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SURVEY

# Edge Technologies for Disaster Management: A Survey of Social Media and Artificial Intelligence Integration

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**ABSTRACT** Within the paradigm of smart cities, smart devices can be considered as a tool to enhance safety. Edge sensing, Internet of Things (IoT), big data, social media analytics, edge computing, and artificial intelligence are key technologies that can be applied through smart devices to create emergency-aware systems. The use of these technologies could make emergency management tasks such as visualizing, analyzing, and predicting disasters easier to perform. The aim of this paper is to conduct a review of recent activities in literature about disaster and emergency management, and showing the role of different edge technologies used in this regard, and through the different stages of dealing with a disaster situation. Special importance is given to two main technologies: Social media analytics and artificial intelligence, due to their exceptional impact on emergency situations. Social media represents a rich source of data while artificial intelligence stands out as the mechanism to deal with the huge amount of data generated by smart devices, and thus needed to tackle all sources of data, in order to predict, detect, manage information, and for authorities to respond to emergency situations. This survey is a comprehensive review for the recent literature on the related topics, providing the reader with a clear overview of the current status and classifying the papers into groups with relations among them. The structuring of the recent literature into four phases makes it easier for the reader to realize the current state of the art. For completeness, this survey ends with a section on open issues and research trends in disaster and emergency management systems.

**INDEX TERMS** Crowd management, event prediction, emergency detection, response to emergency, machine learning, deep learning, artificial intelligence, social media, big data, edge computing.

## I. INTRODUCTION

Massive population growth, big cities urbanization, and world-wide climate change all contribute to an increase in the frequency of crisis, resulting in significant loss of human life and property throughout the world. Technology advancements will compel new techniques, tools, and capacities to aid decision-making in the event of emergencies and crises [1]. The imbalance between high disaster susceptibility, poor crisis response, and crisis resilience constitutes a serious issue for disaster management.

Smartphones, worldwide mobile internet access, social media (SM), and artificial intelligence (AI) have helped to expand the exchange of information in recent years. In addition, these technologies can assist disaster managers create data driven solutions [2]. Emergency managers can use cutting edge technologies to predict, detect, manage, and respond to possible risks in real-time [3].

When a disaster strikes, smart and IoT devices can create massive volumes of data, which emergency responders,

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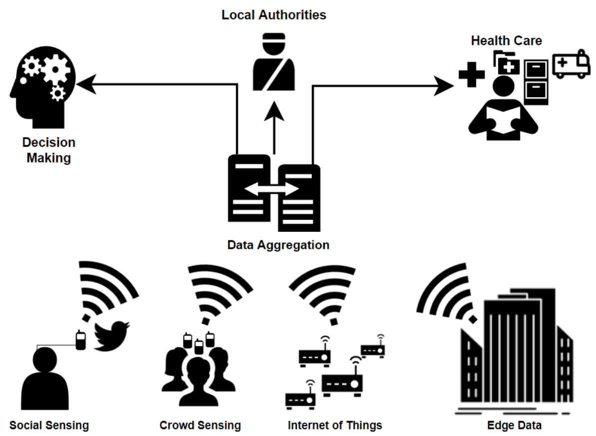


**FIGURE 1.** Technologies used in emergency situations.

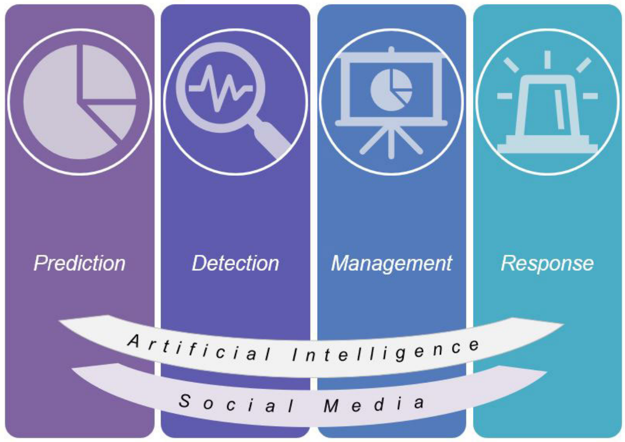


**FIGURE 2.** Paper organization.

decision makers, and citizens could utilize for situational awareness, preparation, accurate judgement, and safe evacuations [4]. Making sense of the created data in time-constrained scenarios, however, is difficult since the volume of data generated can be enormous, necessitating the use of intelligent systems to analyze, process, and display it [5]. AI algorithms focus on tackling this issue by creating systems that are able to deal with large amounts of unstructured data in a time-efficient manner. Figure 1 illustrates technologies used in emergency situations.

Recognizing the extent of harm in a disaster area can be used for both future disaster preparation and the reconstruction of infrastructure. Understanding the condition in disaster areas demands that sensors be allocated tasks to collect data, such as images and sensors readings, to better evaluate the situation. For these reasons, using crowdsourcing and providing appropriate assignments to individuals can be a necessity in crisis situations to rapidly comprehend the damage of the impacted areas [6]. Humans can also function as crowd sensors due to the widespread availability of SM on smartphones since crucial emergency information can be shared across these different SM platforms.

There are several surveys in the literature that address the broad topic of disaster management detection using AI. The focus of [7] is to evaluate the usage of data fusion in crowd monitoring system, to create an intelligent crowd monitoring and management systems through data fusion designs. However, the survey does not focus on addressing the importance of SM analytics in intelligent crowd monitoring for disaster management detection. In addition, the work presented in [8] considers the use of AI and SM in smart response systems from a universal village point of view in multiple instances throughout the survey, with very little focus on highlighting different AI approaches and the magnitude of SM influence. Similarly, the survey in [9], where the main task is to tackle issues in smart city management in terms of node deployment and sensing management to provide solutions, did not discuss the potentials of applying SM and AI algorithms to solve these issues.

Different categories of disasters (natural, industrial, humanistic, etc.) require dissimilar approaches. For example, a terrorist attack requires different activities than flooding or a man-made disaster. We will mainly focus on the natural disasters, where the work presented in this survey divided the process of disaster management into four chronological phases [3]. We believe that our survey creates a comprehensible scheme of how to deal with emergency situations. Moreover, we cover several edge technologies in each of these four phases including sensing, IoT technologies, big data, AI, and SM analytics. A designated section is created per phase, presenting its recent progress, and focusing on two key technologies that have an increasingly wider impact on disaster management systems, SM and AI. This type of presentation allows readers to navigate easier in the specific topics throughout the paper. In addition, a summary table is added per section to allow the reader to locate certain topics. The contributions of this survey are listed below:

- Present a comprehensive literature review of disaster management scenarios, and organize it in four phases.
- Discuss the potential of applying AI algorithms on each one of the phases, while reviewing AI recent works.
- Discuss the potential of applying SM algorithms on each one of the phases, while reviewing SM recent works.
- Review the applications of disaster scenarios in areas such as smart city infrastructure, natural disasters and public safety.
- Discuss the challenges and introduce new research areas in disaster management deployment.

The rest of the paper is organized as the four phases presented in Fig. 2. In section II we discuss emergency prediction technologies in the literature. Section III focuses on emergency detection systems. In section IV the focus is on crisis management technologies, followed by section V for emergency response systems. Conclusions and future works are covered in VI. In each of these sections, there are two designated sub-sections for research that tackle SM and AI, discussing their application and potential to deal with emergency situations. As demonstrated in Fig. 2, there will be overlaps among the four stages since many of these technologies might be labelled differently, depending on the application and scenario.

## II. PREDICTION

The review of previous works is first introduced in Table 1, and then contributions are analyzed and compared for a better comprehension by the reader. Prediction is a mathematical model applied to a set of input data to extract patterns in order to estimate future events or outcomes. It is an important component of data analytics that uses historical and current data to forecast activities, behaviors, and trends. This section starts with a generic review and then it discusses in detail SM and AI impact on disaster prediction.

The work in [10] uses empirical testing to identify 23 characteristics that impact visitor safety in congested areas. The research presents a system model that incorporates a feedback mechanism, to evaluate the safety of highly aggregated tourist crowds and identify instances that require security alerts based on the data collected. Similarly, an application for route predictions using smartphone locators in crowd gatherings is presented in [11], so that they can forecast crowd density in certain areas in the future, which is useful for overcrowding pre-warning systems that can be utilized to avoid stampedes triggered by a disaster warning.

