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DELIVERABLE 4.1

Training Manual

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Contents

PREFACE

This training manual is created within the framework of the activities of the ARTION project. ARTION is funded from the European Union's Call for proposals in the field of Civil Protection under the Union Civil Protection Knowledge Network. The main goal of the project is to establish a Disaster Management Artificial Intelligence Knowledge Network, with the vision to become a world-class network for knowledge sharing in the area of Artificial Intelligence (AI) for disaster management that will guide the development and use of AI tools by first responders across Europe.

ARTION is a strategic partnership between the KIOS Research and Innovation Center of Excellence of the University of Cyprus that has a strong background in ICT technologies and AI, the University of Lille in France with advanced expertise in data analytics, the Space Research Centre of the Polish Academy of Sciences, an established first-responders training and advising body. In addition, civil protection agencies are part of the project consortium, namely the Cyprus Civil Defence and the Civil Protection of the Autonomous Region of Sardinia in Italy.

One of the four strategic pillars of ARTION is devoted to training and networking aiming to upskill first responder stakeholders by exemplifying AI technologies, detailing the data collection and analysis procedures and setting the expectations on what can be achieved by AI tools. The purpose of the training workshops is not only to share knowledge on the topic, but in addition to gather, consolidate and assess the needs of disaster management actors in order to be used by researchers in the further development of AI tools for disaster management. To engage the community and enable further innovations, all the knowledge that will be gained will be made available through an Open Knowledge portal created throughout the project.

This training manual is structured as follows. First, an introduction aims to highlight the usefulness and motivation behind the employment of AI for disaster management (Section 1). Then, an introduction to AI aims to provide a brief background on this scientific field (Section 2). A selection of topics on AI for disaster management is then presented in the following section (Section 3). A summary of the major points on testing and evaluating AI technologies for disaster management is presented in Section 4. This last part is very briefly covered in this manual as because of its practical nature it is more appropriately presented in the form of a presentation, thus the interested reader may refer to the available slides.

This manual aims to summarize the main points of the training workshops conducted as part of the activities for ARTION. The full set of slides can be accessed online at: https://ucy-my.sharepoint.com/:f:/g/personal/mmicha03_ucy_ac_cy/Egvx2-tStjJMiuAeDELeO74Bg94JEgVePoX-LDONXOWVh7A?e=RSSgKh

1. INTRODUCTION

Millions of people around the world are threatened by natural hazards and the dramatic changes in the global climate are likely to worsen the situation. For instance, the global annual average economic loss for floods is estimated at US $104 billion[1] and over the last decade, deadly floods affected over 1.4 billion people. According to an estimation, wildfires in Australia in 2019-2020 have caused an economic loss of approximately US $104 billion, in addition to the loss of life and environmental damage which are irreversible, thus beyond calculation. These severe impacts call for modern societies, specifically for all stakeholders from first responders to disaster managers and scientists, to put maximum effort in improving disaster management.

During the last few years, Artificial Intelligence (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”. The use of data together with advanced AI algorithms can have a transformative effect to the operation of first responders as recognized by the European Commission[2]. For example, in the event of a fire, firefighters can gain better situational awareness and make better decisions by having access to a visualization of the propagation of a fire, receiving live video from the scene or by having an estimation on the number of buildings or people in danger. Real-time deployment of evacuation plans taking into account aspects like traffic prediction, disaster evolution, the map of the area, etc. is another complex and critical task that can be addressed effectively using AI.

In fact, AI can be employed in a plethora of disaster events. First of all, it can prove to be a useful tool in many different types of disasters. From natural disasters, such as earthquakes, floods, landslides, typhoons, tsunamis, to man-made disasters, such as water contamination incidents, explosions, bioterrorism incidents, transportation accidents. Additionally, AI algorithms and AI-powered systems can be used in various disaster management actions offering different types of support. In particular, AI can be used to build:

- Systems that forecast events in order to take actions before a disaster.
- Decision-support systems
- Decision-making systems
- AI-powered automated robotic devices.

In addition, from first-line rescuers to administrative authorities, all stakeholders that are involved in the cycle of disaster management can take advantage of AI-powered tools.

Especially the evolution of automated robot devices, such as drones, can revolutionize disaster management in the years to come as they can easily reach locations that are either unreachable or very dangerous for human responders. In combination with AI algorithms modern robots can not only collect data, but they can interpret them and deliver critical information like, for example, whether there are persons detected in a certain area.

[1] UNISDR, Making Development Sustainable: The Future of Disaster Risk Management. Global Assessment Report on Disaster Risk Reduction (2015), www.unisdr.org/we/inform/publications/42809

[2] COM(2018) 795 Coordinated Plan on Artificial Intelligence

2. INTRODUCTION TO ARTIFICIAL INTELLIGENCE

According to the definition of the online Cambridge dictionary, Intelligence is "the ability to learn, understand, and make judgments or have opinions that are based on reason". Artificial Intelligence (AI) is "the branch of computer science that is concerned with the automation of intelligent behavior"[3]. AI is the simulation of human intelligence by machines in order to have the ability to understand/discover meaning, to learn, to solve problems and to act rationally. To this end, the central principles of AI include perception, learning, reasoning, knowledge, planning, and communication.

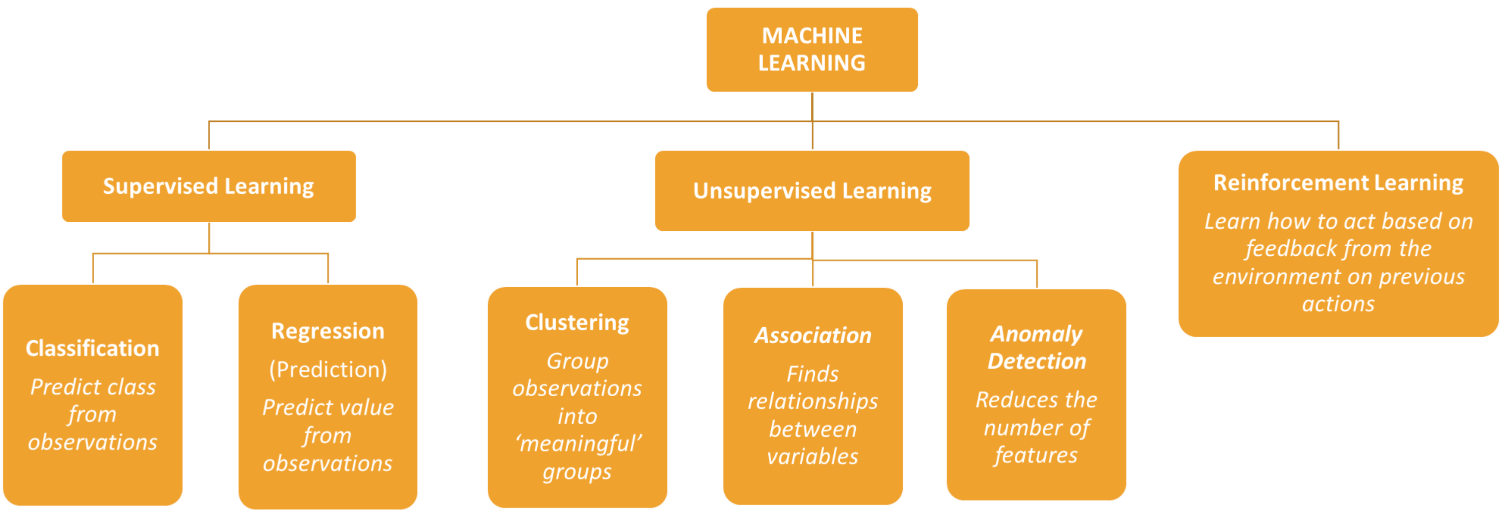
In the present manual we will focus on Machine Learning, a branch of AI that is rather the most widely used in the domain of disaster management.

2.1. Machine Learning

Machine Learning (ML) is a type of AI that provides computers the ability to learn from past experiences without being explicitly programmed. A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at the tasks improves with the experiences[4]. Examples of ML from every day life include chess playing, personalization of suggested content in social media and in the Internet, automatic conversion of speech-to-text, etc.

The main branches of ML are depicted in Figure 1 and presented briefly in the following subsections.

