AIDERS

Deliverable 3.1 Multi-Sensor Data

Coordinator Name: **Christos Panayiotou**

Coordinator Email: **christosp@ucy.ac.cy**

Project Name: **Real-time Artificial Intelligence for DEcision support via RPAS data analyticS**

Acronym: **AIDERS**

Grant Agreement: **873240**

Project Website: http://www.kios.ucy.ac.cy/aiders/

Version: **1.0**

Submission Date: **30/06/2020**

Dissemination Level: **Public**

Contents

Executive Summary

Machine learning algorithms typically rely on training data to learn high-level representations and carry out a given identification, classification, recommendation or prediction task. This deliverable focuses on identifying machine learning algorithms and data that can be used to train those algorithms with goal to achieve increased situational awareness in emergency response. In particular, we a) identify the requirements for gaining situational awareness based on the requirements provided by the end-users, b) associate the user requirements with machine learning algorithms, c) provide an overview of state-of-the-art approaches, d) define the appropriate pre-processing techniques for each data type, e) provide available datasets and present a data collection approach, f) provide an overview of AI applications focused on processing multi-sensor data in emergency response and categorize them into the three scenarios of focus of the AIDERS project being: i) fires, ii) earthquakes and iii) flooding.

1. Introduction

Data and Artificial Intelligence (AI), machine learning algorithms in particular, can be instrumental in assisting first responders in handling emergency situations. 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, receive live video from the scene or be provide with an estimation of the number of buildings or people in danger. The availability of all this information in a single platform has the potential make their emergency response operations faster and more effective. Most importantly, the availability of these data enables the implementation of machine learning algorithms that can make predictions regarding the emergency situation. Such algorithms may include the detection of smoke or fire and estimations regarding its propagation, the altitude and spread of fire, the identification of the vegetation type. The implementation of such algorithms can provide first responders with insights which would be otherwise hard to get and help them in their operating faster and more effective.

An important and challenging part of the implementation of machine learning algorithms, is the collection and automated processing of multi-sensor data (i.e., data collected from various sensors). The main challenges include a) the identification of the data required to cover the user-needs and that can be used to train algorithms, b) the definition of the data collection process, that is the definition of the methodology for collecting the appropriate data and c) the definition of the process for handling and processing the data collected – this is required since the data collected from sensors can be noisy and inaccurate . This deliverable addresses the above challenges while providing an overview of the state-of-the art approaches in terms of machine learning algorithms and data pre-processing techniques relevant to the identified scenarios of focus in this project: a) fires, b) earthquakes and c) flooding.

This deliverable is structured as follows. First, the machine learning algorithms required for gaining situational awareness are identified. To achieve this, an algorithms elicitation via mapping process is undertaken on the end- user requirements, which have been provided in “Deliverable D.2.1 End-User Requirements”. Then, an overview of existing state-of-the-art algorithms that can fulfil the identified requirements is presented. We identify specific algorithms that can be adapted, extended or improved and potentially included in the AIDERS AI toolkit and significantly improve the situational awareness of first responders. Then, we identify and present available, open-source, datasets which can be used to train machine learning algorithms for the identified tasks. In addition, we present the AIDERS methodology for collecting data and creating a dataset using multi-sensor UAV data. The datasets collected will be instrumental for the training of the machine learning algorithms included in the AIDERS AI toolkit. Third, we present the most prominent approaches in data per-processing such as data cleansing, data editing, data reduction and data wrangling. We discuss their role in producing high quality data and we provide an overview of libraries and tools which can be used to achieve effective data pre-processing. Finally, we provide an overview of the outcomes of projects based on the processing of multi-sensor data in emergency response.

2. Data and Algorithms for situational awareness

The end-users of the AIDERS project provided their needs and requirements to an enquiry undertaken as part of the “Deliverable 2.1 End-users requirements”. The outcomes of this enquiry defined the three main emergency response scenarios the AIDERS project should focus on, being: a) forest fires and industrial fires; b) earthquakes and c) flooding.

First responders as experts in their fields, provided the insights, their experience and expertise on how they make decisions in emergency response. This information is extremely valuable in defining machine learning algorithms, which aim to automate the decision making in emergency response. The automated processing and analysis of data can provide first responders with greater situational awareness while produce the required information of decision making more optimally, with better accuracy, with less resources and in less time. In this section, we provide a mapping between the requirements of the users, the indications they use to make decisions, and the machine learning algorithms that can be defined to produce this knowledge and assist first responders in their operations.

2.1. Requirements to algorithms matching

The sections bellow presents the mapping of the end-user requirements to algorithms that can be implemented using AI and data analytics. The mappings are categorized into the areas of focus of the project.

2.1.1. Forrest fires

User Requirements	Potential Solution using AI and data analytics
I as a first responder, want to be able to know the Fire temperature, **which will indicate the thermal power of the fire. Using this information, I will be able to determine the needs for additional ground means and for aerial reinforcements.**	**Fire temperature prediction**
Fire surface **is important for the distribution and quantification of ground means, especially for the boundaries accessible by forest fire protection paths.**	**Fire surface prediction**
Flame height **will indicate the possible ground means position depending on the fire front but most of all their approach possibilities.**	**Flame height calculation**
Smoke color **shows the combustion evolution of flammable materials; shrubs**	**Decide on the appropriateness of usage of UAVs, based on the color of the smoke,**

and trees; a black smoke often indicates that water is lacking and thus a fire not covered by aerial means.	
Vegetation type **correlates, resource commitment,** spread rate **and probable danger.** **Spread rate brings us back to the issue of anticipation of means and actions to be timely distributed on the event.** **It enables at plus 2 or 3 hours to find the proper attack area by concentrating resources and generating a major attack.** **The main spread axis is the course of the fire, the one enabling to measure the future stakes requiring protection or evacuation.**	**Vegetation type detection.** **Calculation of fire spread rate and axis based on vegetation type.** **Notification of potential danger based on spread rate.** **Estimation of resource commitment.** **Recommendation of fire attack area.**
The presence of dwellings **triggers an accurate assessment of required evacuations.**	**Detection of dwellings.**
The presence of population inside the fire area**; here as well requires a very early commitment of evacuation means and anticipation of emergency shelter.**	**Calculation of population inside fire area.**
The presence of public buildings or parcs **is also the same idea but with more population and foreseeable domino effects.**	**Calculation of number of public buildings and parcs.**
The presence of roads **and their** identification**; here as well it is the access roads to forests, they thus need to be cut as early as possible.**	**Calculation of number of roads.**
Fire mapping, **it informs the command post on fire evolution on a map, it enables to complete fire images and also informs on topography and thus on the spread model in relation to real time weather. The tactic situation is pretty much linked to cartography. It identifies the means on spot, actions carried out and actions planned. It is an operational and strategic commandment tool.**	**Prediction of fire evolution.**
The position of teams and means **on the event scene is intended to guarantee a global coverage of the fire by aerial or ground means.**	**Recommending positioning of teams** for maximized coverage using aerial or ground means.
Real time weather conditions and forecasts: **It is the key information for a good anticipation of actions to be done.**	**Weather forecast**

2.1.2. Urban fires

User Requirements	Potential Solution using AI and data analytics
Cut all energies: This is to avoid electrical or explosion risk.	**Electrical or explosion risk estimation**
Find a good **route for rescuers**: It is to save as much time as possible for rescue arrival.	**Route for rescue detection**
Fire temperature: It is to measure the intensity and assess extension risk.	**Fire temperature calculation**
Ensure **volumetric recognition**: It is to ensure a complete and global vision of the fire (vertical and horizontal propagation).	**Volumetric fire calculation and visualization**
Have an architectural **vision of the building**: It is understanding the structure of the building.	**Building structure calculation and visualization**
Determine **fire spread axes, vertical and horizontal**, it is knowing the path of the smoke.	**Fire spread axis detection** **Smoke path detection**
Detect victims and those threatening to leap into the void: It is about saving as many people as possible.	**Victims detection** **Victims resource recommendation**
Find a **good location for vehicles and aerial ladders** *: Here it is favor fight and rescue efficiency.	**Optimal location of rescue**
Evacuate buildings or ensure safety: This is also to avoid an increase of victims.	**Recommend buildings evacuation**
Have a **global vision of the disaster area**: It is the immediate environment of the intervention area with possible impacts on the functioning of this peripheral zone.	**Disaster area visualization** **Predict impact on peripheral zone**
Spray water or extinguishing agents: It is the actual fight and chosen methods.	**Firefighting approach recommendation (spray water or extinguishing agents)**
Measurement of the **thermal effects on nearby or adjacent buildings**: This is the issue of spread to nearby or adjacent buildings.	**Thermal effects on nearby or adjacent buildings estimation and prediction**

Detect other hot spots out of the hearth: It is identifying the elements which through conduction or convection will participate to fire spread.	**Hot spots detection**
Measure flash-over risks: Smoke and unburnt gases concentrations may appear in areas near the hearth and, without sufficient ventilation, will ignite the whole atmosphere.	**Flask-over risks estimation**
Measure smoke explosion risks (back draft) : It is similar to flash-overs but with a more pronounced oxygen intake: window opening.	**Smoke explosion risk estimation**
Monitor personnel safety	**Personnel safety estimation**
Make sure operational conditions, building entries, intervener position is respected and monitor all elements that can lead to accidents, falling objects, floor or roof collapse…	**Prediction of accidents due to failing objects, floor or roof collapse.**
Detect onlookers	**Detect onlookers**
Make sure **no public is in the marked area.**	**Detect the presence of public in the marked area**

