UNICO I+D Project
6G-DATADRIVEN-06

6G-DATADRIVEN-06-E5

Architecture for data and AI use in emergencies: state of the art

Abstract

Artificial Intelligent (AI) and Machine Learning (ML) techniques join nowadays as part of our lives. These are powerful tools that can be used for multiple purposes, being a fast reaction to emergencies being one of those. In addition, new technologies such as 5G and IoT enable a huge potential for remote ML applications. In this document, the main ML techniques are described as well as their application of them to critical problems. These problems include cancer detection or medical triage, in the field of medicine; people tracking and recognition in case a person has disappeared in a remote place; or disaster forecast and actuation in case of volcanic eruptions, earthquakes, or any other phenomenon which requires fast but accurate action.

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List of Acronyms

5th Generation of Mobile Networks (5G)

Artificial Intelligence (AI)

Clinical Decision Support Systems (CDSSs)

Convolutional Neural Networks (CNN)

Corine Land Cover (CLC)

Decision Trees (DT)

Deep Neural Networks (DNN)

Fuzzy Neural Networks (FNN)

Generative Adversarial Network (GAN)

Global Positioning System (GPS)

Internet Of Things (IoT)

Linear Embedding Algorithms (LLE)

Logistic Regressions (LR) and Machine Learning (ML)

Naïve Bayes (NB)

Positive Predictive Value (PPV)

Principal Component Analysis (PCA)

Recursive Neural Networks (RNNs)

Reinforcement Learning (RL)

Support Vector Machine (SVM)

Process Natural Language (NPL)

Unmanned Aircraft Systems (UAAs)

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Resumen Ejecutivo

Este documento proporciona una visión de conjunto de técnicas de inteligencia artificial y aprendizaje automático aplicadas en situaciones de emergencia. Las nuevas generaciones de comunicaciones móviles como WiFi-6 y 5G jugarán asimismo un papel crucial para habilitar dichas técnicas en múltiples escenarios. Este documento clasifica los tipos de técnicas de aprendizaje automático y distingue tres tipos de emergencias en las que pueden ser de aplicadas.

Los tipos de aprendizaje automático considerados y explicados son aprendizaje supervisado, aprendizaje no supervisado, aprendizaje profundo y aprendizaje reforzado. Además, se ponen en práctica algunas herramientas de optimización clásicas.

Los tipos de emergencias están divididas en médicas, gente desaparecida y desastres, siguiendo el estado del arte.

Una tabla resumen con los principales artículos en la literatura, así como su contribución se puede encontrar al final del documento.

El resto del documento está redactado en inglés, de cara a maximizar el impacto del trabajo realizado en este proyecto.

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Executive Summary

This document provides an overview of artificial intelligence and machine learning techniques applied to emergency situations. New generation of wireless communications, like WiFi-6 or 5G, also join a crucial role to enable the potential of these techniques on multiple scenarios. The document classifies the types of machine learning techniques and distinguishes three types of emergencies where these tools are applied.

The types of machine learning considered and explained are supervised learning, unsupervised learning, deep learning, and reinforcement learning. In addition, classical optimization techniques are also needed.

The types of emergencies are divided into medical, lost people and disasters, following state of the art.

A summary table is at the end of the document to feature all the reviewed literature and the main contribution of each paper.

1. Introduction

Machine learning (ML) is a branch of artificial intelligence (AI) where computers learn from data and improve their performance, solving a particular problem without being programmed. The increased data generated in our society allows these applications to extract as much information as possible to perform elaborate tasks previously carried out by humans (Wiens & Shenoy, 2018).

These tools have increased interest in the research community in the last years due to the rise of new training algorithms and the upgrade of the available computational resources. These features allow ML to get better results faster, enabling a vast pool of potential applications, the application of ML to emergencies one of them.

Emergencies are known to be caused unexpectedly and require an immediate response. Medical problems can cause missing people, terrorist attacks, or natural phenomena such as fires, floods, and hurricanes. Applying ML can help reduce the actuation time, enabling better emergency management and solving situations that could have more significant consequences.

For example, ML can help improve medical emergency processes by collecting data over the years and applying it to real-time situations to evaluate a critical condition rapidly. This can be used, for example, on clinical image analysis and classification tasks, avoiding human errors and reducing the workload of medical personnel (Tang et al., 2021).

ML can also help to identify people through cameras, comparing the images to previously obtained data (Solaiman et al., 2022). Once a person is identified, it is easier for authorities to track and find the lost individual. ML is also a powerful tool for searching for people lost in the mountains, as it can learn from previous people moving patterns, the most common areas where people get lost, or rescue routes. In other words, ML can optimize how a person is rescued, reducing the finding time by deciding the search routes with higher chances of success.

Natural phenomena affect people all around the world daily. Human lives are frequently lost as a result of these events. Disasters also result in a significant impact on infrastructures, causing irreparable damage to them sometimes. Prevention and actuation against these phenomena are vital to mitigate the damage and accelerate recovery. ML has critical importance as it can predict these kinds of emergencies to be ready; in addition, once it has happened, it can search for quick response in an accurate and fast way (Linardos et al., 2022)

This deliverable includes a state-of-the-art revision of the current solutions for the mentioned, and it is ordered as follows. Section 1 features the current state of Machine learning and the last advances in algorithms. Section 2 dives into medical emergencies, including potential problems that ML can help solve.