Figure 1: The main branches of Machine Learning



[3] G. F. Luger and W. A. Stubblefield. (1993). Artificial intelligence (2nd ed.): structures and strategies for complex problem-solving. Benjamin-Cummings Publishing Co., Inc., USA.

[4] T. M. Mitchell. (1997). Machine Learning (1st. ed.). MoGraw-Hill, Inc., USA

2.1.1. Supervised Learning

Supervised Learning uses labelled datasets. These datasets are designed to train algorithms into classifying data (classification) or predicting outcomes accurately (regression). Using labeled inputs and outputs, the model can measure its accuracy and learn over time. Supervised learning can be separated into two types of problems: classification and regression.

Classification problems use supervised algorithms to accurately assign objects (input data) into identified categories based on each object's characteristics. Classes are called *labels* or *categories* and the objects (input data) are analyzed into a set of quantifiable characteristics, called *features.* The selected features should be sufficient and appropriately chosen in order to classify objects into the correct category. Examples of classification paradigms are the classification of spam in a separate folder from the inbox, tumor classification from medical images as benign or malignant, classification of a handwritten character as one of the known alphabet characters. Examples of well-known classification algorithms include support vector machines, decision trees, random forest, neural networks.

Regression is another type of supervised learning method that understands the relationship between dependent and independent variables. Regression models predict continuous numerical values based on different input data points. The task of the regression algorithm is to find the mapping function to map the input variable (x) to the continuous output variable (y). Examples of regression cases include the prediction of sales revenue projections for a given business, the prediction of weather based on recorded data, and the prediction of data traffic in a communication network based on previous recorded data rates. Well-known regression methods include linear regression, polynomial regression, support vector regression, decision tree regression, random forest regression.

2.1.2. Unsupervised Learning

Unsupervised learning uses ML algorithms to analyze and cluster unlabeled data sets. These algorithms are intended to discover hidden data patterns with no human intervention. Unsupervised learning models are used for three main tasks: clustering, association, and dimensionality reduction.

Clustering is a data mining technique for grouping unlabeled data into groups, called *clusters*, based on their similarities or differences. Data points in the same cluster are more similar to other data points in the same cluster than those in other clusters. Clustering algorithms fall into two broad groups:

- Hard clustering, where each data point belongs to one cluster
- Soft clustering, where each data point can belong to more than one clusters. Examples include phonemes in speech, which can be modeled as a combination of multiple base sounds.

Clustering examples are the grouping of organisms by genetic information into a taxonomy, grouping of YouTube videos in order to produce recommendations for users similar to what they like, grouping of areas in a video to discriminate burned and healthy vegetation after a fire. Examples of clustering algorithms are K-means, hierarchical clustering, mean-shift clustering.

Association is an unsupervised learning method that uses different rules to find relationships between variables in a given dataset. These methods are frequently used for market basket analysis and recommendation engines, along the lines of "Customers Who Bought This Item Also Bought" recommendations.

Dimensionality reduction is a learning technique used when the number of features in a given dataset is too high. It reduces the number of data dimensions to a manageable size while also preserving the data integrity. Often, this technique is used in the preprocessing data stage, such as when auto-encoders remove noise from visual data to improve picture quality.

2.1.3. Supervised Vs. Unsupervised Learning

The main distinction between supervised and unsupervised learning is the use of labeled datasets. Supervised learning uses labeled input and output data, while an unsupervised learning algorithm does not. In supervised learning the algorithm "learns" from a training dataset by iteratively making predictions on the data and adjusting for the correct answer. For example, a supervised learning algorithm can be trained with forest fire image samples to learn how to detect smoke and fire from a standard camera. While supervised learning models tend to be more accurate than unsupervised learning models, they require upfront human intervention to label the data appropriately. For example, a supervised learning model can predict how long your commute will be based on the time of day, weather conditions and so on. But first, you have to train it to know that rainy weather extends the driving time. Unsupervised learning models, in contrast, work on their own to discover the inherent structure of unlabeled data. Note that they still require some human intervention for validating output variables. For example, an unsupervised learning model can identify that online visitors often purchase groups of products at the same time.

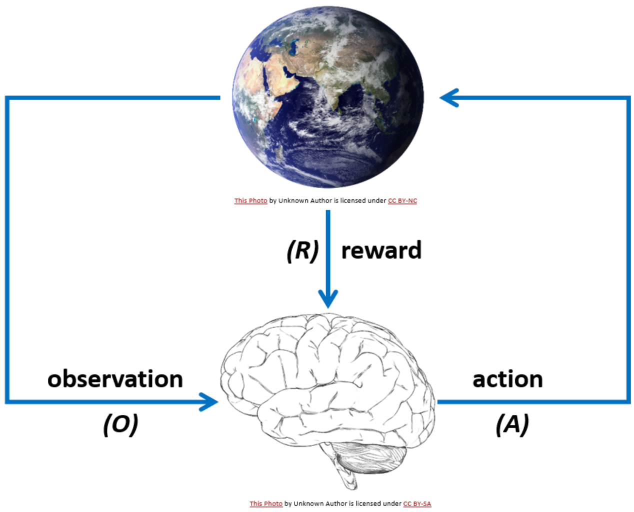
2.1.4. Reinforcement Learning

Reinforcement Learning is the science of learning to make decisions from interactions. In particular, the reinforcement learning problem involves learning what to do —how to map situations to actions— in order to maximize rewards. The learner (agent) is not told which actions to perform, instead it tries out actions to discover the reward they yield and to observe how the environment responds to them. The important features of reinforcement learning are trial-and-error learning and delayed reward. The diagram in Figure 2 shows the interactions between the agent and the environment. Beyond the agent and the environment, the key elements of a reinforcement learning system are:

- *Policy*: the agent's behaviour function, it is a map from state to action,
- *Reward signal:* the agent receives a scalar reward signal upon taking actions,
- *Value function:* indicates how good is each state and/or action, it is a prediction of future reward
- *Model:* agent's representation of the environment, it predicts what the environment will do next

Any real-world problem where an agent must interact with an uncertain environment to achieve a specific goal is a potential application of reinforcement learning. Some examples of reinforcement learning are: a mobile robot deciding which action to take, develop a computer chess master, manage an investment

Figure 2: Sequential Decision Making



portfolio, make a humanoid robot walk, and traffic light control. A challenge that appears in reinforcement learning, and not in other kinds of learning, is the tradeoff between exploitation and exploration. The agent needs to find a balance between exploiting known actions and exploring new actions. In order to receive high rewards, the agent should prefer actions that has tried in the past and found to be effective in producing high rewards. However, to discover such actions, it needs to try actions it has not selected before.

2.1.5. Online Machine Learning

When data becomes available in a sequential order, the available data is used to update the best predictor for future data at each step, as opposed to batch learning techniques which generate the best predictor by learning on the entire training data set at once. Online learning is a common technique used in areas of ML where it is computationally infeasible to train over the entire dataset, requiring the need of out-of-core algorithms. It is also used in situations where it is necessary for the algorithm to dynamically adapt to new patterns in the data, or when the data itself is generated as a function of time—e.g., stock price prediction. Online learning algorithms may be prone to catastrophic interference, a problem that can be addressed by incremental learning approaches.

