Hydrogeological Risk Analysis Using Computer Vision Techniques

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Abstract
Flood events constitute one of the most serious natural threats, causing significant damage to the environment and endangering human life. In response to this issue, we propose an innovative system for automated video analysis of flood events and classification of criticality levels using computer vision. Our approach is based on the YOLOv8 neural architecture, known for its speed and effectiveness in detecting and classifying objects in complex scenes. The system is capable of classifying 5 levels of criticality, from level zero indicating no criticality to level 5 indicating maximum criticality, allowing rapid and accurate assessment of the situation. Experimental results were conducted by considering two real scenarios. The accuracy performance obtained on the 5 criticality classes averaged 98.02%. This study contributes to the advancement of natural disaster monitoring and prevention technologies by providing an efficient and reliable method to assess hydrogeological risk and protect communities from flooding.

Keywords
Hydrogeological risk, Computer vision, Image analysis, Recognition of critical flood levels

1. Introduction

Hydrogeological risk, combined with climate change and rapid urbanization, poses a significant threat to the entire planet [1, 2]. While climate change is altering hydrometeorological patterns in terms of frequency and irregularity [3, 4, 5, 6, 7, 8], rapid urbanization and inadequate urban planning have increased land vulnerability to hydrological disasters [3, 9, 10, 11, 12, 13]. Moreover, between 2000 and 2012, the European Union recorded an average annual damage of €4.2 billion and estimated that it could increase to €23.5 billion by 2050 [14, 15, 16].

Finding a method to monitor and prevent such disasters therefore becomes essential in order to contain not only human losses, but also environmental damage and economic losses.

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In literature, various studies can be found that estimate rainfall intensity using different types of signals, such as audio, image [17], and radio [18, 19, 20] signals, and artificial intelligence techniques for the detection and classification of rainfall levels.

In addition to these works, further studies focus on the use of techniques based on computer vision, a field of artificial intelligence, that allows meaningful information to be gleaned from digital images and videos and actions to be taken or warnings to be formulated based on that information. High-resolution satellite images and aerial imagery are critical for monitoring changing ground conditions, while computer vision techniques can be used to analyze such images and identify significant changes in landscape features, such as soil erosion, sediment accumulation, or changes in vegetation [21].

In the literature, computer vision applied to hydrogeological disruption has been present for several years; this technology can be used as a means of support through:

- Detecting anomalies: some computer vision-based software allows near real-time flood mapping using images captured by satellites or surveillance cameras.
- Prevention and early warning: image and data analysis can be used to develop forecasting models and early warning systems to alert authorities and local communities to potential imminent hazards related to hydrogeological disruption.
- Emergency management: during hydrogeological disruption events, computer vision can be used to monitor the development of the situation in real time, coordinate rescue operations, and assess the damage caused [22].

In the study conducted in [23], a sensor system, called FloodEye, was introduced for monitoring water level during Catastrophic Water Floods (CWF). This system takes advantage of infrared image processing and is able to accurately monitor, without the need for preconfiguration, the water level rise in various situations, even at night, with a margin of error of 1.9%.

The authors in [24], propose a methodology that uses validation data obtained through the use of computer vision to predict flooding. The computer vision algorithm is used to estimate water levels from images that meet the requirements of the proposed guidelines. The results show that the accuracy of flood forecasting can be greatly improved through the use of additional validation data.

Finally, in [25], a technology was developed that can provide accurate and timely estimates from flood hydrographs based on object-based image analysis (OBIA) and segmentation algorithms. This technology was successfully tested in the laboratory and in real situations during Hurricane Harvey.