2.1.3. Industrial fires

User Requirements	Potential Solution using AI and data analytics
It is necessary to check combustion toxicity	**Combustion toxicity calculation**
Check products integrated into the combustion process, their possible toxicity and **physio**-chemical changes induced by the combustion.	**Detection of changes in the toxicity and physiochemical structure.**
Heavy response means with strong extinguishing flows	
Test extinguishing efficiency (foams) and conditions of foam carpet.	**Extinguishing efficiency and foam carpet condition calculation**
Implement thermal or visual measurements to contain or vacuum fire extinguishing waters.	
Check nearby water courses.	**Detect nearby water courses**
Establish a security perimeter and a permanent surveillance of the area	**Security perimeter recommendation and permanent surveillance automation**
Have a precise site plan and permanently maintain reconnaissance actions.	**Site plan visualization**

Smoke direction and concentration of toxic particles	**Detect smoke direction.** **Detect concentration of toxic practices.**
Set up perimeter reconnaissance, map propagation cloud, and measure smoke concentrations and opacity**.**	**Fire propagation cloud mapping** **Smoke concentration and opacity measurement.**
Population information	**Provide population information.**
Inform the population, especially within the smoke propagation cone.	**Inform population approach.**
Make sure nearby traffic lanes are cut off.	**Recommend traffic lanes suspension.**
Maintain a permanent weather monitoring. This is to monitor the evolution of the smoke cloud as well as the changes in wind direction and speed. Anticipate thermal inversion effects.	**Weather monitoring and forecast prediction Smoke cloud evolution.** **Change detection for wind speed.** **Thermal inversion effects estimation.**
The exhaustive list of the different **gases and liquids stored on site** or circulating within the industrial process	**Onsite or nearby gases and liquids detection.**
Respiratory protection for all personnel and uses of ATEX materials in areas where flammable or explosive products are stored.	**Recommendation for usage of respiratory protection in flammable areas or nearby explosive products**
The product pipe scheme	**Product pipe scheme estimation**

2.1.4. Flooding

User Requirements	Potential Solution using AI and data analytics
Water height of the flooded area in cm and m.	**Water height estimation**
It identifies **the level of exposure of resident populations** on the territory and the types of means to be committed on the area such as the **types of units to be sent, divers, lifeguards** It also enables to divide the area into sectors for ground, nautical or aerial means.	**Calculation of population near incident** **Recommend number of units required**
Water speed in m/s	**Water speed estimation** **Estimate risk for responders and population** **Recommend type of means to be involved (helicopter, jet ski)**

Altimetry of the **submerged** area. The knowledge of these values enables to anticipate an area that can be flooded with its level of exposure but also to estimate the required pumping equipment to be committed.	**Altimetry calculation** **Flood prediction.** **Estimate required pumping equipment to be committed.**
Altimetry of protection works. It is the estimation of the overflow level and is correlated to the flood forecast at the time of overflow.	**Altimetry calculation.** **Estimate overflow level** **Flood forecast**
Altimetry of the **water line**. It enables to compare it to the altimetry of the territory to detect flood risk areas.	**Altimetry of waterline calculation** **Detect flood risk areas**
Flooded surface. It is the surface of the affected area and thus the measurement of human and material means which need to be implemented.	**Calculate flooded surface** **Recommend human resources and means to be implemented.**
Actual drainage basin. It can be bigger than the topographic drainage basin and integrates the underground water courses feeding the topographic drainage basin. **Hydrographic network.** It is the analysis area of the different water intakes to integrate all the different possible water intakes **Topographic drainage basin.** It is the rain collection basin, which irrigates the drainage basin	**Drainage basin calculation and visualization.**
Presence of a spring in the high water and low water channels. It is to make sure the flow of a course is impacted or not by the presence of springs or groundwater seepage.	**Detection of springs or groundwater seepage.** **Prediction of impact on flow of a course.**
Presence of **water courses** with their **average flow** and **real time flood discharge.** It is the global vision of the instantaneous intakes of all involved flows as well as the forecasts for the next hours.	**Average flow calculation in water courses.** **Forecast of flow for the next hours**
Overflow areas: These are air or ground identified overflow areas. It is eventually possible to calculate an empirical overflow rate or a leakage rate to plan pump capacities. But most of all historical breaches (flood memory). An empirical overflow rate or leak flow can eventually be calculated to anticipate pump capacity.	**Estimate overflow or leakage rate.** **Pump capacity recommendation based on overflow or leakage rate.**
Type and location of hydraulic structures. It is to properly integrate the role and influence of these structures on the considered flood, especially when they are dikes or dams.	**Identify type and location of hydraulic structures**
Soil type and runoff capacity. Presence of karstic zones. They significantly impact flood kinetic (absorption and restitution).	**Karstic zone detection.** **Prediction of flood kinetic variation**

Presence of jams. Important monitoring points to avoid breaches often destructive or deadly.	**Detection of jams**
Presence of **landslides.** It is a soil liquefaction indicator which causes building, bank and hydraulic structure destruction. It should be monitored.	**Detection of landslides**
Real time weather conditions and forecasts. A key data for both crisis management and stake and action anticipation.	**Real time weather conditions calculations and forecast**
Value of water runoff / rainfall and radar. It is the refining of the water runoff value correlated to the water runoff radar and water runoff rainfall.	**Water runoff value estimation** **Correlation between runoff radar and water runoff rainfall**
Associated runoff-rainfall model. It is the transformation of a rain into an expected flow on a drainage basin.	**Associated runoff-rainfall model**
Presence of isolated dwellings in the area. The point is their surveillance and potential evacuation.	**Detection of dwellings.** **Recommendation of potential evacuation.**
Position of urban areas. It is there that rescues, or evacuations are the most performed, where damage and associated costs are highest.	**Detection of urban areas.** **Estimation of damage and associated costs.**

2.1.5. Earthquakes

User Requirements	Potential Solution using AI and data analytics
Existence and location of sensitive sites	**Existence and location of sensitive sites in earthquake affected area**
Detect surface victims: It is the priority of the first rescuers on spot; assistance to victims.	**Detection of victims on surface**
Detect buried victims: It is the extension of rescue actions in a more complex manner.	**Detection of buried victims**
Analysis of collapse types: This enables to assess potential voids for survival, small voids and big voids	**Collapse types classification: voids for survival, small voids, big voids**
Structure evaluation: It means measuring future collapse risks and anticipating evacuations or securing the entire disaster area	**Building collapse risk estimation.** **Recommendation of areas for evacuation or securing.**
Detect eventual gas leaks: It is to avoid explosion risks and thus pile-up accidents.	**Gas leakage detection** **Probability of explosions or pile-up accidents estimation**

Detect vibrations on the collapse site: It is to prevent a replica or a movement of the collapsed area.	**Detection of vibrations on collapse site. Probability of replica or movement of collapsed area estimation.**
Delineate all impacted or destroyed areas: It is the intervention area and therefore the assessment and quantification of resources.	**Damage assessment**
Measure the altimetric variation at T time or minute ground movements: It is to prevent possible aftershocks and to prevent a landslide or additional collapse.	**Calculate altimetric variation in ground movements.** **Estimate probability of aftershocks or landslides or additional collapses**
Check for noises or sounds	**Detect noise or sounds**
Detect life presence, but also ground movement.	**Detect ground movements.** **Detect life presence**
Measure **local radioactivity and electromagnetic field** variations: It is also to prevent a replica risk.	**Local radioactivity measurement electromagnetic field variations.** **Replica risk prediction.**

2.1.6. Explosions

User Requirements	Potential Solution using AI and data analytics
Detect origin	**Explosion origin detection**
Type of product and eventual hazards for population and responders.	**Product type classification** **Hazards for population and responders prediction**
Analysis of **explosion shape**, its **intensity**	**Explosion shape calculation** **Explosion intensity calculation**
Measure their **range**, in order to identify sectors and a map of the observed effects.	**Explosion range detection**
Detect possible **domino effects**	**Domino effects estimation**
Limit the risk of additional accidents such as broken pipes, and impacts on nearby structures (blast effect and missile effect)	**Impact on Nearby structures prediction** **Broken pipes detection**
Detect surface victims and buried victims	**Detection of on surface and buried victims.**
First aid is always the priority, it is necessary to **ensure quick victim assistance**: emergency care and evacuation.	**Recommend victims emergency care.** **Recommend evacuation.**
Evaluate **building resistance**: Always to avoid additional accidents.	**Building resistance estimation.**
Stabilize the collapse or the collapse.	**Collapse stabilization.**

2.2. Requested algorithms summary

In the previous section, we attempted to translate user requirements into requests for AI algorithms that can be implemented to fulfill their needs. After removing duplicates, we resulted with the following list of 30 algorithms demonstrated at Table 1.

In the next section, we provide a short overview for each algorithm with emphasis on how it was implemented and used by other researchers.

Table 1 Definition of requested algorithms

1. Fire temperature prediction
2. Fire surface prediction
3. Flame height calculation
4. Smoke color detection
5. Vegetation type detection.
6. Calculation of fire spread rate
7. Detection of dwellings.
8. Detect and count people
9. Calculation of number of public buildings and parcs.
10. Calculation of number of roads.
11. Prediction of fire evolution.
12. Weather forecast
13. Electrical or explosion risk estimation
14. Route for rescue detection
15. Detect smoke detection
16. Thermal effects on nearby or adjacent buildings estimation and prediction
17. Hot spots detection
18. Smoke explosion risk estimation
19. Prediction of accidents due to falling objects, floor or roof collapse.
20. Detect onlookers
21. Combustion toxicity calculation
22. Detection of changes in the toxicity and physiochemical structure.
23. Extinguishing efficiency and foam carpet condition calculation
24. Detect nearby water courses
25. Fire propagation cloud mapping
26. Smoke concentration and opacity measurement
27. Onsite or nearby gases and liquids detection.
28. Predict toxic product leakages
29. Estimate explosion risk.

