CHALLENGES OF ARTIFICIAL INTELLIGENCE APPLICATION FOR DISASTER RISK MANAGEMENT

D. Velev [1] *, P. Zlateva [1, 2]

[1] University of National and World Economy, Sofia, Bulgaria – (dgvelev, plamzlateva)@unwe.bg
[2] Institute of Robotics, Bulgarian Academy of Sciences, Sofia, Bulgaria

KEY WORDS: Natural disasters, Disaster risk management, Disaster risk reduction, Artificial Intelligence

ABSTRACT:

Artificial Intelligence (AI) has the potential to play a significant role in disaster risk management - from predicting disasters to optimizing response efforts. However, its application in disaster management also presents significant challenges. These challenges include the need for high-quality and diverse data, compatibility with existing systems and technologies, ethical and social implications, and ongoing research and development. In addition, data privacy and security is a critical issue as the use of AI in disaster management often involves the collection and analysis of sensitive information. Addressing these challenges is crucial to ensuring that AI is developed and used in ways that are fair, equitable, and effective in reducing the impact of disasters. The aim of the paper is to provide an analysis of challenges of artificial intelligence application for disaster risk management.

1. INTRODUCTION

In recent years, there has been a steady increase in natural disasters worldwide (Marshak, Rauber, Johnson, 2022). There is also an increase in their negative impact on societies, economies and ecology. Disasters are events that can cause significant damage, destruction or loss of life and property, and they usually occur unexpectedly or with little warning. Disasters can be natural or they can be caused by human actions. Disasters can have far-reaching consequences on the affected populations, including physical injuries, emotional trauma, economic disruption and social unrest (Cunningham et al., 2023; WEF, 2021). Effective disaster management and preparedness are critical for minimizing the impact of disasters and for helping communities recover and rebuild after such events occur (Bankoff et al., 2004; Castillo et al., 2021).

The most severe natural disasters can be classified as (Murray, et. al., 2021; Relyea, Ricklefs, 2018; Watts, 2022):

- Earthquakes - caused by the movement of tectonic plates and they can lead to widespread destruction and loss of life, especially in densely populated areas.
- Hurricanes and Typhoons - powerful storms that form over oceans and bring high winds, heavy rainfall and flooding to coastal areas.
- Volcanic Eruptions - releases ash, gas, and lava that can destroy homes, crops, and cities, and they can cause widespread health problems from ash inhalation
- Tsunamis - giant ocean waves caused by underwater earthquakes, volcanic eruptions, or typhoons, can cause massive coastal flooding and damage.
- Tornadoes - powerful swirling air columns that can cause extensive damage to buildings and infrastructure, as well as injure or kill people.
- Floods - occur when water overflows the normal riverbeds or other body of water, causing damage to homes, businesses, and infrastructure.
- Wildfires - fast-moving fires that can spread quickly and destroy homes, wildlife habitats, and other property.
- Droughts - prolonged periods of dry weather that can lead to crop failure and water shortages, causing widespread food and water insecurity.

It is important to note that the severity of a natural disaster can be affected by factors such as the level of preparedness of the affected communities and their infrastructure, as well as the response of emergency services and relief organizations (Sandler, Schwab, 2022). Due to that unfavourable trend, the risk management represents an important area field of research for disaster risk reduction and mitigation of the potential damage to people, infrastructures, business, environment, etc. (Sharma, Quah, 2018).

Nowadays, the timely and effective disaster risk management should rely on the processing of real data and information collected from different available resources, which data comes in vast volumes (Eslamian, Eslamian, 2021).

During a disaster, vast volumes of data are generated from different sources, such as mobile communications, social networking sites (Facebook, Twitter, Instagram, YouTube, etc.), sensors performing in Internet of Things environments, images from satellites, etc. (Tatano, Collins, 2019). Although this data acquisition should be considered as a first major step in the preparation for the following disaster risk management, here comes the question what should be the most suitable ICT that will handle effectively such situations. Fortunately enough, artificial intelligence (AI) has a steadily increasing utilization, and its applications gradually cover all types of disasters.

The aim of the paper is to provide an analysis of challenges of artificial intelligence application for disaster risk management. Artificial Intelligence (AI) has the potential to play a significant role in disaster risk management.

