

# Machine Learning for Emergency Management: A Survey and Future Outlook

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**Abstract**—Emergency situations encompassing natural and human-made disasters, as well as their cascading effects pose serious threats to the society at large. Machine learning algorithms are highly suitable for handling the large volumes of spatio-temporal data that are generated during such situations. Hence, over the years, they have been utilized in emergency management to aid first responders and decision makers in such situations and ultimately improve disaster prevention, preparedness, response and recovery. In this survey paper we highlight relevant work in this area by first focusing on the commonalities of emergency management applications and key challenges that machine learning algorithms need to address. Then we present a categorization of relevant works across all the emergency management phases and operations, highlighting the main algorithms used. Based on our review we conclude that machine learning algorithms can provide the basis for tackling different activities across the emergency management phases with a unified algorithmic framework that can solve a large set of problems. Finally, through the systematic literature review we provide promising future directions for utilizing machine learning algorithms more effectively in emergency management applications. More importantly we identify the need for better generalization of algorithms, improved explainability and trustworthiness of machine learning algorithms with respect to the emergency management personnel, as well as more efficient ways of addressing the challenges associated with building appropriate datasets.

**Index Terms**—Machine Learning, Emergency Management, Emergency Response, Disaster, Situational Awareness, Deep Learning, Recognition, Decision Making

## I. INTRODUCTION

NATURAL and human-made disasters, and other emergency events pose serious threats to society, critical infrastructures, the environment and the economy [1]. Such adverse events may happen at any time and can have cascading effects across multiple sectors [2]. On the other hand, recent technological advancements have made it possible to collect huge amounts of data regarding natural and technological disasters [3], [4]. The generated spatio-temporal data can be invaluable in gaining situational awareness and in helping emergency personnel (first responders, strategic and tactical decision makers) make the right decisions, both before and after a disaster happens. However, data are generated in very large volumes and in a rapid manner thus making it difficult for relevant emergency personnel to be able to make sense

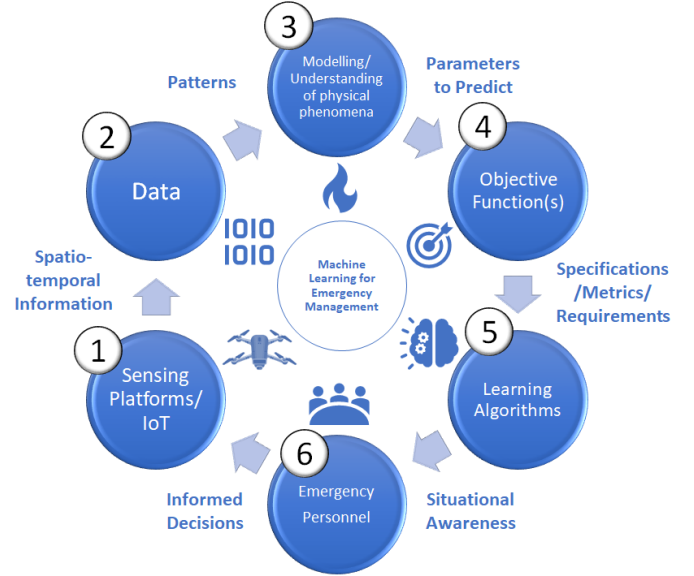


Fig. 1: Machine learning (ML) for emergency management entails carefully tackling various issues from available sensing platforms (1) and data (2), the understanding of disaster phenomena and how to model it (3), to what is objective that such system should meet (4), to the available algorithms (5), and finally, to how such a system cannot only be utilized but also trusted by the emergency personnel and how their needs can influence future iterations. In survey we will review how emergency management can benefit from machine learning by leveraging on the available sensing technologies and generated data leading to better situational awareness and decision making.

of it and utilize it effectively, especially in time-critical and time-varying situations.

Therefore, it is crucial to develop intelligent systems that can identify patterns, automate response, predict situations, and do it in real-time. All of which can aid humans in emergency situations by improving disaster prevention, preparedness, response and recovery [5], [6], [7]. For instance, algorithmic systems are needed to provide prompt detection of irregularities, continuous situation monitoring and prediction, and rapid recovery planning and implementation [8]. Machine learning can be used to analyze the large volumes of heterogeneous spatio-temporal data in critical time-bound situations, in turn providing high-level actionable information that emergency personnel can process effectively [9]. Ideally,

this will lead to systems that can support decision-making in the field, resource allocation and early warning capability, amongst others. To achieve this however, requires addressing key challenges both in the development as well as deployment of machine learning algorithms, such as sensing the right data at the right time, availability of sensors and data, real-time response, limited computational resources, and building trust with end-users (Fig. 1).

While most of the research effort has been on the development of application-specific machine learning algorithms, there are a few studies trying to summarize the work and present it in a concise way as to highlight gaps and future research opportunities. Some survey papers have attempted to capture the relevant literature on machine learning for specific applications of emergency management focusing on what algorithms have been used and how they have been applied. Specifically, the survey in [8] puts the spotlight on recent works on machine learning for the management of pandemics, while [11] focuses on data-driven aspects of building disaster information management systems, such as available data sources, data integration and visualization, as well as predictive analysis techniques. The work in [9] adopted a systematic approach to group the relevant literature for the application of artificial intelligence and machine learning in disaster management, without focusing explicitly on the particular challenges of emergency management. The survey in [12] performs an analysis of relevant literature on how big data have been utilized in emergency response, while [3] provides a survey of recent progress on analytics and machine learning focusing on crowd sourcing and the use of big data in emergency management.

This paper provides a comprehensive survey of machine learning for all phases of emergency management (i.e., mitigation, preparedness, response, recovery), by highlighting key characteristics and challenges, but also how machine learning algorithms can be applied across the different phases and operations. The main contributions of this work are as follows:

- We first discuss the different phases of emergency management and present the operational landscape with emphasis on key challenges that machine learning algorithms need to address for such applications.
- We present a detailed review of machine learning algorithms that have been applied across different emergency management phases and operations to build tools that can help decision making.
- Based on the current state-of-the-art we identify promising future research directions for developing emergency management systems that utilize machine learning components.

The survey is structured in a way that is accessible to both emergency management practitioners but also to machine learning researchers. The former group will be able to better understand in what aspects of emergency management can machine learning provide assistance and how, while the latter will be able to better identify current trends and potential gaps for future research.

Through the survey we demonstrate that machine learning algorithms provide valuable tools for use in emergency management applications and are especially suitable for handling

the high velocity and volume of spatio-temporal data. It is also evident that machine learning algorithms find applications across different emergency events highlighting the fact that there are commonalities worth investigating in order to provide a uniform operational framework for using machine learning in emergency management. Finally, while there has been a lot of work in recent years towards machine learning for emergency management, more effort is needed so that emergency management personnel can gain trust in such algorithms and use them in practice so that the potential benefits can be materialized.

The rest of the paper is organized as follows. In Section II we review the basic concepts and the various phases of emergency management as well as unique challenges and characteristics. Section III then briefly highlights the prerequisites for using of machine learning in emergency management. Sections IV-VIII cover the use of machine learning in various phases of emergency management such as pre-disaster, current state assessment, next state prediction, decision making and actuation, and post-disaster. Section IX provides insights into how emergency management systems that utilize machine learning components should develop in the future and open challenges. Finally, Section X concludes the survey.

## II. EMERGENCY MANAGEMENT: KEY CHARACTERISTICS AND CHALLENGES

Disasters such as fires [13], [14], [15], floods [16], [17], [18], earthquakes [19], [20], [21], and pandemics [22], [23] have devastating effects on human life, the infrastructure, the economy and the environment. To counter their negative impact, emergency management deals with creating a framework within which communities can reduce vulnerability to hazards and cope with disasters [2]. Specifically, the process refers to the organization, management and coordination of the available resources and responsibilities in order to address emergency situations, such as, manmade and natural disasters, terrorist attacks, and large-scale accidents [24], [25]. Among other operations, emergency management involves team coordination, hazard identification and warning initiation, searching for survivors, and minimizing the impacts of environmental crises due to harmful events like, for instance, chemical contamination, explosions, and oil spills.

