# DELIVERABLE 2.1

# Review of Existing AI Tools

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| **Coordinator name**: | Prof. Marios POLYCARPOU |
| **Coordinator email**: | mpolycar@ucy.ac.cy |
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# Contents

# 1. INTRODUCTION

Recent years have shown that natural and human-made disasters and emergency events pose serious threats to human society, infrastructure, environment and economy. These adverse events can happen at any time and can have cascading effects across multiple sectors at once. Recent technological advancements have made it possible to collect huge amounts of data regarding man-made, natural and technological disasters. Generated data can be invaluable in gaining situational awareness and helping stakeholders make the right decisions both before and after a disaster happens. However, data is generated in huge volumes and rapid manner making it difficult for stakeholders and emergency responders to be able to make sense of it, especially in time-critical and time-varying situations.

As such, it is necessary to develop intelligent systems that can aid humans in such situations by improving the disaster preparedness and response. Such systems need to provide prompt detection of irregularities, continuous situation monitoring, and rapid recovery planning and implementation. Artificial Intelligence (AI) 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 which stakeholders and emergency responders can process effectively. Consequently, this can lead to systems that can support decision-making in the field, resource allocation and build early warning systems amongst others. Doing so, however, entails addressing unique challenges for both. the development and deployment of AI algorithms such as sensing the right data at the right time, availability of sensors and data, real-time response, limited resources, and building trust with end-users.

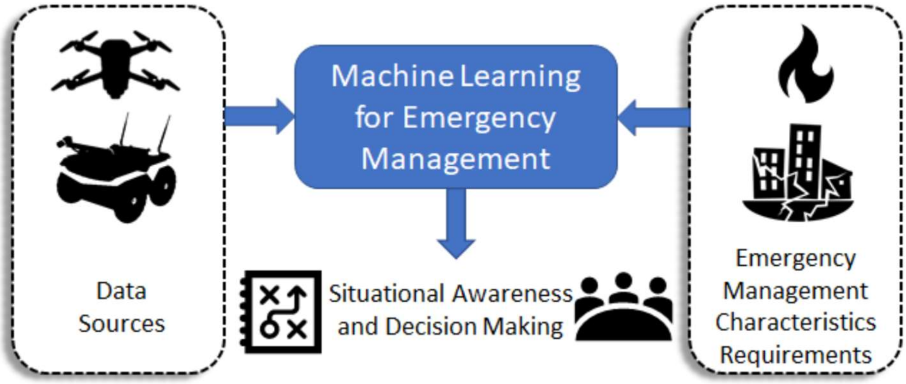
This document aims to overview the work appearing in the literature so far and structure it in a concise way. The majority of the existing work employs Machine Learning (ML), therefore the present review will focus on ML although both terms, ML and AI, will be encountered throughput the rest of this document. Additionally, the terms *emergency management* and *disaster management* appear as equivalent in the literature, hence they will be used interchangeably.

To this end, we consider how ML can help across the different phases of emergency response and the unique challenges that need to be addressed. The basic concept behind the employment of ML for Emergency Management is that appropriate input data can feed ML algorithms designed for emergency management in order to lead to better situational awareness and decision making (Figure 1). First, based on our review of existing literature, we discuss the emergency management operational landscape with a focus on key challenges that ML algorithms face for emergency management applications. Then we highlight relevant work in this area by focusing on the use of ML across emergency management activities such as early detection of hazardous events, search and rescue operations, damage and risk assessment, and planning operations.

# 2. EMERGENCY MANAGEMENT: DEFINITIONS, PHASES, CHARACTERISTICS

Emergency management refers to the organization, management and coordination of the available resources and responsibilities in order to address emergency situations, such as, man-made and natural disasters, terrorist attacks, and large-scale accidents. Among other operations, emergency management

*Figure 1: Input data can feed machine learning algorithms designed for emergency management in order to lead to better situational awareness and decision making.*




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.

ML systems can underpin much of these efforts by aggregating and analysing data collected by drones and satellite imagery, IoT infrastructure, social media, and online heat maps. All this information can help teams identify urgent needs, prioritize responses, and avoid wasted effort. It can also help predict future developments such as potential aftershocks of an earthquake or additional flooding. These emergency scenarios share some commonalities. For example in cases of earthquakes, wild fires, or sea pollution there is a phenomenon occurring that disrupts the normal operations of the society. This phenomenon can evolve in both, space and time, and progressively can affect different parts of the population in different ways. In order to build ML tools, it is important to first detect or predict the occurrence of a such phenomenon and then be able to track its 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 response but also mitigate the negative impacts.