The state of the art in flood monitoring and forecasting includes the use of sensory systems such as FloodEye, computer vision and segmentation-based methodology to

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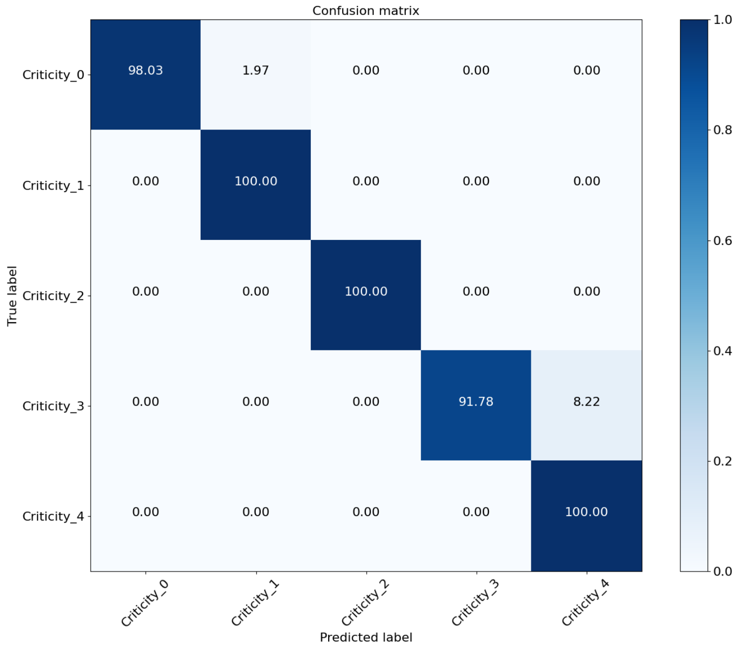

Figure 1: Model confusion matrix containing two scenarios.

improve flood forecasting, and object-based image analysis for accurate estimates of flood hydrographic data.

This, study, on the other hand, proposes the development a system capable of analyzing videos of flood events and classifying them according to different levels of criticality through the use of convolutional neural networks, without performing pre-processing and segmentation.

This paper is structured as follows: Section 2 discusses the methodology used. Then, in Section 3, the results obtained are reviewed and discussed.

2. Proposed method

The paper describes a comprehensive approach for video analysis of flood events by first performing a search for video sources characterizing the event and then selecting suitable sources for neural network training. Next, the methodology for classification of critical water levels is presented, followed by training of the YOLOv8 neural network for identification and classification of flood events according to hazard levels. The study is conducted by considering two flood scenarios.

2.1. Data Collection

First, a vast amount of video documenting flood disasters was collected, involving a diverse selection of sources from various corners of the globe in order to obtain a comprehensive overview of flood events.

Second, a selection was made among the videos to meet certain criteria necessary for proper training of the neural network:

- Timelapse video format: this format, characterized by recording in regular intervals, provides a complete and dynamic view of the evolution of the flood and its impact on the surrounding environment.
- Visibility of the surrounding environment before the onset of flooding: this criterion ensures a clear view of initial conditions, providing a solid reference point for assessing the evolution of events over time.
- Presence of landmarks: these are common objects such as cars, road signs, and other identifiable features that serve as a visual scale to quantify the water level during the weather phenomenon.

The choice therefore fell on two videos, which were divided into a series of frames, each classified with a level of criticality. The dataset used, therefore, for the training and validation phase consists of frames obtained from two different flood videos. This dataset contains 10200 frames, divided into 7100 for the training set and 3300 for the test set. The extracted frames were finally appropriately resized to meet the input size required by the neural network.

2.2. Criticality Classification

The criticality classes were defined based on the height of the water relative to the surroundings, using reference objects found within the different frames as a scaling factor.

The five classes of criticality are as follows:

- Criticality 0 (low): the water level remains within safe limits and poses no threat to infrastructure or public safety.
- Criticality 1 (moderate): the water level is slightly above the safe limit but still manageable. Although road flooding may occur, there is no serious threat to public safety or property preservation.
- Criticality 2 (medium): the water has reached a level that affects the manageability of roads and surrounding areas.
- Criticality 3 (high): water level reaches very high, causing extensive flooding in roads and homes in the affected area, thus threatening public safety.

