by using an SVM classifier. A model based on sentiment analysis of textual content and hashtag for the detection of Chinese bursty events was also proposed [194]. Song et al. (2015) [195] introduced three factors for recommending hashtags about hot topics in Twitter. The factors are the semantic similarity between hashtags and tweets, the user acceptance degree of the hashtag, and the development tendency of the hashtag. They are recommending some related hashtags for users to choose one or more of them as content added to forthcoming tweets. This proposed work is applied to the Chinese micro-blogging website, Sina Weibo, and showed appropriate recommendations using this model for forthcoming tweets.

Arabic language is one of the most used languages in social media as it is the mother tongue of 27 nations and used by many other Muslim countries. The united nations uses Arabic, among six other languages, to write its documents. The Arabic language is classified as a Classic Arabic, Modern Standard Arabic, and Dialectal (Colloquial) Arabic. The first effort to identifying real-world social events in Arabic was presented in [196]. Sentiment analysis plays a significant role in event extraction. The basic features of sentimental analysis approach including, mathematical algorithms for classifying feeling-based features, and determining the best combination which would present new lexicons that are used as a significant indicator of sentiment in the natural language content. A system for detecting and analyzing influenza spread based on Arabic tweets was proposed in [190], which classifies tweets as self-reporting, non-self-reporting, and non-reporting. A linear regression model is applied to classified tweets to predict future hospital visits. Another approach for finding the semantic similarity, considers the sentiment analysis of Arabic tweets related to road traffic congestion in a big data environment [197]. The authors also proposed an approach for analyzing and classifying drivers' feelings and emotions with respect to encountered traffic jams.

Other works on Arabic language studied issues related to sentiment analysis rather than event detection, but we cover some of them, since we believe these approaches can help advancing the global research in social media analysis. Alayba et al. (2017) [186] showed that SVM classifiers gives better results than machine learning algorithms like CNN and DNN on their Arabic opinion dataset. Mountassir et al. (2017) [187] focused only on a method that applies POS, clustering, and analysis using SVM and Naïve Bayes classifiers. Hathlian et al. (2020) [188] used sentiment analysis with subjective analysis of Arabic posts to discover the sentiment of people on a certain issue.

A semantic approach for detecting user attitudes and business insights from Arabic social media was presented in [138]. The proposed method is applied to both standard Arabic and Arabic dialects that express feelings, and also shows how strongly given words can express such feelings. Next approach of Arabic tweets for phrase identification and semantic text similarity analysis. Al-Smadi et al. (2017) [140] adopted several features such as lexical, syntactic, and semantic, to overcome the limitations and weaknesses of the baseline technology for feature extraction in Arabic language. The semantic text similarity analysis was evaluated using a Support Vector Regression (SVR) classifier, which is a variant of the SVM classifier for regression analysis. A survey has been recently released for a comprehensive review of Arabic sentiment analysis [198].

Öztürk et al. [199] analyze public sentiment topics on Twitter, including Turkish and English languages. Abali et al. (2018) [126] developed a smart system to detect city events using traffic updates from Twitter and their actual location with a focus on the Turkish language. Few problems encountered in the creation of the location recognizer, due the structure of the Turkish language. That means some place names are homophones with common words in Turkish, and some of used as a surname in Turkish. This problem is solved by removing common homophone words from the place name list and form a language grammar with regular expressions. Then, supervised learning with trained tweet dataset and a Naïve Bayes classifier were used for detecting traffic-related events.

6.3.2. Multiple languages

Researchers were recently attentive on creating multi-lingual approaches with independent domain for detecting and classifying social media real-time messages. They were detecting and characterizing unexpected high-impact real-world events in social media platforms, specially in case of emergency, by using cross-lingual domain-independent patterns [200]. Such type of techniques should help us better understand social media behavior during the crises in affected locations around the world, regardless of their language, domain, and type of event.

The content in social media written in different languages. The bag-of-words model is not suitable for multi-lingual multi-class classification. Modha et al. (2018) [191] performed experiments on standard machine learning classifiers and found a deep learning model, which outperforms all standard machine learning classifiers. For the text representation, the fastText word embedding method was used. The fastText is an extension of the Word2vec model, and it is more convenient than the Glove. The CNN and LSTM with fastText are better performing models for multi-lingual multi-class classification. Lo et al. (2017) [149] designed an unsupervised learning approach for hot topic identification with a multi-lingual nature, and with minimal manual annotation effort.

Alkouz et al. (2018) [201] presented a method for recognizing location in Arabic and English tweets. This cross-lingual location recognition model supports the standard Arabic tweets as well as UAE Arabic dialect. The traffic classifier algorithm classifies the traffic-related tweets from the filtered and stemmed tweets. The authors in [190,201] developed a new prediction model to predict the spread of influenza from the United Arab Emirates Twitter data streams with a cross-lingual approach. Their previous work [202] analyzing Influenza only from Arabic tweets. Apart from that, the proposed prediction model is called Tweetluenza, and the algorithm uses Arabic and English tweets to improve the evaluation results. The multilingual keywords of the influenza-related keywords and its different forms are cross-validated. They also applied a linear regression model to count hospital visits in the coming weeks.