* Corresponding author

https://doi.org/10.5194/isprs-archives-XLVIII-M-1-2023-387-2023

2. ARTIFICIAL INTELLIGENCE BRIEF

Artificial Intelligence (AI) is one of the fastest developing areas of the information and communication technology. Artificial intelligence refers to the simulation of human intelligence in machines that are programmed to think like humans and imitative their actions. The ideal characteristic of artificial intelligence is its ability to rationalize and take actions that have the best chance of achieving a specific goal (Russel, Norwig, 2021).

A subset of artificial intelligence is Machine Learning (ML), which refers to the concept that computer programs can automatically learn from and adapt to new data without being assisted by humans (Serrano, 2021). Deep Learning (DL) enable automatic learning through the processing of huge amounts of unstructured data such as text, images, or video (Goodfellow, Bengio, Courville, 2016).

AI requires a specialized hardware and software for writing and training its algorithms. AI systems process vast amounts of labeled training data, analyzing the data for correlations and patterns, and using these patterns to make predictions about future states. AI programming focuses on three cognitive skills - learning, reasoning and self-correction.

Recent advances in AI allow scientists and researchers to access and analyze new and bigger data sources than ever before. Studies show that the application of the artificial intelligence for disaster risk management is a promise. With the help of artificial intelligence, it is possible to predict where a natural disaster may occur, what the negative consequences would be, as well as to propose adequate measures for effective disaster risk management (Abid, et al. 2021; Arfan, et al. 2019).

By combining AI and ML with data analytics technologies are creating new AI systems for disaster risk management. These systems enable their users to ask specific and targeted questions and to receive useful answers real-world datasets.

AI techniques such as image recognition and classification can be quite suitable in assessing the damage as they can observe and analyze images and identify objects and features such as damaged buildings, flooding areas, blocked roads, etc. AI and sentiment analysis on social media data (Facebook, Twitter, Instagram, etc.) about natural disaster risk can to provide early warnings, ground-level location data, and real-time reports.

ML approaches such as predictive analytics can also analyze past events to identify and extract patterns and populations vulnerable to natural calamities. A large number of learning approaches are used to identify risk areas and improve predictions of future natural disasters.

3. ESSENCE OF THE ARTIFICIAL INTELLIGENCE APPLICATION FOR DISASTER RISK MANAGEMENT

Natural disasters have a significant impact on the generation and collection of data. During a disaster, the priority is often on immediate response and recovery efforts, which can lead to disruptions in the collection and reporting of data. This can lead to a lack of accurate information on the extent of the disaster, its impact on people and infrastructure, and the resources needed for recovery. The effective use of data in response to natural disasters is critical to ensure that resources are directed to where they are needed most, and that recovery efforts are based on the most up-to-date information. The integration of data from various sources can also help provide a more complete picture of the disaster and its impact. There are successfully developed and implemented information technologies for data acquisition:

Internet of Things (IoT) plays a significant role in improving disaster response and recovery efforts (Azrour, Irshad, Chaganti, 2022). IoT devices can provide real-time data on the conditions in affected areas, allowing responders to make more informed decisions and respond more quickly to the needs of communities (Solanki, Kumar, Nayyar, 2021). IoT can play a role in mitigating the impact of natural disasters by providing early warning systems that can alert communities to potential dangers. IoT-enabled sensors can be used to monitor environment conditions and to trigger automatic alerts to communities in the path of a hurricane or flood. This can provide them with critical time to evacuate or to take other necessary precautions to protect themselves and their property. IoT can also be used to monitor critical infrastructure in real-time, allowing responders to quickly identify and address potential hazards. the integration of IoT devices with other data sources, such as satellite imagery and drone footage, can provide a more comprehensive picture of the disaster and its impact, helping to inform decision-making and response efforts (Taser, 2021).

Edge computing can play a crucial role in the response to natural disasters by providing local processing and data analysis capabilities even in the absence of a stable network connection (Gao, Li, Zhuang, 2021). This can help organizations respond more effectively to the needs of affected communities, especially in remote or hard-to-reach areas. Edge computing supports real-time data analysis, which can be critical in the aftermath of a disaster when time is of the essence. By processing data locally, organizations can quickly analyze information and make decisions, even in the absence of a stable network connection, since it can reduce the amount of data that needs to be transmitted over the network, which can reduce latency and improve the performance of critical systems. Edge computing can support real-time collaboration and information sharing among response teams, even in remote or disconnected areas. This can help organizations coordinate their efforts, pool resources, and make informed decisions (Misra et al., 2022).