2. Machine Learning types

This study reviews the literature and practice of applying AI and ML in emergencies. There are several ways in which ML can be used. This section will briefly explain the ML types that appear in the literature to understand the proposed applications better. The methods will be grouped into five categories: supervised models, unsupervised models, deep learning, reinforcement learning, and deep reinforcement learning, as well as optimization methods (Sun et al., 2020).

2.1. Supervised models

Algorithms that are trained on pre-existing data with human input are referred to as supervised models. Inferring a function from information to output using regression/classification techniques, supervised models estimate the value or category of the output variable using labeled training data with known input and output pairings. Supervised models have generally been utilized for speech recognition, pattern identification, object detection in computer vision, and information extraction.

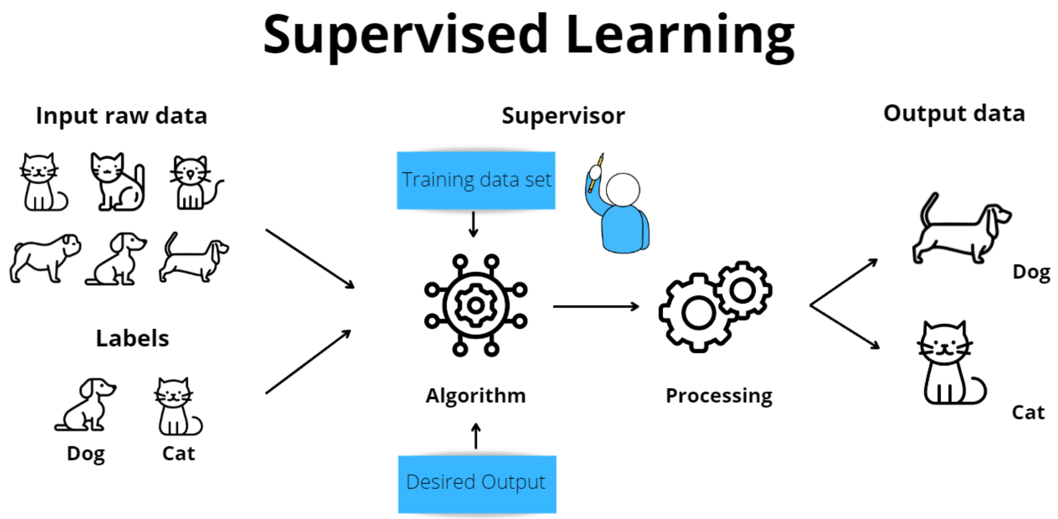

FIGURE 1: SUPERVISED LEARNING SCHEMATIC

2.2. Unsupervised models

Unsupervised models uncover hidden structures from unlabelled data based on intrinsic properties without human intervention. Unsupervised models have several applications for clustering and data aggregation issues and are effective for identifying anomalous data and lowering the data dimension.

To recognize patterns, clustering algorithms divide unlabelled data into several groups based on specific similarity traits. For example, principal component analysis (PCA) is a dimension-reduction approach that can minimize data complexity and prevent overfitting.

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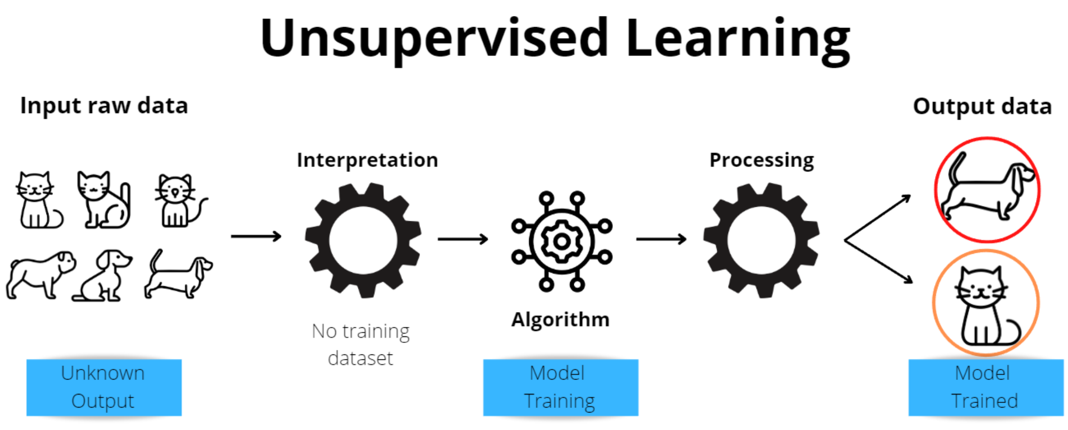

FIGURE 2: UNSUPERVISED LEARNING SCHEMATIC

2.3. Deep learning

Deep learning is a class of algorithms that employs numerous layers to gradually extract features from the input data, improving learning performance and having a wide range of potential applications. These methods are particularly well suited to tackle problems of damage assessment, motion detection, facial identification, and transportation prediction. Natural language processing can help disaster management, despite the disadvantage of requiring a lengthy training period. Recursive neural networks (RvNN) and recurrent neural networks (RNN), for instance, have been used to process natural language satisfactorily (NPL). Convolutional neural networks (CNN) are appropriate for speech processing, computer vision, and image recognition.