## 2.1. Emergency Management Phases

It is first important to highlight the different phases in disaster and emergency management:

- ***Mitigation:*** In this phase the goal is to prevent or reduce disasters and prevent or reduce the negative effects of disasters. Thus, it involves identifying hazards and reducing the risk of those hazards occurring in communities, by training and education and 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 second to plan an effective response to minimize the damage that can be potentially caused by a disaster. These are the actions taken to reduce the damage from that hazard occurring 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. This can happen through a number of actions that have the goal of reducing the death toll, fatalities through injuries, loss and damage of properties.
- ***Recovery:*** The last phase deals with bringing the community back to an acceptable level that is as close to the previous state prior to the hazard occurring, and build back what has been damaged.

In the line of time, mitigation and preparedness take place before the disaster whereas the stages of response and recovery occur after the event. AI can be used in all four stages of the disaster management cycle. It is also evident from the literature that all branches of ML, namely, supervised learning, unsupervised learning and reinforcement learning, are successfully employed in addressing emergency management applications [1].

However, the output of any AI algorithm is as good as the input data set. In particular, the data must be enough in terms of quantity and quality (i.e., accuracy). Data was a scarce resource in the past that was difficult to produce, costly to store and slow to manipulate. However, we already entered the era of big data. Storing and processing large amounts of data has become plausible because of the evolution of modern computers. In addition, the issue of data collection and availability has become nowadays feasible, as reliable devices that can collect large amounts of data are now available at reasonable cost. Examples of such devices are drones (Unmanned Aerial Vehicles, UAVs), Autonomous Underwater Vehicles (AUVs), statically deployed sensors and cameras, wearable devices for first responders equipped with sensors. Additionally, apart from devices deployed in order to collect specific data, data may be available from other sources. For example, videos taken from surveillance cameras may undergo processing for early fire detection. Social media posts, often accompanied by photos, can be used in the case of a disaster event in order to extract information about the existence of victims, to evaluate the situation in the affected area after the hazard, etc.

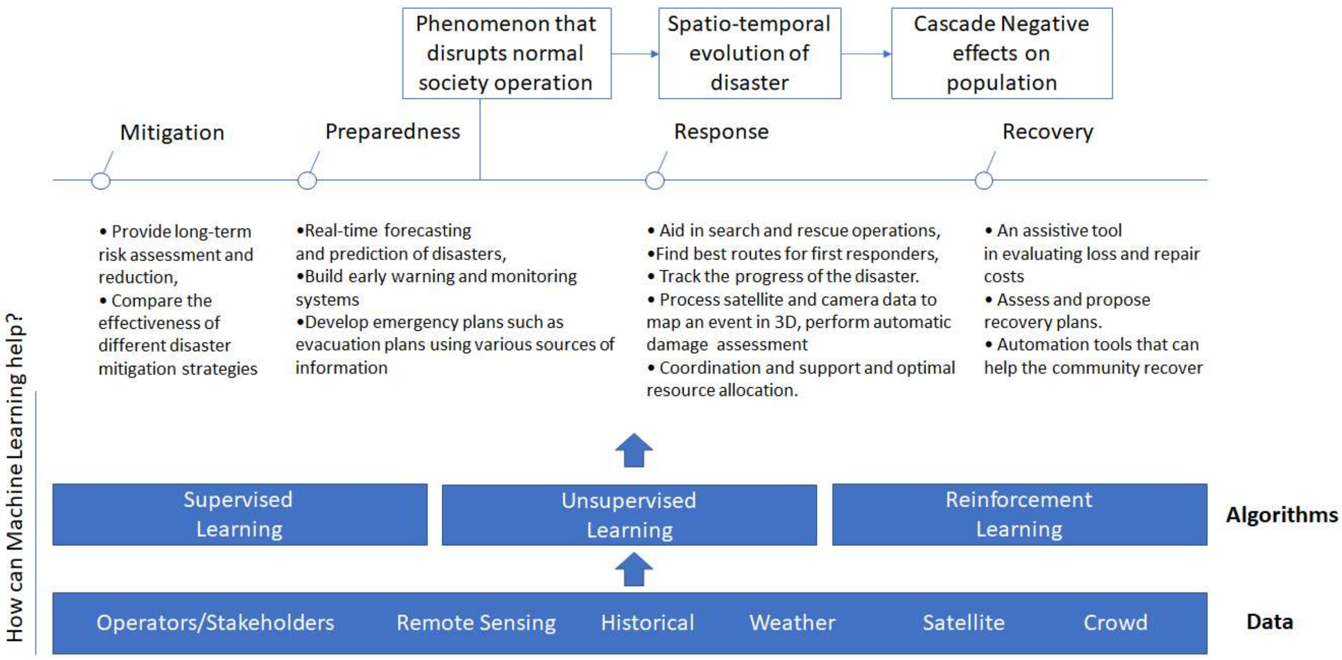
Figure 2 aims to illustrate by means of a diagram this relationship between ML and emergency management and particularly, how ML can facilitate emergency response operations.