Remote sensing can play a critical role in the response to natural disasters by providing real-time information and data about the extent and impact of a disaster (Ahmed, Alam, 2022). This information can help organizations assess the situation, prioritize response efforts, allocate resources, and make informed decisions. Remote sensing can provide real-time information about weather conditions and potential hazards, allowing organizations to proactively prepare for and respond to natural disasters. allowing organizations to focus their response efforts in these areas (Chang, Bai, 2018). Remote sensing can provide information about the location and extent of damage to critical infrastructure, such as roads, bridges, and communication networks, allowing organizations to prioritize their efforts to restore these essential services. In addition, remote sensing can provide information about the extent and impact of environmental degradation, such as soil erosion, landslides, and changes in water quality, allowing organizations to prioritize their efforts to address these impacts (Lavender, S., Lavender, A., 2023). It is also important to consider the integration of remote sensing data with other data sources, such as ground-based observations and social media, to provide a comprehensive and accurate picture of the situation. Remote sensing data can be integrated with other data sources to provide a more complete and accurate picture of the impact of a disaster, allowing organizations to respond more effectively and efficiently (Rosso, Sebastianelli, Ullo, 2021).

Social Media has become an increasingly important tool in the response to natural disasters (Light, Moody, 2020). It allows people to share real-time information on the extent and impact of a disaster, providing valuable data to response teams (Galety et al., 2022). It can also be used to coordinate response efforts, mobilize volunteers, and provide information to affected communities. It could be regarded as a popular means for crowdsourcing information from people on the ground, providing a more comprehensive picture of the disaster and its impac (Gupta, Sahoo, 2021). Social media can be used to monitor the response to a disaster, providing valuable feedback on the effectiveness of response efforts and helping to identify areas for improvement.

Big data plays a significant role in the response to natural disasters by providing real-time information and insights about the extent and impact of a disaster (Rani et al., 2023). This information can support decision-making, prioritize response efforts, and inform long-term recovery planning. Big data can be used to analyze social media and other online sources to provide real-time information about the extent and impact of a disaster (Schintler, McNeely, 2020). This information can be used to identify areas in need of immediate assistance, prioritize response efforts, and support the allocation of resources. Big data can also be used to analyze large amounts of satellite imagery and other remote sensing data to provide a comprehensive picture of the extent and impact of a disaster. This information can be used to support the assessment of the situation, prioritize response efforts, and inform recovery planning. Big data can be used to analyze historical data about past disasters, allowing organizations to identify patterns and make informed decisions about how to respond to future disasters and big data can be used to identify areas that are particularly vulnerable to natural disasters and to support the development of early warning systems and risk mitigation strategies.

Cloud computing can play a critical role in the response to natural disasters by providing on-demand access to computing resources, data storage, and applications (Hurson, Wu, 2021). This can help organizations respond more quickly and effectively to the needs of affected communities. cloud computing can provide organizations with scalable, flexible, and secure data storage, which can be critical in the aftermath of a disaster when large amounts of data need to be collected, processed, and analyzed (Sharma, Sharma, Elhoseny, 2021). This data can be used to inform decision-making, prioritize response efforts, and track progress. cloud computing can provide organizations with access to powerful computing resources, such as high-performance computing and artificial intelligence, which can be used to analyze complex data sets and model potential scenarios in real-time. This can help organizations make more informed decisions and respond more effectively to the needs of affected communities. Another advantage of cloud computing in the context of natural disasters is the ability to collaborate and share information in real-time. This can help organizations coordinate their efforts, pool resources, and make informed decisions.

All the above technologies generate large volumes of data. Data quality and quantity play a crucial role in disaster response and recovery. In the context of natural disasters, the accuracy and timeliness of data can have a significant impact on the effectiveness of response and recovery efforts.

Data quality refers to the accuracy and completeness of the data, and its relevance to the situation (Vluymans, 2018). High-quality data can support effective decision-making, prioritize response efforts, and inform long-term recovery planning. Data quality is particularly important because it can have a direct impact on the safety of affected communities and the effectiveness of response efforts.

Data quantity refers to the amount of data available. Large amounts of data can be generated from a variety of sources, including social media, satellite imagery, and remote sensing data. This data can provide a comprehensive picture of the extent and impact of a disaster, and can support effective decision-making and resource allocation.