2.1.6. Incremental Learning

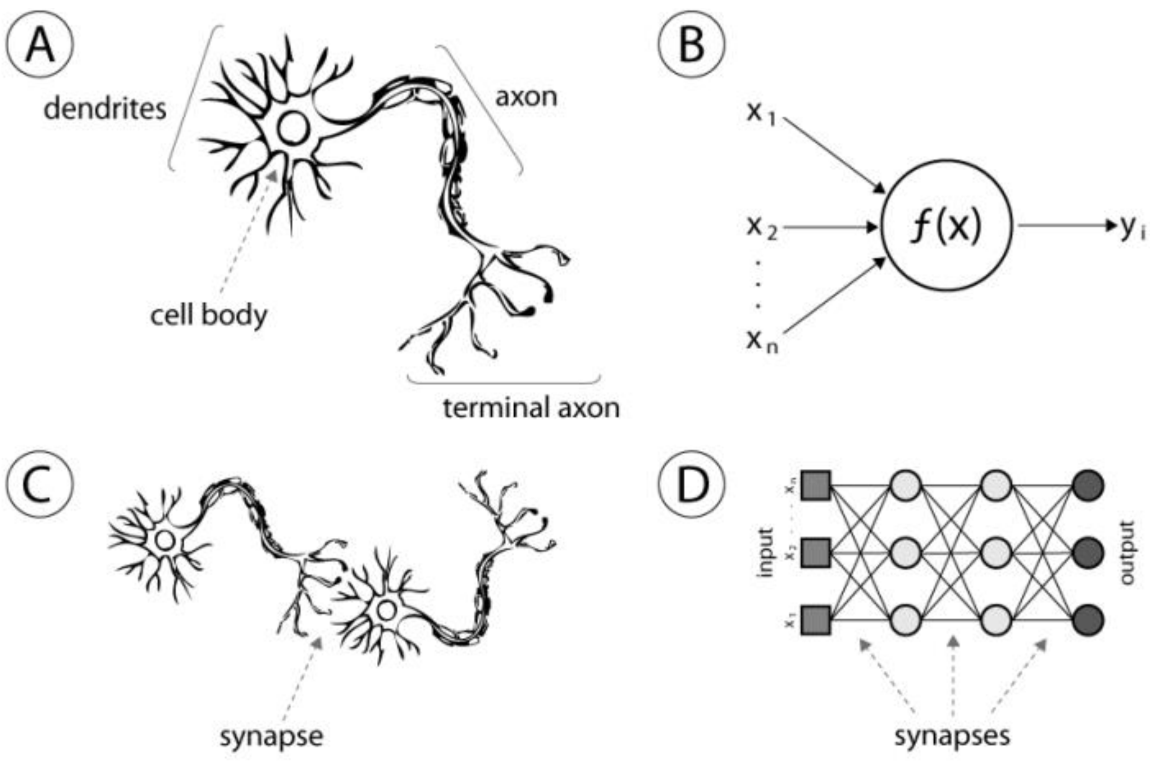
Incremental learning is a method of ML in which input data is continuously used to extend the existing model's knowledge—i.e., to further train the model. It is a dynamic technique of supervised and unsupervised learning and can be applied when training data becomes gradually available over time (like data streams) or when its size reaches out of system memory limits (because of hardware constraints). Also, applying incremental learning to big data aims to produce faster classification or forecasting times. Many traditional ML algorithms inherently support incremental learning. Other algorithms can be adapted to facilitate incremental learning. Some incremental learners have built-in some parameter or assumption that controls the relevancy of old data, while others, called stable incremental ML algorithms, learn representations of the training data that are not even partially forgotten over time.

2.1.7. Artificial Neural Networks

Artificial Neural Networks (ANNs), or simply Neural Networks (NNs), deserve a dedicated subsection in this manual as it is probably the family of most widely employed and most developed methods in the field of ML. They can solve a wide variety of problems of supervised and unsupervised learning.

ANNs are vaguely inspired by the biological neural networks and modelled after the human brain. Our brain is based on a complex network of interconnected *neurons.* Neurons are entities that receive information through a set of synapses, perform some sort of calculation, and pass the result to other neurons through its outgoing synapses. ANNs are computational algorithms that try to mimic this behaviour. They consist of artificial neurons, i.e., a mathematical function that seeks to simulate the behavior of a biological neuron. Each neuron receives a set of input signals, combines them in some way and passes the information along. An ANN is a complex network of interconnected artificial neurons (Figure 3[5]).

Figure 3: (A) Human neuron (B) Artificial neuron (C) Biological synapse (D) an ANN (Source: 5)



[5] Vinícius Gonçalves Maltarollo, Káthia Maria Honório and Albérico Borges Ferreira da Silva (2013). Applications of Artificial Neural Networks in Chemical Problems, Artificial Neural Networks - Architectures and Applications, Kenji Suzuki, IntechOpen, DOI: 10.5772/51275.

ANNs are trained to do specific tasks. They are teached, like children. If you show a child several trees, he will then be able to identify other trees. Similarly, if we want our network to tell whether an image depicts a cat or a dog, we first feed an image of a cat or a dog to the network. The network then does its internal computations and produces and output. This output is compared with the truth. If the network thinks it was given a picture of a dog when in reality the picture was of a cat, it will alter the behaviour of its neurons slightly (by modifying the weights of the connections) in order to make a better prediction of a cat in the future.

There is a plethora of different types of ANNs. They may differ in the arrangement and degree of connectivity of their computational elements, the types of calculations performed within each computational element, the degree of supervision they receive during training, the determinism of the learning process, and the overall learning theory under which they operate. Most common types include feedforward neural networks, convolutional neural networks and recurrent neural networks.

3. ARTIFICIAL INTELLIGENCE IN DISASTER MANAGEMENT

3.1. AI and the Stages of Disaster Management

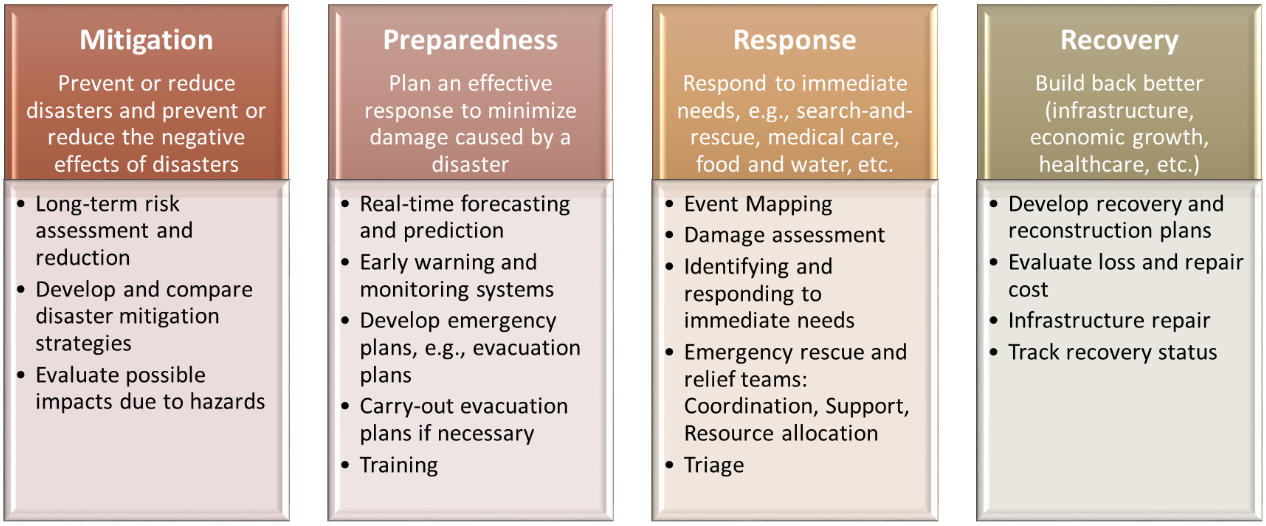
The disaster management cycle is usually divided into four stages: Disaster Mitigation, Disaster Preparedness, Disaster Response and Disaster Recovery. In the line of time, mitigation and preparedness take place before the disaster whereas the stages of response and recovery occur after the event.

The stage of mitigation includes measures taken to prevent or reduce disasters and prevent or reduce their negative effects. Disaster preparedness is about planning an effective response in order to minimize the damage caused by a disaster. After or during a disaster (depending on the type of the event), disaster response is an action which involves any response to immediate needs, like, search-and rescue operations, medical care, provision of food and water, etc. Finally, disaster recovery is about reversing the damages that a disaster caused, by building and repairing infrastructures, taking measures to ensure economic growth, etc. AI can be used in all four stages of the disaster management cycle. Figure 4 lists some examples of operations in which AI can be employed to provide useful tools.

3.2. Prerequisites for Employing AI in Disaster Management

Although the concept of AI has been introduced several years ago and, in fact, the term “Artificial Intelligence” was coined in 1956, it was impossible, mainly due to technological limitations, to address applications of AI similar to what scientists develop nowadays. In order to be able to develop practical AI applications to handle complex situations we may identify three critical prerequisites, namely:

Figure 4: The stages of disaster management and examples of AI operations for each stage.



