

St. Cloud State University

## The Repository at St. Cloud State

---

Culminating Projects in Criminal Justice

Department of Criminal Justice

---

5-2024

### Artificial Intelligence in Disaster Management: Effectiveness and Challenges

Arwa Numan

Follow this and additional works at: [https://repository.stcloudstate.edu/cjs\\_etds](https://repository.stcloudstate.edu/cjs_etds)

---

#### Recommended Citation

Numan, Arwa, "Artificial Intelligence in Disaster Management: Effectiveness and Challenges" (2024).  
*Culminating Projects in Criminal Justice*. 26.  
[https://repository.stcloudstate.edu/cjs\\_etds/26](https://repository.stcloudstate.edu/cjs_etds/26)

This Starred Paper is brought to you for free and open access by the Department of Criminal Justice at The Repository at St. Cloud State. It has been accepted for inclusion in Culminating Projects in Criminal Justice by an authorized administrator of The Repository at St. Cloud State. For more information, please contact [tdsteman@stcloudstate.edu](mailto:tdsteman@stcloudstate.edu).

**Artificial Intelligence in Disaster Management:  
Effectiveness and Challenges**

by

Arwa Numan

A Starred Paper

Submitted to the Faculty of

St. Cloud State University

in Partial Fulfillment of the Requirements

for the Degree of

Master of Science

in Criminal Justice

May, 2024.

Starred Paper Committee:

Douglas Gilbertson

Dick Andzenge

Thea Baker

## Abstract

Based on peer-reviewed research, Artificial Intelligence (A.I.) and cloud-based collaborative platforms gather data in disaster response to present specific plans according to the complexities of emergencies (Gupta et al., 2022). The (RF) algorithm finds the elements influencing household evacuation preparation time (Rahman et al., 2021). A.I. and the cloud-based platform through (Crowdsourcing) coordinate humanitarian needs (Gupta et al., 2022). A.I. and cloud-based systems present the necessary information to emergency responders; the method also effectively assigns resources to respond (Gupta et al., 2022). Geo-AI disaster response makes precise information accessible to disaster responders by presenting accurate mapping analysis (Demertzis et al., 2021). A state-of-the-art deep-learning approach detects changes in satellite images for efficient response (Sublime & Kalinicheva, 2019). AGRA (A.I.), an augmented geographic routing approach, improves routing problems (Chemodanov et al., 2019). Early warning facilitates affected people's evacuation in disasters by applying the AI SVM to analyze the available data to make decisions with either (flood or no flood) for monitoring rooms (Al Qundus et al., 2022). A flood forecasting method that combines artificial neural networks (ANNs) and an Internet (IoT), as well as an ANN based on AI/Machine Learning (ML), works for an early flood warning system. Protecting vulnerable people from flood disasters by the integrated systems of artificial intelligence (A.I.) and machine learning (ML), Geographic Information System (GIS) with unmanned aerial vehicle (UAV) methods, and path-planning techniques for finding the safest evacuation route during a disaster (Munawar et al., 2022). A.I. with UNOSATs for advanced analysis of maps of the areas affected by disasters for early warning (Fusing AI into Satellite, 2021). Based on an online survey, different factors influence public perception of applying A.I. in disasters. Guidelines are presented for A.I. system users to ensure the system's responsibility. (Yigitcanlar et al., 2021).

*Keywords:* artificial intelligence (AI), Artificial neural network (ANN), Machine learning (ML), Unmanned aerial vehicle (UAV), Support vector machine (SVM), Internet of Things (IoT), Geographic information system (GIS), disasters, floods, evacuation, AGRA, Crowdsourcing, Random forest (RF).

## Table of Contents

	Page
Table of Contents .....	3
Chapter	
I. Introduction .....	5
Research Statements .....	5
Key Concepts & Terminology .....	7
Technology Terms & Definition .....	7
Non-Technology Terms & Definition .....	9
Research Design .....	9
Research Objectives .....	9
II. Chapter II: AI in Different Phases of an Emergency Response.....	11
Readiness .....	11
A.I. and cloud-based collaborative platform applications .....	11
(RF) algorithm .....	11
Second Phase .....	12
A.I. and Cloud-based collaborative platforms .....	12
M-A/DCESN, a Geo-AI disaster response .....	13
Third Phase .....	14
A state-of-the-art deep-learning approach .....	14
AGRA (A.I.)-augmented geographic routing approach .....	15
A.I. in Flood Responses .....	15
Flood prediction .....	16

	4
The A.I. model SVM .....	16
(ANN) and an Internet-on-thing (IoT).....	17
Flood Evacuation .....	18
Flood Mapping.....	19
III. Challenges and Opportunities in Applying	
AI for Disaster Management.....	20
Public perceptions of using A.I.....	20
Guidelines for responsible A.I. ....	21
IV. Conclusion & Recommendations .....	23
Study Summary .....	23
Proposed Answers & Actions .....	24
Social & Policy Impact .....	24
References .....	26

## **Chapter I: Introduction**

A disaster causes many casualties and economic loss; for example, in 2022, the U.S. went through 18 natural disasters, costing an estimated 1 billion dollars and causing at least 474 deaths (Smith, 2023). Therefore, disasters become a challenge that all rescue and support services face. When a disaster occurs, emergency decision-makers must make numerous critical decisions quickly and efficiently in an uncertain environment, such as detecting the right location to rescue and evacuate people, vehicles, and sorting stations, as well as decisions on providing first aid kits. Also, they need to arrange human resources to support rescue services. Thus, tools that will be used for disaster response mechanisms should be capable of being in line with these demands, such as being able to gather information instantly and providing real-time mapping of the affected area that can assess situations before and after a disaster (Demertzis et al., 2021).