A more sophisticated scheme is offered in [12], with a novel mobility prediction technique based on a data mining approach using Fuzzy-C to predict outdoor crowded scenarios. The approach divides the mobile user's paths into groups and looks for common mobility patterns that fit the present user path, forecasting their future location, that can be applied for disaster management issues. In addition, a dense point prediction approach for crowd counting and localization is presented in [13]. The authors approach counting and localization tasks as a pixel-by-pixel dense prediction issue turn it into an end-to-end framework, showing exceptional performance when compared to state-of-the-art methods. Another upgrade [14] introduces a method that involves collecting GPS data from users to predict congestion during rush hours. This information is then used for presenting and monitoring overcrowding, as well as giving a heads-up to commuters.

As metropolitan populations rise, many public transport systems are suffering greater congestion and crowding. Overcrowding has been related to negative effects on passengers' well-being, adding feelings of distress, anxiousness, a threat to personal safety, and reduced productivity, due to a lack of seating space in various transit systems as found in [15]. For these reasons, research in [16] tackles the issue of crowding in train carts and analyzes the efficacy of numerous data-driven prediction algorithms. The findings imply that real-time crowding data can be delivered significantly faster than historical averages, and with enough time to impact traveler's route, rail, and automobile choices, hence reducing in-vehicle congestion. With a similar goal, the authors in [17] aimed to create a real-time transit assignment system that takes into consideration passenger's ability to access real-time overcrowding information. This study is important in an evacuation scenario to help people leave a disaster zone efficiently and quickly. Table 2 summarizes the prediction purposes and the methods used.

### A. SOCIAL MEDIA PREDICTION

There are different social media channels, but we are mainly targeting social networks in our survey. The consideration of all social media channels would jeopardize the survey focus on disaster management. After establishing a formalized Weibo information flow model to capture the information diffusion on Weibo and conducting a complete investigation of Weibo information diffusion during earthquakes, researchers in [18] chose two earthquakes in China as a social scenario in their work. The study concluded that symbolic representation with the Weibo information flow model is a viable option for studying human behavior using online SM data sets. Such models help authorities in various situations such as predicting human behavior response during an emergency situation, since these scenarios require an in-depth understanding of how humans behave during disaster events.

Commonly, business based systems may utilize crowdsourcing methods to anticipate the popularity of their brands and adjust their brands based on the input they get based on consumer emotions. However, an emotion prediction technique has been proposed in [19] by gathering real-time Twitter data from users Twitter personal API. Using a variety of AI methods, the system is able to simulate emotions in real-time. Similar to the Weibo results, Twitter can be utilized to predict the occurrences of natural disasters and emergency events as well, which important since human emotions vary dramatically as a result of an emergency event.

A generalization is presented in [20] with the usage of real-time text data from the internet as new inputs to an existing crowd flow forecast baseline model, which can incorporate information on such significant non-recurring occurrences. The research focuses on tweets to reflect non-recurring crowd flows that influences data flow, as it has been shown that Twitter can respond to news events faster than traditional media [21]. Similarly, research in [22] presents a crowd-sensing through a tweet centric strategy for predicting early sudden occurrences on Weibo, through a novel technique predicated on the concept of crowdsensing, which necessitates the identification of sensors who can help in extracting tweets that may contain crucial information in case of emergency.

A required step for prediction is to first classify relevant information from Twitter streams for crisis management using unsupervised domain adaptation and multi-task learning as discussed in [24], while overcoming the challenges of data sparsity and limited labels, which are common challenges faced by researchers when attempting to extract data from SM platforms. The method demonstrated the ability to

**TABLE 1. Summary of previous works on Prediction.**

| Ref. | Strengths | Weaknesses | Application | Method used |
|---|---|---|---|---|
| [10] | Safety forecasting and early warning system for highly aggregated tourist crowds in China. | Only tourist crowds in China. | Early warning of tourist crowds. | Data mining and ML. |
| [11] | Crowd pre-warning system based on mobile locators and behavior prediction. | Limited to mobile locators and behavior prediction. | Crowd pre-warning system. | Mobile locators and behavior prediction. |
| [12] | Novel mobility prediction scheme for outdoor crowded scenarios using Fuzzy C-means. | Only outdoor crowded scenarios. | Mobility prediction in outdoor crowded scenarios. | Fuzzy C-means. |
| [13] | Simple baseline for crowd counting and localization using dense point prediction. | Only crowd counting and localization. | Crowd counting and localization. | Dense point prediction. |
| [14] | Crowd density estimation approach using GPS mobility for its dynamics and predictions. | Limited to GPS mobility. | Crowd density estimation using GPS mobility. | GPS mobility. |
| [15] | Comprehensive analysis of crowding effects on public transport systems. | Strict focus on demand estimation implications. | Public transport planning and operation. | Literature review and empirical analysis. |
| [16] | Data-driven approach using real-time load data for metro train crowding prediction. | Only applicable to metro systems with real-time load data. | Public transport planning. | ML. |
| [17] | Simulation of real-time crowding information on public transport networks. | Limited to the effects of real-time crowding information. | Public transport operation. | Agent-based simulation. |
| [18] | Study of information diffusion on SM during natural disasters. | Not specific to public transport systems. | Disaster management and SM analysis. | Network analysis and modeling. |
| [19] | User emotion prediction approach for crowdsourcing platforms. | Limited application to crowdsourcing platforms. | Online platform design and operation. | ML. |
| [20] | Twitter-informed crowd flow prediction. | Limited scope on the accuracy of prediction models. | Public transport planning and operation. | Text mining and ML. |
| [21] | Efficient framework for collecting and analyzing Twitter data during disaster events, predicting the sentiment of tweets. | Limited to Twitter data only. Not applicable to disaster management scenarios beyond SM. | Disaster management, emergency response. | ML, sentiment analysis, network analysis. |
| [22] | Tweet-centric and crowdsensing methods that take into account the context of tweets. | Limited to Weibo data only. | Predicting topic bursts, SM analytics. | Crowdsensing, tweet-centric method. |
| [23] | Enhancing crowd wisdom from SM, to mitigate groupthink and increase diversity in decision-making. | Not applicable to other scenarios beyond SM. | Crowd wisdom, decision-making, SM analytics. | ML, diversity measures. |
| [24] | Uses unsupervised and interpretable domain adaptation to rapidly filter tweets for emergency services. | Requires pre-existing labeled data, and not effective for filtering non-emergency tweets. | Emergency services, tweet filtering. | Domain adaptation, unsupervised learning. |
| [25] | Predict the location of SM users during disaster events. | Requires training data and features for location prediction. | Disaster management, evacuation planning. | Random forest, location prediction. |
| [26] | Predicts event popularity using influential hashtags from SM. | Evaluation limited to a specific event dataset. | Event popularity prediction, SM analytics. | ML, hashtag analysis. |
| [27] | Factors that influence the spread of rumors during public emergencies. | Evaluated on a limited dataset. | Public emergency management. | ML on social network analysis. |
| [28] | Uses a multi-relational graph to model crowd behavior. | Not scalable to large crowds or in real-time scenarios. | Crowd density prediction. | Multi-relational graph. |
| [29] | Model and predict crowd flow. | Computationally expensive and may not be practical for real-time predictions. | Crowd flow prediction. | Attentive convolutional LSTM. |
| [30] | Detects abnormal crowd behavior in videos for predicting crowd disasters. | Relies on video data and is not applicable if video surveillance is not available. | Crowd disaster prediction. | Deep CNN. |
| [31] | Predicts the direction of dense crowd movements. | Not suitable for sparse crowds or in crowded environments with irregular shapes. | Crowd movement prediction. | Long short-term memory-based approach. |
| [32] | Detects and predicts crowd congestion on a foot over bridge. | Not applicable in other types of environments or for different types of crowd behavior. | Crowd congestion prediction. | ML and computer vision. |
| [33] | Able to predict crowd density in real-time using video data. | Only focuses on short-term predictions and it relies heavily on accurate video data. | Public safety, event management, traffic control. | v-SVR. |
| [34] | Predict crowd flow between different locations using multiattention and 3D residual NN. | Requires large amounts of training data to accurately predict crowd flow. | Public safety, event management, transportation planning. | Multiattention 3D Residual NN. |
| [35] | Predicts patient flow in emergency departments. | Only applicable to emergency departments. | Healthcare management. | DL. |
| [36] | Predict hospital admissions. | Limited to predicting hospital admission within 24 hours. | Healthcare management, hospital operations. | CNN. |
| [37] | Employs traffic disaster data to predict earthquakes. | Requires accurate traffic disaster data. | Disaster management. | ML. |
| [38] | Predicts earthquakes in Turkey. | Requires access to accurate and up-to-date earthquake data. | Earthquake prediction. | Structural RNN. |
| [39] | Utilizes IoT and Edge computing for flood prediction. | Limited to flood prediction. | Flood prediction. | NN. |
| [40] | Flood prediction through IoT for data collection. | Limited to flood prediction. | Flood prediction. | NN. |
| [41] | Hybrid prediction model for Typhoons. | Limited to power transmission line damage prediction. | Power line damage prediction under typhoon. | NN and grey system theory. |
| [42] | New damage class prediction method. | Limited to power system damage prediction. | Typhoon disaster power system damage prediction. | Logistic regression. |