3. AI algorithms Overview

This section provides an overview of AI algorithms that can be utilized as part of an AI toolkit and cover the needs of first responder. In particular, we provide a short review of the state-of-the-art approaches for each algorithm and we present selected representative approaches.

3.1. Detecting smoke and flames

Fire disasters are one of the most frequently occurred emergencies and have catastrophic effects for the environment. The early and reliable detection of fires is crucial for preventing unforeseen circumstance, and enables the implementation of evacuation measures, activating fire suppression units and initiating smoke control systems.

Conventional fire detection technologies are based on smoke or heat sensors that collect samples of soot particles, product gas, temperature or radiant heats [1-3]. Machine learning detectors trained and developed based on such sensors, suffer in terms of accuracy, particularly when used in large space or out-door scenes due to the noise and frequent variations in the detectable parameters.

The current state-of-the art approaches in fire detection are based on processing video frames collected from cameras, whether these are stationary, such as part of a Closed-Circuit Television (CCTV) or mobile, for attached on UAVs. These approaches work by capturing images of the observed scene to provide abundant and intuitive information of fire detection using machine learning and image processing algorithms. Using video streams to detect fire evidently provides more reliable and cost-effective information compared to conventional approaches based on heat sensors.

A representative approach in this field, presented by Chen et al., [1] utilized multi-feature fusion-based algorithms for video flame detection. Their approach works by applying background subtraction to extract moving regions, identify foreground objects, use color rules for fire detection and classify the movement of the object as a fire-like object before raising an alarm.

Flame detection open source algorithm are available at https://github.com/liberize/flame-detection-system

An extension of this approach was presented by Bhowmik et al. [4]. In their research paper, they presented an improved approach that utilizes machine learning and claims a maximum accuracy of 0.92 for whole for whole image binary fire detection and a 0.89 accuracy using a machine learning network architecture of significantly reduced complexity. Their approach is based on a Convolutional Neural Network (CNN) which employs a series of convolution and max pull layers as well as layers borrowed from the open-source and well-known model called Inception. An example of their detection is presented below. As shown, the approach can distinguish the fire from the background and track the fire movement in the sequent frames. Their approach is open source available at https://github.com/tobybreckon/fire-detection-cnn

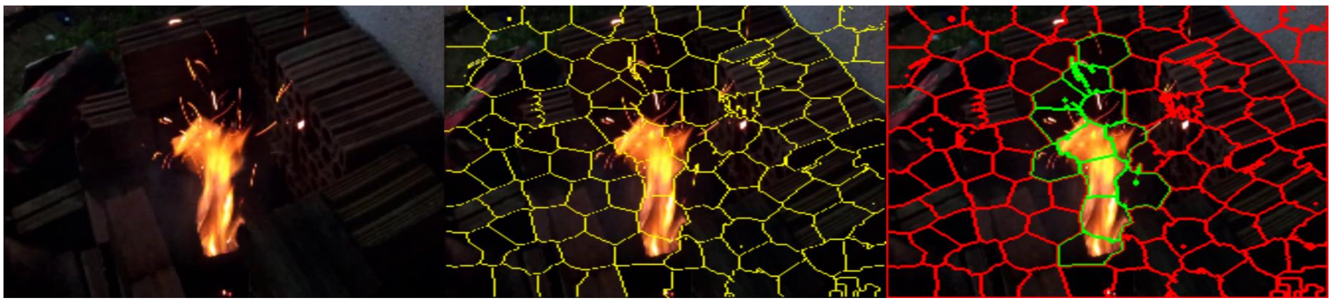

Figure 1 Fire Detection by Bhowmik et al. 2019

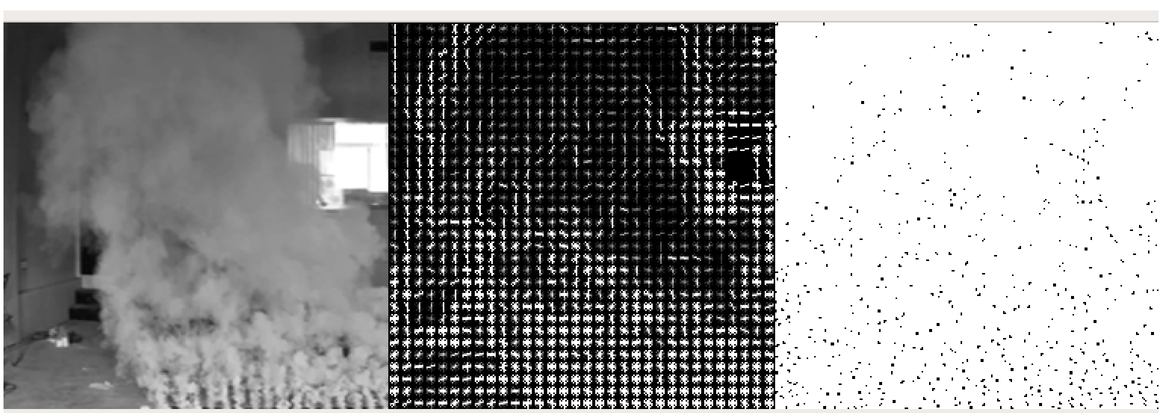

Figure 2 Smoke detection example by Yuan et al.

Smoke detection is a very useful and popular aspect since it can assist as early warning of a fire disaster and provide information regarding the type of the fire [5, 6]. Generally speaking, video-based smoke detection methods distinguish smoke from non-smoke objects based on some distinctive features such as motion, edge, color and texture, and while the majority of the approaches are based on computer vision methods, combining the features detection with machine learning models leads to higher accuracy levels.

For example, Yuan [7], produced extensive research in the areas smoke recognition and smoke density estimation using deep learning. His approach for smoke detection is based on a novel deep multi-scale CNN (DMCNN) for smoke recognition. The basic block consists of several parallel convolutional layers with the same number of filters but different kernel sizes for scale invariance. Each convolutional layer is followed by a batch normalization to normalize the output of the convolutional layer. Then the basic block sums up all normalized outputs from multi-scale parallel layers and activates the sum as the final output of the block. To fully extract scale invariant features, they cascade eleven basic blocks, which are followed by a global average pooling and a 2D fully connected layer. His experimental results provide evidence of higher detection rates, higher accuracy rates and lower false alarm rates when compared to existing methods. His approach is available at https://github.com/ML-Song/Smoke-Detection.

Figure 3 Detecting smoke in images

3.1.1. Building damage assessment and crack detection.

Capturing damage distribution immediately after the occurrence of any natural disaster such as an earthquake or a flood is very important for both emergency management and disaster recovery works. The state-of-the art approaches focus on utilizing aerial photos to carry out building damage assessments and use colors and codes to define the level of visual damage in the buildings. Producing such a map is beneficial for first responders and decision makers involved in the disaster management process since it can help in allocating resources more optimally and producing disaster management plans. In addition, using an automated approach for damage assessment, the first responders and engineers could remain safe, out of any unstable structures and still gather the information they need to perform a detailed damage assessment.

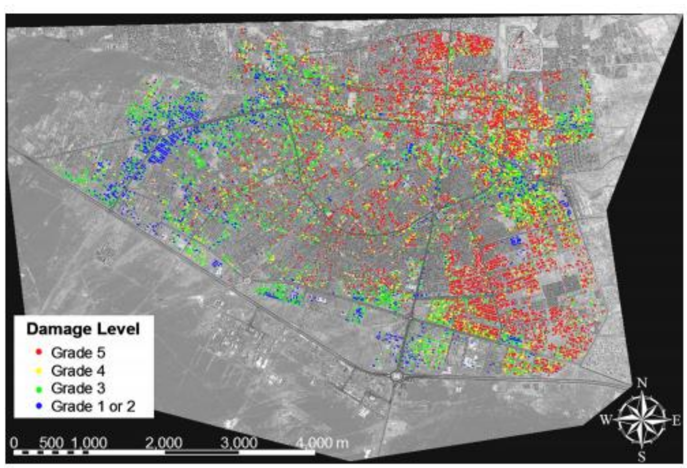

Figure 4 Yamazaki et al. using colour and cods for damage level identification

A representative approach was presented by Torok et al. [8], who produced an image based automated 3D crack detection approach for producing a post-disaster building assessment. Their approach assumes that if an element of a building (e.g., a column) is undamaged, its surface normal should be perpendicular to the element's axial direction. An undamaged element can have any consistent cross-section, On the other hand, if an element is damaged, then some of its surface normal should not be perpendicular to the element's axial direction

Figure 5 Cracks detected by the approach suggested by Young-Jin Cha and Wooram Choi

Cha et al. [9] produced a machine learning, deep-learning approach in particular, for detecting crack in images using Convolutional neural networks. Their CNN architecture includes various layers. The first layer is the input layer of 256 × 256 × 3-pixel resolutions, where each dimension indicates height, width, and channel (e.g., red, green, and blue), respectively. Input data pass through the architecture and are generalized with spatial size reduction to 1×1×96 at L5. The vector, including the 96 elements, is fed into the rectified linear unit (ReLU) layer. Finally, the SoftMax layer was included to predict whether each input data is a cracked or intact concrete surface after the convolution. BN and dropout layers were also included although they were not visualized into their architecture. The model was trained on 40K labeled images of 256 x 256 in combination with a sliding window technique and recorded accuracies of 98.22% out of 32K images and 97.95% out of 8K images in training and validation respectively.