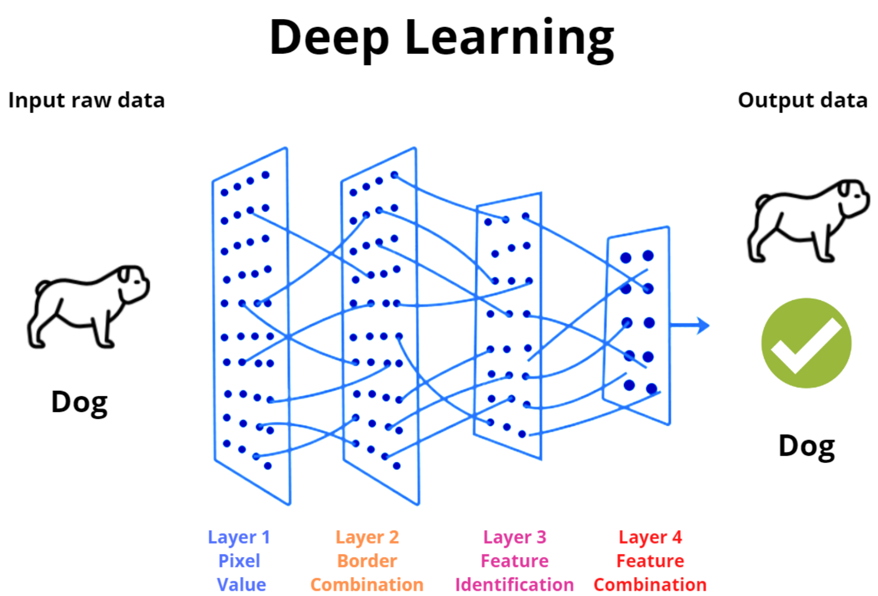

FIGURE 3: DEEP LEARNING SCHEMATIC

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2.4. Reinforcement learning

Reinforcement learning algorithms are represented as Markov decision processes to address goal-oriented problems for sequentially making decisions. Those algorithms learn from a succession of reinforcements (using punishment and rewards as positive and negative signals). Robotics, resource management, and traffic light control are three areas where reinforcement learning has been successfully applied. Reinforcement learning is suitable for tackling issues requiring making judgments in a complex and uncertain environment. Creating a training environment that is appropriate and closely related to the tasks needed is the main problem in reinforcement learning.

2.5. Deep reinforcement learning

Deep reinforcement learning aims to create software agents that can learn on their own to design successful policies for maximizing long-term rewards. To achieve this goal, deep reinforcement learning blends reinforcement learning and deep neural networks (DNN). Deep reinforcement learning performs better at tackling issues involving complicated sequential tasks, such as computer robotics, smart grids, and vision. Deep reinforcement learning can occasionally become very computationally expensive because it needs a lot of training data and time to perform reasonably.

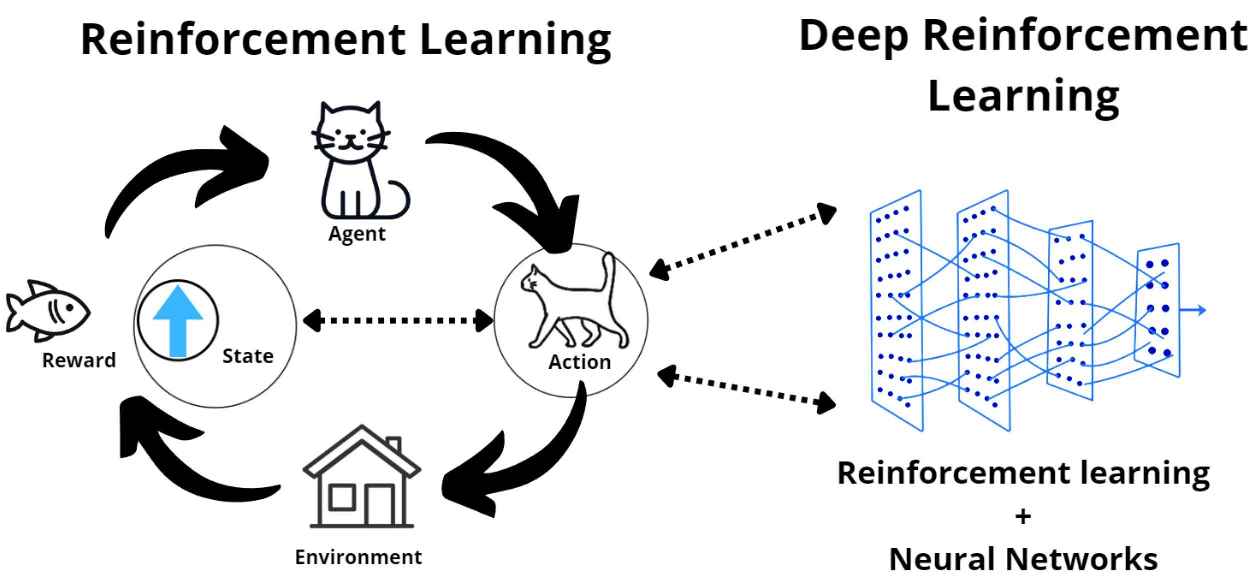

FIGURE 4: DEEP REINFORCEMENT LEARNING SCHEMATIC

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3. Machine Learning in medical emergencies

Using techniques like ML can help access the available data collected over the years more efficiently and smartly. As a result, this has wide applications in health and medical emergencies. The primary use cases in this field include clinical image analysis and classification tasks, illness diagnosis through apps, emergency triage, or pandemic screening and management, which has increased interest after the COVID-19 outbreak. This section will go through the primary literature available for these applications, explaining which kind of ML is used and how this technique helps deal with the problem in terms of speed, efficiency, and quality of the solution (Mendo et al., 2021).