**TABLE 2.** Section prediction summary.

| Purpose | References | Method Used |
|---|---|---|
| Predict stampedes and overcrowding | [10] - [17] | Empirical Testing, Phone locators |
| Forecast from SM Data | [18] - [27] | SM and ML |
| Various Applications | [28] - [42] | AI techniques |

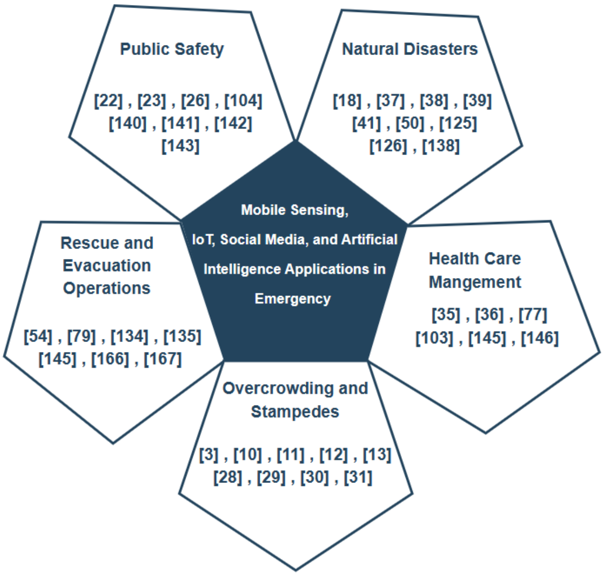


**FIGURE 3.** Summary of applications.

predict whether a tweet is significant or not; which is a binary classification job.

Through aggregating a population sample from a group of people, a more precise prediction can be produced than when collected from individuals. When members of a crowd provide diverse perspectives to decision-making, this impact is known in literature as the wisdom of the crowd. As a result of this variety, there are uncorrelated prediction mistakes that cancel out because of aggregating the diverse solutions picked from the crowd. A crowdsourcing strategy based on SM messages is introduced in [23], showing several solution techniques to this problem. The research employed tweet categorization to predict participant's behaviour, categorizing them using the binomial test to find groups of people who use the same strategy.

Determining the geographical location of emergency events is critical for rescuing those who are in danger or require aid. Only a few communication links, however, provide their initial geographical locations on Twitter which helps in identifying the location of those in need during emergency events. To tackle the problem of unlabeled data, an upgrade is presented in [25] with a proposed solution that employs a semi-supervised approach to combine unlabeled Twitter data, which is frequently plentiful at the start of a crisis, with fewer labeled data. To learn the semi-supervised model, the system approaches Tweets with an iterative random forest fitting prediction framework, [26] predicts event popularity, where an event is defined as a collection of messages including several hashtags. By mining the impact of an influential hashtag set on event propagation, the presented work offers a unique hashtag-influence-based event popularity prediction, as another parameter that can be predicted from SM data. The quality of the performance of the suggested framework has been demonstrated by experimental findings.

Beside popularity, rumors in SM have an impact on the quality of information available to users. When an emergency occurs, the quick spread of rumors can cause panic and worry. A region based convolutional neural network (R-CNN), is provided in [27] as a model for predicting rumor retweeting behavior. Experiments based on two rumor data sets of emergencies retrieved from Weibo confirmed the model's predictive capabilities with excellent results.

### B. ARTIFICIAL INTELLIGENCE PREDICTION

Several applications, including emergency evacuation and rescue, require knowledge of people and vehicle movement patterns in a city. Multiple technological approaches are used for various applications as demonstrated in Figure 3. This section focuses on AI approaches which can project citywide crowd movements in the future by modeling spatial and temporal patterns of present crowd flows, that in turn helps enhance emergency management.

*Congestion Prediction:* To give a new aggregated human mobility data set produced from a real-world smartphone application, authors in [1] investigated the difficulty of forecasting crowd density and in-out flow of crowds. The research develops pyramid structures and high-dimensional attention mechanisms based on convolutional long short-term memory (LSTM) neural networks, to create a novel deep learning (DL) model called DeepCrowd for large-scale crowd data collection. The work in [28] focused on urban crowd density and proposed a multi-relational graph convolutional gate recurrent unit model, achieving improved prediction when spatiotemporal information is available. In a similar fashion, [29] presents AttConvLSTM, a new DL model for predicting crowd flows in cities that combines a convolutional LSTM neural network with a convolutional neural network (CNN). Such combination preserves spatial information as much as possible during sequential analysis, which allows the attention mechanism to focus on important crowd flow variations that typical recurrent modules cannot detect.

Focusing on the crowd mobility analysis, the work in [30] presents CrowdVAS-Net framework which takes into account velocity, acceleration, and saliency aspects in video frames of a moving crowd. CrowdVAS-Net uses a deep convolutional neural network (DCNN) to extract motion and appearance feature representations from video frames, allowing authorities to assess crowd-motion behavior as abnormal or normal based on a brief video clip. A random forest classifier is then used to train these feature representations. On the other hand, for pedestrian trajectory, [31] introduces a new prediction model based on an LSTM network. The model depends on the last direction's values for each participant, as well as the average speed for each individual user.

Moreover, with the use of object identification and object tracking techniques, [32] provides a software-based strategy for congestion control called congestion control early warning system. Such system predicts congestion through R-CNN architecture employed for object detection, in which the Google inception model is used as a pre-trained CNN model, and the crowd abnormality, which could indicate a disaster starting, is examined using the suggested object tracking approach. In order to minimize the training complexity, [33] suggests a support vector regression-based modeling approach for prediction, matched with an online training technique. The results are very specific to high crowd density and does not address other scenarios. The problem of city-wide origin to destination population flow forecast is tackled in [34], that can be used to effectively plan transportation services and establish efficient schedules, by understanding the origin to destination trips and population flow distribution at a city-wide level.

Another critical overcrowding problem is the crowding at emergency departments in hospitals, and it's impact on emergency prediction, which creates a major public health issue because it has a significant influence on patient's well-being. Accurate patient flow prediction in emergency units is critical for increasing operational efficiency and quality of service. A DL framework is provided in [35] for predicting patient flow rates in emergency departments, recording the rates of patient entrance, treatment, and discharge at various triage levels. To predict hospitalizations after the operations are done is of great importance as well, and [36] presents a method that uses the patient's emergency department electronic health record. The input for the suggested system is generated using a data-to-image conversion, and the classifier used is a convolutional neural network which achieved high accuracy.

The model presented in [37] gathers data on earthquake-related transportation system damage over the last two decades, data mining and AI technologies are coupled in this work to create an earthquake intensity disaster prediction model, then trains the model using several AI algorithms such as the KNN method, SVM algorithm, logistic regression algorithm, and decision tree algorithm; before establishing earthquake prediction models. Based on the damage characteristics of the transportation system, this technology can invert the seismic crisis condition and anticipate the earthquake severity. On the other hand, the scholars in [38] were able to create earthquake predictions using structural recurrent neural networks, which deal with the temporal and geographical patterns of earthquakes in general.

Exploiting the IoT technology with neural networks, a system that leverages IoT and artificial neural networks to anticipate short-term floods was demonstrated in [39], with the prediction computation taking place on a low-power edge device. The system leverages temporal correlative information from real-time rainfall and water level sensor data to anticipate flood water levels ahead of time utilizing LSTM. The most distinguishing characteristic of this system is that the predictions are made on a low-power edge computing device, thus the presented technique may be used on IoT devices that run on batteries. This implies that raw sensor data is not provided over the internet in real-time for immediate flood prediction, but just the forecast's outcome when it is needed. With a similar goal, the work presented in [40] has a primary goal of tracking humidity, temperature, pressure, rainfall, and river water levels to determine their temporal correlations for flood prediction.