## 2.2. Application Requirements, Issues and Characteristics

Developing ML algorithms that can provide situational awareness and real-time threat assessment using diverse streams of data requires to address simultaneously different issues and challenges. Due to their effectiveness at handling large amounts of data, learning input characteristics, and demonstrating high accuracy during inference of unseen inputs, ML systems have proliferated to numerous real-world applications. While in many applications a mistake made by an ML system can be harmless, in many safety-critical applications such as emergency response, errors can lead to catastrophic results. Below are the basic characteristics that are of utmost importance in the development of ML applications for emergency response:

- ***Sensing and Data:*** Large data sets are key elements for building accurate ML models. Data is first required to pre-train models, and then to improve such models on domain specificities. The unpredictability and rare occurrence of disaster events make the collection of data a difficult problem. High quality data is the foundation for understanding natural hazards, and building ML systems around them. This necessitates providing ground truth and calibration data to achieve

*Figure 2: How can Machine Learning help in the different Emergency Management Phases*




reliable algorithms. Comparatively rare events like avalanches offer limited training data for ML algorithms. Nowadays, numerous sources can be used for collecting data for ML applications for emergency response. It is possible to use data from various sensors either static of mobile, i.e., usually mounted on moving devices (e.g., drones, robots, etc.). Other data sources include satellite and topographic data, weather-radars, crowdsourcing, data mined from social-media, etc.

- ***Time Criticality:*** Timely detection of emergency situations and making this information rapidly available to key stakeholders is critical to properly mitigate any negative effects. In this aspect, ML algorithms should be able to provide real-time collection of relevant data, and filter the most critical information of relevance to the situation. Coupling of ML with efficient IoT systems can play significant role in this aspect.
- ***Connectivity:*** Another challenge is that connectivity can be limited or absent in cases of emergency response. ML algorithms will not be always executed on powerful workstations, hence, the algorithm selection is critical when considering emergency response applications.
- ***Explainability and Trust:*** ML systems for Emergency Management need to provide support for management oriented decisions for optimizing recovery tasks and logistics. To do so in a manner that enables transparent and responsible, ML systems for disaster and risk management need to not only give a prediction/recommendation but also a set of quantitative reasons as to why it has reached the given conclusion.

## 3. MACHINE LEARNING IN EMERGENCY MANAGEMENT

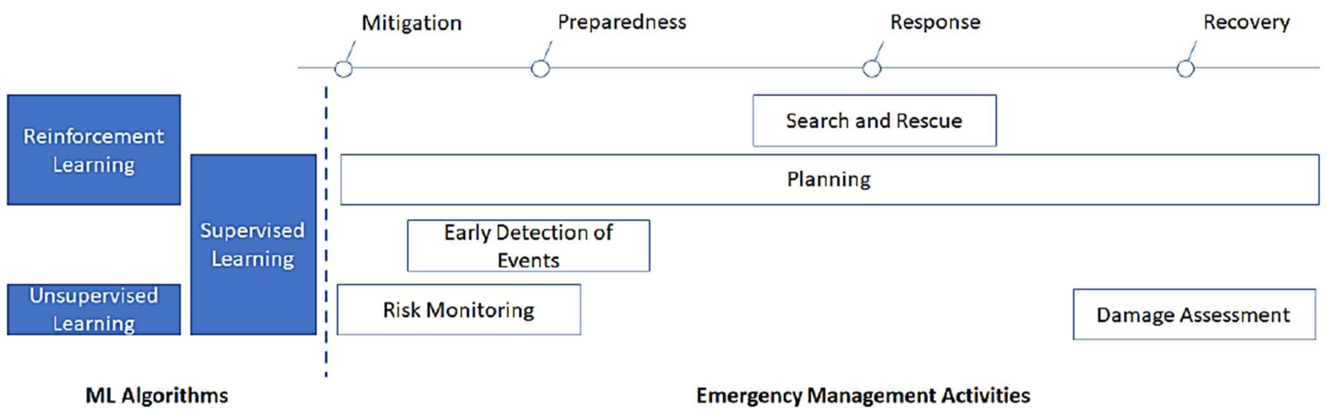
The role of an ML system is to first extract knowledge from a given dataset, and then use that knowledge to assess or generate a corresponding output for a new situation. However, unlike traditional systems, the ML system is capable of learning via input features and using the learned features in decision making, which provide ML systems with the ability to perform tasks that are very challenging to perform using traditional systems (i.e., for which no explicit program can be written). To this end, ML can help decision makers in estimating when an event will occur and forecast its impact, how many people will be affected, etc. ML can play a role across different phases of emergency management as well as across different mission types.