In clinical image analysis and classification, ML techniques can not only help with work overload to medical personnel but enhance decision-making by identifying patterns that may not be visible to humans' sight. A clear example of the power of these tools is shown by (Mun et al., 2021), where authors propose three pathways for AI's role in radiology through Convolutional neural networks (CNN) on pattern recognition. CNNs are a specialized type of artificial network that uses convolution operations in some of their layers to connect neurons. These kinds of networks are specifically designed for image recognition to process the data pixel by pixel, allowing the identification of patterns that can indicate the presence of disease, no matter how small the evidence is (Mun et al., 2021).

Other papers where ML helps make clinical decisions on emergency scenarios are (Heard et al., 2019; Schwartz et al., 2021). The first one uses wearable sensors, video, and ML to recognize clinical procedures within an environment. The system proved how this information could improve the accuracy of pathology recognition. In addition, they propose using other techniques like deep learning to enhance the accuracy of diagnosis. The second paper studies the implementation of clinical decision support systems (CDSSs) that use ML to analyze health record data to assist nurses and doctors with decision-making and prognostic. It concludes that clinical expert involvement is most frequent in the development stage of the CDSSs but decreases in the verification and validation of the models, which handicap the use of these technologies.

Common diseases like cancers can be diagnosed faster, as explained in(GOODFELLOW et al., 2016), where the AlexNet CNN system describes the diagnosis of breast lesions, detecting potential cancer. This approach is shown in Figure 5, where microscopic images of the lesion are treated and classified into benign or malignant, allowing fast and precise analysis of the observed pattern.

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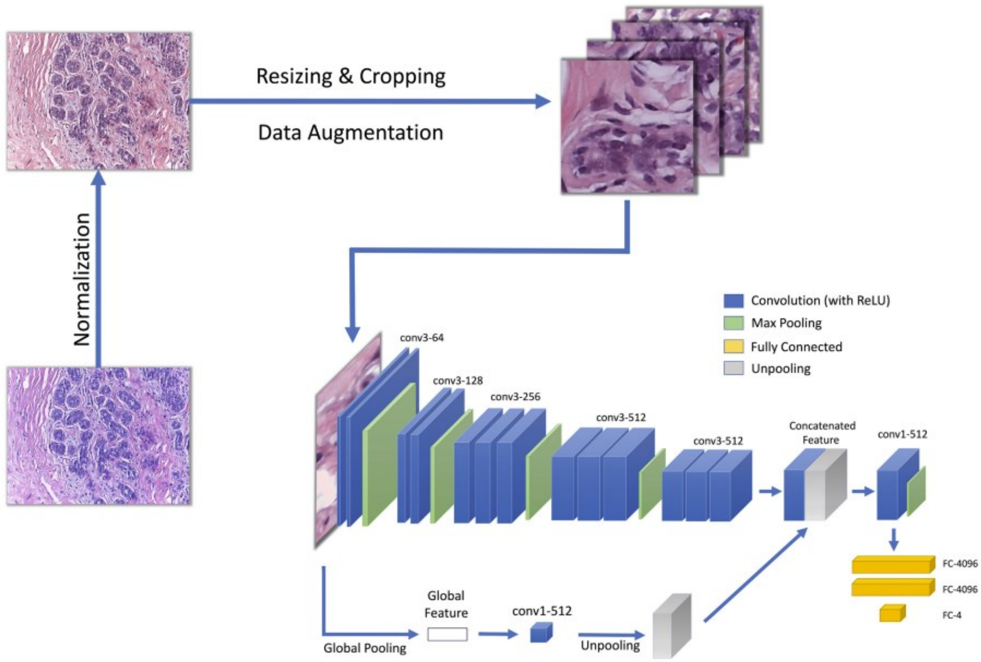

FIGURE 5: ALEXNETT FOR BREAST CANCER DETECTION (GOODFELLOW ET AL., 2016)

Moving onto pre-hospital medical care and disease screening, incoming technologies like 5G can help to monitor and decrease response time, as shown in (Senan et al., 2021), where authors present a real-life proof-of-concept of an e-Health system, saving minutes on the emergency and performing triage more efficiently. ML can also join an essential role in this realm by tying to new wireless technologies. For example, (Antevski et al., 2021) feature a healthcare monitoring system using IoT and 5G while adding ML models, as shown in Figure 6. In the scenario formulated, ML algorithms are used by processing measuring parameters such as pulse rate, temperature, and blood pressure, among others. This way, it can predict health conditions using supervised learning algorithms such as decision trees, logistic regressions, or naïve Bayes.