To ensure data quality and quantity, it is important to have a well-defined data management and processing strategy in place. This should include protocols for collecting, storing, and processing data, as well as for verifying the accuracy of the data. Data sources should be carefully selected and monitored to ensure that the data is relevant, accurate, and up-to-date (Srivastav et al., 2020; Tagarev, 2019). In the context of natural disasters, data can be sourced from a variety of sources, including government agencies, non-profit organizations, and individuals. It is important to consider the reliability and credibility of each data source and to ensure that data is collected and processed in a consistent and transparent manner. It is important to have a robust system in place for data analysis and interpretation. This could include advanced analytics and machine learning algorithms to process and analyze large amounts of data, and to support informed decision-making and resource allocation.

Data and AI are closely interconnected (Sipola, Kokkonen, Karjalainen, 2023). AI relies on data to learn and make decisions. AI models cannot be trained or improve over time without data. Data is the fuel to the AI algorithms, and the more data that is available, the more accurate and effective AI systems become (Sutton, 2021). The process of training an AI model involves feeding it large amounts of data and allowing it to learn from that data by identifying patterns and making predictions. Data plays a critical role in the development of AI models. Data scientists and engineers use data to train and refine AI models, and to validate their accuracy and performance.

Combining with the processing of large volumes of generated data, there is an increasing number of AI solutions that can be used for disaster risk management:

Machine learning algorithms can be used to analyze large amounts of data from a variety of sources, such as satellite imagery, weather data, and social media, to identify patterns and make predictions about the impact of a disaster (Joshi, 2023). The machine learning algorithms can be used to predict the spread of a fire, the likelihood of flooding in a certain area, or the extent of damage caused by an earthquake (Marques, González-Briones, López, 2022).

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Deep learning algorithms can be used to process large amounts of data, such as satellite imagery and sensor data, to support disaster response and recovery efforts (Hong et al., 2020). The deep learning algorithms can be used to identify objects, such as buildings and roads, in satellite imagery, to support damage assessment efforts.

Artificial neural networks can be used to process large amounts of data to make predictions about the impact of a disaster. The algorithms can be used to predict the spread of a fire or the likelihood of flooding in a certain area (Asadnia et al., 2022).

Reinforcement learning algorithms can be used to support decision-making in real-time during a disaster. The algorithms can be used to optimize the deployment of resources, such as emergency supplies and personnel, to ensure that they are delivered to the areas that need them most (Abdel-Basset et al., 2022).

Decision tree algorithms can be used to support decision-making during a disaster (Agrawal et al., 2022). The algorithms can be used to determine the most effective response to a disaster based on a range of factors, such as the size of the affected area, the number of people affected, and the availability of resources.

Natural language processing (NLP) can be used to analyze unstructured data sources, such as social media, news articles, and online forums, to identify areas that have been affected by a disaster, to monitor the spread of false information, and to support effective communication and information sharing among response and recovery organizations (Campesato, 2020).

Predictive modeling can be used to forecast the impact of a disaster before it occurs. AI can be used to predict the path of a hurricane or the potential impact of an earthquake on a particular region. This information can be used to prepare for and respond to disasters more effectively (Subramanian et al., 2023).

Predictive maintenance can be used to monitor critical infrastructure, such as power plants and communication networks, to identify potential failures and take proactive measures to prevent or mitigate their impact (Sakurai, Shaw, 2021).

Image and video analysis be used to analyze satellite imagery, drone footage, and other visual data sources to support disaster response and recovery efforts. The algorithms can be used to identify areas that have been affected by a disaster, to assess the extent of damage, and to support search and rescue operations.

Optimization algorithms can be used to optimize the deployment of resources, such as emergency supplies and personnel, to ensure that they are delivered to the areas that need them most. These algorithms can also be used to support logistics and resource allocation during a disaster response.

Early warning systems - AI can be used to develop early warning systems that alert people to the approach of a disaster. AI can be used to analyze data from sensors and other sources to detect the early signs of a landslide, a flash flood, or a tornado.

Decision support systems - AI can be used to support decision-making during a disaster by providing real-time information about the situation on the ground (Sumathi et al., 2022). AI can be used to analyze data from sensors, drones, and other sources to provide up-to-date information about the extent of the disaster, the number of people affected, and the availability of resources.