Disasters and emergency situations can start quite unexpectedly and last for varying periods of time. Their impact can become more disastrous in severe weather conditions, which often makes them extraordinary due to their size, intensity and deep and long-lasting social, economic and environmental impact. Furthermore, across disaster events it is often the case that the same organizations, governmental agencies, and public/private bodies such as police, civil defense, and medical experts are responsible to handle the effects of a disaster across emergency management phases. So it makes sense that many tools can be shared and used interoperably by different personnel and across different disaster events. These characteristics in emergency situations necessitates viewing them under a common framework as they share many commonalities (Fig. 2). For instance in such large scale events the normal function of the society is disrupted [26]. Additionally, these phenomena

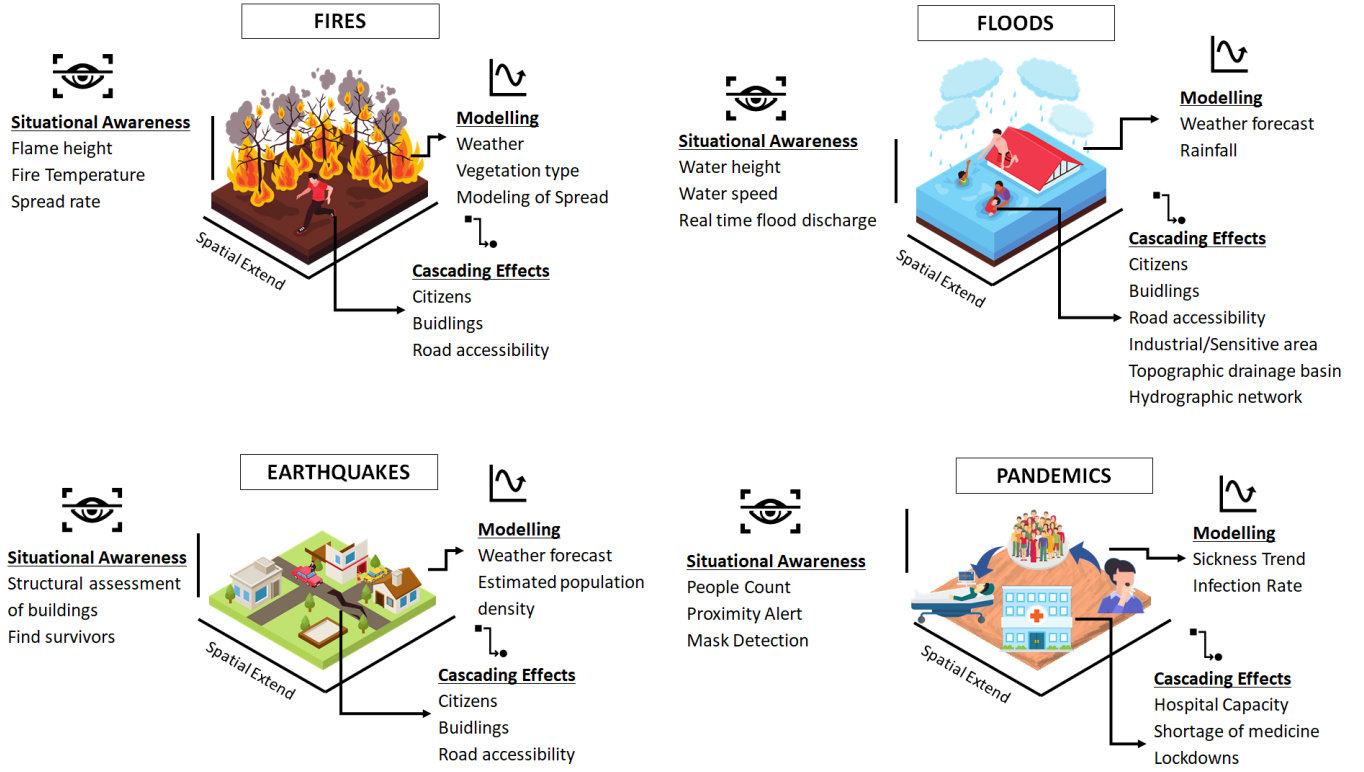


Fig. 2: Disaster events have common characteristics such as spatiotemporal evolution and cascading effects. For example fires, earthquakes, and floods can all impact road accessibility and power outage, while dynamics used in modeling fires could be adapted to also model disease spread during pandemics [10]. Machine learning can play a key part in the development of novel tools to identify useful characteristics of disasters in due time, provide means for situational awareness, facilitate modeling of various phenomena, and alert for potential cascading effects.

evolve both in space and time and can progressively disable the functioning of the society through cascading effects.

Thus the emergency management cycle looks into all the activities related to preventing, preparing, responding and recovering from emergencies. The ability to do so effectively is currently mostly dependent on the emergency personnels ability to understand the emergency and its potential evolution. New technological capabilities can give these emergency personnel access to novel data and insights that they can use to be more effective. Importantly, machine learning systems can underpin much of these efforts by aggregating and analyzing information collected by multiple sources, such as, drones, satellites, IoT sensors, social media, and online heat maps [27], and in real-time. The aggregated information can help emergency personnel identify urgent needs, prioritize responses, avoid wasted effort, and predict the evolution of the emergency situation such as potential fire spread or excess flooding [11].

As such, machine learning can be an important paradigm to address this set of challenges as it can provide a common framework needed to handle the characteristics behind emergency situations [1]. It can also augment other approaches and existing human expertise in dealing with emergency situations. Machine learning tools can first detect or predict the occurrence of such phenomena and then be able to track their evolvable dynamics over space and time. In this way forecasting the future impact of such events can help in better

measuring the effectiveness of a certain action and also recover from negative impacts.

#### A. Emergency Management Phases

First we briefly highlight the different phases in disaster and emergency management where machine learning can play an important role. These are outlined in Fig. 3. In the line of time, mitigation and preparedness take place before the occurrence of a disaster whereas the stages of response and recovery occur after the event. The four phases are briefly described below:

- **Mitigation:** In this phase the goal is to prevent disasters from happening or reduce their magnitude as well as prevent or reduce the negative effects of disasters. Therefore mitigation involves identifying hazards and reducing the risk of those hazards from occurring in communities, by training and education, uptake of new technologies, hazard and vulnerability assessment, and improved infrastructure.
- **Preparedness:** In this phase the goal is to first identify an impending hazard that is coming, and secondly, plan an effective response to minimize the damage that can potentially be caused by a disaster. Preparedness includes the actions taken to reduce the damage from an occurring hazard such as, deriving emergency response plans, and early warning systems.
- **Response:** In this phase the goal is to respond to immediate needs once a disaster has occurred. Emergency response

includes actions that aim to reduce fatalities and injuries, loss and damage of property and the environment.

- **Recovery:** The last phase deals with reversing the damages that a disaster has caused, and bringing the community back to an acceptable level that is close to the previous state prior to the hazard occurring, including building and repairing infrastructures, taking measures to ensure economic growth, etc.

Across all these phases, emergency management needs to be supported by data collection and analysis, prediction and modeling of past and future events such as reconstructions, forecasts, and projections. Due to their capability to learn without being explicitly programmed, and handle large amounts of data, ML algorithms can play an important role in identifying, responding and mitigating crises and disasters.

### B. Application Characteristics and Challenges

The nature of emergency response operations exhibits certain characteristics which pose challenging requirements on ML applications that need to be considered during the design of the ML algorithm.

The *space-time dynamics* of hazards are driven by complex interactions that are difficult to foresee. The evolution of most types of disaster events, like fires, floods, and oil spills, exhibit a highly complex spatiotemporal behavior that depends on several dynamic factors such as weather conditions, ground conditions, etc [28]. To this end, employed ML methods need to handle spatiotemporal input data. Furthermore, analytical modeling of hazards in order to accurately predict their evolution is often prohibitively time consuming, if not impossible. Therefore, ML algorithms that are based on models of disasters to support emergency response operations must not be based on predictions that are made long ahead of time, but need to be able to adapt to continuously updated models, and real-time data.

*Cascading effects* are undoubtedly adding to the complexity of emergency management situations [29]. Identifying all dependent elements whose interconnection will lead to cascading disasters or effects is not straightforward. However, this aspect is highly critical as ignoring or missing such a dependency can easily render a system or algorithm unreliable and possibly put, for instance, first responders and survivors at risk. Designing ML algorithms to address scenarios of cascading effects is challenging because understanding and modeling the interdependencies of these effects is very complex. In addition, defining a problem that addresses multiple dependent elements results in large, hence complex, ML models, i.e., with large parameter space, large training datasets, etc.

In realistic conditions, ML models for disaster response operations often need to work with *incomplete or partial information* [30]. During emergencies data collection cannot be guaranteed, either because a data source cannot collect the required data as expected, or because communicating the data experiences disruptions, thus the possibility of incomplete input information must be considered. Additionally, often such operations involve multiple decision-makers with each of them having a restricted view of the situation. In general,

ML algorithms excel in capturing uncertainty in the data, yielding effective predictions during inference of unseen input. Another source of concern when developing ML algorithms for emergency management is that of data ambiguity [31]. Data ambiguity arises when the data can have more than one interpretation, which can lead the algorithm to draw false assumptions and correlations. This can happen in cases when values can be interpreted as having different meaning either due to varying biases or experiences by the experts. As such, it is important to always consider the effects of such data quality issues when utilizing machine learning models in emergency management for decision making.

Another challenging characteristic related to the input data is the need to *integrate data from various sources* [32]. First, this usually leads to large input datasets and large parameter space of the ML algorithms. Furthermore, incorporating multiple data sources usually means collecting heterogeneous data that might represent diverse things, cover different geographical areas and correspond to different levels of accuracy and granularity. This feature sometimes calls for adopting data processing techniques like data cleaning, dimensionality reduction and instance selection as it is required to reduce the size of the datasets as well as to help the ML model to extract and use only the useful information contained in the data [33].

*Network connectivity* constitutes another challenge in applications of emergency management [34]. It is not uncommon for disasters, to occur in remote areas where connectivity is limited or absent, while other times connectivity problems may arise due to disaster-related infrastructure impairments. However, connectivity is necessary for the transmission of real-time data that is collected in the area and for access to data from other sources, for instance, through the Internet. Additionally, communication between devices is vital for exchanging feedback information as sometimes distributed and decentralized algorithms are employed. If communication through infrastructure is not available for any reason, connectivity through ad hoc networks and rapid deployment of connectivity services is established. However, in such cases the network capacity is probably limited, therefore ML algorithms for emergency response operations must be carefully designed with respect to their network capacity requirements.