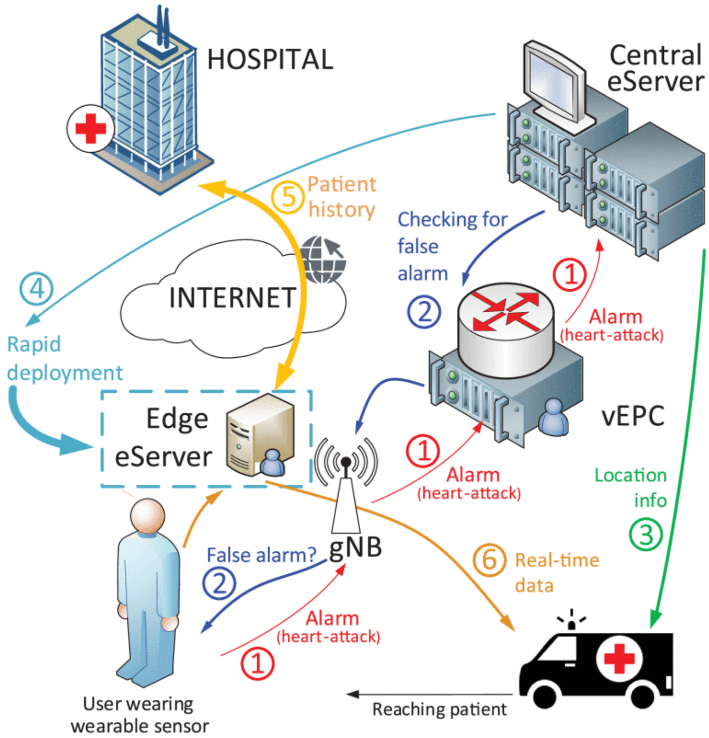

FIGURE 6: E-HEALTH EMERGENCY SYSTEM (ANTEVSKI ET AL., 2021)

Furthermore, (Badgujar & Pillai, 2020) implements an elder care system enhanced by ML. It states that one of the most common causes of health degradation or even death of old people is caused by falls, being critical of the reaction time from the event timestamp to the ambulance arrival. ML algorithms and decision trees detect and classify falls, decreasing the reaction time when necessary.

Emergency Care Systems (ECS) in hospitals sometimes have to support many patients simultaneously. This requires accurate triage systems to prioritize urgencies that can be more critical, needing immediate actuation to save a life. As a result, authors (Miles et al., 2020) explore using ML to triage the acuity of patients who enter the emergency system to optimize the available medical resources. The paper features a broad model review that separates hospitalization emergencies from critical care needs using neural networks and tree-based methods.

Pandemic situations are also on the eye of the storm after COVID-19. Proper management of these situations is a public interest emergency, and decision-making can sometimes be complex and controversial. In this scenario, the literature includes ML models enhancing the actuation against pandemic situations. Diagnosing is hard at the start of a pandemic since resources are minimal and infections are massive. This has already happened with the PCR tests on COVID-19. However, it is a situation that can be repeated in future pandemics. As a result, the existence of ML models that can help diagnose using more accessible data is of great importance. Authors in (Cabitza et al., 2021) developed ML models that successfully identified SARS-COV2 with simple blood tests, which can be especially useful when facing a rapid increase in contagions or in developing countries that cannot access specific medical resources.

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Contact tracing is also vital in these situations. Studies have proven that ML and AI techniques can help predict future problems. A real-time forecasting model is presented in (Chakraborty & Ghosh, 2020), where datasets from several countries are collected, and prediction models based on time series and regression trees are presented.

Machine learning technologies are becoming increasingly popular because of the emergence of mobile health devices that can use data to assess a patient's health status in real-time. Those complex algorithms using multiple variables are expected to enhance medical emergency treatment. ML can help automate large-scale analysis using available computational resources, which is especially interesting when tracking data from pandemics or diagnosing complex diseases. Together, these tools will enable a fast and efficient healthcare system, increasing life expectancy and improving quality of life.

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4. Machine Learning locating lost people

The "missing person" problem, formally proposed by J.D Hirschel in 1988 (Hirschel & Lab, 1988), has created much research. Correctly identifying a missing person can exponentially speed up the search. In addition, missed people moving patterns can help reduce the search area, leading to a faster and more successful exploration. ML has much to say in this field since new methods are being explored to solve this emergency. As a result, the research community has recently included this area of investigation as a hot topic.

For example, authors (Solaiman et al., 2022) present an exciting system that integrates multiple data sources to find missing persons. The feature extraction machine learning model uses pcolor recognition, question answering, color analysis or transfer learning. This data is processed and stored. Afterward, real-time data obtained through cameras or other available devices can be compared with the database. Face recognition through AI and ML is a well-known problem where multiple approaches have been made. In (Sharma et al., 2020), a technique to differentiate people in various scenarios is presented. Identifying people in well-taken photos can be easy with classic ML models. However, sometimes data is not perfect, maybe because of partial facial occlusion, illumination, or posture variety. New ML models such as the one presented in this paper, using linear discriminant, multilayer perceptron, or Naïve Bayes, reach nearly 100% recognition accuracy. ORL dataset is used to train the model, including different perspectives from the same person, as shown in Figure 7.

FIGURE 7: AN EXAMPLE OF ORL DATASET

Another interesting use case of ML in lost people emergencies focuses on search area predictions using regression or transfer learning models. A good paper explaining new novel methods can be found in (Šerić et al., 2021), where GPX trails were used to train models for walking patterns. GPX trails consist of GPS data in an XML format. Data was provided by Croatian Mountain Rescue Service and processed, including geographical information such as terrain type, elevation, and speed of walking, among others. Calculations of speed depending on the most common paths, such as going to a high area or speed, and were taken to reach common spots where people are found can help perform real-time analysis of where the lost person is. Transfer learning approaches allowed here to create a lost person speed of walking model without sufficient data to perform a classic machine learning model. Figure 8 shows a simulation example of a lost person search, taking into consideration a starting point and 30m isochrones, which consider all possible locations within 30 minutes walk from the original search point. These simulations also considered the terrain type with the Corine Land Cover (CLC) class (Centro Nacional de Información Geográfica MINISTERIO DE TRANSPORTES, 2018).