**TABLE 3. Artificial intelligence techniques for prediction.**

| Type | References |
|---|---|
| CNN | [28] , [30] , [32], [36] |
| RNN | [38] , [40] |
| KNN | [37] |
| LSTM | [1] , [31] , [39] |
| SVM | [33] , [42] |
| Combination | [29] , [41] |

Another type of natural disasters are typhoons, and the authors in [41] present a holistic architecture of wind disaster warning for transmission lines to improve the resilience of electric power networks against typhoon disasters. The authors introduce a hybrid prediction model based on extreme value type 1 probability distribution combined with the Monte Carlo technique, and random forest to estimate transmission line damage likelihood in the event of a typhoon disaster. With the focus on typhoon disasters, the work in [42] presents a prediction approach using an AI algorithm based on actual power system damage data after typhoon disasters. Table 3 summarizes the artificial intelligence techniques used for prediction.

## III. DETECTION

Smart cities nowadays have a very large number of sensors which may create large volumes of data that might provide insight at events, with smartphones playing a major role as they provide multiple sensors at the individual level, opening up new avenues for research into human behavior. Moreover, it is critical to reduce the time it takes to alert medical services, as the victims may only have a few minutes to spare while suffering injuries. However, unforeseen delays in receiving medical assistance are common. As a result, as soon as an accident happens, emergency services must be contacted with the minimum amount of delay between detection and contacting the authorities. Before considering detection in SM and AI, this section will briefly introduce event detection and natural disaster detection.

*Event Detection:* The challenge of detecting an abnormal change in a monitored sensory variable that is suggestive of an emergency scenario is investigated in the literature [43].

**TABLE 4.** Section detection summary.

| Purpose | References | Method Used |
|---|---|---|
| Emergency Event Detection | [43] - [63] | WSNs, IoT Crowdsensing |
| Classify and Analyse Data | [64] - [81] | Social Media |
| Disaster Detection | [82] - [101] | AI |

Particularly, detecting a shift in some observable phenomena using sensor-enhanced smart devices, which might indicate an impending or ongoing emergency scenario is, studied in [44]. On the other hand, [45] describes a greedy user reputation aware algorithm that attempts to strike a compromise between decision time and decision quality, accompanied by extensive simulations to demonstrate how this technique enhances the right detection rate over a reputation unaware baseline.

Backed with simulations to demonstrate a system that can reliably recognize human crowds, [46] developed a unique local event detection technique, which successfully integrates physical crowd behavior sensing with laser range scanners (LRS) sensors and geo-social multimedia mining. The proposed system uses LRS sensors to dynamically identify human crowds, which often gather around centers of attraction that draw attention. The proposed technology quickly discovers data that is likely to aid event localization by extracting geo-tagged postings that are placed in regions with human crowds. As a result, it can reduce the amount of data required while also minimizing the number of false positive event detection.

However, the lack of control over the spatial distribution of the edge sensor nodes is one of the key drawbacks of crowdsensing. Because the edge sensor nodes, or smart gadgets, are carried by the participants, the density of the sensory network is closely associated with the population density. The crowdsensing member's everyday activities, such as leaving to work in the morning and coming home at night, alters both the population density and the geographical density of the sensor network continuously. Table 4 summarizes the detection purposes and the methods used.

Residents of a smart city can participate to a crowd sensing system in order to identify various sorts of spatial events that are correlated or uncorrelated with population density [6] and be involved in the study of the detection probability for all sorts of events. The findings in [6] indicate that correlated events may be recognized with a great probability and within a short time after they occur. Events that are uncorrelated with the crowd density, on the other hand, are more difficult to identify using a crowd sensing based technique. Interesting results are discussed in [47], where an alarm management service for on-campus emergency named SHIELD is presented, by taking advantage of an infrastructure-free platform built on proximity-based (through Bluetooth/Wi-Fi) trust and collaboration. More on Bluetooth, presented in [48] is Insight, a warning system that recognizes signals from Bluetooth beacons identifying danger zones, without requiring an internet connection or any other communication infrastructure, making it resilient to communications outages during emergencies.

*Natural Disasters Detection:* Natural disasters are becoming increasingly common across the world as a result of global warming and environmental pollution, particularly in developing nations where such disasters produce larger and more severe crises. Detection of natural disasters would be of great benefit to the community and to disaster managers, thus motivating large contributions in literature about this topic. An aggregated statistics and basic anomaly detection algorithms [49] to show how raw smartphone data (not SM data) may be used to identify, monitor, and analyze the impact of various natural disasters, such as hurricanes and wildfires, on population density and movement patterns.

Earthquakes gathered a lot of attention both in literature and in deployed systems [50], as several areas worldwide are identified as potential areas for earthquakes. An earthquake early warning (EEW) system [51] can offer timely information ahead of the damaging seismic waves striking a populated location and is one possible technique to limit the damage caused by earthquakes. One of the most important issues of such a system is the precision with which it can detect the start of an earthquake in real-time. Traditional earthquake detection systems are often based on criterion-based schemes, which rely on empirically determined characteristics and thresholds for certain criteria. As a result, traditional approaches frequently generate an excessive number of false alarms, imposing the additional expense of human inspection on event monitoring.

Modern data acquisition systems are made up of a fixed sensor network, the size and design of which can vary dramatically depending on the application and technology used [52]. When compared to data acquired by an equivalent number of dispersed stationary sensors, mobile sensor data has a higher spatial resolution. In the current digital era, increasing smartphone ownership rates in metropolitan centers have decreased the need for specialized equipment to cover a city densely. Hand-held smart devices, in particular, provide a large-scale mobile sensor network.

Researchers in [53] proposed a system to detect an earthquake and notify people in danger by sending an alert message to the public through an IoT wireless sensor network [54]. The benefits of the best potential distributions for wireless sensor networks are further analyzed in [55]. This is done through implementing various energy-based wireless sensor networks (WSN) in the tectonic plate area, which can aid in faster detection times of earth crust movement, to be then sent immediately to base stations for preparedness steps via radio signals.

Sensors included in smartphone models are not created for scientific uses; they are chosen based on parameters like manufacturing cost, battery consumption, size/design, and functionality [56]. The accuracy of the sensors in smartphones is impacted by the age of the smartphone and the category of the smartphone, which varies between different devices [57]. Moreover, because of the urban buildings and structures in which they are situated, and their cost-quality trade-off, the signals captured by mobile devices are usually noisy, which makes them an unreliable option to raise an alarm for an emergency event. To tackle these issues, a proposed solution in [58] is using an artificial neural network (ANN) technique for dealing with the problem of detecting false alarms in IoT devices, showing outstanding results.

A framework for earthquake detection in real-time was in presented in [59]. The detection of an event is not adequate in and of itself; rather, it seeks to execute a timely detection in real-time. The system's goal is to be able to identify an earthquake before the publication of the relevant news through official channels. It is worth mentioning that the suggested approach is sufficiently broad and extensible to different sorts of emergency events. With a similar goal, [60] uses neural networks to determine if an earthquake has happened or not by using data from Twitter, obtaining an acceptable level of accuracy.

As an alternative to EEW, [61], [62] suggested a technique to accomplish simple sample collecting, with directly relevant and usable information on the received signal to produce a quick earthquake detection system. This technique is directly performed on smart sensors on the edge of the network, and it is meant to function in real-time.

The collected data from edge mobile sensors proved to provide important information to civil engineers in assessing the status of structures. To adequately assess a bridge's status and avoid its collapse in potential disasters, its daily operational behavior must be tracked over an extended period of time. Mobile sensor networks are well-suited to continuously monitor the vibrations of metropolitan bridges, as evidenced by current structural monitoring studies.

In [63] reference sensors' peak scores are consistent with those from the aggregated smartphone data. It is discovered that acceleration data gathered from moving cars on a bridge (through the drivers' smartphones) provided consistent and substantial indications of the bridge's status. When data from other smartphone data sets are pooled, the results were even more exact. A summary of natural disaster applications is presented in Figure 4.