Risk assessment - AI can be used to assess the risk of a disaster occurring in a particular region (Müller, 2016). AI can be used to analyze data about past disasters, as well as data about factors such as weather patterns, geology, and infrastructure, to identify areas that are at high risk of future disasters (Roberts, Tonna, 2022; Tamboli, 2019).

Post-disaster analysis - AI can be used to analyze data after a disaster has occurred to identify patterns, determine causes, and support recovery efforts. AI can be used to analyze satellite imagery and other data to identify areas that have been affected by a disaster and to support damage assessment efforts.

Robotics - AI algorithms can be used to control robots and drones that can be deployed in disaster zones to provide real-time information and support the response effort. Robots and drones can be used to inspect damaged buildings, assess damage, and transport supplies.

The specific algorithms used may depend on the type of disaster, the data and resources available, and the goals and objectives of the response and recovery effort. It should be noted that these AI methods and algorithms are not mutually exclusive, and that they can be combined and integrated in various ways to support disaster response and recovery efforts.

4. ARTIFICIAL INTELLIGENCE LIMITATIONS FOR DISASTER RISK MANAGEMENT

Although AI is advanced enough to help manage natural disaster risk, its limitations prevent its widespread application in real world. To reduce AI limitations, it is necessary to: employment of experienced researchers and technical experts; collect good quality data for training the AI-powered applications; conducting multiple trainings with the data and adaptation of the obtained results, etc.

There is still much research to be done in order to fully leverage the potential of AI in disaster risk management. Some of the key challenges and limitations could include:

Data quality and quantity - One of the biggest challenges in applying AI to disasters risk management is the quality and quantity of available data. In many disaster scenarios data can be scarce, unreliable or inconsistent, which can make it difficult to train AI models and to make accurate predictions (Özyer, Bakshi, Alhajj, 2019).

Privacy and security - The use of AI in disaster risk management often involves processing large amounts of personal data, which raises privacy and security concerns (Douglass et al., 2023). It is crucial to ensure that the data is securely stored and processed in accordance with privacy regulations and that the rights of individuals are protected (Gerunov, 2023; Montasari, 2022).

https://doi.org/10.5194/isprs-archives-XLVIII-M-1-2023-387-2023

Computational resources - Applying AI to disasters can require significant computational resources, especially for complex models such as deep learning algorithms (Akerkar, 2020). In some disaster scenarios, such as in remote or isolated areas, there may not be adequate computational resources available to support AI-based solutions.

Integration with existing systems - AI solutions for disasters must be able to integrate with existing systems, such as command and control centers, emergency response networks, and sensor networks (Wang, Moriarty, 2018). This can be challenging, especially when dealing with heterogeneous systems and data formats.

Real-time performance - real-time performance is critical in many disaster scenarios. AI-based solutions must be able to process and analyze large amounts of data in real-time in order to support decision-making and to provide real-time situation awareness.

Explainability and transparency - AI-based solutions must be transparent and explainable, especially in high-stakes scenarios such as disasters (Masakowski, 2022). Decision-makers must understand the decisions made by AI models and the reasoning behind those decisions.

Bias and fairness - AI models can perpetuate biases and unfairness if the data used to train them is biased or if the algorithms are designed to perpetuate certain biases. This can be especially problematic in disaster scenarios, where decisions made by AI models can have ambiguous consequences.

Responsibility and accountability - The deployment of AI in disaster scenarios can raise questions about the responsible and accountable persons for the decisions made by AI algorithms. It's essential to establish clear rules of responsibility and accountability for AI decision-making in disaster scenarios.

Transparency - The deployment of AI in disaster scenarios can raise questions about the transparency and interpretability of AI algorithms. Hence, it is essential to ensure that AI algorithms are transparent and their decision-making processes can be understood and scrutinized.

Ethical and legal considerations - AI solutions for disaster management must be designed and deployed in an ethical and legally compliant manner, which should include considerations such as privacy, data protection, and liability.

Lack of human interaction - AI algorithms can lack the human interaction and intuition that is often necessary in disaster scenarios, especially in complex and unpredictable situations.

Limited adaptability - AI algorithms may not be able to adapt to new and unexpected scenarios, especially in rapidly evolving disaster situations.

Algorithm specificity - AI algorithms may be designed for specific types of disasters or scenarios and may not be applicable to other types of disasters.

Overreliance on technology - Overreliance on AI technology can lead to a decrease in human decision-making skills and a lack of situational awareness (Forney, Sadar, 2021).

