Supporting geospatial climate hazard reporting using computer vision and text generation of social media imagery

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Summary

Citizen reports and social media images that capture the aftermath of natural disasters contain important information for emergency responders. Currently, these data sources are not fully integrated into existing systems or require labour-intensive user input, which can be challenging in critical situations. In this paper, we apply computer vision services to publicly available imagery to derive meaningful information, extract objects and create text descriptions. This research builds on our previous work and enhances available hazard maps with (near) real-time weather and traffic information. Through this geospatial-based workflow, we aim to reduce climate hazard reporting friction and support operational response to incidents.

KEYWORDS: social media images, citizen reporting, real-time data, hazard maps, flooding incidents

1. Introduction

When citizens want to report an incident, such as a flood, they can visit the central gov.uk website, from which they are redirected to the website of the respective local authority (Newcastle City Council 2022). These tools often require citizens to register, upload a picture of the incident, describe the incident, and indicate the incident's location on a map. This process can be labour-intensive and yield variable analysis results, as the data accuracy heavily depends on the data provided by citizens. As a result, the stakeholders receiving the report may not have sufficient data, which may cause the incident not to be resolved in the intended manner. In line with the UK government's commitment to levelling up and responding to climate change, incident-relevant location data can help emergency services obtain real-time information and reduce response time (Geospatial Commission 2020). In this study, we aim to reduce the friction in reporting weather-related hazards through a deep-learning-based workflow that helps to detect objects and generate text from publicly available images. The underlying hypothesis is that computer vision can improve current hazard reporting, assist emergency services in their operational response to incidents and help communities recover more quickly.

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2. Background

According to the Intergovernmental Panel on Climate Change (2022), natural hazards are more likely to become more frequent and intense due to the rise in weather and climate extremes, leading to adverse impacts and risks to human and natural systems worldwide (United Nations 2015). To support the UN Sustainable Development Goal 13 to combat climate change and its impacts while improving resilience to natural hazards, we need effective tools for assessing hazard impacts.

With the increasing number of internet-enabled devices and the proliferation of social media posts, we can now enhance our previous work on available hazard maps with (near) real-time weather and dynamic traffic information. While CCTV camera images might show a snapshot from one angle for a specific location at a set angle at a specific time and date, citizens can take pictures from different angles which can, during dynamic events, such as flooding, hold more significant value. These data can capture a wide range of information, as they can show emergency services the current depth level of flooding and impacted infrastructure, for instance, roads, buildings and cars.

Artificial Intelligence (AI) can help in different phases of emergency response: Mitigation, preparedness, response, and recovery (Ali 2022). Computer vision is a field of AI developing algorithms to automatically interpret and understand the content of visual information (Iqbal et al. 2021). We can identify water-related building damage (Kim et al. 2022), classify objects, such as flood and fire, detect people and vehicles in danger (Giannakeris et al. 2018), and automatically generate description based on the objects inside the pictures. The use of automation to minimise human effort has further been explored in other areas, such as healthcare (Rahman et al. 2018). Using computer vision algorithms and cloud computing resources, we can now better leverage existing social media data, while reducing the time and effort required to create incident reports.

3. Methods

In Wolf et al. (2022), we describe the general spatial framework to enhance current existing hazard maps through real-time data from Internet-enabled devices. We use ESRI ArcGIS Pro 2.5 software to model the geospatial database. All data extraction, transformation and analysis steps are performed in the integrated Jupyter Notebook environment using core Python libraries, ArcPy and ArcGIS API for spatial queries. Building on this work, we now deploy Microsoft Azure's Application Programming Interfaces (APIs) to process flood-related images posted on social media and online newspapers (Microsoft 2023). Using Microsoft Azure, we implement the following complementary methodologies (1 & 2) using Python in Jupyter Notebooks:

- **(1) Unsupervised object extraction and classification from social media images related to flooding events:** We use the off-the-shelf Microsoft Azure Cognitive Image API to detect and extract objects from images indicating if urban assets, environmental infrastructure, and people are located in the spatial proximity and could be impacted by the hazards.

- **(2) Unsupervised image description using social media flood-related incidents:** We provide a text description of the image using Microsoft Azure Cognitive Image API.

We convert the final model outputs of the computer vision algorithms to text in a comma separated value (CSV) file. This CSV file containing the image analysis results is then integrated into the existing geospatial data model using ArcGIS Pro 2.5 and visualised in an operational dashboard using ESRI ArcGIS Operations Dashboard. Additionally, the model outputs can be presented in an automatically generated standardised report and shared with emergency services.