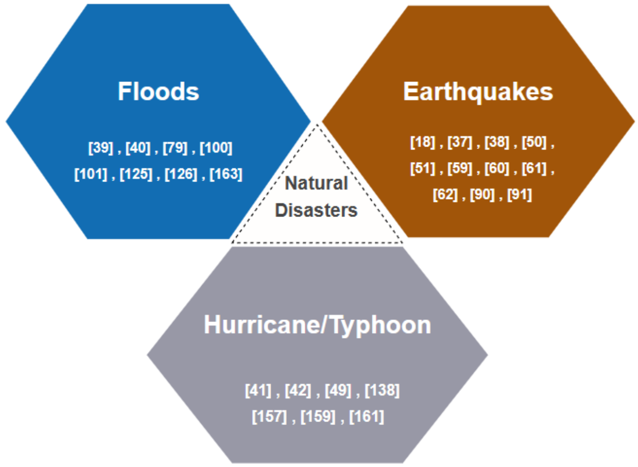


**FIGURE 4.** Summary of natural disasters applications.

### A. SOCIAL MEDIA FOR EMERGENCY DETECTION

For emergency events detection, leveraging SM as a source of information is an ideal method to reach the different demographics of the community, especially between individuals of the younger generation, who utilize such tools as a primary source of information [64]. Instead of waiting for a disaster to happen to then start using SM to communicate with the public, municipal government would benefit from incorporating SM tools with the public, because it allows them to link into and build a network for event detection, reducing response time from the authorities [65]. Moreover, emergency detection systems have a unique chance to examine daily phenomena of the real world and to directly engage with communities because of the great popularity of SM among citizens. The concept behind social sensing is that communities or groups of individuals may offer data equivalent to that obtained from a physical sensor. Among the several disciplines of research in social sensing, the management, prediction, response and detection of emergency events is one of the most intriguing. However, data gathered from SM also presents challenges such as data management, interpreting, and handling, imposing careful handling of such data. Some of the characteristics unique to SM are now described below:

#### 1) HIGH VOLUME

Unlike traditional data sources, which usually have a centralized content-generating agent, SM allows people to create their own content, which produces a huge amount of data [66]. SM is recognized as a powerful data source in both academia and the industry due to the large number of users and the massive volume of structured and unstructured data continuously provided by the users [67], [68]. Dealing with a large amount of data, however, various issues occur, such as identifying accuracy, truthfulness, data security and privacy [69].

#### 2) DATA VARIABILITY

Social networking platforms have a huge amount of data flowing into and out of them. Typical devices used to access SM, such as smartphones, have been increasingly adopted by people throughout their daily lives, which increases the over-all amount of data flow. Acquired SM data is generally uploaded to a storage server or data center in almost real-time. However, the rate at which SM data is collected is quicker than the rate at it is processed and analyzed to be useful for detecting an emergency [70], [71]. Therefore, real-time processing and interpreting of SM data is a main challenge to researchers and engineers due to the fast pace of data flow, especially in emergency events.

#### 3) DIVERSITY

Data from SM is collected from a variety of devices, including smartphones, desktops, and tablets. Aside from the various devices, the spatial information of devices originates from several regions. The ability of SM data to spread quickly adds to the resource's diversity [72]. Different data from various devices is processed and evaluated in the urban emergency event detection system, for example, to identify associated temporal and geographical information. The wide range of SM devices creates a significant problem for processing and managing SM data that is dispersed.

The benefit of using SM over traditional techniques such as television station announcements and amber alerts in emergency management stems from the user's spontaneous engagement. In terms of SM features, Twitter has a few quirks that make it a particularly good data source for social sensing systems. Twitter users frequently discuss their own activities and, as a result, what is going on in the world around them [73]. Furthermore, Twitter is more engaging and responsive than other famous platforms such as Facebook: because public communications are limited in length so users are motivated to tweet more frequently [59], thus producing a huge amount of data for big data mining, which can be useful for local authorities in case of an emergency [5].

Twitter tweets can actually be classified for emergency detection, as shown in [74], while CrowdMonitor [75] was developed to enable coordination methods for communicating and working with the public during emergencies. It has the capability for gathering on-the-ground movements, publicly requesting data, and accessing SM information, so it may be utilized for both real and virtual activities. An improved version is provided in [76] with a system discovers urban emergency occurrences and annotates them using geographic information system through information gathered from Weibo.

With SM application in other fields, an effective method for allergy monitoring and the aggravation of allergy disorders is introduced in [77], by combining publicly accessible information from SM with the notion of crowd sensing and raw sensor data to create a holistic m-Health participatory surveillance system. Allergic sickness management is covered by the multi-module system, which includes allergen identification, season onsets, patient stratification, allergy control, and treatment progress monitoring. Subjective data from users and Twitter posts, as well as objective environmental data from fixed stations, are combined in the system for privacy-conscious processing and analysis. Pollen seasons start time detection, text analysis of Twitter tweets, and densely obtained subjective data from users might reveal how people engage with pollen information.

The analysis of raw text field of SM data, i.e., text mining, has not been fully realized, even though it is the most valuable and readily available data on the platform. Text processing may have a great deal of useful information that can aid emergency awareness and the extraction of actionable responses. In these cases, identifying important text data would eventually lead to an event detection, which is difficult to track effectively in a short length of time [78].

Interesting results are obtained in [79] by looking at text data from both Telegram and Twitter messages, to see how SM had a part in the 2019 flood crisis in Iran, where real-time SM data can offer authorities vital information for more effective rescue operations and make informed timely judgments. Another key finding of this work is that during the crisis, the majority of the news on Twitter is based on the personal opinions of people with biases and had more negativity when compared to messages from Telegram.

Another suggested technique in [80] is also based on Twitter data analysis that identifies Twitter texts concerning emergency situations. One vendor deployed the approach mentioned in the article in the context of detecting power outages as part of their complete social engagement platform and performed well. The work in [81] created a data filter based on characteristics such as keywords, the number of times they appear, and their context. The work also shows that the legitimacy of their method is not limited to a single context or language but can be adapted to a wide range of topics.

On the other hand, the developed prototype in [59] illustrates the method in the context of seismic occurrences, i.e., earthquakes, the suggested architecture is also flexible enough to be extended to various applications such as floods, landslides, and wildfires. One key finding from this study is that at night time, people have a considerably reduced sensitivity, since most people would be asleep and therefore the number of tweets regarding an event is reduced. Therefore, a stronger incident is required to get data from people at nighttime.

### B. ARTIFICIAL INTELLIGENCE FOR EMERGENCY DETECTION

An enormous amount of data is created in the case of a disaster through SM, sensors, satellites, CCTVs, drones, and other edge technologies. This data becomes ultimately a helpful and a necessary resource for the emergency responders who are involved in gaining situational awareness and making judgments. Although the necessary information for emergency responders is accessible, making sense of it in a time-sensitive scenario is difficult [82], [83] due to the great volume, variability, and diversity of data, as previously noted. Furthermore, emergency responders will be unable to manually analyze the massive volume of data [75], in order to manage the incident effectively and in a time efficient matter. Table 5 summarizes the artificial intelligence techniques used for detection.

AI plays an important role in analyzing large volumes of diverse data and turning it into logical and useful information.

**TABLE 5. Artificial intelligence techniques for detection.**

| Type | References |
|---|---|
| CNN | [86] , [87] , [90] , [96] , [99] |
| KNN | [98] |
| LSTM | [88] , [89] |
| SVM | [98] |
| Combination | [91] , [92] , [94] , [95] |
| Other | [93] , [100] , [101] |

AI is defined as the study and advancement of software technologies that can imitate human intelligence in order to capture high-level abstractions in huge data sets, resulting in considerable improvements for various activities, processes, and pattern discovery in massive amounts of data [84]. Machine learning (ML), on the other hand, is best thought of as a "subset of AI" that involves complex statistical techniques that allow machines to improve at tasks over time. DL is included in this category as a branch of AI that consists of methods that allow software to train itself, to execute tasks by exposing multi-layered neural networks to large amounts of data [85].

The capsule neural network (CapsNet) is first introduced by [86] to address the shortcomings of the convolutional neural network (CNN). CapsNet is a new kind of DL architecture that allows the network to train without the use of a pooling layer (without losing information) as opposed to a typical CNN model. An upgrade is presented in [87] have shown that when compared to benchmark methods, CapsNet has an excellent performance.

A DL model for recognizing human actions is proposed in [88], in order to identify emergencies such as fire and terrorism promptly. Four types of data on human activity were acquired using the smartphone's acceleration and gyroscope sensors, and human behavior is categorized using the Long short-term memory (LSTM) DL model. The human behavior recognition system is upgraded in [89] to analyze people's movements and to identify the occurrence of emergencies when they occur indoors, also by using LSTM.