In order to provide an overview of the existing research works on ML algorithms for disaster management, we identified the following categories of emergency operations:

- Automated Detection of Events/Objects/Regions of Interest
- Risk Monitoring and Damage Assessment
- Search-and-Rescue
- Planning

How these categories correspond to the different phases of disaster management and to the different branches of ML is depicted in Figure 3.

*Figure 3: The landscape of Machine Learning algorithms in Emergency Management activities.*




## 3.1. Automated Detection of Events/Objects/Regions of Interest

Some relevant works for the problem of automated detection of important events and objects with ML in emergency management are described. Such frameworks can be seen as the basis for building event prediction and early warning systems.

### 3.1.1. UAV and Aerial Imagery

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 [2], Gaussian mixture models which require empirical tuning [3], and Support Vector Machines [4]. The success of deep learning and CNNs in particular for different kinds of image analysis tasks has also led the research community to investigate their suitability for such applications. Such approaches have first been proposed for ground robots such as the work in [5] and later also used to interpret aerial images [6].

Deep learning has 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. In [7] the authors propose a cloud based deep learning approach for fire detection with UAVs. The detection uses a custom convolutional neural network 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.

In [8] a method is proposed for detecting objects of interest in avalanche debris using the pre-trained inception Network for feature extraction and a linear Support Vector Machine for the 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. The application is executed on a desktop computer.

Similarly, the work in [9] also targets fire detection application with deep learning. Specifically, two pre-trained convolutional neural networks are used and compared, namely VGG16 [10] and Resnet50 [11] as 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 [12] proposes an approach for wildfire detection from UAV platform. The overall approach comprises of a convolutional neural network called Fire Net consisting of a structure similar to the VGG16 network. It is accompanied by a region proposal algorithm that extracts image regions from larger resolution images so that they can be classified by the neural network.

In the work of Kamilaris et al [13] a deep convolutional neural network is trained to classify aerial photos in one of five classes corresponding to natural disasters. The VGG [10] network is used as the base feature extraction and a fully connected is placed on top of it to perform the transfer learning for the new task.

Kyrkou and Theocarides [14] focused on the use of UAVs in order to assign automatically a semantic label to characterize the aerial image that the UAV captures. To do so, they first constructed a database considered as Aerial Image Dataset for Emergency Response Applications (AIDER), which contained manually collected images of 4 disaster types: fire/smoke, flood, collapsed building/rubble and traffic accidents, but also of a 5$^{th}$ type, namely, normal situation. They used here a Convolutional Neural Network (CNN) for the Aerial Disaster Classification so they applied randomly multiple image transformation to each image before adding them to the batch for training, such as rotations, translations, horizontal axis mirroring, cropping, zooming, illumination changes, color shifting, blurring, sharpening, shadowing) and then it was resized depending on the network used. This work is improved and extended in [15], in which Atrous Convolutional Feature Fusion is employed managing to upgrade significantly the training speed.

Haiyu Wu et al. [16] focused on fires, specifically, on realizing a real-time system for fire detection and expansion analysis and, to do so, they noticed the lack of huge datasets for training with Deep Learning. They used mobileNetV2, an architecture to implement Transfer Learning because it does not require a huge dataset and is much faster than usual architectures.

### 3.1.2. Predicting Emergency Situations

It is especially interesting to report that Google has already launched an AI-based flood warning service that covers all of India and parts of Bangladesh. In particular, they launched a flood prediction service, which uses ML to identify areas that are prone to flooding and alert users before the waters arrive. It is based on a mix of historical and contemporary data about rainfall, river levels and flood simulations using ML to create new forecast models [17].