### **Research Statements**

The study explores artificial intelligence (A.I.) in disaster management. According to Coursera Staff (2023), A.I. refers to a computer system built to do complex tasks that only used to be executed by humans in the past, such as reasoning, making decisions, or resolving problems. With its numerous advantages, this innovative technology can assist disaster response teams in making better decisions related to disasters despite the challenges. This paper explores the significant role of artificial intelligence (A.I.) in all disaster response phases, the challenges of applying A.I., and ways to overcome it.

The paper studies A.I. and cloud-based collaborative platforms that gather data in disaster response to present specific plans according to the complexities of emergencies for fast execution and recovery (Gupta et al., 2022). Besides, the paper touches on the role of the random forest (RF) algorithm in finding the elements influencing household evacuation preparation time

(Rahman et al., 2021). In addition, the role of A.I. and the cloud-based platform through (Crowdsourcing) for coordinating humanitarian needs is shown (Gupta et al., 2022). Also, the paper investigates the ability of A.I. and cloud-based systems to present the necessary information to emergency responders, in addition to the role of the method in assigning resources to respond to extreme weather, disaster coordination, and setting up business recovery centers (Gupta et al., 2022).

The paper also studies Geo-A.I. disaster response, making precise information accessible to disaster responders by presenting accurate mapping analysis (Demertzis et al., 2021). Furthermore, it introduces a state-of-the-art deep-learning approach to detecting changes in satellite images for timely and efficient response (Sublime & Kalinicheva, 2019). Moreover, AGRA (A.I.), an augmented geographic routing approach, is highlighted to improve geographic routing problems for effective response emergency coordination (Chemodanov et al., 2019).

In addition, the paper addresses the impact of flood disasters and the need for early warning to facilitate affected people's evacuation by applying the AI SVM to analyze the available data to make decisions with either (flood or no flood) for monitoring rooms (Al Qundus et al., 2022) Also, a flood forecasting method that combines artificial neural networks (ANNs) and an Internet (IoT), as well as an ANN based on A.I./Machine Learning (ML) to have an early flood warning system, is presented. The study also delves into protecting vulnerable people from flood disasters by the integrated systems of artificial intelligence (A.I.) and machine learning (ML), Geographic Information System (GIS) with unmanned aerial vehicle (UAV) methods, and path-planning techniques to find the safest evacuation route during a disaster (Munawar et al., 2022). Furthermore, the paper examines using A.I. with UNOSATs for

advanced analysis of the maps of the areas affected by disasters for early warning purposes (Fusing AI into Satellite, 2021)

Based on an online survey, the paper touches on different factors influencing public perception of applying A.I. in disasters and the urgent need to build public support and awareness of the system for a strong application. Besides, the study reveals guidelines for A.I. systems users to ensure the system's responsibility, explanation, ethics, trustworthiness, and frugality. (Yigitcanlar et al., 2021).

## **Key Concepts & Terminology**

### **Technology Terms & Definitions**

**Artificial intelligence (A.I).** A computer system built to do complex tasks that only used to be executed by humans in the past, such as reasoning, making decisions, or resolving problems (Coursera Staff, 2023)

**Crowdsourcing.** A collaborative method that quickly processes large amounts of data for a group of people to achieve a goal. It can assign work, gather information, and predict (Lin et al., 2018).

**Random Forest (RF).** An approach to predict household evacuation preparation time. It focuses on cyclone runs by inserting demographic and behavioral data (Rahman et al., 2021).

**Synthetic Aperture Radar (SAR).** A radar that can penetrate clouds and gather high-resolution data in various weather conditions (Demertzis et al., 2021).

**The M-A/DCESN Geo-AI Disaster Response Computer Vision System.** A system that supports decision-makers in emergency response by helping them understand the conditions of the disaster area. This approach makes the accurate and necessary information accessible to disaster responders through its ability to provide precise analysis of real-time maps during disasters,



including spatial-temporal area comparisons and object recognition, applying SAR materials to record, map, and detect disaster zones (Demertzis et al., 2021).

A State-of-the-art deep-learning. An unsupervised deep neural network that uses basic clustering algorithms to detect changes in satellite images, such as flooded zones and damaged structures (Sublime & Kalinicheva, 2019).