Convolutional neural network (CNN) [90] is used to extract important characteristics from seismic wave forms, allowing the suggested classifier to achieve a reliable performance in detecting the essential earthquake parameters. It shows great accuracy for the classification of magnitude, origin time, depth, and location [90]. False alarms induced by local impulsive noise degrade the performance of an earthquake early warning systems and generate unnecessary fear among people. To address this issue, many AI-based approaches [91] have been suggested to combat inaccurate readings. The recurrent neural network (RNN) with LSTM cells models in [92] construct a real-time accurate early earthquake warning system. The proposed method is intended to detect the existence of an earthquake as well as the duration of the P-wave and the S-wave.

Training is very important for AI systems, and thus the work in [93] uses 300,000 wave forms collected in southern California and Japan to train a generative adversarial network (GAN), to understand the properties of first-arrival earthquake P-waves. Such training considerably minimizes the amount of faulty and noisy alerts. A convolutional-recurrent neural network model is presented in [94], compromising a network system that monitors ground vibrations and detects earthquakes using low-cost acceleration sensors. The approach of using a mixed neural network composed of a CNN and RNN (CRNN) aims to guarantee a great detection performance while keeping false alarms at a minimum. Combining CRNN model with LSTM units for earthquake detection, [95] can achieve improved performance. In addition, researchers in [96] propose a system based on a highly scalable convolutional neural network for earthquake identification and localization from a single waveform, which makes use of recent breakthroughs in AI.

To geographically assess disaster-related text tweets, researchers in [97] propose a DL-based system ConvNet (CNN), that proves binary categorization to be beneficial during crises for swiftly locating people in affected regions, as well as after disasters to undertake post-disaster investigations. Three AI techniques are used in [98] to undertake seismic event detection, which are Support Vector Machine (SVM), K-nearest Neighbors (KNN), and a classification tree method. The detection performance of the AI-based methods excelled the classical criterion based techniques, according to the trials conducted in the research. Notably, the SVM and classification tree have a lower detection time than the KNN. However, KNNs need no training time as opposed to the two other methods.

The work in [99] presented a novel multitasking learning (MTL) attention-based CNN architecture for seismic multi-event categorization. The classification issue is formulated as a binary classification problem, which is detecting earthquakes versus noise and a three-classification problem which is detecting earthquakes against micro-earthquakes and random noise. The testing findings showed that the suggested technique is a good structure for classifying different earthquake occurrences and outperformed single task structures.

Inductive transfer learning techniques [100] have been demonstrated in [101] to be quite useful in detecting floods through limited labeled data gathered from SM platforms. The researchers use Twitter data from one of the flood areas and a pre-trained a language model to accurately classify flood-related tweets in under 10 seconds, whereas similar results would normally take thousands of labeled tweets and a long time. In time-sensitive applications such as crises, the use of pre-trained models with minimum space and time complexity can be extremely beneficial since millions of tweets must be processed and classified with delay constraints according to their content with high performance without losing accuracy.

## IV. MANAGEMENT

The possibility of tragedies such as stampedes, suffocation, and congestion become more likely without adequate crowd

**TABLE 6.** Section management summary.

| Purpose | References | Method Used |
|---|---|---|
| Avoid stampedes | [3] , [102] , [106] | IoT |
| Smart evacuation | [103] , [104] | Crowdsensing |
| Government management | [105] - [110] | Various Methods |
| Evaluation, Resource Allocation | [115] - [123] | SM Data Management |
| Various Applications | [125] - [136] | AI techniques |

management and control. Currently, the Internet of Things (IoT) and its supporting technologies offer cost-effective solutions for smart crowd management, casualty reduction, and the integration of various intelligent technologies. The author of [102] aimed to combine the precision of data collected by sensors with more contextual information offered by individuals through crowd sensing, in order to improve existing methods for recognizing and handling emergency situations. Smart IoT for crowd control and congestion avoidance is presented for the specific case of Mecca [3]. The method employs a learning mechanism that categorizes pilgrims based on the data collected, and it takes advantage of both IoT and cloud infrastructures to monitor crowds in congested areas, identify evacuation routes for pilgrims, and guide pilgrims to avoid congestion in real-time. Table 6 summarizes the management purposes and methods presented in this section.

It is crucial to tackle the issue of how to properly deploy safety police in order to maximize positive emotional contagion, to reach the greatest amount of people who are distressed. Research presented in [103] suggests an IoT-based positive emotional contagion strategy for crowd evacuation to tackle this challenge. Moreover, the research in [104] presents a unique IoT-based approach for educating people, as well as a mobile application that leverages crowd-sourced data from smartphones to give safe evacuation suggestions during emergency scenarios. As an improved version, the work in [105] discusses a strategy to build an emergency system at the provincial and municipal levels with the primary purpose of averting human-made catastrophic events.

In order to bridge the gap between classic, authority sensing-based situation awareness systems and crowd sensing-based situation awareness, a reference architecture [106] is presented to extend the well-known JDL data fusion model for automated social evaluation with new system components that address the issues of integrating crowd sensed data into situation awareness systems.

Empirical research, data analysis, and other approaches [107] are tackled to reinforce the building of a big data platform, which will not only increase government efficiency in emergency management, but also improve government governance skills and management standards. A new government emergency management system is presented on intelligent computing technologies [108] to take full advantage of the benefits of intelligent computing and employs a reliable and sophisticated algorithm. In order to increase the system's accuracy, the emergency system employs a mathematical model-building approach.

Innovative ways to solve challenges of controlling the functioning and growth of complex coordination systems are discussed in [109]. The suggested models and techniques provide a methodological foundation for the construction of a decision support subsystem in an automated control system for emergency scenarios, which will allow for the automated execution of a variety of control functions. The suggested design in [110] is utilized to feed a disaster management control centers a knowledge base, which might profit considerably from mobile networks for assessing the health of structural buildings.

In order to achieve deep integration of big data and emergency intelligence analysis, there is a need to construct an emergency management information system model guided by big data [111], through in-depth investigation of the application demands of big data for emergency management, considering the many connections between each module presented in the work.

Cloud services are utilized in most accident management systems to get information and alert emergency management authorities such as hospitals, ambulance staff, and police. Although cloud servers may provide the precise information required in such instances, connection and information transit time issues may arise. In emergency situations, where a rapid and swift reaction is usually required, these flaws might be dangerous [112]. The goal is to create a fog computing based system that is low-cost and time efficient for disaster management architecture that has lower latency than a central cloud-based system. From a different perspective, the work in [113] focuses on road accident management using a joint fog/cloud computing for a smart city application. An IoT network architecture based on UAVs and fog computing to assist first responders in managing rescue operations in collapsed structure is discussed in [54].

### A. SOCIAL MEDIA FOR EMERGENCY MANAGEMENT

When a crisis hits, emergency responders must quickly obtain situation awareness of the emerging crisis situation, determining what has occurred and where assistance and resources are required. Nowadays, SM platforms can be utilized as a real-time communication center for exchanging information such as on-the-ground observations, recommendations, and requests, and may therefore act as a network of human sensors for recovering information in crisis circumstances.

After a major disaster, emergency resources are usually insufficient to meet all demands for professional assistance and resource allocation [114]. In a mass casualty crisis, the focus switches from providing the best possible outcome for each individual patient to ensure the best possible outcome for the largest number of patients. Multiple manual and computerized medical triage systems have been employed in the past, both in civil and military situations, to identify the priority and sequence of emergency care, transportation, and the best potential destination for patients [115]. Nevertheless, none of these methods has proven to be sufficiently flexible, precise, adaptable, or unobtrusive to match the public's needs [116].

The researchers in [117] provide their first attempt at fully integrating SM-based crowd sensing with automated situational awareness systems, describing an architecture for a situational awareness framework that uses both traditionally felt data and unstructured SM information. After that, their work proceeds by introducing their situation adaptive prototype in [118] and examine its possibilities in a case study on a real-world Twitter crisis data set, demonstrating the implementation of a situation adaptive crowd-sensing and information extraction system.