Liu et al. (2020) [192] used an evolution graph technique to detect events from multi-lingual text streams, which are noisy and domain-independent. This method represents the multi-lingual social post by word2vec, which helps merging the same entities and similar words from different languages. An SVM classifier is employed for classifying the posts into their domains. Then, the sentiments are determined using a Bayesian classifier. The technique also determines the relationship between two events or event correlation analysis based on event properties. Rather than point clustering, the technique used line clustering on the evolution graph, because it is assumed that events may evolve into a very different event after a certain period of time. Although this model shows reasonable accuracy for event detection, it does not support domain knowledge, which will make it difficult for this model to detect specific-domain events.

6.3.3. Supporting dialects

The dialects are a version of the language in a specific region which linguistically constitute separate languages. In the case of Arabic language, approximately 60 billion words derived from 10,000 roots. Moreover, classical Arabic (found in the Quran), modern Arabic (period of Pre-Islamic Arabia), and colloquial Arabic. Identifying dialects from social media posts is gaining interest among researchers despite its difficulty. Abdulkareem et al. (2017) [185] developed and used many Part of Speech Tagging classifiers, such as the naïve bayes, K-nearest neighbor and decision tree for many Arabic dialects including Iraqi, Saudi and Lebanese.

7. Event visualization

Event visualization can be categorized based on the multiple dimensions that define an event. Spatial, temporal, network-based and topic-based visualizations can be adopted for better understanding of the social content being discovered. Time series sequences can be visualized using scatter plots, timelines or line graphs, whereas network-based or topic-based visualizations use node-link diagrams or word clouds. In this survey, we focus on the geospatial and spatio-temporal visualization of social events, because of their multi-dimensional nature, and topic-based visualization techniques can be reviewed in [203,204].

Countable apps are available world-wide to explore the clear vision of geo-located PoIs and for navigation purposes. This section focuses on describing the available techniques to extracting and visualizing the exact location of social events by using the features and dimensions described in earlier sections. An online community may casually reveal event or post locations either manually or with the help of GPS, or otherwise the system would need to infer that location as explained in Section 5.1. The inferred location information sometimes makes accurate and clear visualization of the event, but can sometimes provide inaccurate or misleading location on map.

7.1. Event location visualization

Determining a social event location is a difficult task. We define the event localization process as follows.

Definition 4 (*Social Event Localization*)**.** Given a streaming of social media, event localization is the task of identifying the location of an event by processing its related social media posts and their meta-data to extract shared spatial properties at a given time instance.

In the above definition, the input is the streaming social media, such as a stream of tweets, and the output is the predicted event location. This task requires efficient processing of the streaming social media to cluster the social media posts, where each cluster represents an event. The clustering algorithm should be incremental and efficient to process the social stream in real-time.

Google introduced a native topic visualization through Google+ Ripples, as explained in Viégas et al. (2013) [205]. It provides a graphical representation of social influencers. Ripples use a visualization technique based on a hybrid circular treemap, and a traditional node-link tree diagram. Textual based or content based location prediction was done either by estimating the probability of the location of a given word P(location| given the word) in the text; or with the probability of generating a tweet at a given location P(generating tweet|location). The STEWARD user interface introduced in [206] was a first attempt to support visualization of spatio-textual queries related to hot topics from the web. It was extended with additional features and modules developed in a new system called 'NewsStand' [207]. NewsStand is automatically extracting geographical content from news articles. Different techniques for topic detection were used including Named Entity Recognition, rule-based, statistical-based, and similarity-based feature extraction, to get a better result for recognizing news at a given geospatial resolution. Their method finds inductive locations for news and visualizing them on maps by using properties, such as word frequency, inverse term frequency, geographical spreads and density [208].

The authors in [209] have introduced a FluxFlow system, which gives an interactive visual exploration of anomalous information spread on social media. The visualization module of a FluxFlow shows anomalous threads and their contextual information with various views. The system detects anomalous retweeting threads by traditional sequential anomaly detection mechanism, and generate a tweet homogeneous graph with temporal dependency for visualization purposes. This article designs the rationale for visualizing retweeting threads. This visualization component can serve a more generated tool for visual exploration of information propagation on social media, and as a flexible timeline visualization for retweeting threads. Lu et al. (2017) [210] developed a visual analytic framework for identifying critical information, which explores topic drivers by linking time series data that is annotated from multiple media sources. For annotation purposes, a widget enabling domain experts to manipulate social media data by keywords cluster splitting, and merging using semantic matching. This keyword-based semantic grouping tool can serve as an appropriate semantic bridge to derive causality measures between time series data. These causality links can show that some previous events in a time series A may impact and predict the time other event would appear in another time series B.

7.2. Spatio-temporal scope visualization

A model that discovers unusual events in social media streams using the space–time features was proposed in [211]. They extract the major topics contained in the textual part of social media by using the Latent Dirichlet Allocation (LDA). The abnormality of the topic is detected based on probabilistic topic modeling; then, the situational awareness task is ranked by employing Seasonal-Trend Decomposition procedure based on loss smoothing. The visual dashboard includes abnormality estimation charts, a topic exploration map and tables with word clouds for message content. Another dynamic visualization of social media information was introduced in [136]. This visual analytic system, called SocialWave, integrates the spatial and temporal patterns to characterize information diffusion. The proposed dynamic social gravity model (SGM) quantifies the dynamic spatial interactions among users. The model was integrated with ground-truth data to measure the diffusion power in the temporal dimension. SocialWave contributes a temporal visualization that reflects the spatial features of the diffusion network. Among the features used to capture the interactions among users are the geographic distance, cultural proximity, and linguistic similarity. Multi-granularity analysis was supported through scaling the spatial dimensions.