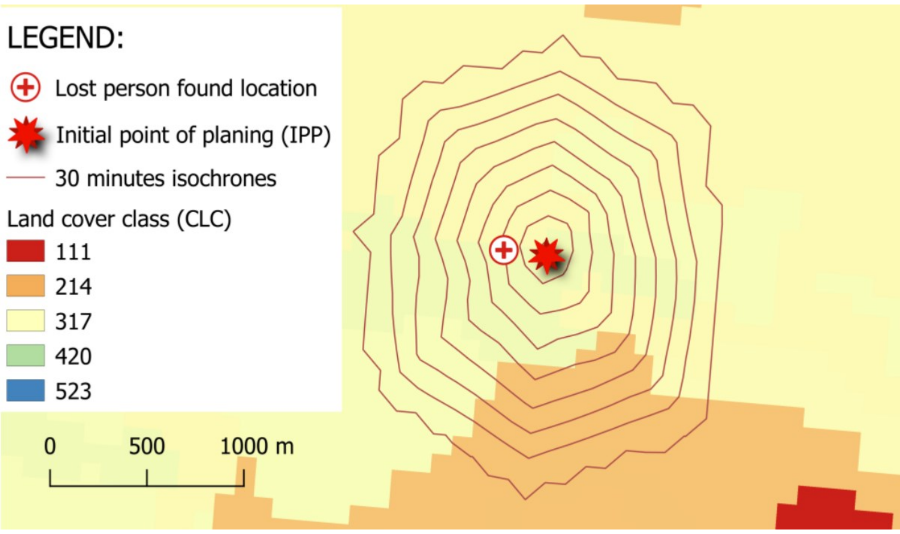

FIGURE 8: SEARCH ISOCHRONES OF A LOST PERSON SEARCH (ŠERIĆ ET AL., 2021)

Sometimes, extra devices such as Unmanned Aircraft Systems (UASs) are used in search and rescue operations. The UASs are used to scan the terrain and take photos of the hard visitable areas for humans. The rescue team members analyze the images afterward to detect missing people or find any clues. This is a time-consuming process that can also lead to human error. As a result, convolutional neural networks (CNNs) are trained on a specifically developed database for these scenarios named HERIDAL (Gotovac et al., 2020). Figure 9 below summarizes the CNN (VGG-16) used for the feature extraction, and Figure 10 shows some people identifications performed by the system.

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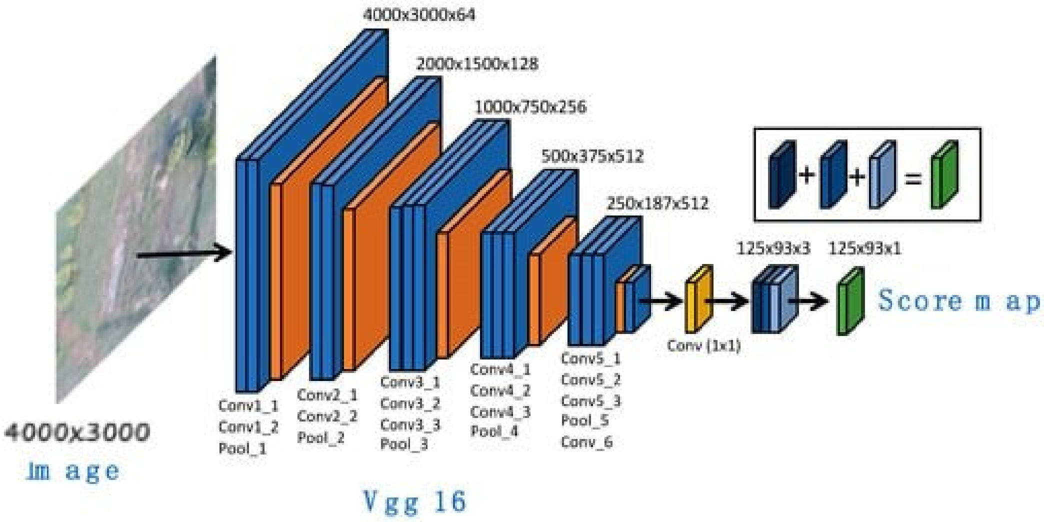

FIGURE 9: CNN VGG 16 FOR FEATURE EXTRACTION (GOTOVAC ET AL., 2020)

FIGURE 10: PEOPLE IDENTIFICATIONS BY VGG 16 (GOTOVAC ET AL., 2020)

5. Machine Learning in natural disasters

Natural disasters impact the lives of people all around the world. Even if no human losses occur, impacts on infrastructure and properties can be caused. The time and the economic cost of recovering from a natural disaster make it interesting to research disaster management. These operations are performed before, during, and after the accident, helping prevent damage and re-establish normalcy. Tough decision-making needs to be done during this situation, and AI and ML can help treat such complex problems (Altay & Green, 2006). Applications include hurricanes, floods, wildfires, volcanic eruptions, and landslides. Spain is known for having significant issues with wildfires in its territory, especially in summer, when the dry weather makes the fire advance easy, and decisions must be taken quickly. Also, volcanic eruptions can happen in the territory due to the nature of the Canary Islands, where the demolishing power of the La Palma volcano was recently experienced. Climate change will make storms and floods more common, leading to significant economic losses and thousands of humans being affected.

As a result, disaster management can be classified into three phases: prevention, actuation, and recovery. Prediction models can help in emergency planning, prepositioning supplies, and eviction plans of civilians for a determined area. Actuation happens once the disaster is live, including emergency rescue, medical care, resource distribution, and damage assessment. In this situation, the speed of decision-making plays a vital role, so techniques must accurately decide in a critical time. Last, recovery includes the reconstruction of crucial infrastructures that were damaged during the disaster. In addition, resilience is necessary, adapting the buildings or infrastructures to the possible disasters that can happen (Linardos et al., 2022).