- High Computing Power and Storage
- Sufficient Input Data
- AI Algorithms

3.2.1. Computing Power and Storage

It is evident that especially during the last decade computing devices have evolved drastically. The latest computing devices have high computing power and storage capacity, sufficient to process large amounts of data and execute complex algorithms fast. By means of AI algorithms and modern computers it is possible to process large inputs providing human-like interpretations of the situation and perform actions like perception, prediction, learning, reasoning, planning, and communication. In fact, the contribution of machines and AI is not just helpful but imperative for the completion of some tasks as it would be impossible for the human brain to receive the amount of information an AI algorithm can analyse in just a couple of minutes.

3.2.2. Input Data

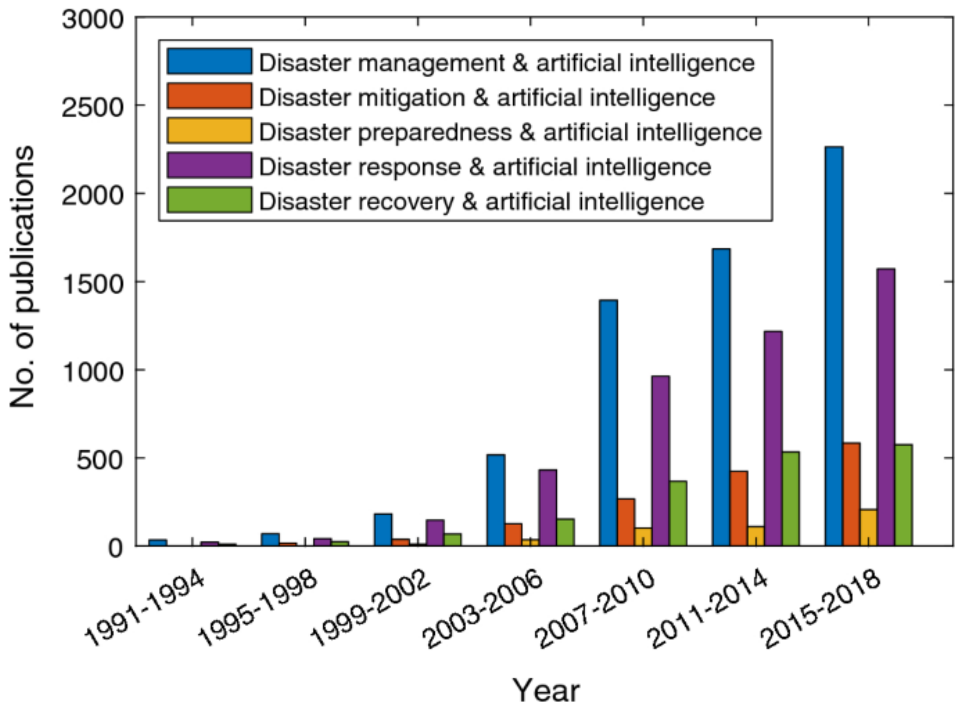
The output of any AI algorithm is as good as the input data set. In particular, the data must be enough in terms of quantity and quality (i.e., accuracy). Data was a scarce resource in the past that was difficult to produce, costly to store and slow to manipulate. However, we already entered the era 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.

A multiplicity of data sources (e.g. satellite and topographic data, weather-radar, drone sensors) that increasingly become readily available can greatly improve situational and needs assessment. Further, the wealth of data that first responders are increasingly able to collect (from dedicated sensors and external sources), can prove invaluable in the disaster management cycle (e.g. used for forecasting and rapid assessment, informed decision-making and improved efficiency), and result to significant reductions in the risk and impact of disasters. The Sendai Framework for Disaster Risk Reduction[6] urges for a paradigm shift towards a risk-based approach as it emphasizes the need for preventing new risk, reducing existing risk and strengthening resilience. The importance of this domain is also illustrated with the recent launch of the EU Risk Data Hub, and the Copernicus program, which stimulates the integration of Earth observation data into service-oriented products for emergency and risk management.

3.2.3. AI Algorithms

With the evolution of processing power and data availability, the interest of the scientific community for the development of practical AI algorithms is naturally increasing during that last few years. This trend is evident by observing Figure 5[7], showing the number of publications found online at the websites of Google Scholar and Web of Science, requiring joint presence of both keywords.

Figure 5: The number of online publications on the employment of AI for disaster management (Source: 7)



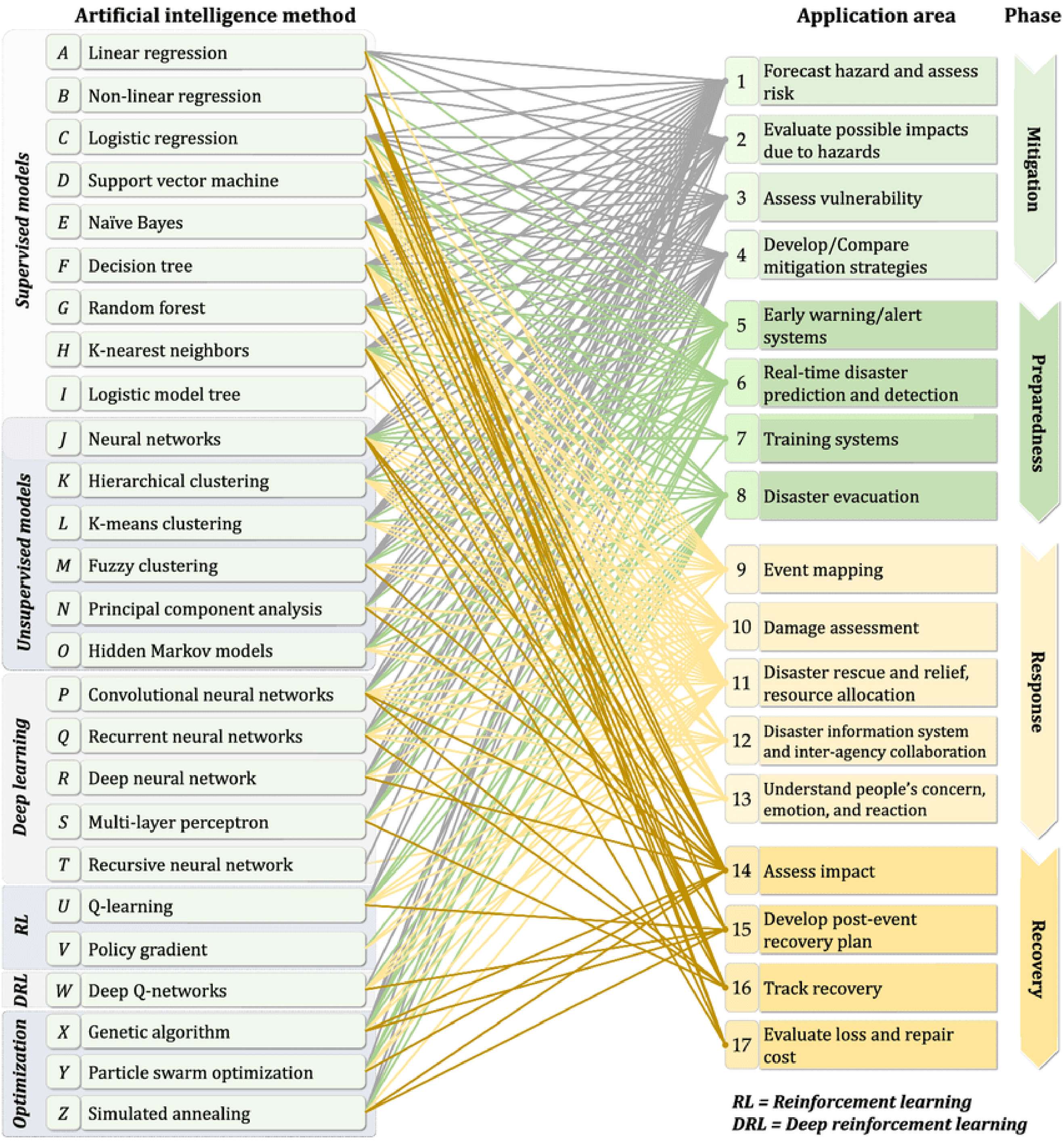
[6] UNISDR, Sendai Framework for Disaster Risk Reduction 2015-2030 (2015), https://www.undrr.org/publication/sendai-framework-disaster-risk-reduction-2015-2030

[7] Sun, Wenjuan & Bocchini, Paolo & Davison, Brian. (2020). Applications of artificial intelligence for disaster management. Natural Hazards. 103. 2631-2689. 10.1007/s11069-020-04124-3.