Jeitler et al. (2019) [212] provide a visual exploration tool, called RescueMark, that characterizes the spatial, topic, and temporal dimensions for identifying disaster situations. The framework extracts crisis-relevant data, and applies word embeddings using the fastText algorithm and k-means clustering. After removing the clusters of unrelated messages, the Latent Dirichlet Allocation (LDA) algorithm used to extract topic terms for each message and Kleinberg's burst detection algorithm is used to burst analysis. An efficient combination of pattern-matching analysis and contextual information could help visualize reliable dashboard from fatality reports, including an interactive city map, events on critical situations, a timeline, and trending topics. Another approach on spatial event visualization was introduced in [25], where an automatic extraction mechanism of events of interest from crowdsourced data, to be displayed at different spatial scales based on their worthy attention. The proposed Hadath framework is providing an efficient and scalable technique for the management of a large number of micro-blogs and for visualizing events on map based on their level of significance. Therefore, events of local interest may appear at finer zoom levels, whereas global events would appear on larger map scales (e.g., city, county and country levels). StreamExplorer is another visual exploration tool for social streams with different levels of granularity [213]. This framework facilitates the visual analysis, tracking, and comparison of a social stream at a macroscopic level using a visual tree of sub-events, a map visualization of topical or geographic summary of tweets at a mesoscopic level, and finally, visually interactive lenses to enable an intuitive browsing of words or the network at the microscopic level. This framework only works with the English language and cannot cope with non-English social streams.

8. Big data frameworks

Big data depicts the massive sizes of currently available datasets, which may be terabytes, petabytes, or even exabytes. These datasets exhibit the five keys of such grand scale including volume, velocity, variety, veracity and value, and they require special care in terms of management, storage, and efficiency. Social channels can be considered a main category for such huge datasets, and a real-time social event detection platform must take these big and streaming data processing challenges into account. A wide variety of domain can benefit from the social big data techniques. Furthermore, their experimental evaluation usually measures the efficiency, correctness and effectiveness of the proposed technique.

Traditional data analysis algorithms and techniques cannot scale their performance on a worldwide level due to the increase in data size and geographical spread. The productive use of data mining methods and machine learning algorithms in the different domains are leverages by the MapReduce paradigm [214]. The big data frameworks, such as Apache Hadoop [215] and Spark [216] enable large scale data processing. Apache Hadoop, which is an open-source software framework written in Java, is used for the distributed storage and processing of huge datasets. But, this framework has some limitation with respect to its lack of support of stream and real-time data processing, since it support batch processing only. For the distributed programming and filesystems, commonly used MapReduce-Based systems are Apache Pig, Apache Storm, Apache HDFS, and Stratosphere. The document and graph data models are also offered by Apache Cassandra, Apache Giraph, and MongoDB. Libraries for machine learning are Apache Mahout [217], SparkMLlib [218], and MLBase [219]. Lastly, Apache Nutch, Apache Zeppelin, Pentaho, and SparkR are used for business intelligence and data analysis applications.

Data stream management systems (DSMS) refer to the types of database systems that handle continuous data streams. A DSMS manipulates dynamic and real-time queries, and is usually characterized by a limited main memory and high update rate of incoming unstructured data streams [220]. Many DSMSs are available in the market, including proprietary systems, such as, Google cloud dataflow, IBM streams, Amazon kinesis. In addition, other available open-source frameworks include Spark Streaming, Storm, Kafka Streams, Samza, and Flink. Continuous processing is required to manipulate the unbounded social media streaming. Such processing is classified into two categories [221]: (i) Native stream processing: means each arrived record is processed as soon as it arrives without delay; and (ii) micro-batch processing, which processes data streams with groups of small batches (usually of a few minutes). While many technologies and tools were presented to manipulate data streams, we will have a brief overview on the following data streaming tools: Apache Flink, Apache Storm, Apache Spark, and Apache Kafka.

- Flink is an open-source data streaming framework that handle on record-by-record basis (i.e., true streaming) [222]. Flink can work on batches as a special case of streaming with bounded data. There are many features of using Flink, such as, low latency (refers to how soon record might be processed), high throughput (refers to how many records can be processed per seconds), and is considered as a relevant tool for real-time event detection and processing.
- Storm, also called 'real-time Hadoop', is a distributed framework used to handle real-time streaming data. Storm processes data on item-by-item basis instead of batching. Stateless processing is supported by Storm, which gives a low latency and high throughput. With good hardware specifications, Storm can handle millions of byte messages per second per processing node [223]. Although there are many features available by using storm, there is no guarantee on the ordering of message processing. Furthermore, sometimes there might be some duplication in processing messages, but no message loss.
- Spark is a framework basically used for batching data processing, but can support streaming data by micro-batching, which can be manipulated via the native semantics of the batch engine [224]. Technically, spark is similar to the MapReduce paradigm with a difference in accelerating the batch processing using full in-memory computational power. That means all data is processed in memory, the storage is used only to load data into memory and export the results. In terms of development, Spark can be installed alone or on the top of Hadoop instead of the MapReduce engine. In addition, Spark offers machine learning libraries with a diverse set of algorithms (e.g. Classification, Regression, Collaborative Filtering and clustering). Although Spark is considered as an efficient tool for machine learning and interactive queries, it has some limitation in terms of performance due to the increasing throughput. Moreover, since Spark relies on RAM for data processing, the cost is another issue due to expensive cost of RAM comparing to disk-based processing.
- Kafka is a distributed streaming open-source framework, mainly used for distributed messaging purposes [225]. Kafka aims to fix scalability issues resulting from the rapid technologies growth needs [226]. Kafka uses publish and subscribe approach, which was used in LinkedIn. Kafka guarantees durability of messages that allows us to build micro services and event driven processing. It is considered as a reliable storage since it stores data in disk for a particular period and propagate the data for fault tolerance [227]. While connecting data sources in simple and relevant way, Kafka plays a data pipeline role between them. Consumer and producer APIs are used to allow reading and writing messages from Kafka topics. Kafka supports event stream services such as joins, aggregation, ingestion and processing time. Moreover, Kafka has an SQL engine that allows developers to write SQL statements on streaming data.

