AI System for Disaster Impact Analysis

use

Section 1 Information on the System's Use and Teams

1.1 **System's Use.**

content generated by FillGen

Purpose. Assessing damage after natural disasters.
Capability. Disaster impact analysis.
Domain. Essential private services and public services and benefits.
AI User. Emergency services.
AI Subject. Disaster victims.

1.2 **Components.** The system consists of three machine learning modules for (1) image recognition, (2) temporal analysis and (3) anomaly detection. The image recognition module (1) utilizes Convolutional Neural Networks to identify and classify various elements in satellite images, such as damaged buildings, flooded areas, or blocked roads. The temporal analysis module (2) utilizes Recurrent Neural Networks and Long Short-Term Memory networks to analyze sequential satellite images over time to detect changes and trends, essential for understanding the progression of damage or recovery. The anomaly detection module (3) identifies unusual patterns or severe damages that might not be immediately apparent on satellite images.The system relies on external providers for satellite imagery. All satellite images, processed data, and model outputs are stored in third-party cloud-based system for scalability and accessibility.The processed data from ML models are integrated with GIS tools. This allows for mapping of the analyzed data onto geographical locations, providing spatial context and making it easier for emergency services to plan interventions. Emergency services can interact with the system through a specialized dashboard. It displays the analyzed data, offers insights, and allows users to query specific areas or types of damage.The dashboard also includes additional explainability features. The members of the emergency services underwent training and received clear guidelines on how to use the dashboard and interpret the system's output.The system's performance is continuously monitored through automated algorithms and regular manual reviews to ensure accuracy, reliability, and timely updates.

1.3 **Data.** The input data for the system comprises the latest available high-resolution satellite images, including multi-spectral and radar data. This dataset is augmented with historical temporal satellite data to facilitate current assessments and enable temporal comparisons. To prepare for analysis in machine learning models, these images are preprocessed to enhance quality, align for comparison, and normalize for consistent evaluation. For training, the system utilizes a dataset of labeled satellite images from past disasters, fostering supervised learning. To ensure a diverse representation of disaster types and geographical areas, the datasets are augmented. This augmentation includes data merging, which involves overlaying images of damage onto regions that have not experienced these specific disasters, and generating artificial images through algorithms that simulate various disaster scenarios in different geographical settings.
For validation, the system utilizes a separate set of labelled images, not used in training, to fine-tune the model parameters. Meanwhile, the testing data includes a diverse array of unseen satellite images, utilized to evaluate the model's generalizability and accuracy.

1.4 **Evaluation.**

Evaluation at development stage. During the development stage, the system's evaluation centered on enhancing model accuracy and processing efficiency. Comprehensive testing was conducted using a variety of disaster scenarios to assess the performance of the image recognition, temporal analysis, and anomaly detection models. Regular validation was performed to mitigate overfitting and to address technical challenges such as cloud coverage issues in satellite images. Additionally, the system underwent evaluation with end-users from emergency services to ensure its practical applicability and efficiency in real-world scenarios.

Evaluation at deployment stage. During the deployment stage, the system underwent extensive evaluation for its real-time processing capabilities and adaptability in real-world scenarios. Performance was stringently monitored under various environmental conditions to ensure robustness. The system's accuracy was continually adjusted based on real-world data feedback, addressing the challenges of managing large data volumes and ensuring seamless data flow. Crucially, the system was also evaluated in collaboration with end users from emergency services, gathering vital feedback to refine usability and functionality in line with on-ground operational needs. This stage was pivotal in fine-tuning the system for deployment in emergency situations.

Evaluation at use stage. In the operational phase, the system was consistently monitored for latency and downtime to maintain stable performance. Its accuracy was continually enhanced through the integration of new data, preserving relevance and precision. The system's adaptability to new disaster types and integration with existing emergency systems underwent proactive evaluation, confirming its effectiveness in dynamic scenarios. Moreover, the system was continually evaluated with feedback from end users in emergency services..

1.5 **Teams.** The development team, comprising AI experts, data scientists, software engineers, GIS specialists, and disaster management professionals, represented a culturally diverse skill set.

Section 2 Risks

Assessing damage after natural disasters is a critical task that significantly influences the dispatching and prioritization of emergency response services. Given its intended use by emergency services, which are classified as 'Essential private services and public services and benefits' under EU AI Act (Annex III), this system is categorized as high risk due to its direct impact on crucial emergency operations.

2.1 **Capability Risks**

Data Reliance. The system heavily relies on satellite data, and any disruption in data feed (e.g., satellite malfunction or loss of connectivity) could hinder emergency response.

Privacy Concerns. Satellite imagery can inadvertently capture private property or sensitive information, potentially violating privacy rights.