From the same source[7], Figure 6 depicts a diagram pairing the AI tools and disaster management applications according to the studies found in the existing literature. Every solid line indicates the presence of a scientific study employing the application of the corresponding AI method to a certain area of disaster management. It is interesting to observe that, in general, each AI algorithm is not specific to solving a few problems, but if employed appropriately it can handle several, if not any, types of problems.

Although big data have become a reality in recent years, intelligent algorithms for data analysis are essential in order to be able to exploit the information therein. AI is a powerful field used in data

Figure 6: Pairing of the AI tools and disaster management applications according to the studies found in the existing literature



analytics. Specifically AI algorithms can be used for extracting insights and patterns from large sets of data, for analyzing historical data to predict future outcomes, for planning optimal solutions, etc.

The space-time dynamics of hazards are driven by complex interactions that are difficult to foresee while cascading effects lead to further complications which put first responders at further risk. In the case of floods for instance, uncertainty in rainfall forecasts and unpredictability of other incidents is currently captured by computationally intensive models and scenarios with long simulation times. On the contrary, state-of-the-art AI and ML algorithms excel in capturing the uncertainty in the data and the models to facilitate effective predictions even with sparse data sets.

3.3. AI-powered Autonomous Robot Devices

The emergence of autonomous robot devices has been a driving force in exploiting AI in disaster management. It is a growing category of devices including drones, autonomous underwater vehicles, unmanned ground vehicles, etc. These autonomous robots can be programmed to perform tasks with little to no human intervention. Increasingly, autonomous robots are powered with AI algorithms in order to recognize and learn from their surroundings, to take actions and to collect data.

When available, autonomous robots are an asset for a variety of tasks especially in disaster management operations. They can be exposed to dangerous environments and provide greater probability of mission success without the risk of loss of injury of persons. Furthermore, manned aircrew can lose concentration compared to robot devices as very often disaster response operations have to be executed under conditions that are far from ideal, namely under stress and during difficult and long hours. In the field, the information to process is often too much for the human brain, especially under high pressure and stress. In addition to all these, the personnel may be limited.

In particular, autonomous robots may be used in emergency response situations for applications like:

- Mapping and reconnaissance,
- Monitoring and tracking,
- Temporary utility infrastructure, and
- Delivery of help-aid

3.4. Computer Vision Technologies

Computer Vision is a powerful branch of AI dealing with how computers can gain high-level understanding from digital images and videos. Its applications in emergency response are numerous as the input data can be collected from several sources, such as:

- Videos from cameras deployed for other purposes, like, security surveillance cameras (CCTV).
- Static cameras deployed for a specific disaster management applications
- Drone-mounted cameras (or robot-mounted cameras in general)
- Photos uploaded by users to social media

There is wide range of computer vision tasks that can deliver different types of information and information of various precision levels. Typical computer vision tasks for disaster management operations include:

- Recognition: Determining whether or not the image data contains a specific object, fearure, activity, etc. Different varieties of the problem include: recognition, identification and detection.
- Motion Analysis: An image sequence (video) is processed to produce an estimate of the velocity of objects captured at the video.
- Image Classification: Identifying what class, i.e., category, the object belongs to.
- Object Tracking: Identify and track specific objects (or persons) in a video.

Several applications of computer vision technologies for emergency response are included in the presentation slides.

3.5. Modelling of Natural Disasters

Computer Modelling is the process of constructing computer-based mathematical, graphical or algorithmic representations of real life systems of phenomena. A computer-based model consists of a set of algorithms or equations used to capture the behaviour of a system. Modelling is a useful tool used in the context of many scientific fields. Some examples are traffic modelling, building structural modelling, car crash modelling, weather modelling, hurricane modelling, epidemic modelling.

The major benefits of using computer-based models include, but are not limited, to the following:

- Gain greater understanding of a process
- Identify problems and bottlenecks in processes
- Evaluate effect of system changes
- Identify actions needed upstream or downstream relative to a certain operation, organization, or activity to either improve or mitigate events
- Evaluate impact of changes in policy prior to implementation

In disaster management, computer models of hazards and disasters are a key element in developing AI tools. A model of a disaster event, like a fire, a hurricane or a flood, is what provides the system with a machine-interpretable understanding of the situation.

In order to provide an understanding of this important element in the following subsection we will present an overview of modelling for wildfires and floods.

3.5.1. Wildfire modelling

Wildfires over the years have been proven a real threat to natural ecosystems, wildlife, infrastructures and human lives. Wildfires remain a great concern in the European Union since around 400000 hectares of natural land were burned in 2019, with approximately 48% falling within the Natura 2000 protected areas causing unparalleled damage with many years necessary to restore. Furthermore, wildfires are also considered significant contributors to forest loss and a barrier to the fight against climate change.

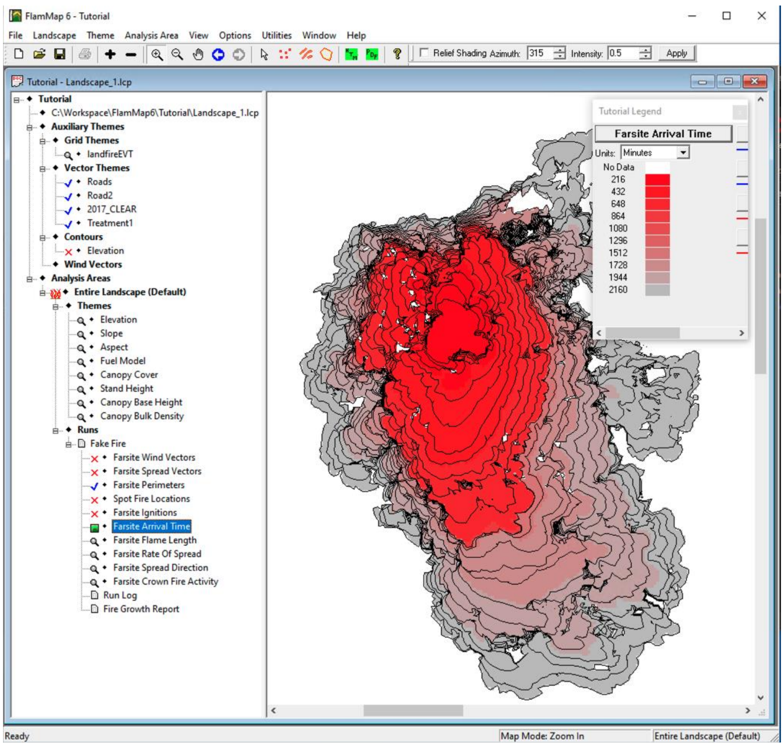
Fighting wildfires is a dangerous and high risk job for fire fighters that requires tremendous skills and precise timing to keep the fire under control. An important tool that can assist in compacting wildfires is their modelling and simulation. Wildfire modelling enables the understanding of the situation and can help in the prediction of the fire behaviour. It can thus help in devising plans to effectively compact the fire, improving the safety of firefighters and the public, reducing risk and minimizing damage, as well as protecting ecosystems, watersheds, and air quality.

Fire modelling denotes the mathematical representation of wildfires that allows its numerical simulation in order to understand and predict its spatio-temporal behavior. Although fire models have been developed since 1940 due to their complexity they remain still an active research area. Fire models can be classified to:

- Empirical models
- Physical models
- New generation models

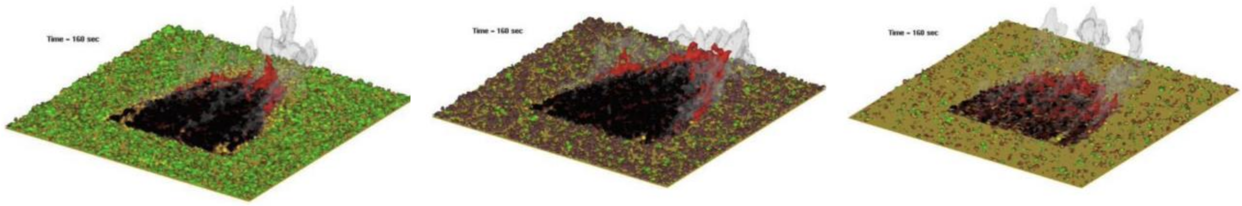
Empirical Fire Models rely upon a top-level model to determine the magnitude of heat exchanges and they depend on a simplified analytical rate of spread (ROS) to predict the propagation of a fire as a function of time. Because they are based on simplified mathematical models they can solve the fire propagation problem faster than real-time. Figure 7 shows an example of a fire empirical model generated be FlamMap, a fire analysis application that simulates fire behavior by creating a variety of vector and raster maps of potential fire behavior characteristics (e.g., spread rate, flame length, crown fire activity) and environmental conditions that can be used for decision support and planning).