The rest of the big data benchmarking technologies are Geospark, Hive, Geomesa, and Elasticsearch. GeoSpark [228] is an open-source geospatial data processing library that requires a large amount of storage because each dataset has two RDDs (Resilient Distributed Datasets) in memory and disk. The major drawback of GeoSpark is that data indices have to be rebuilt every time before running the queries. And it does not provide a way to index any other data types except geospatial data. The next open source data warehouse software is Hive [229], which is set on top of Hadoop, and it provides summarization, different types of queries, and analysis of data. GeoMesa [230] is an open-source, distributed, Spatio-temporal Bigtable-style database. Finally, the Elastic search [231] is a search engine based on the open-source. Elastic search and the Hive offer a very user-friendly monitoring tool.

Table 7 describes how some studies have used big data processing tools for large-scale event detection. The table shows whether a given approach is providing real-time response in event detection, whether it has been tested on big data, and that the approach is covering world-wide scale and incremental or not. Walther et al. (2013) [232] have chosen MongoDB database system to support temporal and geospatial indices, and fast accessing time. Apache Kafka and Apache Samza infrastructure widely do personalized online services and real-time predictive analytics. Kleppmann et al. (2015) [227] explains the reason for designing Kafka and Samza and its limitations. These frameworks designed with high throughput, operational robustness, low latency, and long-term maintenance. Nodarakis et al. (2016) [233] performed a sentimental Twitter analysis using Apache Spark. Spark overcomes the limitations of the Hadoop. The Spark has DAG execution engine, and it supports cyclic data flow in-memory computing so that It works 100x faster than Hadoop. For supporting multiple machine learning algorithms, the Spark framework introduces a multi-algorithm library called MLlib. The Manhout and SparkMLlib libraries designed to build an efficient application based on a machine learning algorithm. By the use of the cascade learning concept, Gupta et al. (2017) [218] integrated the Spark and the deep learning computation models to maximize the extracted information to attain maximum accuracy. Furthermore, the model addresses the class imbalance problem effectively addressed in a large scale real-world dataset. Karaman (2019) [234] collected data, and it transferred to the Apache Spark [106] environment for detailed analysis. Afyouni et al. [2] developed a big data platform for the incremental extraction of social events while tracking their spatio-temporal extents in near-real-time order. The authors have used a combination of big data and stream processing tools such as Kafka, NiFi, and Geomesa on top of Accumulop database to ensure efficient indexing of spatio-temporal events and excremental clustering of incoming streams. We note that despite the huge number of works on event detection from social media streams, only very few works have utilized the Big Data platforms and tools in their event detection systems.

9. Evaluation

To understand the development and improvements in new approaches, there is a need for benchmarks and evaluation analysis. The evaluation analysis refers to training and testing the corresponding model using the existing methods and associated with historical practices. The standard classification metrics for evaluation procedure are precision, recall, and F-measure to evaluates the effectiveness of the

Table 7
Large-Scale event detection.

Reference	Platforms	Update frequency (Periodicity)			Scalable		Incremental
		Real-time	Near real-time	Historical	Data size	Worldwide coverage	
Walther et al. (2013) [232]	MongoDB (NoSQL, JSON			✓	✓		
Nodarakis et al. (2016) [233]	Apache Spark		✓		✓	✓	
Gupta et al. (2017) [218]	Apache Spark		✓		✓	✓	
Karaman et al. (2019) [234]	Apache Spark (HTML & Angular JS)		✓				
Afyouni et al. (2020) [2]	Kafka, NiFi, Geomesa and Accumulo		✓		✓	✓	✓

proposed techniques. In the event detection technique, precision refers to the metric measuring the percentage of detected relevant events out of all relevant events in the answer set. High precision relates to the low false-positive rate of the event detection system. The Recall metric is the ratio of correctly identified events from all the relevant events in the data stream. F-measure is more helpful to find the accuracy, and it is the weighted average of precision and recall.

Social media event detection is a relatively complex problem, as it involves many different components, each one of them can have an impact on the overall performance of the system. Real-world datasets are required to evaluate the effectiveness of the proposed techniques. Then, most authors evaluated their event detection techniques based on the happenings of global events and during the time when they take place. These evaluation procedures are beneficial to understand the accuracy of the framework in detecting social events and how much improvements are needed. Table 10 in Appendix shows the datasets used in each research study, and Table 8 shows the average performance for each approach.