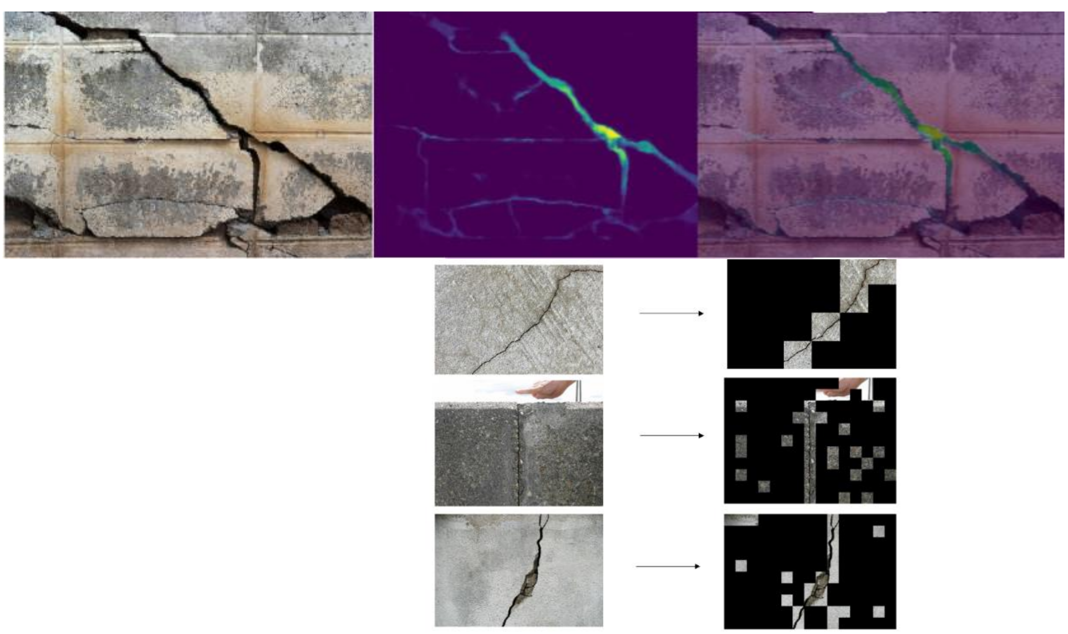

Figure 6 Cracks detected by the approach suggested by Cha et al. 2017

An interesting and very promising approach in the area of crack detection was presented by Zhang et al.[10]. In their approach, they tried to handle the noise introduced in the images by the nature, such as the distinguish of a crack from a tree, title lines and other noise introduced by the reality of the photos. Their suggested model, is based on building a network using transfer learning on two popular deep learning models evidently effective in other detection and classification tasks: VGG16 and Resnet 101. In particular, their proposed crack detection method consists of two steps: image classification and image segmentation. Firstly, an image is classified as either positive or negative using a deep convolutional neural network. The positive images are then processed using an adaptive thresholding method. The cracks in the positive images can therefore be extracted. In their experimental results they provide evidence of precision of the image classification task of 99.92% while their pixel-level segmentation accuracy is around 98.70%.

3.2. Search and Rescue

3.2.1. People Detection

Detecting people is very important in any emergency response scenario. Whether first responders have an emergency search and rescue mission, such as looking for missing people in a forest or any other emergency situation such as fire, flooding or earthquake, saving people lives is always the first priority. Detecting people can be extremely challenging for both human observers and machine learning algorithms [11]. The challenge is more pronounced when the visibility is restricted due to smoke or darkness, when people are hidden/ have fallen on the ground or when people are in the sea.

To overcome these barriers, state-of-the art approaches train machine learning approaches using multi-sensor data. That is, utilizing streams received by multi-spectral cameras, using depth sensors or combining thermal and conventional RGB cameras. In this section we overview of selected state-of-the-art, representative approaches for effective people detection.

3.2.2. Fallen Person Detection

Fallen person detection systems typically utilize cameras and are based on computer vision algorithms, that use some form of background subtraction to firstly distinguish between the environment and the person and secondly reason whether a person is fallen. For example, T. Lee and A. Mihailidis [12] used a ceiling mounted camera to detect full body images using background subtraction. However, there approach is limited in identifying only one person and cannot detect occluded people. Cucchiara et al. [13], address the issue of occlusion using a multi-camera setup and a trained classification model.

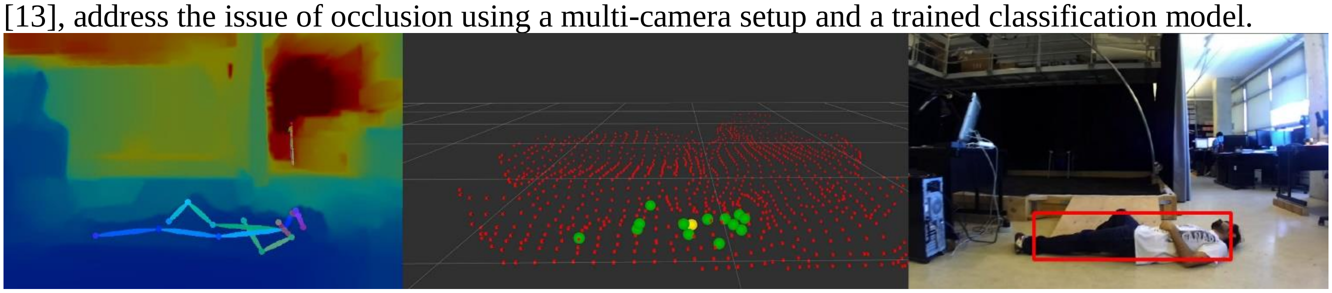

Figure 7 Vision-Based Fallen Person Detection

Significant improvement in fallen person detection was made possible only after combining background extraction with human pose estimation. For example, Solbach and Tsotsos [14] used only a single camera to sense the environment yet they combine it with human pose estimation algorithms. In particular, they employed a Convolutional Neural Network (CNN) based human pose estimator that utilizes the camera data to reconstruct the human pose in 3D and estimate the ground plane in 3D, as shown in Figure 2. They evaluated their approach in different scenarios and in the homes of elderly people in particular. According to their evaluations, the system produced high accuracy and nearly classified correctly all the detections. Their code and data are available at https://github.com/TsotsosLab/fallen-person-detector.

3.2.3. Multispectral Pedestrian detection

Pedestrian detection is an active research area in the field of computer vision and it is essential and significant for any surveillance or tracking system, for pedestrian safety and very applicable in emergency response scenarios. Although it has been extensively studied and various methods have been suggested, it is still regarded as a challenging problem, limited by tiny and occluded appearances, cluttered backgrounds and bad visibility at night.

To address these challenges, Hwang et al. [15], developed a multi-spectral pedestrian dataset which provide thermal and color image sequences captured by multi-spectral cameras. Through the experiments they conducted, they provided evidence of the potential of the joint use of color-thermal images when training machine learning detectors. The effectives of using multi-sensor data was evident in both day and night settings and examples are presented below. Their approach is available as open source at https://github.com/Li-Chengyang/MSDS-RCNN

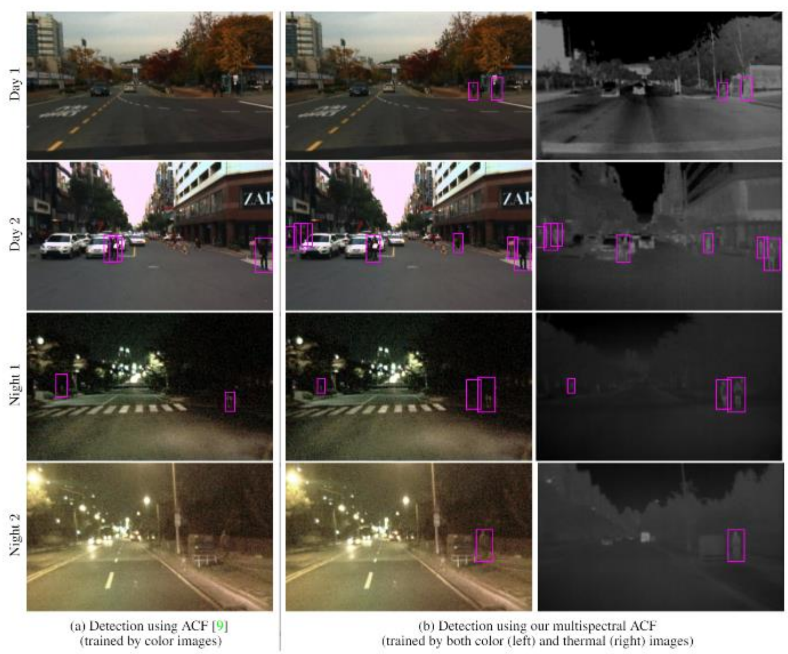

Figure 8 Multispectral pedastrian detection by Hwang et al.

3.2.4. Water level identification

One of the needs of first responders for improving their effectiveness in emergency response in the events of flooding was water level identification. This can be achieved by producing accurate surface water maps, typically achieved using water segmentation.