The techniques used for assisting disaster management include ML methods such as Naïve Bayes (NB) classification methods, decision trees (DT), and logistic regressions (LR). It also considers some DL methods like convolutional neural networks (CNN) or deep neural networks (DNN) (Figure 11).

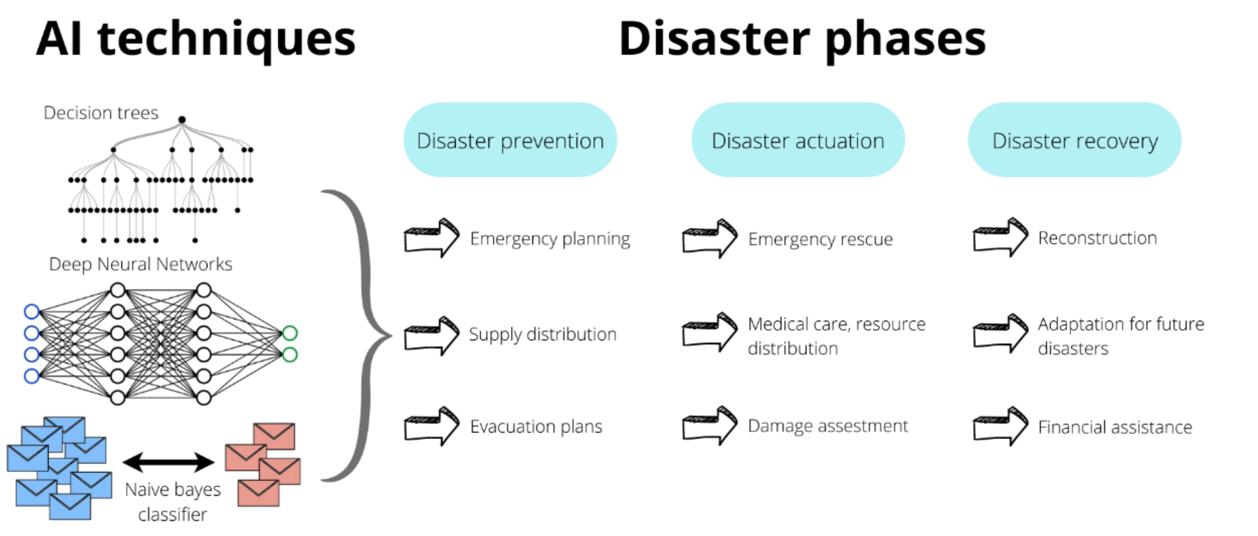

FIGURE 11: SUMMARY OF DISASTER PHASES AND MOST USED TECHNIQUES

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These techniques can easily manipulate data from different sources and determine patterns, providing intelligence impossible to divulge with other methods. Big data can be obtained through multiple sources, such as satellite imagery, social media, sensors, and geographical information systems… among others. AI techniques enable the utilization of big datasets to develop strategies to predict disasters and assist during actuation and recovery. Next, current literature will be classified depending on the phase of the tragedy where ML/DL techniques are applied.

5.1. Disaster prediction and prevention

In disaster prediction, data needs to be analyzed to anticipate the event and actuate accordingly. For example, Sankaranarayanan et al. (Sankaranarayanan et al., 2020) propose a method to predict floods based on temperature and rainfall intensity. The technique used deep neural networks (DNN), achieving an accuracy of 89.71%, outperforming traditional ML methods. Other literature focused on a forecast for floods appears in (Huang et al., 2018), where authors propose the use of fuzzy neural networks (FNN) combined with locally linear embedding algorithms (LLE) to predict precipitations during tropical cyclones.

Some early warning systems have also been developed for disaster prediction. An example is (Chin et al., 2019), where earthquakes' false alarm detection was the focus. ML-based algorithms like classification trees and K-Nearest neighbours were adopted. The study shows that ML-based methods reduced false alarm rates by increasing detection accuracy. In this topic, Li et al. (Z. Li et al. 2018) also aimed to treat false alerts and earthquake warning systems. The authors trained a generative adversarial network (GAN) to classify waveforms coming from recordings. The radio frequency classifier identified 99.2% of P waves from earthquakes.

5.2. Disaster actuation

Live monitoring plays a vital role during disasters, making monitoring optimization crucial. Domala et al. (Domala et al., 2020) worked on crisis management using news data and processing it with ML models. Using network scrapping in an automated system, these techniques were applied to identify relevant data. The ML models classified disaster news into relevant news data or irrelevant data. A similar approach was made by (Gopal et al., 2020), where online information was used for real-time disaster monitoring. Data is collected from websites, social networks, and other online sources, then supervised ML models were used to filter irrelevant or unconcise data.

Damage assessment is also considered in disaster actuation to scale damage done and calculate the resources needed for the response. In this scenario, authors in (Presa-Reyes & Chen, 2020) propose a convolutional neural network (CNN) to classify structures, differentiating up to four damage levels with high accuracy. Features from the pre-and post-damage aerial images were used to train the model. Once damage to structures is clear, resources needed can be better allocated. Another interesting research on this topic is (X. Li et al., 2018), where Li et al. developed a CNN-based method

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to identify and assess damage in disaster areas. The method evaluated data from different disaster events, using CNN to classify images into damage or no damage, class activation mapping, and damage severity score. An accuracy of 90.1% was reached while evaluating it with data from Matthew, Ecuador (earthquakes and typhoons).