Applications in the field of emergency management are *time critical* [35]. It is crucial to process real-time data and make decisions fast in order to reduce casualties. Rapid response in emergencies can make enormous difference in various aspects like, for instance, in preventing the exposure of first responders to danger, saving disaster victims, mitigating propagation of a disaster and, thus, limiting damages. Furthermore, emergency situations tend to progress and propagate very fast, thus if the process from data collection until we reach a decision is long, the decision might even be ineffective as it is based on outdated data. In this aspect, machine learning algorithms should be able to provide real-time collection of relevant data, and filter the most critical information of relevance to the situation. Furthermore, it is sometimes the case that ML algorithms are to be executed on devices with *limited computing capabilities*. Therefore, although in general the field of ML flourishes due to the power of modern computers, at emergency sites

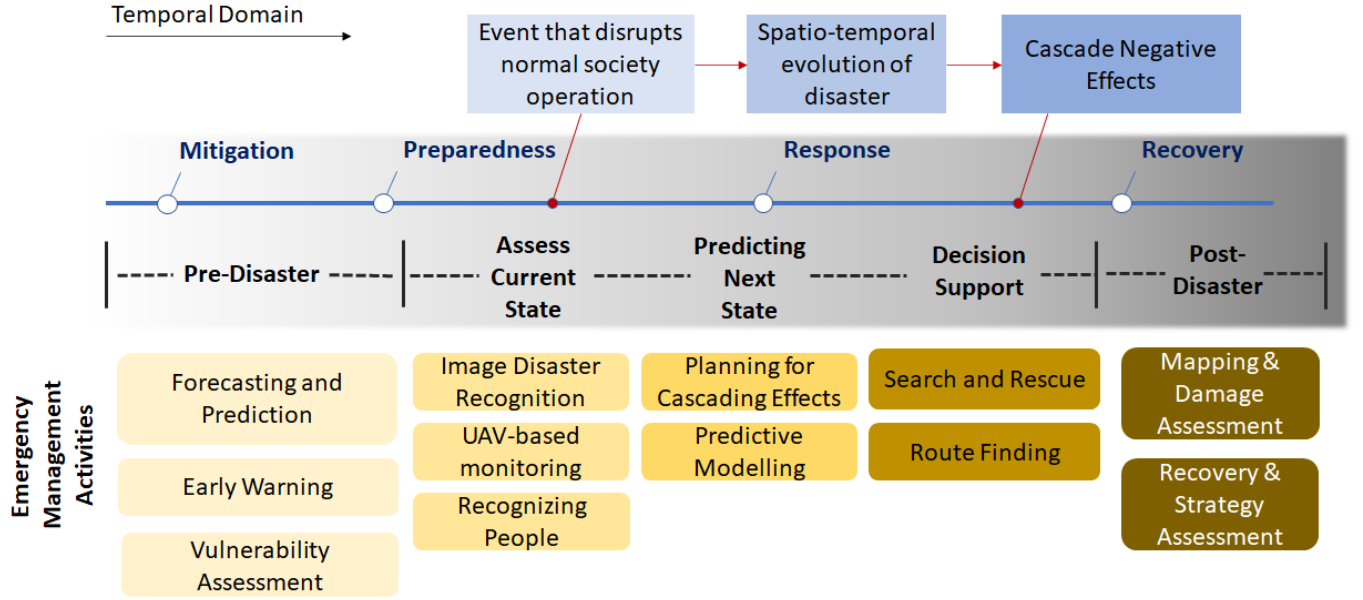


Fig. 3: Emergency management phases and activities where machine learning has been utilized to automate and improve the operational efficiency.

algorithms often need to be executed on resource-constrained computers or even on small devices, such as drones. Therefore, the algorithm selection is critical when developing emergency response applications. Coupling of ML learning with efficient IoT systems will play significant role in this aspect as it can facilitate the rapid availability of vast amount of real-time data to key emergency personnel [36].

Another important challenge is related to human in the loop factors affecting machine learning algorithms either directly or indirectly. First, humans themselves can be the target of ML algorithms i.e., tracking first responders or searching for survivors. On the other hand ML algorithms may analyze data that is collected from wearable sensors, or sensors controlled by humans. In such cases the unpredictability in their actions and decisions has a direct effect on the ML algorithm and if it is not properly addressed can lead to unexpected behaviour. On the other hand emergency personnel can be the recipients of information generated by an ML algorithm. In such case, which part of the information is shown to them, and the way it is presented has an influence on the human-level decision making.

Finally, while in many applications a mistake made by an ML system can be harmless, in *safety-critical* applications such as emergency management, errors can potentially lead to catastrophic results. Therefore, it is important that decisions and predictions provided by ML algorithms are *trusted* [37]. ML systems for emergency management are also used to provide support for management-oriented decisions in order to optimize recovery tasks and logistics. These recommendations need to be transparent, explainable, and trustworthy especially [38]. To this end ML systems for disaster and risk management need to not only give a prediction or recommendation, but also a set of quantitative reasons as to why a certain outcome is reached [39]. The reasoning acts as a means of evaluation by

experts of the decisions suggested by the ML system.

### C. Sensing and Data for Emergency Management

The availability of multiple and diverse data is key in enabling the employment of ML in emergency management solutions [40]. Data is required to pre-train ML models and subsequently to improve them on domain specificities. The quantity as well as the quality of the available data needs to be sufficient in order to be able, first, to train successfully a ML model by means of the training data and, subsequently, to produce accurate results based on the evaluation data. Nevertheless, the unpredictability and often rare occurrence of emergency and disaster events can pose challenges in harnessing data and be able to provide ground truth and calibration information to realize reliable and trustworthy algorithms. Available categories of data that can be utilized in emergency management are categorized as follows:

- *Static data*: Static data that can be collected for an emergency event include historical data (related to disaster type, weather, etc.), geological data, area maps, infrastructure mapping data around the affected area, population and demographic data etc.
- *Relevant data*: This category includes data that are relevant to a disaster event, but their collection is carried out routinely by organizations or authorities not responsible for emergency management operations. This encapsulates for example, weather forecast information, road traffic information, measurements monitoring the water distribution system, etc.
- *Satellite data*: Maps and satellite imagery can provide up-to-date spatial data which are of great importance for disaster management support such as planning the logistics of relief actions in the field immediately following a disaster, and

can be exploited in combination with computer-vision and other processing techniques [41].

- *Cameras and IoT sensors*: This includes data collected from sources that are already deployed for other purposes beyond emergency management, for example, smart cameras to monitor people [42], or IoT sensors deployed for monitoring the water distribution system. Additionally, various data sources can be deployed for and dedicated to emergency management purposes, like air quality monitoring sensors or cameras which can be deployed in high risk areas for air contamination accidents or fires, respectively.
- *Remotely controlled or autonomous devices*: Devices and platforms that can be spatially deployed on the ground, in the air or underwater, equipped with various sensors for remote data collection. An advantage of such devices is that they provide access to areas that is dangerous or inaccessible for humans.
- *Crowdsourced Data*: This data category related to collecting information from first responders during emergency operations through their mobile phones or other specialized devices that can be developed specifically for such purposes. For instance heterogeneous big data from multiple data sources processed through distributed frameworks can help in cases of floods where fast response time is needed [43]. Crowdsourcing can go beyond just first responders to also include other actors such as civilians through specialized data collection applications for mobile phones. However, care should be taken when using crowdsourced data as there may exist noisy labels [44].
- *Social media data*: Although this category can be considered as crowdsourcing, it is not limited to data of a single user but instead can also make use of social network graphs, as an additional information, and has received increasing attention by the scientific community [45], [46], [47]. Such data can include, for instance, photos posted in social media, information drawn from tweets or posts by means of natural language processing and text mining techniques, etc.

Sometimes it is also practical to categorize data based on their spatial characteristics, namely fixed and mobile data. Fixed data are collected from static locations, thus georeferencing measurement locations is required only initially. In addition, several features of the collected dataset, such as location granularity, are sustained. On the contrary, the case of mobile data is more challenging with respect to the utilization of the data as input to ML models, since location measurements may not be constant. In this case, the location-related characteristics of the dataset are dynamic, therefore spatial correspondences need to be tracked and maintained. Another essential difference between data sources concerns the timing of the data collection (i.e., mobile data sources vs. data sources that collect and send data on-the-fly). In the former case, the measurement locations are changing over time, yet controlled, therefore the coverage of an area by sensors is executed according to a plan depending on the situation. In the latter case there is no control over the locations of the measurements, thus for certain areas there might be abundance of data during a time period while, at the same time, other

areas might remain uncovered.

#### D. Traditional Modelling Techniques in Emergency Management

The application characteristics and aforementioned data sources provide opportunities for ML. However, it is also worth considering the alternative approaches that can often be complementary. Herein we provide a few examples of such techniques, however, since this is out the scope of this survey we refer the reader to [48], [49] for additional details. For instance, wildfires are complex physical processes that involve different interrelated factors, including weather, topography, soil moisture, type of fuel, and the location and type of the source. In addition, wildfires are dynamic and can occur in different spatial and temporal scales. In a non-ML approach all these factors should be characterized by appropriate modelling and equations to describe their behaviour. As such it requires modelling of complex functional relationships between numerous data. This is quite tedious especially if some aspects and prior information are unknown. Another example is that of disaster damage detection. A common non-ML approach is template matching method across time intervals which requires setting manual parameters, and heuristically set thresholds [50],[51]. This is the easiest and most straightforward way to implement detection systems as it does not require collecting massive amounts of data but human expertise is often relied upon. Disaster are often modelled as out of distribution events. This requires modelling various distributions and making various assumptions on probability distributions of different events [52]. For spatial data sources such as images video and audio traditional techniques rely on empirically chosen features and associated metadata that may also be available to try and detect emergency events [49].