Figure 7: A fire empirical model generated by the fire analysis application: FlamMap.



Physically based fire models consider the fire behaviour in presence of combustion chemistry, heat transfer, and fluid dynamics. These models determine the heat, mass, and momentum fluxes released from the burn fuel that are transferred to surrounding unburnt fuel and the atmosphere. Physical fire models numerically solve equations for the fluid dynamics and thermochemistry of fires. Accurate physical equations can be formulated but all require numerical solutions that are generally slower than real-time. Figure 8 illustrates an example of an illustrated physically-based fire model using HIGRAD/FIRETEC, a physics-based, 3-D computer code designed to simulate the constantly changing, interactive relationship between fire and its environment. This tool combined computational fluid-dynamics models and physics models. Due to its requirements for huge computational resources is currently a research tool only.

Figure 8: A physically-based fire model using HIGRAD/FIRETEC



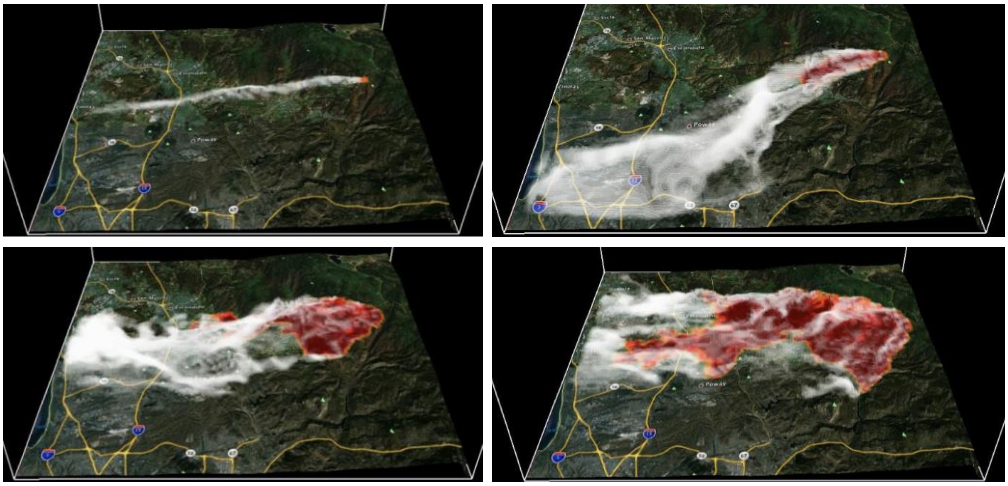
New generation fire models combine both physical and empirical fire models coupled to a numerical weather prediction (NWP) model or a computational fluid dynamics model (CFD). The coupled models include the interaction of wildfire with the surrounding atmosphere by means of changing the fire environment via humidity, temperature, and wind speed and direction. These models are four-dimensional models (three dimensions in space and one in time). Wildfire can impact the atmosphere directly via its heat and moisture fluxes or smoke. Figure 9 shows an example of an WRF-Fire simulation from the Santa Ana (California) fires in 2007. WRF-Fire (SFIRE) is a fire modelling tool that allows users to model the growth of a wildland fire in response to environmental conditions of terrain slope, fuel characteristics, and atmospheric conditions, and the dynamic feedbacks with the atmosphere. Its two-way coupling between the fire behaviour and the atmospheric environment allows the heat released by the fire to alter the atmosphere surrounding it.

In conclusion, the current approaches in fire modelling are very promising, but can be further improved based on better knowledge on how wildfires ignited, spread, and were extinguished. Advancements in high-performance computing and satellite platforms would enable the operational use of the promising wildfire–weather models.

3.5.2. Flood modelling

Flood events are one of the most destructive events that can happen. They can cause loss of life, severe damage to properties and adverse economic and environmental impact. As a natural disaster, flood risks cannot be completely eliminated, but flood modelling is a base for the development of many tools that can support decision-making in order to take precautions and minimize the consequences of a potential flood.

Figure 9: A new generation fire simulation with WRF-Fire from 2007 Santa Ana fires



Flooding models are developed to predict the floodplain of a flood. Three main model types exist:

- Empirical models,
- Hydrodynamic models
- Simplified models.

These models provide flow and level forecasts at selected key locations. By exploiting the results of a flooding model, such as prediction of the water height and 2-dimensional velocity, it is possible to develop algorithms that can identify and monitor closely the most hazardous areas. The main features of the three types of models are summarized in the following table:

Empirical models	Hydrodynamic models	Simplified models
	Assets	
Relatively quick and easy to implement Based on observation	Direct linkage to hydrology Detailed flood risk mapping Can account for hydraulic features/ structures Quantify timing and duration of inundation with high accuracy	Computationally efficient
	Limitations	
Non-predictive No/indirect linkage to hydrology (difficult to use in scenario modelling)	High data requirements Computationally intensive Input errors can propagate in time	No inertia terms (not suitable for rapid varying flow) No/little flow dynamics representation

Application range		
Flood monitoring	Flood risk assessment	Flood risk assessment
Flood damage assessment	Flood damage assessment	Water resources planning
	Real-time flood forecasting	Floodplain ecology
	Water resources planning	River system hydrology
		Catchment hydrology
		Scenario modelling

A flood model is in the heart of the development of many AI systems in all stages of disaster management. It can be useful in the development of early warning systems, as soon as the event starts to occur, in flood monitoring systems operating during the flood, and in damage assessment after the flood.

3.6. Applications of AI in Disaster Management

This Section presents a selection of AI applications for disaster management.

3.6.1. Air Quality monitoring using UAVs

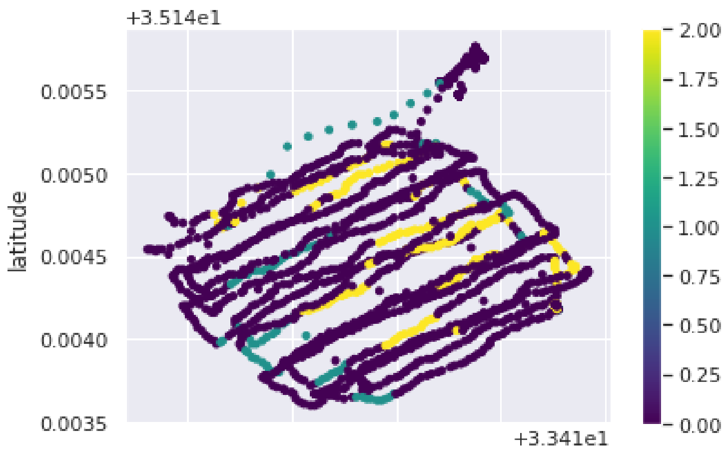
Nowadays, air quality monitoring in urban areas is developed at high level as there are many fixed stations equipped with appropriate air quality sensors that detect the air pollutant levels and warn people in case of an emergency. On the other hand, in rural areas this method in not developed yet, so a potential solution is to flight an Unmanned Aerial Vehicle (UAV) equipped with onboard air quality sensors to detect air pollution levels and warn the community in case of a disaster.

A hardware board containing air quality sensors is commonly used to measure pollutants like Particulate Matter (PM), Carbon Dioxide (CO_2), as well as humidity and temperature levels. A custom board developed by KIOS CoE as well as the UAV with the board attached to it are depicted in Figure 10. These sensors are controlled via an Arduino Mega 2560 microcontroller with the use of a software written in Arduino IDE to capture the data from each sensor. After capturing the data, it is sent through serial communication to a Robotic Operating System (ROS) that is installed on Nvidia Jetson Xavier NX (onboard PC). A publisher node is launched and then the data is passed through ROS topic to a subscriber, who is responsible to store the data. A MySQL database was created to store the sensor data to a specific database table and the results from ML algorithms to another database table.

