A Bibliometric review on the use of Artificial Intelligence for Image recognition applied at Risk Reduction

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Abstract— **With the advent of deep learning systems, the potential applications of machine learning and artificial intelligence have expanded to include image interpretation. Specifically, AI-driven image recognition has proven to be a valuable tool in emergency situations. When a disaster occurs, both rapid response times and accurate information are crucial. Image recognition technology helps quickly identify the type of disaster and determine an effective intervention strategy, thereby facilitating rescue efforts and minimizing damage. In this article, the authors analyze two scientific literature databases on the topic, using specific keywords and the VOSviewer software. While the scientific community largely agrees that image recognition technology is essential for providing accurate and rapid responses to various hazards, the authors argue that current technological advancements can be harnessed synergistically to address all disasters that threaten public safety.**

I. Introduction

For several years now, the occurrence of extreme weather events has posed serious risks to public safety. Additionally, numerous emergencies in densely populated environments have driven scientific research to focus not only on the prevention of such disasters but also on effective crowd management during panic situations. In fact, panic triggered by sudden catastrophic events can give rise to behaviors that are even more dangerous than the event itself. For this reason, acting in advance—or at least with great speed—is essential to warn individuals at risk and to enable rapid rescue interventions, thereby reducing potential harm [1].

In this context, the main objective is to reduce risk, which depends on three key factors: occurrence, vulnerability, and exposure. While vulnerability can be addressed at the infrastructural level—though never entirely eliminated—once a disaster strikes, exposure becomes the only component that can be actively managed [2].

This study investigates the potential of artificial intelligence, particularly through machine learning and image recognition, to improve disaster response strategies. By processing large volumes of visual data in real time, these technologies can support critical decision-making processes—such as dynamically updating evacuation plans and issuing early alerts—thereby increasing the speed and accuracy of emergency responses [3].

Image recognition plays a central role in this framework. It enables precise assessment of the damage inflicted on infrastructure by catastrophic events [4]. Furthermore, deep learning techniques make it possible to identify the nature of the triggering events based on the visual characteristics of the damage. These methods can also be applied to satellite imagery to forecast severe weather phenomena before they occur [5].

To support this analysis, the study draws on a broad range of literature sources. Articles from Scopus and Web of Science were selected, merged manually, and analyzed using the VosViewer software.

II. Literature Review

A. VOSviewer

To conduct the following bibliometric analysis, the authors employed the VOSviewer software. VOSviewer is a tool capable of handling large volumes of articles to create bibliometric networks, which are displayed as maps and can be interactively explored by researchers. Maps can be created using existing networks, or new networks can be created based on scientific publications, research publications, research organizations, countries or keywords. The elements of these networks, identified as "items" from VOSviewer, can then be linked through co-authorship, co-occurrence, citation, co-citation or bibliographic coupling relationships [6]. The data relating to the material to be analyzed are taken from pre-established databases. In fact, VOSviewer software supports only files downloaded from some publication databases, such as Scopus, Dimension, Lens and PubMed. Once the datasets containing scientific literature articles are obtained, the parameters for the analysis can be defined. In this study, the articles were analyzed based on their keywords.

* This study was carried out within the research project "RISK: Recovery Increasing by Social Knowledge" – 022B4TT2M (CUP C53D23004800006), PIANO NAZIONALE DI RIPRESA E RESILIENZA (PNRR) Missione 4 "Istruzione e Ricerca" – Componente C2, Investimento 1.1 "Fondo per il Programma Nazionale di Ricerca e Progetti di Rilevante Interesse Nazionale (PRIN)", D.D. n. 104 del 2 febbraio 2022, ERC SH7 "Human Mobility, Environment, and Space". This paper reflects only the authors' views and opinions; neither the European Union, the European Commission nor Italian Ministry for Universities and Research can be considered responsible for them.