### III. DRIVERS FOR MACHINE LEARNING IN EMERGENCY MANAGEMENT

A machine learning algorithm first extracts knowledge from a given dataset, in the form of learnable parameters that are tuned to meet a specific objective, and then uses that knowledge to asses and generate a corresponding output(s) for a new situation. This enables machine learning based systems to perform challenging tasks for which no explicit code can be written. This provides a key advantage in emergency response applications where it is more difficult to explicitly model all possible scenarios and events. Another key benefit of viewing emergency management under a common framework, where multiple tasks can be solved with machine learning arises from the fact that knowledge and common factors affecting multiple emergency situations and potential interdependencies can be identified. One example stems from the fact that phenomena such as climate change can lead to multiple severe hazards occurring which need to be managed simultaneously [53]. Furthermore, developing machine learning in such a way will lead to their interoperability and transferability across tasks thus holistically improving the emergency management capacity. Lastly, it can help researchers better understand the risks for



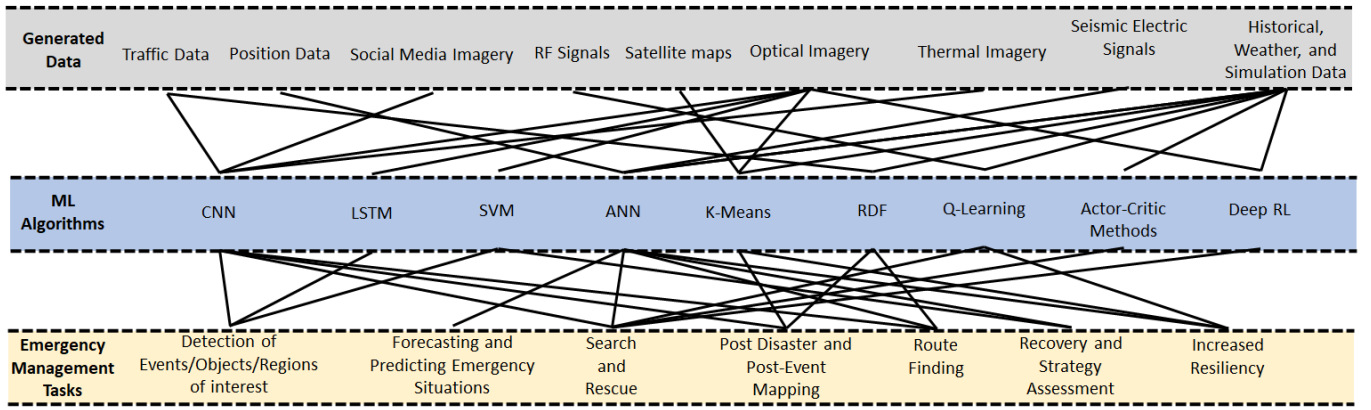


Fig. 4: Summarization of sensing technologies, data types, and algorithms that facilitate the realization of automated emergency management tasks.

safety and limitations of current machine learning algorithms by examining them under different relevant domains.

Hence, machine learning can play a role across different phases of emergency management as well as across different mission types. Specifically, it can be used to implement tools that assist decision makers by providing answers and estimations for questions such as: i) when will an event occur? ii) how severe will its impact be? iii) how many people will be affected? Some common machine learning algorithms that are used to build systems capable of helping towards these goals are Support Vector Machines (SVM), Random Decision Forests (RDF), Logistic Regression (LR), K-means, Artificial Neural Networks (ANNs), Reinforcement Learning (RL) and more recently deep learning and its derivations (Deep Neural Networks (DNNs), Convolutional Neural Networks (CNNs), Recurrent Networks using Long Short Term Memory (LSTM), etc.) [54]. These algorithms are augmented with sufficient data and sensing technologies (see Fig. 4) to realize the automation of various emergency management tasks [55].

Several technological advancements that we have available today allow us to monitor several different phenomena during an emergency situation thus making emergency management tasks highly data rich. As such, through the use of machine learning algorithms to analyze data arriving in high velocity and volume in real-time it is possible to uncover patterns that would otherwise be unnoticed to human observers, thus making it possible to predict cascading effects and progression of a phenomenon. In order to develop practical ML tools that are sophisticated enough to handle complex situations as in emergency management, we identify three critical prerequisites, namely: high computing power and storage, sufficient input data and suitable ML algorithms.

*Computing and Storage:* During the last decade computing devices have evolved drastically [56]. The recent generation of computing devices have high computing power and storage capacity, sufficient to process large amounts of data and execute complex algorithms fast [57]. Coupled with the fact that machines using modern hardware can simultaneously perform perception, prediction, learning, reasoning, planning, and communication, they can be used in remote inaccessible

areas to perform tasks which are impossible for humans considering the amount of information that needs to be processed. However, even if small-sized electronic devices have adequate computing capabilities to run demanding algorithms [58], [59] there is still a limit and such constraints should be taken into consideration, especially in highly uncertain emergency situations where several scenarios need to be considered.

*Data:* The availability of relevant data is changing dramatically the landscape of emergency management. But as is the case with any data-driven application deriving effective and trustworthy ML algorithms is dependent on the input data set. In particular, the data must be enough in terms of quantity and quality to express the right underlying patterns. While data was a scarce resource in the past, difficult to produce, costly to store, and slow to manipulate, things have changed [60]. Nowadays data collection and availability has become feasible, as reliable devices that can collect large amounts of data are now available at reasonable cost. Hence the wealth of data that first responders are increasingly able to collect can prove invaluable in the disaster management cycle and greatly improve situational and needs assessment [3]. Examples of such devices are drones (Unmanned Aerial Vehicles, UAVs), Autonomous Underwater Vehicles (AUVs), statically deployed sensors and cameras, and wearable sensor devices for first responders [61]. Additionally, data may be available from other sources not directly related to emergency management. For example, videos taken from surveillance cameras may be processed to provide early damage assessment to evaluate the situation in the affected area after a hazard. Social media posts, often containing photos/videos and text, can be used in the case of a disaster event in order to extract information about the existence of victims.

*AI/ML Algorithms:* The evolution of *computing and storage* and availability of *data* has been met with an increasing interest by the scientific community for the development of practical ML algorithms over the last few years [4]. Intelligent algorithms for data analysis are essential in order to be able to exploit the information therein and lead to improved automation and capabilities. The rapid increase in available computational power has enabled researchers to experiment

with new algorithms that are capable of harnessing the large amount of data. This is evident with the recent developments in deep neural networks that have contributed towards tangible advancements in many fields [54].

In the following sections we will highlight emerging efforts in using machine learning based systems for emergency management applications focusing on the relevant tasks that it can provide assistance in. We cluster the various works, as shown in Fig. 3, as follows: i) pre-disaster activities that encapsulates both mitigation and preparedness phases, ii) then the response phase, where the majority of work is currently found, is split in three thematic groups based on first assessing the current state, then predicting the next state and future dynamics, and finally the decision support step, iii) in the last section we review post-disaster activities.

#### IV. PRE-DISASTER ACTIVITIES

Machine learning algorithms can be used to predict impending emergency events such as earthquakes, storm surges, and floods, and effectively assist emergency management personnel needs and service requirements, identify vulnerable population, and take evasive actions.

##### A. Forecasting and Predicting Emergency Situations

Predicting and forecasting deals with associating impending disasters with preceding patterns and phenomena. For example, the study by Moustra et al. [62] utilizes feed forward artificial neural networks with various types of input data for the prediction of earthquake magnitudes. Specifically, the prediction of the earthquake magnitude of the following day and the magnitude of the impending seismic event. The neural networks developed for each respective use-case made use of time series magnitude data as input, and seismic electric signals. An earthquake prediction system based on artificial neural networks has been studied in [63]. It is used to forecast probabilities of occurrence and re-occurrences of earthquakes based on a novel combination of seismicity indicators and careful adjustment of thresholds, leading to small spatial and temporal uncertainty.

Prediction of storm surge is necessary for emergency managers to make critical decisions for evacuation of an area. A feed-forward artificial neural network algorithm has also been applied into the development of a time series forecasting model of storm surge [64]. The developed surrogate model was validated with measured data and high-fidelity simulations of two historical hurricanes. It exhibited a fast execution time in the order of a few seconds allowing for real-time predictions for a range of hurricane conditions and tracks that are statistically plausible, and allows for probabilistic simulations to evaluate risk and support decision making.

Floods are recurring hazards in some regions of the world, but their impact on human life and health can be alleviated through a reliable forecasting model. The work in [65] proposed an ML model for forecasting 1-day-ahead monsoon river flows which are difficult to model as they are characterized by irregularly-spaced spiky large events and sustained flows of varying duration. Their forecasting model utilized discrete

wavelet transform for preprocessing the time series and genetic algorithm for optimizing the initial parameters of an artificial neural network prior to the network training. Their model has been shown to predict relatively reasonable estimates for significant flows.

According to studies<sup>1</sup>, combining weather data with deep learning and image classification can lead to better prediction of the probability of a forest fire. Deep learning algorithms are used to analyze the images and predict the amount of dead fuel present in the sensed area. Combined with live weather data, the model can then predict the probability of fire. Real-time risk prediction can be obtained by integrating this into dedicated smart wildfire sensor which can be deployed in the forest.