Another solution for real-time patient evaluation that employs mobile electronic triaging and crowd sourced input is CrowdHelp [119]. Even before assigning a response team to the event, emergency management experts may get the majority of the information they need to prepare themselves to offer fast and correct treatments to their patients using the presented system. A crowdsourcing system named CrisisTracker [120], is an online system that records dispersed situation awareness reports, based on SM activity in real-time during a large-scale crisis like natural disasters. Using Twitter, CrisisTracker records collections of keywords and creates social media stories by grouping related tweets based on their lexical similarity.

In terms of collection of relevant, precise, and hyperlocal information, interactive crowdsourcing has been found to be superior than standard crowdsourcing [121]. The rising prevalence of SM has made it a critical tool in times of disaster. The prototype described in [122] serves as a proof of concept for demonstrating the benefits of interactive crowdsourcing via Twitter and SMS texts, as well as providing impetus for the proposed model's continued refinement and scale. To differentiate abnormal activity in mega cities, a methodology for identifying clusters of human activity and explore distinct temporal patterns is presented in [123], comparing them to historical averages. To identify the use of locations based on clusters of activity, the presented methodology employs natural language processing of geo-textual data from various SM platforms such as Instagram, Twitter, Flickr and YouTube.

### B. ARTIFICIAL INTELLIGENCE FOR EMERGENCY MANAGEMENT

AI algorithms are highly adapted for crucial associated tasks such as recognition, classification, and can handle multidimensional big data that usually arises in disaster and pandemic management situations. Moreover, AI algorithms can help with crisis forecasting and emergency management activities including selecting crowd evacuation routes, evaluating SM posts, and dealing with the aftermath of a disaster. AI algorithms are also useful in pandemic management scenarios, such as predicting outbreaks, tracking pandemic spread, and diagnosing diseases [124]. Table 7 summarizes the artificial intelligence techniques used for management purposes.

**TABLE 7. Artificial intelligence techniques used for management.**

| Type | References |
|---|---|
| KNN | [131] |
| CNN | [128] , [127] |
| SVM | [129] |
| Random Forest | [129] , [136] |
| Other | [125] , [126] , [129] , [131] , [132] |

Flood emergency management has become a serious concern in recent decades, as it has the potential to disrupt human lives, the economy, and property destruction. Developing a multimedia big data platform for flood disaster management using DL techniques is a great benefit [125], [126]. It can mine multimedia data such as SM data (Twitter and Facebook), satellite image data, crowdsourcing, and sensor network data, all of which are publicly available.

Despite the fact that the behavior of pedestrian crowds under severe conditions is critical for crowd safety during large events and emergency evacuations, there are currently few empirical research on extreme crowding. Video data may be adopted to examine high-density settings, as shown in [127]. However, other studies consider counting of individuals in a video or photo, for example, is inefficient in terms of time and can be quite labor expensive. A fully optimized convolutional neural network for crowd counting is presented as a solution in [128] that is both simpler and quicker through a full optimized CNN. It is a fully optimized approach for building the network to reduce the computational cost of training neural networks. To further enhance the intelligent management of crowd powered AI, techniques and algorithms for the dynamic collecting of training and testing data are presented in [129].

The use of tweets for appropriate scenario analysis and decision-making by disaster management authorities is problematic, motivating a decision-support framework [130] that collects situational information from the public present at the disaster site through interactive crowdsourcing via SMS, and summarizes such responses to provide situational awareness and appropriate damage or needed evaluation for decision-making. Hierarchical clustering AI is used for an automated strategy for detecting events and their correlations from Twitter feeds [131].

A two-level clustering strategy is adapted in the suggested method, the first of which finds big events across various tweets, while the second level of clustering considers their spatial, temporal and semantic links to identify micro-events of a particular large event. It is upgraded by tackling the issue of how to extract meaningful information from a massive data pool in the least amount of time while keeping the data usable and actionable is addressed in [132], with an actionable data extraction technique using data from Twitter. The information categorization from the gathered tweets is manually carried out, and subsequently the tweets are utilized to train an AI system to identify future tweets.

The interdependence of scheduling and allocation duties, time constraints, resource shortages, and the diverse capabilities of rescue teams are among the primary difficulties that emergency operations centers must deal with. A Monte Carlo-based heuristic solution approach for a non-linear optimization model, to tackle such managemental issues is provided in [134]. Moreover, self-organizing networks and AI algorithms should be combined according to [135], to close significant technology gaps that are preventing the successful deployment of deplorable technologies in disaster and incident management. Shorelines [136] are an interesting use case as they stand as an important source of data for environmental management, disaster management, and coastal erosion research, where different approaches for extracting shoreline data have been developed in the literature. One of the outstanding strategies employed in this study for coastline extraction is Random Forest. This algorithm is a decision tree-based AI approach, which is utilized to analyze training data classes and generate classification rules.

## V. RESPONSE

Catastrophes are frequent dramatic occurrences that differ greatly from previous experiences, requiring unique and immediate responses and the relevance of disaster effect information should never be ignored. Poor information flows, for example, hampered disaster response operations after Hurricane Katrina, as did the inability to analyze and process essential data in a timely manner [137]. In practice, the value of data or knowledge collected during severe occurrences is frequently undervalued [138]. During catastrophes, decision-makers seek knowledge to build their point of view as part of a sense-making process. New information arriving provides evidence to absorb new knowledge into what is previously known, leading to better response decisions in emergencies [139]. For instance, the method in [140] combines data gathered from extremely high-resolution remotely sensed photos with crowd sourced data from volunteers on the ground using their smartphones. Table 8 summarizes response systems purposes and methods presented in this section.

The work demonstrated in [141] examines the issue of missing children and the value of crowdsourcing in resolving this issue. Using the sophisticated characteristics of mobile devices, this approach enables for close collaboration between the crowd and government institutions by encouraging the public to lend a hand in the search process. A Wi-Fi enabled micro-controller based system [142] is interfaced with a cloud platform and a few sensors such as vibration and shock sensors, temperature and cardiac pulse sensors to send emergency SMS and email messages in the event of an emergency. These cloud-based systems can be beneficial to

**TABLE 8.** Section response summary.

| Purpose | References | Method Used |
|---|---|---|
| Various Applications | [137] - [52] | Crowdsensing and IoT |
| Data Storage | [147] [148] | Edge Storage |
| Processing Data | [149] - [151] | Fog Computing |
| Various Applications | [155] - [163] | Social Media |
| Disaster Response | [164] - [174] | AI and Robots |

those with disabilities or the elderly, especially that they are usually easy to implement.

Similarly, mobile apps for disaster response crowdsourcing are based on several requirements such as user friendliness, anonymity, real-time updating and viewing of geographic information [143], while offering bidirectional communication between users and first responder teams for emergency, simple interface design, and simple installation. During a crisis, mobile apps are extremely valuable for developing and sharing high-quality immediate geographic information. iSagip [144] is an app that aims to enable afflicted communities to notify authorities about their situation, by crowdsourcing their current status and their required supplies and help. Such applications can be very beneficial for humanitarian aid groups that can use this mobile app as a tool for disaster relief efforts.

A framework for an emergency event reporting system to support respond teams is required in the field. [145] is based on crowdsourcing, which employs participatory sensing to allow numerous smartphone users collectively report emergency incidents. This in turn allows volunteers in the area of an event to be able to send an alarm message to rescue services and first responders' vital information such as the geographical coordinates, nature of occurrence, and number of casualties. The service is upgraded with a smart medical response plan [146], that monitors the physiological indicators of individuals in a community and provides frequent feedback and warns hospitals, accordingly, based on the benefits of smart healthcare architectures. The suggested framework gives feedback on a variety of dimensions, maintaining the well-being of individuals and warning them of potential health problems.

The problem of crowdsourcing mobile videos for disaster response systems is addressed in literature [52] by identifying two distinct main challenges. These two challenges are prioritizing visual data collection and transmission under bandwidth constraints caused by damaged communication networks, as well as evaluating the gathered data in a timely manner to be useful to disaster responders. A novel crowdsourcing platform is presented in [52] for capturing and analyzing mobile videos using fine granularity geographical information of video content tackling these two challenges.

A different issue for emergency response systems is data storage systems during emergencies [147]. While storing sensor data in the cloud has several advantages [148], it also necessitates ongoing internet access, making the platform unsuitable in emergency scenarios where internet access might be limited or completely unavailable. EdgeStore [148] is an edge-based distributed storage system to overcome the previously mentioned difficulties, by adding a game-theoretic resource incentive framework. EdgeStore delivers considerable performance advantages over typical distributed storage systems in terms of throughput, energy consumption, and latency.