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B. *Keywords Selection*

Artificial intelligence image recognition technology with machine learning techniques has recently become a highly discussed topic. It is widely used in various fields, from medicine, where it helps make more accurate diagnoses, to botany, where it monitors plant growth, and engineering, where it is used to monitor the state of infrastructure [7][8]. For this reason, in order to carry out more accurate and detailed research on the use of image recognition technology to manage emergency situations, the authors had to carefully select the keywords that would collect the right scientific articles. As previously mentioned, the field of image recognition is currently widely explored in various fields of research. Therefore, simply searching "image recognition" would yield an extremely large number of scientific articles. Therefore, to obtain a more accurate selection, it was decided to link the chosen keywords with "and", which restricts results to articles whose titles or abstracts include all specified terms. If the words have been joined by "or", the search engine would have retrieved all the articles containing at least one of the keywords from the selection, but also those that did not include all the keywords. In this case, there was a risk of including articles that were not relevant to the research topic. However, when selecting "image recognition" along with words more closely related to urban danger situations, the selection of scientific literature articles turned out to be too limited, especially because of the "and" operator that constrained the keywords.

As a result, the decision was made to modify the keyword selection. Instead of using "image recognition," the authors decided to combine the keywords "image," "machine learning," "AI," and "disaster" ("image" AND "machine learning" AND "AI" and "DISASTER"). By grouping these terms, it became almost automatic that the output would include articles related to image recognition, which indeed turned out to be the case. With this refined selection of keywords, the authors were able to extract 73 articles from the Scopus database. To broaden the scope of the search and achieve more comprehensive results, the authors also turned to the Web of Science database, from which, using the same keywords, another 35 articles were retrieved.

C. *Merging Database*

Usually, the VOSviewer software analyzes only one database at a time. Furthermore, different data sources provide files in different formats. For instance, Scopus and Lens export data in .csv format, while Web of Science exports data in Excel format. To analyze a larger dataset and perform a more accurate bibliometric analysis, the dataset obtained from Scopus was merged with the one obtained from Web of Science. To achieve this, it was necessary to modify the files to make them compatible with each other. The files were converted into Excel format and organized according to the same criteria, grouping the data under uniform columns: "authors," "title," "year," "source title," "number of citations," "DOI," "affiliations," "abstract," "author keywords," "index keywords," "document type," "conference name," "conference date," "conference location," "ISSN".

It was crucial to ensure that certain columns contained accurate data, particularly those related to keywords, since VOSviewer relies on keywords for analysis. This ensured there was no risk of mismatched information. Retaining other information, such as the DOI or the number of citations, was equally important to enable comprehensive bibliometric analysis.

III. CLUSTERS' DIVISION

Once a single dataset was obtained, the file was loaded into the VOSviewer software, and the analysis was performed. As mentioned earlier, the authors chose to create a network based on the co-occurrence of all the keywords. This decision led to the formation of 4 clusters. Each Cluster contains several items. Below is the table that groups the items of each cluster, and then it is explained what can be deduced about the selected bibliography, starting from the division into clusters of the keyword that presents the greatest co-occurrences among them. In some cases, the most cited articles dealing with the topics mentioned in the cluster were also cited (Table 1).

TABLE I. CLUSTERS DIVISION

Clusters' Division	**Satellite Analysis and Damage Detection via Convolution Neural Network** ***(Red Cluster)***	**Flood Management and Prevention Strategies in the Context of Climate Change** ***(Green Cluster)***	**Analysis and Enhancement of Synthetic Aperture Radar Images by Artificial Intelligence** ***(Blue Cluster)***	**Analysis and Interpretation of Images from Remote Sensors with Artificial Vision and Semantic Segmentation Techniques** ***(Yellow Cluster)***
	Antennas	Climate change	Artificial intelligence	Computer vision
	Classification	Decision Making	Image analysis	Image processing
	Convolutional Neural Network	Disaster management	Image enhancement	Image segmentation
	Damage detection	Disaster prevention	Machine learning	Remote sensing
	Deep learning	Disasters	Radar imaging	Semantic segmentation
	Image classification	Floods	Synthetic aperture radar	Semantics
	Learning algorithms	Risk assessment		
	Learning systems			
	Satellite imagery			

A. *Red Cluster – "Satellite Analysis and Damage Detection via Convolution Neural Network"*

The Red Cluster is the largest one and has been named "Satellite Analysis and Damage Detection via Convolution Neural Network (CNN)". The keywords in this cluster indicate how scientific research has extensively worked on the recognition of images collected by satellites using artificial intelligence and machine learning techniques, in particular using CNN for the analysis and classification of these images. CNN is a type of artificial neural network that is widely used in image processing.