##### B. Early Warning

Setting up prediction systems for real-time early warning is a key preparation component for handling impending disasters [66]. Practical solutions have been recently proposed and make use of IoT, and cloud network services that can rapidly and accurately share information on disaster situations [67]. Such developments have been foundational in internet-based platforms for early flood warnings, and in the development of machine learning methods, such as bayesian models, Neural networks, boosted decision trees and decision forests, has been developed for detecting abnormal behaviors based on the analysis of thousands of sensor streams [68]. The work in [51] demonstrates that data captured from distributed acoustic sensors can facilitate low deployment cost and dense sampling capability when paired with machine learning algorithms. Specifically, it trains a deep neural network to automatically detect earthquakes using acoustic sensors with a limited number of positive samples. The approach relies on a preprocessing procedure to improve signal quality and a method to expand the training dataset with data augmentation to overcome the lack of positive samples. [69] investigates two types of elastic body waves for earthquake monitoring, namely the primary wave (P-wave) and the secondary wave or shear wave (S-wave). Two recurrent neural network models using the long short-term memory (LSTM) cells are developed is used to identify the occurrence of an earthquake event, and the duration of the P-wave and the S-wave. A comparative study for earthquake detection is performed in [50]. It compares K-nearest neighbour (KNN), decision trees, and support vector machine (SVM) against a traditional criterion-based method demonstrating that the ML solutions exhibit higher detection accuracy with much reduced false alarm rate.

##### C. Vulnerability Assessment

Predictive modeling in case of earthquakes can be used to account for the potential damage but also organize better the use of resources based on population and built-up area<sup>1</sup>. In this context, ML algorithms can be used to monitor urban growth focusing on the built-up area and building height. Similarly, inspection of buildings is an important issue to

<sup>1</sup>"Machine Learning for Disaster Risk Management", GFDRR, 2018



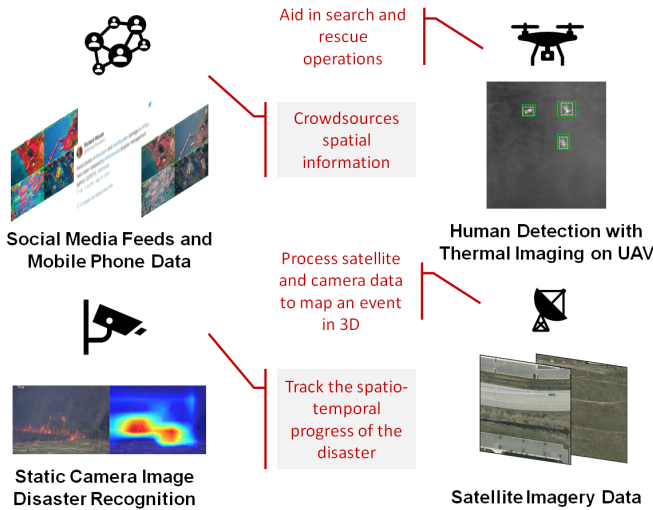


Fig. 5: Example data used for automated detection of events, objects, and regions of interest include social media images and posts, thermal imaging for detecting people, UAV imaging for fire recognition. All these data can facilitate various emergency management operations.

mitigate risks of fire or other damages after an earthquake. Gradient boosting and random forests can be combined to assess which buildings have the higher risk in order to be inspected based on geospatial data and building attributes (duration between inspections, past violation, type of violation, building vacancy, location variables, etc.). A machine learning method to quantify the complicated role of social vulnerability in hurricane damage has been proposed in [70] by using random forest regression algorithm.

Utility companies can also use AI- an ML- based tools to estimate likely damage locations and service outage duration in order to get prepared accordingly<sup>2</sup>. Furthermore, ML algorithms, such as SVM, can improve the power availability during disastrous events [71] by directly controlling the operations of different power modules in grid connected electronics.

## V. ASSESSING THE CURRENT STATE

In this section some relevant works for the problem of automated detection of important events and objects of interest in emergency management using machine learning are described. These works can form the basis for building systems that can provide situational awareness and assist in capturing what is the current state of an area during a disaster. By state we mean any relevant information that can characterize an emergency situation such as the type of disaster or its location and extend.

### A. Image- and Video- based Disaster Recognition

Different methods have been proposed over the years such as detecting various disasters in images such as image-processing-based with thresholds to perform pixel-level classification [72], Gaussian mixture models which require empirical tuning [73], SVMs [74] as well as various combinations

of algorithms [75]. In recent years, the success of deep learning and Convolutional Neural Networks in particular for different kinds of image analysis tasks has also led the research community to investigate their suitability for such applications, especially in combination with robotics platforms [76].

Recent methods for early detection of disasters, such as fires, have utilized video processing to combine spatio-temporal information [77]. In [78], the authors have used deep learning approaches such as the Faster Region-based CNN (R-CNN) to detect suspected regions of fire and of non-fire based on their spatial features. Then, the summarized features within the bounding boxes in successive frames are accumulated by an LSTM to classify in a short-term period whether there is a fire or not. This demonstrates the effectiveness of combining spatio-temporal information to identify disaster events. More general approaches, as in [79], attempt to classify multiple natural disasters, damage, and incidents from arbitrary images from social media sources over time. They make use of residual CNNs and develop a large-scale human-labeled dataset towards the goal of building a system that can automatically and systematically detect various incidents.

### B. Situational Awareness with UAVs

UAVs possess some powerful characteristics, such as versatile movement, which combined with special features such as lightweight chassis and onboard sensors can open a world of possibilities for monitoring terrain that is difficult to traverse and observe. Hence UAVs constitute an important platform that provide many advantages in emergency management operations as many emergency personnel needs can be met with technical capabilities found in UAV systems [80]. Recent technology platforms, such as [81], have enabled easier integration of machine learning methods with remote sensing platforms such as UAVs. Concurrently, deep learning has recently gained a prominent role as an approach for aerial image classification for emergency response and disaster management applications due to its higher classification accuracy and generalization capabilities [82]. Hence, herein we provide a summary of the novel capabilities that are enabled through the integration of machine learning with UAV platforms.

Airborne detection of forest fires is an important application of emergency management [83]. In [84] the authors propose a cloud based deep learning approach for fire detection with UAVs. The detection is based on a customized CNN which is trained to discriminate between fire and non-fire images. The system works by transmitting the video footage from a UAV to a workstation where the algorithm is executed. Similarly, the work in [85] targets fire detection applications with deep learning. Specifically, two pre-trained CNNs are used and compared, namely VGG16 [86] and Resnet [87] as a base architectures to train fire detection systems. The architectures are adapted by adding fully connected layers after the feature extraction to measure the classification accuracy. The work in [88] proposes an approach for wildfire detection from UAV platform. The overall approach comprises of a CNN called *Fire\_Net* consisting of a structure similar to the network in *VGG16*. It is accompanied by a region proposal algorithm that

<sup>2</sup>A. McConnon, "AI helps cities predict natural disasters", Wall Street Journal, 2018

extracts image regions from larger resolution images so that they can be classified by the neural network.

Various disaster recognition systems have been proposed for applications beyond fires. In [89] a method is proposed for detecting objects of interest in avalanche debris using the pre-trained inception network for feature extraction and a linear SVM for classification. They also propose an image segmentation method as a preprocessing technique that is based on the fact that the object of interest is of a different color than the background in order to separate the image into regions using a sliding window. In addition, they apply post-processing to improve the decision of a classifier based on hidden Markov models. An extensive analysis for flood recognition from top-view UAV imagery is presented in [90]. Results demonstrate performance of various algorithms for the purpose of classification, segmentation, and visual question-answering, highlighting the challenge of perceiving smaller objects. The authors in [91] propose a hybrid SVM and K-means system to detect flooded areas. It first uses the K-means to identify visual works and then performs binary classification of aerial images, in flood and non-flood affected areas, through an SVM. The Principal Component Analysis (PCA) is also used to reduce the dimensionality of the feature vectors.

Finally, general UAV-based recognition systems that simultaneously attempt to recognize multiple disaster events at the same times have been proposed. The works in [92], [93] target real-time on-board UAV processing classify aerial photos in one of 5 classes corresponding to natural disasters. In the work of Kamilaris et al [94], a deep convolutional neural network is trained to recognize disaster events. The video is streamed on a remote server where the processing and recognition takes place.

Beyond optical and thermal sensors, UAVs can be equipped with other sensing modalities that combined with machine learning may facilitate better situational understanding in cases of ongoing emergency situations such as earthquakes [95]. For example, the study in [96] utilized a microphone array could be used to localize the sound source and classify it through a pattern recognition approach.

### C. Humans Recognition in Emergency Situations

The precise detection of humans in peril is of paramount importance in some emergency situations. Moreover, this is often a time-critical situation. This necessitates developing detection systems that are capable of locating humans either through imaging or other sensors to aid the task of first responders [97]. The work in [98] explores the use of deep learning techniques, capable of detecting open water swimmers. The work combines global navigation satellite system (GNSS) techniques and computer vision algorithms for both precise human detection and rescue apparatus release. Similarly, the work in [99] proposed an image-processing and region-proposal algorithm based on deep CNN for human detection in aerial RGB images. Human detection can also be performed through thermal imaging as shown in [100]. To achieve real-time operation on board the UAV the authors first employ an optimized YOLOV3-MobileNetV3 as the detection

model which is trained through knowledge distillation from a teacher model.

Other works have looked into more specialized scenarios such as searching under dense forests, which is a more challenging situation. Recent techniques utilize thermal imaging and multiple images to first defocus occluding objects such as the tops of trees, and secondly highlight the heat emitted from a warm body. Then a machine-learning algorithm such as a CNN is used to determine if the heat signals correspond to those of humans, animals or other sources [101],[102]. This system is employed on a UAV so that when a human is identified it gives a signal to the search team with the coordinates.