On the processing side of the spectrum, fog computing can also play a vital role in emergency response systems since it provides various benefits such as reduced latency [149], offloading network usage, and increases geographical spread of data sources which in turn increases coverage in a crises situation. By processing data on the edge of the network, a fog computing based system to respond to emergencies in real-time is presented in [150], by handling massive amounts of data coming from devices and edge sensors.

Fog computing is found to improve the efficiency compared to cloud computing, and the inclusion of smartphone sensors considerably reduced the total cost of the system. Similarly, the work in [151] proposes a fog computing-based method for swiftly deploying emergent distributed services to enable individuals in afflicted locations to regain network resources through deploying accessible equipment such as routers and mobile devices as fog nodes to provide emergency networking and communication.

Distributed mobile sensing-based crowd evacuation system is of great importance [152], [153], where BigActor is a model presented in [154], and its main purpose is to employ smartphones to sense crowd dynamics and actuate crowd movement during evacuation as a response to an emergency.

### A. SOCIAL MEDIA FOR EMERGENCY RESPONSE

In the plethora of user-generated text messages, news, images, or videos on SM, real-time and essential crisis information is generally concealed. Data from SM has been utilized in disaster response systems, particularly in crises such as earthquakes, hurricanes, floods, and other natural disasters. The ability to gather, filter, extract, and manage SM data and information to aid disaster response is becoming increasingly important. Ongoing attempts are in place to construct an efficient disaster relief system that integrates data from SM networks and authoritative sources [155], to aid in real-time relief response to a crisis occurrence. However, many works combine three components which are SM data analysis, forecasting rescue need, and optimizing relief distribution.

Indeed, SM, SM analytics, and volunteer incentives have had a substantial impact on the data acquired through crowdsourcing [156], [157]. Moreover, theoretical frameworks might assist disaster relief personnel in better coordinating their efforts, by utilizing important information obtained through a crowdsourcing framework.

**TABLE 9.** Artificial intelligence techniques for response.

| Type | References |
|---|---|
| DRL | [165] , [167] , [168] , [170] , [169] |
| CNN | [166] , [173] |
| SVM | [171] , [172] |
| Other | [174] , [171] , [172] |

Satellite pictures are frequently utilized for quick mapping and recovery, but the streams of SM data are a great data source, not just for validation, but also for fusion to improve estimates for better emergency response. Multi-modal fusion systems [158], [159] are important for merging satellite pictures with SM data for emergency response, such as flood monitoring and extreme weather conditions in polar areas. Additionally, to quickly extract meaningful disaster information from the enormous SM data, a unique multi-modal fusion approach is presented in [160].

By matching feature terms linked to crisis information contained in the SM data, improved performance for extracting disaster loss information from SM communications is achieved [161], by using Weibo as a main data source, for the purpose of enhancing disaster response team's knowledge. Similarly, a system that captures data in an adaptive manner from Twitter is presented in [162] by going through disaster-related tweets. It is important to analyze the behaviour of relief groups, governments, and people utilize SM, such as Facebook, during times of disaster [163]. The researchers developed an emergency supply and demand workflow in a system that incorporates the usage of social networks. It is proposed that the National Disaster Management Agency Malaysia (NADMA) use the system for better decision making in future disaster relief operations.

### B. ARTIFICIAL INTELLIGENCE FOR EMERGENCY RESPONSE

IoT can be used with ground, surface, aerial, and underwater robots, for the purpose of deploying smart AI emergency response over sensors to collect environmental data from the disaster site, and then send it through an available network [164]. Reinforcement learning is used to accomplish task allocation in multi-robot emergency response systems [165], which are used in rough environments, solving the challenge of dynamic distribution task allocation in multi-robot systems; their learning algorithm is based on the two separate non-cooperation and cooperation approaches. Table 9 summarizes the artificial intelligence techniques used in response systems.

Similarly, to provide a completely autonomous airborne robotic method for performing complicated search and rescue missions in unstructured indoor situations, a supervised learning classifier based on a computationally efficient CNN trained for target and background categorization is included in the target recognition capabilities [166].

In order to examine cluttered environments and look for possible victims, mobile rescue robots deployed in search and rescue missions must cross unfamiliar tough terrain. These robots must identify routing pathways to safely move in these congested surroundings with an unknown topography with no previous knowledge of the environment in order to act semi-autonomously or fully autonomously.

To investigate the problem of automatic robot exploration in an unknown environment, which is a key aspect of using a robotic system to perform emergency response tasks, [167] proposes a deep reinforcement learning-based decision algorithm that learns an exploration strategy from a partial map using a deep neural network. On the other hand, [168] can take input from the robot's on-board sensors, to select a sequence of local navigation tasks for a mobile robot to carry out. Combination of the classic technique of frontier based exploration with deep reinforcement learning would be of great enhancement [169] to enable a robot to explore unexpected, crowded areas. Several challenges face every local-range sensing deep reinforcement learning strategy for local planning in unknown hard terrain. Self-attention modules into the deep reinforcement learning architecture can be a solution [170] to improve the explainability of the learned information.

Another challenge is to decrease reaction time in emergency scenarios, where image processing application [171] with a ML approach can obtain great performance, by applying histogram of oriented gradients and a SVM classifier to recognize target items such as specific sorts of explosive devices [172].

In the aftermath of a disaster, remote sensing and AI approaches can be utilized to quickly recognize structures through high-resolution satellite imagery [173]. Finding shelter is one of the most pressing demands of affected people who have been affected by a disaster. While the proliferation of crisis data is already assisting in the saving of lives, detecting building damages, assessing shelter needs, and locating ideal locations for emergency shelters or settlements all require a wide range of data to be quickly merged, where AI through its several variants [174] can solve this gap and make progress in comprehensive evaluations of any procedure aimed at quickly fusing and analyzing multi-modal data.

## VI. CONCLUSION AND FUTURE WORKS

The adoption of innovative edge technologies such as sensing, IoT, SM, big data analytics and AI techniques can decrease the number of casualties and reduce the large-scale infrastructure damage caused by natural and human-made crises. This survey examines recent research on emergency prediction, detection, management, and response systems with a focus on SM- and AI-based technologies, outlining the available disaster management technologies and their appropriateness for use in crisis circumstances. A summary of existing research in these topics is provided together with their classification and through several metrics. Despite all of the possible benefits revealed by the numerous methods mentioned in this survey, there are still some issues to be addressed.

### A. THE FOCUS ON MICRO-BLOGGING SYSTEMS

Beyond enhancing the accuracy and precision of detecting relevant messages, AI-based emergency management models encounter other hurdles. One of the disadvantages of the existing studies on SM crowd management is that the bulk of the literature focuses on utilizing Twitter as the main source of data. When people communicate information on platforms other than Twitter, the nature of synchronization and reaction might be different. This issue is because of some platforms, such as Facebook, do not yet permit the extraction of statistics. The consideration of other SM platforms is an open challenge, specially when considering the different quality of data that they can provide. For example, based on the age of usual participants in specific platforms, the nature/quality of data could be very different.

### B. USER PARTICIPATION

It is vital to gain high end-user engagement for technologies like crowdsourcing, big data and SM to actually work. This is true in many instances when incentives are provided, but in other cases, it is reasonable to suppose that users would not require additional incentives to participate in a communal effort that is only for the benefit of society [157]. The decisions on how many to incentivize (quantity) and whom to incentivize (quality) remain as open questions that have been partially tackled by literature, but need further study.

### C. INDIVIDUAL PRIVACY

The safety of residents is always the primary concern while dealing with emergency situations. Respecting privacy, on the other hand, is critical in order to protect the well-being of rescued people. Personal and private information are collected during a crisis, which creates security concerns in disaster management. Malicious attackers should not be able to tamper with the data acquired from affected sites or events. This privacy-efficiency trade-off requires further analysis and optimization, that will allow systems to decide on the best point on the trade-off for each case/scenario.

### D. COST REDUCTION

Experts all around the world are concentrating their efforts on lowering equipment / software costs in disaster management technology deployments while increasing system performance. Disaster management is a life-saving activity, which is why global businesses should explore developing efficient edge technologies in this area to further reduce costs. Notice that emergency systems are not expected to work every day, but in very occasional situations, so the investment in them is not being exploited in non-emergency situations, raising questions about their cost/efficiency. Therefore, novel strategies to benefit from emergency equipment while they are on idle situation are needed, but without affecting/delaying their performance in case of emergency situations.

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