Table 10 in Appendix indicates that most of collected textual datasets for the purpose of event detection are from the Twitter data stream. For the image datasets, Instagram and Flicker were the main sources of data collection. As seen from Table 8, systems that fuse data from multiple sources were able to reach higher precision, recall and F1 scores of event detection. Therefore, their accuracy is higher than those systems that rely on only a single source of data.

10. Applications

Social media platforms are the most common place for informing users of what is happening around them. This section discusses the main applications of event detection systems and methods. In general, event detection can help in many recommendation tasks, ranging from tourism, to crisis management and prediction of natural disasters, to dynamic multi-dimensional city exploration, among others. Event detection is the same as a detecting trending topic, which increases the situational awareness picture about the area responsible for police forces, fire departments, and governmental organizations. It can also allow journalists and news agencies to instantly be informed about breaking events. Private customers are also useful to find what is going on in their area like, parties, conferences, etc. Multimedia social event analysis used in the field of hot event analysis, social public opinion analysis, and prediction. Therefore, event-enriched systems may be found in a variety of domains including:

- Trip Plan Recommendation Systems
- Market predictions and Marketing intelligence
- Business Analysis and Favorability Analysis
- News focus detection and Emotion Detection
- Impact on Information privacy, health, and medicine

The following sections highlights a few application perspectives, related to recommendations in different fields, but also discusses the impact on emerging major events, such as the COVID-19 pandemic, among the many others application fields that can be enriched by such event detection and monitoring platforms.

10.1. Trip plan recommendation system

The geotagged photos provide essential information to customize trip planning for tourists. In particular, geotagged photos can benefit trip planners decide on the order of visiting destinations, the popularity of places, time management of each visiting area and the typical travel path. In recent years, tourism benefited form social media, especially in interacting with tourists, searching for information, and making decision related to tourism. Tourists used social media and online tools to perform various actions to manage and plan their trips.

Lu et al. (2010) [236] addressed the automatic trip planning problem by discovering three modules such as Destination discovering module, Internal path discovering module, and Trip planning module. They are discovering destinations by using more than 20 million geotagged photos collected from Panoramio. Also, 200K travelogues leveraged to map geotagged photos, destination style, and visiting time preferred to worldwide destinations, which are employed in the customized and interactive trip planning module. Internal path discovering algorithm merges incomplete paths encoded in geotagged photos from different individuals to reconstruct some representative paths. Trip planning algorithm customizes trip plans by considering travel location, duration, visiting time, and other preferences of users.

Majid et al. (2013) [237] propose a method to recommend locations and points of interests for tourists based on their preferences. This recommendation system uses publicly available Flickr dataset containing photos. These photos consist of textual information such as tags, titles, notes, and descriptions. In addition, they are tagged with temporal and spatial context. The result of this technique shows that context-aware personalized methods are able to predict tourist's preferences in a new or unknown city more precisely and thus generate better guidance compared to previous recommendation methods. Pan et al. (2013) [238] addressed the problem of detecting traffic anomalies from human mobility and social media by using crowdsensing. The traffic anomaly detection system provides real-time alerts when users are nearby. This process made by offline mining, anomaly detection, and anomaly analysis. The dataset collected from a Twitter-like social site in China called Weibo.

Han et al. (2014) [239] propose an approach that uses the trips' spatial and temporal properties to recommends landmarks to tourists. In this method, analyzing the relationship between popular places and properties of the photos taken in those places. The system recommends personalized landmarks that reflect local events or seasonal changes based on the analysis of approximately 327 000 geo-tagged Flickr photos in New York. García-Palomares et al. (2015) [240] expose the possible photo-sharing services in eight major European cities to recognize, examine, and determine the main tourist attractions. The model classified the geotagged photographs on Panoramio into two classes: taken-by-tourists and taken-by-residents. Then, they examined the spatial distribution patterns using existing spatial statistical techniques.

Bao et al. (2015) [241] gives a systematic assessment of recommendations in location-based social networks. Sloan L, and Morgan J (2015) [242] give an understanding of the relationship in geo service and geotagging and how opting into either of these behaviors associated with gender, age, class, and the language. Hu et al. (2017) [235]

Table 8
Summary on performance evaluation.