One of the most prominent approaches in water segmentation is the deep learning approach suggested by Isidogan et al. [16] Their model is able to learn both spatial and spectral characteristics of water bodies using satellite images. The model consists of various layers including both downscaling and upscaling units and accepts both raw and radiometrically calibrated images as input and can segment water on images collected from different sensors, having overlapping but not identical spectral bands.

In 2019, the model produced by Isidogan [16] et al, produce a 0.97 precision in classifying water segments and outperformed all previous approaches. An example of the output produce from their model is presented below. Their approach is publicly available at https://github.com/isikdogan/deepwatermap.

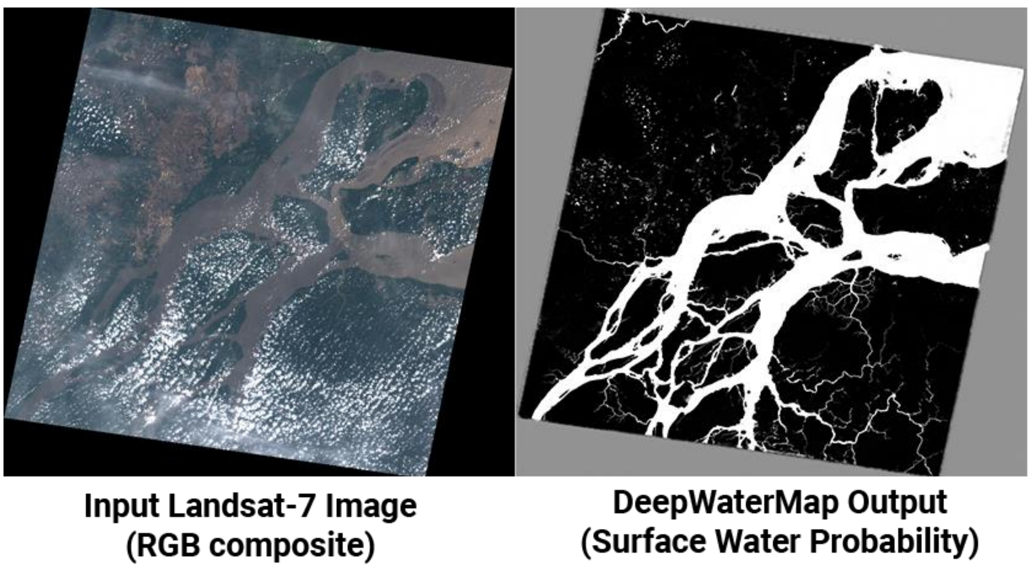

Figure 9 Water level segmentation by Isidogan et al.

4. Review of data pre-processing techniques

Data pre-processing is a critical step in any data analysis process. Data acquisition methods and tools are often loosely controlled, possibly resulting in out-of-range values (*e.g.*, altitude: −100), impossible data combinations (*e.g.*, Battery: 0%, Mode: Inflight), missing values, etc. Analyzing data that has not been carefully screened for such problems can produce misleading results. Thus, the representation and quality of data is the first and foremost concern before running an analysis. Therefore, data pre-processing is considered as the most important phase of a machine learning project, in particular when dealing with mission-critical systems.

If there is too much irrelevant and redundant information present or noisy and unreliable data, then knowledge discovery during the training phase is more difficult. Data preparation and filtering steps can take considerable amount of processing time. Data pre-processing includes cleaning, Instance selection, normalization, transformation, feature extraction and selection, etc. The result of data preprocessing is the final training set.

4.1. Pre-processing tasks

4.1.1. Data cleansing

Data cleansing or *data cleaning* is the process of detecting and correcting (or removing) corrupt or inaccurate records from a record set, table, or database and refers to identifying incomplete, incorrect, inaccurate or irrelevant parts of the data and then replacing, modifying, or deleting them. Data cleansing may be performed interactively with data wrangling tools, or as batch processing.

4.1.2. Data editing

Data editing is defined as the process involving the review and adjustment of collected survey data. The purpose is to control the quality of the collected data. Data editing can be performed manually, with the assistance of a computer or a combination of both.

4.1.3. Data reduction

Data reduction is the transformation of numerical or alphabetical digital information derived empirically or experimentally into a corrected, ordered, and simplified form. The basic concept is the reduction of multitudinous amounts of data down to the meaningful parts.

When information is derived from instrument readings there may also be a transformation from analog to digital form. When the data are already in digital form the 'reduction' of the data typically involves some editing, scaling, encoding, sorting, collating, and producing tabular summaries. When the observations are discrete but the underlying phenomenon is continuous then smoothing and interpolation are often needed. Often the data reduction is undertaken in the presence of reading or measurement errors. Some idea of the nature of these errors is needed before the most likely value may be determined.

4.1.4. Data wrangling

Data wrangling, sometimes referred to as *data munging*, is the process of transforming and mapping data from one "raw" data form into another format with the intent of making it more appropriate and valuable for a variety of downstream purposes such as analytics.

This may include further munging, data visualization, data aggregation, training a statistical model, as well as many other potential uses. Data munging as a process typically follows a set of general steps which begin with extracting the data in a raw form from the data source, "munging" the raw data using algorithms (e.g. sorting) or parsing the data into predefined data structures, and finally depositing the resulting content into a data sink for storage and future use.

4.2. Pre-processing libraries

Following the above classification of data pre-processing tasks, state-of-the-art toolkits are offering reusable libraries to process raw input data, depending on their class.

For image pre-processing, SciKit-Image (https://scikit-image.org/)[1] is an open-source image processing library for the Python programming language. It includes algorithms for segmentation, geometric transformations, color space manipulation, analysis, filtering, morphology, feature detection, and more. It is designed to interoperate with the Python numerical and scientific libraries NumPy and SciPy.

For video stream pre-processing, OpenCV (*Open Source Computer Vision Library*, *https://opencv.org/*) is a library of programming functions mainly aimed at real-time computer vision.

For discrete data, Scikit-learn (https://scikit-learn.org/) is a free software machine learning library for the Python programming language. It features various classification, regression and clustering algorithms including support vector machines, random forests, gradient boosting, k-means and DBSCAN, and is designed to interoperate with the Python numerical and scientific libraries NumPy and SciPy. The toolkit encloses various pre-processing algorithms : https://scikit-learn.org/stable/modules/preprocessing.html

Summary. As part of the AIDERS project, the consortium aims to leverage state-of-the-art algorithms and existing libraries to process incoming data streams forwarded by drones and other sources of information. We therefore intend to establish bindings with these tools and fusion the resulting data into a common knowledge representation that can be rendered to the first responders with an appropriate visualization.

[1] Stéfan van der Walt, Johannes L. Schönberger, Juan Nunez-Iglesias, François Boulogne, Joshua D. Warner, Neil Yager, Emmanuelle Gouillart, Tony Yu and the scikit-image contributors. scikit-image: Image processing in Python. PeerJ 2:e453 (2014) https://doi.org/10.7717/peerj.453

5. Datasets

5.1. Publicly available datasets for emergency response.

Datasets for building software systems and algorithms are made public through their usage in online competitions or as part of open access policies in researcher. In this section, we overview some of the datasets we identified as useful and applicable to the DG ECHO AIDERS project. The datasets are categorized based on the type of emergency mission and extensive details are provided regarding their structure and format.

5.1.1. Fire

There are various datasets available for training models to predict forest fires, their burned area, detect smoke both from stationary cameras and UAVS. In this section, we present some representative datasets which have been used in machine learning competitions and in research and are applicable for the purposes of the DG ECHO AIDERS project.

Dataset 1 - Predicting forest fires f2019

The predicting forest fires dataset was compiled in 2019 and was made available at the Kaggle platform to promote and attract the development of machine learning algorithms for forest fire prediction. The dataset is provided in Comma Separated Values (csv) files and is separated into training, testing and validation sets. The table below provides a summary of the variables included in the dataset. The dataset is publicly available at https://www.kaggle.com/c/predicting-forest-fires-f2019/overview.

Variable	Description
X	x-axis spatial coordinate within the Montesinho park map: 1 to 9
Y	y-axis spatial coordinate within the Montesinho park map: 2 to 9
Month	month of the year: "jan" to "dec"
day	day of the week: "mon" to "sun"
FFMC	FFMC index from the FWI system: 18.7 to 96.20
DMC	DMC index from the FWI system: 1.1 to 291.3
DC	DC index from the FWI system: 7.9 to 860.6
ISI	ISI index from the FWI system: 0.0 to 56.10
temp	temperature in Celsius degrees: 2.2 to 33.30
RH	relative humidity in %: 15.0 to 100
wind	wind speed in km/h: 0.40 to 9.40
rain	outside rain in mm/m2 : 0.0 to 6.4

area	the burned area of the forest (in ha): 0.00 to 1090.84 (this output variable is very skewed towards 0.0, thus it may make sense to model with the logarithm transform).

Dataset 2 – Wildfire smoke detection

Image and Video smoke detection datasets were produced and made publicly available by Center for Wildfire Research of University of Split in Croatia. The datasets have been made available freely to foster the development and testing of wildfire smoke detection. The data are available organized into geotagged images and video are available at http://wildfire.fesb.hr/index.php?option=com_content&view=article&id=62:image-and-video-databases&catid=35:articles&Itemid=72 .