Artificial neural networks where used to predict impending emergency events such as earthquakes, storm surges, and floods. Moustra et al. [18] utilize Artificial Neural Networks (ANNs) 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 ANN has been studied in [19]. 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.

In [20], deep features of a Convolutional Neural Network is used to detect fire at an early stage under varying conditions, in indoor and outdoor environments, using videos captured from surveillance cameras. The authors propose an adaptive prioritization mechanism for cameras in the surveillance system, which can adaptively switch the status of camera nodes based on their importance. Furthermore, the system contains a high-resolution camera that can be activated for capturing the important scenes when fire is detected. This can be helpful for disaster management systems in confirming the fire and analyzing the disaster data in real time.

Prediction of storm surge is necessary for emergency managers to make critical decisions for evacuation of an area. A feed-forward neural network algorithm has been also applied into development of a time-series forecasting model of storm surge [21]. The developed surrogate model with 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 probabilistic simulations to evaluate risk and support decision making.

Floods are recurring hazards, but their impact on human life and health can be minimized through a reliable forecasting model. The work in [22] proposed a 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 can predict relatively reasonable estimates for the extreme flows.

Another application for flood prediction is proposed in [23] using ANNs. In particular, the objective was to establish, train and evaluate a neural network for the detection of flood hazards and concrete water levels in the area around Goslar, Germany (4-hour warning). A transfer to another scenario in Bad Harzburg, Germany, takes place to verify the validity of the proposed method, where a flood prediction for another environment is made using another measuring station (2-hour warning).

## 3.2. Risk Monitoring and Damage Assessment

### 3.2.1. Building Damage Assessment

Automated ML systems can be used to assess structural vulnerability of buildings instead of sending in teams of responders. Such capabilities in urban areas is critical to identify high-risk buildings and potentially save lives. Drone-based imagery, elevation data, and satellite observations can help assess physical construction factors of vulnerability. Using annotated data by experts, supervised regression learning algorithms can be trained to automatically give a vulnerability score for buildings in an area [24].

Predictive modelling 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 [24]. In this context, ML algorithms can be used to monitor urban growth focusing on built-up area and building height. Similarly, inspection of buildings is an important issue to mitigate the risks of fire. However, it is becoming progressively more difficult to decide which buildings to inspect. 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.).

Damage assessment models for flood, utilize water depth to calculate damage curves based on location and flood conditions. Bayesian networks and regression random forests were used to associate the relative building damage reported through surveyed households to various attributes [24].

Combining weather data with deep learning and image classification can lead to better predict the probability of a forest fire occurring [25], [24]. Deep learning algorithms are used to analyze the images and predict the amount of dead duel 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 a dedicated device, which can be deployed in the forest.

### 3.2.2. Post Disaster Event Mapping and Damage Assessment

ML systems have been developed for post-disaster damage assessment and event mapping to help in the recovering and management. Developing maps of the affected area is essential for situation awareness and disaster response operations like planning search-and-rescue operations, delivering needed supplies to affected individuals, etc.

Disaster-related data that can be used for generating disaster event maps are collected from various sources, e.g., satellites, UAVs, robots and social media. Crowdsourced information draws also an increasing interest. After typhoon Haiyan in Philippines on November 8, a large team of more than 1000 volunteers from 82 countries worked with crowdsourced information for generating devastation maps of the affected areas enabling damage assessment and efficient response efforts [26].

Images harvested from social media are utilized as input for remote sensing image analysis in [27]. After an initial evaluation and analysis of the situation, images of higher resolution collected for certain areas from other sources, e.g., from satellites, are collected and added to the analysis. From the ML perspective, this work is mainly based on classification methods, a class of methods that is often used when it comes to analyzing maps and images in disaster management applications.

An ML algorithm is presented in [24] to show the extend of flood and map it. 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.

Another important aspect is also the assessment of service disruptions due to infrastructure damage. For example, in [27] the authors beyond disaster event mapping, analyze the damage caused to the transportation infrastructure.

## 3.3. Search and Rescue

ML algorithms can provide increased capabilities for remote sensing technologies such as Unmanned Aerial Vehicles (UAVs)/drones, expanding the operation area and providing new insights for many emergency response and disaster management applications. In particular, such systems can provide a valuable tool during search and rescue (SAR) operations. 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.

ML can be used to further advance technologies to be used in search and rescue operations such as autonomous unmanned systems (aerial, terrestrial, and marine). SAR operations can benefit greatly from such advancements as this can speed up the searching time and execute typical tasks such as mapping, observation, and supply delivery.