Reference	Benchmark	Multi-source	Qualitative (Effectiveness)			Qualitative (Efficiency)
			Precision	Recall	F-score	Execution time
Wang et al. (2014) [184]	Systematic	Weibo	0.776	0.812	0.772	NG
Tartir et al. (2017) [138]	Manual	Twitter	0.741	0.747	NG	NG
Katragadda et al. (2017) [182]	Manual	Twitter Tumblr	0.817 0.644	0.839 0.216	0.855 0.323	42 s 23 s
Wang et al. (2017) [141]	Manual	Twitter Instagram Fusion	0.870 0.632 0.70616	47 110 149	0.47 0.69 0.82	NG
Ozdikis et al. (2017) [78]	Systematic	Twitter	0.81	0.59	0.66	0.2 s to 1.8 s
Jin et al. (2017) [173]	Systematic	Twitter Weibo	0.78 0.86	0.615 0.686	0.689 0.7	NG
Hathlian et al. (2020) [188]	Systematic	Twitter	SVM 0.79 NB 0.88	SVM 0.964 NB 0.872	SVM 0.868 NB 0.853	NA
Li et al. (2017) [137]	Systematic	Twitter	0.96	0.77	NG	NG
Hua et al. (2017) [235]	Manual	Twitter	0.98	0.83	0.81	2.42 Days
Hasan et al. (2018) [8]	Systematic	Twitter	0.89	0.96	NA	212 min for 17 million tweets.
Alkouz et al. (2018) [202]	Systematic	Twitter	English 100 Arabic 100	English 83.3 Arabic 70.4	English 91.2 Arabic 82.6	NG
Morabia et al. (2019) [82]	Manual	Newswire	0.762	0.645	0.699	NA
Singhal et al. (2019) [156]	Systematic	Twitter Weibo	0.751 0.902	0.900 0.964	0.82 0.847	NG
Khattar et al. (2019) [157]	Systematic	Twitter Weibo	0.801 0.854	0.719 0.769	0.758 0.809	NG
Qi et al. (2019) [176]	Systematic	MVNN	0.809	0.857	0.832	
Han et al. (2019) [144]	Systematic	Twitter	0.82	0.78	NG	NG
George et al. (2019) [133]	Systematic	Twitter & Flickr	0.89	0.667	NG	NG
Alkouz et al. (2020) [24]	Systematic	Twitter Instagram	English 0.797 Arabic 0.9217 English 0.4603 Arabic 0.5625	English 0.9669 Arabic 0.8455 English 0.9355 Arabic 1.0000	English 0.738 Arabic 0.9135 English 0.6170 Arabic 0.7200	NG
Liu et al. (2020) [192]	Systematic	MLEM model	0.6891	0.7833	0.7332	2.90 s
Senarath et al. (2020) [153]	Systematic	Twitter	44.7 82.7	77.9 97.8	56.8 65.7	NG

proposed a multi-source topical package approach to mine travelogues and check-in records to understood the user's real intention. For experimental evaluation, the dataset collected from Igo-Ugo.com, and it contains 24,008 travelogues and 150,101 checks in records. Cenamor et al. (2017) [120] addressed a PlanTour system to create personalized tourist plans using human-gene-rated information. This framework supports the management and planning of digital contents and services for bus travelers of the particular company. The automated tourist planner module is maximizing the user utility of visiting places and minimizing the total traveled route.

Figueredo et al. (2018) [51] detect implicit tourist preferences based on social media photos and recommend a set of tourism attractions by using convolutional neural networks and fuzzy logic. The proposed method used three thousand photos to test each binary classifier in the scene recognition process, and all classifiers reach over 82% on the accuracy metric.

10.2. COVID19 related events

Social media has been a great sources of data for analysis. As the news of COVID-19 keep spreading globally, some countries are yet to believe the existence of the deadly disease, and some other are struggling with the vaccination process and partial lock-downs towards reaching the herd immunity within their local communities. Since then, many research studies have been carried in order to extract insights regarding the pandemic through social media, such as predicting the outbreak coverage, and tracking major events related to COVID19 [158, 158].

A research was carried out among residents in Wuhan by [243], which was the origin of COVID-19 outbreak virus. The authors examined how the health information on social media was processed by Wuhan residents and how their use of social media could reveal a risk to mental health at the highest rate of the Wuhan-19 Outbreak. The results of their study can help to explain the potential connections between the use of social media and the mental distress experienced by individuals in the public health crisis. Furthermore, the study also provides insights into the mechanism of health training and public reaction to pandemics for a deeper understanding. However, the study does not address how to design potential interventions and health policy that alleviate the impact on mental health during or after the COVID-19 crisis. In addition, from the perspectives of the pandemic in Atlanta, San Francisco and Washington DC offer practical lessons for city governments and highlight the theoretical value of focusing on public relations methods through government. As a result, [244] carried out an exploratory investigation which is based on Functional fragmentation in city hall using data from city agency Twitter accounts and key informant interviews to validates the significance of fragmentation for core organization, as well as public outreach. However, this study was conducted in the early time period during the response to COVID-19 in the United States.

Table 9
Applications of event detection.

Reference	Purpose		Definition/Category	Description
	Specific	Generic		
Öztürk et al. (2017) [199]	✓		Syrian refugee crisis	Sentiment analysis
Hu et al. (2017) [235]	✓		Personalized Recommendation systems	Multi-source topical package
Cenamor et al. (2017) [120]	✓		Recommender systems	PlanTour
Figueredo et al. (2018) [51]		✓	Tourism recommender	Pre-Tourist and Post-Tourist Experience
Alkouz et al. (2019) [190]	✓		Health (Predicting flu)	Multi-lingual keywords of the influenza-related keywords and their different forms.
Alkouz et al. (2020) [24]		✓	Road traffic analysis	Social Network Sites Jam

10.3. Impact on information privacy, health, and medicine

A user's regular usage of social accounts implicitly reflect their habits, preference, and feelings, and it is feasible to monitor and evaluate the wellness as well as a healthier lifestyle of the user. Connecting the inter-relatedness among distinct events in social media and health informatics makes a direction towards downstream applications such as personal care management, patient stratification, and personalized lifestyle planning.

Akbari et al. (2016) [245] propose an optimization framework for wellness event detection from a real-world dataset of Twitter. This framework achieves better performance compared to previous experimental models such as the Logistic regression model with Lasso regularizer (1990), Group Lasso regularizer (2010), and Trace Norm Regularized Mtl (2010). AdedoyinOlowe et al. (2016) [1] apply the Transaction-based Rule Change Mining(TRCM) technique in tweets from two different domains sports and politics. TRCM combines with time windows, which accurately detect and track newsworthy content from the 2012 FIFA world cup and US presidential election. The TRCM identifies rules based on the hashtags and similarity measures, which makes a high performance on classifiers. Alkouz et al. proposed different approaches in event detection at different areas such as, [24] for predicting road traffic analysis, [190] for predicting flu trends, and [202] for the predicting flue by considering only Arabic tweets (see Table 9).