Figure 10: The developed hardware board equipped with air quality sensors (left) and the board attached to the UAV (right)

The next step is to divide an area to smaller area clusters based on the concentration of a specific air pollutant. Clustering is a data mining technique for grouping unlabeled data based on their similarities or differences. For example, K-means clustering algorithms assign similar data points into groups, where the K value represents the size of the grouping and granularity. By means of a K-means clustering algorithm, based on the data acquired from our sensors attached to a drone, we divide an area into smaller area clusters according to the concentration levels of the contaminant CO_2. Figure 11 shows the result of K-means clustering based on the CO2 pollutant concentration in the area.

Figure 11: K-means clustering for an area based on the CO2 pollutant concentration



Furthermore, we plan to develop additional ML algorithms in order to localize the source of the air pollution and to track the plume of the pollution during the flight of the drone. The DJI Matrice 300 RTK drone will flight autonomously using DJI’s Onboard Software Development Kit (OSDK) and these ML algorithms will run online on the Nvidia Jetson Xavier NX and will send through ROS commands to navigate the drone and track the plume of the air pollution.

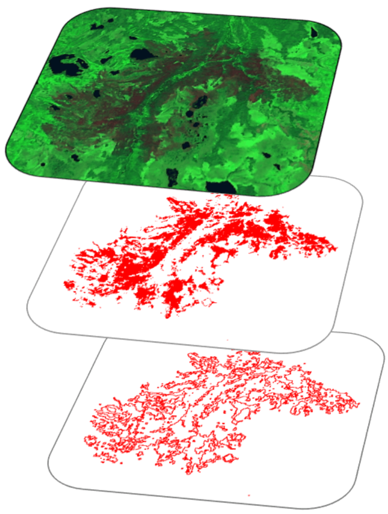
3.6.2. Calculation of burned area index using UAVs

We present AIDERS, a multi-drone web-based platform developed by KIOS CoE that aims to assist first responders in taking actionable decisions during emergency situations. This is achieved by using multiple UAVs along with AI and Computer Vision algorithms.

One of the methods used in order to develop this platform is Remote Sensing. Remote Sensing is the science of obtaining information about objects or areas from a distance, typically from an aircraft or a satellite. This helps in understanding the characteristics of the ground, the vegetation or the atmosphere, and therefore assist the first responders in taking better decisions. To acquire such information from a distance, high quality multispectral cameras are used. These cameras capture image data at specific frequencies or specific bands across the electromagnetic spectrum. The captured spectral images also allow for extraction of additional information, which the human eye fails to capture. A multispectral index is a mathematical equation that is applied on the various multispectral bands of an image per pixel. These indices are the ones that can help us extract information about the ground, the vegetation or the atmosphere of an area. For example, the most common index used to assess the vegetation of an area is the NDVI (Normalised Difference Vegetation Index). Values above 0.5 indicate a healthy plant.

In case of a fire event, first responders need to quickly gain situational awareness of the affected area in order to take better decisions. An aircraft equipped with a multispectral camera will capture images of the region of interest, and at the same time process them to calculate the Burned Area Index (BAI) in real time. The BAI is another index that uses the red and near-infrared bands of the camera spectrum to identify the areas of the terrain affected by fire (see example in Figure 12).

Figure 12: The red and near-infrared bands of the camera spectrum (two lower layers) used to identify burned areas



Once BAI is calculated, the captured images are then georeferenced and attached to the map. The region of the burned area is also calculated, georeferenced and then highlighted on the image as a red polygon. This helps first responders as they can acquire the exact location of a burned area and take actionable decisions. An example of a final result after following the described workflow is illustrated in Figure 13. The red polygons indicate the exact location of burned terrain.

Figure 13: Identification of the burned areas (red polygons) after following the workflow described above.

We have decided to use remote sensing as it is proven to be a useful methodology to extract information. Although it is generally considered to be a reliable method, there are some limitations due to hardware or software constraints, or due to atmospheric conditions. However, several ML methods are jointly employed in order to increase the accuracy of the results.

3.6.3. Person Detection and Tracking using UAVs

The system for identifying individuals consists of two main components, detection and tracking. This is achieved by utilizing footage captured from various test missions using UAV (Unmanned Aerial Vehicles). Person detection is done by means of computer vision algorithms and a Convolutional Neural Network whereas tracking is achieved by means of a combination of algorithms. Furthermore, upon detecting and tracking the persons, all the data collected from the whole process is then saved in CSV files for further analysis.

For the person detection algorithm, YOLOv4[8] was trained. YOLOv4 is an object detection algorithm that is an evolution of the YOLOv3 model, which is a real-time object recognition system that can recognize multiple objects in a single frame. For the model to recognize persons, a dataset of images was initially

[8] A. Bochkovskiy, C.-Y. Wang, and H.-Y. M. Liao, "Yolov4: Optimal speed and accuracy of object detection,"arXiv preprint-arXiv:2004.10934, 2020

created. Around 2500 images were collected and annotated. Some of those were captured from real life test missions and the rest were taken from the Heridal Database[9]. In order to increase the accuracy of the detector and to increase the dataset size, some image augmentations were implemented on several images and used as separate images for the training dataset. These augmentations include brightness, contrast, sharpness, and saturation. Image augmentation helps to enhance the details of the images which is helpful since the altitude at which the drones fly is usually high. The training was done using the Darknet Framework, an open-source neural network framework written in C and CUDA.

Upon detecting the persons in a frame, tracking algorithms starts processing them. Initially the tracking utilizes the Hungarian Algorithm[10], which uses the Intersection of Union of the detections compared to the previous detections as a similarity metric score. The matching association for each person detection is executed in the current frame with the highest achieved Intersection over Union score of the previous frames. Apart from the Intersection over Union matching, a distance matching algorithm is also implemented, assuming the scenario of having no detections matched with previous person already detected, using the Intersection over Union score. The distance matching algorithm calculates the Euclidean distances of a person's last position, to all other detected persons of the current frame. Then, if the nearest bounding box area and size match approximately the area of the previously tracked person's box, the newly detected person is the previously targeted person. Furthermore, a Kalman filter is used to estimate the position of the tracked person in case of any occlusion, such as trees, or if the detector fails to detect the person but the person was moving. The Kalman filter updates its variables using the x, y coordinates of the matched box in the current frame, assuming a nearly constant speed model. Finally, all the data collected from the whole process is saved in CSV format files in order to be further processed for data collection and analysis. These files contain the location and trajectories of the persons in x,y pixel coordinates, and the moving direction for each person for each frame. Figure 14 shows a screenshot from a video captured during a field exercise where all persons are detected and marked with blue boxes.

Figure 14: A screenshot from a video captured during a field exercise where all persons are detected (marked with blue boxes)

[9] D. Božić-Štulić, Ž. Marušić, S. Gotovac: Deep Learning Approach on Aerial Imagery in Supporting Land Search and Rescue Missions, International Journal of Computer Vision, 2019

[10] G. A. Mills-Tettey, A. Stentz, and M. B. Dias, "The dynamic Hungarian algorithm for the assignment problem with changing costs,"Robotics Institute, Pittsburgh, PA, Tech. Rep. CMU-RI-TR-07-27, 2007

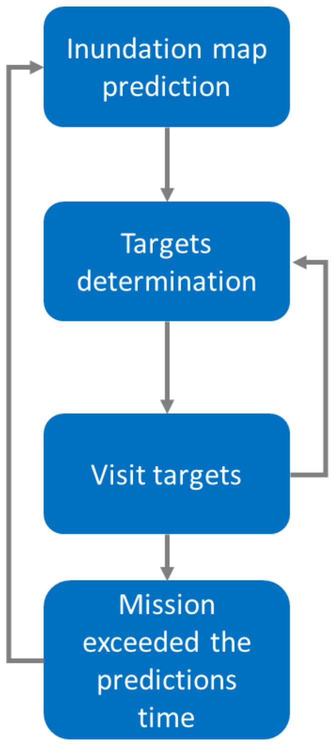
3.6.4. Monitoring Water Contamination Events using UAVs

Pathogens can easily spread via water leading to serious health complications. Due to the nature of their work, first responders are at a high risk to become contaminated while operating in areas where water is present. It is, therefore, critical to be able to extract knowledge and suggest recommendations in order to manage the contamination event, assess the risk and forecast its evolution, as well as to develop forensic investigation tools.