Recently developed human detection systems using deep convolutional neural networks (e.g., [103],[104]), can be repurposed in the wake of emergency situations such as pandemics [105], to perform crowd monitoring for authorities to monitor and enforce social distancing guidelines. Specifically, optical, thermal as well as wireless positioning systems have been effectively used to identify individuals at risk, and measure the distances among people and alerting them when they are too close to each other [106].

## VI. STATE PREDICTION AND PLANNING

Machine learning approaches can also aggregate and accommodate data from multiple resources such as weather data or open maps [107], health status and whereabouts of citizens [108],[109], as well as infrastructure capacity and resource availability [110], [111]. By integrating such data, machine learning algorithms are used to identify areas in need of urgent assistance and direct relief efforts there. For example, they can predict cascading effects affecting critical infrastructures such as power outages [112] and medical centers [113]. Machine learning tools can also predict how emergency situations can evolve and help humanitarian agencies in decide how to handle them [114].

### A. Resilience Planning for Critical Infrastructures

To assist preventative emergency planning efforts, a machine learning predictive algorithm is presented in [112] in order to estimate outages, and ultimately prevent damage of assets in the electrical network during a disaster. The model is trained on historical interruption data and by considering physical properties and historical weather data, as well as environmental information it can predict interruptions across an electrical network based on events such as extreme weather.

Post-disaster utility (e.g., power and communication) outages can have even more detrimental consequences to the everyday quality of life. As such proper planning for recovering critical infrastructures is critical in such cases [115]. With regards to communication utilities high-mobility drones acting either as aerial base stations or simply relay nodes can potentially provide communication services in disaster stricken areas. In such scenarios, efficient planning for their deployment is very important. To tackle this problem, the authors in [116] propose unsupervised modified K-means approach for 3-dimensional drone deployment to aid emergency

communications over a given large area, while also minimizing the transmit power. Similarly, in [117], a Q-learning-based reinforcement learning approach is proposed in order to find the best position of multiple drone base-stations in an emergency scenario by maximizing the coverage of users.

In emergency situations proper planning for medical services is also an important issue. This has been the subject of the work in [113], where machine learning methods are used to generate emergency call volume estimations. Given that demands for emergency medical services can fluctuate in both space and time, different methodologies are proposed. An artificial neural network regression model was used to generate call volume predictions for daily and hourly forecasts. The spatial aspect is incorporated by using a K-means clustering algorithm to produce heterogeneous clusters based on location and train the ANN using this additional information thus producing more granular predictions that can be more helpful to emergency responders.

### B. Disaster Evolution Models with Machine Learning

Predicting how a disaster will unfold and how it can evolve are crucial aspects towards better planning and actuation, especially for disasters where there is lack of knowledge about their evolution and the ways to best address them [118]. Evolution refers to an event that is triggered by other events and may itself also trigger subsequent events. In essence, there is a cause-and-effect relationship among multiple events. Under this premise, different works have attempted to build prediction systems based on machine learning. The work in [119] investigates the evolution mechanism of emergencies and explores the probability of predicting secondary disasters. A novel multi-label learning vector quantization (LVQ) neural network is proposed to construct the prediction model able to forecast the type of sub-events. Spatial clustering of social media events generated by smart phones during a disaster over a geographical region is utilized in [120], to predict and assess the needs of the people affected by a disaster. Two machine learning algorithms (ANN and SVM) are used in [121], to process remote sensed data collected from satellite images over large areas and extract insights from them, to predict the occurrence of wildfires in an effort to avoid such disasters. The study in [114], models the probabilities for predicting landslides, land subsidence, and flood hazards, using machine learning models that include SVM, boosted regression tree, and generalized linear model. Also predictive maps for multi-hazard assessment are produced to aid risk management. From algorithms that have been investigated, SVMs have been shown to be the most accurate for predicting such events.

The authors in [122] explored different machine learning models (SVM, LR, ANN, and RDF) based on their predictive ability for applications related to landslide susceptibility mapping. In their work, they augment machine learning techniques with a synthetic minority oversampling technique (SMOTE) to oversample the training dataset thus leading to improved prediction results. The work in [123], entails a new approach that combines IoT and machine learning for the prediction of water level in association with flood severity. Specifically, it

presents an ensemble learning method that combines Long-Short Term Memory model and random forests to outperform individual models.

## VII. DECISION SUPPORT

This section covers ML approaches that have been utilized to provide additional information towards decision support for taking action. For example, we consider the problem of where to move a UAV when searching for missing people or how to navigate through an evacuation route.

### A. Search and Rescue

Machine Learning algorithms can provide increased capabilities for remote sensing technologies to be used in search and rescue operations such as autonomous unmanned systems (aerial, terrestrial, and marine) in both indoor and outdoor environments[124], thus expanding the operation area and providing new insights for many emergency response and disaster management applications [125]. In particular such systems provide a valuable tool during search and rescue (SAR) operations [126], [127]. SAR operations occur during or after natural disasters. SAR teams are tasked with searching, recognizing, and/or geo-referencing missing persons over interior waters or remote and difficult to access areas. When subjects are not located during the early period, search operations can last days, and even more. Thus improving the search effort at these initial stages is critical to a successful SAR operation. As this can speed up the searching time SAR operations can benefit greatly from such advancements and execution of tasks such as mapping, observation, and supply delivery.

Section V-C has reviewed machine learning methods for perception and detection of events and objects. This section complements those techniques by reviewing methods that aim at training software agents to perform search operations and that can optionally be equipped with advanced sensing systems. Reinforcement learning methods have traditionally been used for planning purposes by solving a Markov Decision Process (MDP) through the interaction between an agent and the environment in a learning by experience paradigm [128], as shown in Fig. 6. For a more in-depth review on deep reinforcement learning and drones/UAVs we refer the reader to [129].

Recent efforts have focused on taking advantage of deep reinforcement learning methods in order to teach an autonomous UAV to perform search operations [130]. The authors in [130], [131] use a deep reinforcement learning algorithm and train it on a virtual vehicle simulator to learn how to search and identify objects. Such efforts have also been explored for search and rescue in coastal environments [131]. In particular an approach is proposed to process images acquired by the UAVs to identify the possible location of the victims. It first identifies hypothesis of promising areas to search in and then those areas are input to a CNN to distinguish whether any person is in the area. Such systems can reduce the rescue time and increase search efficiency especially when using a cluster of UAVs.

With regards to executing complex SAR missions in unstructured indoor environments, the work in [132] incorporates into a robotic platform target recognition capabilities through a supervised learning classifier based on a CNN model trained for target/background classification, as well as an image-based visual servoing algorithm which integrates the Deep Deterministic Policy Gradients (DDPG) reinforcement learning method. By combining these features it achieves continuous control and thus immediate interaction with the target to facilitate delivering some required items such as medicines, equipment, etc.

Another relevant problem related to the utilization of mobile robot platforms for urban SAR operations is that of exploring the boundaries of an area, which is also called frontier exploration. Environments affected by disasters are unpredictable as their layout can significantly change post-disaster, making the reliance on a-priori information and static solutions not possible. For example, in case of collapsed buildings from an earthquake, the potential pathways, search area and layout are altered. Thus navigating based on a priori information is suboptimal. A solution proposed in [133] uses novel deep reinforcement learning network architecture for frontier exploration to allow a robot to autonomously explore unknown environments. The objective of the approach is to maximize the robot's information gain early on during exploration. This is a desired behavior to allow the robot to find trapped victims within an environment as quickly as possible.

Reinforcement learning approaches have also been extended to multi-agent search missions [134]. This approach utilized the Asynchronous Advantage Actor-critic (A3C) framework in a distributed manner to coordinate multiple Unmanned Aerial Vehicles (UAVs) for the exploration of unknown regions.

For applications where it is necessary to search for a victim in the wild, large regions have to be navigated and as a result the environment is partially observable at any given time. Hence appropriate strategies need to be developed. The work in [135] tackles this problem by discretizing the continuous space into equally sized regions and utilizing a quad-tree data structure to make the search problem tractable. This makes it possible to use reinforcement learning algorithms such as double deep recurrent Q-Learning stacked with an LSTM layer to train an agent for the tasks of target search and region exploration. Finally, with the emergence of low-cost sensors and platforms it has become possible to utilize multiple robots for autonomous exploration. This has been the subject of the work in [136], where a team of networked robots coordinate to explore an unknown environment collaboratively.

Beyond the visual domain, SAR strategies have also been built around other modalities, for example directional antennas [137]. A scenario where this can be used is when a UAV tries to locate a victim trapped in an indoor environment by sensing the radio-frequency signals emitted from a device held by the victim. A reinforcement-learning-based SAR operation method can be formulated in the presence of directional antennas on both the UAV and the victims device [138]. In case of emergencies, the agent learns to sense the RF signals which are emitted intermittently from the victim to navigate through indoor environments.

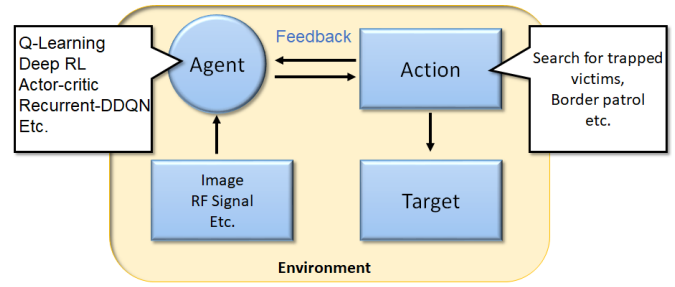


Fig. 6: Approaches for SAR operations have explored reinforcement learning methods, where an agent uses sensed information such as imaging or RF signals to try and detect a target/victim. By taking an action and interacting with the environment the agent gets feedback which is then used for training through algorithms such as Q-learning and its recent variations incorporating deep learning.