11. Discussion and open problems

The key challenges for event detection in the online community are discussed in this survey. Firstly, to achieve high accuracy, the detection techniques should have the ability to use both textual and visual content from social media. Moreover, they should scale to massive amount of social data under the one-pass constraint of streaming scenario.

As an outcome of Rapid digital transformation that happened in the last few decades, people are living and connected as a global society through the Internet. The activities of an online community does not only depend on the user's home location, but also directly or indirectly interlinked through others' network. The use of geo services on social media, particularly on Twitter and Facebook, depends on other demographic characteristics and while the behavioral difference related to gender, age, economic, and language. Research on this area will help to categorize events on those demographic and behavioral types, which is more interesting for some applications. Predicting the location mentioned in a tweet allows for better understanding of tweet content that can be used in location recommendation, and disaster and disease management. However, symbols and unmeaning characters in tweets in addition to their short nature degrades location prediction. To overcome these problems, event detection systems should support massive datasets for the training and testing process.

Traditional event detection techniques use either the spatial or temporal dimensions. As a result, they do not predict events accurately. From the analysis of existing research papers, a combination of the Spatio-temporal event detection technique offers improved accuracy in different aspects like finding the proper location of a real-time event. Current social media analysis systems only support keyword search, which cannot identify complex events. For future work on real-time event detection from social media, event detection should involve the combination of spatial, temporal, and semantic analysis. A multinomial spatial scan obtains the best performance compared with the original spatial scan method.

The typical evaluation metric uses representation of predicted and ground truth locations are categorized based on the distance or token. The distance error is predicted by applying a mathematical equation on the distance between the actual location and inferred location of tweet with its corresponding longitude and latitude. According to Sloan et al. (2015) [242], overall, 58.4% of users do not have their location enabled while 41.6% do. In the case of geotagging individual tweets, 96.9% do have geotagged information, and only 3.1% are geotagged. Therefore, location prediction of social events is an essential module in the event detection system, and thus, more sophisticated techniques to correctly predict event locations at different spatial granularities are yet to be proposed.

The big data framework, such as Spark, efficiently handled a large volume of data. But it raises some fundamental questions such as, (a) How to effectively address the class imbalance of large scale real-world datasets, (b) in what manner it incorporates the recent approaches made in the field of Artificial Intelligence, (c) which subset of pre-existing features in a dataset will result in the optimum accuracy. The big data frameworks analyze a detailed large scale dataset in both forms of text and images.

Some of the social media data have limited textual information like Twitter. To overcome the sparsity of textual information available in social media, multiple data sources, modals, and languages should be used by event detection systems. The rich cross-media information carried by the multi-modal data has a broad audience, genuinely reflects the social realities, and brings about a much more significant social impact than any single media information. Cross-domain event tracking algorithm helps obtain actual events when the strength of one domain complement the weakness of the other. For better performance, adopting a multi-language and multi-source data to explore the relationship in detected events and fabricate a hierarchical view at several abstraction levels, which would be worthwhile to users.

Specific domain knowledge required Keyword-based approaches to filter relevant data about a real-world situation. Also, they need supervised methods to determine whether the identified data corresponds to a new real-time event. Consequently, the modeling of keyword-independent methods helps generalize existing approaches. Each language and culture can have their particular terms to refer to

Table 10
Appendix: Summary on datasets used in literature.

Reference	Corpus size	Collection period	Mode		Source	
			Uni-modal	Multi-modal	Uni-source	Multi-source
Reuter et al. (2014) [246]	430,000 photos from Flickr and 21,000 social events — ground truth	SED Multimedia Evaluation 2013	✓		✓	
Ahmad et al. (2016) [4]	490,000 images from Flickr	7th and 20th of September 2015	✓		✓	
Hua et al. (2016) [139]	305 million tweets	July to Dec 2012, Jan to May 2013	✓		✓	
Tartir et al. (2017) [138]	1100 tweets	September 2013	✓		✓	
Tonon et al. (2017) [142]	195.7 million tweets	Jan to June 2015	✓		✓	
Wang et al. (2017) [141]	31.6 million geo-tagged tweets	July 13 to Dec 17, 2015	✓			✓
Li et al. (2017) [137]	120 million tweets	Oct 12 to Nov 12, 2012	✓		✓	
Katragadda et al. (2017) [182]	2.1 million tweets & 348 thousand Tumblr post	Apr 30 to May 6, 2013	✓			✓
Giridhar et al. (2017) [81]	295 643 Tweets & 5688 Instagram Posts	February 2016	✓			✓
Jin et al. (2017) [173]	40 k micro-blogs & 13 000 tweets	May 2012 to Jan 2016		✓		✓
Wang et al. (2017) [141]	295 643 tweets & 5688 Instagram posts	Feb 1 to Feb 29, 2016	✓			✓
Ozdikis et al. (2017) [78]	2 373 492 tweets	Apr 1 to Apr 10, 2014	✓		✓	
Huang et al. (2018) [104]	4.2 million multi-modal tweets	2013 2017		✓	✓	
Öztürk et al. (2017) [199]	1,353,367 English tweets and 1,027,930 Turkish tweets	Mar 29 to Apr 30, 2017		✓		✓
El-Masri et al. (2017) [187]	6268 documents, and 33 000 sentences	NA	✓			✓
Alayba et al. (2017) [186]	Collecting 126 959 tweets and it decreased to 2026 tweets after filtering and pre-processing	Feb 01 to July 31, 2016	✓		✓	
Qian et al. (2018) [175]	2000 to 5000 document	NG		✓		✓
Hasan et al. (2018) [8]	120 million tweets	Oct 9 to Nov 7, 2012	✓		✓	
Modha et al. (2018) [191]	19 338 tweets and fb posts	NG		✓		✓
Alkouz et al. (2018) [202]	2 588 570 tweets	Nov 2016 to Jan 2017	✓		✓	
Tiwari et al. (2018) [159]	38,18,223 no of tweets, 11 615 Flickr images, and 28 095 Instagram images.	Wimbledon ’15. Oscars ’16. Ultra ’17. NBA ’17. London ’17. Daytona ’17		✓		✓
Liu et al. (2019) [74]	569 ACE 2005 newswire articles	2005	✓		✓	
Qi et al. (2019) [176]	9528 post	July 2017 to Dec 2017	✓			✓