KIOS CoE developed a system where an AI-powered drone will be able to strategically choose specific high-risk target locations and monitor them as fast as possible. At the heart of the system is a hydrodynamic flood prediction model. Hydrodynamic models can simulate the height of water depths and the velocities in x and y directions. Considering the velocities and the water depths, waypoints are extracted so that the drone is able to monitor the more dangerous locations.

In particular, after a flooding event has occurred in an area the flooding prediction software will be employed. The used flooding model predicts the state of water for approximately 1 hour ahead and projects it on a grid map with a cell size of about 50m. Each minute all the targets that are worth to be visited, based on the momentum of the water, are selected for further monitoring. The drone computes online its trajectories in order to visit the targets in the minimum time. It will arrive before the flood reaches an area and will send valuable information to first responders to enhance decision making. Hence, first responders would be able to extract information on the potential hazardous areas before the water reaches that area. After all targets are visited, the process is repeated. The diagram describing the whole process is depicted in Figure 15.

Figure 15: Diagram of the monitoring procedure

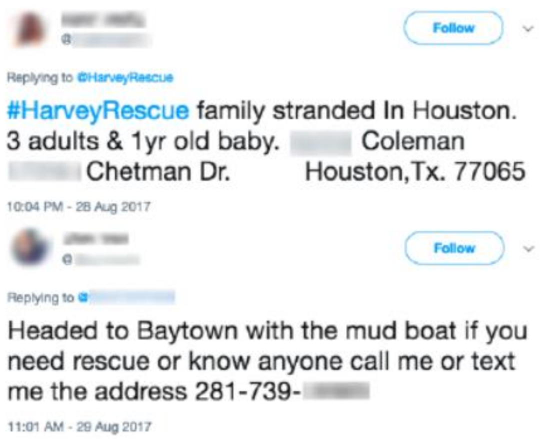


3.6.5. Employing Reinforcement Learning in Disaster Management

Reinforcement learning has a strong potential in disaster management applications. It can find an optimized strategy by means of learning from its own experience (i.e., actions) without requiring any prior knowledge of the system behavior. It can be, therefore, used to model systems whose behavior exhibits changes and uncertainties. Furthermore, reinforcement learning can be trained for objectives that are hard to optimize directly because of the lack of precise model, a feature that is very useful when addressing an emergency, unpredicted situation.

In order to illustrate the usefulness of reinforcement learning we present an example of an application found in the literature employing reinforcement learning to solve typical problems arising in disaster management. It is one of the first attempts to formulate a large-scale disaster rescue problem by means of a reinforcement learning problem using massive social network data[11]. Specifically, the study presents a scheduling algorithm based on reinforcement learning to organize the rapid deployment of volunteers to rescue victims in dynamic settings. The objective is to quickly identify victims and volunteers from social network data and then schedule the rescue teams for helping the victims. The algorithm has been demonstrated in a case study using Twitter data collected during Hurricane Harvey in 2017 (Figure 16).

Figure 16: Tweets related to Hurricane Survey in 2017. Sample tweets requesting and offering help (left) and the distribution of volunteers and victims in the Houston area on August 28, 2017 (right). (Source: 11)



This approach aims to match volunteers and victims for faster relief and efficient use of limited public resources by introducing a new disaster relief channel that can serve as a backup plan when traditional helplines are not sufficient. Experimental results have shown that the proposed framework can respond to dynamic requests and achieve an optimal performance in terms of both space and time.

[11] L. Nguyen, Z. Yang, J. Zhu, J. Li, and F. Jin, “Coordinating Disaster Emergency Response with Heuristic Reinforcement Learning”, arXiv e-prints, 2018

4. TESTING AND EVALUATING AI TECHNOLOGIES

It is of great importance that the development of novel methods for disaster management is followed by their successful trials in realistic field exercises. Throughout a trial the objective is to identify gaps and find an appropriate way to address them. Furthermore, innovation does not necessarily mean experiencing an immediate gain. It is important to apply adequate methodological know-how before investing in a solution in order to identify whether it can be useful and in which context.

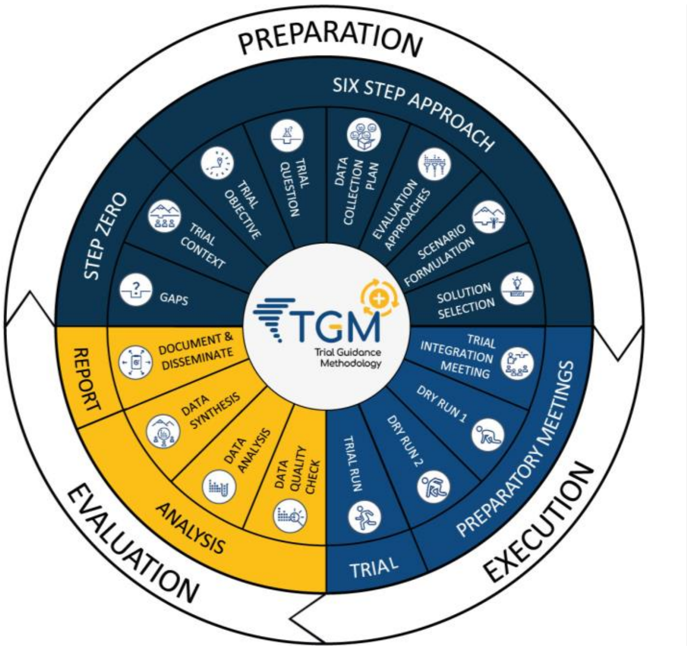
However, in order to be effective, trials need to follow a structured methodological approach, especially when they have to do with the assessment of solutions through the involvement of several stakeholders, from first responders to solution providers. In general, well-defined tests achieve more precise results. In addition, a co-creative approach helps to address stakeholders needs and allows exchange of knowledge among different entities. A structured setup sets a benchmark for future solutions and preserves also the possibility to reproduce the trial, especially if it is to be repeated by others.

To this end, we propose the employment of the Trial Guidance Methodology (TGM), a framework that was developed as part of the activities of the EU funded Driver+ project (Grant Agreement 607798)[12]. TGM provides a practical guide for organizations that are involved in crisis management. The objective is to assist the involved stakeholders in creating realistic environments for testing novel tools in order to be able to identify needs as well as to test and assess potential solutions by means of a structured methodology. The methodology, which is depicted in the TGM Wheel (Figure 17), consists of three main phases:

- Preparation
- Execution
- Evaluation

and a number of steps within each phase.

Figure 17: The TGM Wheel



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[12] https://www.driver-project.eu/

During the preparation phase, the trial context is defined and gaps relevant to it are identified. The design of the trial follows an iterative and non-linear six step approach. The objectives of the trial need to be defined and appropriate research questions need to be formulated in order to generate robust outcomes regarding the added value of the solutions under trial. To do this, a structured data collection plan is needed as well as evaluation approaches and metrics to analyze the data at the end of the trial. Finally, realistic scenarios must be developed and solutions must be selected to allow you to ascertain whether they could be innovative.

In this process, iterativeness is a key. We need to plan it, check it, adjust it and try it before the final run. In each step previous decisions must be open to readjustments. For example, a small change in the research question might require to look back at Key Performance Indicators, to adjust the data collection plan and correct the scenario.

After designing the trial we are ready for the execution phase. Rehearsals and meetings are crucial to align perspectives among all stakeholders and to make sure that everything fits the plan decided in the preparation phase. Rehearsing also assists the detection and mitigation of various processual influences (biases). Full rehearsal of the trial is called dry run 2 and after that, we are ready to run the trial.

After the execution of the trial, the collected data can be checked and analyzed according to the evaluation approaches selected during the preparation phase. After analyzing the data, we are ready to synthesize the results providing evidence on the impact of the tested solutions. Finally, the dissemination of results to the disaster management community is an important part of the evaluation phase.

CONCLUDING REMARKS

The applications of AI in disaster management are many and powerful. The development of AI algorithms combined with the availability of big data, powerful computing devices and automated robots can not only make several tasks and processes easier, but can facilitate operations that could not be possible without their employment. The potential benefits can cover an endless variety of aspects, from the safety of first responders, to the faster rescue of the victims, to the elimination of damages.

The topic is too extensive to be covered in this training manual, however this material aims to give all interested stakeholders an understanding of the broad scope and numerous applications of artificial intelligence in emergency response.