An Augmented Geographic Routing (AGRA). An approach to avoid the problem is constantly exhibited in routing. This approach uses data from satellite imagery and applies deep learning and recovery algorithms to solve geographic routing problems, such as detecting the best path for transferring data (Chemodanov et al., 2019).

The A.I. Model (SVM). The developed support vector machine model analyses the data to make single decisions with either (flood or no flood) (Al Qundus et al., 2022).

Artificial Neural Networks (ANN). Artificial intelligence learning through networks. (Munawar et al., 2022).

Internet On Thing (IoT). Connecting devices to the internet through different technologies.

Machine learning (ML). A type of artificial intelligence (AI) focused on building computer systems that learn from data (Munawar et al., 2022).

Geographic Information System (GIS). A computer system for capturing and processing positions on Earth's surface.

Unmanned Aerial Vehicle (UAV). An aircraft that carries no human pilot or passengers. (Munawar et al., 2022).

Path-Planning Techniques. A system that can find the safest evacuation route to help protect vulnerable people (Munawar et al., 2022)

end-to-end pipeline. The system deals with information flowing from one end to another (Overview of Data Pipeline, 2022)

UNOSAT. United Nations program for satellite imagery analysis.

### **Non-Technology Terms & Definitions**

The Second Phase. (during disasters and extreme weather) aims to reduce casualties and damage by using any possible means to help resolve this quickly (Ruggiero et al., 2021).

Frugal. Accessible and affordable (Yigitcanlar et al., 2021).

### **Research Design**

This paper is based on peer-reviewed research to determine how A.I. can assist disaster response teams in making better disaster-related decisions even with encounters. It investigates the significant role of artificial intelligence (A.I.) in all disaster response phases, the challenges of applying A.I., and ways to overcome them.

Based on an online survey of people of different ages and occupations from residents of three large Australian cities, the paper studies different factors shaping public perception from different categories of applying A.I. in disasters to determine how to build public support and awareness of the system for a strong application. Besides, based on related studies, the study shows guidelines for A.I. system users to ensure the system's responsibility, explanation, ethics, trustworthiness, and frugality (Yigitcanlar et al., 2021).

The research does not delve deeply into how technology mechanisms work in disaster management. It only focuses on using A.I. systems in disaster management, public perception of A.I. applications in disaster management, challenges, and guidelines.

### **Research Objectives**

This paper aims to discover how A.I. can help disaster response teams make better disaster-related decisions despite the challenges. It researches the significant role of artificial intelligence (A.I.) in all disaster phase responses, the challenges of applying A.I., and ways to overcome them. The study delves deeply into flood disasters as the main disaster and the role of A.I. in eliminating these catastrophe casualties and economic loss.

Grounded on an online survey, the paper investigates factors influencing public perception of applying A.I. in disasters to determine how to build public support and awareness of the system for a strong application. Furthermore, the study aims to uncover guidelines for A.I. systems users to guarantee the system's responsibility, explanation, ethics, trustworthiness, and frugality (Yigitcanlar et al., 2021).

## **Chapter II: AI in different phases of an emergency response**

A.I. can play a significant role in different phases of an emergency response to a disaster.

A study by Gupta et al. (2022) explores using cloud platforms and A.I. to help handle the different phases of an emergency, such as extreme weather and disasters.

### **Readiness**

In the pre-disaster phase (Readiness), public systems should be prepared with plans for all different aspects of disaster emergencies, such as extreme weather that has become more frequent in recent years, for an effective response and a strong recovery.

### **A.I. and cloud-based collaborative platform applications**

A.I. and cloud-based collaborative platform applications gather data from various resources and businesses such as local communities, governments, forecasts, observations, sensors, and spatial or non-spatial data from different approaches and perspectives and build on them; the collaborative platform designs actions and plans that are suitable to levels and complexities of emergencies. On the one hand, cloud platforms allow multiple occupants, such as public and private entities, to utilize their storage capacity. At the same time, A.I. expands the ability of cloud platforms to extract and collect needed data in pre-disaster to develop alerts during disasters, perform rescue operations, and distinguish prioritization. Implementing these tasks, A.I. and cloud-based platforms can aid disaster response systems and communities in preparing for disaster by offering an early warning system that can help save more lives through fast execution and recovery (Gupta et al., 2022).

### **(RF) algorithm**

Another A.I. tool used in the first disaster phase is proposed in a study by Rahman et al. (2021), which presents the random forest (RF) algorithm as the first approach for predicting

household evacuation preparation time. The approach focused on cyclone runs by inserting demographic and behavioral data. The approach assesses the variable significance and partial dependence chart to identify factors influencing household evacuation preparation time during disasters, such as age, disabilities, and shelter conditions. The prediction model results can significantly assist emergency response and evacuation planners in developing effective evacuation strategies that account for household evacuation preparation time for future disasters.