Inaccurate Assessments. If the system produces inaccurate damage assessments, it could lead to inadequate relief efforts or delays in assistance.

2.2 **Human Interaction Risks**

Training and Adoption. Poor training or resistance to adoption of new technology could hinder the system's effectiveness.

Resource Allocation. Uneven distribution of resources based on AI recommendations may leave some areas underserved.

Misinformation. Inaccurate or misinterpreted data could lead to misinformation and unnecessary panic among the general public.

2.3 **Systemic Impact**

Acceleration of Technological Dependence. As societies become more reliant on AI for disaster management, there might be a gradual erosion of traditional skills and knowledge in disaster response and environmental management. This could lead to a reduced capacity for independent decision-making in emergency services.

Environmental Impact of the System's Infrastructure. The extensive computational resources required for processing high-resolution satellite images and running the machine learning modules can have a significant environmental footprint. This includes high energy consumption, which contributes to carbon emissions, and the electronic waste generated from hardware turnovers.

Section 3 Mitigation Strategies

The AI system can become limited risk as per EU AI Act if it is redesigned to serve as a supplementary tool for emergency services, providing additional data and insights rather than making critical decisions on disaster impact analysis. The system should not replace human decision-making in assessing damage after natural disasters, but rather support it with additional data.

3.1 **Mitigations of the Capability Risks**

Data Reliance. Secure access to multiple satellite data sources to reduce reliance on a single provider.

Privacy Concerns. Implement algorithms to automatically blur or anonymize sensitive information in satellite images to protect privacy.

Inaccurate Assessments. Provide clear and transparent information to disaster victims and institutions about the system's capabilities and limitations to manage expectations.

3.2 **Mitigations of the Human Interaction Risks**

Training and Adoption. Ensure that members of the emergency services are adequately trained to use the system. In the future the system will be accompanied by an intensive training program that covers all aspects of the system. It will include hands-on sessions where users can interact with the system under supervision, understand its functionalities, and learn how to interpret the data and results it provides.

Resource Allocation. Combine AI recommendations with on-ground assessments to ensure equitable distribution of resources.

Misinformation. Provide clear, transparent information about the system's capabilities and limitations to the general public.

3.3 **Mitigations of the Systemic Impact**

Acceleration of Technological Dependence. Regularly conduct disaster response exercises without relying on the AI system and engage with local communities and experts who have traditional knowledge and experience in disaster management. This approach helps maintain and enhance the decision-making skills of emergency personnel.

Environmental Impact of the System's Infrastructure. Implement strategies to manage the demand for computational resources. This could involve prioritizing certain tasks and optimizing algorithms for better performance with lower power consumption.

Section 4 Benefits

The system improves emergency response, ensures safety for responders, aids long-term planning, promotes equality, mitigates socioeconomic impacts, and enhances disaster resilience.

4.1 **Human Interaction Benefits**

Improved Safety for Responders. The system enhances the safety of emergency responders. By providing detailed satellite images and analysis, it reduces the need for ground teams to enter potentially dangerous or unstable areas for initial assessments. This not only protects the lives of responders but also allows them to focus on critical tasks without unnecessary risk.

Enhanced Response Efficiency. The system significantly improves the efficiency of emergency response efforts. By quickly analyzing satellite images, it enables emergency services to pinpoint the most severely affected areas and prioritize their response.

Swift assistance. The system supports right to life, liberty, and security (HR Article 3) by providing timely information to prioritize and respond to areas in need, potentially saving lives. Additionally, it aids in upholding right to an adequate standard of living (HR Article 25) by efficiently allocating resources like food, shelter, and medical care to individuals and families affected by natural disasters.

4.2 **Systemic Impact Benefits**

Equality and Universal Access. The system promotes equality (HR Article 1) and ensures social security by the provision of services and information to all individuals, regardless of their status or location (HR Article 22).

Socioeconomic Impact Mitigation. The system contributes to mitigating the socioeconomic impacts of disasters and climate-related events, addressing poverty reduction (Goal 1), improving overall health and well-being (Goal 3) and infrastructure resilience (Goal 9).

Historical Data Comparison. In addition to real-time data, the system leverages historical satellite data for comparative analysis. By comparing current images with past data, emergency services can assess the progression of damage and recovery efforts over time. This historical context is essential for long-term planning and understanding the evolving impact of a disaster.

Disaster Resilience and Climate Change Mitigation. The system's ability to provide accurate and timely data on disaster impacts strengthens early warning systems, risk reduction, and adaptive capacity to climate-related hazards (Goal 13), thereby fostering inclusivity, safety, resilience, and sustainability in cities and human settlements (Goal 11).