Dataset 3 – Forest fire through UAV imagery

Images collected from UAVs during forest fires have been compiled into a dataset and made available through the “LeadingIndiaAI” initiative. This initiative is a UK nationwide initiative that has been approved by Royal Academy of Engineering, UK under Newton Bhabha Fund with goal to promote "AI and deep learning Skilling and Research". The dataset includes images and is organized into “fire” images and “no fire” images with the first section including images that contain a fire and the second images in which no fire appears. The dataset is available at GitHub at https://github.com/LeadingIndiaAI/Forest-Fire-Detection-through-UAV-imagery-using-CNNs

5.1.2. Earthquakes

Dataset 1 - Predicting magnitude and depth of Earthquakes in Philippine.

This dataset is part of the United States Geological Survey database, limited to just PH earthquakes and it made available from the “Women Foundation Machine Learning” for the purposes of their hackathon hosted at the Kaggle platform. The dataset is provided in CSV files and contains various fields such as latitude and longitude, place, magnitude and others .The dataset is available at https://www.kaggle.com/c/model-the-impossible-predicting-ph-earthquakes

Dataset 2 - Predicting earthquakes

This dataset was made available by the Los Alamos National Laboratory through a Kaggle Competition. The Los Alamos National Laboratory enhances national security by ensuring the safety of the U.S. nuclear stockpile, developing technologies to reduce threats from weapons of mass destruction, and solving problems related to energy, environment, infrastructure, health, and global security concerns.
The competition was initiated to foster the development of algorithms that can predict when an earthquake will take place. Specifically, it was focused on predicting the time remaining before laboratory earthquakes occur from real-time seismic data. The dataset is available at https://www.kaggle.com/c/LANL-Earthquake-Prediction

The training data are provided as a single, continuous segment of experimental data. The test data consists of a folder containing many small segments. The data *within* each test file is continuous, but the test files do not represent a continuous segment of the experiment; thus, the predictions cannot be assumed to follow the same regular pattern seen in the training file. A description of the variables included in the dataset are presented below.

Variable	Description
acoustic_data	the seismic signal [int16]
time_to_failure	the time (in seconds) until the next laboratory earthquake [float64]
seg_id -	the test segment ids for which predictions should be made (one prediction per segment)

Dataset 3- Earthquake damage assessment.

The dataset mainly consists of information on the buildings' structure and their legal ownership. Each row in the dataset represents a specific building in the region that was hit by Gorkha earthquake. This dataset was developed to initiate the development of algorithms that can predict level of damage to the building that was hit by the earthquake. The damage can be represented in three levels: 1 - represents no damage, 2 - represents a medium amount of damage and 3- represents almost complete destruction. The dataset contains the following variables and additional variables that represent superstructures and are available in the website of the dataset at https://www.kaggle.com/c/datacept-earthquake-damage

Variable	Description
geo_level_1_id, geo_level_2_id, geo_level_3_id	(type: int): geographic region in which building exists, from largest (level 1) to most specific sub-region (level 3). Possible values: level 1: 0-30, level 2: 0-1427, level 3: 0-12567.
count_floors_pre_eq	(type: int): number of floors in the building before the earthquake.
age	(type: int): age of the building in years.
area_percentage	(type: int): normalized area of the building footprint.
height_percentage	(type: int): normalized height of the building footprint.
land_surface_condition	(type: categorical): surface condition of the land where the building was built. Possible values: n, o, t.
foundation_type	(type: categorical): type of foundation used while building. Possible values: h, i, r, u, w.
roof_type	type: categorical): type of roof used while building. Possible values: n, q, x.
ground_floor_type	(type: categorical): type of the ground floor. Possible values: f, m, v, x, z.
position	(type: categorical): position of the building. Possible values: j, o, s, t.

5.1.3. UAVs collected dataset

Dataset 1- UAVs Point clouds

This dataset includes files of Point clouds (in ply extensions) generated by UAVs. In particular, the dataset contains three 3D point clouds, generated by a fixed wing UAV equipped with downward looking camera. The three-point clouds files capture the same area and have been acquired and generated on three different days.

These point clouds were primarily acquired to detect, and count trees present at the location

The data are available at https://www.kaggle.com/ahmadkamalnasir/3d-point-clouds/data#

5.2. The AIDERS dataset creation methodology

During the AIDERS project, datasets will be created to enable the development of AI algorithms for emergency response. In this section, we describe the methodology followed for the development of the first dataset to train ML algorithm that can detect the presence of a fire, smoke and predict its propagation.

The data is collected by flying two UAV on top of specified rectangle area. In this area, we initiated a small fire and the two UAVs will be flying on top of the area while recording their altitude, latitude, longitude and while taking pictures with a downfacing camera and recording the wind direction and levels

The dataset produced includes various variables, we briefly provide the most important in the table below.

Variable	Description
timestamp	The current time
altitude	The height of the drone from the sea level
heading	The direction of the drone
longitude	The longitude of the drone
latitude	The latitude of the drone
Heading	The direction of the drone
Battery level	The battery level of the drone
barometer	The recorded barometer
Wind direction	The direction of the wind
Wind speed	The speed of the wind in terms of Beaufort.
Payload data	Sensor readings from RGB camera or thermal camera?
Accelerometer	The current speed of the drone
Angular Velocity XYZW	The velocity of the drone
Orientation XYZW	The orientation of the drone

In addition, we provide the following data visualizations produced as indicative of the data collected. These visualizations serve as a) a validation of the correct data collection process, b) an approach to explore the potential provided by the data and c) design and develop software solutions that can visualize the data in easy to use and easy to understand manner.

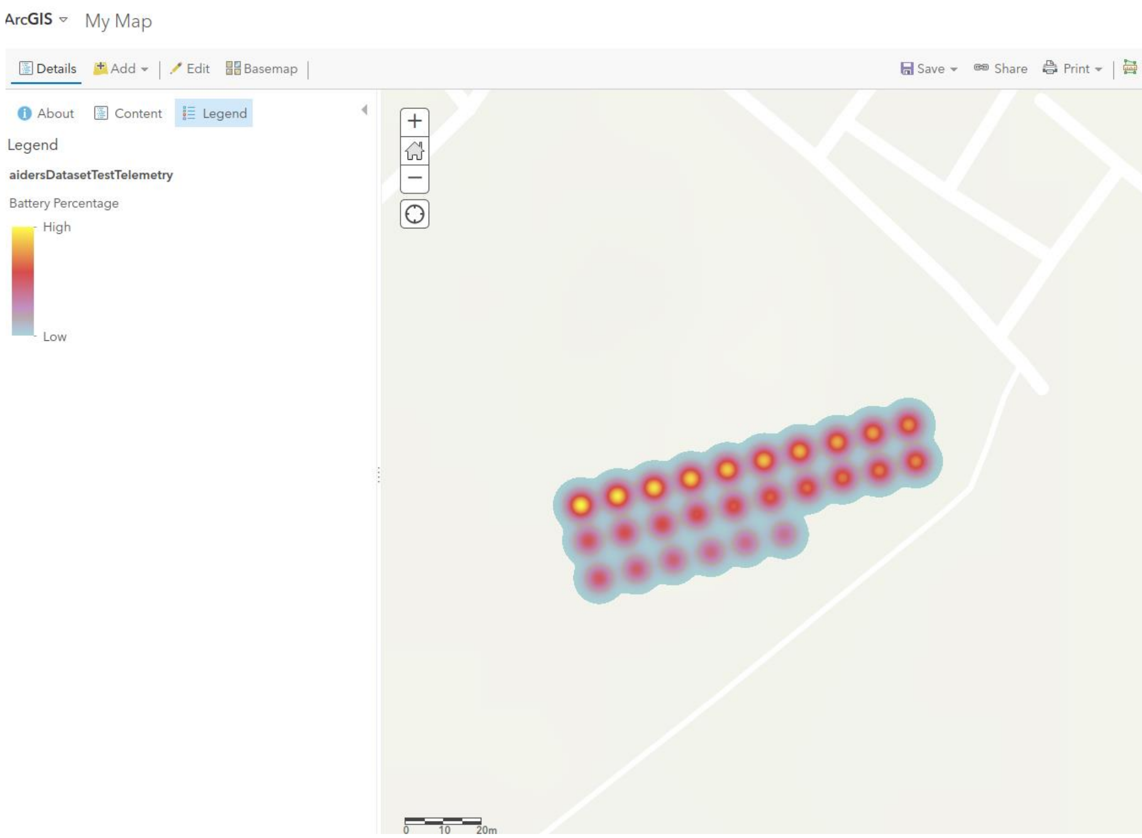

Figure 10 Indicative visualisation of the battery levels of the drones while monitoring an area using one of the datasets collected during the AIDERS datasets collection process.