In the context of the cluster, CNNs are used to analyze satellite images for various purposes, such as damage detection or object classification. In particular, one of the most frequently mentioned applications is "damage detection". This involves evaluating the use of CNNs to identify and assess visible structural or environmental damage from satellite images. In particular, C. Cheng, A. H. Behzadan, and A. Noshadravan propose to improve the post-disaster preliminary damage assessment (PDA) and to achieve this, they suggest using a stacked damage assessment model (SPDA) that employs two convolutional neural networks. One, model L, uses Mask R-CNN to localize buildings in the images, and the other, Model C, uses MobileNet to classify the damage levels of the detected buildings [9]. The work of Sathishkumar et al. focuses on the use of AI and, therefore, CNNs for the recognition and automatic detection of fires. To reduce training times while continuing to ensure high performance capabilities, the authors propose the use of “learning without forgetting” (LwF), which trains the network on new tasks while keeping its preexisting abilities intact [10]. The keywords "classification" and "image classification," in addition to demonstrating the success of the authors' decision not to restrict the search to "image recognition," indicate that the cluster also pertains to the categorization of elements within satellite images. This could encompass the classification of various types of terrain, vehicles, obstacles, buildings, and other visible features. Finally, the keywords "deep learning", "learning algorithms" and "learning systems" suggest that the cluster explores various algorithms and learning systems used to train CNN models. These algorithms are essential to improve the accuracy and effectiveness of classifications and detections.

B Green Cluster – *“Flood Management and Prevention Strategies in the Context of Climate Change”*

Based on the keywords it includes, this cluster can be described as concentrating on the management and prevention of natural disasters, with a specific focus on the effects of climate change. Indeed, climate change affects the frequency and intensity of natural disasters, particularly "floods". Since disasters caused by “climate change” are sudden, “decision making” is crucial in “disaster management”. Disaster management involves the strategies and actions implemented to address the consequences of natural disasters. Ultimately, "disaster prevention" and "risk assessment" are central to disaster management, providing the opportunity to take proactive measures to reduce the likelihood and extent of damage to people and infrastructure. In their work, Yuan-Fu Zeng et al., focus on the development and evaluation of an AI-based flood detection system. The studied system is based on surveillance camera images and images obtained from the Internet. The collected images were manually annotated by the authors to create a flood recognition dataset. They then used a super-resolution generative adversarial network (SRGAN) to improve the resolution of the original images, thus improving the accuracy of flood recognition. The authors also emphasize that climate change has made it particularly urgent to develop a technology capable of predicting and recognizing floods, which have now become very frequent due to adverse weather events [11]. Another significant contribution is the work by Algarni et al., who explore the application of artificial intelligence to enhance flood forecasting and mitigation. Their study examines the use of AI techniques in both flood forecasting and flood control, utilizing data sources such as satellite imagery and Internet of Things (IoT) sensors to improve forecast accuracy. An additional key aspect of their research is the role of AI in flood management, which includes the implementation of early warning systems, resource allocation, and planning through the use of simulation technologies. It is then highlighted how climate change has made it necessary to use traditional knowledge integrated with new technologies, in order to effectively address the challenges related to adverse weather events [12].