5.3. Disaster recovery

The post-disaster response includes event evaluation to respond to immediate needs, perform search and rescue operations and quantify the impact of the disaster. Various activities must be performed, and medical rescue and recognition of people are crucial. This is also related to the previous sections of ML In emergency use cases. An interesting paper that merges disaster situations and medical emergencies are (T. Li et al., 2020). The authors elaborated a decision table based on medical rescue by incorporating the medical features of different types of disasters. To classify disasters, medical features were analyzed using genetic algorithms. Recommendations were made based on this classification, and the traits that disaster personalities have in common helped a rescue management system based on medical emergencies plan the rescue operation.

An efficient approach for classifying photos from earthquake-damaged smart urban settlements was presented by Chaudhuri and Bose (Chaudhuri & Bose, 2020). The authors used a DL technique based on CNN versions AlexNet, Inception-V3, and ResNet-50 to find survivors among the rubble. Additionally, ML techniques like ANN and SVM were employed. Because of the performance study, it was shown that DL approaches beat ML methods for classifying images. ResNet50 demonstrated the best performance, scoring 90.81% for positive predictive value (PPV) and 0.9205 for F1.

To help with post-disaster response, Li et al. (H. Li et al., 2018) presented an approach for automatically analyzing tweets. The suggested methodology used source-labeled data and unlabelled target data to train classifiers. It was based on domain adaptation classifiers. The technique incorporated Naïve Bayes (NB) and an iterative self-training approach (NB-ST). The trials were carried out using a dataset of tweets called CrisisLexT6. With an accuracy of 86.91%, the NB-ST technique outperformed conventional supervised ML classifiers.

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6. Contributions summary table

TABLE 1: CONTRIBUTIONS SUMMARY OF ML IN EMERGENCIES

Publication	Emergency	AI/ML Methods	Contribution
(Badgujar & Pillai, 2020)	Medical	Support Vector Machine (SVM) and decision tree	Detection of falls on elderly people to detect potential emergencies and speed up the reaction time.
(Cabitza et al., 2021)	Medical	Random Forest (RF), naive Bayes (NB), logistic regression (LR), support vector machine (SVM)	Detection of SARS-CoV-2 with a simple blood test. Training datasets to match parameters of infected patient blood reach an accuracy of ≈ 85%.
(Chakraborty & Ghosh, 2020)	Medical	Time series and regression trees	Real-time forecasting model on SARS-CoV-2.
(Chaudhuri & Bose, 2020)	Disaster	Deep neural networks (DNN)	Post-disaster decision support recovery on a fast and efficient way.
(Chin et al., 2019)	Disaster	Classification trees and K-Nearest neighbors	False alarm detections in disasters like earthquakes or volcano eruptions.
(Domala et al., 2020)	Disaster	Multinomial Naive Bayes, logistic regression, SVM, Xtreme gradient boosting, and random forest	Monitoring disaster and crisis management using news data and processing it with ML algorithms.
(Gopal et al., 2020)	Disaster	Naive Bayes, SVM, decision trees, and multi-Layer perceptrons	Monitoring disasters using data from social networks and websites
(Gotovac et al., 2020)	Lost people	Convolutional Neural Network (CNN) VGG-16	Locating lost people by extracting features from drone images and identifying human beings.
(Heard et al., 2019)	Medical	Supervised decision trees	Analysis and detection of potential emergencies during the transfer of the patient to the hospital in the ambulance. Use of wearable sensors and video to recognize clinical procedures.
(Huang et al., 2018)	Disaster	Fuzzy neural networks (FNN) combined with locally linear embedding algorithms (LLE)	Prediction of big precipitations and tropical cyclones.

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(H. Li et al., 2018)	Disaster	Naïve Bayes (NB) and an iterative self-training approach (NB-ST). Dataset: CrisisLexT6	Analyzing tweets to train classifiers mainly to help post-disaster response with real-time data.
(T. Li et al., 2020)	Disaster + Medical	Decision tables based on genetic algorithms	Medical rescue incorporates medical features of different types of disasters and adapts the response accordingly.
(X. Li et al., 2018)	Disaster	Convolutional Neural Networks (CNN)	Identify damage in disaster areas by evaluating damage from image classification. The model assigns a damage score depending on how severe it is.
(Z. Li et al., 2018)	Disaster	Generative Adversarial Network (GAN)	Classify the waveform of earthquakes to identify P waves.
(Miles et al., 2020)	Medical	Bayesian Networks, Logistic regressions, Neural networks, Tree-based methods	Application of triaging the acuity of patients presenting in the Emergency Care System (ECS). Difference between levels of risk for each patient.
(Mun et al., 2021)	Medical	Convolutional Neural Networks (CNN)	Pattern identification in images for medical disease diagnosis
(Presa-Reyes & Chen, 2020)	Disaster	Convolutional Neural Networks (CNN)	Classify damaged structures by differentiating up to four levels of damage using aerial images.
(Sankaranarayanan et al., 2020)	Disaster	Deep Neural Networks (DNN),	Flood prediction based on parameters such as temperature and rainfall intensity.
(Senan et al., 2021)	Medical	Deep Learning (DL)	Early detection of breast cancer by performing image classification using deep learning techniques.
(Šerić et al., 2021)	Lost person	Regression model and transfer learning	Data were processed, including geographical information such as terrain type, elevation, and speed of walking.
(Sharma et al., 2020)	Lost person	Linear discriminant, multilayer perceptron, or Naïve Bayes	People identify in photos with partial facial occlusion, low illumination, and posture variety.

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