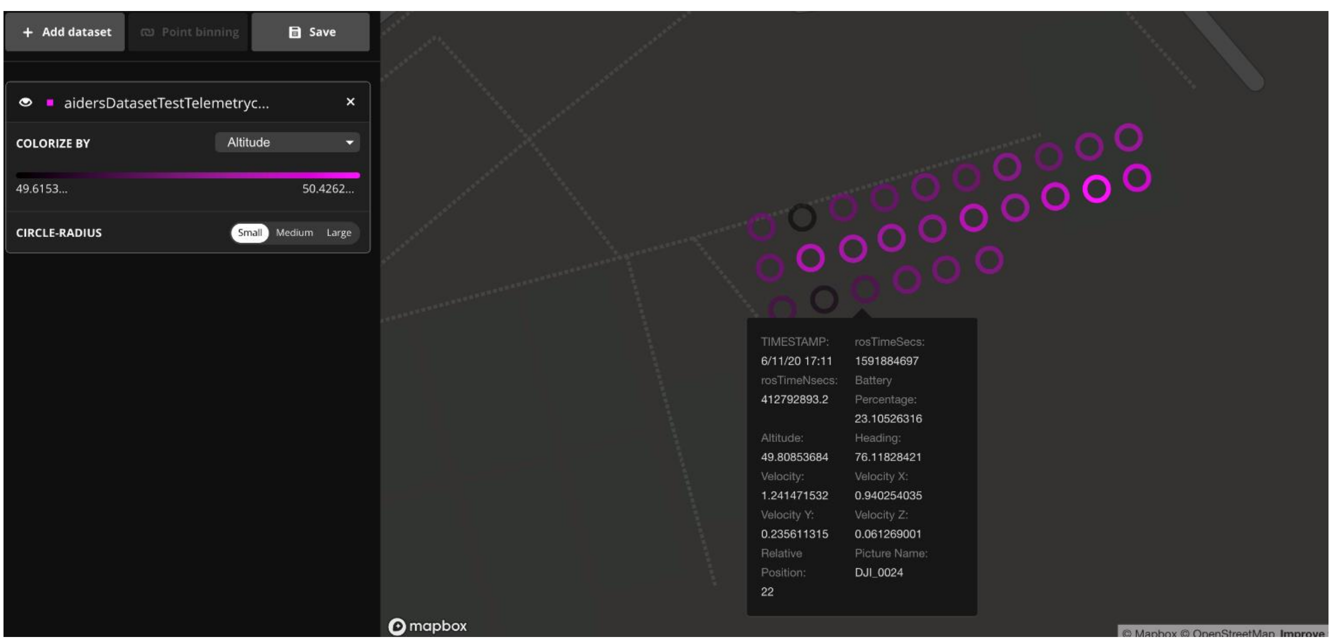

Figure 11 Indicative visualisation of the telemetry of the UAV during a monitoring area trial for the purposes of the AIDERS project

6. Review of applications of multi-sensor data and AI in emergency response.

This section provides a review of existing systems and projects that aim to utilize data and AI to help first responders and improve emergency response. For each of the projects/systems identified we provide the sensors used to collect the data and a short description of the methodology and outcomes.

6.1. General

Name	Provider	Sensors	Short Description
FASTER	https://www.faster-project.eu/	optical and thermal cameras, environmental, nuclear, biological, chemical, radiological and explosives	FASTER will develop a set of tools towards enhancing the operational capacity of first responders while increasing their safety in the field. It will introduce Augmented Reality technologies for improved situational awareness and early risk identification, and Mobile and Wearable technologies for better mission management and information delivery to first responders. Body and Gesture based User Interfaces will be employed to enable new capabilities while reducing equipment clutter, offering unprecedented ergonomics. Moreover, FASTER will provide a platform of Autonomous Vehicles, namely drones and robots, aiming to collect valuable information from the disaster scene prior to operations, extend situational awareness and offer physical response capabilities to first responders. FASTER will gather multi-modal data from the field, utilizing an IoT network, and Social Media content to extract, either locally or in the cloud, meaningful information and to provide an enhanced Common Operational Picture to the responder teams in a decentralized way using Portable Control Centers. It will additionally use blockchain technology to keep track of needs and capabilities using smart contracts for maximum efficiency.
OSIRIS	https://cordis.europa.eu/project/id/033475	fire detectors, cameras, water and ground pollution sensors, etc.	OSIRIS (Open architecture for smart and interoperable networks in risk management based on in-situ sensors) was a FP6 project funded by the European Commission. The project focused on integrating and providing access to various types of sensors (fire detectors, cameras, water and ground pollution sensors, etc.) based on one common service-oriented architecture.
DITSEF	https://cordis.europa.eu/project/id/225404	CBRN, fire detections, optical and thermal cameras, Tactical belt, SLAM radar, head	The main problem of First Responders (FR) (fire fighters, police, etc...) in case of crisis at critical infrastructures are the loss of communication and location and the lack of information about the environment (temperature, hazardous gases, etc.). Therefore, during the intervention, there is a gap between the First responders' situation (positioning, health, etc) and the overall view of at their mobile headquarter. DITSEF aims at increasing the effectiveness and safety of First Responders by optimal information gathering and sharing with their higher command levels.

		orientation sensor, External temperature sensor, Attitude sensors	
TOXI-triage	http://toxi-triage.eu/content/project-facts	CBRN, optical cameras, IR cameras	TOXI-triage project addresses the operational, technological, ethical and societal dimensions of CBRN response and recovery, and importantly the economic base from which sustainable CBRN and multiuse systems are derived. The approach defines a concept of operations that envisages accelerated delivery of situational awareness through an ensemble of embedded sensors, drones, standoff detectors (including cameras), artificial intelligence for processing sensor signals and web-traffic from social media, and centralized command and control. Wireless traceability of casualties provides dynamic mapping including medical care. Distinctive technological attributes of TOXI-triage include: Rapid non-invasive assessment of exposure/ injury through monitoring metabolic markers of injury, Managing and exploiting the semantic web, Traceability by design, Aptamer-based biosensing, Casualty-to-discharge system integration, Integrated environmental and stand-off hazard designation

6.2. Industrial and Forest fires

Name	Provider	Sensors	Short Description
FIRESENSE	www.cordis.europa.eu/project/id/244088/reporting	optical cameras, infrared cameras at different wavebands, passive infrared (PIR) sensors, wireless sensor network of temperature, humidity sensors and local weather stations on the deployment sites	In the context of the FIRESENSE project, an automatic early warning system integrating multiple sensors to remotely monitor areas of archaeological and cultural interest for the risk of fire and extreme weather conditions was developed. The signals and measurements collected from these sensors are transmitted to the control center, which employs intelligent computer vision and pattern recognition algorithms as well as data fusion techniques to automatically analyze and combine sensor information and detect the presence of fire or smoke.
FERMIS	www.fermis-project.eu	Relative Humidity, Temperature, Wind Direction, Wind Speed, Gasses, Camera, Hybrid color, Thermal Sensor (IR)	Firefighting, by detection, prevention, monitoring and analysis is commonly based on estimations made by experts from visual observations and data provided from ground stations, satellites and other means. The evolution of Unmanned Aerial Vehicles (UAVs) technologies, the miniaturization of sensors and the new advances in communication and control systems have extended UAV technology to a wide range of civilian applications such as fire detection, localization and observation. FERMIS aims to fulfill the expectations and needs of the market for the next generation of Airborne sensors, by providing a complete set of tools and sensors that will improve current supported UAV features and will further expand them into "multi-sensing flying platforms".
SmokeBot	www.smokebot.eu	LIDAR, optical camera, novel 3D radar camera, stereo thermal camera, and high-bandwidth gas sensors	SmokeBot will exploit the complementary characteristics of different sensor modalities to develop sensor fusion based mapping approaches, which allow to build detailed models of the environment despite limited visibility conditions. To render high resolution maps of the environment, the robot will integrate sparse patches - delivered by traditional sensors in robotics (laser range finder and camera) when they glimpse through smoke or dust - with radar depth measurements. Based on input from thermal cameras and range sensors we will develop methods to truthfully map surface temperatures onto 3D structures in the environment. Sensor fusion will be crucial to be able to handle reflections and gas radiation. We will also investigate how thermal imaging can aid localization so as to make the developed approach to SLAM in feature-sparse environments more robust.
SmokeD	www.smokedsystem.com	optical camera, thermal camera, gas sensors	The SmokeD Early Wildfire Detection System by IT for Nature is unparalleled in its ability to provide near real-time surveillance and rapid detection of wildfires in forest areas. The SmokeD detectors are sophisticated devices intended for early fire detection and an immediate notification of users about their occurrence. For that purpose, artificial intelligence (AI) has been applied resulting in fast, effective, and accurate detection of smoke and flames up to 10 miles.

6.3. Earthquakes

Name	Provider	Sensors	Short Description
INACHUS	www.inachus.eu	Radar, Mobile Phone Detector (MPD), LIDAR, infrared cameras, optical cameras, chemical sensing, vibrometry	The various components of the INACHUS framework will work in close cohesion and an interoperable manner to provide an innovative end-solution for assisting first responders in rapidly locating disaster victims inside collapsed structures. Specifically, the INACHUS simulation and visualizations methods will provide accurate prediction models of collapsed structures allowing the best assessment of survival spaces, and the determination of rescue routes for fast access to survivors and their safe extraction. Furthermore, the innovative sensing elements will determine the maximum likelihood of surviving humans using a combination of elements, such as radar, chemical sensing, vibrometry, motion detection, IR cameras, and mobile phone detection. Easier access to the survivor locations will be achieved by the snake robot.
TURNkey	www.earthquake-turnkey.eu	automated damage detection, forecast, cameras, Mobile Phone Detector, infrared cameras	The development of the TURNkey multi-sensor unit and the cloud-based TURNkey FWCR platform, which will, for the first time, consolidate currently widely-dispersed tools within a ready-to-deploy system, which is also easily customizable, for a tangible real-time earthquake risk reduction. The sensors of the multi-sensor-based earthquake information system and TURNkey platform will provide multiple possibilities for applications within OEF and EEW as well as for RRE. The overall purpose of the sensors and platform is to serve the public, authorities and stakeholders as a new tangible, cost- effective and easy-applicable tool, which will lead to a significant reduction in uncertainties regarding seismic hazard and structural vulnerabilities.
A Distributed Multi-Sensor Machine Learning Approach to Earthquake Early Warning	https://www.unavco.org/projects/major-projects/earthcube/geosciframework/Fauvel_etal_AAAI2020_Distributed_Multi-Sensor_Machine_Learning_Approach_to_Earthquake_Early_Warning.pdf	GPS stations and seismometers	The research aims to improve the accuracy of Earthquake Early Warning (EEW) systems by means of machine learning. EEW can be seen as a typical classification problem in the machine learning field: multi-sensor data are given in input, and earthquake severity is the classification result. In this paper, it is introduced the Distributed Multi-Sensor Earthquake Early Warning (DMSEEW) system, a novel machine learning-based approach that combines data from both types of sensors (GPS stations and seismometers) to detect medium and large earthquakes. DMSEEW is based on a new stacking ensemble method which has been evaluated on a real-world dataset validated with geoscientists. The system builds on a geographically distributed infrastructure, ensuring an efficient computation in terms of response time and robustness to partial infrastructure failures.