(continued on next page)

an events. Those terms may not be representative of the same event in another language; therefore, the keyword independent methods are helpful in cross-lingual event identification.

Computing tools used in the event detection play an important role in the efficiency and correctness of the detection results. Machine learning algorithm, like SVM (Support Vector Machine), was found to be not suitable for the massive amount of multi-class problems like millions of tweets and geo-locations. For this problem, machine learning algorithms can be easily trained and retrained to incorporate new form of the data stream. In future work, incremental algorithms with adaptive selection of the parameter values should be investigated.

Table 10 (*continued*).

Reference	Corpus size	Collection period	Mode		Source	
			Uni-modal	Multi-modal	Uni-source	Multi-source
Shah et al. (2019) [107]	3.6 million tweets	13 July 2017 to 31 Jan 2018	✓		✓	
Wei et al. (2019) [17]	2.7million geo-tagged tweets	Aug 01 to Nov 30, 2014	✓		✓	
Ahuja et al. (2019) [83]	715 262 tweets 148 769 news article	June to Dec 2016	✓			✓
Morabia et al. (2019) [82]	11,705,978 tweets containing 3,653,039 distinct segments.	Oct 11 - Oct 17, 2012	✓			✓
George et al. (2019) [133]	203 519 geotagged tweets 100M Flickr messages	2017	✓			✓
Han et al. (2019) [144]	Around 150million tweets 9.5million geo-tagged tweets 920 thousand geo-tagged tweets	2012 to 2016 Aug 01 to Nov 30, 2014 2014 to 2018	✓			✓
Singhal et al. (2019) [156]	17 000 Tweets # Weibo news not given	Tweet data NGWeibo: May2012 - June 2016		✓		✓
Liu et al. (2020) [192]	6.4 billion tweets & weibos, 7.8 million news, 15.6 million forum messages	Feb 12 2016	✓			✓
Senarath et al. (2020) [153]	DWMW17 - 25k tweets, FDCL18 - 60k tweets	NG	✓		✓	
B. Alkouz and Z. A. Aghbari et [24]	50 million post	Nov 2016 to Jan 2017	✓			✓

Also, historical data should be utilized by developing statistical learning tools to help ease the understanding of user behavior and urban data.

12. Conclusions

In the development of event detection and visualization in social media, the number of research works discussed in this survey include effective models and methods, and they made remarkable achievements. However, in the new era of Big Data, where the data is massive, versatile, and fast, there are still many problems to be solved. This paper formally presents the research progress in each field of social event detection and tracking, and the complete overview of the most recent techniques that emerged during the last few years. Furthermore, we focused on challenges, state-of-the-art data stream, advanced features, information fusion, visualization, and database frameworks had to be utilized.

Considering that a very low percentage of tweets are geo-tagged, finding location inference methods that can go beyond the geo-tagging capability is undoubtedly the priority research area. The majority of the previous research heavily depends on the text and metadata features in a single source, along with a single language. To improve fact analysis, we need to extract features from the text, user metadata, image, audio, and video with multiple platforms presented in a different language. Existing approaches focus on features that do not reflect the character of the social network. Therefore, it fails to detect events in the context of the social network as a whole, which results in lower accuracy in detecting events. To address the problem, the temporal approach for processing a social network as we can identify an event from multiple temporal images.

The contribution of this article, is to investigate event detection systems in the literature and introduce an overview of the main challenges in the social media research process. The next contribution to the literature, is to point out the possible solutions for these challenges. Researchers, policymakers, business practitioners, and healthcare leaders are increasingly monitoring these findings to extract purposeful information from SMD for their decision making. For example, current COVID-19 scenario policymakers are looking for improved intellectual output from social media data to track the pandemic hotspots accurately.

CRediT authorship contribution statement

Imad Afyouni: Conceptualization of this study, Methodology, Writing – original draft. **Zaher Al Aghbari:** Writing - Review & Editing, Validation. **Reshma Abdul Razack:** Investigation, Resources.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix. Dataset summary table

See Table 10.

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