### **Second Phase**

The second phase (during disasters and extreme weather) aims to reduce casualties and damage using any possible means to help resolve this quickly (Ruggiero et al., 2021). According to Ruggiero et al. (2021), This period between “the event” and the reconstruction is considered critical after a natural disaster. In this phase, which is often more prolonged than the first phase, evacuation shelters for the first emergency mostly cannot maintain the desired quality of life. This time frequently initiates unpleasant social and psychological impacts. Psychological care often needs to be provided to victims who are suffering the loss of life, home, and social connections and who may be disturbed by the uncertain future because of the catastrophe.

#### **A.I. and cloud-based collaborative platforms**

A.I. and cloud-based collaborative platforms can provide quicker responses in this phase than traditional approaches. The platforms can help plan, analyze, and ease threats in disasters, extreme weather, and emergencies (Gupta et al., 2022). Crowdsourcing is a collaborative method that quickly processes large amounts of data for a group of people to achieve a goal. Using crowdsourcing has improved efficiency. It can assign work, gather information, and predict (Lin et al., 2018). Crowdsourcing through cloud computing algorithms can aid in coordinating basic needs such as health, safety, food, shelter, and clothing (Gupta et al., 2022).

In addition, A.I. and cloud-based systems combine sensor data and images from several resources and present this necessary and precise information to emergency responders through the collaborative platform to establish effective and quick responses. Furthermore, these platforms can effectively assist in assigning public and private resources to respond instantly to extreme weather, disaster coordination, and relief activities. Also, business recovery centers can be set up by applying mapped locations in the platform to facilitate virtual communication among critical decision-makers at different sites (Gupta et al., 2022).

### **M-A/DCESN, Geo-AI disaster response**

Another use for A.I. in the second phase response started to be applied after the Beirut explosion in the port of the Lebanese capital, which was caused by 2,750 tons of stored ammonium nitrate. A massive part of the city was destroyed, with hundreds of people stuck in the rubble of buildings (Demertzis et al., 2021). Aerial observations and satellite images often play an important role in disasters like Beirut, such as Synthetic Aperture Radar (SAR). SAR can penetrate the clouds and gather high-resolution data in different weather conditions and lights. However, this approach can be inadequate due to humans' limited observation ability. This risk reveals the urgent need for advanced computer vision technologies and artificial intelligence (A.I.) assistance (Demertzis et al., 2021). The study by Demertzis et al. (2021) explores and proposes the M-A/DCESN, a Geo-AI disaster response computer vision system. The M-A/DCESN Geo-AI disaster response computer vision system can support decision-makers in emergency response by helping them understand the conditions of the disaster area. This approach makes the accurate and necessary information accessible to disaster responders through its ability to provide precise analysis of real-time maps during disasters, including spatial-temporal area comparisons and object recognition, applying SAR materials to record, map, and

detect disaster zones. The approach presents a meta-learning technique that applies innovative memory to a reservoir computing system so that the model can instantly learn and adapt to new environments. The system employs a Deep Convolutional Echo State Network (DCESN), constructed for sequential data to store needed data from earlier processes using external storage memory while assisting the fast integration of new information without needing to train the network. The proposed system was evaluated, and its ability to detect scenes from remote sensing images in the SpaceNet Multi-Sensor All-Weather Mapping Dataset was shown. The findings prove that the proposed system could work in advanced-level geospatial data analysis processes, such as wide-ranging classification, recognition, and observation of particular patterns (Demertzis et al., 2021). Therefore, with the model's ability to develop a reliable geospatial analysis of affected landscapes, it can support disaster responders in knowing and assessing the disaster situation and the level of damage or changes in disaster areas for better planning, response, and decision-making.

### **Third Phase**

In the third phase (recovery), landslides can leave roads inaccessible after a natural disaster. Emergency medical responders need an adequate damage assessment to assemble resources and provide relief. Emergency teams use mapped data to enhance recovery plans and make disaster response faster and more effective. (Leman, 2018). Also, Applications for disaster incident response create busy amounts of data and need extensive computational resource access.

#### **A state-of-the-art deep-learning approach**

According to Sublime & Kalinicheva (2019), various remote-sensing satellites take pictures of Earth and get instant images from areas hit by a disaster before and after the hits. While applying the manual study of such images is shown to be a complex task that consumes

much time, Sublime & Kalinicheva (2019) proposed artificial intelligence and deep-learning techniques that showed their ability to quickly analyze such images to detect areas where a disaster has damaged and based on it evaluate the area and the level of the damage. A state-of-the-art deep-learning approach is an unsupervised deep neural network that uses basic clustering algorithms to detect changes in satellite images, such as flooded zones and damaged structures. This approach first detects the image differences and then compares the affected regions before and after the disaster damage, making them uncomplicated to process. This system makes precise damage assessments accessible to emergency responders to assist them in developing a recovery plan, assembling resources, and providing relief quickly (Sublime & Kalinicheva, 2019).

#### **AGRA (A.I.)-augmented geographic routing approach**

Applications for disaster incident response create heavy amounts of data and need extensive computational resource access. Routing is the infrastructure management mechanism for such a system (Chemodanov et al., 2019).