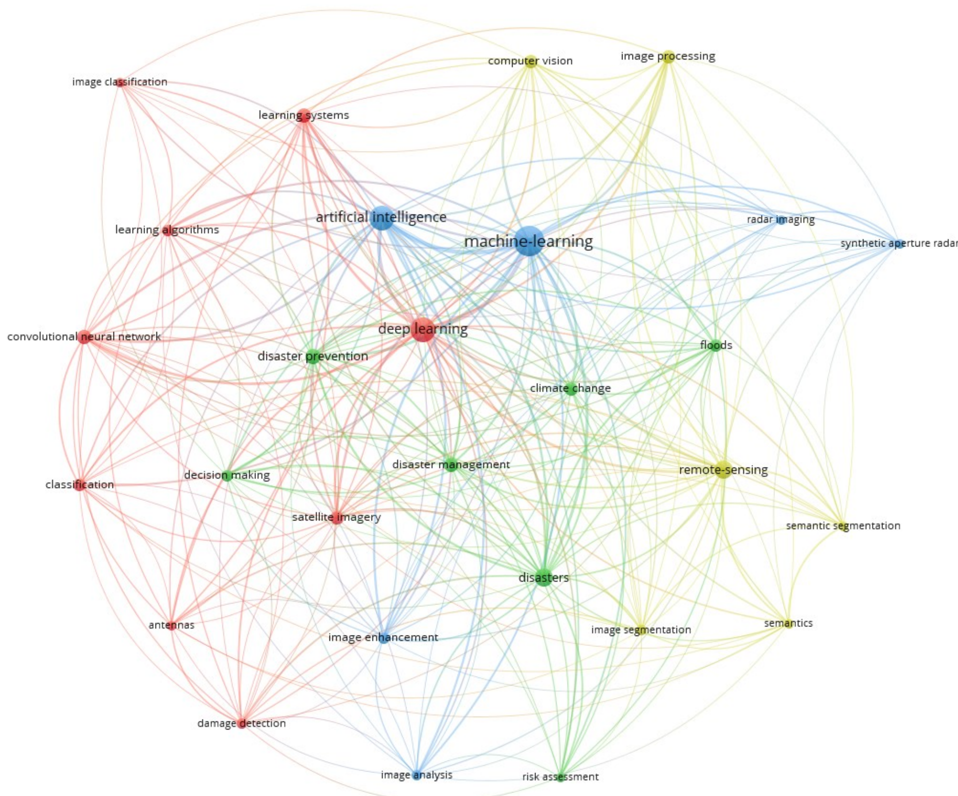
Because of these considerations, this cluster, the green cluster, has been named "Flood Management and Prevention Strategies in the Context of Climate Change". By now, climate change is the main cause of disasters and emergencies in urban centers. For this reason, most of the collected articled include “climate change” among the keywords.

C. Blue Cluster – *“Analysis and Enhancement of Synthetic Aperture Radar Images by Artificial Intelligence”*

This cluster, the blue cluster, focuses on the application of “artificial intelligence” and “machine learning” technologies to “analyze” and “enhance” “radar images”, particularly those obtained by “synthetic aperture radar” (SAR). While radar imagery refers to the use of radar to capture images, SAR is a specific radar imaging technique that uses the motion of the radar platform – such as an aircraft or satellite – to synthesize a large antenna, thereby improving the special resolution of the images.

Sousa et al. used InSar, Interferometry Synthetic Aperture Radar, a technique that provides high level of precision for monitoring changes in earth’s surface to forecast and to identify the formation of landside events. The work also evaluates the use of InSAR technology to develop a risk warning and monitoring system for cultural heritage sites. [13]. In another research, Rambour et al. discussed the use of AI to detect flood events using time series of optical and SAR images. In particular, they highlight how SAR images offer an alternative to optical images since they can be acquired independently of sunlight and cloud cover, as floods are often associated with cloud cover [14]. In this case, image analysis is a key component of the cluster, as it includes the use of algorithms to extract useful information from radar images, such as object detection and change tracking. Another important aspect, highlighted by the keywords belonging to the cluster, is image enhancement, which can be achieved through artificial intelligence and machine learning techniques that reduce noise, improve resolution, and increase the clarity of radar images (Fig. 1).

Figure 1. Network representation of cluster division



Therefore, machine learning algorithms are essential to train models that can analyze and enhance radar images. These models can be trained on large data sets to recognize complex patterns and provide accurate predictions. Considering the keywords, it contains the title assigned to the cluster is "Analysis and Enhancement of Synthetic Aperture Radar Images by Artificial Intelligence".