Multisensor surveys of tall historical buildings in high seismic hazard areas before and during a seismic sequence	www.earth-prints.org/handle/2122/12715	terrestrial laser scanning, geophysical measurements, thermal	A seismic sequence that included a moment magnitude M-W = 5.9 earthquake struck three regions of Northern Italy (Emilia Romagna, Veneto and Lombardy) in May-June 2012. The sequence caused significant damage to several historical buildings and in some cases caused complete structural collapse. Cracks appeared in the belfry and cusp of the 69 m high, similar to 3 degrees leaning bell tower of Ficarolo (Rovigo). A project aimed at studying the geometry of the tower, possible local seismic amplification and soil-structure interaction began in early 2013 before the earthquake. The data were provided by terrestrial laser scanning, low-cost operational modal analysis and geophysical measurements. The repetition of the surveys during and after the seismic sequence, which was augmented by thermal imaging measurements, allowed an evaluation of the changes caused by the earthquake. In addition to an evaluation of the damage, the data allowed the development of a method based on fast and relatively low-cost measurements that provide useful information for cultural heritage management purposes. The results highlighted that the surveys can be carried out during a seismic emergency and that preventive measures can be carried out under reasonable time and budget constraints in high seismic hazard areas.

6.4. Search and Rescue

Name	Provider	Sensors	Short Description
DARIUS	www.cordis.europa.eu/project/id/284851	Chemical sensor, optical camera, infrared camera	The DARIUS (Deployable SAR Integrated Chain with Unmanned Systems) project will leverage previous R&D efforts on technologies and possible added value of unmanned systems for situation awareness to envisage their adaptation and integration in complex multi-national/agency SAR operations. The main objective of DARIUS is to reach effective levels of interoperability so these systems can be shared between several organizations. DARIUS will adapt existing unmanned systems and their payloads (air, ground and maritime) to the specificities of Search and Rescue missions. The expected impact from DARIUS is the better integration of the systems in real operations and in enhancing the safety of citizens.
SARA	www.thesaraproject.eu	optical sensor, EO satellite data, Thermal	SARA solution is conceived to build up a semi-automatic system using Earth Observation data to preliminary detect suspect pontoons' trajectories (Surveillance) and supporting SAR operations based upon a deployable RPAS (Remotely Piloted Aircraft System) which is tightly coupled with a ship architecture through a cable (tethered flight): as soon as its function is needed, the aircraft flies from its home (a dedicated hangar on the top of the ship), and becomes a "virtual pylon" which elevates a VIS-TIR sensor (Visual Spectrum and Thermal Infrared); captured images are processed in real time by a local computer. Both RPAS and hangar are equipped with 2 high accuracy EGNSS receivers (i.e. Galileo ready) in order to provide the relative positioning between the hangar and the RPAS hovering on the target.
SGL FOR USAR	www.cordis.europa.eu/project/id/217967	Optical and audio sensors, Thermal and visual (wide angle) cameras, Five gas sensors, Ion Mobility Spectrometer	SGL for USaR concept is structured around the development of man-portable devices and network of sensors as resource multipliers and search accelerators that are managed by a field deployable command and control center. The project is based on three pillars: detection and identification of multi-type human signatures in entrapment, integration of multiple sensing elements into operational devices and development of a platform for managing resources and data. The project developed innovative portable devices and probes for locating entrapped victims and continuously monitoring the conditions in the voids. This novel, integrated approach has been organized around multi-sensory localization systems and devices supported by a command and control framework.
SWIFTERS	www.kios.ucy.ac.cy/swifters	optical camera, infrared camera	The main output of the proposed action will be a software package, which will be released under open-source license, featuring emergency operation planning capabilities enabled by UAV swarms such as task allocation to individual UAVs of the swarm (e.g., monitoring emergency event progress, identifying stranded survivors, marking the evacuation path, etc.), and path planning for each UAV. In addition, detailed training material and procedures will be developed through SWIFTERS to enable the consortium partners (3 Civil Protection organizations and 2 Research Institutes) and other interested parties to master the skills on UAV operations and familiarize in using the automated features proposed within SWIFTERS through small, medium and large scale exercises.

7. Conclusion

This deliverable provided fundamental insights in collecting and utilizing multi-sensor data for the purposes of developing AI algorithms for the AIDERS project. An initial mapping of user requirements to algorithms enabled the identification of machine learning algorithms that can be utilized to meet the user requirements. We provided an overview of existing state-of-the art algorithms that can be adapted or expanded to cover the needs of the AIDERS project.

In addition, we identified the data required for training machine learning algorithms, we have presented publicly available datasets that can be utilized for the purposes of the project and a methodology for developing a dataset. Furthermore, we provided the state-of-the art approaches in data pre-processing and popular approaches and tools for data cleansing, data reduction and data wrangling have been presented. Finally, we have provided an overview of other projects and systems developed towards the handling multi-sensor data in emergency response, and in fires, earthquakes and search and rescue in particular.

Using the insights presented in this deliverable, the DG ECHO AIDERS consortium will proceed to the design and implementation of machine learning algorithms to solve the problems faced by first responders, assist them in capacity building and improve emergency response.

8. REFERENCES

[1] Chen, X.H., Zhang, X.Y. and Zhang, Q.X., 2014, October. Fire alarm using multi-rules detection and texture features classification in video surveillance. In *2014 7th International Conference on Intelligent Computation Technology and Automation* (pp. 264-267). IEEE.

[2] Muhammad, K., Ahmad, J., Mehmood, I., Rho, S. and Baik, S.W., 2018. Convolutional neural networks based fire detection in surveillance videos. *IEEE Access*, *6*, pp.18174-18183.

[3] Muhammad, K., Ahmad, J. and Baik, S.W., 2018. Early fire detection using convolutional neural networks during surveillance for effective disaster management. *Neurocomputing*, *288*, pp.30-42.

[4] Bhowmik, N. and Breckon, T.P., 2019. Experimental Exploration of Compact Convolutional Neural Network Architectures for Non-temporal Real-time Fire Detection. *arXiv preprint arXiv:1911.09010*.

[5] Çelik, T., Özkaramanlı, H. and Demirel, H., 2007, September. Fire and smoke detection without sensors: Image processing based approach. In *2007 15th European Signal Processing Conference* (pp. 1794-1798). IEEE.

[6] Chen, T.H., Yin, Y.H., Huang, S.F. and Ye, Y.T., 2006, December. The smoke detection for early fire-alarming system base on video processing. In *2006 International Conference on Intelligent Information Hiding and Multimedia* (pp. 427-430). IEEE.

[7] Yuan, F., 2011. Video-based smoke detection with histogram sequence of LBP and LBPV pyramids. *Fire safety journal*, *46*(3), pp.132-139.

[8] Torok, M.M., Golparvar-Fard, M. and Kochersberger, K.B., 2014. Image-based automated 3D crack detection for post-disaster building assessment. *Journal of Computing in Civil Engineering*, *28*(5), p.A4014004.

[9] Cha, Y.J., Choi, W. and Büyüköztürk, O., 2017. Deep learning-based crack damage detection using convolutional neural networks. *Computer‐Aided Civil and Infrastructure Engineering*, *32*(5), pp.361-378.

[10] Zhang, M. and Jin, Y., 2008. Building damage in Dujiangyan during Wenchuan earthquake. *Earthquake Engineering and Engineering Vibration*, *7*(3), pp.263-269.

[11] Snoek, C.G., Worring, M., Van Gemert, J.C., Geusebroek, J.M. and Smeulders, A.W., 2006, October. The challenge problem for automated detection of 101 semantic concepts in multimedia. In *Proceedings of the 14th ACM international conference on Multimedia* (pp. 421-430).

[12] Lee, T. and Mihailidis, A., 2005. An intelligent emergency response system: preliminary development and testing of automated fall detection. *Journal of telemedicine and telecare*, *11*(4), pp.194-198.

[13] Cucchiara, R., Prati, A. and Vezzani, R., 2007. A multi-camera vision system for fall detection and alarm generation. *Expert Systems*, *24*(5), pp.334-345.

[14] Solbach, Markus D., and John K. Tsotsos. "Vision-based fallen person detection for the elderly." In *Proceedings of the IEEE International Conference on Computer Vision Workshops*, pp. 1433-1442. 2017.

[15] Hwang, S., Park, J., Kim, N., Choi, Y. and So Kweon, I., 2015. Multispectral pedestrian detection: Benchmark dataset and baseline. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 1037-1045).

[16] Isikdogan, L.F., Bovik, A. and Passalacqua, P., 2019. Seeing through the clouds with deepwatermap. *IEEE Geoscience and Remote Sensing Letters*.