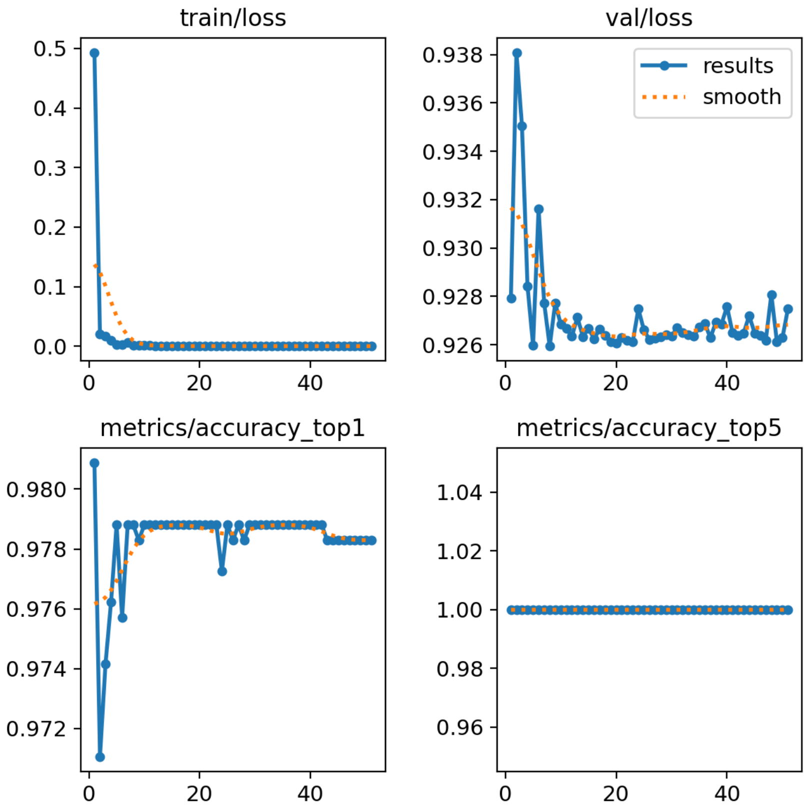

Figure 2: Training and validation loss/accuracy

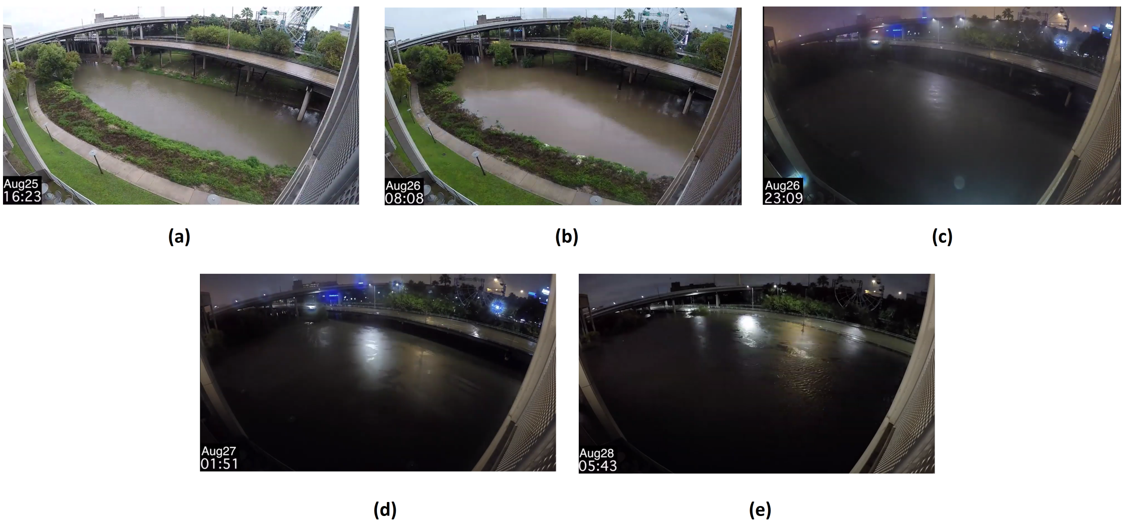

Figure 3: Examples of images belonging to each criticality class - Scenario 1

- Criticality 4 (maximum): the water level is extremely high, significantly endangering property and lives.