### B. Route Finding

Natural disasters, such as earthquakes, severely damage buildings and introduce obstacles to people trying to evacuate an affected area, as well as for first responders that need to reach an affected area. Hence, methodologies for planning optimal routes and evacuation plans have been proposed in the literature. Evacuation route recommendation plays an important role in emergency safety management, especially for natural disasters and fires. Similarly to finding best routes for emergency vehicles it is also important to find appropriate and safe routes in cases of evacuation.

For example, several large cities throughout the world have problems with traffic in urban areas. This can be intensified in cases of emergency situations. In such cases it is necessary to decrease the response time of emergency vehicles. By utilizing traffic information such as real-time measurements of vehicle flow [139], a machine learning algorithm can be trained to control traffic signals in order to reduce travel time of emergency vehicles [140]. This can be combined with traffic prediction mechanisms based on deep learning for more accurate planning [141]. The work in [142] studies how to increase the effectiveness of an evacuation plan by increasing the flow of evacuation traffic based on demand while retaining the availability of incoming traffic. At the core of the method is a supervised decision tree learning algorithm that decided which routes can be used such that the delays encountered during evacuation remain minimal.

A machine learning based method to quickly find the global optimal evacuation route is presented in [143] that addresses the high dimensionality problem. The proposed method first employs a multilayer perception based auto-encoder algorithm to reduce data dimensionality so it can be visualized in a 2D scatter plot, which can fully retain all the important features. Then, a reward-based prediction model is proposed to design the global optimal evacuation route through analyzing evacuation routes using meteorological data.

In [144] a model that integrates image segmentation and classification with a shortest path algorithm is proposed. First, a segmentation model identifies the buildings in pre-disaster



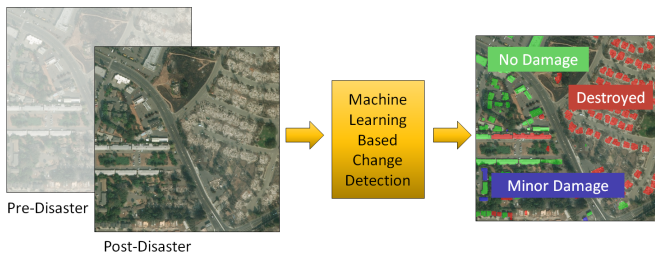


Fig. 7: Damage assessment can be examined under a general change detection framework where the previous normal state is compared with the current state under an emergency situation. The comparison can lead to identification of damaged regions and thus help better assess the cost of damage and management of resources to recover from a disaster.

satellite images and then a classification model is responsible for classifying those buildings into four categories in the post-disaster image. Both these models use deep CNN models whose output is fed into the route detection model that uses the Dijkstras algorithm to find the safest and shortest route between the origin and a rescue shelter.

## VIII. POST-DISASTER ACTIVITIES

Understanding the extend of a disaster and its impact on the population is critical in better managing the available resources but also minimizing the impact of negative aftereffects. ML algorithms along with large-scale spatial data, crowdsourced data, and geotagged imagery can form the basis of damage assessment models, as well as assistive tools in evaluating loss and repair costs.

### A. Mapping and Damage Assessment

Automated machine learning systems can be used to assess structural vulnerability of buildings instead of sending in teams of responders. Such capabilities in urban areas are critical to identify high-risk buildings and potentially save lives. For example a deep learning pipeline for fine-grained classification of UAV imagery for damage assessment is presented in [145]. In addition to drone-based imagery, elevation data, and satellite observations can also help assess physical construction factors of vulnerability. Regression learning algorithms can be trained to automatically give a vulnerability score for buildings in an area <sup>1</sup>.

Natural disaster can alter the appearance of the landscape where it hits. Therefore, change detection techniques based on machine learning have been developed for post-disaster damage assessment and event mapping to help in the recovery and management [146], [147], as shown in Fig. 7. A major focus is on damage assessment after natural hazards like earthquakes, floods, or tsunamis [148], [149].

- **Earthquakes:** The applicability of recent algorithms using deep learning for image analysis for assessing building damage in case of earthquake or explosion has been investigated in [150]. Through a thorough study it is demonstrated that the performance of the algorithms is strongly related to

the availability of training datasets in areas with similar typologies of damages, as well as the heterogeneity of data sources.

Saha et al. [151] proposed an unsupervised methodology for detecting collapsed buildings from synthetic aperture radar images. The methodology relies on tuning a CNN for extracting spatio-temporal deep features that are compared to identify the changed areas. The approach also leverages on the double bounce property of the buildings in synthetic aperture radar images for further analysis. The method utilized by Ji et al. [152] again used deep features extracted through a CNN and put them into a random forest classifier to detect post-seismic destroyed buildings using pre- and post-disaster remote sensing images.

The majority of existing research tackles the task of damage assessment as a simplified pure classification problem. Ci et. al. [153] identify this as a limitation and propose to instead assess the different levels of damage. They propose a new approach based on CNNs for extracting features and ordinal regression for assessing the degree of damage caused by earthquakes with aerial imagery.

The work in [154] makes use of a random forest classifier to detect building damage in post-event imagery in the absence of reference data to achieve a more timely production of damage maps. This results in eliminating the need for manual georeferencing of images.

Beyond the identification of damaged buildings, the work in [155] addresses the complexity and costs of compiling a training data set after a large-scale disaster. In particular, it proposes a procedure based on the automatic selection of training samples for learning and calibrating an SVM classifier. Such efforts can reduce the amount of time needed to collect labeled building samples via field surveys and/or visual inspection of optical images.

Towards the goal of more rapid and efficient mapping of damages, the work in [156] addresses this problem by exploiting ancillary sources of data, namely maps or GIS data layers and proposes a detection algorithm based on neural-network classification tools. In [157] the authors combine deep learning with the full time history of SAR observations of an impacted region in order to detect anomalous variations. Specifically, a recurrent neural network (RNN) is used to learn the normal behavior through time by training on SAR coherence time series data spanning a large area, then forecast the probability distribution of the coherence without any disaster. The deviation between the observed and forecast coherence can signal collapsed buildings.

The problem of detecting damages in buildings inherently faces the challenge of unavailability of a sufficient number of training samples. In [158] this is tackled by proposing a procedure that is based on the automatic selection of training samples for learning and calibrating the standard support vector machine classifier along with two regularization parameters to facilitate small sample learning. A landslide hazard detection technique is proposed in [159] which applies the minimum redundancy maximum relevance (mRMR) feature selection technique to improve the detection accuracy by removing redundant features, and also



proposes a methodology to detect slides from background using support vector machine (SVM) classification and SAR data.

In [160] the authors demonstrate a system capable of detecting surface cracks caused by earthquakes, using a low-altitude unmanned aerial vehicles (UAVs), that can obtained very high-resolution aerial images of the earthquake-stricken area. They propose a novel terrain surface crack detection convolutional neural network, which differs by the introduction of deformable convolutions that address the problem of special sinuous and irregular shapes of cracks.

More recent works as in [161], attempt to learn to distinguish real changes from irrelevant changes by leveraging context information high-resolution (HR) satellite data through the use of Transformers. Specifically, by encoding high-level concepts of the change of interest in just a few visual words, i.e., semantic tokens. the approach manages to improve the context modelling demonstrating improved effectiveness and efficiency.

- **Flood:** The work in [162] also tackled the problem of developing an unsupervised deep-learning method for the detection of non-trivial changes (flood areas, damaged buildings) between two remote-sensing images of the same place. The model is based on an convolutional autoencoder architecture that discriminates between changed and non-changed areas, and a K-means on top to cluster the damaged regions. Overall, it demonstrated that good accuracy results can be achieved with performance that is comparable to supervised methods.

To address the problem of non homogeneous background in satellite imagery for predicting the flood extend in urban mapping, the work in [163] proposed a patch similarity CNN using satellite multispectral imagery. The proposed two-branch CNN-based data fusion framework, can perform urban flood extent mapping using both pre- and post-flooding satellite imagery. On the other hand, [164] obtains a difference Image for use in multitemporal SAR images for flood monitoring, by combining pixel- and object- level change detection approaches to incorporate local as well as neighborhood information.

Damage assessment models for flood, utilize water depth to calculate damage curves based on location and flood conditions. Bayesian networks and regression RDF were used to associate the relative building damage reported through surveyed households to various attributes <sup>1</sup>.

ML algorithms have also been developed to show the extend of flood and map it <sup>1</sup>. The algorithm utilized deep learning for analyzing synthetic aperture radar and optical satellite imagery to categorize at-risk areas and help identify the extend of the flood. UAV optical imagery and deep learning were combined to first recognize buildings and then identify damage levels caused by cyclones.

- **Tsunami:** The survey in [165] includes both supervised and unsupervised techniques for formulating the problem of damage assessment in tsunami-induced flood scenarios. It concludes that further work is still needed in order to achieve robust results and a combination of unsupervised and generative modeling shows promise for building tsunami damage

assessment systems.

The work in [166] demonstrates a change detection method based on object detection and segmentation on natural disaster videos after tsunami and landslide events. The proposed approach combines the characteristics of optical flow data, a new objective function based on the ratio of maximum between-class variance and minimum within-class variance has been constructed and two key steps are motion detection based on optical flow estimation using deep learning method and changed area segmentation based on an adaptive threshold selection.