Chemodanov et al. (2019) introduced the AGRA (A.I.)-augmented geographic routing approach, evaluated by numerical and event-driven simulations that evidenced its success in avoiding the problem constantly exhibited in routing. This approach uses data from satellite imagery and applies deep learning and recovery algorithms to solve geographic routing problems, such as detecting the best path for transferring data. This approach applies the algorithm to ensure quick and effective data delivery from IoT devices to the central setting for decision-making to help develop effective response emergency coordination without experiencing the common routing problem.

#### **A.I. in Flood Responses**



Floods are the most common and costly natural disasters. According to Al Qundus et al. (2022), between 1980 and 2014, natural disasters, 36% of them were floods, led to nearly 226,200 fatalities and total losses of US\$ 4200 billion, 40% of them were caused by floods. In 2016, 2017, and 2018, the share of floods and mass movements increased to 50%, 47%, and 45%. Experts often classify vulnerable areas to help authorities prepare a response and act and find solutions. One of the tools for flood preparation is early warning. Early warning is beneficial for preparing for floods, as it can give affected populations enough time to evacuate. Climate change and the development of urban areas that do not give substantial priority to sustainable drainage systems for rainwater result in flooding in many parts of the world, leading to the loss of many lives, many injuries, and significant economic costs. It is noteworthy that flood disasters occur continually, even in places where they are well-invested and equipped to be prepared for potential flood disasters. Also, insignificant rainfall can result in flood disasters, so even seasonally dry areas with little rain can also be affected by flood disasters. As a result, the authorities need systems to prevent disaster consequences; artificial intelligence should make it possible (Al Qundus et al., 2022).

## **Flood Prediction**

### **The A.I. model SVM**

The study conducted by Al Qundus et al. (2022) suggests a system to help monitor rooms to effectively respond to flood disasters by receiving accurate data about the likelihood of potential flood disasters and using it as an early warning for the affected population. The system uses a wireless sensor network to detect flood disasters by watching changes in weather conditions and historical information at a given place. The setup gathers information such as air pressure, wind speed, water level, temperature, humidity, and precipitation from various sensors

measuring in different locations. Google API Sea-level presents air pressure and rainfall data. The data that has been collected is transmitted via Long Range Wide Area Network (LoRaWAN). The A.I. model SVM, the developed support vector machine model, analyses the data to make single decisions with either (flood or no flood). Subsequently, the decision, which proved to be 98% accurate, is transferred to a cloud server associated with monitoring rooms that decide to respond to flood disasters.

### **(ANN) and an Internet-on-thing (IoT)**

Another flood prediction system was introduced in a study by Farazmehr & Wu (2023). This new flood forecasting method combines artificial neural networks (ANNs) and an Internet-on-thing (IoT) Based flood monitoring model factors to improve the accuracy and efficiency of flood prediction to help emergency responders prepare and make proper decisions related to flood disasters. This method focuses on the temporal correlation of environmental data for flood prediction analysis by tracking different environmental factors, including temperature, humidity, pressure, rainfall, and river water levels. The system works in two steps. First, IoT was applied to gather the needed data from the sensors and transmit data through Wi-Fi. Then, the system applied an ANN technique for data analysis in flood prediction.

According to Munawar et al. (2022), additional use for ANN in flood prediction is in the Hawkesbury-Nepean Valley, Australia, which is crossed by a more than 470 km long river and over 2.2 million hectares. Flood incidents have affected this region, causing many mortalities, infrastructural losses, and significant economic impacts. In response, the federal and local governments put a serious effort into developing flood risk management plans for proper evacuation strategies for vulnerable communities from different buildings, such as hospitals, schools, childcare facilities, and aged care facilities, during a flood incident. However,

specialized response and evacuation plans for aged care facilities were still found challenging in lowering the number of casualties of flood events in the region, especially in aged care facilities, due to this population's typical features and characteristics. Therefore, a study by Munawar et al. (2022) examines using artificial intelligence (AI) techniques during flood events to decrease flood risks based on the AI/Machine Learning (ML) strategy to have an early flood warning system for a timely decision, enhanced disaster prediction, effective response and overcome the flood risks related with aged care facilities within the Hawkesbury-Nepean region. ANN and Support Vector Machine (SVM), the machine learning algorithms that can be applied for several tasks, including classification and image classification (Support Vector Machine, 2023), have been successfully used in various case studies related to flood prediction. ANN has been trained using data based on water levels at three upstream river locations for rainfall and daily water data collection. This approach can effectively forecast the water levels after 24, 48, and 72 hours. Rainfall and river flow data have trained a Support Vector Machine (SVM) classifier to predict river flow change and peak flow within 48 hours (Munawar et al., 2022). ANN has shown encouraging findings. It has been proven to be faster and more accurate than other tools for flood-related predictions. Also, it only requires one input variable, which makes it a valuable approach for predicting flood-related predictions when information related to the problem is lacking; for example, the ANN system can protect river flows at a specific location in the river reach based on flow at upstream locations only (Munawar et al., 2022).