D. Yellow Cluster – "Analysis and Interpretation of Images from Remote Sensors with Artificial Vision and Semantic Segmentation Techniques"

The last cluster is the yellow cluster. Looking at the keywords in this cluster, it is clear that it focuses on the use of computer vision techniques and image processing to analyze and interpret images obtained from remote sensors. Specifically, "computer vision" is a discipline that aims to teach machines to understand what they see, extracting meaningful information from images or videos. Within this cluster, computer vision is related to the analysis of images obtained from "remote sensing". "Remote sensing" captures data from long distances, often via satellites or drones. The cluster also contains the keyword "image segmentation", which is a process of breaking down an image into segments or regions that are meaningful to the application in question. This could include breaking down satellite images into regions of interest such as forests, buildings, or bodies of water. Related to this is "semantic segmentation", which is an advanced image segmentation technique that assigns a label to each pixel in the image based on the class of object it belongs to.

The work of Qin and Chi introduces a universal lifecycle for deep semantic segmentation of remote sensing images, called RSImageNet. In this work, the aim is to address the lack of labeled data needed to train deep neural network (DNN) models for generating remote sensing image classification maps. The authors highlight that remote sensing images are essential for various application fields, such as disaster monitoring, disease control, and urban planning. [15].

Furthermore, semantic segmentation is particularly useful for remote sensing applications, where different types of terrain and objects need to be identified and classified. Some scientific research uses remote sensing as an alternative solution for large-scale population estimation. In fact, Sugandha Doda et al. present an interpretable deep learning framework for large-scale urban population estimation using Earth observation data. That is, the proposed framework provides accurate and transparent population estimation at 1 km resolution. The authors state that this can be useful for real-world applications such as urban planning and risk analysis [16]. Another keyword is "semantics", which in this context is the understanding of the meaning and context of images. The title assigned to this cluster, based on the keywords it contains, is "Analysis and Interpretation of Images from Remote Sensors with Artificial Vision and semantic Segmentation Techniques".

Finally, the four clusters deal with the use of image recognition techniques, through artificial intelligence and machine learning algorithms, to identify emergency and risk situations, in order to intervene promptly, also thanks to other machine learning techniques. On the previous page is the image of the connection network returned by VOSviewer. It is possible to recognize the different clusters classified with the four colors mentioned.

IV. THE USE OF IMAGE RECOGNITION IN DISASTER MANAGEMENT

The use of image recognition, through machine learning techniques, can therefore bring significant improvements in the management in disaster management. Below are the key points illustrating how this technique can provide concrete support during emergencies.

- Damage detection and assessment using collaborative neural networks to identify structural or environmental damage through satellite images and classification of destroyed buildings, interrupted roads, and compromised infrastructures after catastrophic events. This phase is very important for identifying critical points. Once these have been identified, it is possible to intervene with rescue and reprogram escape routes based on free sections to save people.
- Monitoring environmental changes using radar images, in particular SAR, to monitor changes in the territory before and after a disaster. In this way, it is possible to track landsides, deforestation and coastal erosion in order to prevent risks.
- Prevention and flood prevention through image analysis in order to identify areas at high risk of flooding. Artificial intelligence can be used to process climate data and consequently improve disaster management strategies.
- Real-time decision support through the rapid identification of critical areas so that emergency interventions can be facilitated. In this context, it seems essential to support operations with decision-making systems to coordinate relief efforts and optimize available resources.
- Image classification and segmentation for a targeted response through the use of computer vision and semantic segmentation to precisely distinguish the different types of terrain, bodies of water, buildings, and vehicles present in remote images. In this way, it will also be possible to identify safe evacuation routes and locate available shelters.
- Improvement of image quality for more precise analysis through the use of image enhancement techniques that reduce noise and increase the resolution of radar images. Thanks to the use of artificial intelligence, it is possible to have greater accuracy of forecasts.