Cost - Implementing AI-based solutions for disasters can be expensive, especially for developing countries that may lack the resources and infrastructure to support such solutions.

Technical expertise - Developing and deploying AI-based solutions for disasters requires a high level of technical expertise, which may not be readily available in many disaster-affected areas (Forsyth, 2019).

Despite these challenges, there is a growing consensus among experts in the field that AI has the potential to significantly improve disaster response and recovery efforts. By leveraging AI algorithms to process and analyze large and complex datasets, organizations and governments can make more informed decisions, allocate resources more effectively, and respond to disasters more quickly and efficiently.

In the future, AI is expected to play an increasingly important role in disaster management and response. Some of the key trends in the use of AI in disasters include:

Improved prediction and early warning systems - AI algorithms can be used to analyze large amounts of data from a variety of sources, including weather patterns, satellite imagery, and social media, to make more accurate predictions about natural disasters, such as hurricanes, earthquakes, and tsunamis (Prakash et al., 2021).

Automated damage assessment - AI algorithms can be used to analyze satellite imagery and other data sources to quickly assess the extent of damage caused by a disaster and prioritize response efforts.

Integration with IoT and 5G technology - AI algorithms can be integrated with IoT devices and 5G networks to provide real-time information and facilitate rapid response in disaster scenarios (Hussain, Sheng, Peng, 2022).

Increased use of unmanned aerial vehicles (UAVs) - AI algorithms can be integrated with UAVs to quickly assess damage and prioritize response efforts, as well as to deliver supplies and aid to affected communities (Koubaa, Azar, 2021; Yamagata, 2020).

Personalized and targeted response - AI algorithms can be used to analyze data from a variety of sources to personalize and target disaster response efforts based on the specific needs and vulnerabilities of affected communities.

Improved resource allocation - AI algorithms can be used to analyze data on resource needs, supply chain disruptions, and other factors to optimize resource allocation and logistics in disaster scenarios (Pani et al., 2021).

Enhanced collaboration and communication - AI technologies, such as chatbots and voice assistants, can be used to facilitate communication and collaboration between disaster response organizations and affected communities (Saroliya et al., 2023).

Human augmentation - AI can be used to augment the abilities of human responders in disaster scenarios, by providing real-time information, automating critical tasks, and reducing response times (Priyadarshini et al., 2022).

Scalability - The use of AI in disaster risk management needs to be scalable to accommodate different types and sizes of disasters. This requires the development of AI systems that can be easily adapted to different disaster scenarios and that can be deployed quickly and effectively in response to a disaster.

Cost-effectiveness - AI systems for disaster risk management need to be cost-effective as resources for disaster response and recovery efforts are often limited. This requires the development of AI systems that are both efficient and effective in their use of resources, while still providing the necessary information and support to decision-makers.

Evaluation and assessment - The impact and effectiveness of AI systems for disaster risk management need to be regularly evaluated and assessed. This requires the development of appropriate metrics and methods for evaluating the performance of AI systems, and the collection and analysis of data to understand their impact on disaster response and recovery efforts.

Public awareness and acceptance - there is a need to increase public awareness and acceptance of AI in disaster risk management. This requires effective communication and education strategies to build trust in AI systems and to ensure that they are used in ways that are ethical, responsible, and in the best interest of disaster-affected communities.

5. CONCLUSIONS

The use of AI holds promise in helping avert, mitigate and manage natural disaster risks by analysing large pools of data. However, more efforts are required to ensure that AI technologies are deployed in a responsible manner. All interested institutions to make informed decisions on natural disaster risk reduction can successfully use the proposed analysis of AI application challenges. Despite these challenges, the benefits of AI in disaster risk management are too great to ignore. Investment in research, innovation, and collaboration among stakeholders will be necessary to overcome the challenges and unleash the full potential of AI in disaster risk management. By addressing these challenges, AI has the potential to transform disaster risk management, improving the speed and accuracy of disaster prediction, enhancing early warning systems, and facilitating more effective response and recovery efforts.

ACKNOWLEDGEMENT

The first author has been financially supported by National Science Fund of Bulgaria under the Grant №KP-06-H55/5 from 15.11.2021, titled "Smart risk management for business from adverse events and natural disasters". The second author has been financially supported by the Science fund of the University of National and World Economy, Sofia, Bulgaria under the Grant № NID NI 1/2021 titled "Development and use of artificial intelligence in education and economy".

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