### **Flood Evacuation**

The previous study also introduces the integration of artificial intelligence (A.I.) and machine learning (ML), Geographic Information System (GIS) with unmanned aerial vehicle (UAV) methods, and path-planning techniques to find the safest evacuation route during a

disaster, particularly when evacuating residents from aged care facilities. Every method performs a specific task in this approach: GIS helps gather and analyze spatial data, such as maps and geographical information, to understand flood areas' geography. AI and ML analyze different factors related to flood events, including flood prediction, while UAVs gather real-time data, such as images and information about the affected areas. Path planning algorithms locate safe and efficient routes to evacuate aged facility residents. This approach in this study was proposed and suggested to increase the speed of disaster response and evacuation efforts to ensure individuals' safety in aged care facilities during flood events and ensure more responsible disaster management to save lives and minimize damage (Munawar et al., 2022).

### **Flood Mapping**

Computing and machine learning present additional automatic methods to reduce the response time to a flood disaster. Creating an end-to-end pipeline that deals with information flowing from one end to another (Overview of Data Pipeline, 2022) can help improve the time specialists need to deliver and process flooded maps. Machine learning algorithms automatically download and process images of flood-prone areas to output disaster maps. When applied by a direct partner, the technique starts to live-stream precise mapping services. Also, the method can automatically start when needed in flood disaster situations. Using UNOSAT's historical flood maps, A.I. technology was trained to find flooded areas in satellite and human map images with high accuracy, exceeding 97% (Fusing AI into Satellite, 2021). Inducing A.I. with UNOSATs helps first responders respond to crises quickly and make adequate decisions to help affected populations by fastening the delivery and processing of the images of flood-prone areas.

### **Chapter III: Challenges and Opportunities in Applying AI for Disaster Management**

Even though A.I. is bringing up so many opportunities in terms of disaster management, studies are stressing the importance of gaining people's trust from different backgrounds in utilizing A.I. in sensitive domains such as disaster response for effective support and collaboration between disaster responders' teams and populations affected by disasters (Kankanamge et al., 2021). Also, more studies highlight the importance of following guidelines when incorporating A.I. in disaster responses, such as equity, ease of use, ethics, reliability, cost-effectiveness, and privacy (Yigitcanlar et al., 2021).

#### **Public perceptions of using A.I.**

Kankanamge et al. (2021) studied public perceptions of using A.I. for disaster management to understand community thoughts on inducing A.I. in sensitive sectors such as disaster management. The study data was collected through an online survey from residents of three large Australian cities. The study revealed several findings. Firstly, the study found that the younger generation positively perceives applying A.I. in disaster response. They believe A.I. is a useful tool for disaster management, such as crowd mapping technology. With these encouraging results, the study recommended creating novel platforms and more channels for younger people to join AI-driven crowdsourcing applications. Secondly, the study has shown that occupations with a technical orientation trusted using A.I. for disaster management. However, what should be considered is that employees in professions such as healthcare and social assistance, information, media, and telecommunication have less trust in A.I. as a tool for disaster management.

So, based on the study, people with different educational levels of occupation and professional types do not have the desired confidence in A.I. in disaster management except for

the young age groups. Therefore, this study highlights the importance of building community trust in using and benefiting from A.I. in disaster management to avoid the lack of community-supporting disaster management decisions that may result from insufficient knowledge about its advantages. In addition, the analysis stresses the relationships between the level of education and community perceptions of using A.I. for disaster management. It concludes that awareness of A.I. technology in disaster management is necessary for the public to strengthen community trust in A.I. to manage disasters. Support and collaboration of people who see A.I. as a potential tool in disaster management can help the response team successfully apply A.I. in disaster response (Kankanamge et al., 2021).

### **Guidelines for responsible A.I.**

Local governments need clear guidelines for responsible A.I. practices to build people's trust and awareness of AI. Yigitcanlar et al. (2021) study aims to increase awareness of responsible AI uses by developing AI operating guidelines for all public organizations, including public safety. The study indicates that operating A.I. in local government systems should include the following characteristics: being explicable, ethical, trustworthy, and frugal.

First, the success of A.I. systems involves a machine's ability to describe its program to human users. The users must be able to understand the A.I. operator to trust it. Explainable AI (XAI), a technique that interprets A.I. decisions for humans, must be applied (Yigitcanlar et al., 2021)

Second, the system should ensure socially desirable A.I. consequences by avoiding the unethical outcomes of A.I. systems. The system should be able to prevent the misuse and underuse of these technologies. While A.I. technology benefits communities and government simultaneously, it poses risks, such as algorithmic bias caused by a lack of data and proper

training, privacy violations, separating human responsibility, and lack of transparency. The study indicates that the public is uncertain about many A.I. decisions and is traumatized by A.I. systematic racism in the US (Yigitcanlar et al., 2021). Tian et al. (2021) found that developing a new A.I. system to eliminate bias is necessary after many A.I. applications develop social bias, such as classifying non-white faces as non-human or animals because of the training data applied. In addition, while there is insufficient understanding of the mechanism, no serious plans exist to resolve the bias. To avoid these risks and gain public trust, A.I. must implement the most active ways to avoid the risk and be trustworthy.