In [167] the authors employ a deep encoder-decoder architecture known as U-Net to develop a semantic segmentation approach for tsunami damage mapping. The proposed system is capable of classifying areas in satellite images in four damage types and can provide satellite-based operational damage-mapping in 2-15 minutes.

- **Fire:** A semantic segmentation approach to the change detection using deep learning that allowed automatic mapping of the disaster areas was presented in [168]. It processed a 6-band image (3 bands before and 3 bands after) to identify damaged and non-damaged buildings. The proposed workflow was evaluated in the assessment of the damage caused by the wildfires in California in 2017. The work in [169] focuses on post-fire activities to map forest disturbance and formulate forest vegetation recovery plans. The methodology used an SVM classifier and historical fire records to separate burned patches from disturbance patches. Afterward, step-wise multiple linear regression (SMLR), SVM, and RDF were applied to assess the statistical relationships between vegetation recovery characteristics and various influential factors.

## B. Recovery and Strategy Assessment

Post-disaster recovery can be a complex, long-lasting, resource intensive process. In [170], support vector machine in combination with texture features and local binary patterns was employed to develop an image-based recovery assessment that ranks areas according to the state of their recovery. The work in [171] analyzes geo-tagged images from earthquake-hit regions from social media through the use of deep learning to identify survivors in images of debris. The study in [172] performs flood hazard mapping and evaluates community flood coping strategies. A scaled conjugate gradient ANN model coupled with a hydrodynamic model are first used to predict a flood probability map. Based on these predictions they then evaluated various coping strategies using qualitative data, and information. Such, works demonstrate the potential of using machine learning methods along with accurate mathematical models that can capture world dynamics very well in order to provide a more robust solution overall. The work in [173] investigates risk-based and physically informed model for near real-time estimation of the potential property damage of flood events. Specifically, it develops a system using a random forest classifier with a variable selection method, that can be used for both classification to estimate whether the flood caused any property damage or not, and regression to estimate the

amount of property damage. To aid reconstruction missions after a natural disaster [174] proposes a multi-source data fusion approach based on CNNs. The model is tasked with detecting damage and assessing the state and availability of the road network based on the satellite imagery data and UAVs.

## IX. PROMISING FUTURE DIRECTIONS AND OUTLOOK

It is evident from the previous sections that machine learning has gained a lot of interest within different phases and operations of the emergency management process both with classical machine learning algorithms as well as more recent developments using deep learning. However, several challenges and open issues remain not only to further develop the machine learning algorithms themselves and improve data pipelines, but also how they can be better utilized within the emergency management context. Hence, in this section we identify a number of promising future research directions which cover a wide range of topics ranging from interaction with emergency personnel and operators to the security and safety aspects of using machine learning algorithms for automated decision making. We believe that these aspects are important both for machine learning interested looking at emergency management applications, as well as emergency management personnel that need to be aware of the challenges of utilizing machine learning algorithms.

### A. Generalizability and Adaptation

Existing studies utilizing machine learning focus mostly on single events to develop and test the different methodologies. While results across various tasks have been promising, a challenge that still remains is the variation in performance due to heterogeneous data sources and deviation from the training set distribution. Hence, to build trust amongst emergency management personnel that such systems can be used in real missions, it is necessary to test scenarios and approaches to ensure robust operations across events happening in various spatial and temporal locations [175]. For example optical images can vary greatly from one region to another due to differences in the vegetation and, most importantly, in the local architecture of the buildings, thus making a model trained over one area difficult to reapply to a different country, even for images of the same format and resolution. A promising approach is the use of deep generative models such as Diffusion Models [176] and Generative Adversarial Networks (GANs) [177] that are capable of generating novel points, transforming data from one format to another and even to upscale images [178], which could potentially help solve the issues of different source data and domain adaptation [179],[180].

### B. Virtual Environments and Digital Twins

A major challenge for developing machine learning algorithms for emergency response is the rareness of events. This imposes problems in two ways. First, the amount of training data is limited and scarce, and second, the opportunity for end-users to interact with them and use them in practice in real scenarios is limited. Digital twins provide a virtual

representation of physical spaces that models relationships among people, places, and devices [181], [182]. The promise of virtualized real-life environments and digital twins is that it will be possible to train and develop machine learning algorithms in a life-like scenario that is close to the real situation as possible (Fig. 8). This will provide an abundance of data to train machine learning models and also validate them under different scenarios. This also gives the opportunity to emergency responders and safety officials to further examine the behaviour of the ML system and evaluate its suitability and understand how to better utilize them [183].

### C. Trustworthy and Explainable ML

Beyond improving and developing machine learning systems that can help in emergency management operations it is equally important to consider how the different actors, technology experts, humanitarians, operators, can not only use machine learning systems more effectively but also gain trust in their decisions. An important aspect is how the predictions and information provided by machine learning can be properly visualized and presented to support efficient decision making in a way that is intuitive and interpretable by humans (i.e., explainable). The integration of these assets into day-to-day operations involves complex interactions with other factors and thus evaluation of the costs and benefits of these systems must take place both in controlled field trials/demonstrations but also in a realistic context determining what the right applications are, and ethical issues to be dealt with in an effective and impactful manner. Without appropriate collaboration across all levels of decision making with local governments and institutions across the emergency management cycle, the additional insight provided by machine learning cannot be fully utilized.

### D. Safety and Security of Machine Learning in Emergency Management

Through the survey it is evident that a lot of attention in the research community has been steered towards deep learning models. However, machine learning algorithms, and more specifically deep learning algorithms, have been shown to be vulnerable to adversarial attacks, and this limits the application of machine learning, especially in non-stationary environments such as in emergency situations [184]. In addition, machine learning systems for emergency management can deal with sensitive information [185][186]. Hence, it is important to ensure the safety and security of the information that is passed to and from the machine learning model, but also the integrity of the machine learning models themselves. Incorporating defense mechanisms during the development phase of machine learning algorithms is crucial to safeguard their operation in real-life [187].

### E. Multi-modal Machine Learning

As discussed in this survey, there is a wealth of available data generated in emergency management operations such as data from earth observation/satellite data [92], street-level imagery [188], social media [189], data from connected devices



Fig. 8: Digital environments provide an opportunity for both training and assessing machine learning models, but also help emergency personnel learn how to use them and built trust with such systems.

[190], and geographical details [107]. This opens up new opportunities towards ML-based systems that can combine such data sources to obtain a more holistic view of a situation thus resulting in more informed decisions. This provides a promising path towards integrated situational and contextual awareness in emergency management [191]. For example, multi-spectral imagery might be cloudy for some flooding events, resulting in insufficient data. By also exploiting synthetic aperture radar images along with multi-spectral imagery it reduces the impact of clouds, which contributes to more robust monitoring. A promising direction to advance the state of machine learning algorithms for emergency management is to work on expanding the training data with multiple sensor modalities to achieve more robust representations. Recent machine learning techniques relying on the transformer architecture [192] provides the foundation for developing machine learning models that can process multiple modalities simultaneously such as text, video, lidar, and speech, time series data and others [193],[194].

#### F. Ubiquitous machine learning for early warning systems

To react to a disaster in a timely manner and reduce casualties constant monitoring at scale will be necessary, which in turn requires being able to deploy optimized machine learning on resource-constrained edge devices [195], [196], [197]. This has a lot of applications when low-latency, low power, and low bandwidth are necessary [198]. Hence, this technology, referred to as tinyML [199], enables devices to run unplugged on batteries for weeks, months, and even years, while running ML applications on edge. It can also have tremendous implications for emergency management applications [200]. Small sensors that can harvest energy and transmit only relevant data can be deployed in remote areas to detect fires early [201], [202], or detect seismic activity in dangerous areas [203]. Moreover, tinyML can also be used to monitor the individual state and condition of first responders through wearable technology.

#### G. Combining Machine Learning with other Approaches

As highlighted in this survey, machine learning systems have a big part to play in automated decision support systems that can help emergency personnel take more informed actions [204]. However, their role and capabilities should not be overstated. It can be challenging with today's knowledge and data availability for ML systems to replace handcrafted models built based on our physical understanding of the real world and decades of research in interaction and observation of physical phenomena. In addition the unpredictability and often rare occurrence of disaster events make the collection of data for training machine learning algorithms a difficult task. Consequently, it is necessary to combine machine learning methodologies with modelling approaches to compensate for lack of data in some cases, so that we can capture real-world phenomena and help improve the predictions of data-driven methods.

### X. CONCLUDING REMARKS

Machine Learning algorithms can form an essential component of emergency management systems. In recent years, aided by emerging technologies that allows us to obtain large amounts of data from heterogeneous sources we have moved beyond manual use of thresholds and feature combinations based on prior knowledge and limited data, to the use of ML algorithms. These algorithms are capable of classifying and predicting various disaster events, and consequently even powerful deep-learning methods in combination with rich sources of remote sensing data have been employed in multiple facets of emergency management. Not every emergency situation is unavoidable but ML systems provide the technology to predict and prevent crises by giving emergency personnel access to real-time data to aid them in making an informed decision faster, thus reducing the additional loss of life.

This survey first highlighted some important concepts, characteristics, and phases of emergency management as well as

specific issues associated with each one. Following we discussed how machine learning can leverage the data generated in emergency management to provide actionable insights on how to better mitigate, prepare, respond, and recover from disasters. Then we outlined recent works that use machine learning to develop intelligent decision making systems that can aid in emergency management across various phases and activities. Finally, considering current progress and emerging trends we have also identified some key areas and promising directions for future machine learning research.

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