Fig. 3 and Fig. 4 show examples of images, for each scenario, belonging to each criticality class.

2.3. Neural network training and testing

YOLO (You Only Look Once) was chosen as the architecture for image classification and model training. YOLO is a particularly effective neural architecture for class and bounding box prediction, widely used for various purposes such as image classification, object detection and pose estimation. The version employed in this study is YOLOv8 [26].

The neural network underwent a supervised training process using the training dataset described earlier, taking special care to ensure a balanced distribution of different criticality stages among frames [27, 28].

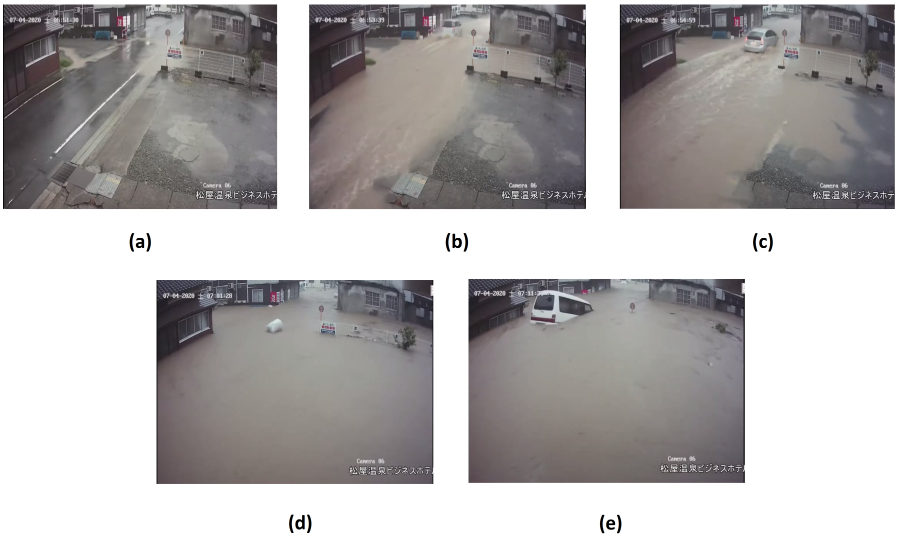

Figure 4: Examples of images belonging to each criticality class - Scenario 2

3. Experimental Results

The neural network model trained with the set of images characterizing the two different flood scenarios demonstrated an excellent ability to recognize the level of criticality independently. In fact, the average accuracy level in classifying the five levels of criticality is 98.02%.

In order to evaluate the performance of the model, it is possible to visualize in Fig. 1 the confusion matrix related to the validation dataset and in Fig. 2 the trends of loss and accuracy for the training and validation phase of the model.

In order to validate the proposed model, videos totally unknown to the neural network were given in inference to the network model because they contained scenarios different from those in the training dataset. As can be seen in Fig. 5 the trained network manages to classify criticality classes well on average even in totally unknown scenarios.

4. Conclusion

This study focused on creating a system capable of analyzing videos of flood events and classifying them according to different levels of criticality using the YOLOv8 neural architecture.

The use of an Artificial Intelligence model proved to be efficient in the assessment of hydrogeological risk, and the results obtained confirm the validity of the approach taken.

The main limitations of this study stem from the training phase of the neural network. It was trained using images related to a few scenarios, which could affect the performance of the network in classifying criticality in other scenarios not present in the training dataset.

To overcome these limitations and further improve the accuracy of the model, future research could extend the study by considering a wider variety of flood scenarios. Integrating data from different sources and incorporating additional information, such as meteorological and topographic data, could help create a more robust and generalizable model. In addition, using active learning techniques could enable the neural network to acquire knowledge from new scenarios, gradually improving its classification capabilities in different and more complex situations.

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(a)

(b)

Figure 5: Examples of classification of frames related to scenarios unknown to the network (a) and (b).

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