Fourth, A.I. systems should be frugal, making A.I. systems accessible and affordable. AI systems are considered a significant investment for local governments. However, many of these organizations have a duty of rationalizing the investments in the cost of A.I. implementation for taxpayers; therefore, A.I. technology implementation should use scarce resources, including time, workforce, and energy, without risking the delivery of high-value outputs to ensure gaining public support and effective implementation (Yigitcanlar et al., 2021).

## Chapter IV: Conclusions & Recommendations

### Study Summary

While emergency decision-makers must make critical decisions quickly and efficiently in an uncertain environment when a disaster occurs (Demertzis et al., 2021), Artificial intelligence (A.I.) has shown its significance in current disaster response in all disaster phases when responding to the critical needs of disasters.

The A.I. and cloud-based collaborative platforms present specific actions and plans corresponding to the difficulty level in emergencies for fast execution and recovery. AI and the cloud-based platform (Crowdsourcing) assist in coordinating humanitarian needs in the second phase of disasters. A.I. and cloud-based systems present the necessary information to emergency responders by combining sensor data and images from several resources; they also help allocate resources to respond to extreme weather, coordinate disaster coordination, and sign business recovery centers (Gupta et al., 2022). Also, (RF) has efficiently identified the factors shaping household evacuation preparation time for fast evacuation (Rahman et al., 2021). Moreover, Geo-AI disaster response provides necessary data to disaster responders by providing precise mapping analysis (Demertzis et al., 2021). A state-of-the-art deep-learning approach identifies changes in satellite images to affected areas for timely and effective response (Sublime & Kalinicheva, 2019). In addition, AGRA (A.I.) is an augmented geographic routing approach that can fix geographic routing problems for improved emergency coordination (Chemodanov et al., 2019).

In flooding disasters that cause many losses, the A.I. SVM analyses the data to decide whether there is a flood or no flood for monitoring rooms to use as an early warning (Al Qundus et al., 2022). Also, a flood forecasting method of artificial neural networks (ANNs) and an



Internet (IoT), as well as an ANN based on AI/Machine Learning (ML), works together to develop an early flood warning system. During flood disasters, integrated systems of artificial intelligence (AI) and machine learning (ML), Geographic Information Systems (GIS) with unmanned aerial vehicle (UAV) methods, and path-planning techniques can find the safest evacuation route to help protect vulnerable people (Munawar et al., 2022). A.I. with UNOSATs can analyze the map of the areas affected by disasters for early warning purposes (Fusing AI into Satellite, 2021)

An online survey indicates that different factors, such as age and level of education, influence public perception of applying A.I. in disasters. There is an urgent need to build public support and awareness of the system for an effective application (Kankanamge et al., 2021). Also, the paper researched guidelines that were proposed to ensure AI applications' responsibility, explanation, ethics, trustworthiness, and frugality (Yigitcanlar et al., 2021).

### **Proposed Answers & Actions**

A.I. has a major role in improving disaster response efficiency. However, more studies are needed to improve the effectiveness of A.I. technology in disaster response, especially in the pre-disaster phase, to prevent disaster damage before the disaster starts for safer communities with fewer casualties and less economic loss.

Also, clearer guidelines for local government and private agencies and authoritarian Sanctions for Violation acts are needed to ensure active obedience to the guidelines and responsible A.I applications.

### **Social & Policy Impact**

Due to fast climate changes, disasters such as earthquakes, floods, pandemics, and droughts occur repeatedly today. These events threaten millions of lives, infrastructure,

agriculture, and the economic system. The loss of lives occurs primarily due to insufficient and delayed information distribution, proper resource allocation, and risk minimization. A.I. can help improve disaster response and eliminate loss of lives and economic damage (Gupta et al., (2022).

People with different educational levels of occupation and professional types do not have the needed confidence in AI in disaster management, excluding the young age groups.

Awareness of A.I. technology in disaster management is necessary for the public to increase community trust in A.I. to manage disasters. Support of people who see A.I. as a possible tool in disaster management can aid the response team in successfully applying A.I. in disaster response (Kankanamge et al., 2021).

Also, clear guidelines for A.I use are needed to ensure A.I applications' responsibility, explanation, ethics, trustworthiness, and frugality (Yigitcanlar et al., 2021).