4. Results and discussion

This work introduces a case study to demonstrate how we can enhance currently exiting hazard maps and our previous research through integrated social media imagery analysis. Figure 1 provides a snapshot of the analysis results for a publicly available image example during an autumnal flood event on 5 October 2021 in Newcastle upon Tyne (UK):

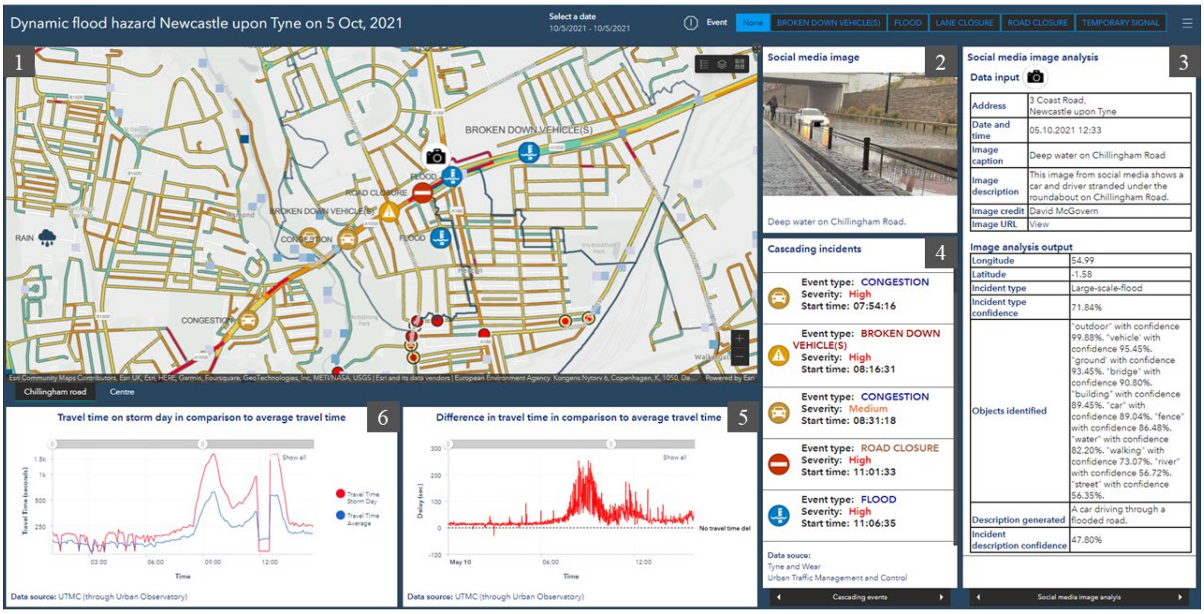

Figure 1: Dynamic hazard map for Newcastle upon Tyne during autumnal storm event (own figure, developed using Esri (2020))

1. Map extract visualises different types of incidents, current traffic flow and real-time hazards for the area around Chillingham Road.
2. Social media image that was uploaded to an online newspaper outlet.
3. Social media image analysis presents the text input and the computer vision generated output based on visual image information.
4. Incident details as recorded by the Urban Traffic Management and Control Centre (UTMC).
5. Travel time on day of the storm in comparison to average travel time (historical four weeks).
6. Difference in travel time on day of storm in comparison to average travel time.

Using the image analysis from the computer vision algorithms, we can derive the following information:

(1) The image shows a flood-related incident.
(2) The location information provided with the image can be geocoded and visualised on the map, adding (near) real-time information to the event-based location analysis.
(3) Detected objects on the image, such as trees, fences, water, and others, can be further assessed to support operational response strategies and provide emergency systems with answers to questions such as these: What environment is impacted?).

The image analysis above demonstrates how we can generate insights from publicly available data using cloud computing resources and integrate AI-based model results into our existing GIS solutions. Further, the algorithms applied help to ensure a standardised analysis of images, which can be further enhanced through more detailed user inputs (such as image captions or descriptions). Thus, we can move towards a more integrated incident reporting approach that can support emergency services.

5. Summary and future steps

Using the outputs from this study, we are able to enhance our existing geospatial hazard map containing (near) real-time location-based information from the Urban Observatory, Environment Agency and UTMC with AI-supported image analysis. This innovative approach helps to reduce friction in the existing reporting process through a third-party application, which requires user input and can result in varying data accuracy. In addition, it provides emergency services with an initial impact assessment about where to allocate resources. In future, we aim to refine our approach to incident impact prioritisation. Based on the information obtained from the images, various prioritised actions can be derived for different stakeholders, including the police and fire departments. Further, pretrained language models can be used to generate structured text descriptions based on keywords and predicted class labels provided by Microsoft's Azure Cognitive Image API.

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Prof. Arnab Nandi is Associate Professor in the Department of Computer Science and Engineering at The Ohio State University. His research focuses on various aspects of human-in-the-loop data infrastructure.

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