V. SYNERGISTIC ACTION OF EXISTING TECHNOLOGIES

As previously discussed, image recognition techniques represent essential support in disaster management and disaster prevention. However, when it comes to public safety, the precautions and means adopted to protect it are never enough. In the article we discussed the use of artificial intelligence to interpret images and to support rescue operations, in order to provide a timely and effective risk response. Artificial intelligence can in fact be useful to quickly calculate new escape routes and make rational and timely decisions, where a human would take longer also due to panic. Artificial intelligence, however, is not the only tool that can concretely support risk management.

In carrying out the RISK project: Recovery Increasing by Social Knowledge, the authors have explored how the use of digital twins, IoT, big data and blockchain can concretely reduce exposure to danger. Thanks to digital twins it is possible to recreate physical cities and simulate possible emergency scenarios. In this environment it is possible to simulate the closure of roads and visualize different evacuation scenarios in complete safety. The deployment of various IoT in urban environments allows real-time monitoring, providing concrete and timely information about what happens during emergencies. Not only can this information be used to intervene promptly, but it can also be collected in datasets and used to make reviews or to support the decision-making process should there be future emergencies.

Each of these technologies has great potential, therefore using them in a synergic way can be a valid support to minimize risks when major disasters occur that put public safety at risk.

VI. CONCLUSION

This study focuses on the crucial role that image recognition techniques based on artificial intelligence and machine learning play in disaster management and prevention. After analyzing two datasets from two different databases, thanks to the use of VOSviewer software, some interesting conclusions have been drawn. The use of image recognition techniques allows us to promptly and effectively identify the damage caused by sudden catastrophic events, providing a rapid response and facilitating the planning of relief interventions and minimizing the consequences on the population.

The use of convolutional neural networks (CNN) for the analysis of satellite images allows an accurate classification of damage to infrastructures, while radar technologies, such as Synthetic Aperture Radar (SAR), support environmental monitoring before and after a disaster. Furthermore, semantic segmentation techniques improve the interpretation of images from remote sensors, allowing a more targeted response to emergencies.

The study makes an original contribution by offering a methodological approach, which combines bibliometric analysis with a refined keyword-based strategy to identify the most relevant research in the field. Thanks to the intuition related to the integration of data from multiple sources and the clustering capabilities of VOSviewer, the study manages to reconstruct the current state of scientific knowledge, highlighting not only consolidated applications but also emerging trends. Furthermore, this work offers a broader perspective by correlating image recognition technologies with other digital tools such as digital twins, IoT, big data and blockchain, thus demonstrating how their synergic use can significantly improve the predictive and operational capabilities of risk management systems.

Bibliometric analysis conducted through VOSviewer software identified four clusters containing key themes that reflect the wide application of image recognition in emergency management. These clusters concern satellite analysis and damage detection, management of floods caused by climate change, improvement of radar images through artificial intelligence and interpretation of images with computer vision techniques.

However, to maximize the effectiveness of risk management strategies, a synergic action between different technologies is essential. The authors therefore suggest using the integration of digital twins, IoT, big data and blockchain with image recognition in order to offer an even more complete and predictive approach to emergency management. This is because the simulation of scenarios through digital twins, together with real-time monitoring via IoT and the use of big data can improve intervention planning and offer solutions that can help reduce risk exposure and ensure a more effective response in emergency situations.

In conclusion, synergistic action of these technologies not only improves the capacity to respond to disasters but also represents an opportunity to develop more effective prevention strategies. The future of emergency management will increasingly depend on the ability to synergistically exploit these technological innovations to protect public safety.

ACKNOWLEDGMENT

This study was carried out within the research project "RISK: Recovery Increasing by Social Knowledge" – 022B4TT2M (CUP C53D23004800006), PIANO NAZIONALE DI RIPRESA E RESILIENZA (PNRR) Missione 4 "Istruzione e Ricerca" – Componente C2, Investimento 1.1 "Fondo per il Programma Nazionale di Ricerca e Progetti di Rilevante Interesse Nazionale (PRIN)", D.D. n. 104 del 2 febbraio 2022, ERC SH7 "Human Mobility, Environment, and Space". This paper reflects only the authors' views and opinions; neither the European Union, the European Commission nor Italian Ministry for Universities and Research can be considered responsible for them.

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