## References

- Al Qundus, J., Dabbour, K., Gupta, S., Meissonier, R., & Paschke, A. (2022). Wireless sensor network for AI-based flood disaster detection. *Annals of Operations Research*, 319(1), 697–719. <https://doi.org/10.1007/s10479-020-03754-x>
- Chemodanov, D., Esposito, F., Sukhov, A., Calyam, P., Trinh, H., & Oraibi, Z. (2019). AGRA: AI-augmented geographic routing approach for IoT-based incident-supporting applications. *Future Generation Computer Systems*, 92, 1051–1065. [DOI: 10.1016/j.future.2017.08.009]
- Coursera Staff. (2023, November 29). *What Is Artificial Intelligence? Definition, Uses, and Types*. Coursera. <https://www.coursera.org/articles/what-is-artificial-intelligence>
- Demertzis, K., Iliadis, L., & Pimenidis, E. (2021). Geo-AI to aid disaster response by memory-augmented deep reservoir computing. *Integrated Computer-Aided Engineering*, 28(4), 383–398. <https://doi.org/10.3233/ICA-210657>
- Farazmehr, S., & Wu, Y. (2023). Locating and deploying essential goods and equipment in disasters using AI-enabled approaches: *A systematic literature review*. *Progress in Disaster Science*, 19, 100292-. <https://doi.org/10.1016/j.pdisas.2023.100292>
- Fusing AI into Satellite Image Analysis to Inform Rapid Response to Floods*. (2021, April 13). UNITER. <https://unitar.org/about/news-stories/news/fusing-ai-satellite-image-analysis-inform-rapid-response-floods>.
- Gupta, S., Modgil, S., Kumar, A., Sivarajah, U., & Irani, Z. (2022). Artificial intelligence and cloud-based Collaborative Platforms for Managing Disaster, extreme weather and emergency operations. *International Journal of Production Economics*, 254, 108642-. <https://doi.org/10.1016/j.ijpe.2022.108642>

- Kankanamge, N., Yigitcanlar, T., & Goonetilleke, A. (2021). Public perceptions on artificial intelligence-driven disaster management: Evidence from Sydney, Melbourne, and Brisbane. *Telematics and Informatics*, *65*, 101729-.  
<https://doi.org/10.1016/j.tele.2021.101729>
- Leman, J. (2018, July 6). *Updating maps swiftly after natural disasters*. Inside Science.  
<https://www.insidescience.org/news/updating-maps-swiftly-after-natural>
- Lin, W.-Y., Wu, T.-H., Tsai, M.-H., Hsu, W.-C., Chou, Y.-T., & Kang, S.-C. (2018). Filtering disaster responses using crowdsourcing. *Automation in Construction*, *91*, 182–192.  
<https://doi.org/10.1016/j.autcon.2018.03.016>
- Munawar, H. S., Mojtahedi, M., Hammad, A. W. A., Ostwald, M. J., & Waller, S. T. (2022). An AI/ML-Based Strategy for Disaster Response and Evacuation of Victims in Aged Care Facilities in the Hawkesbury-Nepean Valley: A Perspective. *Buildings (Basel)*, *12*(1), 80.  
<https://doi.org/10.3390/buildings12010080>
- Overview of Data Pipeline*. (2022, July 7). GeeksforGeeks. Retrieved February 20, 2024, from  
<https://www.geeksforgeeks.org/overview-of-data-pipeline>
- Rahman, M. A., Hokugo, A., & Ohtsu, N. (2021). Household evacuation preparation time during a cyclone: Random Forest algorithm and variable degree analysis. *Progress in Disaster Science*, *12*, 100209-. <https://doi.org/10.1016/j.pdisas.2021.100209>
- Ruggiero, R., Kobayashi, H., Cognoli, R., & Kaito, S. (2021). Digital innovation for the post-earthquake “second emergency phase” (SEP). Research experience in Central Italy. *International Journal of Disaster Risk Reduction*, *61*, 102293-.  
<https://doi.org/10.1016/j.ijdrr.2021.102293>

- Smith, A. B. (2023, January 10). *2022 U.S. billion-dollar weather and climate disasters in historical context*. Climate.gov. <https://www.climate.gov/news-features/blogs/beyond-data/2022-us-billion-dollar-weather-and-climate-disasters-historical>
- Sublime, J., & Kalinicheva, E. (2019). Automatic Post-Disaster Damage Mapping Using Deep-Learning Techniques for Change Detection: Case Study of the Tohoku Tsunami. *Remote Sensing*, *11*, 1123.  
<https://www.semanticscholar.org/reader/592a91282b1351b865b5abee0cf0e350d80f6f95>
- Support Vector Machine (SVM) Algorithm*. (2023, June 10). GeeksforGeeks. Retrieved February 20, 2024, from <https://www.geeksforgeeks.org/support-vector-machine-algorithm>
- Tian, J., Xie, H., Hu, S., & Liu, J. (2021). Multidimensional Face Representation in a Deep Convolutional Neural Network Reveals the Mechanism Underlying AI Racism. *Frontiers in Computational Neuroscience*, *15*, 620281–620281.  
<https://doi.org/10.3389/fncom.2021.620281>
- Yigitcanlar, T., Corchado, J. M., Mehmood, R., Li, R. Y. M., Mossberger, K., & Desouza, K. C. (2021). Responsible urban innovation with local government artificial intelligence (AI): A conceptual framework and research agenda. *Journal of Open Innovation*, *7*(1), 1–16.  
<https://doi.org/10.3390/joitmc7010071>