Recent efforts have focused on taking advantage of deep reinforcement learning methods in order to teach an autonomous UAV to perform search operations [28]. Reinforcement Learning methods can be used to solve a Markov Decision Process (MDP) through the interaction between an agent and the environment. The authors in [28], [29] 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 investigated for search and rescue in the survey of coastal environment [29]. 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 convolutional neural networks 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.

Beyond the visual domain, SAR strategies can also be built around other modalities, for example directional antennas [30]. A scenario where this can be used is where 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 victim's device [31]. In case of emergencies learns to sense the RF signals which are emitted intermittently from the victim to navigate through the indoor environment.

## 3.4. Planning

Several cities throughout the world have problems with traffic in urban areas. This can be exemplified 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 an ML algorithm can be trained to control traffic signals in order to reduce travel time of emergency vehicles [32].

Evacuation route recommendation plays an important role in emergency safety management, especially for natural disaster. Similarly to finding best routes for emergency vehicles it is also important to find appropriate and safe routes in cases of evacuation. An ML based method for evacuation route recommendation, which employs the auto-encoder method to reduce the data, and then conducts a reinforcement learning based route selection algorithm on the reduced data [33].

Nevertheless, planning does not only refer to problems related to traffic and transportation. It includes all operations under the umbrella of disaster management that are related to any sort of planning. In fact, the possible applications are so numerous and diverse, so that they cannot be explicitly listed. This fact is also evident from the two following examples. A system for planning patient admissions to Emergency Departments during a Mass Casualty Incident (MCI) is proposed in [34] by means of multi-agent Reinforcement Learning. It is especially interesting that the particular work refers also to a situation that often occurs in disaster management, namely a situation in which multiple decision makers are involved and each decision-maker needs to make decisions given only incomplete information on the current situation in order to achieve a shared objective.

A scheduling algorithm based on heuristic multi-agent reinforcement learning is developed to schedule effectively a rapid deployment of volunteers to rescue victims in dynamic settings [35]. This study is based on information gathered by mining social media data regarding volunteers and victims and proposes ResQ, an algorithm capable of adapting dynamically as information comes in and makes recommendations to minimize the total distance travelled by all volunteers to help the maximum possible number of victims.

# 4. SPECIAL TOOLS OF MACHINE LEARNING FOR EMERGENCY RESPONSE

Although not precisely belonging to one of the above sections, there are a couple of ML tools that are worth mentioning in order for this review to be complete.

## 4.1. TinyML

TinyML is an ML branch concerned with deploying models on constrained edge devices. This has a lot of applications when low-latency, low power and low bandwidth are necessary. Hence, this technology enables devices to run unplugged on batteries for weeks, months, and in some cases, even years, while running ML applications on edge.

It can, therefore, have tremendous implications for emergency management applications. Small sensors that can harvest energy and transmit only relevant data can deployed in remote areas to detect fires early on, or detect seismic activity in dangerous areas. Beyond that tinyML can also be used to monitor the individual state and condition of first responders through wearable technology.

## 4.2. Virtual Environments and Digital Twins

Digital twins provide a virtual representation of physical spaces that models relationships among people, places, and devices. The promise of digital twins and real-life simulation environments is that it will be possible to train and develop ML algorithms in a life-like scenario that is close to the real situation as possible. This also gives the opportunity to emergency responders and safety officials to further examine the behavior of the ML system and evaluate its suitability.

For an example of a disaster city digital twin the interested reader can refer to [36], in which a framework with four pillars is proposed covering the following aspects. Multi-data sensing for data collection, data integration and analytics to provide complete knowledge and assessment of the situation, multi-actor game-theoretic decision making and dynamic network analysis in order to increase the visibility of network dynamics among heterogeneous relief actor.

# 5. CONCLUDING REMARKS

During the last few years, AI has been recognized as a powerful technology that can provide groundbreaking and invaluable tools for all stages of the disaster management cycle, from disaster mitigation to disaster recovery. Novel AI technology can support first responders and enable "collective intelligence".

To this end, it is evident that the interest of the scientific community has not only increased during the past few years, but remains high as every year a plethora of scientific articles are published in this domain. As the amount of existing work is already vast, the importance of systematic literature reviews is crucial in the sense that they can act as guides for the interested scientists to acquire information about the state-of-the-art in the field, and for the interested researchers to identify gaps and open problems and deliver novel methods and result. The present review is not a complete list of all scientific publications; our objective was to present, based on the literature review, an overview of the existing work in a structured manner since to our opinion this is more useful for the scientific community.

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